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Persistent effect of El Niño on global economic growth

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El Niño–Southern Oscillation (ENSO) shapes extreme weather globally, causing myriad socioeconomic impacts, but whether economies recover from ENSO events and how anthropogenic changes to ENSO will affect the global economy are unknown. Here we show that El Niño persistently reduces country-level economic growth, attributing $4.1T and $5.7T in global income losses to the 1982–83 and 1997–98 events, respectively. Increased ENSO amplitude and teleconnections from warming cause $84T in 21st-century economic losses in an emissions scenario consistent with current mitigation pledges, but these effects are shaped by stochastic variation in the sequence of El Niño and La Niña events. Our results highlight the sensitivity of the economy to climate variability independent of warming and the potential for future losses due to anthropogenic intensification of such variability.

As the leading mode of interannual climate variability, El Niño–Southern Oscillation (ENSO) integrates a wide range of Earth system processes (*1*). El Niño events shift deep convection from the western to the eastern Pacific, shaping global weather through "teleconnections" (*2*, *3*). The resulting temperature and hydroclimate extremes have many well-documented impacts, including flooding (*4*, *5*), crop losses (*6*, *7*), and civil conflict (*8*). Many climate models project that warming will increase El Niño amplitude (*9*, *10*) and frequency (*11*), with potentially devastating socioeconomic impacts (*12*).

Despite ENSO's global impacts, however, empirical climate-economy studies have generally focused on temperature and rainfall averages (*13*–*16*) or variability (*17*), leaving the costs of changes in modes of climate variability unquantified. While studies have shown that El Niño reduces contemporaneous economic growth (*18*–*20*) and drives commodity price fluctuations (*21*–*23*), it remains unclear if and for how long its impacts persist. Distinguishing between transient and persistent impacts on economic growth is essential. Transient impacts ("level effects") are quickly recovered, as an economy rebounds to its original trajectory. Persistent impacts ("growth effects") reduce an economy's ability to grow, compounding exponentially in time. Poor observational constraints on growth effects limit our understanding of the economic costs of ENSO and climate damages broadly (*24*–*26*).

Here we estimate the effect of ENSO on past and future economic growth, accounting for the spatiotemporal heterogeneity of ENSO teleconnections. We define ENSO by the E-index and C-index (*27*) (fig. S1). These metrics of El Niño and La Niña, respectively, capture the nonlinear feedbacks that drive ENSO (see methods in the supplementary materials). We define country-level teleconnections for each index (τ^E and τ^C) using correlations between the indices and country-level temperature and rainfall (methods and fig. S2). Teleconnections are strongest in tropical countries and weaker in the midlatitudes (Fig. 1A), consistent with the physical responses of regional climate to tropical variability (*28*).

We use a distributed lag regression model to quantify the effect of ENSO on growth in national Gross Domestic Product per capita (GDPpc) from 1960–2019. Departing from previous work (*8*, *19*, *20*), we interact the E- and C-indices with teleconnections to allow the economic effect of ENSO to vary smoothly as a function of teleconnection strength (*29*) (methods). Our model compares economic growth before and after El Niño events to assess their cumulative effects over time and distinguish growth from level effects (methods). We focus on the five years following El Niño events, but also evaluate effects for more than ten years as well as for La Niña. We then couple these empirical estimates with climate model projections to assess the future economic effects of changes to ENSO amplitude and teleconnections.

El Niño persistently reduces economic growth

El Niño events persistently decrease economic growth (Fig. 1B). The magnitude of this effect is determined by the strength of each country's E-index teleconnection. In Peru (τ^E = 1.18), for example, a 1-standard-deviation (s.d.) El Niño event decreases growth by 1.3 percentage points (p.p.) in the year of the event [95% confidence interval (CI): 0.9–1.7 p.p.]. After five years, growth in Peru has declined by 6.2 p.p. (CI: 4.7–8.2) (Fig. 1B). By contrast, weakly teleconnected countries experience small and uncertain effects (Fig. 1B). Interacting El Niño and teleconnections allows us to calculate marginal effects for each country based on their τ^E value (Fig. 1C) and allows statistical significance to be determined by uncertainty in the distributed lag model (Fig. 1C hatching), rather than prescribing "teleconnected" and "non-teleconnected" countries. 56% of countries experience significant declines in growth 5 years after El Niños, averaging 2.3 p.p., not simply level effects from which they recover immediately (Fig. 1D).

