Climate change increases bilateral trade cost

Maximilian Huppertz*
Bank of England

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Abstract

It is well established that climate change affects productivity, 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. An augmented gravity framework shows that rising temperatures at the origin or destination country increase bilateral trade cost. This seems to be driven by the vulnerability of sea ports to climate change. Adaptation to these impacts appears slow. Combining these results with a standard international trade model, I find that 2010s welfare would increase by 1.6 percent if we could undo the impact of climate change on trade cost over the preceding 100 years. Welfare gains depend not only on countries' own climate trends, but also on their neighbors' trajectories. Poor and rich countries are roughly equally harmed. Smaller economies, which are more reliant on international trade, are especially affected. Ignoring this trade cost channel and focusing only on productivity changes leads to a nine percent underestimate of the welfare effect of climate change. Because it is based on a gravity framework, my methodology can easily be embedded in studies of the impact of climate change.

*Contact: maximilian.huppertz@bankofengland.co.uk. Any views expressed are solely those of the author and so cannot be taken to represent those of the Bank of England or to state Bank of England policy. This paper should therefore not be reported as representing the views of the Bank of England or members of the Monetary Policy Committee, Financial Policy Committee or Prudential Regulation Committee.

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, such as 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? If so, does ignoring this mean we underestimate the impact of climate change?

I use trade and weather data covering 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' climatic environment, allaying these identification concerns.

I present additional reduced form results suggesting the impact is driven by maritime trade in particular. This squares up with recent research on weather impacts on ports (Astier 2025; Massoni 2025) and anecdotal evidence from policy makers and port operators. I also show that impacts are especially severe for countries with lower benchmark temperatures and countries which see especially rapid climate change. This suggests that countries can adapt to these effects, but this adaptation process is slow.

I embed my estimates in a standard model of international trade (Eaton and Kortum 2002) to quantify welfare impacts. I find that welfare in the 2010s would have been 1.6 percent higher if climate change had not increased trade cost over the preceding 100 years. This is due purely to the resulting reduction in trade cost, shutting down any productivity impacts completely. 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 climate change thus also benefits i less, since its relative position declines. Poor and rich countries benefit equally. Smaller economies see especially large welfare gains, because they are more reliant on international trade. Finally, I show that ignoring this trade cost channel and focusing solely on productivity leads to a nine percent underestimate of the welfare impact of climate change.

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.

I contribute to the literature on the impacts of climate change in equilibrium. Existing studies generally estimate how trade affects productivity (Costinot, Donaldson, and Smith 2016; Cruz and Rossi-Hansberg 2021; Desmet, Kopp, Kulp, Nagy, Oppenheimer, Rossi-Hansberg, and 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 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 will be worse. Using current trade networks to assess the baseline impact of climate change thus underestimates its impact. My results also show that the micro impacts of weather on ports (Astier 2025; Massoni 2025) translate into long-term climate change damages observable in decadal shifts.

Second, I contribute to the debate about the magnitude of the welfare impacts of climate change. 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. They are only about ten percent of direct estimates of climate productivity damages (e.g. Burke, Hsiang, and Miguel 2015; Ramey, Nath, and Klenow 2025). They are also only about five percent of the welfare impact of one degree of warming estimated in Bilal and Känzig (2024), who combine 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 overall larger estimates of the impact of climate change.

Finally, my results also relate to the literature on the carbon cost of trade. Trade itself generates considerable carbon emissions (Shapiro 2016; Cristea, Hummels, Puzzello, and Avetisyan 2013). 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 compares to productivity impacts, 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 and Hugot 2016). These 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 and Dimsdale 2017).[1]

I combine these trade flows with Berkeley Earth (BKE) data on monthly average temperature (Rohde, Muller, Jacobsen, Muller, Perlmutter, Rosenfeld, Wurtele, Groom, and 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 virtually 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). I 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. One additional step I have to take here deals with the fact that GADM covers only currently existing countries, while TRADHIST 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 and historical maps of the country. Appendix C shows these added maps.

For counterfactual exercises, I need data that cover not only international but also current

[1] 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.

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, and Yotov 2021; Borchert, Larch, Shikher, and Yotov 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 and 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 and 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 and van Wincoop 2003) or country (Eaton and 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 and 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, and 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 and Tenreyro 2006), which I follow here.

Because I deal with temperature changes over long time horizons, I estimate this model across decades rather than using yearly data. 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.

2.1 Identification

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 three ways — using countries' average temperature between 1950 and 1980, countries' temperature change between the 1900s decade and the 2000s decade, and countries' latitude. I calculate deciles of each of these variables and interact them with distance, allowing for different levels of trade cost for countries with different baseline climates. I additionally estimate a specification with trade cost time trends for each decile. The full specification with different trade cost levels and trends is

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

Here, α_D allows for separate coefficients on distance — separate trade costs — for each decile D of a given measure of climatic environment, e.g., 1950–1980 average temperature. τ_D allows for separate time trends in the coefficients on distance — separate time trends of trade costs — across deciles.

Note that the specification using 1900s to 2000s climate change as a measure of climatic environment is very conservative. It sets aside trade cost differences across countries with different long-run climate trends. It assumes those differences are not driven by climate change. It then uses only the remaining decadal variation among countries with similar climate trends to estimate the impact of climate change. This inherently discards a lot of the identifying variation and limits the potential impact of climate change. Estimates from this specification are therefore a lower bound on the impact of climate change on trade cost.

2.2 Heterogeneity

I also study heterogeneity of the impact of climate change on trade cost. As I explain below, this can help shed some light on patterns of adaptation to climate change. To do this, I modify equation (2), letting the coefficients on distance by decade and the core interaction terms vary by climatic environment,

$$\mathbb{E}\left(X_{nit}|\mathbf{D}_{nit}\right) = \exp\left\{\gamma_{it} + \xi_{nt} + \left(\sum_{Q=1}^{4} \alpha_{tQ}\tilde{d}_{ni} + \delta_{1Q}\tilde{d}_{ni}\Delta T_{it} + \delta_{2Q}\tilde{d}_{ni}\Delta T_{nt}\right) + \mathbf{C}'_{nit}\boldsymbol{\beta}_t\right\} \quad (4)$$

Here, I use similar measures of heterogeneity as I did to control for climatic environment above — 1950s–1980s average temperature and 1900s–2000s climate change. I use fewer bins, however, since I am not just controlling for potential confounders. Instead, here I want to estimate impacts within each bin, which requires sufficient sample sizes for each bin. I therefore use quartiles Q (instead of deciles) of 1950–1980 average temperature and 1900s–2000s climate change, and estimate separate effects of climate change on trade cost for each quartile.

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. 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$^{\text{st}}$ and 99$^{\text{th}}$ 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.

Figure 9 shows a coefficient plot for the coefficients of interest — those on the interaction between distance and temperature change — across a number of specifications. These include estimating(2), the climatic environment robustness checks following (3), and some additional robustness checks as well as a benchmark specification excluding temperature variables. Table 1 shows the results in table form, including additional coefficient estimates, for example on log distance. 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 pair of coefficients (*Basic*) is for the basic model (2). The following pairs are for the climatic environment decile regressions specified in (3). These allow the effect of distance — and hence trade cost levels and trends — to differ by countries' 1950–1980 average temperature decile (T_{50-80}, with *t.t.* indicating the specification with time trends), their 1900s to 2000s climate change (CC) and their latitude (Lat).

I present some additional robustness checks as well. These use population-weighted great circle distance instead of the unweighted measure (d_{popw}), drop China from the data set (*No CHN*), subset to the 1950s onwards ($t \geq$ '50s), and interact the additional bilateral controls with temperature changes as well (labeled $C_{nit} \times \Delta T_{it}$, but note this interacts with both origin and destination temperature change). A final robustness check uses residualized temperatures from an autoregression, akin to Ramey et al. (2025).[2] This is a different approach to addressing the

[2] The specification is

$$T_{it} = \left(\sum_{l=1}^{3} \beta_{1l} T_{it-l} + \beta_{2l} \bar{T}_i^{50\text{-}80} T_{it-l} \right) + \gamma_i + \nu_t + \varepsilon_{it}$$

potential spurious correlation between climate and trade cost trends by detrending temperature. Finally, the last column of Table 1 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 but imprecisely estimated 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. Across specifications, I consistently find negative and significant effects. Using the most conservative specification, which allows for different trade cost levels and trends based on countries' long-term climate change, I find that a one degree increase in temperature at the origin decreases trade flows by a further 0.053 percent. Similarly, a one degree increase in temperature at the destination decreases trade flows by an additional 0.014 percent, though the destination effect is not significant in this 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.

using three lags of decadal average temperature interacted with countries' baseline temperature, plus country and decade fixed effects. I then use residuals from this regression instead of ΔT_{it} to estimate the impact of climate change.

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

My 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, and Nyshadham 2019; Carleton and Hsiang 2016; Huppertz 2024; Nath 2020; Somanathan, Somanathan, Sudarshan, and Tewari 2021; Zhang, Dêschenes, Meng, and Zhang 2018). Through the same channels that climate change affects manufacturing firms, it can also affect the efficiency of dock and freight operations. Brancaccio, Kalouptsidi, and Papageorgiou (2020), for example, 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 predominantly uses maritime shipping, rather than land or air freight. Maritime trade is at a higher risk from climate because of its dependence on ports.

Maritime trade has to go through sea ports. These tend to be relatively few, and they are especially affected by weather hazards, as I discuss below. Because climate change makes those hazards more frequent, climate change also affects sea ports. This is especially detrimental to the cost of maritime trade, driving the impacts I find.

Land freight, by contrast, 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 makes it relatively resilient against adverse weather events affecting specific roads or production locations — other roads or production locations can function as substitutes. Maritime trade does not have this degree of flexibility.

To support the argument that maritime trade is driving my results, I first discuss the impact of adverse weather events on ports. I then show patterns in the trade cost results suggesting that maritime trade is driving force the impact of climate change on trade cost.

3.2.1 Weather impacts on ports

Recent work shows that adverse weather events, such as storms, increase port congestion and decrease port efficiency (Astier 2025; Massoni 2025). As climate change makes these events more frequent, it can thus affect port efficiency in the longer term. I do not have port efficiency data going back long enough to estimate decade to decade impacts of climate change on ports. I also cannot go into as much depth on the impact of severe weather on ports as those papers, since that it not my focus here. I do, however, replicate the basic impact these papers find. I use data on port throughput from the United Nations Conference on Trade and Development (UNCTAD) to estimate

$$\Delta \log\left(\mathrm{TEU}_{it}\right) = \beta_1 \Delta T_{it} + \beta_2 \bar{T}_i^{50\text{-}80} \Delta T_{it} + \gamma_i$$

Note that t denotes years here, not decades. The outcome is country i's container port throughput in year t, expressed in twenty-foot equivalents (hence TEU), i.e., a measure of freight quantity processed. I use year-to-year temperature changes ΔT_{it} as my measure of temperature shocks. The impact is allowed to vary by countries' 1950s to 1980s baseline temperature. Figure 10 shows the marginal effect of temperature shocks across baseline temperature, as well as a histogram of baseline temperature. The impact is negative for most countries and significant especially for hotter countries. Here, of course, I cannot control for productivity differences using country fixed effects. Instead, Figure 11 shows a version of this model controlling for changes in GDP per capita. This is an endogenous regressor, so results are harder to interpret. Even in this specification, however, I find a negative effect for most countries, though with a significant positive impact on the coldest countries.

I additionally observe that policy makers are concerned about ports and climate change and ports. UNCTAD 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, and Decker 2022).

Furthermore, 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).

3.2.2 Maritime trade drives trade cost impacts

I find a number of results which are consistent with the idea that climate change especially affects maritime trade cost, which then drives the overall results. 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 and 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 12 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 13 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 consistent with (i) the coefficient estimates I find in my main results, (ii) recent research on the impact of weather on ports, policymakers' concerns regarding the vulnerability of sea ports to climate change and port operators' costly adaptation efforts, and (iii) 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.

3.3 Patterns of adaptation to climate change

Before turning to welfare impacts, I briefly discuss countries' ability to adapt to the impact of climate change on trade cost. To shed light on this, I analyze how the effect of climate change on trade cost varies with climatic environment. As I explained above, I do this by estimating equation (4), a version of my main estimating equation (2) which lets the impact of climate change on trade cost vary across climatic environments. Analogous to my core robustness checks above, I consider two dimensions of climate heterogeneity. First, I assess how the impact of climate change varies across quartiles of countries' 1950–1980 average temperature. Second, I estimate how that impact varies across quartiles of countries' average temperature change between the 1900s and 2000s decades.

Figure 14 shows the coefficients on the temperature interactions across 1950–1980 average temperature quartiles. I see significant negative impacts in the lower two quartiles of the temperature distribution, while estimates for the upper two quartiles are much noisier. This suggests that the same temperature change is especially detrimental to countries that are adapted to a colder climate, and thus see a larger relative change. Figure15 shows the corresponding coefficient estimates across quartiles of 1900s–2000s temperature change. One might expect that countries which see faster climate change have more of an incentive to adapt to it. If this incentive leads to actual adaptation, these countries would then see smaller impacts. I find, however, that the upper two quartiles — countries which see relatively rapid climate change — see clear negative impacts, while I find no significant impact on the lower two quartiles. It seems, therefore, that countries can adapt to slower changes in temperature, but find it harder to deal with rapid changes in their climatic environment.

Together, these results suggest that adaptation to the impact of climate change on trade cost is relatively slow. Warmer countries see less of an impact from decade to decade climate change, which suggests that in the long run, countries were historically able to adapt to a relatively stable climatic environment. Countries seem unable, however, to adapt to rapid climate change in real time. This is concerning given the increasing pace of climate change, which makes future climate change especially hard to adapt to. Furthermore, we can expect to be in a unstable climatic environment for the foreseeable future, which could lead to countries being continuously less well adapted to this changing environment than they historically were to a more stable climate.

4 Welfare impacts

I now assess 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 primes to denote counterfactual quantities. For example, using the basic distance-based specification and hats to denote the ration of counterfactual to observed quantities, the change in the bilateral resistance term would be

$$\hat{\phi}_{nit} \equiv \frac{\phi'_{nit}}{\phi_{nit}} \overset{(1)}{=} d_{ni}^{\delta_1(T_{is}-T_{it})+\delta_2(T_{ns}-T_{nt})} \tag{5}$$

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

To estimate the change in bilateral resistance terms, I use a specification that is consistent with maritime trade being the main driver of the impacts I observe. To do so, I estimate the impact of climate change on trade for countries with at least four land borders between them, compared to trade between direct neighbors. This is similar to the coefficient in Figure 12 for $b = 4$. I allow for the impact of trade cost to vary by origin and destination 1950s to 1980s temperature. This allows countries' climatic environment to drive their reactions to climate change. Using baseline temperature to do this is common in the literature on climate impacts on productivity (e.g. Burke et al. 2015; Ramey et al. 2025). I estimate

$$\begin{aligned}&\mathbb{E}\left(X_{nit}|\mathbf{D}_{nit}\right)\\&=\exp\left\{\gamma_{it}+\xi_{nt}+\alpha_t b^4_{ni}+\delta_1 b^4_{ni}\Delta T_{it}+\gamma_1 b^4_{ni}\Delta\bar{T}^{50\text{-}80}_i T_{it}+\delta_2 b^4_{ni}\Delta T_{nt}+\gamma_2 b^4_{ni}\bar{T}^{50\text{-}80}_n\Delta T_{nt}\right\}\end{aligned} \tag{6}$$

Here, b^4_{ni} is an indicator for the minimum number of land borders between n and i being four or greater. I estimate this using only direct neighbors and countries with at least four land borders between them, like for the donut hole specification above. This creates a clear comparison between likely maritime and likely non-maritime routes. I omit the additional controls $\mathbf{C}_{nit}$ since they do not affect my main results and slow down computation of this already complex model.

Figures 16 and 17 show the marginal effect of origin and destination temperature across 1950s to 1980s temperature. I find consistently negative impacts, with some variation across baseline temperature but not necessarily significant differences. I can back out the change in bilateral resistance from these results, similar to (5). (For neighboring countries and those with two or three land borders between them, I assume there is no impact of climate change on trade cost.)

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 in 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 previous decades in my data. Under the Eaton and Kortum (2002) model, the bilateral resistance term is equal to $\phi_{nit} = \tau^{-\theta}_{nit}$ where τ_{nit} is a measure of how difficult it is to ship goods from i to n and $\theta > 0$ measures productivity dispersion in the Fréchet distribution of technology underlying the Eaton and Kortum (2002) model.

To estimate welfare impacts, I rewrite the model in changes (Dekle, Eaton, and 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 change in trade shares $\hat{\pi}_{nit} \equiv \pi'_{nit}/\pi_{nit}$ resulting from a change $\hat{\tau}_{nit} \equiv \tau'_{nit}/\tau_{nit}$ is

$$\hat{\pi}_{nit} = \frac{\hat{A}_{it}(\hat{\tau}_{nit}\hat{w}_{it})^{-\theta}}{\sum_{k=1}^{N}\pi_{nkt}\hat{A}_{kt}(\hat{\tau}_{nkt}\hat{w}_{kt})^{-\theta}} \tag{7}$$

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 $\hat{w}_{it} \equiv w'_{it}/w_{it}$ 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

$$\hat{W}_{it} \equiv \frac{W'_{it}}{W_{it}} = \hat{A}_{it}^{\frac{1}{\theta}} \hat{\pi}_{iit}^{-\frac{1}{\theta}} \tag{8}$$

4.1 Welfare impact of climate change through the trade cost channel

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 $\hat{\phi}_{nit}$. I can then solve the system of equations (7) 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 (8). Following Dekle et al. (2008), I set the only unknown parameter $\theta = 8.28$.[3]

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 18 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 1.6 percent increase in welfare if we reverted trade cost increases due to climate change over the last 100 years. This is a relatively sizeable effect, comparable to estimates of the impact of climate change based on field-level or firm-level data (Costinot et al. 2016; Nath 2020) but compatible with direct country-level estimates of the productivity impact (Burke et al. 2015; Ramey et al. 2025; Bilal and Känzig 2024). I discuss this comparison to productivity impacts in mode detail below.

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 1.8 percent, whereas for the 1950s I estimate an average welfare increase of 1.2 percent. For the most recent decade, the 2000s, I estimate an 0.2 percent welfare increase, on

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

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 5.5 percent in the 1880s counterfactual.[4]

4.2 Drivers and distribution of welfare gains

Figure 19 shows a map of welfare gains across countries for the 1910s counterfactual. There is considerable heterogeneity across the globe, with larger gains in southern, western and northern Africa, Argentina, northern Latin America and Central America, the Arabian Peninsula, and south-eastern Asia. Australia, Iceland and Ireland also have somewhat larger gains than other rich countries. What determines who gains more or less from undoing the trade cost impact of climate change?

The most obvious factor are climate trends: I would expect that countries which see more climate change or whose neighbors see more climate change would benefit more from undoing those changes. Figure 20 shows welfare changes in the 1910s counterfactual across countries' own temperature change between period the 1910s and the 2010s. Figure 21 shows welfare changes across the inverse distance weighted change in other countries' change in temperatures, which is calculated as

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

where ΔT_{nt} is country n's change in temperature between period t and the 2010s. This measures climate change in the rest of the world, but weighted towards countries' neighbors. Interestingly, both measures of climate trends are somewhat negatively correlated with welfare gains.

These temperature measures are, of course, correlated. Figure 22 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, but note that these welfare outcomes are generated regressors, which I ignore here. I treat these results as interesting suggestive evidence for directions of change, not as a true test for significantly different

[4] Appendix Figure 31 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.

welfare effects.

The first column again highlights that, somewhat surprisingly, countries' own temperature change is negatively correlated with welfare gains. The second column shows that inverse distance weighted change is also negatively correlated with countries' own welfare changes. Column three combines the two and shows that once I take both changes into account, countries' own temperature changes are only weakly negatively correlated with welfare changes. Surrounding countries' temperature changes, however, are still strongly negatively correlated with welfare gains. The fourth column shows that when controlling for 1950s to 1980s temperature change (which drives heterogeneity in trade cost impacts), the correlation become weaker, but own trends now have the expected (positive) sign and neighbors' trends retain the negative sign.

