Climate change increases bilateral trade cost

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October 21, 2024

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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, possibly driven by the vulnerability of sea ports to climate related adverse weather events. I use a standard international 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 average welfare in the 2010s by 2.6 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 ten percent underestimate of the welfare impact of climate change. The welfare effects I find are consistent in magnitude with recent, larger estimates of the overall 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 decade-to-decade changes in average temperature at the origin and destination countries. I find that climate change significantly raises trade cost. The core identification concern is that countries which see more rapid climate change are different along other dimensions as well, and would have seen trade cost increases even absent climate change. I show that my results are robust to allowing for heterogeneity in trade cost levels and trends based on countries' climate change paths, allaying these identification concerns. I present anecdotal evidence and supporting reduced from results suggesting this could be driven by sea ports being especially vulnerable to climate related adverse weather events.

I embed my estimates in a standard model of international trade (Eaton & Kortum, 2002) to quantify welfare impacts. I find that welfare in the 2010s would have been 2.6 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 ten 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 my reduced form results rely on a simple 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.

Second, I contribute to the debate about the magnitude of the welfare impacts from climate change. Recently, Bilal and Känzig (2024) estimate welfare impacts of climate change through productivity that are an order of magnitude larger than many previous analyses' findings. Using a long time horizon and considerable variation in decade-level average temperatures, I can directly estimate the impact of climate change on trade cost, without having to extrapolate from weather fluctuations to climate change impacts. The welfare impacts I find for these trade cost changes are comparable to the welfare impacts from productivity impacts found in Costinot et al. (2016) and Nath (2020), for example, but are only about ten percent of the total welfare impact estimated in Bilal and Känzig (2024), which combines trade cost and productivity impacts. In workhorse models of international trade, the welfare impacts of trade cost changes (the gains from trade) tend to be small relative to the impacts of productivity changes. The welfare impacts of trade cost changes I find are thus consistent with the overall larger impacts of climate change estimated in Bilal and Känzig (2024).

Finally, 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. This novel channel is important to take into account when modeling 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

This section presents the data sources I use and some descriptive statistics on climate trends in my sample. 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 90 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

This section presents the estimation framework I used for my core reduced form results. 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

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

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_t could capture preferences (Anderson & van Wincoop, 2003) or country (Eaton & Kortum, 2002) or firm productivity dispersion (Melitz, 2003). This varies over time to capture global changes in trade cost. I augment this basic specification by allowing the effect of distance to vary as average temperature changes,

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

T_{ct} is average temperature in country c during period t, and $\Delta T_{ct} \equiv T_{ct} - T_{ct-1}$ is the change from period $t-1$ to period t. This enters in the model 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 ΔT_{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

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

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.

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.

In principle, it would be interesting to think about climate change along the route between origin and destination. That route, however, is unobserved, and even if I observed it, it would be endogenous to climate change. Suppose, for example that extreme weather made the Suez Canal impassable. Shipping operators would then have to divert their route, for example by going around the southern coast of Africa, or they could use multi modal transport, leading to a complicated optimal transport problem. There are only two points along the route which are not endogenous — the origin and destination. There is no way to connect Italy and India, for example, that doesn't start or end in Italy and India. My specification therefore uses the only two non-endogenous points along the route to measure climate change, and the two points where all fixed cost associated with the trade route is accrued, a non-negligible part of the cost of international trade.

Note that, while temperatures are interacted with distance, this specification captures changes in both the fixed and variable costs of trade. 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 distance (and a few other 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 is separated from every other country by a set of bilateral distances. Shipping goods requires bridging those distances, and that is costly. As a country — Germany, for example — experiences climate change, the specification I use can tell whether it becomes more costly for Germany to bridge those distances and send goods abroad. Likewise, it can tell whether it becomes more costly for other countries to bridge that distance and send goods 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.

It is true, however, that the significance and sign of the estimated δ_1 and δ_2 coefficients can convey information about how climate change affects trade cost if it does affect them. If the estimated coefficients are insignificant, I of course cannot conclude that climate change has an impact. If they are significant and negative, for example, this suggests that climate change has a larger impact on trade cost for longer-distance trade. This could provide a starting point for mechanisms behind the effect, as I discuss below.

The core identification concern is that countries which have different climatic environments, and hence see more rapid climate change, might have different trade cost trends for other reasons. They might have different trade cost trends because of their geographic location or sectoral make-up, for example. This would create a spurious correlation between decadal temperature changes and trade flows.

To address this concern, I capture countries' climatic environments in two ways. First, I calculate each country's average temperature between 1950 and 1980, a period of relatively little climate change often used to benchmark average temperatures. I then interact average 1950–1980 temperature deciles with distance, allowing for different levels of trade cost for countries with different baseline climates. I also allow for time trends in trade cost based on temperature decile. That is, I estimate

$$
\begin{aligned}
&\mathbb{E}\left(X_{nit}|\mathbf{D}_{nit}\right) \\
&= \exp\left\{\gamma_{it} + \xi_{nt} + \alpha_t \tilde{d}_{ni} + \left(\sum_{D=2}^{10} \alpha_D \tilde{d}_{ni} + \tau_D t \tilde{d}_{ni}\right) + \delta_1 \tilde{d}_{ni} \Delta T_{it} + \delta_2 \tilde{d}_{ni} \Delta T_{nt} + \mathbf{C}'_{nit} \boldsymbol{\beta}_t \right\} \qquad (3)
\end{aligned}
$$

Here, α_D allows for separate coefficients on distance — separate trade costs — for each decile D of

1950–1980 average temperature, and τ_D allows for separate time trends in the coefficients on distance — separate time trends of trade costs — for each decile D of 1950–1980 average temperature.

Second, I calculate each country's change in average temperature between the 1900s decade and the 2000s decade. That gives me an estimate of the amount of climate change experienced by each country over those 100 years. I then calculate deciles of climate change and estimate (3) using deciles D of the 1900s–2000s climate change. This now allows for different levels and trends for trade cost based on countries' climate change regime. If changes in decadal average temperature have no effect on trade cost, and it is only the case that countries with different climatic environments have different levels and time trends of trade cost, this specification would pick that up and estimate no effect of climate change on trade cost.

Note that this specification is arguably very conservative. It only uses deviations from climate change trends to identify the impact of climate change. Linear time trends in trade cost, even if they are caused by climate change, will be captured in τ_D and discarded. That means estimates from this specification are likely to be a lower bound on the impact of climate change on trade cost.

3 Gravity estimation results

3.1 Impact of climate change on trade cost

This section presents my core reduced form results, based on the estimation framework laid out in the previous section. Table 1 shows the results of estimating(2), the climatic environment robustness checks following (3), and two additional robustness checks as well as a benchmark specification excluding temperature variables. Figure 9 shows a coefficient plot of the coefficients of interest — the coefficients on the interaction between distance and temperature change — across specifications. I estimate all regressions via PPML, using the `R` command `fepois` from the `fixest` package to deal with the high dimensional fixed effects involved (Bergé, 2018). I capture d_{ni} using the great circle distance between the origin and destination countries in kilometers. 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, and show robustness to using the population-weighted distance measure. As temperature measures, I use the decadal mean of the yearly average of daily average temperatures in °C. Decadal temperature changes are winsorized at the 1^{st} and 99^{th} percentiles. Figure 6 shows a histogram of the winsorized decadal temperature changes, highlighting the source of my identifying variation. The additional bilateral controls $\mathbf{C}_{nit}$ contain a common language indicator, contiguity indicator and indicators for current and past colonial relationships. Again, I take decadal means for all variables. Standard errors are clustered by country pair, since that is the unit at which treatment $d_{ni}\delta T_{ct}$, $c \in \{i, n\}$ is assigned. I show p-values in brackets.

The first column shows results for the basic model (2). The second and third column show results for the robustness check specified in (3), allowing the effect of distance — and hence trade cost — to differ by countries' 1950–1980 average temperature decile (column two), and additionally allowing for decile-specific time trends in trade cost (column three). The fourth and fifth column implement a similar robustness check, using deciles of countries' change in temperature between the decade of the 1900s and the decade of the 2000s. The sixth and seventh column show an additional robustness check using deciles of country centroid latitude to capture countries' climatic environment based purely on their geographic location. The eighth column uses the population-weighted great circle distance instead of the unweighted measure. The downside of this weighted measure is that it is not available in TRADHIST for countries which no longer exist, so I lose some observations. Finally, the last column shows a benchmark model excluding temperature variables.

As expected from the gravity literature, I consistently find a negative and significant effect of distance on trade flows. My baseline specification yields that, at zero change in origin and destination temperatures, a one percent increase in distance in the 2010s decreases trade flows by 0.552 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. Figure 7 shows the coefficients on distance across decades, highlighting that there is a slight decrease in trade cost over time. Figure 8 shows a similar figure for the benchmark model excluding temperature variables.

The novel empirical result in this paper is 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 — climate change hence increases trade cost. Using the most conservative specification from column five, allowing for different trade cost levels and trends based on countries' climate change regimes, I find that a one degree increase in temperature at the origin decreases trade flows by a further 0.053 percent. Similarly, a one standard deviation increase in temperature at the destination decreases trade flows by an additional 0.014 percent, though the destination effect is not significant in this most conservative specification. Overall, I thus find that climate change increases trade cost, especially through temperatures at the origin of a given trade relationship.

To put these numbers into perspective, between the 1910s and the 2010s, for example, the average country saw a temperature increase of about 1.3°C. Comparing the estimated impact of temperature from column five with the average impact of distance on trade from column one, over the last 100 years, the average origin country saw the effect of distance on trade flows increase by about 12.5 percent ($\approx (1.3 \times .058)/.552$), and the average destination country saw an increase of about 3.3 percent (calculated analogously). It is important to keep in mind, however, that this trade cost increase applies to every connection a country has to the rest of the world, which could compound the equilibrium effect of these changes. In addition, climate change affects all countries, so all countries simultaneously see their trade costs 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).

3.2 Mechanisms

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 of port efficiency (modeled as port cost in their paper) in particular.

As I mentioned in Section 2, the sign of the estimated coefficients provides suggestive evidence as to which kinds of trade are most affected. A significant and negative coefficient suggests that the impact of climate change is larger for longer-distance trade cost. One salient difference between short and long distance trade is the mode of transportation — longer distance trade by and large uses maritime shipping, rather than land or air freight. Importantly, land freight is relatively decentralized. Producers can load goods onto trucks at their production facility, and trucks can use the entire road network to reach their destination. This means that land based trade is relatively resilient against adverse weather events which affect specific roads or specific production locations, since other roads or production locations can function as substitutes. If climate change increases the frequency and severity of adverse weather, land based trade can benefit from this flexible, decentralized setup. Maritime trade, on the other hand, has to go through sea ports. These tend to be relatively few, and they are especially affected by weather hazards, as I discuss below. It is therefore possible that climate change affects sea ports, which is especially detrimental to the cost of maritime trade. Maritime trade, in turns, tends to be longer distance trade, and this explains why I observe significant and negative coefficients on the distance-temperature change interactions.

Indeed, while we lack research on the impact of climate change on sea port efficiency, policy makers are concerned about this issue. The United Nations Conference on Trade and Development has noted that sea ports 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).

I cannot investigate the impact of climate change on sea port efficiency directly, but I now present some results which are consistent with the idea that climate change especially affects maritime trade cost. First, Table 2 shows results for gravity estimations similar to my main specification (2), but using alternatives to distance to measure bilateral trade cost. The first column uses an indicator which is equal to one if the only connection between the origin and destination is via the ocean. All trade between these country pairs thus has to use maritime shipping. As might be expected, since this sea-only trade indicator is correlated with distance, I find similar patterns to my main results — climate change at the origin, especially, significantly increases the cost of trade for country pairs which are forced to used maritime shipping. The second column of the table instead uses a long distance indicator. This is one if the distance between the origin and destination country is equal to or larger than the median distance between country pairs that have only an ocean-based connection. The pattern I find is similar, but note that the coefficient on the long distance-climate change interaction is now no longer significant. That is, the coefficient on sea-only trade in the first column captures something that this purely distance based indicator misses. This suggests that ocean based trade, rather than generic long distance trade, is driving the results.