These negative effects are robust to using alternative ENSO indices, growth data, standard error clustering, or teleconnection metrics, as well as excluding the most strongly teleconnected countries (supplementary text and figs. S3 to S5). They also vary little over the 1960–2019 period, indicating little effect heterogeneity in time (fig. S6). ENSO indices vary through time but not space, raising the possibility that our results are confounded by time-varying global economic shocks. However, alternative specifications demonstrate that time-varying confounders are not driving our results: Adding country-specific trends to control for technological or demographic changes has little effect (fig. S4) since ENSO is stochastic (*30*) and measured by detrended indices. Using a spatially varying country-level index of ENSO or discretizing the sample into teleconnected and non-teleconnected groups allow us to include both country and year fixed effects, and yield results as strong as our main estimates (methods and fig. S7), but we do not use these models in our main analysis since they do not preserve the independent and joint effects of ENSO amplitude and teleconnections (methods). Bootstrap resampling by year or dropping each year or country, ensuring that single years or countries are not driving the results, yield similar effects (fig. S3). Finally, dropping the 1983 and 1998 El Niño events, which coincided with financial crises, reduces the magnitude of ENSO effects by only ~12% (fig. S4).

Our main observational analysis (Figs. 1 and 2) uses 5 lags, which reflects a balance between tracing the long-run response to ENSO and a concern for statistical power given the short observational record. Additional lags fit the data better, but at the cost of model stability; using 5 lags balances these effects (fig. S8). Yet models with more lags reveals that El Niño effects can persist to 12 years or beyond, though a rebound begins after ~10 years (figs. S8 and S9), implying that our 5-year results for the historical costs of El Niño are conservative. After >14 years, the effects of ENSO cannot confidently be distinguished from zero. However, data simulations using a perfect model framework, where we impute a permanent effect of El Niño to data, demonstrate that models with many lags can yield insignificant coefficients due to the reduced sample size and large number of parameters (methods and fig. S8). The perfect model framework implies that, even if the real-world effects of ENSO were permanent, we may not be able to detect them given the short observational record. Finally, even if economies do eventually rebound from ENSO, the fact that damages accumulate for more than a decade means that the costs of climate variability are much larger than typically assumed in climate-economy models (*31*).

Our empirical model includes both the E-index and C-index, allowing us to distinguish the effects of eastern Pacific (EP) El Niño and central Pacific (CP) La Niña (methods). CP La Niña events have beneficial effects (fig. S10), but they are several times weaker than the negative effects of EP El Niño and statistically insignificant under alternative standard error clustering (table S2). These results reflect the skewness of ENSO itself, whereby EP El Niños tend to be stronger than both La Niñas and CP El Niños, and are consistent with studies showing that La Niña's economic effect is small (*19*, *20*).

The countries most affected by ENSO are generally lower-income, tropical countries (*19*). However, high-income countries also experience significant negative effects (fig. S4), consistent with work showing that these countries are impacted by extreme rainfall (*32*) and heat (*33*), both of which ENSO affects. We also identify persistent losses across countries that experience wetting and drying in response to El Niño (fig. S4), as both anomalously low and high rainfall can be damaging (*32*). We emphasize that some regions may experience benefits from El Niño or losses from La Niña. Our goal is to estimate a globally generalizable response to ENSO. That our findings are robust across multiple lines of country heterogeneity provides confidence that they are generalizable, even if individual regions may respond differently.

Losses from historical El Niño events

The persistent effect of ENSO implies that historical El Niño events have altered the income growth of teleconnected countries, potentially generating large economic losses. Here we quantify the costs of the two largest El Niño events in the last 60 years, in 1982–83 and 1997–98 (Fig. 2). Because an El Niño can trigger a subsequent La Niña (*34*), our analysis incorporates both the negative effects of each El Niño and the benefits of the following La Niña (methods). Furthermore, because these events coincided with unrelated currency crises, we use a model excluding these events to more conservatively calculate their impacts (fig. S4).