The negative impact of neighbors' temperatures 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. The key takeaway is the importance of considering neighbors' climate trends, not just countries' own climate trends.

To understand the distribution of gains across countries, Figure 23 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 24 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.

That larger economies benefit less is not surprising — they are less reliant on international trade, since they have larger domestic markets. (See Figure 25, which shows that larger economies tend to have higher own trade shares.) To show that this is driving the difference in welfare gains by GDP, the fifth column of Table 3 shows a regression of welfare gains on log 2010s GDP. Across periods, GDP and welfare gains are strongly negatively correlated. The sixth column of Table 3 additionally controls for countries' 2010s own trade share. Once I take that into account, larger economies actually benefit more from trade cost decreases. Not surprisingly, though, a larger own trade share is correlated with lower welfare gains, because international trade is less important for the economy.

The final column of the table again controls for the 1950s to 1980s average temperature, which does not change results much. All told, larger economies benefit less from undoing climate change impacts on trade cost, because they are less reliant on international trade.

4.3 Comparing trade cost and productivity channels

As mentioned above, the welfare gains are sizable — the average 1910s welfare gain of 1.6 percent is comparable to estimates of the welfare effects of climate change through agricultural and overall productivity (Costinot et al. 2016; Nath 2020). It is about ten percent of the impacts found in estimates of the global impacts of climate change, depending on the exact specification (e.g. Burke et al. 2015; Ramey et al. 2025), and about five percent of the welfare loss from one degree of warming found in Bilal and Känzig (2024).

To compare welfare impacts due to productivity and trade cost channels, I estimate the impact of climate change on productivity with a setup similar to Ramey et al. (2025). I use decade to decade variation, however, to line up with the trade cost estimation and my focus on climate change. I also use GDP data from TRADHIST to be consistent with those results. I estimate

$$\Delta \log (y_{it}) = \beta_1 \Delta T_{it} + \beta_2 \bar{T}_i^{50\text{-}80} \Delta T_{it} + \gamma_i + \varepsilon_{it} \tag{9}$$

where y_{it} is country i's average GDP per capita during decade t, as a measure of productivity. I allow for the effect of temperature to vary with 1950s to 1980s temperature. I do not include lagged impacts since existing estimate of the impact of weather shocks on GDP have not gone beyond a ten year horizon, and I am working on a decadal scale. Figure 26 shows the marginal effect of temperature shocks across baseline temperature. I find consistently negative impacts of decadal temperature changes on productivity, though with less negative impacts in colder countries.

I then back out implied technology changes $\hat{A}_{it}$, using that in the model, GDP per capita is

$$y_{it} \equiv \frac{w_{it}}{\mathcal{P}_{it}} = \Gamma \left(\frac{\theta - \sigma + 1}{\theta} \right)^{\frac{1}{\sigma - 1}} \left(\frac{A_{it}}{\pi_{iit}} \right)^{\frac{1}{\theta}}$$

where $\mathcal{P}_{it}$ is the optimal CES price index, Γ indicates the Gamma function and π_{iit} is country i's own trade share (domestic trade) during decade t. In general, this depends on all countries' temperature shocks through the trade network. This is reflected in the denominator of (7), showing that changes in trade shares depend on all countries' shocks. In autarky, however, which I can approximate by taking trade cost to infinity, I have $d_{nit} \to +\infty \, \forall \, i, n \neq i$ and $\pi_{iit} \to 1$. Then, $\hat{y}_{it} = \hat{A}_{it}^{\frac{1}{\theta}}$. The reduced form (9) estimates $\log(\hat{y}_{it})$, and I can back out $\hat{A}_{it} = \exp\{\theta \log(\hat{y}_{it})\}$

The insight that this only works in autarky but not when countries trade is due to, and brought out in much more generality in, Astier, Barrows, Calel, and Ollivier (2025). They show that productivity regressions of this form suffer from a stable unit treatment value assumption violation, rendering them generally invalid. They also find, however, that these regressions do better for past climate change than for projecting out into the future. I rely on this finding, and the fact that these are widespread in the literature, to use (9) as my productivity benchmark. Very importantly, note that my trade cost regressions control for shocks at all origins and destinations using fixed effects and thus control for changes via the trade network. They therefore do not suffer from this problem.

I can now estimate three different counterfactuals — undoing the impact of climate change (i) *only* on trade cost, as above, (ii) *only* on productivity, and (iii) on *both* trade cost and probability. This allows me to compare the welfare implications of both channels and assess whether we meaningfully underestimate the welfare impact of climate change when we focus exclusively on productivity.

Figure 27 shows average welfare gains across the trade cost only, productivity only, and combined counterfactuals for the 1910s climate counterfactual. I break these up by small (below median 2010s GDP) and large countries. Gains from increased productivity alone are considerably larger than gains from trade cost alone, as would be expected from most trade models. Welfare gains from the combined counterfactual are also appreciably larger, however, 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 28 shows a histogram of the welfare gain ratio between the combined and productivity only counterfactual. That is, this shows the welfare gain from undoing both trade cost and probability impacts divided by the welfare gain from only undoing productivity impacts. The average country has about a nine percent larger welfare gain from also undoing trade cost changes. Figure 29 shows a histogram of the difference between the two welfare changes, rather than the ratio. The average welfare gain difference is about two percentage points, which is slightly larger than the average welfare gain through trade cost alone. The two channels are thus somewhat complementary.[5]

[5] Of course, reducing trade cost and increasing productivity at the same time would always lead to an impact larger than the sum of its parts. Due to the heterogeneity by baseline temperature, however, it would have been possible for the estimates to produce any pattern of additional gains, including a negative correlation between trade cost

As discussed above, the welfare impact oc climate change varies depending on countries' trade openness as well as their exposure. Figure 30 shows a world map of the welfare gain ratio showing the global distribution of additional welfare gains. Again, especially poorer countries gain more, but the UK and Ireland also stand out compared to continental Europe, for example.

This simple exercise suggests that, while productivity is the main driver of climate impacts, ignoring the trade cost channel leads to an appreciable underestimate of the overall effect. This underestimate is larger, and thus more important to take into account, for smaller countries, including rich countries which are especially open to trade.

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 seems to be driven by impacts on ocean-based trade, potentially because sea ports are especially vulnerable to extreme weather events and hence to damages from climate change. Adaptation to these impacts seems slow.

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 1.6 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 nine 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. There, the impact on trade cost can be estimated independently of the model and then incorporated into counterfactuals via simple hat algebra without computational overhead. I hope that this simple methodology will

and productivity changes.

aid future analyses 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	Drop CHN	Decade $\geq$ '50s	Full interaction	Residual T	Benchmark
$\tilde{d}_{ni} \times$ 2010s	−0.552	−0.899	−0.903	−0.744	−0.791	−0.663	−0.974	−0.590	−0.548	−0.620	−0.552	−0.581	−0.565
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$\tilde{d}_{ni} \times \Delta T_{it}$	−0.095	−0.125	−0.134	−0.048	−0.053	−0.156	−0.192	−0.137	−0.122	−0.096	−0.099	−0.204	
	[0.000]	[0.000]	[0.000]	[0.031]	[0.010]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	
$\tilde{d}_{ni} \times \Delta T_{nt}$	−0.066	−0.089	−0.090	−0.038	−0.014	−0.116	−0.123	−0.098	−0.090	−0.069	−0.070	−0.199	
	[0.011]	[0.000]	[0.000]	[0.081]	[0.485]	[0.000]	[0.000]	[0.000]	[0.004]	[0.011]	[0.017]	[0.000]	
$\tilde{d}_{ni} \otimes$ decade	Yes	Yes	Yes	Yes	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	No	No	No	No
$\tilde{d}_{ni} \otimes T_{50-'80}$ decile$_n$	No	Yes	Yes	No	No	No	No	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	No	No	No	No
$\tilde{d}_{ni} \otimes T_{50-'80}$ decile$_n \times$ decade	No	No	Yes	No	No	No	No	No	No	No	No	No	No
$\tilde{d}_{ni} \otimes$ CC decile$_i$	No	No	No	Yes	Yes	No	No	No	No	No	No	No	No
$\tilde{d}_{ni} \otimes$ CC decile$_n$	No	No	No	Yes	Yes	No	No	No	No	No	No	No	No
$\tilde{d}_{ni} \otimes$ CC decile$_i \times$ decade	No	No	No	No	Yes	No	No	No	No	No	No	No	No
$\tilde{d}_{ni} \otimes$ CC decile$_n \times$ decade	No	No	No	No	Yes	No	No	No	No	No	No	No	No
$\tilde{d}_{ni} \otimes$ Lat. decile$_i$	No	No	No	No	No	Yes	Yes	No	No	No	No	No	No
$\tilde{d}_{ni} \otimes$ Lat. decile$_n$	No	No	No	No	No	Yes	Yes	No	No	No	No	No	No
$\tilde{d}_{ni} \otimes$ Lat. decile$_i \times$ decade	No	No	No	No	No	No	Yes	No	No	No	No	No	No
$\tilde{d}_{ni} \otimes$ Lat. decile$_n \times$ decade	No	No	No	No	No	No	Yes	No	No	No	No	No	No
$\mathbf{C}_{nit} \otimes$ decade	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin-decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-decade FE	Yes	Yes	Yes	Yes	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	237,391	323,031	326,747	324,433	327,550
Clusters	28,993	28,993	28,993	28,993	28,993	28,993	28,993	22,118	23,078	23,078	28,993	28,943	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. $\tilde{d}_{ni} \equiv \log(d_{ni})$ 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 decade 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 decile of latitude. Models with these decile controls include separate trade cost levels and, for the *time trend* version, trade cost time trends for each 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). *Drop CHN* drops China from the estimation sample. *Decade* $\geq$ *'50s* only uses decades from the 1950s onwards. *Full interaction* interacts temperatures not only with distance, but also with the variables included in $\mathbf{C}_{nit}$. *Residual T* uses temperature residuals obtained from an AR(3) estimation with heterogeneity by 1950s–1980s average temperature, similar in spirit to Ramey, Nath, and Klenow (2025). 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		−0.443 [0.000]
Long distance$_{ni}$ × ΔT_{it}		−0.101 [0.107]
Long distance$_{ni}$ × ΔT_{nt}		−0.028 [0.626]
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	28,993	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. 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.

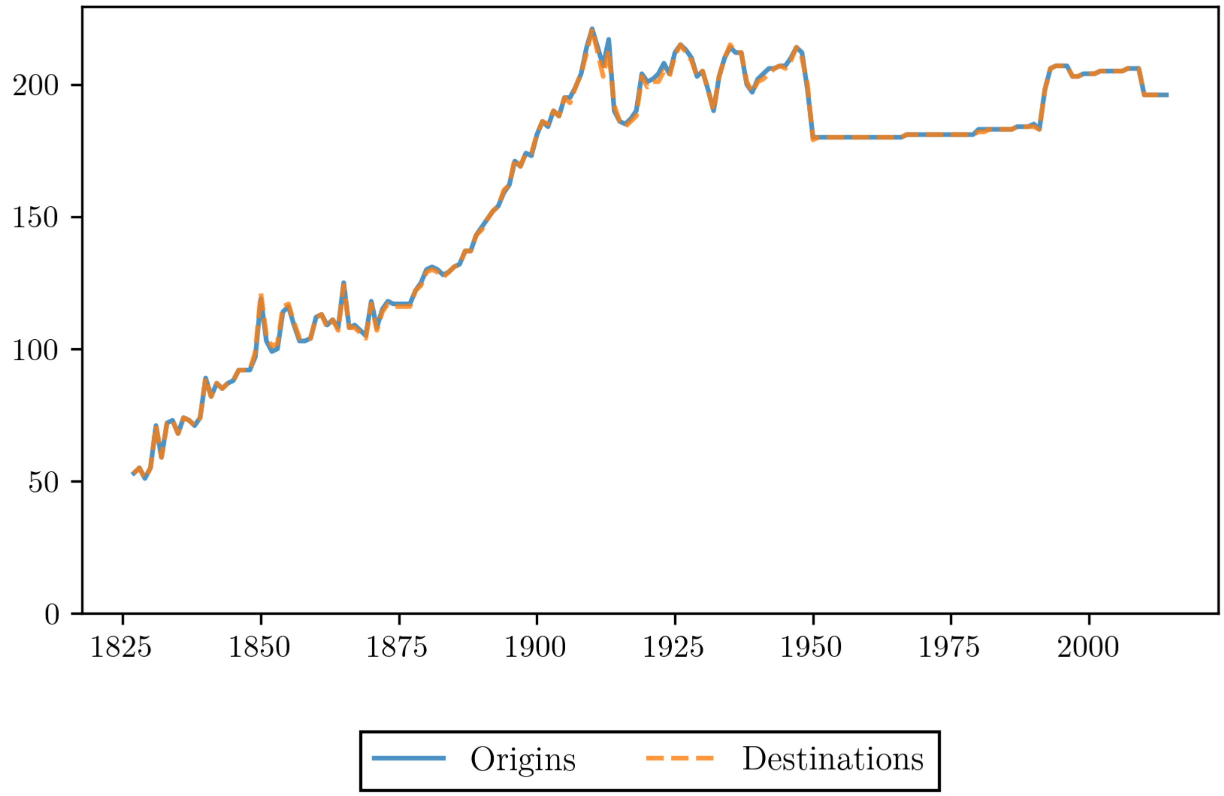
Table 3: Correlates of welfare changes

Variable	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$
Own ΔT	−1.661 [0.000]		−0.111 [0.873]	0.310 [0.630]			
Inverse distance weighted ΔT		−4.729 [0.000]	−4.512 [0.007]	−1.521 [0.367]			
Log 2010s GDP					−0.233 [0.000]	0.112 [0.048]	0.198 [0.001]
2010s own trade share (%)						−0.060 [0.000]	−0.054 [0.000]
1950s–'80s $\bar{T}$				0.112 [0.000]			0.078 [0.000]
Decade FE	Yes	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. *1950s–'80s* $\bar{T}$ is countries' average temperature from the 1950s to the 1980s. Standard errors clustered by country, p-values in brackets.

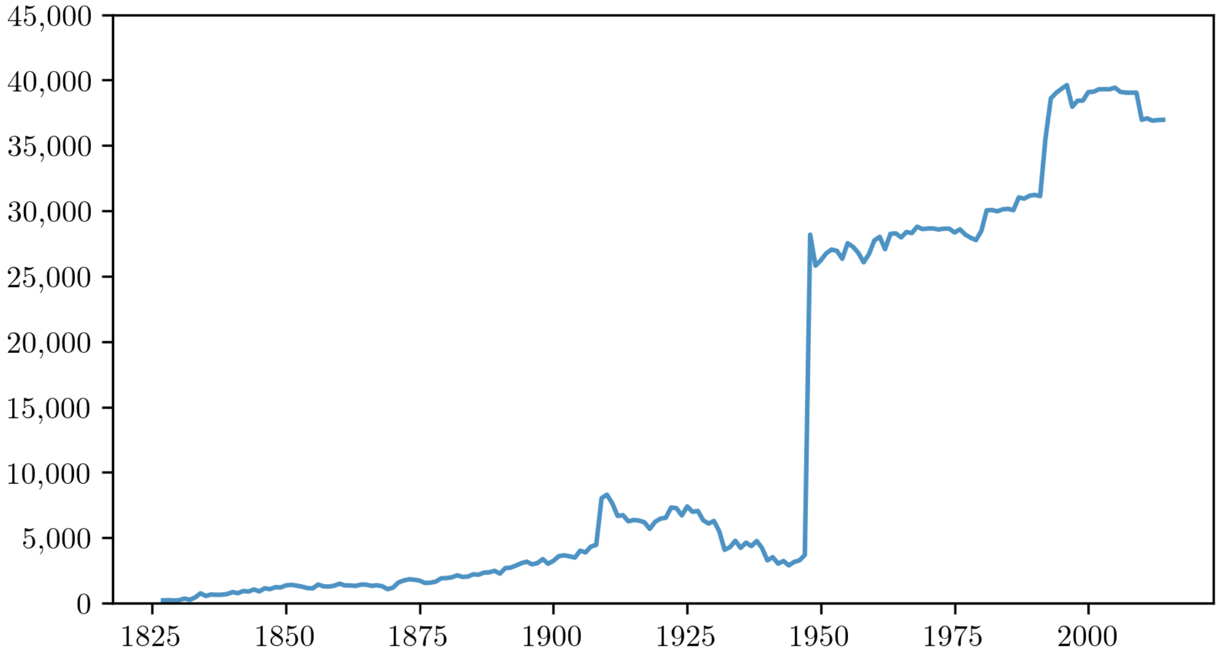
Figures

Figure 1: Trade data country counts by year



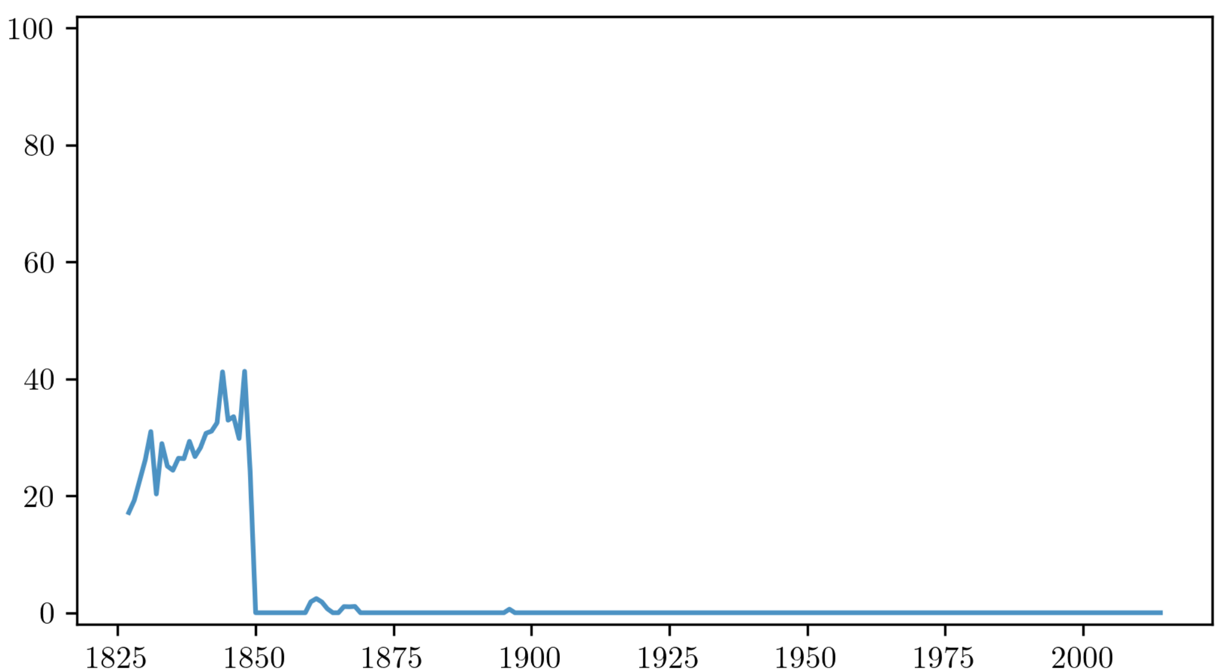
Note: The figure shows the number of countries observed in the TRADHIST trade data by year. I subset to observations with non-missing trade flows and distance information.