To highlight this point a different way, I conduct two sets of 'donut hole' estimations. First, I use the fact that ocean based trade becomes more attractive not only with distance, but also with the number of land borders which would need to be crossed in order to go from the origin to the destination via a land route. This is because border crossings incur fixed costs (Anderson & van Wincoop, 2003). I calculate, for each origin-destination pair, the number of land borders which would have to be crossed to get from one to the other. (For country pairs with no land based connection, the number is infinite, $\text{Land borders}_{ni} = \infty$.) I then estimate regressions similar to my main specification (2), but using an indicator which is zero if the origin and destination are neighbors ($\text{Land borders}_{ni} = 1$) and one if the number of land borders between the origin and destination is at least b ($\text{Land borders}_{ni} \geq b$), for $b = 2, 3, \ldots, 10$. For each estimation, country pairs which are not neighbors, but have fewer than b land borders in between them (i.e., $\text{Land borders}_{ni} \in (1, b)$) are discarded. (These countries are in the donut hole.) I thus compare country pairs with progressively costlier land trade routes (and with progressively more attractive maritime trade routes) to country pairs which are neighbors. If it is true that climate change especially affects ocean based trade, I would expect to see negative coefficients on the interaction between the minimum gap size and origin and destination temperature change. If this is indeed driven by maritime trade being much more attractive once a certain number of land border would need to be crossed, I would further expect these coefficients to remain roughly stable in magnitude as I increase the minimum gap size

b beyond that threshold.

Figure 10 shows the estimated coefficients on the interaction between minimum gap size for each estimation and origin and destination temperatures. When only two land borders would need to be crossed, I do not yet see a difference, but coefficients become progressively more negative and are significant once four land borders would need to be crossed. Note that, though confidence intervals become wider (because larger donut holes mean fewer total observations), coefficients remain fairly stable across larger minimum gap sizes. I thus find that where maritime trade is more attractive relative to land based trade I see a significant increase in trade cost. Consistent with the idea that maritime trade is preferable once a threshold number of borders have to be crossed, this difference becomes more pronounced up to a point, but then stays relatively stable, suggesting I am not picking up some kind of mysterious correlated of distance, but rather a differential impact on maritime as opposed to land based trade.

To again highlight that this is not simply because larger gap sizes mean larger distances, Figure 11 shows results for a similar estimation, but using indicators for the distance between origin and destination being equal to or greater than a given distance decile $d = 2, 3, \ldots, 5$. Here, coefficients again show again only a much noisier version of the sea trade based analysis — I find significant and negative effects for some, but not all comparisons. This suggests that sea based trade picks up a pattern in the data that is correlated with distance, but not purely based on distance.

Ultimately, while I believe this discussion highlights a plausible mechanism behind my main results, I of course cannot directly test the hypothesis that climate change especially affects the cost of maritime trade. As I just discussed, however, this hypothesis is (i) consistent with the coefficient estimates I find in my main results, (ii) consistent with policymakers' concerns regarding the vulnerability of sea ports to climate change, and (iii) consistent with my additional reduced form analyses showing that where maritime shipping is the only option, or a more attractive option based on the political geography of land borders, I clearly see a differential impact on trade cost.

For the remainder of the paper, I nevertheless rely on my main results, which use a distance based parameterization of trade cost, for two reasons. First, I cannot directly assess the full extent to which climate change affects maritime trade cost, since I do not observe trade routes and modes. I have to rely on correlates that make maritime shipping more attractive on a certain route. Second, a distance based specification could pick up additional mechanisms I cannot investigate here. (For example, variable cost, too, might be differentially affected by climate change, depending on fuel cost or personnel availability is affected.) It is therefore more parsimonious than focusing solely on maritime trade.

4 Welfare impacts

This section explores the welfare implications of my reduced form results through the lens of a workhorse model of international trade. 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 decade $s \neq t$. I can do this by plugging temperature changes between decade s and t 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

$$\hat{\phi}_{nit} \equiv \frac{\phi'_{nit}}{\phi_{nit}} \overset{(1)}{=} d_{ni}^{\delta_1(T_{is}-T_{it})+\delta_2(T_{ns}-T_{nt})} \tag{4}$$

Importantly, all non-temperature covariates remain constant — I simply estimate the change in bilateral resistance stemming from the changed temperature variables.

To estimate the changes in bilateral resistance terms, I use the most conservative specification, column five in Table 1, which includes differences in trade cost levels and trends based on countries' climate change decile. Since the coefficient on destination temperature is negative but insignificant in this specification, I additionally make the estimate of the welfare impact more conservative by treating this coefficient as zero.

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 decade t. The counterfactual trade shares π'_{nit} resulting from a change $\hat{\tau}_{nit} \equiv \tau'_{nit}/\tau_{nit}$ are

$$\pi'_{nit} = \frac{\pi_{nit}\hat{A}_{it}(\hat{\tau}_{nit}\hat{w}_{it})^{-\theta}}{\sum_{k=1}^{N}\pi_{kt}\hat{A}_{kt}(\hat{\tau}_{nkt}\hat{w}_{kt})^{-\theta}} \tag{5}$$

Here, $\hat{A}_{it} \equiv A'_{it}/A_{it}$ 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

$$\hat{W}_{it} \equiv \frac{W'_{it}}{W_{it}} = \hat{A}_{it}^{\frac{1}{\theta}}\hat{\pi}_{iit}^{-\frac{1}{\theta}} \tag{6}$$

For now, I focus on the impact of climate change on trade cost only, keeping technology unchanged ($\hat{A}_{it} = 1$). 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 (4). I can then solve the system of equations (5) 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 (6). 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 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 12 shows the population-weighted mean welfare change across decades, as well as the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentile of welfare changes. (Appendix Table 4 shows the same information in table form.)

Looking at the results for the 1910s, I estimate that the average country would see a 2.6 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 similar in size, for example, to the 2.6 percent

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

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). This might seem surprising, since the welfare impact of productivity shocks tends to be larger than the impact of trade cost changes (the gains from trade). I suspect the reason for the difference is that I can estimate the impact of climate change directly, rather than having to go from weather shocks to climate change, as, for example, Nath (2020) has to do. Note that Bilal and Känzig (2024) estimate that a one degree warming scenario results in roughly a 30 percent welfare loss overall. Since they do not explicitly take impacts on trade cost into account, their estimate combined both productivity and trade cost effects. Their 30 percent overall welfare loss is considerably larger than my results from trade cost alone, and their estimate and my results are therefore more consistent with each other.

The welfare impact of trade cost changes tends to be larger when switching to earlier climates, since temperatures are increasing over time and reverting to an earlier period's climate thus results in a larger temperature change. For example, the mean increase for the earliest decade, the 1880s, is estimated to be 2.9 percent, whereas for the 1950s I estimate an average welfare increase of 1.9 percent and for the most recent decade, the 2000s, I estimate an 0.4 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 10.5 percent in the 1880s counterfactual.[2]

Figure 13 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, and south-eastern Asia. What determines who gains more or less from undoing the trade cost impact of climate change? The most obvious factor are climate trends. Figure 14 shows welfare changes in the 1910s counterfactual across countries' own temperature change between period the 1910s and the 2010s. Figure 15 shows welfare changes across the inverse distance weighted change in other countries' change in temperatures, which is calculated as

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

[2] Appendix Figure 23 and Appendix Table 5 show versions of these results without population weights. As I discuss below, larger countries benefit less from trade cost reductions, so the unweighted average welfare changes and percentiles are somewhat higher.

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 be a surprisingly bad predictor of their welfare gains.

These temperature measures are, of course, correlated. Figure 16 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 3 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 only weakly correlated with welfare gains. The second column shows that inverse distance weighted change is (again, somewhat weakly) negatively correlated with countries' own welfare changes.

Column three, however, shows that once I 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 there is a simple explanation. 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 17 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 18 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 3 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 3 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 19 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 2.6 percent is comparable to estimates of the welfare effects of climate change through agricultural and overall productivity (Costinot et al., 2016; Nath, 2020), and about ten percent of the overall impact of climate change under a one degree warming scenario, a welfare loss of 30 percent (Bilal & Känzig, 2024). A different way to assess the effect size is to disentangle the combined welfare effects of climate change estimated in Bilal and Känzig (2024) and split them into a productivity and a trade cost component. I can then compare the combined welfare impact to the welfare effects of productivity or trade cost changes alone. This also shows by how much we underestimate the welfare impacts of climate change when we ignore trade cost effects and only focus on estimating productivity impacts, for example, using firm-level data.

I thus calibrate a counterfactual scenario that un-does the overall 30 percent welfare loss from climate change under a one degree warming scenario estimated in Bilal and Känzig (2024). That is, this counterfactual raises average welfare by about 43 percent ($\approx 1/(1-0.3\%)$).[3] I use the

[3] I rely here on the Bilal and Känzig (2024) estimate looking only at productivity differences. Since they do not differentiate between productivity and trade cost impacts, their estimate combines the two effects. Note that they estimate an even larger impact of climate change when we take capital adjustments into account. Even including rented capital in a trade model can change the implications of climate change and related policy recommendations (Huppertz, 2024). Here, however, I abstract from capital and so use the productivity-only results from Bilal and Känzig (2024) as a benchmark. Again, because they do not take trade cost changes into account, these productivity-only results actually combine both productivity and trade cost impacts.

1910s counterfactual as the reference period, since average temperature changes since then have been about 1.3°C, which is relatively close to the one degree results in Bilal and Känzig (2024). I calibrate this counterfactual by first un-doing the impact of climate change on trade cost. This results in a 2.6 percent welfare gain, which is short of the overall 43 percent impact I am targeting. I then pick a common change in technology $\hat{A}_{it} = \hat{A}_t$ for all i which results in the targeted welfare gain, again using (5) to solve for wage changes and calculating welfare changes from (6). 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 or trade cost effects alone.

Figure 20 shows average welfare gains across the trade cost, productivity, and combined counterfactuals for the 1910s climate counterfactual.[4] I break these up by small (below median 2010s GDP) and large countries. While gains from increased productivity alone are considerably larger than gains from trade cost alone, welfare gains from the combined counterfactual are also appreciably 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 underestimating the welfare impacts of climate change.

To quantify how large the underestimate is, Figure 21 shows a histogram of the additional welfare gain from the combined counterfactual compared to the productivity-only exercise. The average country has a ten 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. Figure 22 shows a world map highlighting this heterogeneity in additional welfare gains across countries.[5] 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 ten percent. That is a sizable understatement, again highlighting that the trade cost channel I highlight matters.

5 Conclusion

I show, using an augmented gravity specification, that decade-level average temperature changes at the origin or destination country increase bilateral trade cost. This is possibly driven by the

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

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

fact that sea ports are especially vulnerable to extreme weather events and hence to damages from climate change. 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 about 2.6 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 benefits 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 ten 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 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 that this simple methodology will enrich our future analysis of the impact of climate change.