Consider strongly teleconnected Peru (τ^E = 1.18): Its GDPpc declined in 1998 and stagnated for three more years (Fig. 2A). Given the 1997 financial crisis, Peru's slower growth in 1998 is not entirely attributable to ENSO, but Peru's economy would have grown more quickly if the 1997–98 El Niño had not occurred (methods). Income for the average Peruvian would have been some $1,246 greater five years later in 2003 absent the event (CI: $853–$1,793), a 19% increase (Fig. 2A). Other tropical countries such as Ecuador, Brazil, and

Indonesia lost anywhere from 5% to 19% of GDPpc (fig. S11).

We estimate global losses from the 1982–83 and 1997–98 events to be trillions of dollars each (Fig. 2B and fig. S11). Our estimates exceed previous ones because we account for ENSO's growth effects: one study placed the total costs of the 1997–98 El Niño at $36 billion (*35*). Our accounting has losses from the 1997–98 event rising to three orders of magnitude more than that estimate, some $5.7T by 2003 (CI: $2.3T–$9.2T). The earlier 1982–83 event tallied $4.1T by 1988 (CI: $2.3T–$6T). The greater costs of the 1997–98 event result both because it was a stronger El Niño and because the global economy was larger. Absent the compensating benefits of the subsequent La Niñas, the 1983 (1998) event would have produced losses of $4.4T ($8T) (Fig. 2B).

We focus on 5 lags in this historical analysis to balance the imperatives of tracking the effects of ENSO and maximizing statistical power (fig. S8). Because the effect of El Niño appears to persist for more than five years (fig. S8), the ultimate toll of these events may be even higher than we show here. In fact, by incorporating growth reductions following the event and including all countries in a single framework, we show that estimates focusing on physical asset losses in low-income countries have strongly underestimated the global economic toll of El Niño.

Climate model projections of ENSO

ENSO's persistent effect raises the question of how it will shape the global economy with further warming. Using climate model simulations from the sixth phase of the Coupled Model Intercomparison Project (CMIP6) that skillfully simulate eastern Pacific SSTs, we analyze projected changes to ENSO under four Shared Socioeconomic Pathways (SSPs) (methods).

El Niño amplitude and teleconnections both increase with warming in CMIP6 (Fig. 3). This response is not scenario-dependent, likely due to the influence of internal climate variability on forced ENSO changes (*36*–*38*). Median amplitude increases by 5–21% across scenarios (Fig. 3A), a function of stronger wind-ocean coupling in the eastern Pacific (*9*, *12*). Global mean teleconnections increase by 4–15% (Fig. 3B), consistent with a more energetic atmospheric response to El Niño (*39*, *40*). Despite these forced responses, internal variability (proxied by multiple realizations from each model) can vary these responses by >60 p.p. (Fig. 3, A and B, lower lines).

Beyond amplitude and teleconnection changes, climate projections differ in their E-index time series. Due to ENSO's sensitivity to initial conditions (*36*–*38*) and multidecadal variability (*41*, *42*), a wide range of E-index values across models and scenarios can occur in a given year, even controlling for amplitude (Fig. 3C and fig. S12). For example, Fig. 3C shows two SSP2-4.5 simulations with similar amplitude changes and E-index skewness but different sequences of EP El Niños and La Niñas. As quantified by the sum of the E-index over the 21st century, MIROC-ES2L r6i1p1f2 experiences strong El Niño events while CESM2-WACCM r3i1p1f1 is dominated by La Niña events. Such differences in the ENSO sequence shape projected damages, as an El Niño–dominated time series yields greater damages than a La Niña–dominated one due to their differential effects (fig. S10). Crucially, because El Niños are stronger than La Niñas, the expectation from increased ENSO amplitude is net losses.