Figure 2: Trade flow counts by year



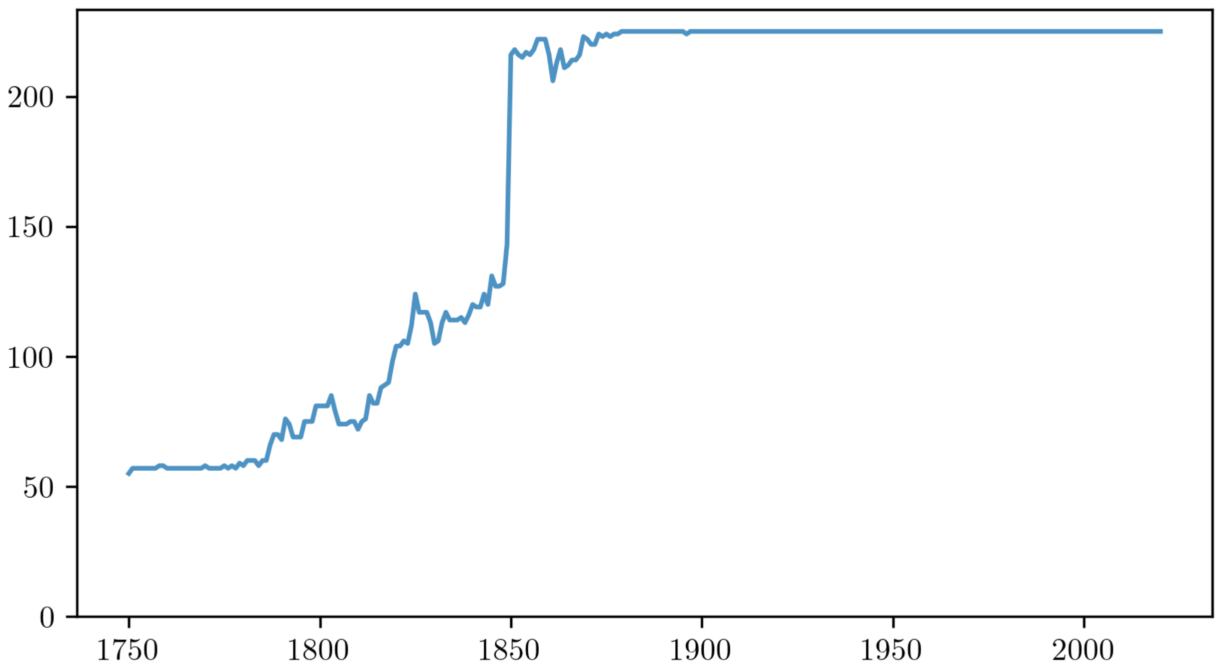
Note: The figure shows the number of trade flows observed in the TRADHIST trade data by year. I subset to observations with non-missing trade flows and distance information.

Figure 3: Unmatched trade flows (percent) by year



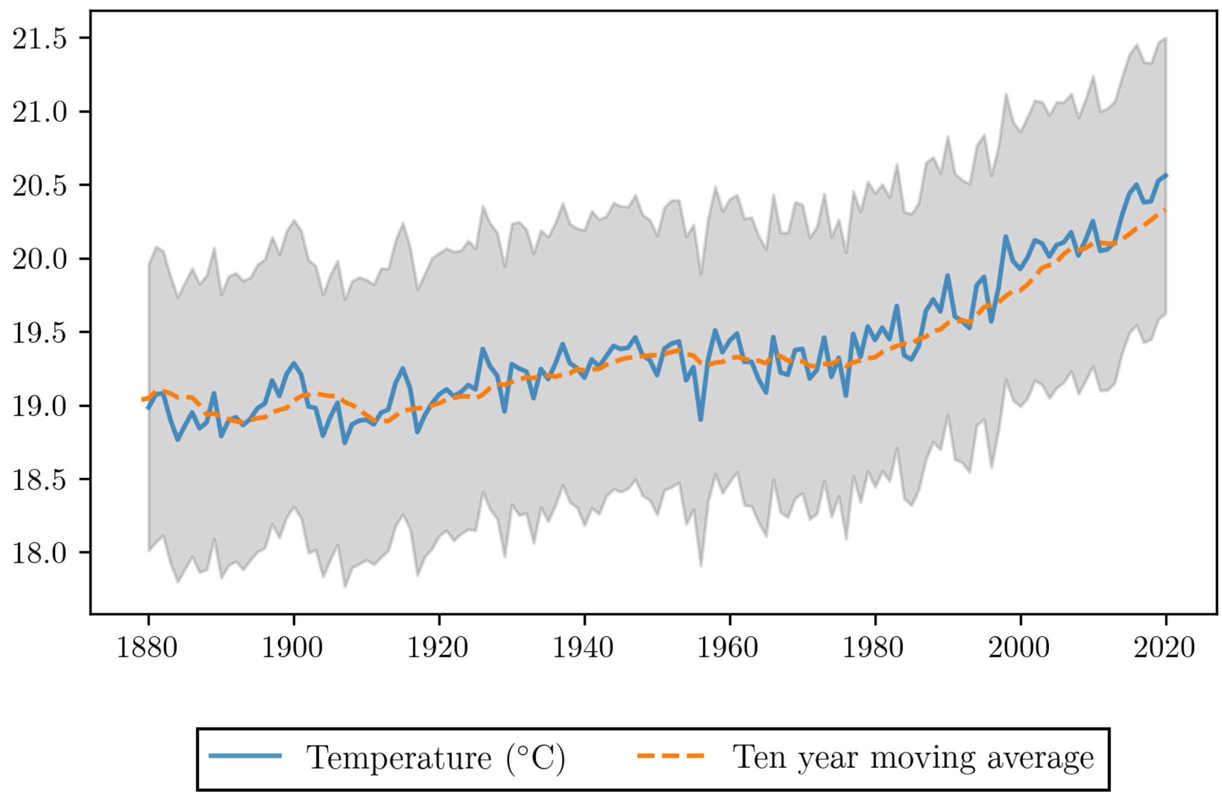
Note: The figure shows the percent of TRADHIST trade observations which cannot be matched to weather information by year. I subset to observations with non-missing trade flows and distance information.

Figure 4: Weather observation counts for current countries by year



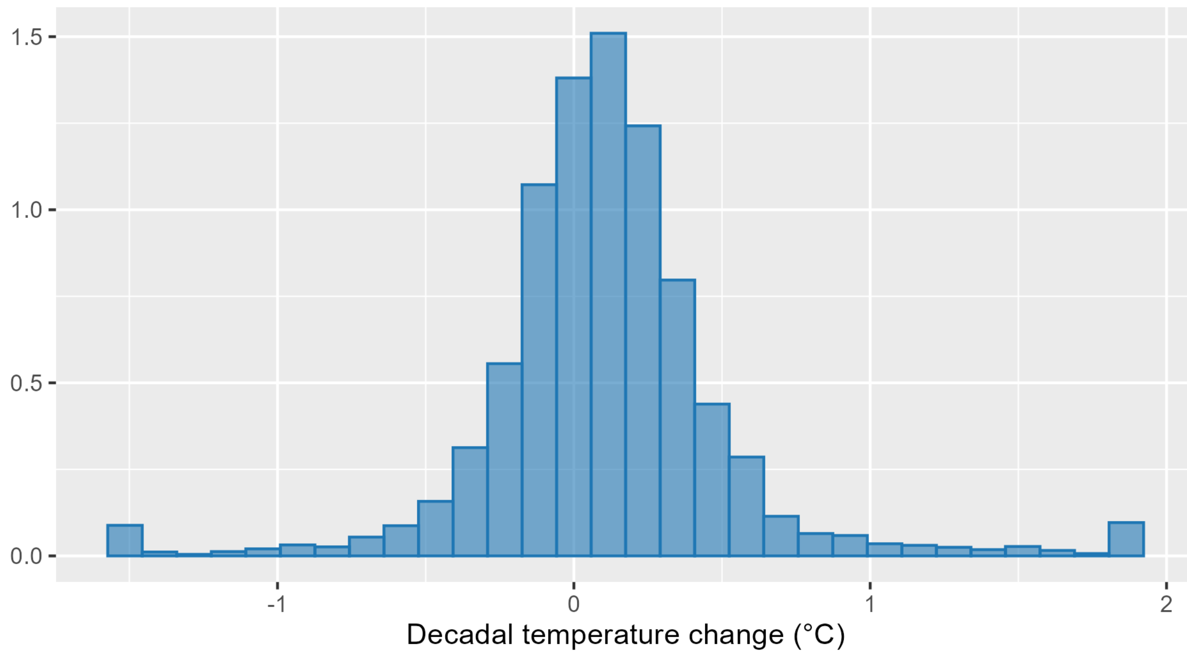
Note: The figure shows the number of countries with non-missing weather observations by year. I subset to countries which currently exist and ever appear in the TRADHIST trade data. (For example, in this plot, I include Germany, which currently exists and appears in the trade data, but not the former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



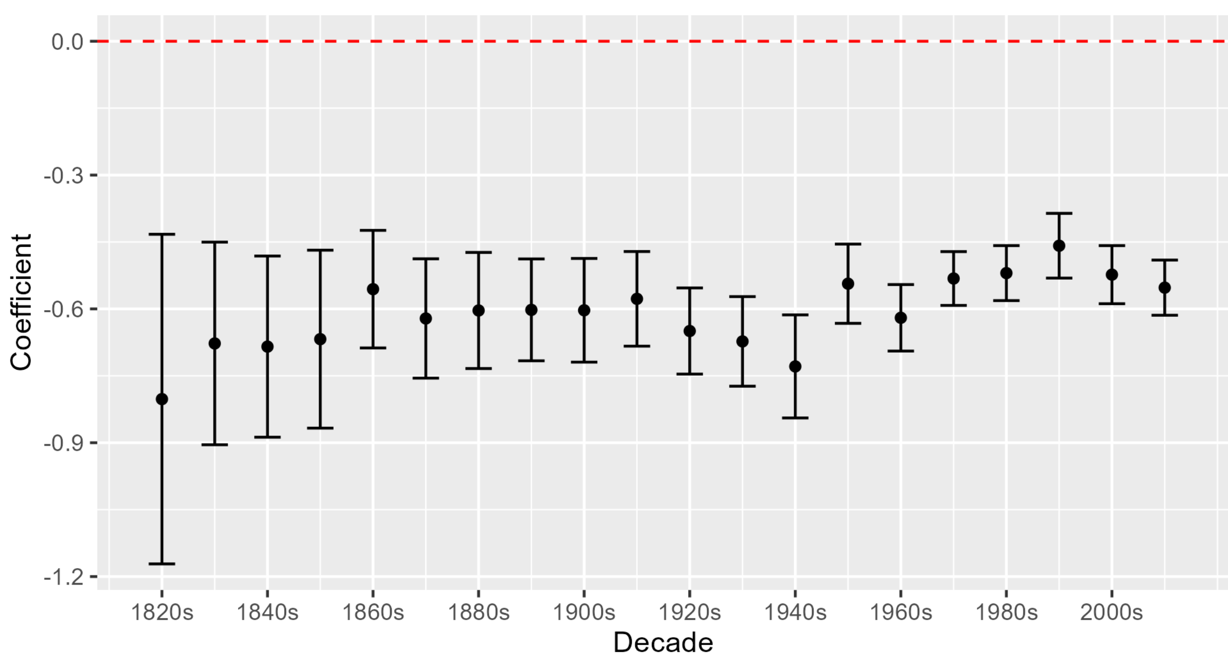
Note: The figure shows the average temperature across years. The figure starts in 1880, where I have global weather coverage. I subset to countries which currently exist and ever appear in the TRADHIST trade data. (For example, in this plot, I include Germany, which currently exists and appears in the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



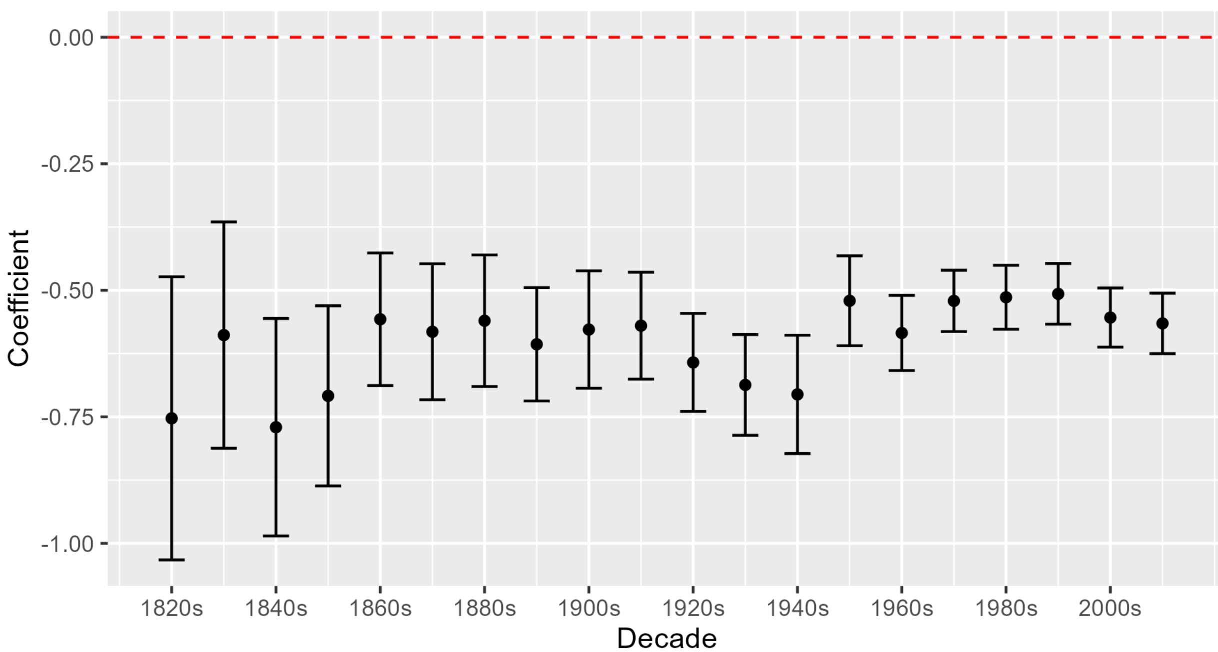
Note: The figure shows the distribution of decadal temperature changes across all countries and decades. As in my gravity estimations, decadal temperature changes are winsorized at the 1st and 99th percentiles.

Figure 7: Coefficients on log distance across decades



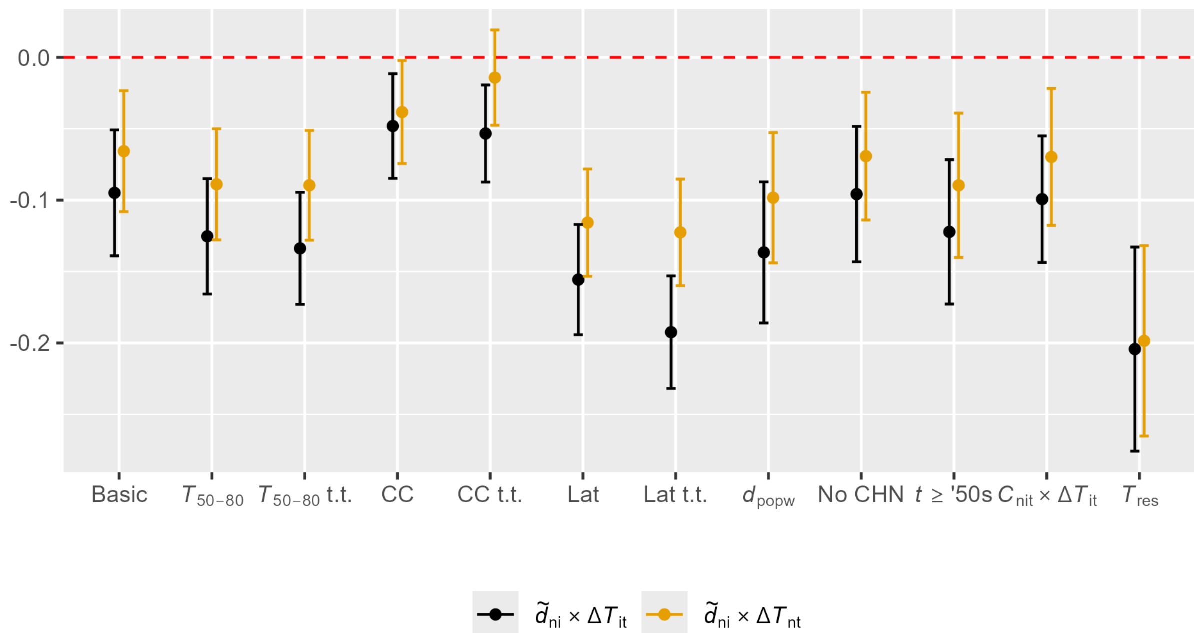
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate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



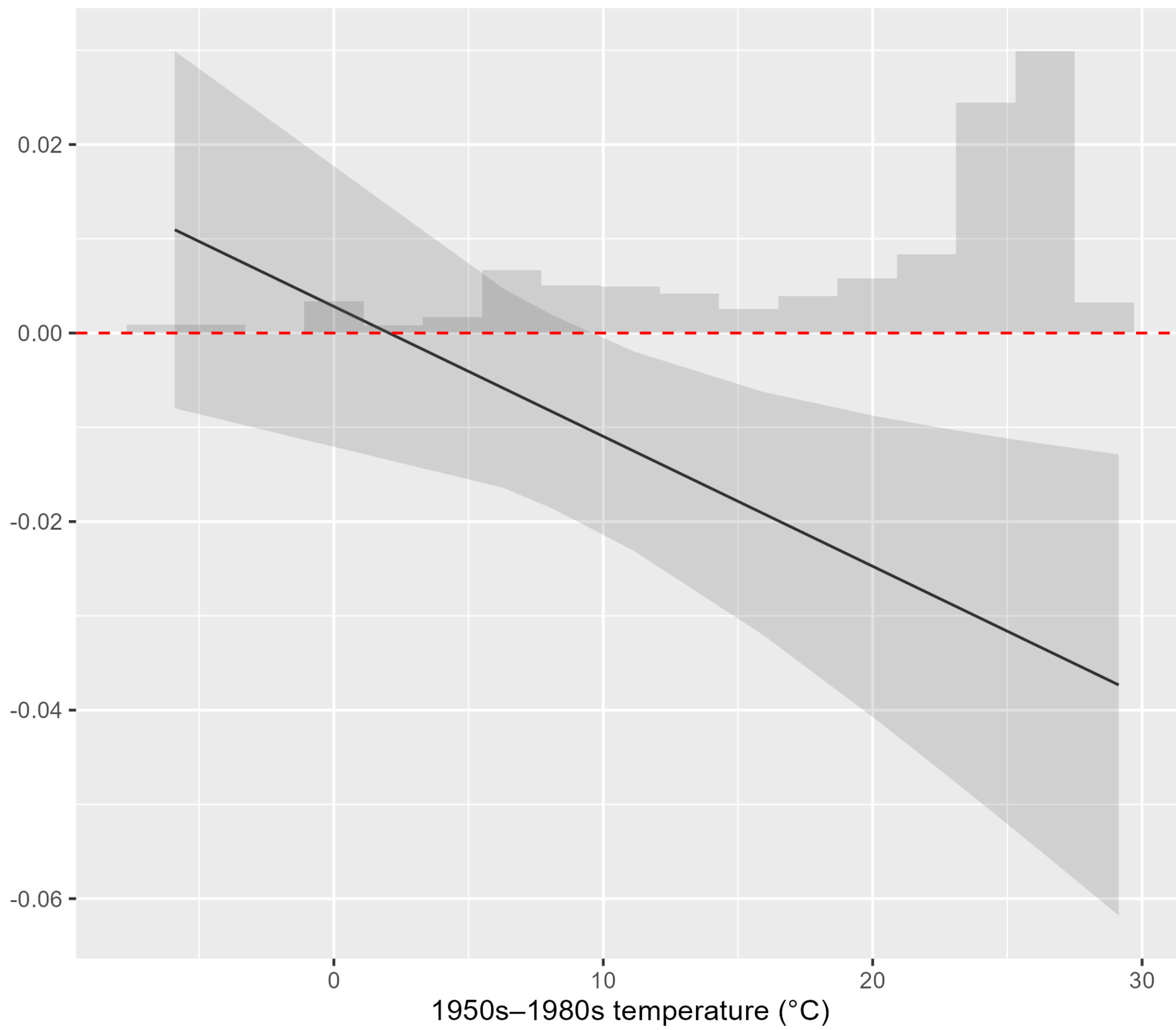
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate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