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Tables

Table 1: Gravity estimation results

Variable	Basic model	$T_{'50-'80}$ deciles	$T_{'50-'80}$ deciles & time trend	CC deciles	CC deciles & time trend	Lat. deciles	Lat. deciles & time trend	Weighted distance	Benchmark
$\tilde{d}_{ni} \times$ 2010s	−0.552 [0.000]	−0.899 [0.000]	−0.903 [0.000]	−0.744 [0.000]	−0.791 [0.000]	−0.663 [0.000]	−0.974 [0.000]	−0.590 [0.000]	−0.565 [0.000]
$\tilde{d}_{ni} \times \Delta T_{it}$	−0.095 [0.000]	−0.125 [0.000]	−0.134 [0.000]	−0.048 [0.031]	−0.053 [0.010]	−0.156 [0.000]	−0.192 [0.000]	−0.137 [0.000]	
$\tilde{d}_{ni} \times \Delta T_{nt}$	−0.066 [0.011]	−0.089 [0.000]	−0.090 [0.000]	−0.038 [0.081]	−0.014 [0.485]	−0.116 [0.000]	−0.123 [0.000]	−0.098 [0.000]	
$\tilde{d}_{ni} \otimes$ decade	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\tilde{d}_{ni} \otimes T_{'50-'80}$ decile$_i$	No	Yes	Yes	No	No	No	No	No	No
$\tilde{d}_{ni} \otimes T_{'50-'80}$ decile$_n$	No	Yes	Yes	No	No	No	No	No	No
$\tilde{d}_{ni} \otimes T_{'50-'80}$ decile$_i \times$ decade	No	No	Yes	No	No	No	No	No	No
$\tilde{d}_{ni} \otimes T_{'50-'80}$ decile$_n \times$ decade	No	No	Yes	No	No	No	No	No	No
$\tilde{d}_{ni} \otimes$ CC decile$_i$	No	No	No	Yes	Yes	No	No	No	No
$\tilde{d}_{ni} \otimes$ CC decile$_n$	No	No	No	Yes	Yes	No	No	No	No
$\tilde{d}_{ni} \otimes$ CC decile$_i \times$ decade	No	No	No	No	Yes	No	No	No	No
$\tilde{d}_{ni} \otimes$ CC decile$_n \times$ decade	No	No	No	No	Yes	No	No	No	No
$\tilde{d}_{ni} \otimes$ Lat. decile$_i$	No	No	No	No	No	Yes	Yes	No	No
$\tilde{d}_{ni} \otimes$ Lat. decile$_n$	No	No	No	No	No	Yes	Yes	No	No
$\tilde{d}_{ni} \otimes$ Lat. decile$_i \times$ decade	No	No	No	No	No	No	Yes	No	No
$\tilde{d}_{ni} \otimes$ Lat. decile$_n \times$ decade	No	No	No	No	No	No	Yes	No	No
$\mathbf{C}_{nit} \otimes$ decade	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin-decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	326,747	326,747	326,747	326,747	326,747	326,747	326,747	293,461	326,747
Clusters	28,974	28,974	28,974	28,974	28,974	28,974	28,974	22,118	28,974

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. $\tilde{d}_{ni} \equiv \log(d_{ni})$ is the log of the great circle distance d_{ni} between the origin and destination countries in km. Since the coefficient on that variable is allowed to vary across decades, I only report the coefficient for the latest period, $\tilde{d}_{ni} \times$ 2010s. ΔT_{ct} is the change in decadal mean temperature in country c between decades t and $t-1$ in °C. Temperature changes are winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles. $\mathbf{C}_{nit}$ contains a common language indicator, contiguity indicator and two indicators for current and past colonial relationships, taking decadal means for all variables within each origin-destination pair. Decades t are the decades from 1820 to 2020. $T_{'50-'80}$ *decile*$_c$ is country c's decile of average temperature between the 1950s and 1980s. *CC decile*$_c$ is country c's decile of average temperature change (i.e., climate change) between the 1900s and 2000s decades. *Lat. decile*$_c$ is country c's centroid's latitude decile. *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: Mechanisms behind main results

Variable	Sea only trade	Long distance trade
Sea only$_{ni}$ × 2010s	-0.564 [0.000]	
Sea only$_{ni}$ × ΔT_{it}	-0.165 [0.004]	
Sea only$_{ni}$ × ΔT_{nt}	-0.036 [0.507]	
Long distance$_{ni}$ × 2010s		-0.442 [0.000]
Long distance$_{ni}$ × ΔT_{it}		-0.102 [0.106]
Long distance$_{ni}$ × ΔT_{nt}		-0.027 [0.632]
Sea only$_{ni}$ ⊗ decade	Yes	No
Long distance$_{ni}$ ⊗ decade	No	Yes
$\mathbf{C}_{nit}$ ⊗ decade	Yes	Yes
Origin-decade FE	Yes	Yes
Destination-decade FE	Yes	Yes
Observations	326,747	326,747
Clusters	28,974	28,974

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. Sea only$_{ni}$ is an indicator for there being no overland connection between the origin and destination countries. Since the coefficient on that variable is allowed to vary across decades, I only report the coefficient for the latest period, Sea only$_{ni}$ × 2010s. Long distance$_{ni}$ is an indicator for the distance between the origin and destination being greater than or equal to the average distance between country pairs that only have a sea-based connection (that is, pairs which have Sea only$_{ni}$ = 1). Again, I only report the coefficient for the latest period. ΔT_{ct} is the change in decadal mean temperature in country c between decades t and $t-1$ in °C. Temperature changes are winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles. $\mathbf{C}_{nit}$ contains a common language indicator, contiguity indicator and two indicators for current and past colonial relationships, taking decadal means for all variables within each origin-destination pair. Decades t are the decades from 1820 to 2020. Standard errors clustered by country pair, p-values in brackets.

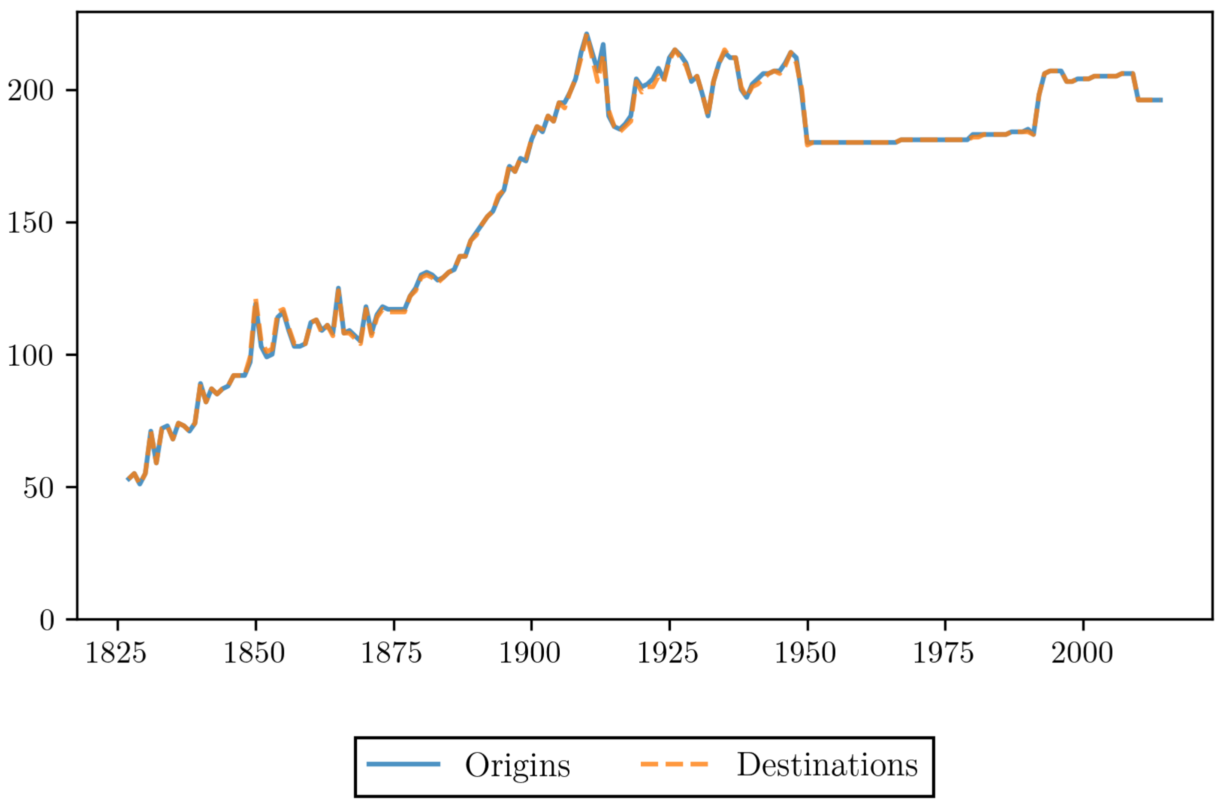
Table 3: Correlates of welfare changes

Variable	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$
Log 2010s GDP				-0.282 [0.000]	-0.371 [0.000]	0.213 [0.000]
Own ΔT	0.187 [0.726]		2.620 [0.003]		2.751 [0.000]	
Inverse distance weighted ΔT		-1.974 [0.121]	-7.082 [0.001]		-5.113 [0.003]	
2010s own trade share (%)						-0.087 [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* ΔT is a country's change in temperature between each decade and the 2010s, whereas the *inverse distance weighted* ΔT for country i is the average change in all other countries' temperatures, weighted by the inverse of their distance to i. Standard errors clustered by country, p-values in brackets.

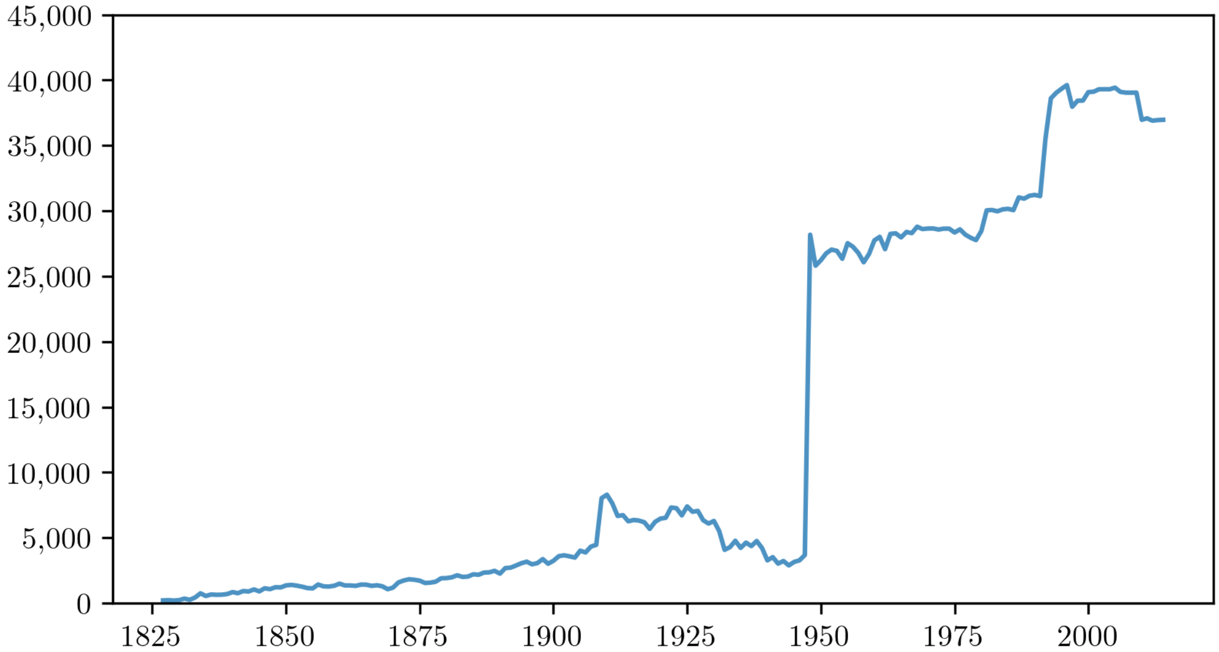
Figures

Figure 1: Trade data country counts by year



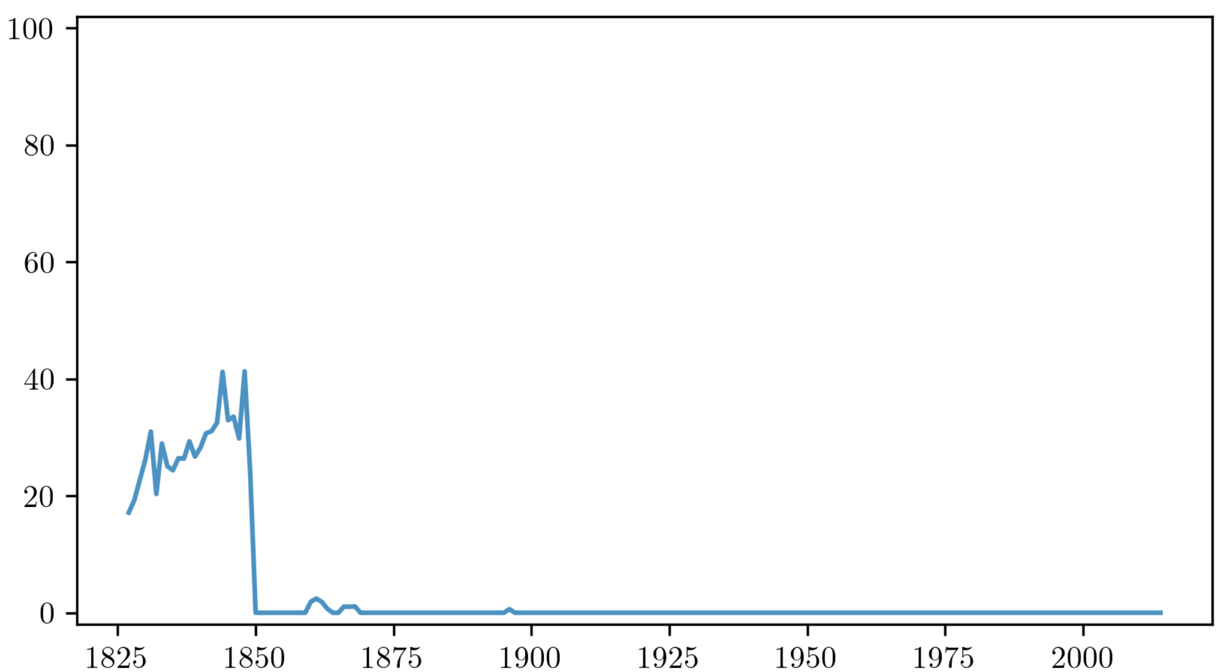
Note: The figure shows the number of countries observed in the TRADHIST trade data by year. I subset to observations with non-missing trade flows and distance information.