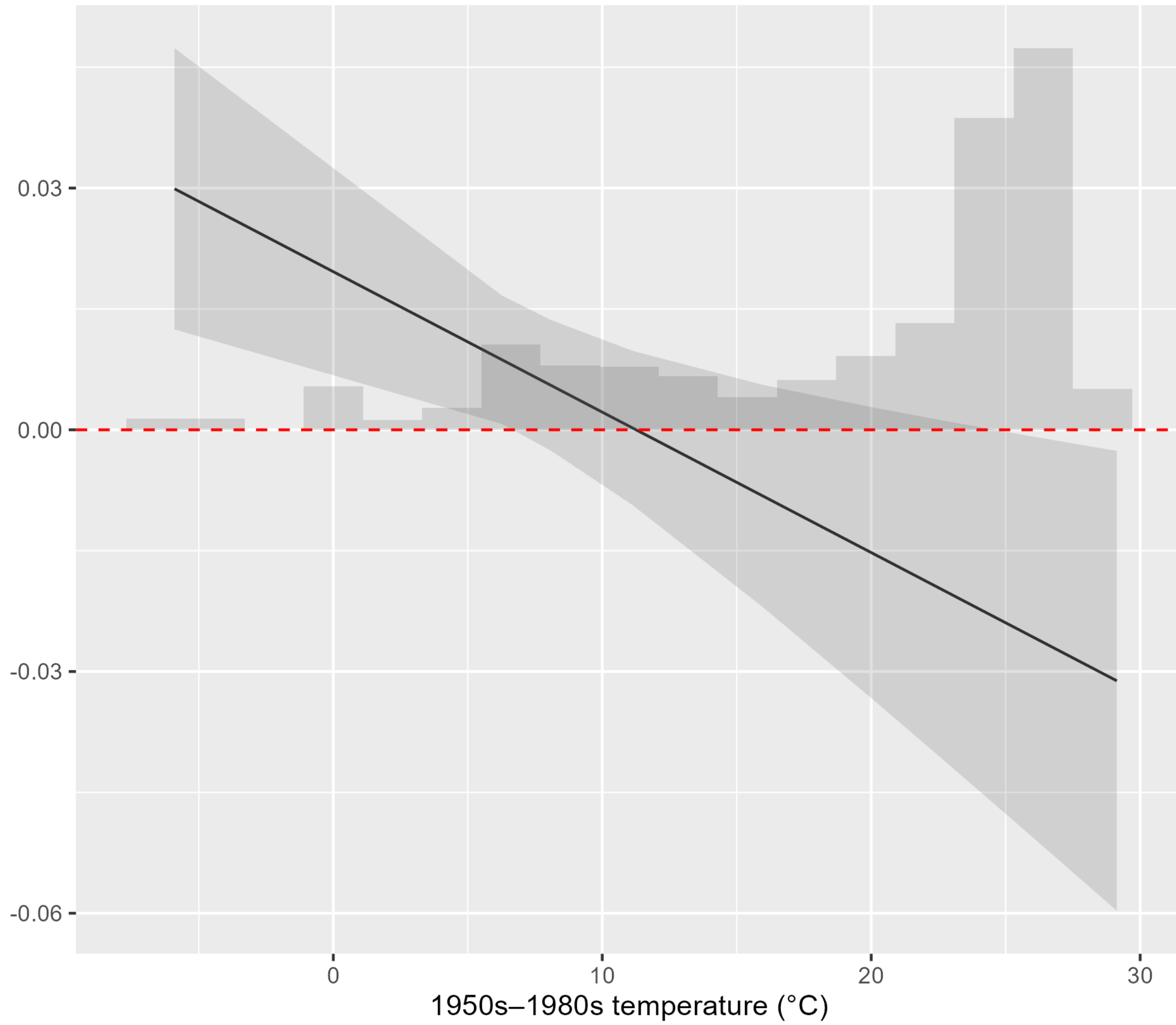
Note: The outcome are decade-level average trade flows from country i to country n, winsorized at the 99$^{\text{th}}$ percentile. The estimation uses pseudo-Poisson maximum likelihood (PPML) to accommodate zero trade flows. $\tilde{d}_{ni} \equiv \log(d_{ni})$ is the log of the great circle distance 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 decade 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 decile of latitude. Models with these decile controls include separate trade cost levels and, for the *t.t.* version, trade cost time trends for each decile. d_{popw} 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). *No CHN* drops China from the estimation sample. $t \geq$ *'50s* only uses decades from the 1950s onwards. *Full interaction* interacts temperatures not only with distance, but also with the variables included in $\mathbf{C}_{nit}$. *Residual T* uses temperature residuals obtained from an AR(3) estimation with heterogeneity by 1950s–1980s average temperature, similar in spirit to Ramey, Nath, and Klenow (2025). Standard errors clustered by country pair. Vertical lines and whiskers indicate 90 percent confidence intervals.

Figure 10: Marginal effect of year-to-year weather shocks on container port throughput



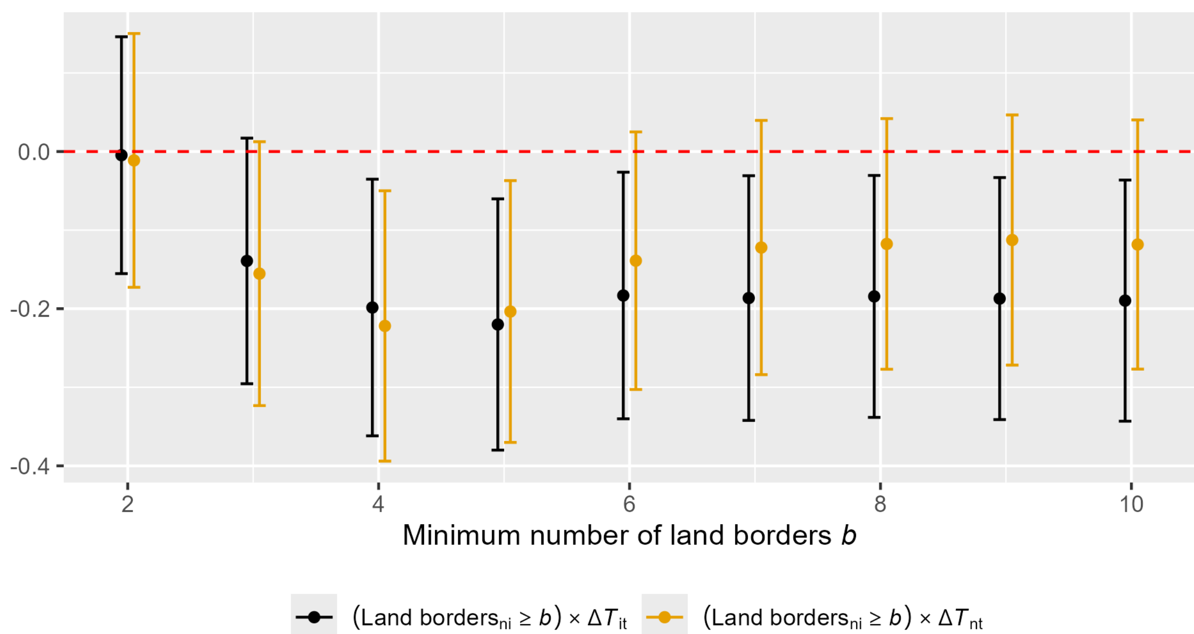
Note: Results are from a regression of log change in container port throughput on temperature changes and country fixed effects. The effect of temperature varies with countries' 1950s to 1980s average temperature. This graph shows the marginal effect of temperature shocks across that baseline temperature. The graph also shows a histogram of 1950s to 1980s average temperature. The shaded area indicates a 90 percent confidence interval.

Figure 11: Marginal effect of year-to-year weather shocks on container port throughput, controlling for change in GDP p.c.



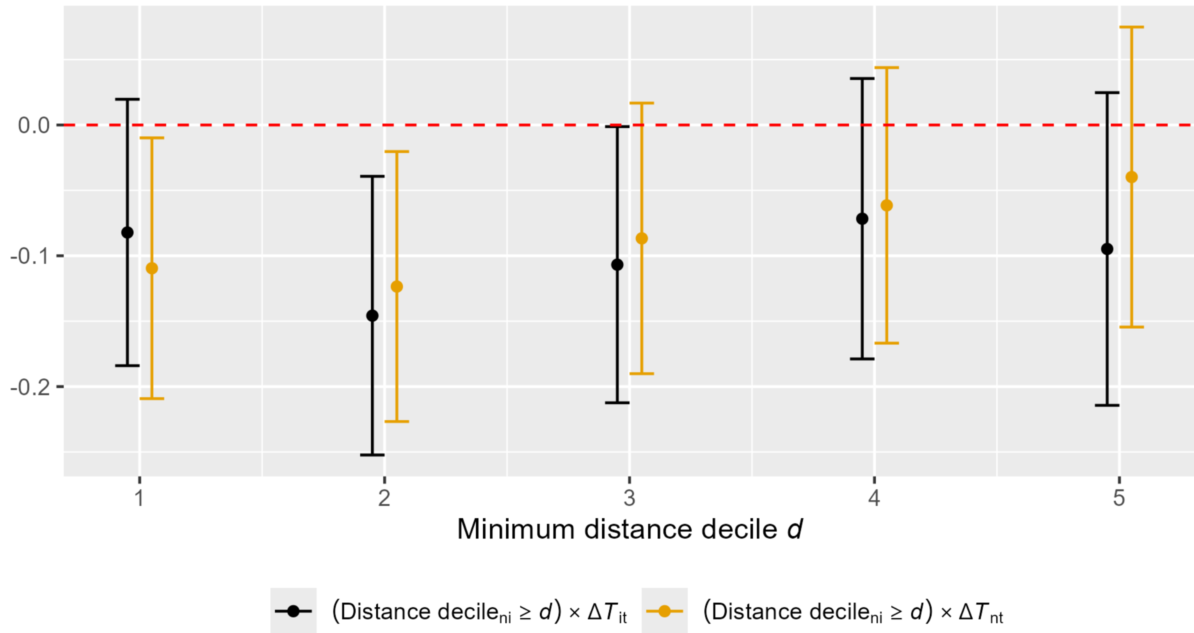
Note: Results are from a regression of log change in container port throughput on temperature changes and country fixed effects, controlling for changes in log GDP per capita. The effect of temperature varies with countries' 1950s to 1980s average temperature. This graph shows the marginal effect of temperature shocks across that baseline temperature. The graph also shows a histogram of 1950s to 1980s average temperature. The shaded area indicates a 90 percent confidence interval.

Figure 12: Land border crossing donut hole estimation



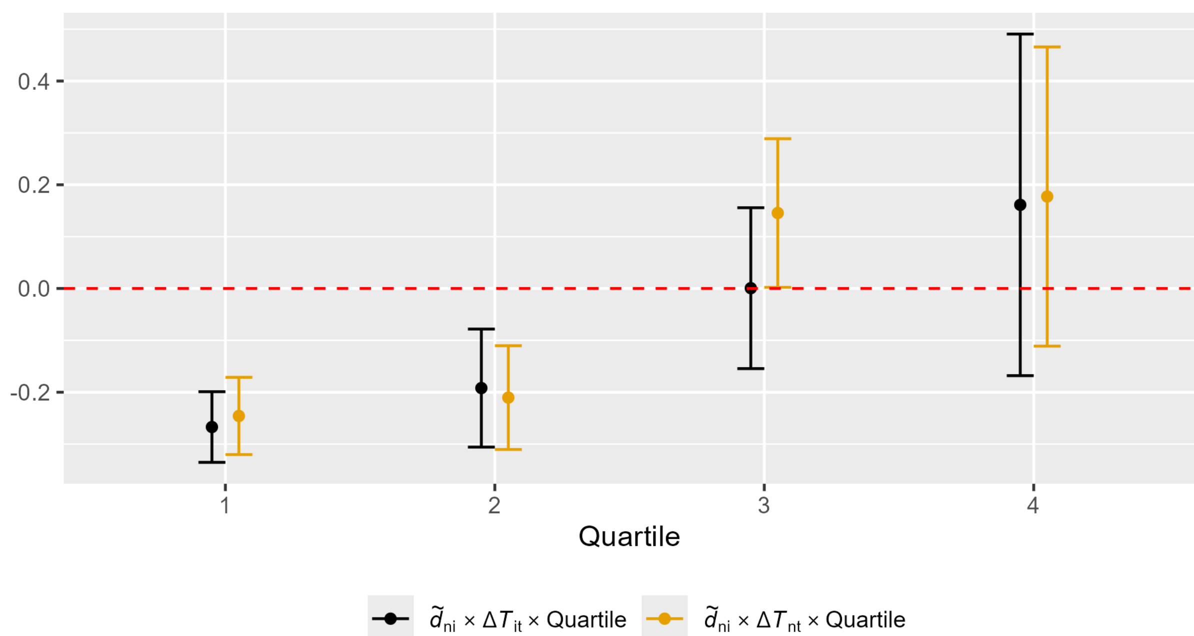
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Gap_{ni} is an indicator; it is equal to one if the number of countries that need to be crossed to get, via a land route, from the 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^{st} and 99^{th} percentiles. Vertical lines and whiskers indicate 90 percent confidence intervals.

Figure 13: Distance decile donut hole estimation



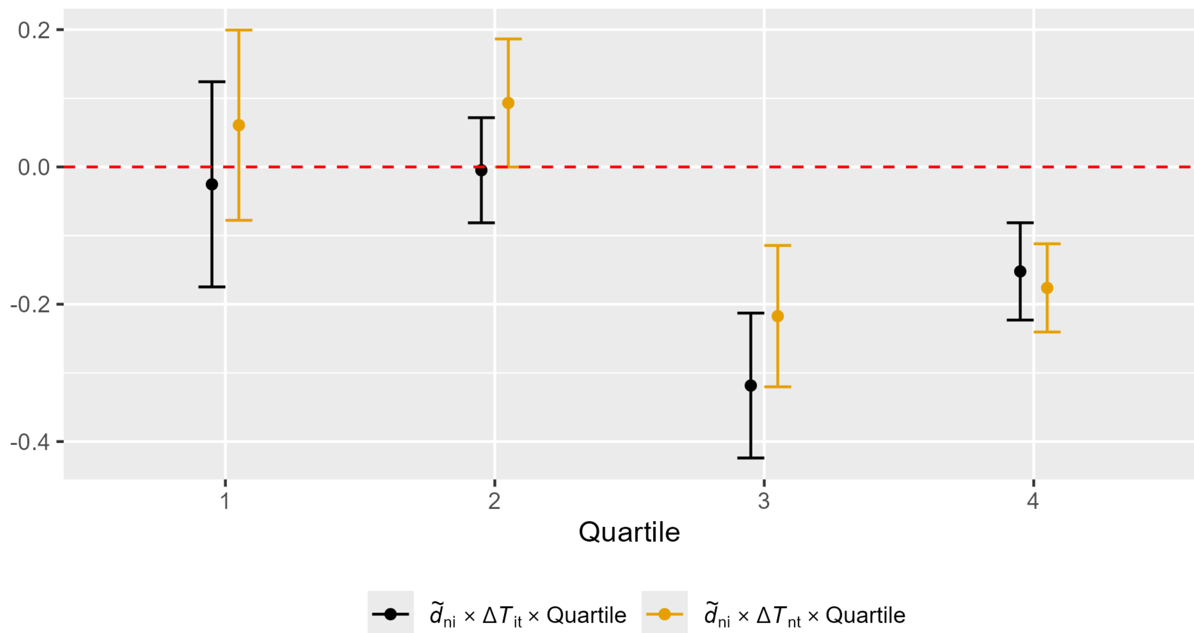
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Distance decile$_{ni}$ is an indicator; it is equal to one if the distance between the origin to the destination country is greater 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 °C. Temperature changes are winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles. Vertical lines and whiskers indicate 90 percent confidence intervals.

Figure 14: Coefficients on temperature interactions across 1950–1980 average temperature quartiles



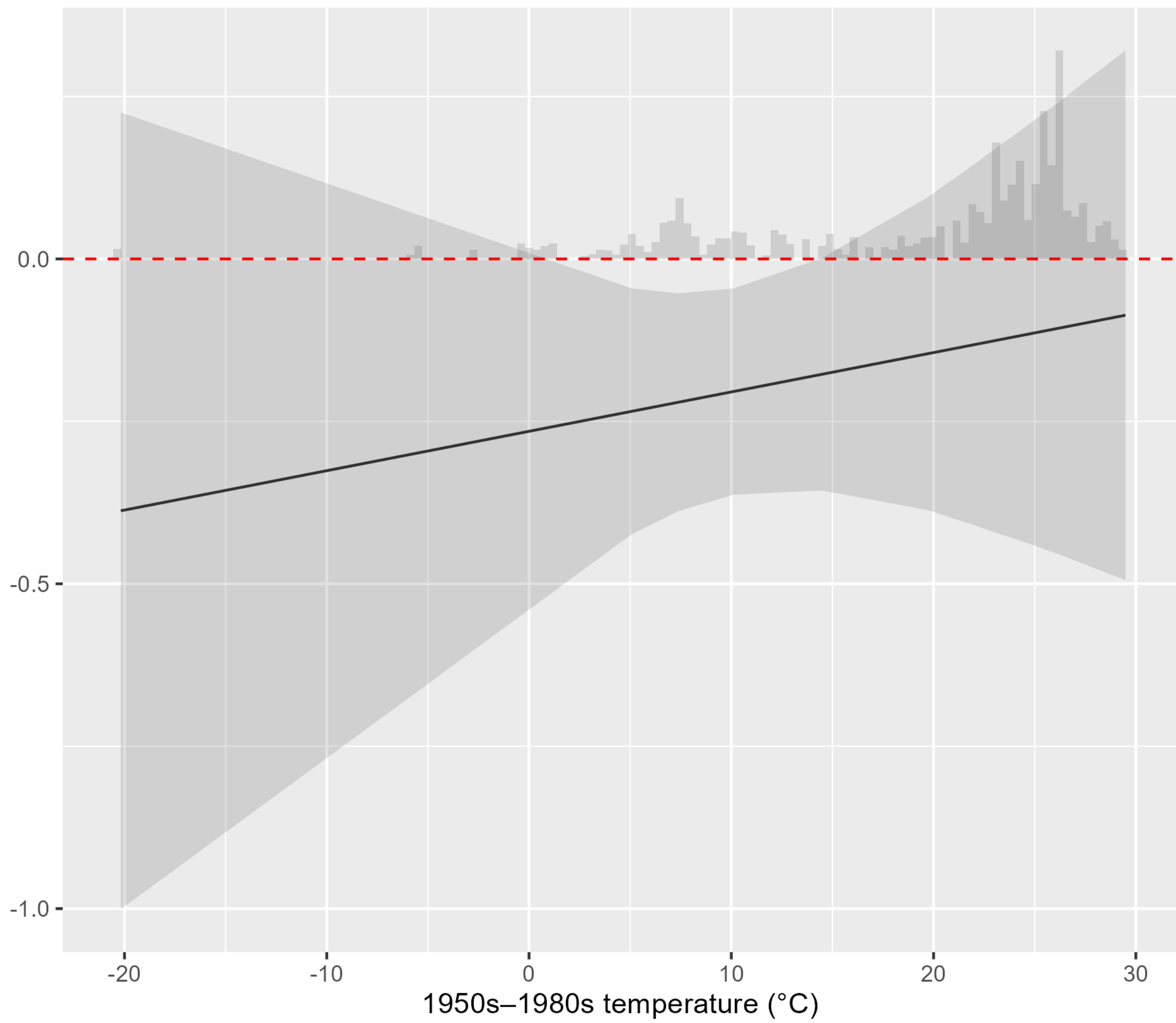
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. $\tilde{d}_{ni} \equiv \log(d_{ni})$ is the log of the great circle distance d_{ni} between the origin and destination countries 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 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles. *Quartiles* are country quartiles of countries' average temperature between the 1950s and 1980s. Vertical lines and whiskers indicate 90 percent confidence intervals.

Figure 15: Coefficients on temperature interactions across 1900s–2000s climate change quartiles



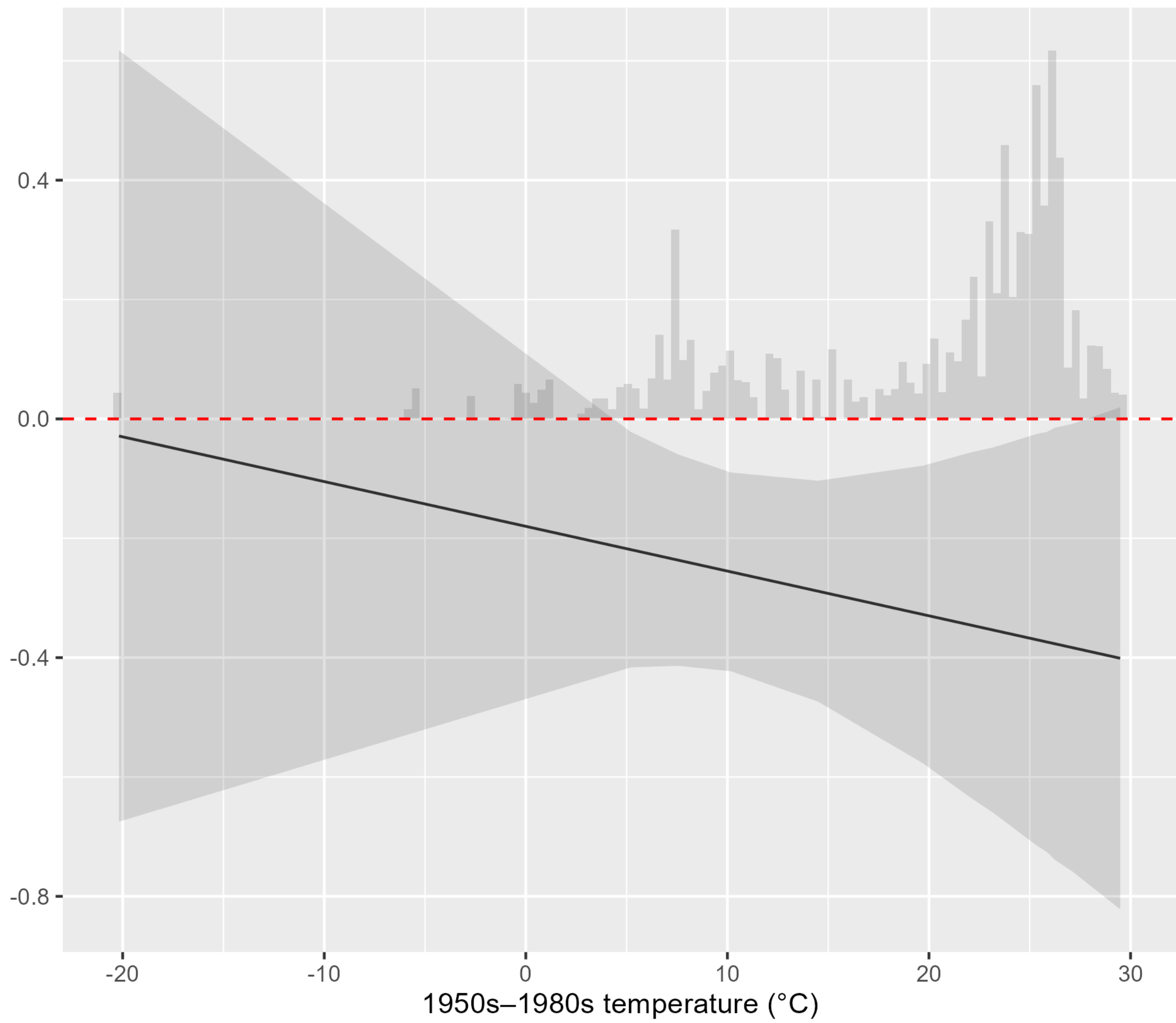
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. $\tilde{d}_{ni} \equiv \log(d_{ni})$ is the log of the great circle distance d_{ni} between the origin and destination countries 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. *Quartiles* are country quartiles of countries' average temperature change (i.e., climate change) between the 1900s and 2000s decades. Vertical lines and whiskers indicate 90 percent confidence intervals.

Figure 16: Marginal effect of origin temperature on trade cost, donut hole specification using four or more land borders



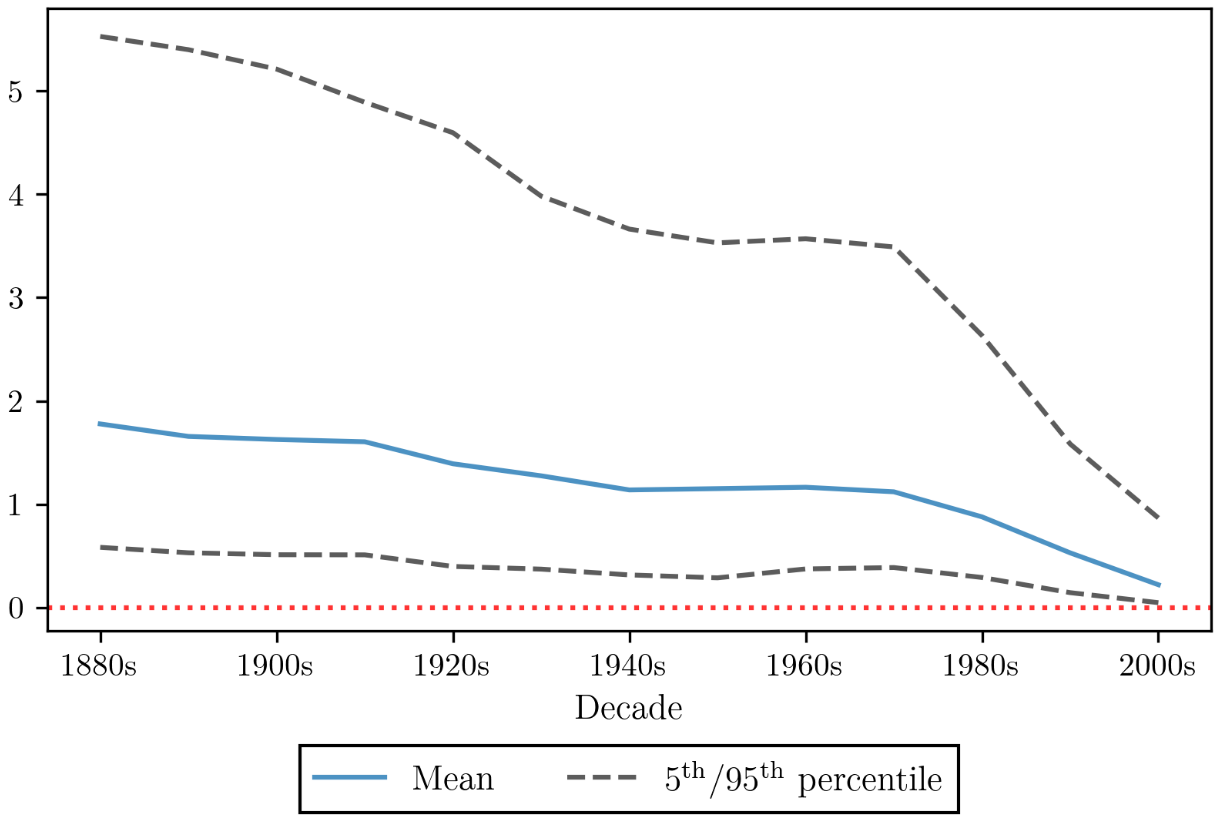
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Decadal temperature changes are interacted with an indicator for four or more land borders between countries, compared to neighboring countries. I include a further triple interaction between the land border indicator, temperature changes and countries' average temperature between the 1950s and 1980s. This graph shows the marginal effect of origin temperature changes across that baseline temperature. The graph also shows a histogram of 1950s to 1980s average temperature. Temperature changes are winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles. The shaded area indicates a 90 percent confidence interval.

Figure 17: Marginal effect of destination temperature on trade cost, donut hole specification using four or more land borders



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. Decadal temperature changes are interacted with an indicator for four or more land borders between countries, compared to neighboring countries. I include a further triple interaction between the land border indicator, temperature changes and countries' average temperature between the 1950s and 1980s. This graph shows the marginal effect of destination temperature changes across that baseline temperature. The graph also shows a histogram of 1950s to 1980s average temperature. Temperature changes are winsorized at the 1st and 99th percentiles. The shaded area indicates a 90 percent confidence interval.

Figure 18: Population-weighted summary statistics for welfare change (percent) across decades



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

Figure 19: Welfare change (percent) in 1910s climate counterfactual across countries

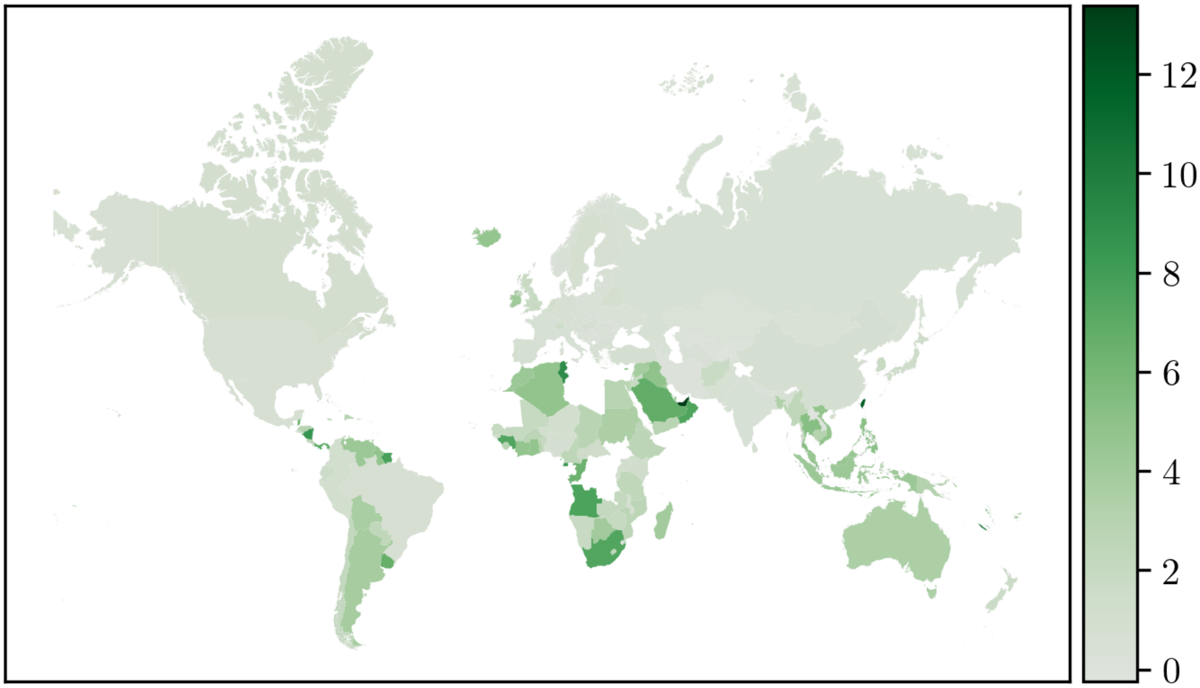
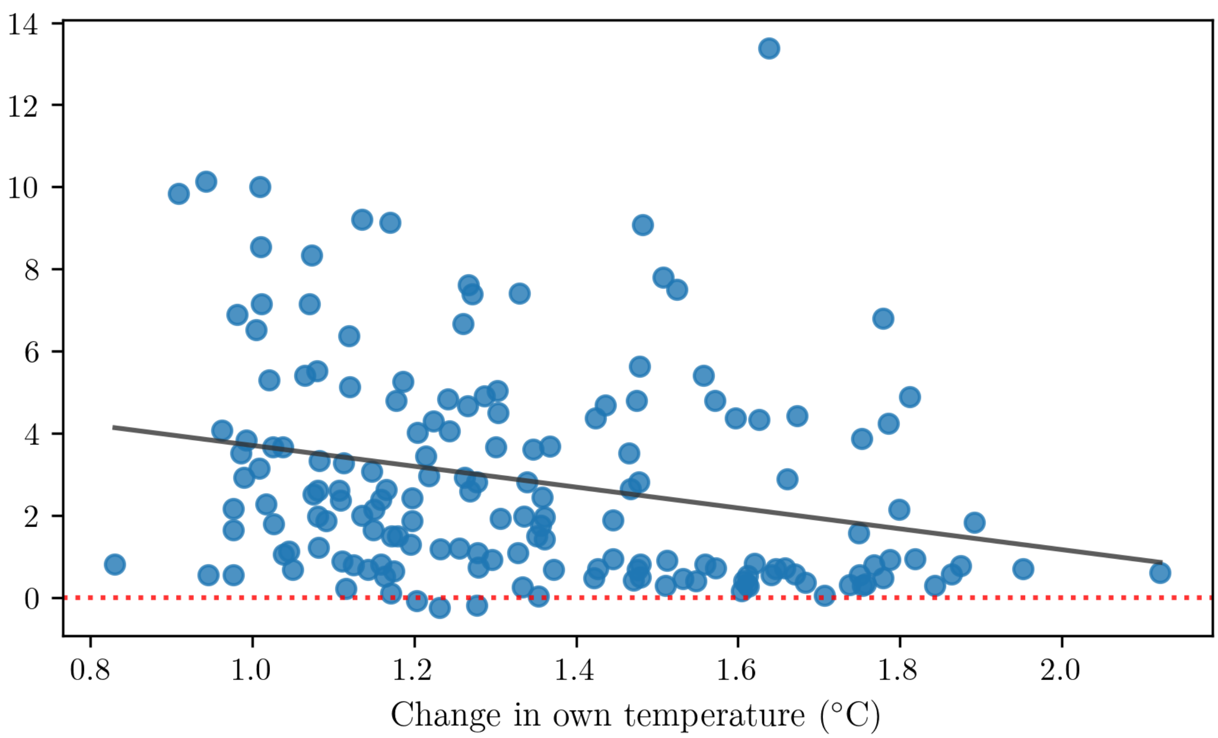
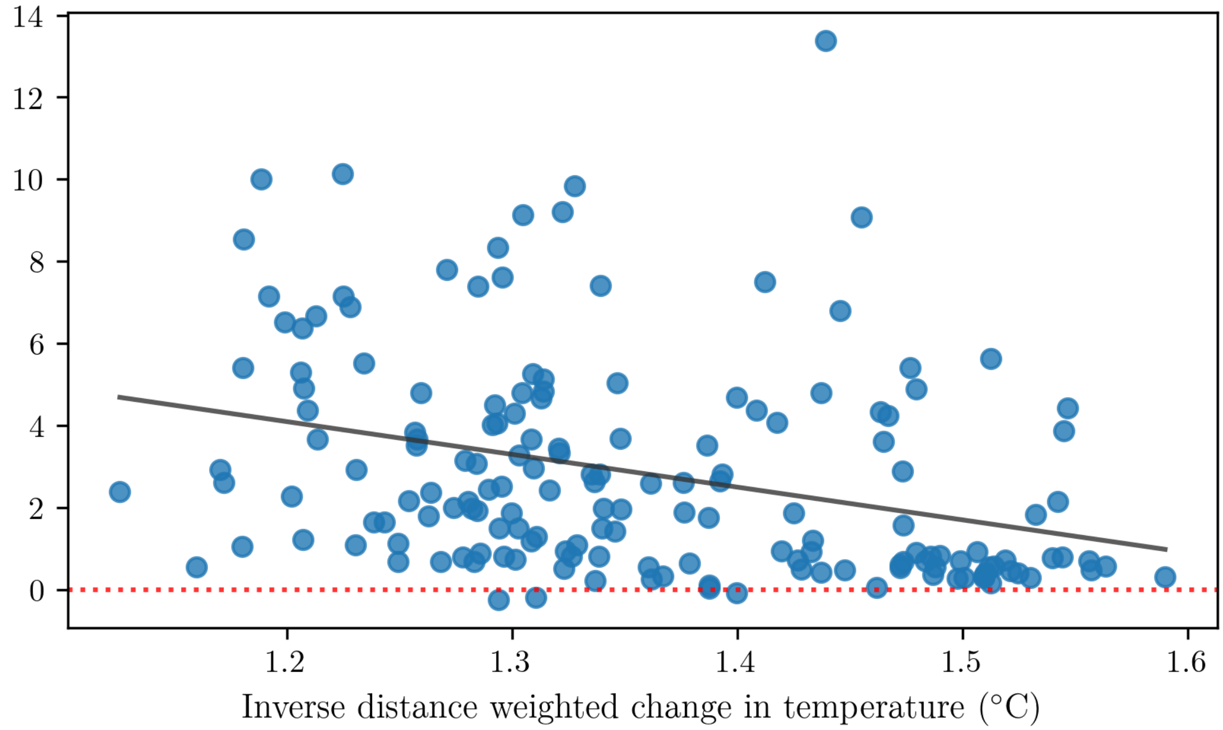


Figure 20: Welfare change (percent) in 1910s climate counterfactual across change in own temperature between the 1910s and 2010s



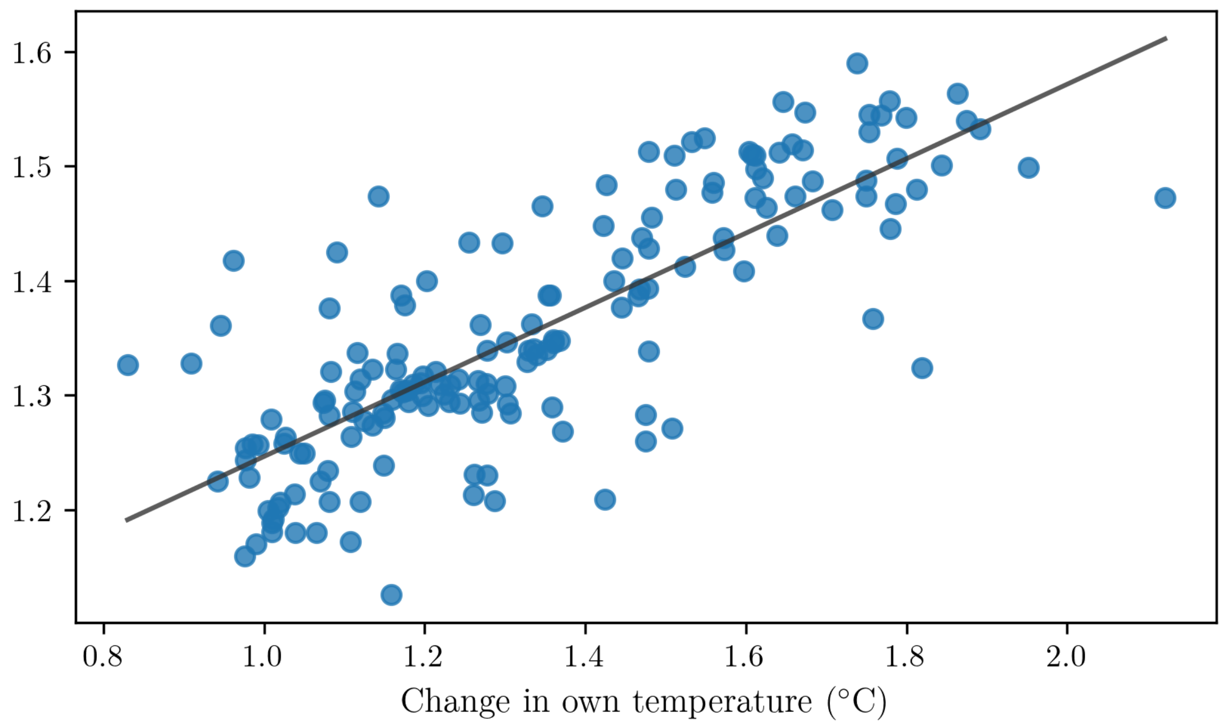
Note: Change in own temperature is the change in country i's own temperature between the 1910s and 2010s. The solid line shows a linear fit.