Figure 2: Trade flow counts by year



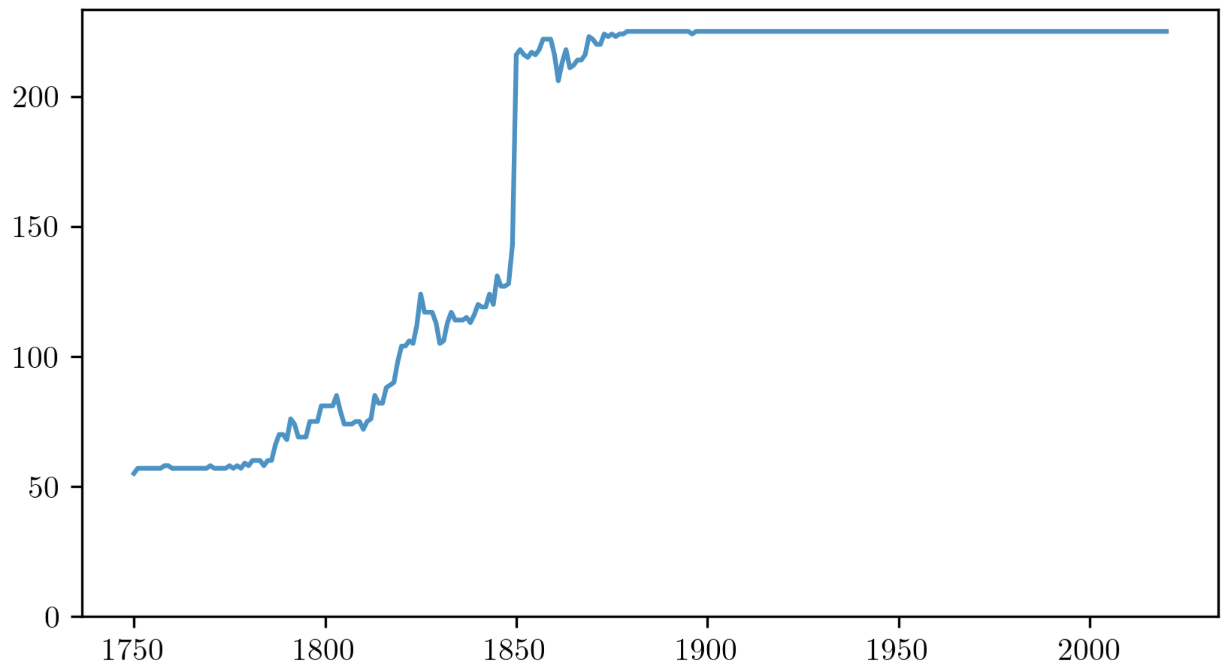
Note: The figure shows the number of trade flows observed in the TRADHIST trade data by year. I subset to observations with non-missing trade flows and distance information.

Figure 3: Unmatched trade flows (percent) by year



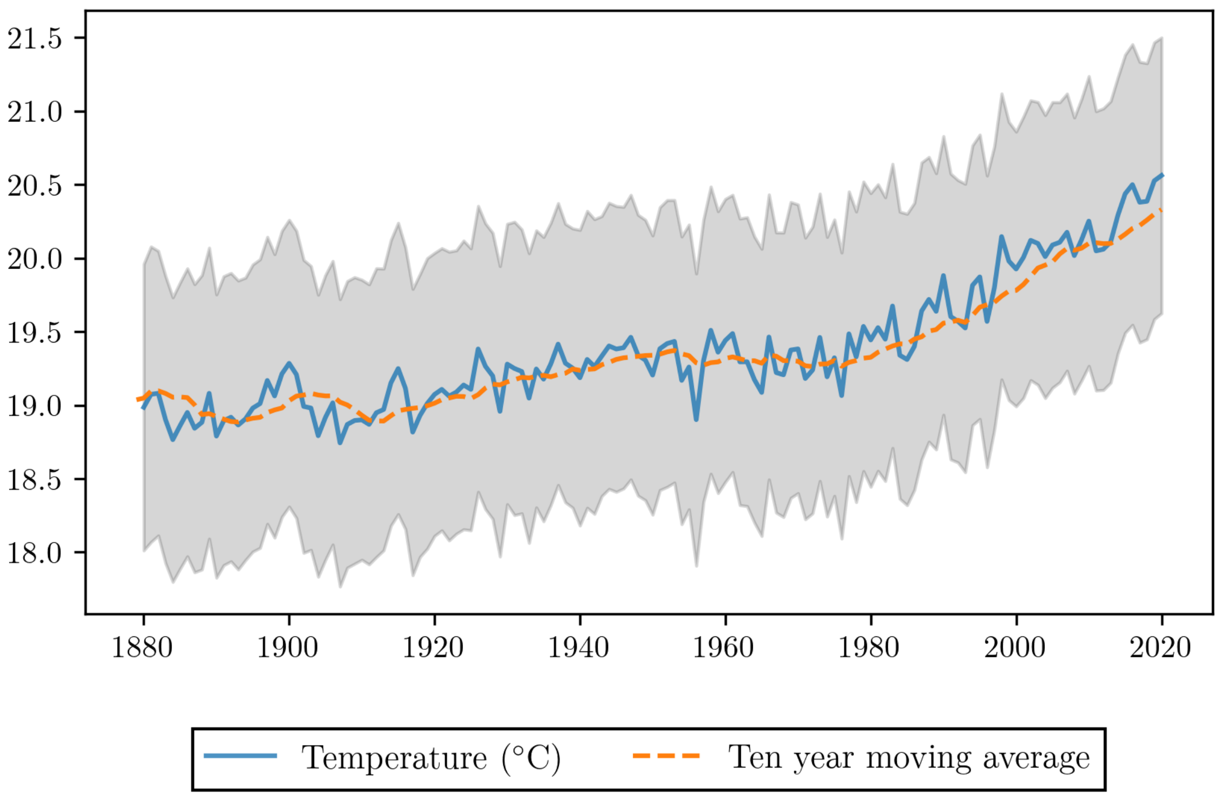
Note: The figure shows the percent of TRADHIST trade observations which cannot be matched to weather information by year. I subset to observations with non-missing trade flows and distance information.

Figure 4: Weather observation counts for current countries by year



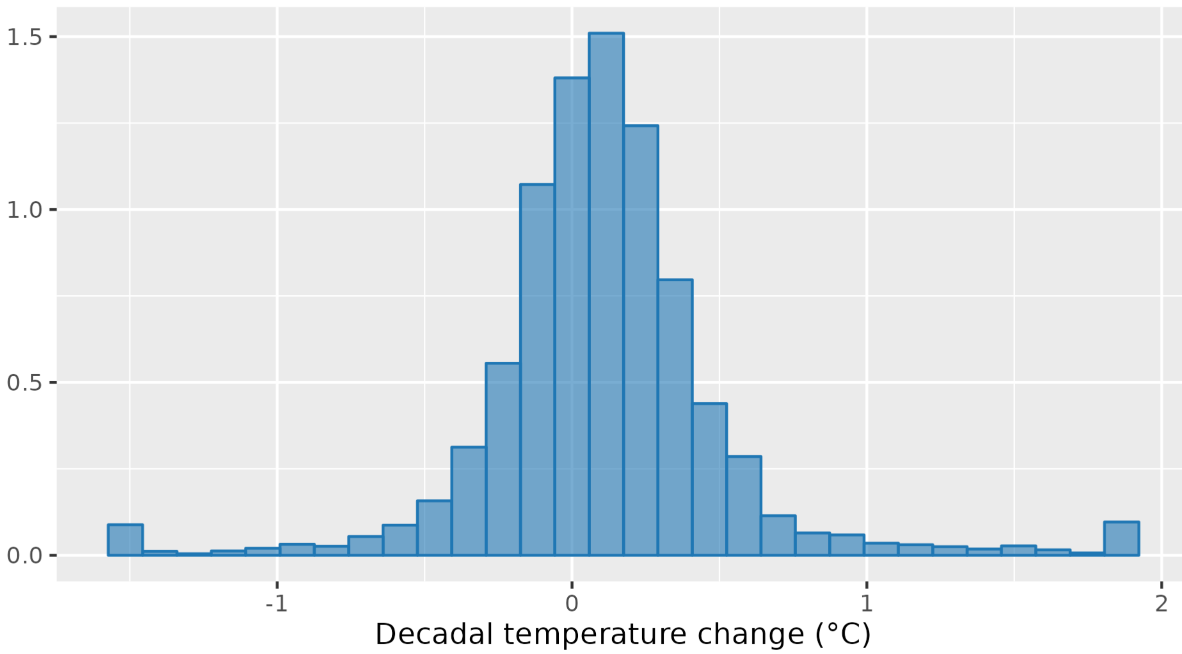
Note: The figure shows the number of countries with non-missing weather observations by year. I subset to countries which currently exist and ever appear in the TRADHIST trade data. (For example, in this plot, I include Germany, which currently exists and appears in the trade data, but not the former 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



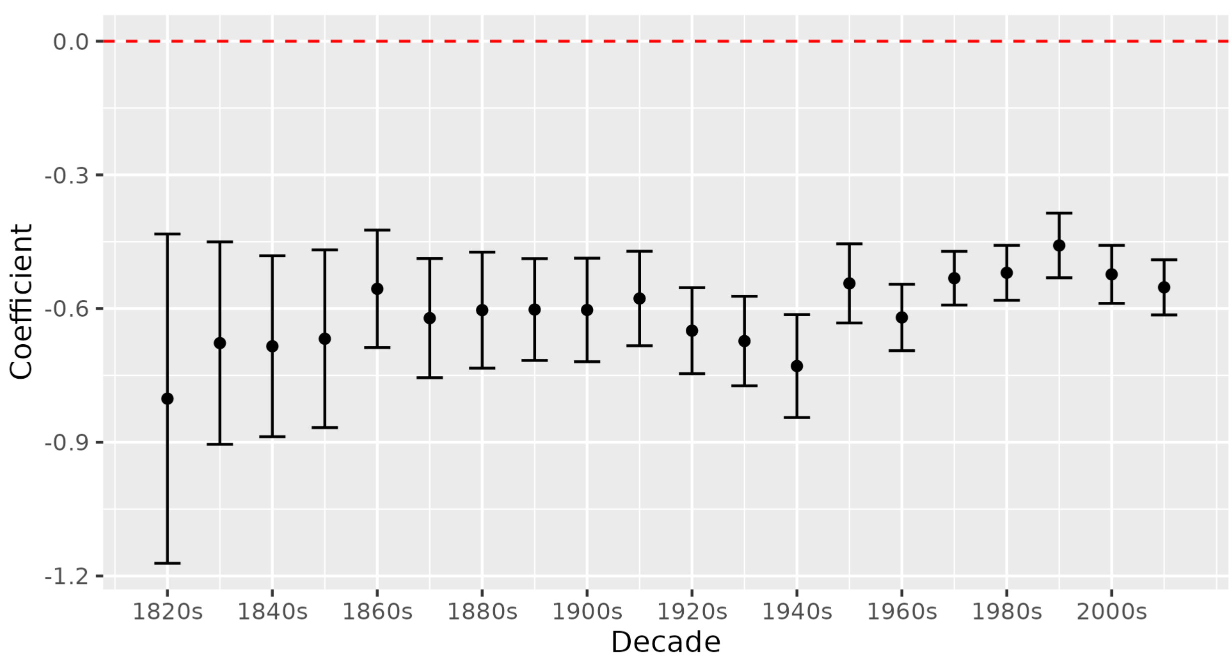
Note: The figure shows the average temperature across years. The figure starts in 1880, where I have global weather coverage. I subset to countries which currently exist and ever appear in the TRADHIST trade data. (For example, in this plot, I include Germany, which currently exists and appears in the 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 90 percent confidence intervals for the yearly means.