Figure 21: Welfare change (percent) in 1910s climate counterfactual across inverse distance weighted change in other countries' temperature between the 1910s and 2010s



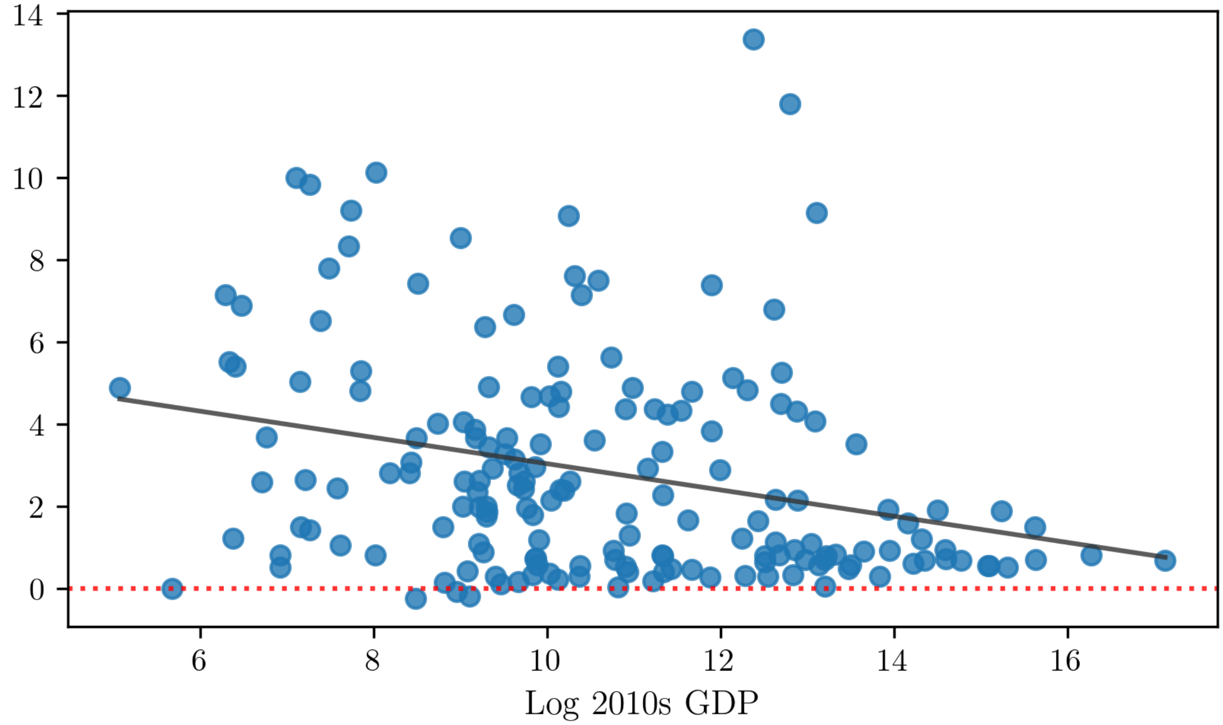
Note: The inverse distance weighted change for country i is the average change in all other countries' temperatures, weighted by the inverse of their distance to i. The solid line shows a linear fit.

Figure 22: Inverse distance weighted change in other countries' temperature between the 1910s and 2010s across change in own temperature between the 1910s and 2010s



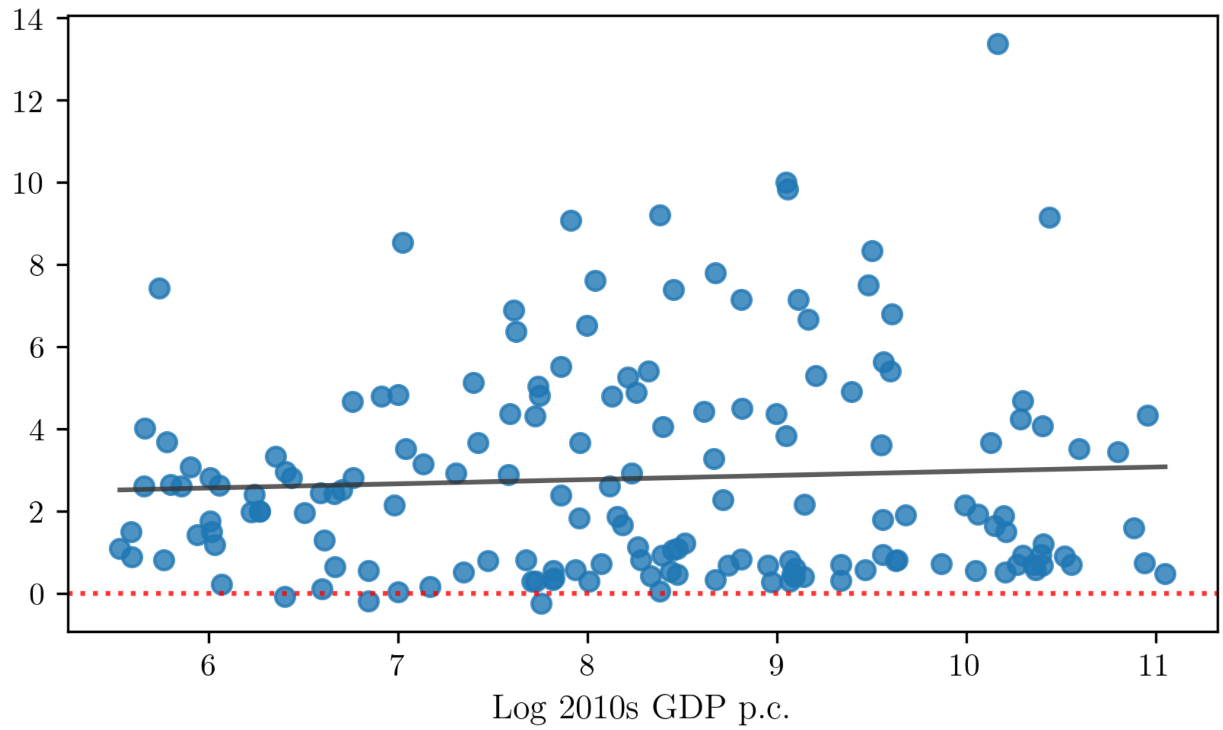
Note: The inverse distance weighted change for country i is the average change in all other countries' temperatures, weighted by the inverse of their distance to i. The solid line shows a linear fit.

Figure 23: Welfare change (percent) in 1910s climate counterfactual across 2010s GDP



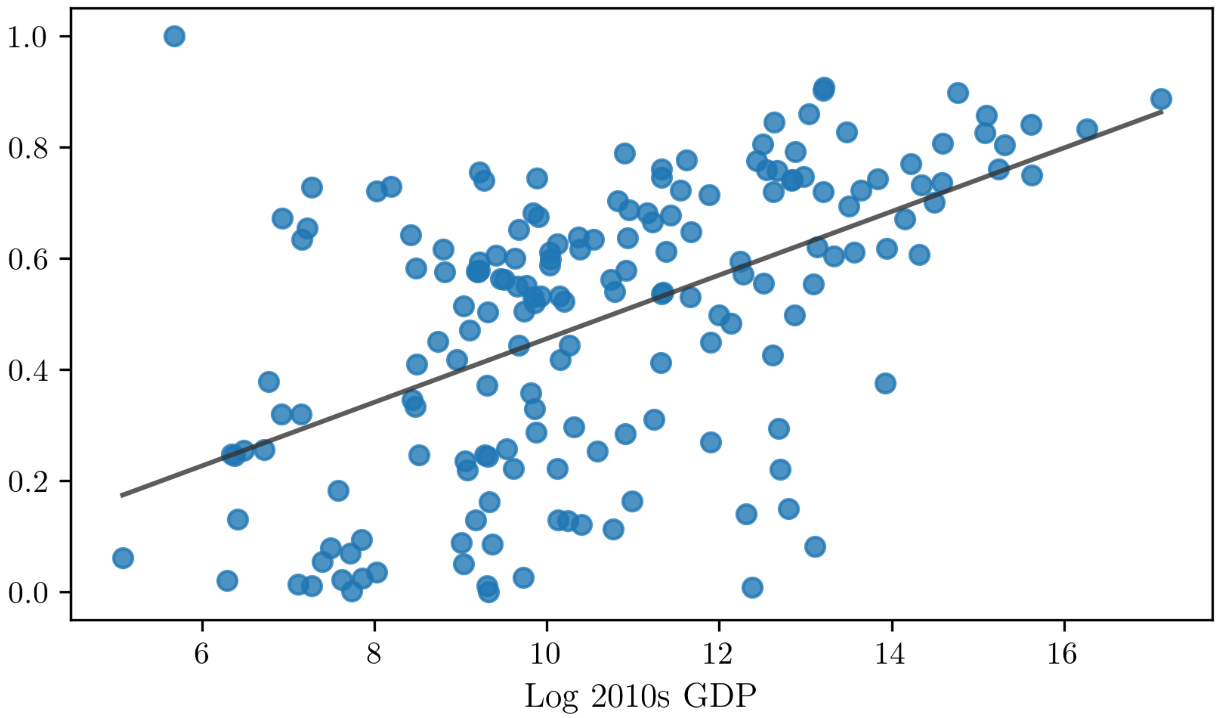
Note: The solid line shows a linear fit.

Figure 24: Welfare change (percent) in 1910s climate counterfactual across 2010s GDP per capita



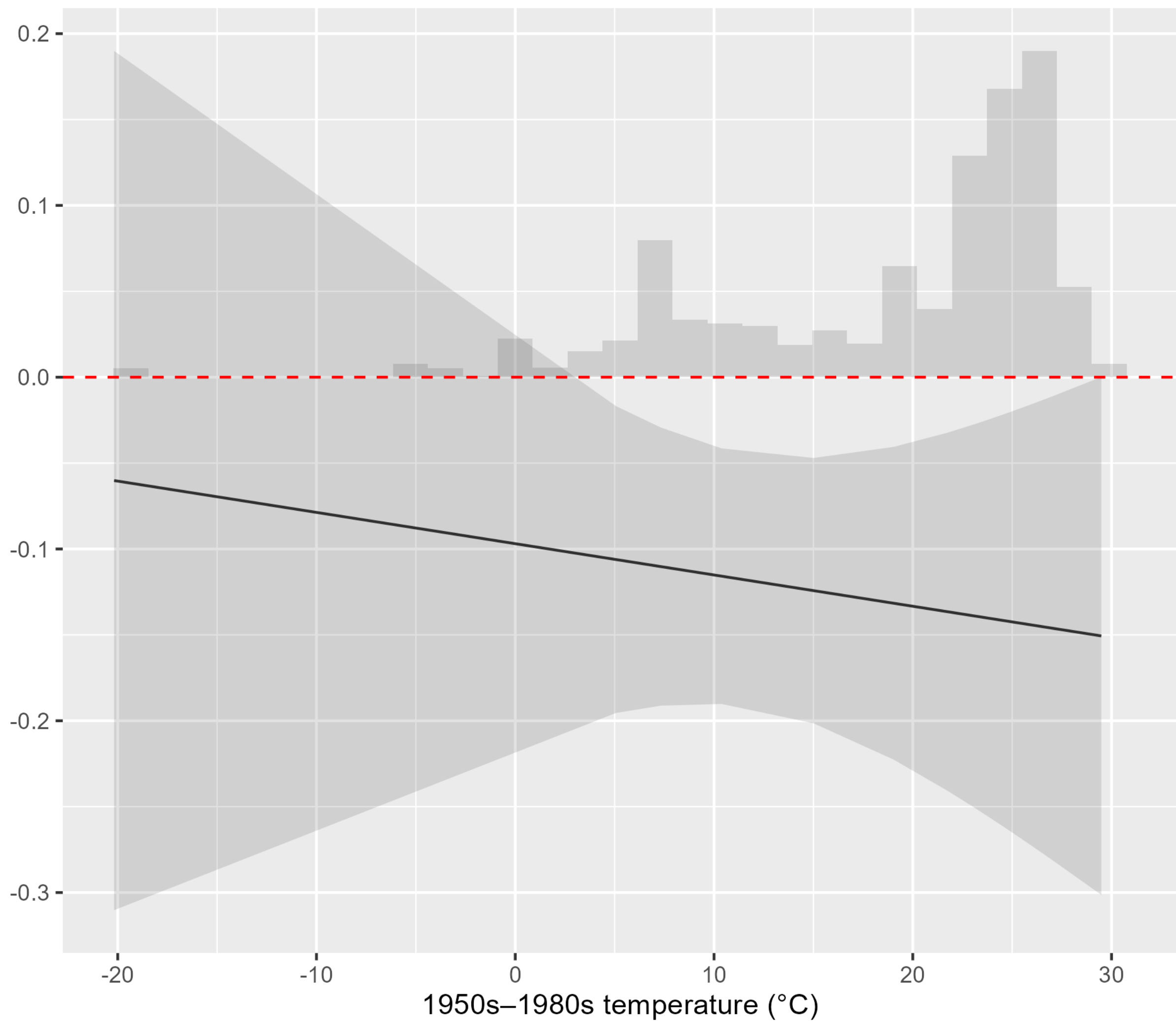
Note: The solid line shows a linear fit.

Figure 25: 2010s own trade share across 2010s GDP



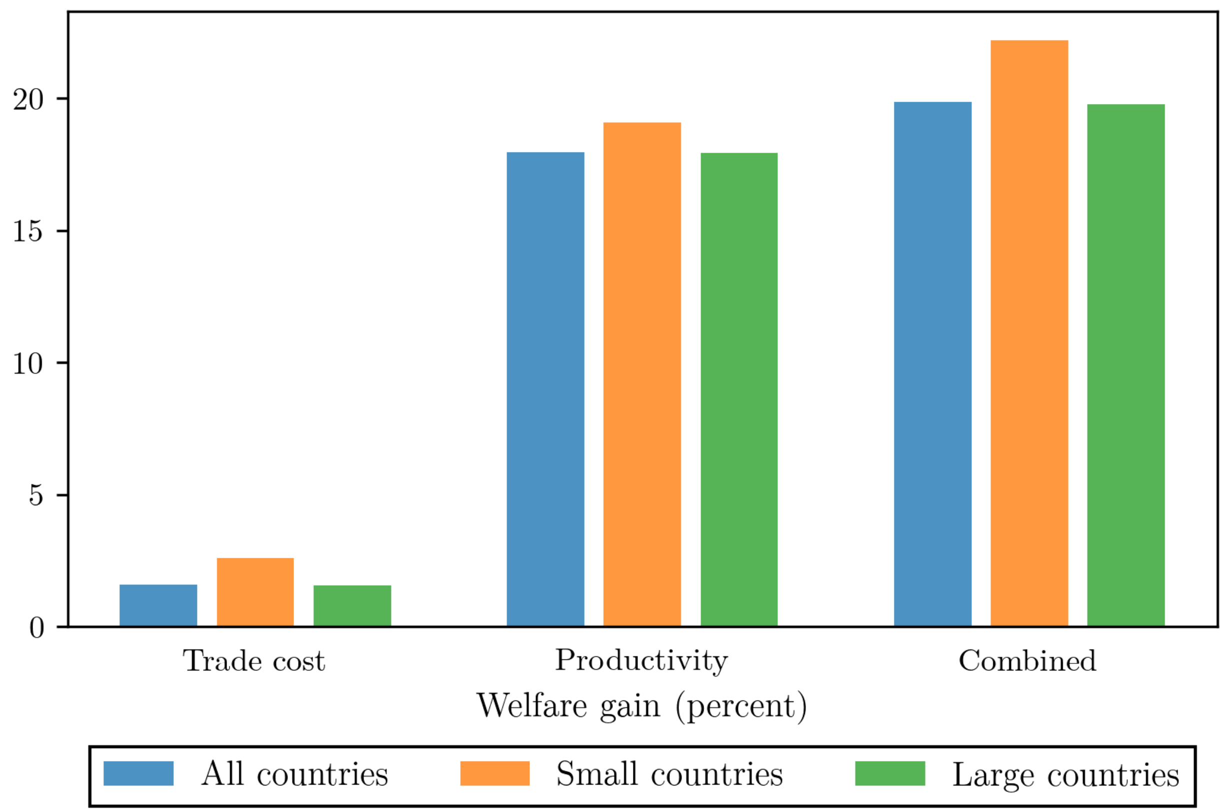
Note: The solid line shows a linear fit.

Figure 26: Marginal effect of decadal temperature changes on log GDP per capita



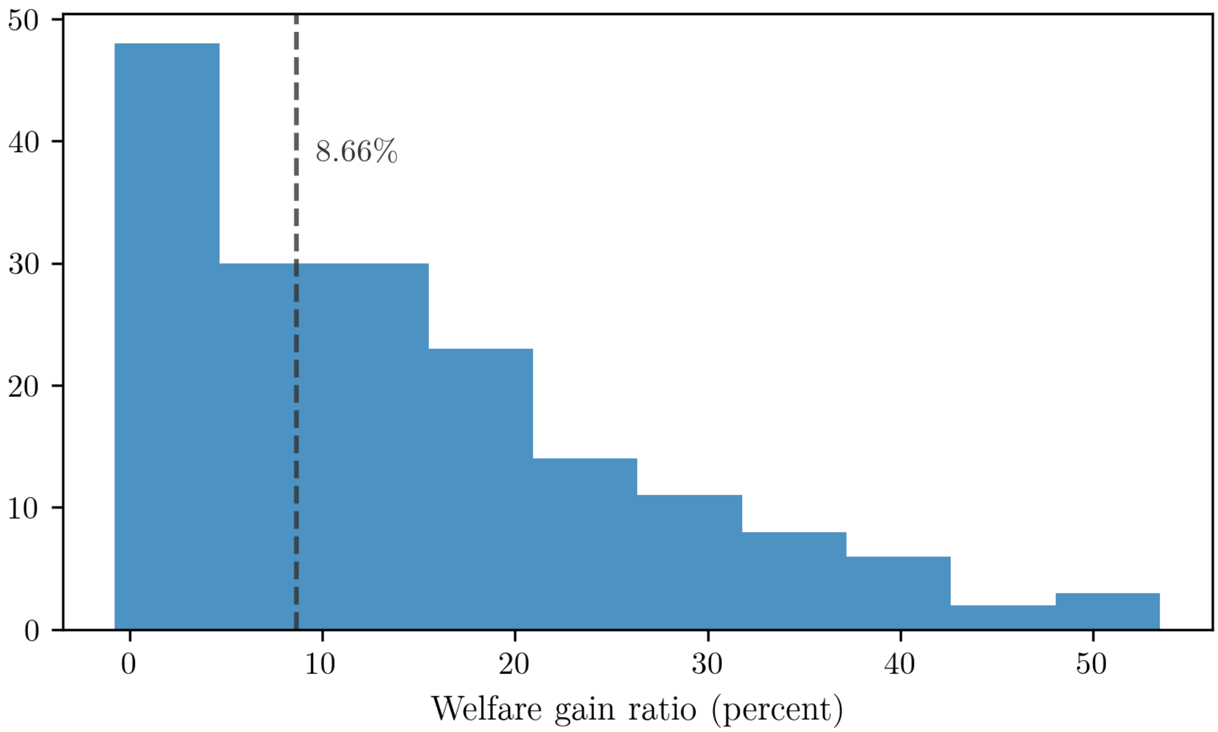
Note: Results are from a regression of log change in decadal average GDP per capita on decadal temperature changes and country fixed effects. The effect of temperature varies with countries' 1950s to 1980s average temperature. This graph shows the marginal effect of temperature shocks across that baseline temperature. The graph also shows a histogram of 1950s to 1980s average temperature. The shaded area indicates a 90 percent confidence interval.

Figure 27: Population-weighted average welfare gains (percent) across different scenarios for 1910s climate counterfactual



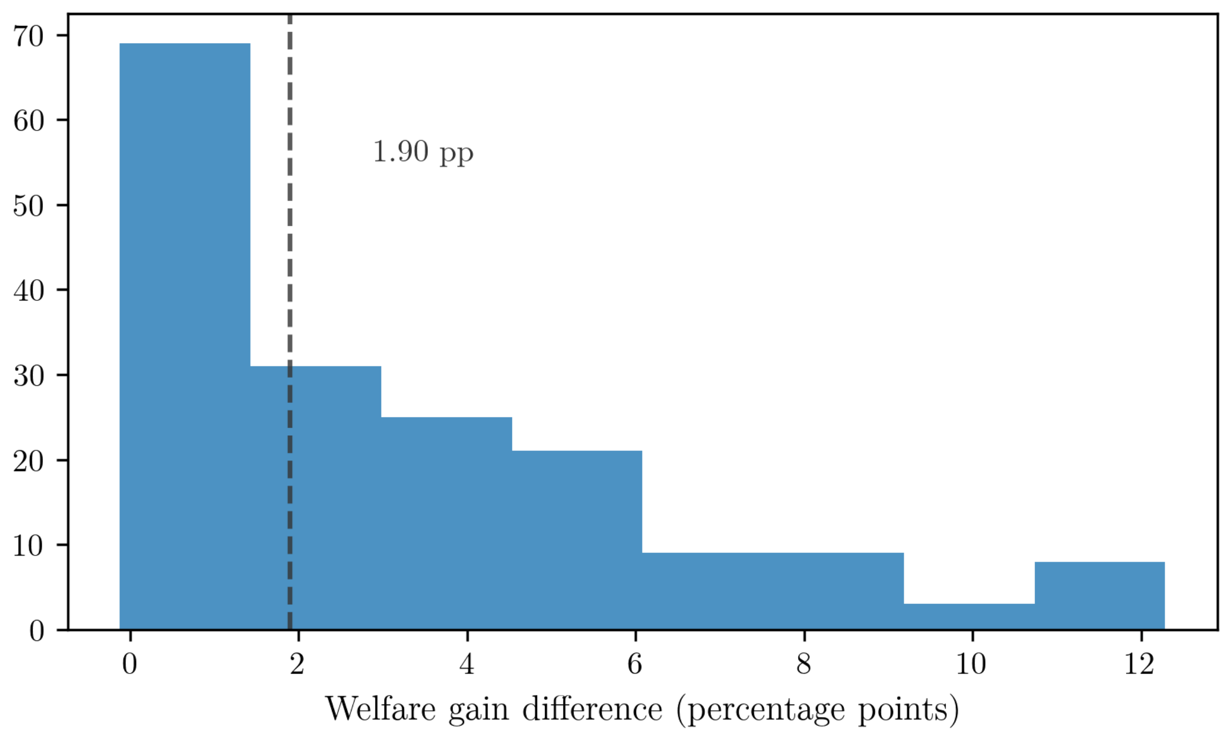
Note: The figure shows population-weighted average welfare gains under each scenario. *Trade cost* undoes the impact of climate change on trade cost. *Productivity* undoes the impact of climate change on productivity. *Combined* undoes both. *All countries* shows the average for all countries in the 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 28: Additional welfare gains from combined trade cost and productivity change vs. productivity change alone for 1910s climate counterfactual — welfare gain ratio



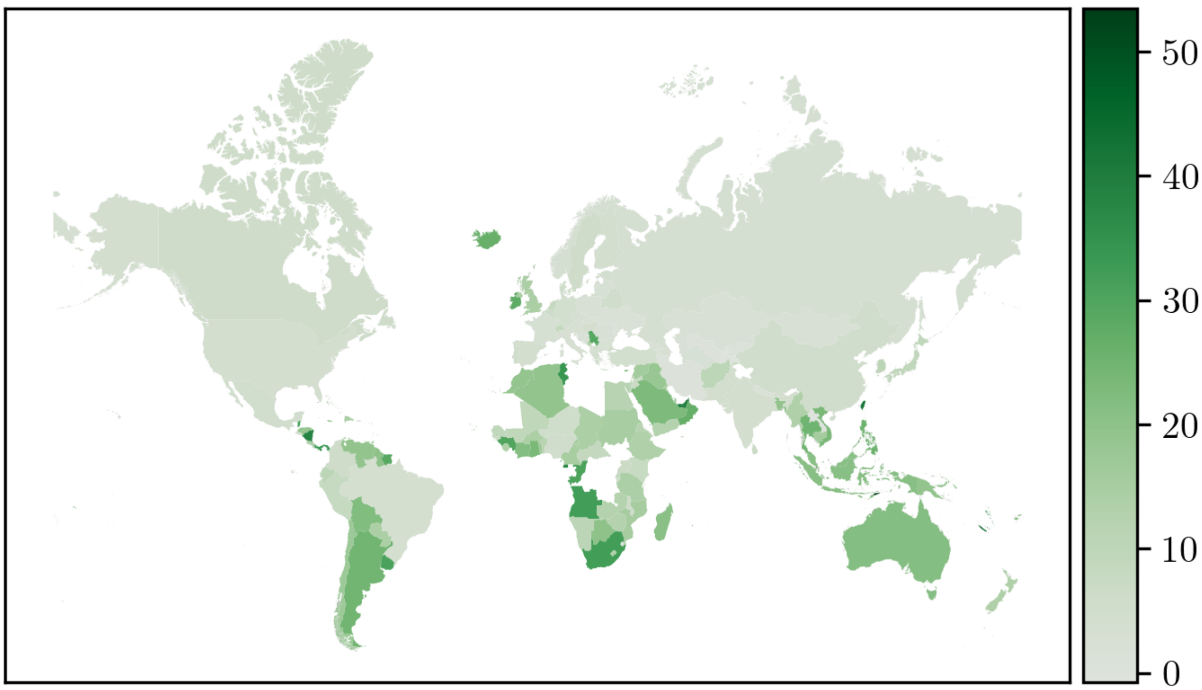
Note: This graph shows a histogram of the welfare gain ratio between the trade cost and productivity and the productivity only counterfactual. The welfare gain ratio is the welfare change from undoing climate change impacts on both productivity and trade networks divided by the welfare change from only undoing the impact on productivity. A welfare gain ratio of 10 percent, for example, means that welfare gains from undoing both effects are 10 percent larger than those from only undoing productivity effects. The dashed line indicates the population-weighted average of the welfare gain ratio.

Figure 29: Additional welfare gains from combined trade cost and productivity change vs. productivity change alone for 1910s climate counterfactual — welfare gain difference



Note: This graph shows a histogram of the welfare gain difference between the trade cost and productivity and the productivity only counterfactual. The welfare gain difference is the welfare change from undoing climate change impacts on both productivity and trade networks minus the welfare change from only undoing its impact on productivity. A welfare gain difference of 10 percentage points, for example, means that welfare gains from undoing both effects are 10 percentage points larger than those from only undoing productivity effects. The dashed line indicates the population-weighted average of the welfare gain difference.

Figure 30: Additional welfare gains from combined trade cost and productivity change vs. productivity change alone for 1910s climate counterfactual across countries



Note: This map shows the global distribution of the welfare gain ratio between the trade cost and productivity and the productivity only counterfactual. The welfare gain ratio is the welfare change from undoing climate change impacts on both productivity and trade networks divided by the welfare change from only undoing the impact on productivity. A welfare gain ratio of 10 percent, for example, means that welfare gains from undoing both effects are 10 percent larger than those from only undoing productivity effects. The dashed line indicates the population-weighted average of the welfare gain ratio.

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	1.777	1.656	1.626	1.604	1.391	1.275	1.138	1.151	1.164	1.120	0.878	0.529	0.221
p_5	0.583	0.530	0.511	0.510	0.398	0.372	0.316	0.288	0.374	0.387	0.291	0.144	0.047
p_{10}	0.664	0.532	0.511	0.554	0.463	0.441	0.399	0.394	0.426	0.409	0.306	0.197	0.056
p_{25}	0.664	0.543	0.559	0.558	0.471	0.467	0.399	0.394	0.426	0.418	0.333	0.238	0.069
p_{50}	0.882	0.824	0.827	0.811	0.683	0.680	0.525	0.603	0.586	0.556	0.461	0.241	0.085
p_{75}	2.453	2.134	2.103	1.992	1.792	1.699	1.434	1.584	1.629	1.522	1.167	0.630	0.213
p_{90}	4.503	4.458	4.149	4.309	3.743	3.289	3.107	2.898	2.924	2.580	2.118	1.264	0.601
p_{95}	5.527	5.399	5.211	4.890	4.595	3.982	3.663	3.530	3.569	3.490	2.633	1.583	0.867

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.

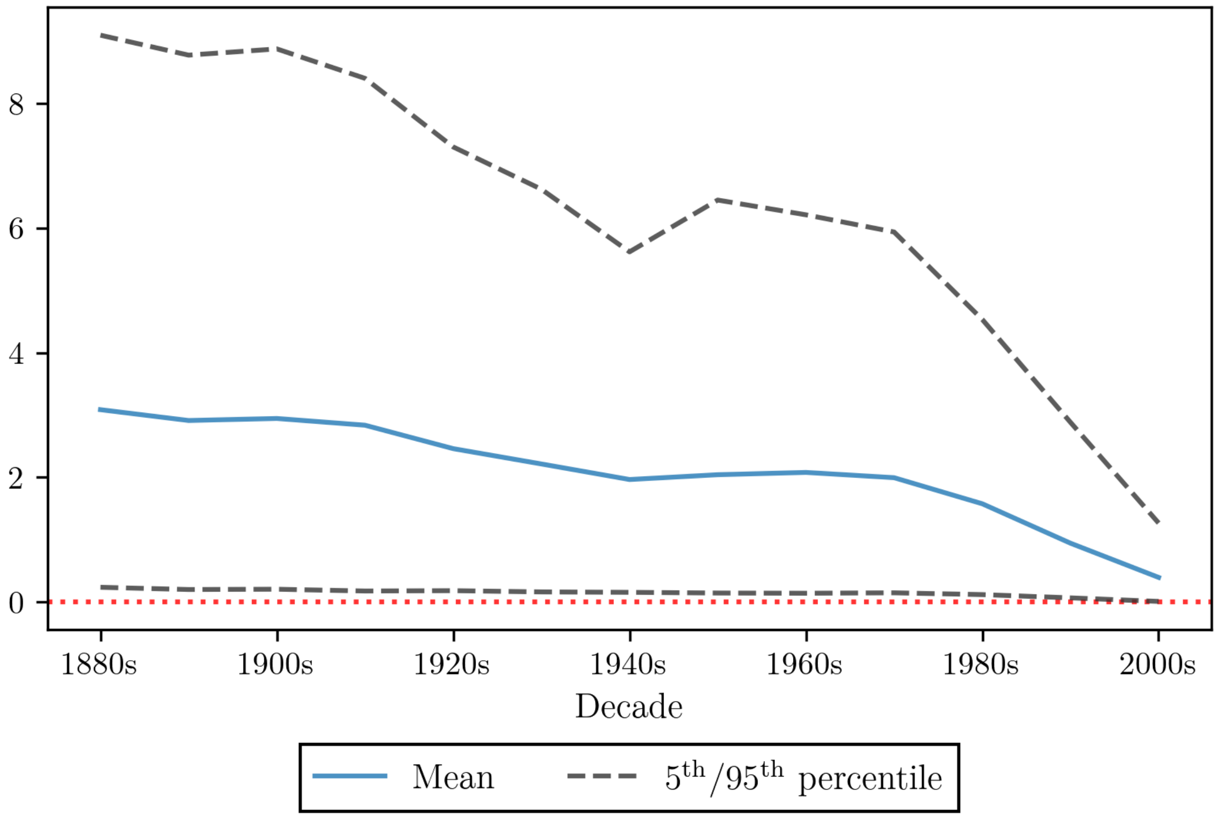
Table 5: Summary statistics for welfare change (percent) across decades

Statistic	1880s	1890s	1900s	1910s	1920s	1930s	1940s	1950s	1960s	1970s	1980s	1990s	2000s
Mean	3.086	2.912	2.944	2.836	2.460	2.215	1.965	2.042	2.079	1.994	1.576	0.943	0.394
p_5	0.236	0.200	0.205	0.176	0.181	0.162	0.155	0.144	0.140	0.147	0.118	0.066	0.009
p_{10}	0.407	0.374	0.365	0.328	0.327	0.227	0.307	0.276	0.257	0.260	0.243	0.136	0.034
p_{25}	0.859	0.751	0.772	0.718	0.635	0.512	0.526	0.536	0.554	0.557	0.441	0.237	0.084
p_{50}	2.292	2.134	2.089	1.992	1.659	1.605	1.396	1.566	1.530	1.483	1.016	0.597	0.218
p_{75}	4.801	4.325	4.252	4.322	3.612	3.305	2.877	2.957	2.946	2.988	2.381	1.419	0.597
p_{90}	7.334	7.096	7.201	6.854	5.827	5.430	4.638	4.929	4.923	4.631	3.729	2.240	1.005
p_{95}	9.094	8.774	8.874	8.402	7.302	6.622	5.618	6.449	6.212	5.937	4.533	2.883	1.267

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



Appendix C Maps of added countries

This appendix shows maps of all TRADHIST reporting units that are not currently in the GADM database. These maps were created by matching existing GADM administrative units at different levels to historical maps of each reporting unit. Map titles are CEPII's additional ISO codes for each reporting unit as found in Table 4 of the TRADHIST documentation, available at https://www.cepii.fr/PDF_PUB/wp/2016/wp2016-14.pdf.

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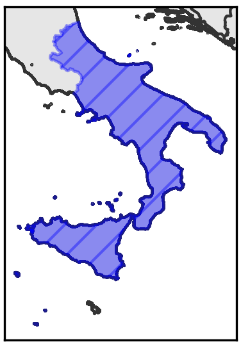

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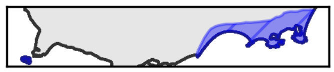

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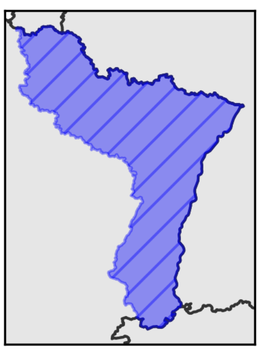

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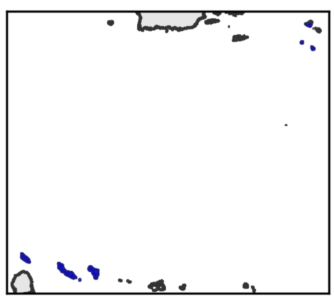

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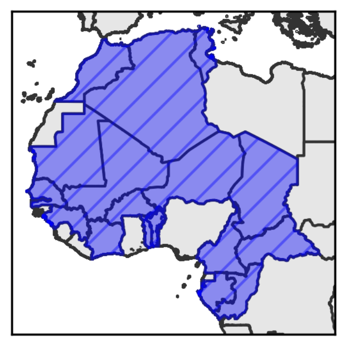

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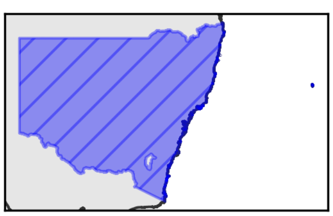

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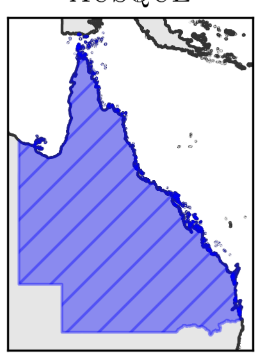

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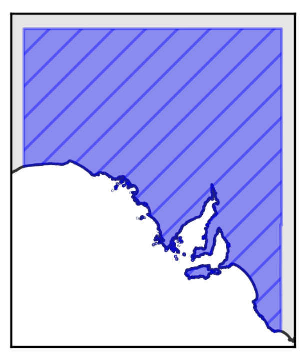

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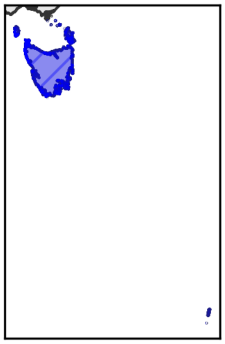

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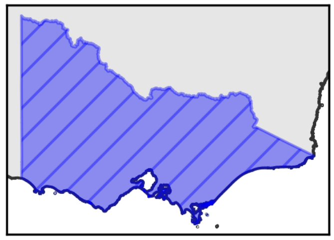

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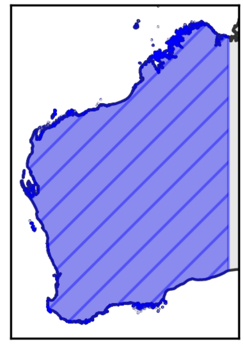

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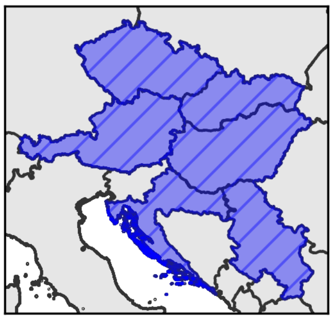

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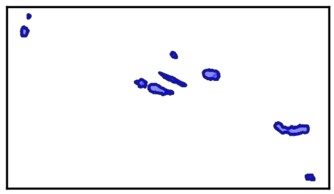

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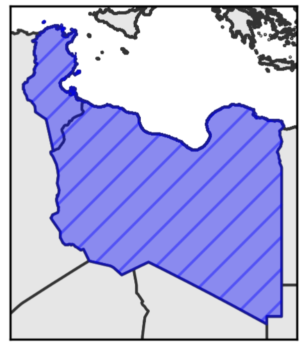

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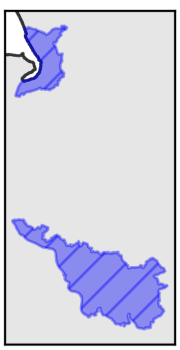

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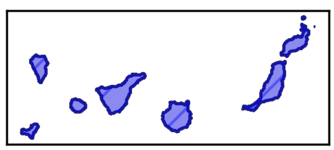

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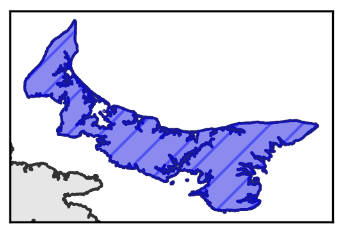

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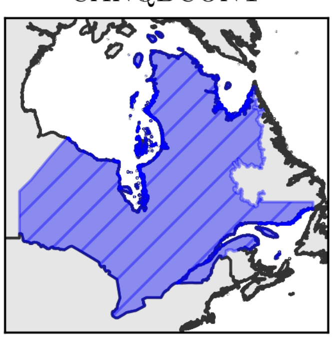

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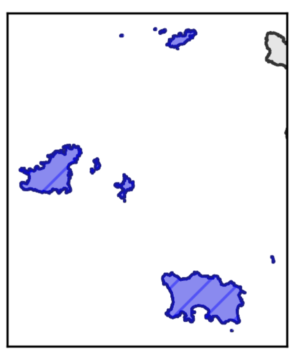

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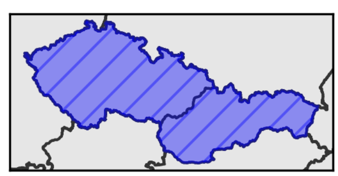

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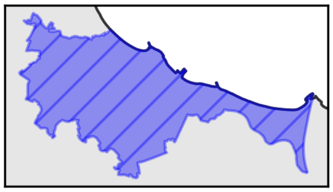

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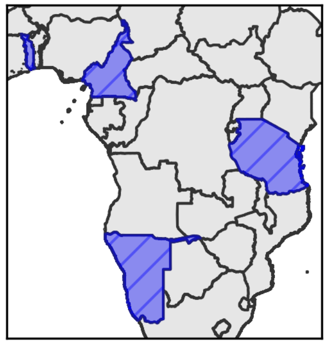