Figure 6: Decadal temperature changes



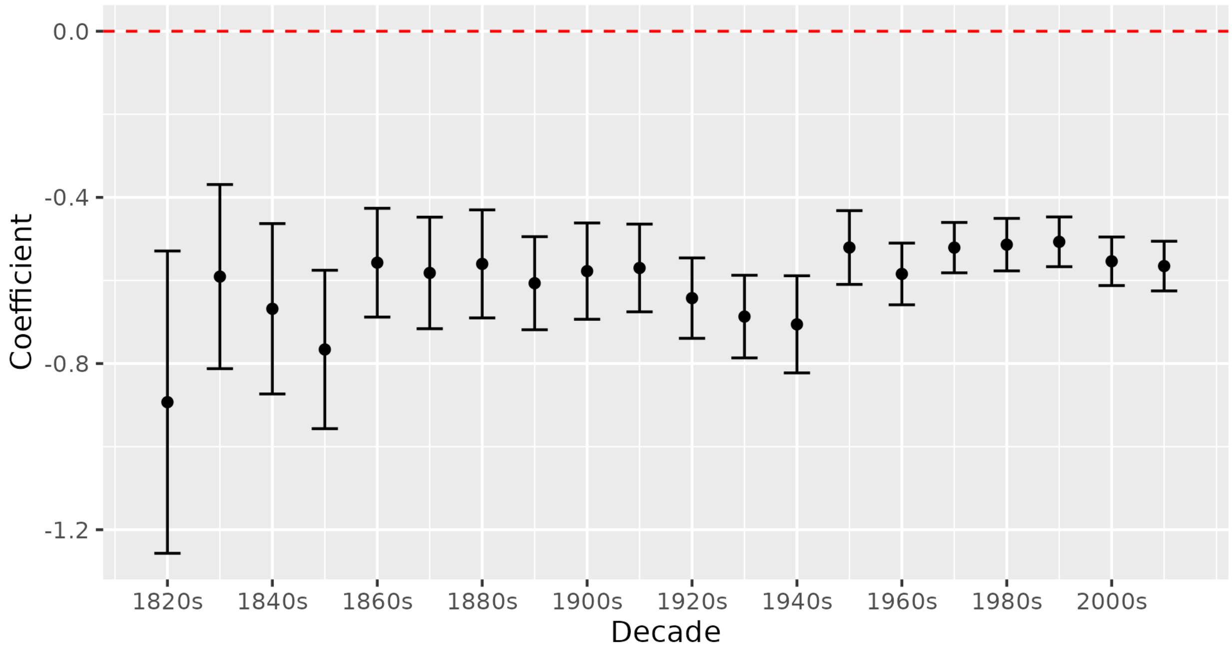
Note: The figure shows the distribution of decadal temperature changes across all countries and decades. As in my gravity estimations, decadal temperature changes are winsorized at the 1st and 99th percentiles.

Figure 7: Coefficients on log distance across decades



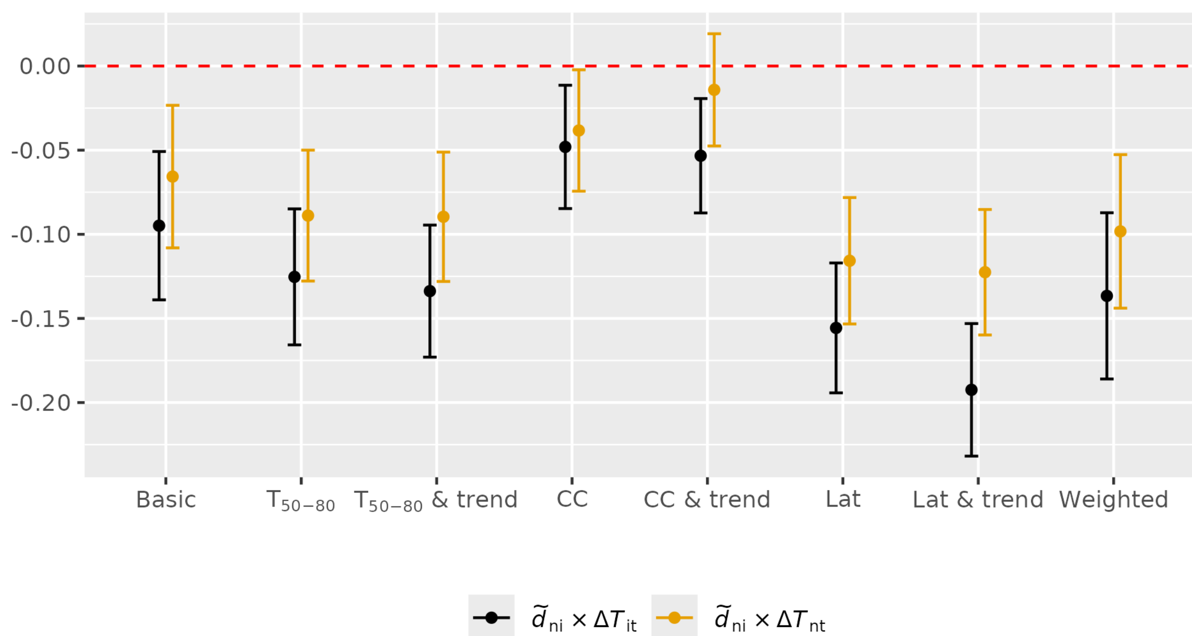
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate 90 percent confidence intervals. Other coefficients in the model, including those on origin and destination temperature, do not vary across decades.

Figure 8: Coefficients on log distance across decades (benchmark excluding temperature variables)



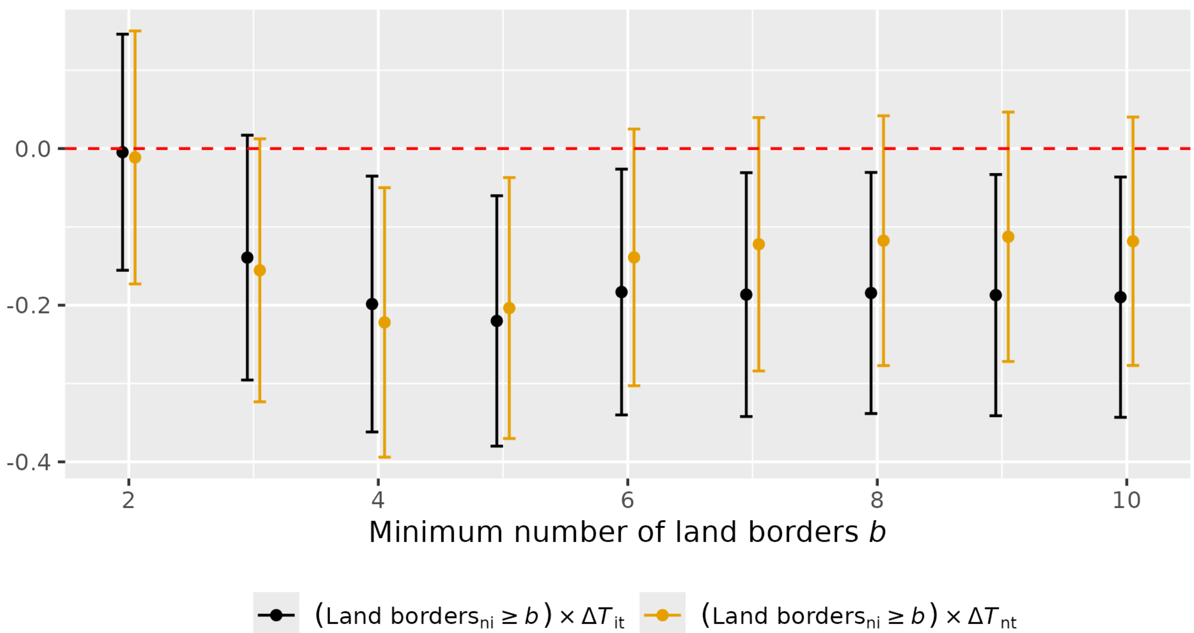
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate 90 percent confidence intervals. Other coefficients in the model do not vary across decades. This benchmark specification does not include origin and destination temperatures.

Figure 9: Coefficients on temperature interactions across specifications



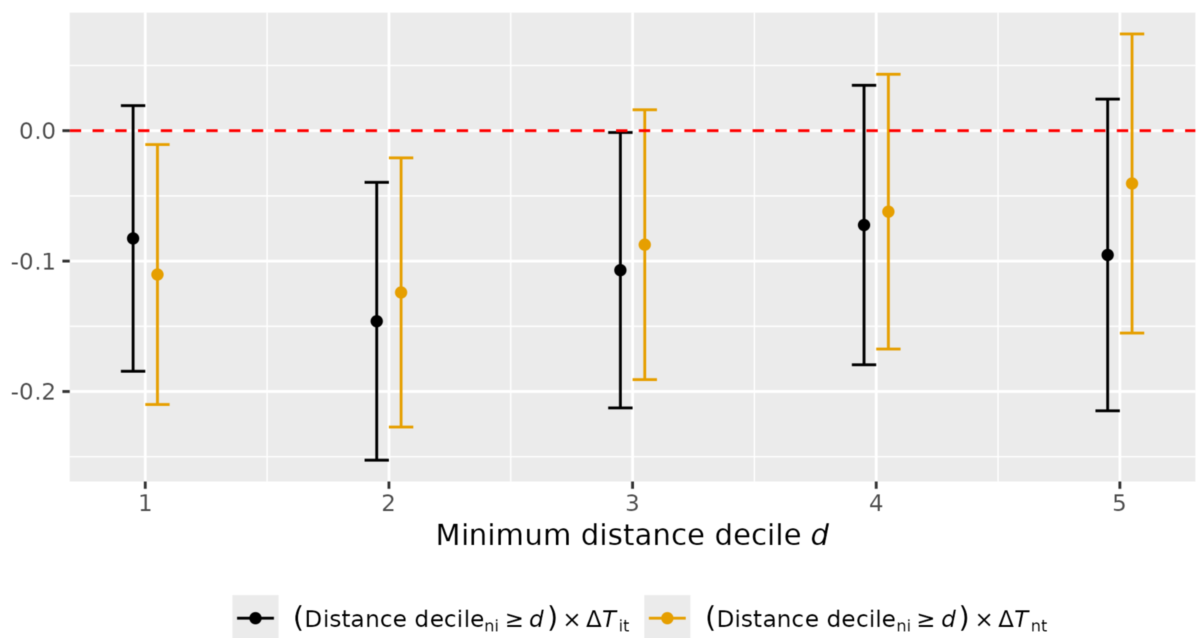
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. $\tilde{d}_{ni} \equiv \log(d_{ni})$ is the log of the great circle distance d_{ni} between the origin and destination countries in km. ΔT_{ct} is the change in decadal mean temperature in country c between decades t and $t-1$ in °C. Temperature changes are winsorized at the 1st and 99th percentiles. Vertical lines and whiskers indicate 90 percent confidence intervals. Other coefficients in the model, including those on origin and destination temperature, do not vary across decades.