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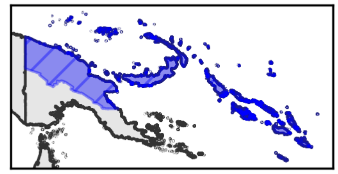

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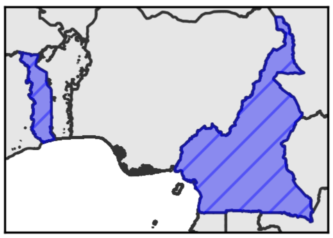

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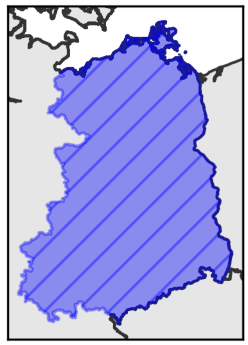

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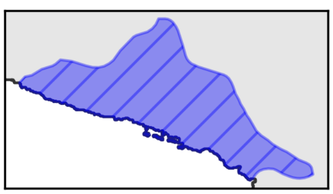

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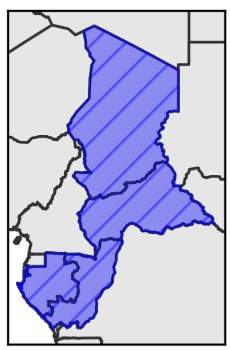

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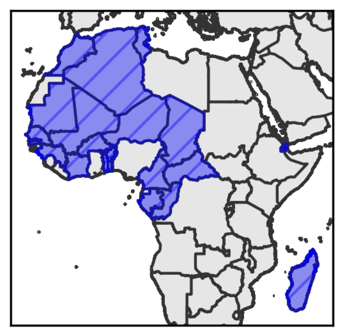

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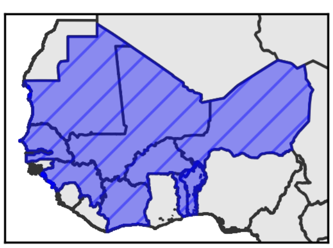

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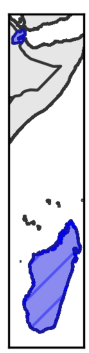

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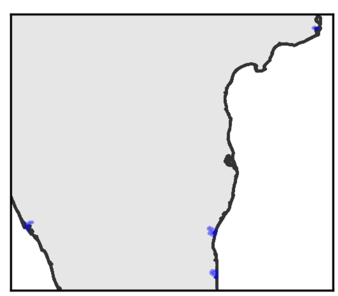

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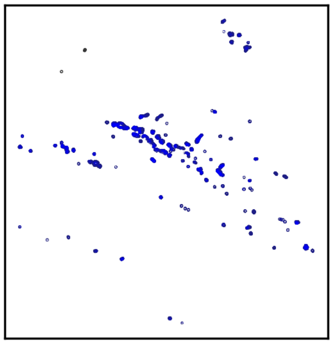

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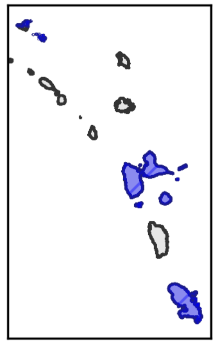

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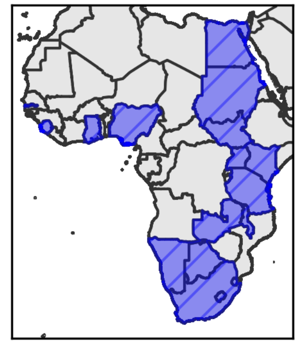

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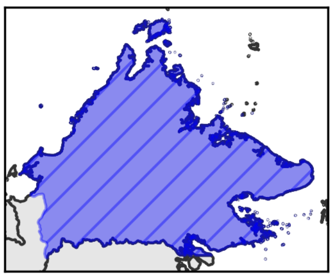

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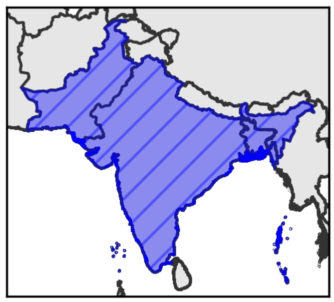

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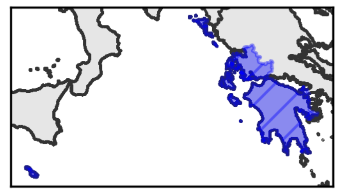

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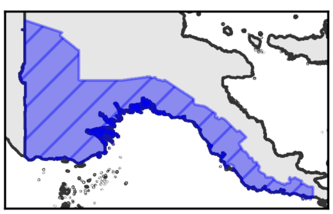

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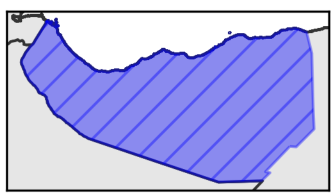

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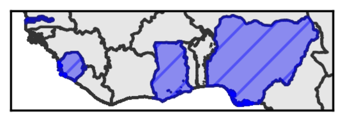

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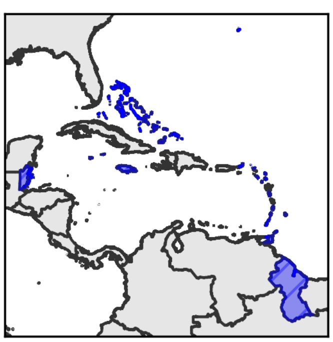

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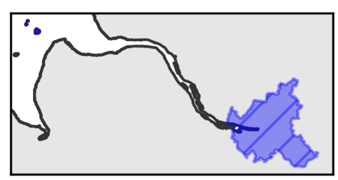

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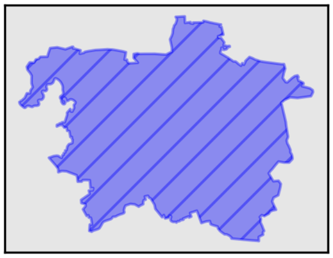

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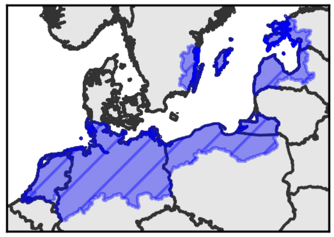

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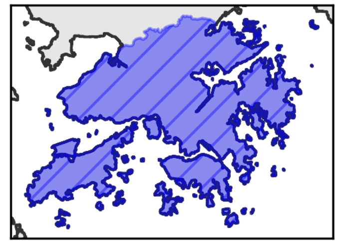

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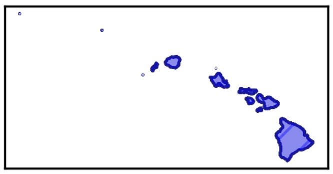

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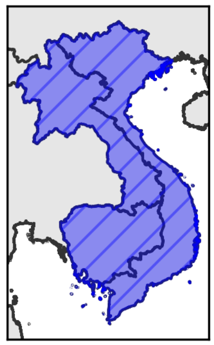

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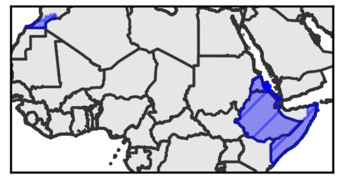

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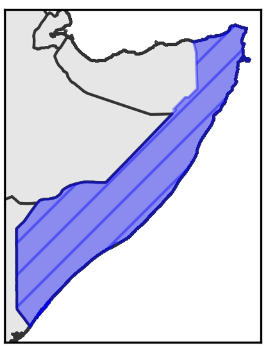

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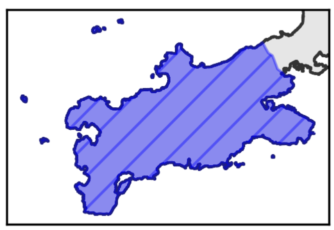

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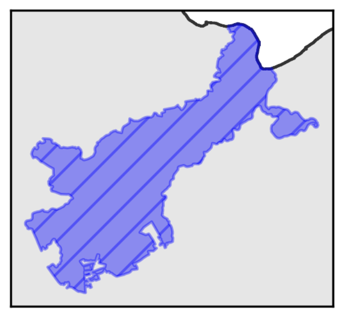

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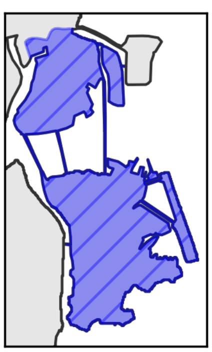

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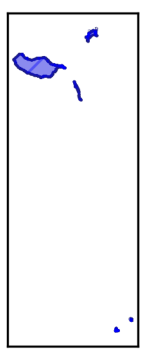

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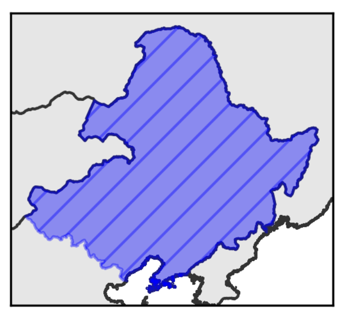

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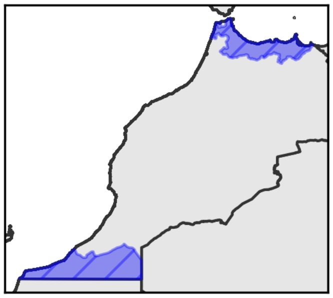

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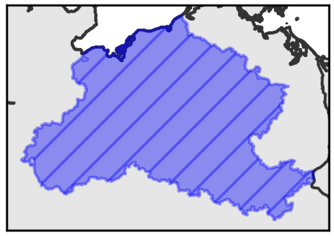

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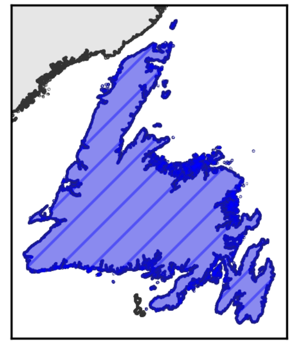

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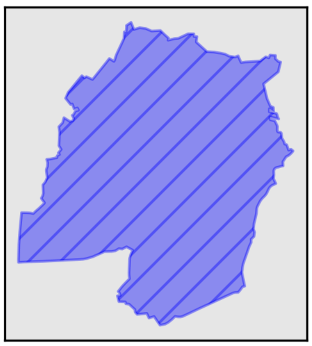

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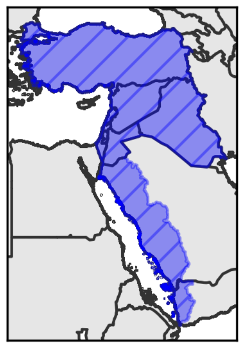

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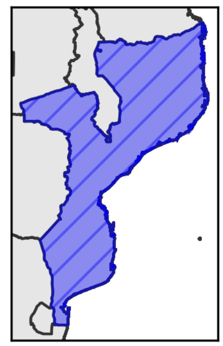

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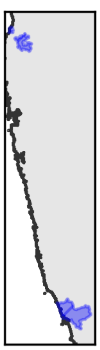

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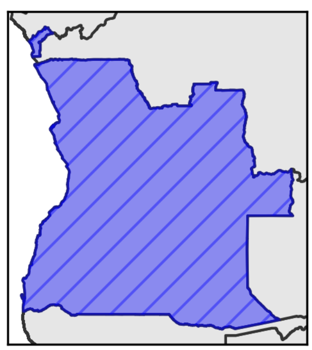

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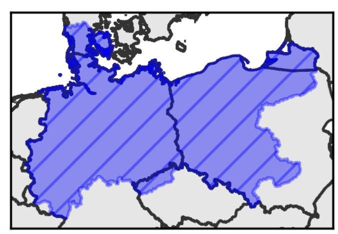

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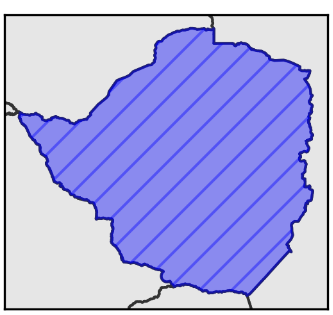

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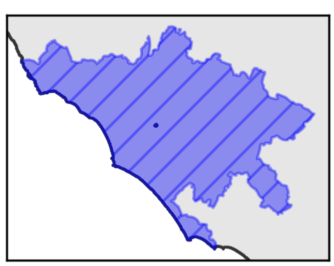

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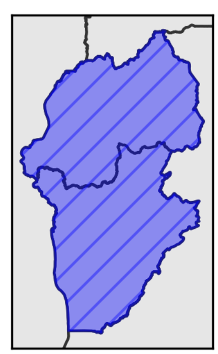

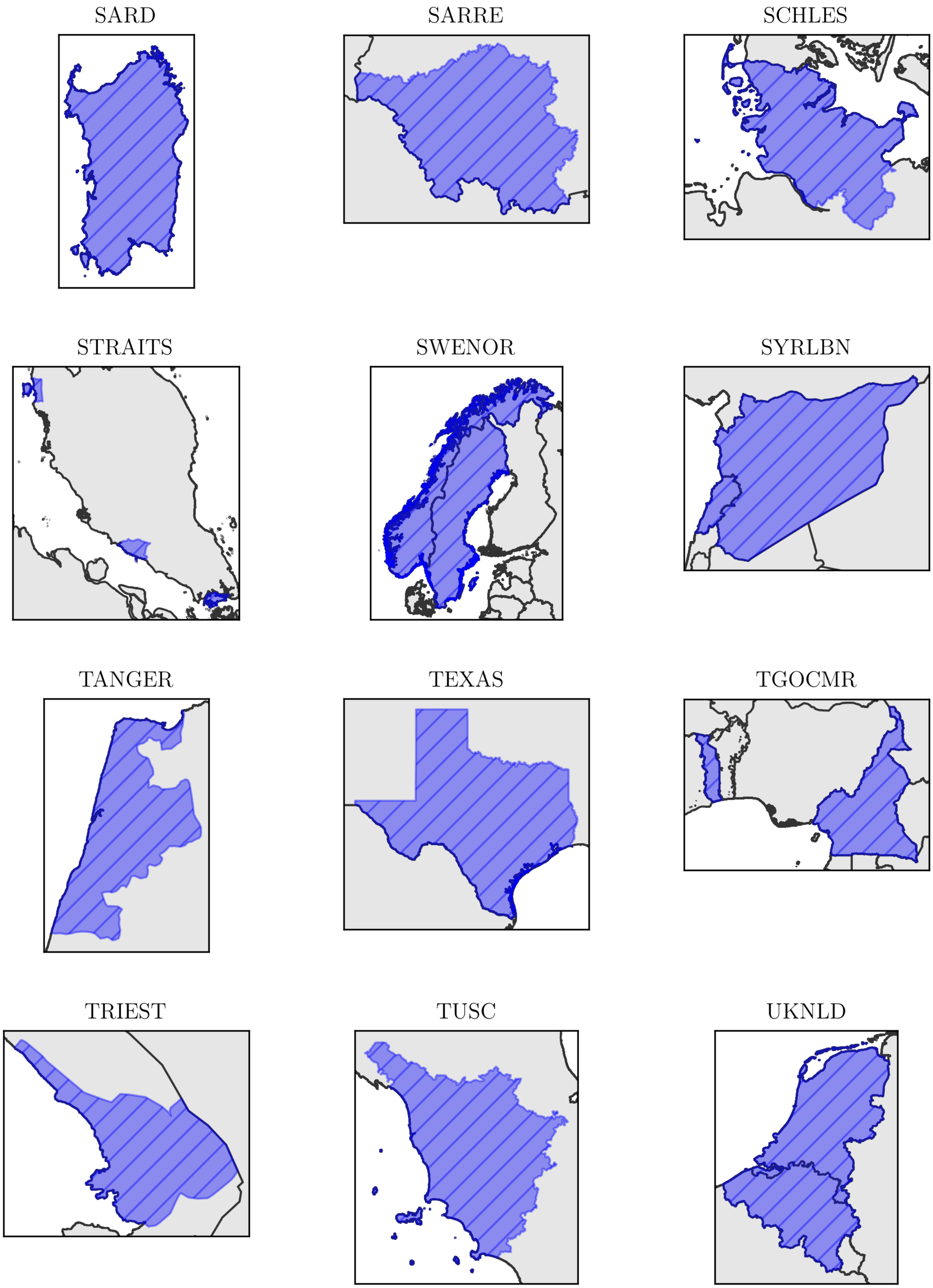
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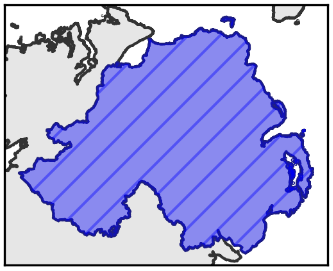

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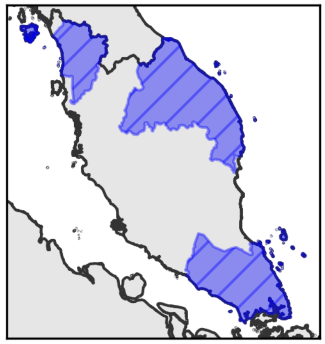

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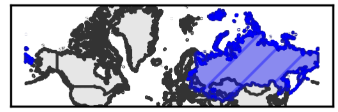

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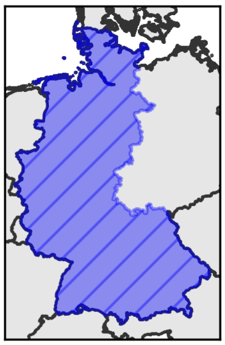

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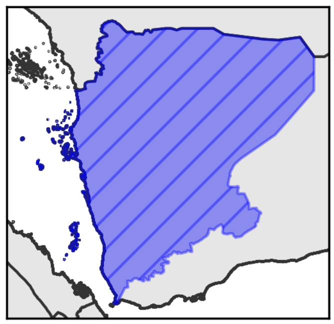

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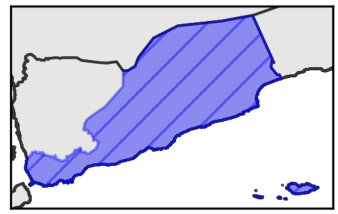

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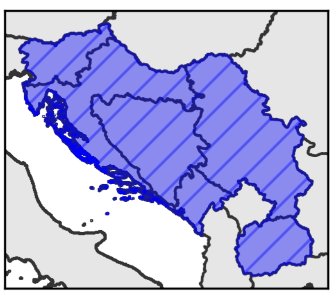

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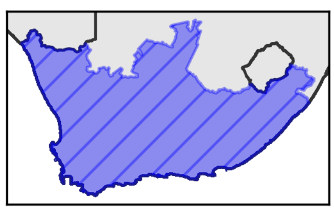

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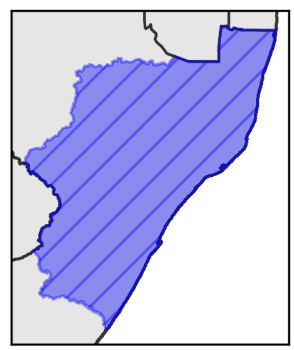

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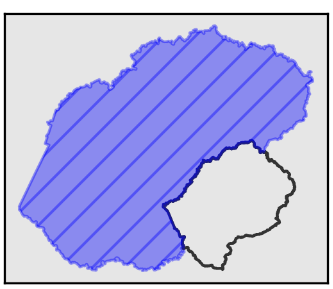

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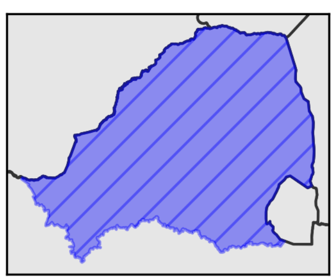

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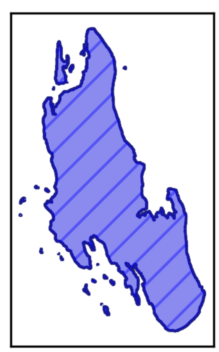

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