Figure 10: Land border crossing donut hole estimation



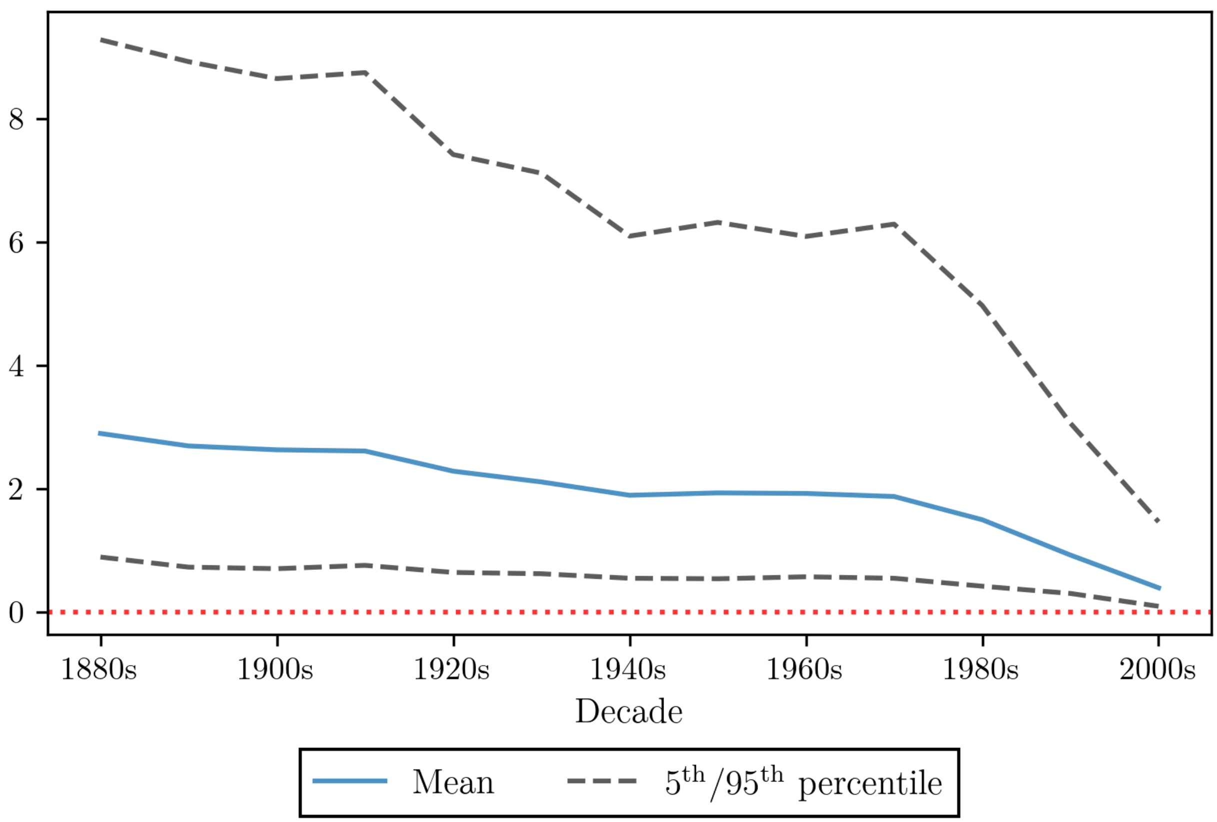
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Gap$_{ni}$ is an indicator; it is equal to one if the number of countries that need to be crossed to get, via a land route, from the origin to the destination country is greater than or equal to the indicated gap size. It is equal to zero if the two countries are neighbors. For all other country pairs (those in the donut hole), the indicator is missing — they are discarded. Each coefficient is from a separate estimation for a different donut hole size. ΔT_{ct} is the change in decadal mean temperature in country c between decades t and $t-1$ in °C. Temperature changes are winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles. Vertical lines and whiskers indicate 90 percent confidence intervals. Other coefficients in the model, including those on origin and destination temperature, do not vary across decades.

Figure 11: Distance decile donut hole estimation



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. Distance decile$_{ni}$ is an indicator; it is equal to one if the distance between the origin to the destination country is greater than or equal to the indicated distance decile. It is equal to zero if the two countries are closer to each other than the first distance decile. For all other country pairs (those in the donut hole), the indicator is missing — they are discarded. Each coefficient is from a separate estimation for a different donut hole size. ΔT_{ct} is the change in decadal mean temperature in country c between decades t and $t-1$ in $^\circ$C. Temperature changes are winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles. Vertical lines and whiskers indicate 90 percent confidence intervals. Other coefficients in the model, including those on origin and destination temperature, do not vary across decades.

Figure 12: Population-weighted summary statistics for welfare change (percent) across decades



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

Figure 13: Welfare change (percent) in 1910s climate counterfactual across countries

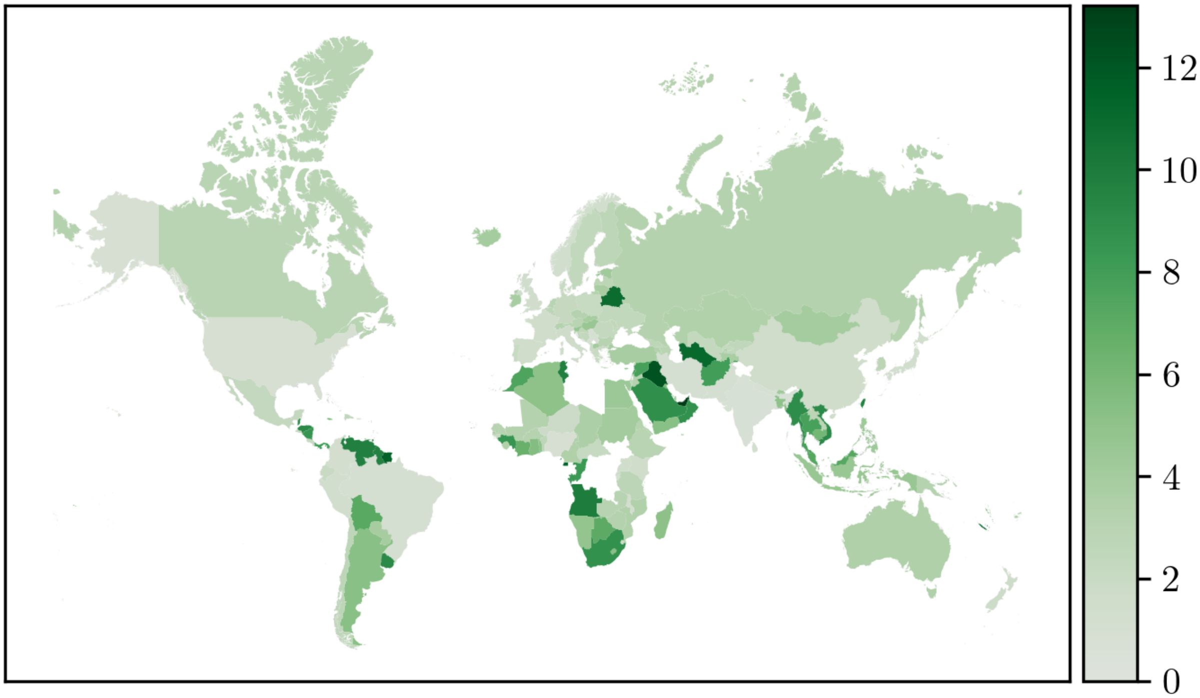
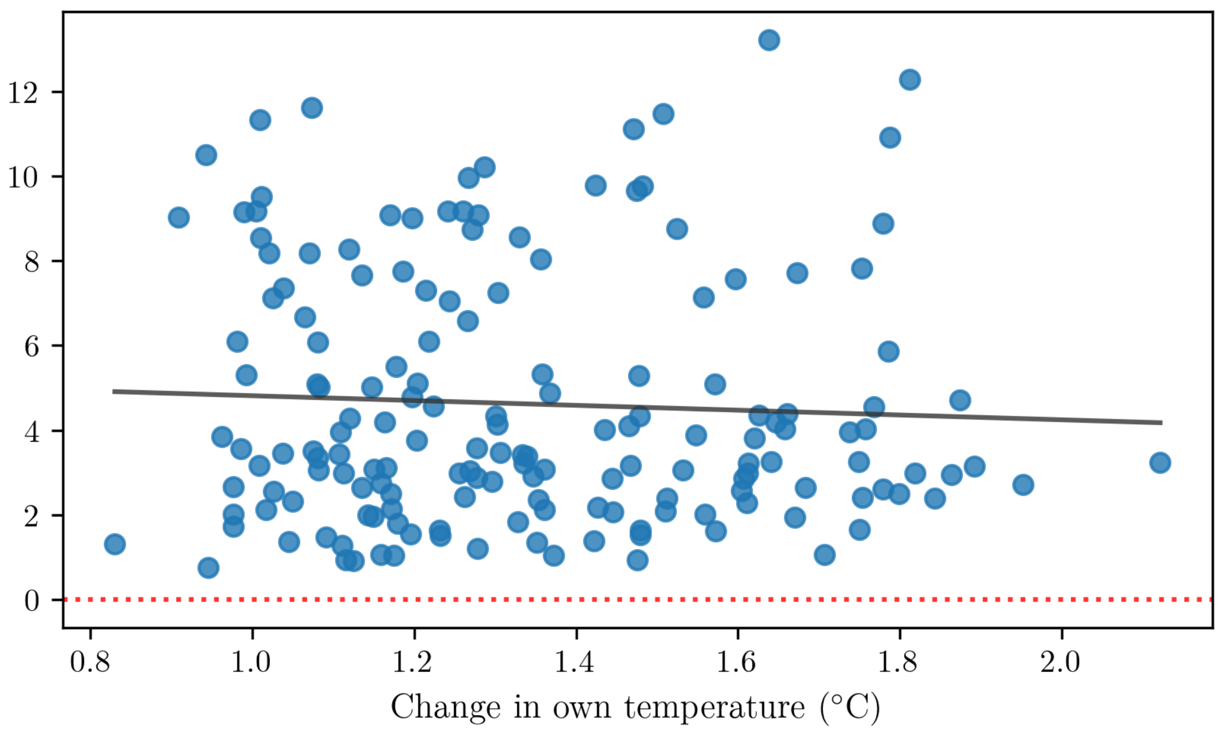
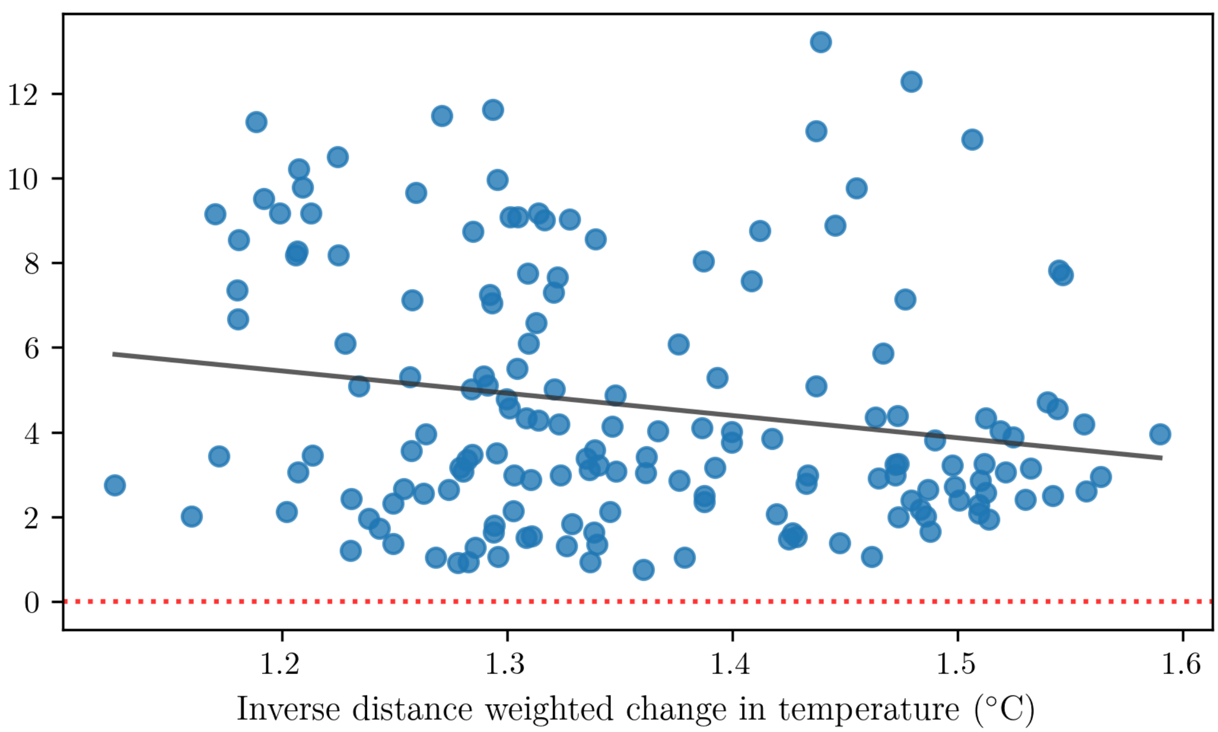


Figure 14: Welfare change (percent) in 1910s climate counterfactual across change in own temperature between the 1910s and 2010s



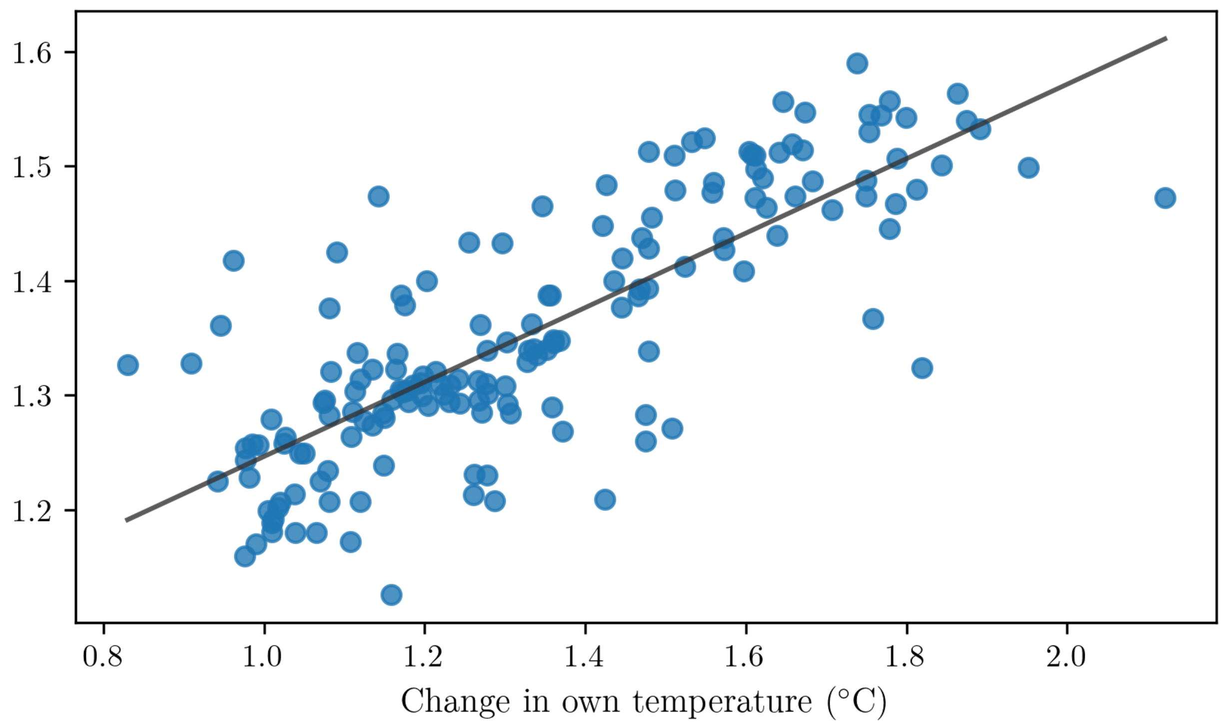
Note: Change in own temperature is the change in country i's own temperature between the 1910s and 2010s. The solid line shows a linear fit.

Figure 15: Welfare change (percent) in 1910s climate counterfactual across inverse distance weighted change in other countries' temperature between the 1910s and 2010s



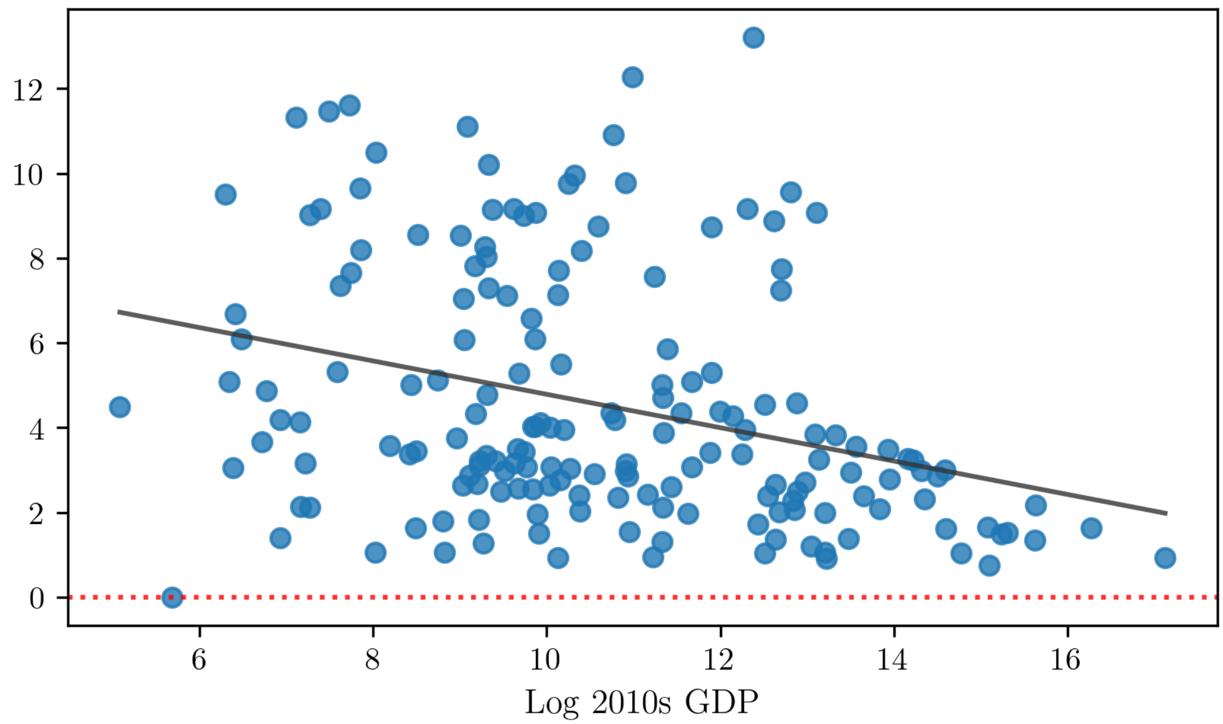
Note: The inverse distance weighted change for country i is the average change in all other countries' temperatures, weighted by the inverse of their distance to i. The solid line shows a linear fit.

Figure 16: Inverse distance weighted change in other countries' temperature between the 1910s and 2010s across change in own temperature between the 1910s and 2010s



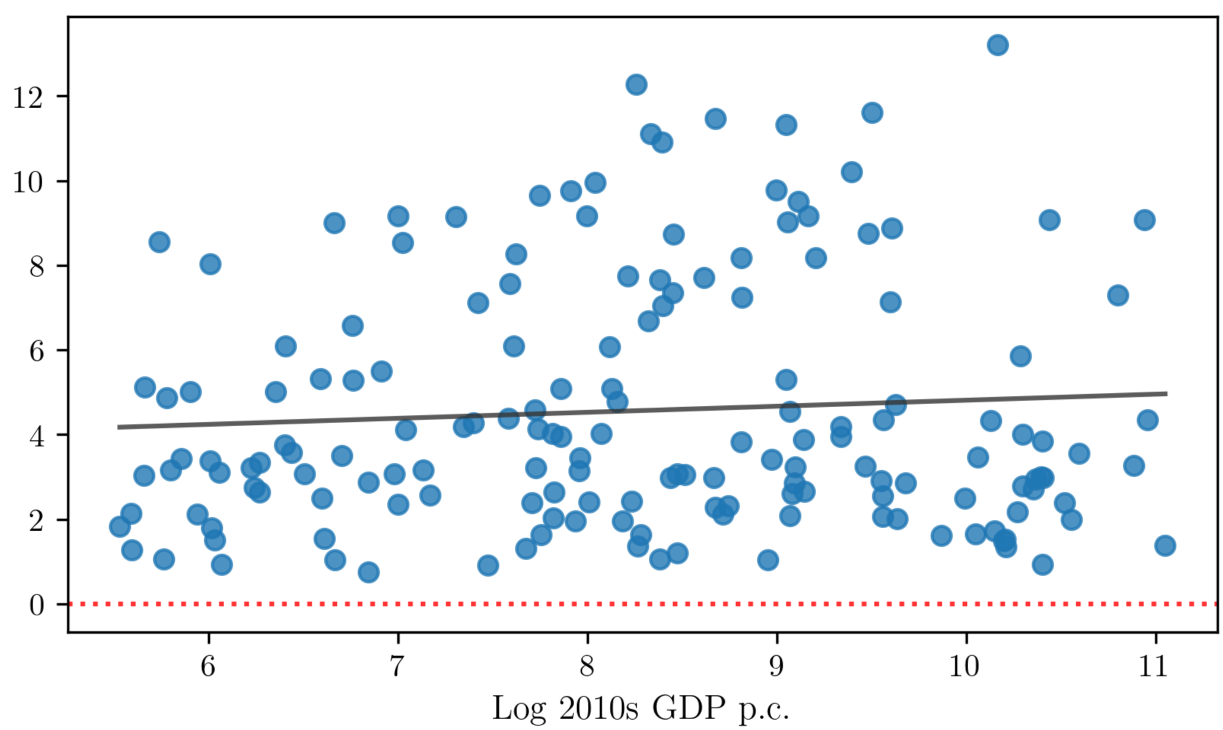
Note: The inverse distance weighted change for country i is the average change in all other countries' temperatures, weighted by the inverse of their distance to i. The solid line shows a linear fit.

Figure 17: Welfare change (percent) in 1910s climate counterfactual across 2010s GDP



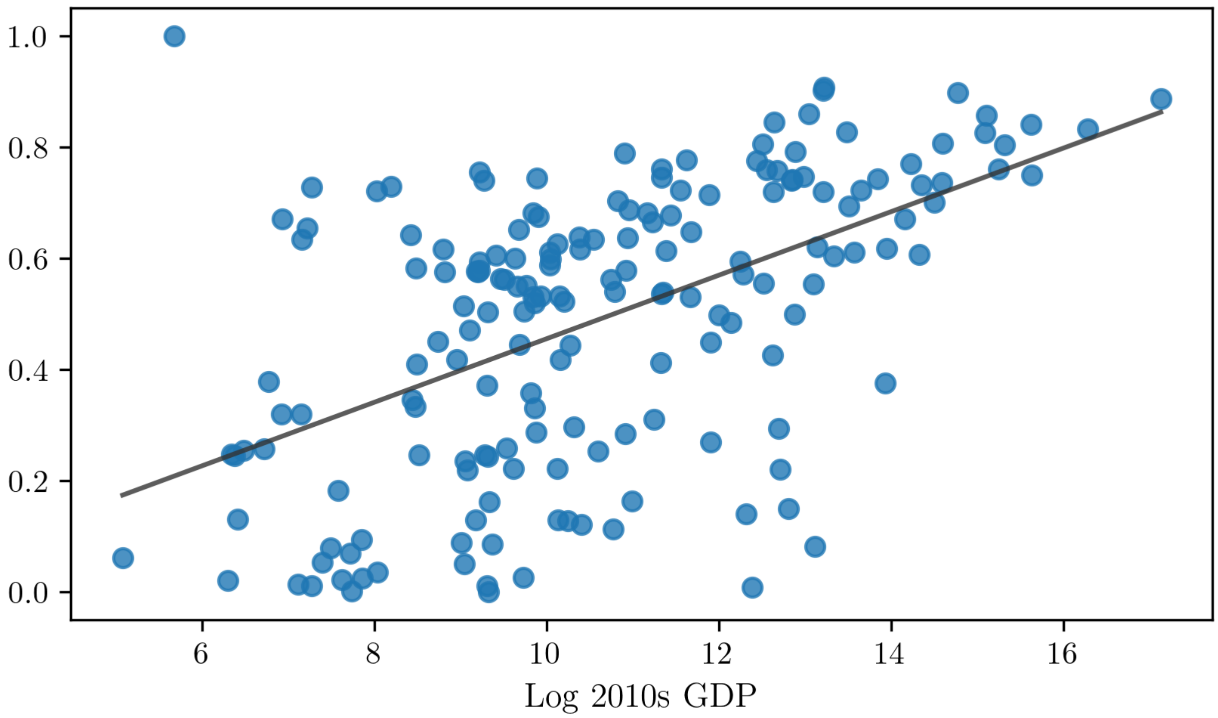
Note: The solid line shows a linear fit.

Figure 18: Welfare change (percent) in 1910s climate counterfactual across 2010s GDP per capita



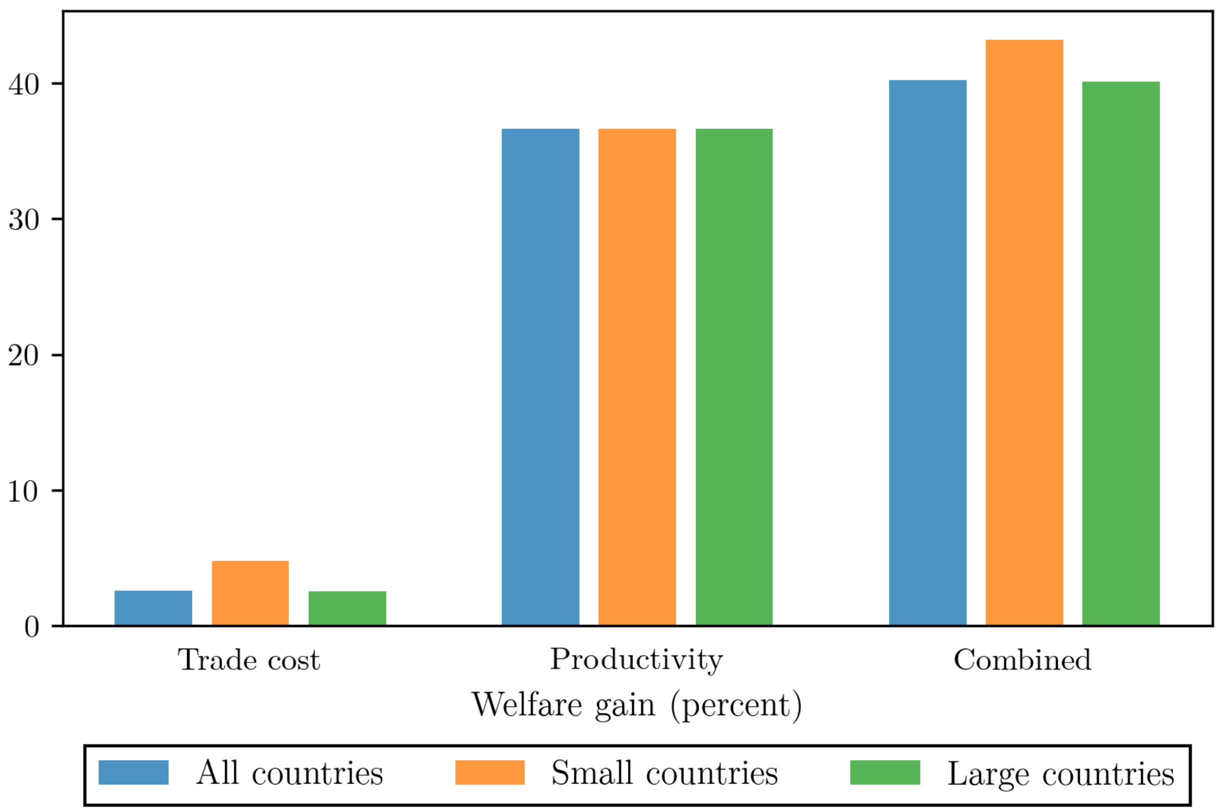
Note: The solid line shows a linear fit.

Figure 19: 2010s own trade share across 2010s GDP



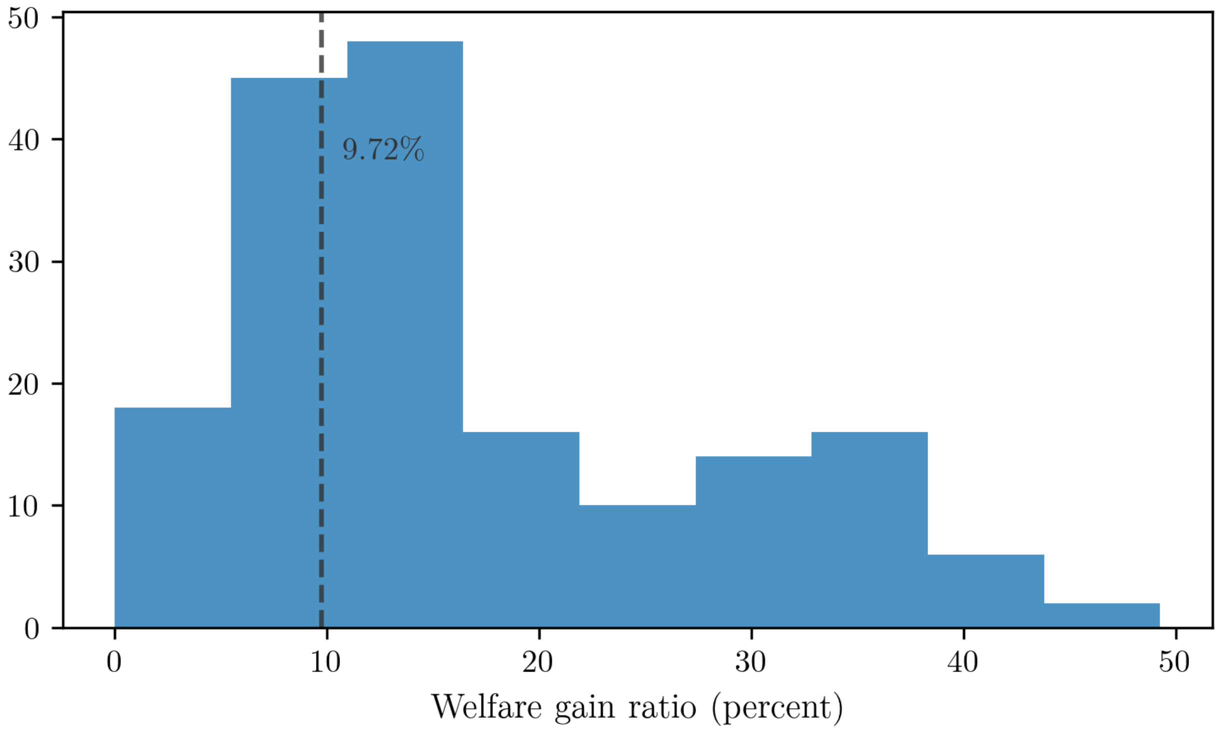
Note: The solid line shows a linear fit.

Figure 20: Population-weighted average welfare gains (percent) across different scenarios for 1910s climate counterfactual



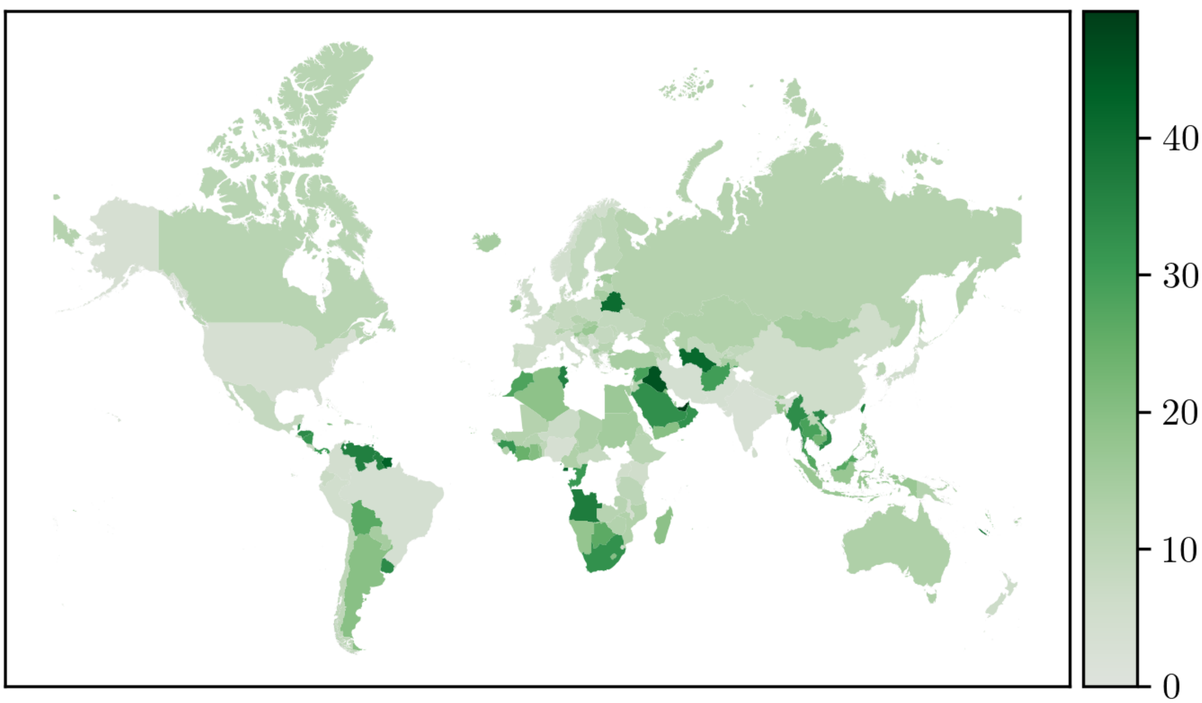
Note: The figure shows population-weighted average welfare gains under each scenario. *Trade cost* undoes the impact of climate change on trade cost. *Combined* uses these trade cost impacts as a starting point and calibrates a common technology shift that undoes the 30 percent welfare decline due to a one degree warming scenario from Bilal and Känzig (2024). *Productivity* shows the impact of the productivity shift alone, ignoring trade cost changes. *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 21: 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 population-weighted average of the welfare gain ratio.

Figure 22: Additional welfare gains from combined trade cost and productivity change vs. productivity change alone for 1910s climate counterfactual across countries



Appendix A Additional tables

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	2.893	2.691	2.628	2.609	2.282	2.108	1.892	1.930	1.921	1.872	1.495	0.922	0.391
p_5	0.890	0.727	0.702	0.755	0.641	0.620	0.547	0.538	0.570	0.546	0.418	0.300	0.092
p_{10}	0.890	0.727	0.702	0.755	0.641	0.640	0.547	0.538	0.570	0.546	0.418	0.303	0.094
p_{25}	1.095	0.993	1.026	0.928	0.793	0.640	0.606	0.747	0.741	0.691	0.493	0.315	0.094
p_{50}	1.805	1.674	1.671	1.633	1.398	1.375	1.102	1.238	1.204	1.127	0.968	0.506	0.169
p_{75}	3.732	3.395	3.395	3.239	2.810	2.571	2.416	2.587	2.675	2.469	1.898	1.165	0.503
p_{90}	6.298	5.896	5.529	5.303	4.457	4.486	3.861	4.333	4.086	4.067	3.210	2.031	0.945
p_{95}	9.275	8.919	8.645	8.742	7.414	7.112	6.092	6.314	6.087	6.286	4.967	3.060	1.460

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.

Table 5: Summary statistics for welfare change (percent) across decades

Statistic	1880s	1890s	1900s	1910s	1920s	1930s	1940s	1950s	1960s	1970s	1980s	1990s	2000s
Mean	4.963	4.695	4.685	4.537	4.000	3.597	3.283	3.391	3.404	3.313	2.653	1.631	0.702
p_5	1.192	1.103	1.082	1.053	0.974	0.873	0.802	0.769	0.795	0.806	0.630	0.362	0.087
p_{10}	1.570	1.515	1.512	1.432	1.236	1.115	0.993	1.075	1.110	1.055	0.785	0.462	0.137
p_{25}	2.689	2.531	2.550	2.390	2.120	1.682	1.753	1.748	1.822	1.720	1.384	0.768	0.275
p_{50}	3.980	3.785	3.882	3.459	3.160	2.717	2.720	2.757	2.704	2.592	2.149	1.259	0.520
p_{75}	6.909	6.925	6.783	6.631	5.666	5.192	4.672	4.633	4.805	4.619	3.619	2.239	0.950
p_{90}	9.826	9.336	9.236	9.159	8.052	7.429	6.442	6.753	6.699	6.451	5.185	3.261	1.555
p_{95}	11.243	10.119	10.194	10.037	9.106	8.144	6.980	7.478	7.640	7.823	6.187	3.821	1.882

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 23: Summary statistics for welfare change (percent) across decades