We combine these projections with our empirical estimates to quantify the economic effects of changes in ENSO. We use the SSPs as baselines against which we calculate country-level growth changes based on ENSO amplitude and teleconnection projections (methods). Departing from our historical estimates (Figs. 1 and 2), we project future ENSO damages with a model that extends damages out to ~14 years because we can confidently detect damage accumulation that long, yet cannot identify truly permanent growth effects due to the short observational record (fig. S8). As such, we make the conservative choice to allow economies to fully recover from future ENSO events after 14 years in our projections (methods). This simplifying choice assumes that the time persistence of ENSO impacts is homogenous. However, it is possible that different countries recover over different time scales. For example, weakly teleconnected countries may rebound more quickly (Fig. 1D), and the sectoral makeup of an economy (e.g., agriculture- versus manufacturing-dependent) may affect the speed with which it can reinvest in new growth after El Niño events. Further research into whether, how, and over what time scales economies recover from El Niño events would reduce uncertainty in our projections and help economies manage extreme climate events more broadly.

Economic impacts of future ENSO changes

Projected anthropogenic changes to El Niño amplitude and teleconnections will likely cause substantial economic losses over the 21st century (Fig. 4). Under a 2% discount rate (*43*) and a socioeconomic scenario consistent with current pledges to reduce greenhouse gas emissions (*44*) (SSP2-4.5), the median cumulative 2020–2099 global losses are $84T (Fig. 4A), a ~1% reduction in global economic output over the 21st century. In all four scenarios, median losses exceed $18T and damages are negatively skewed, consistent with the asymmetry in ENSO itself.

The range of these projections is large. Under SSP2-4.5, the 95% range spans losses of $453T to benefits of $80T (we write this CI as −$453T to +$80T) across 86,000 combinations of 86 simulations and 1,000 regression bootstraps (Fig. 4A). Reducing the discount rate to 1% amplifies median losses under SSP2-4.5 to $130T (−$687T to +$130T), while increasing it to 5% diminishes losses to $26T (−$162T to +$34T). The extreme end of these ranges implies a ~5% reduction in global economic output. In highly teleconnected countries, ENSO changes cause GDPpc reductions of >1% per year, though uncertainty is high even in these countries (fig. S11).

Despite this range across realizations, models, and scenarios, increases in ENSO amplitude and teleconnections are systematically related to greater economic losses (Fig. 4, B and C). Each 1% increase in ENSO amplitude is associated with \$4.1T in additional discounted losses over the 21st century ($p < 0.001$), and each 1% increase in teleconnections is associated with \$6.3T in losses ($p < 0.001$). These findings build upon previous projections of changes in ENSO amplitude (*9*, *11*) and teleconnections (*39*, *40*), demonstrating global socioeconomic effects of these physical changes.

These relationships, however, are heterogeneous, as the largely stochastic sequence of El Niños and La Niñas shapes the direction and magnitude of damages. Simulations with E-index sums greater than 0 (i.e., El Niño–dominated time series) exhibit a negative relationship between ENSO amplitude increases and damages (Fig. 4B, red dots), but the opposite is true for La Niña–dominated time series (blue dots). The same pattern holds for teleconnection changes (Fig. 4C). Critically, because El Niños are stronger than La Niñas, there are many more El Niño– than La Niña–dominated time series. On average, therefore, increases in ENSO amplitude and teleconnections produce large economic losses.

Alternative analytical choices, including incorporating C-index changes or holding teleconnections constant, alter the magnitude of losses but do not change the core result of negative damages with warming (fig. S13). Using only one realization per model increases uncertainty across scenarios (fig. S13B), highlighting the importance of large ensembles to capture ENSO variability (*37*). Assuming that damage persistence is permanent substantially increases the magnitude and uncertainty in projected damages (fig. S13D). Finally, controlling for country-average temperature in our regression does not alter the effect of ENSO (fig. S14), meaning our results are distinct from temperature-based damage projections (*13*). ENSO affects sub-national and sub-annual extreme heat or rainfall, and other hazards such as drought, all of which have independent impacts (*32*, *45*, *46*).

Our findings have implications for climate mitigation and adaptation. All else being equal, increased ENSO amplitude and teleconnections will generate major economic losses not currently included in assessments of climate damages or mitigation benefits. However, the facts that (i) ENSO-driven damages do not depend strongly on emissions scenario (Fig. 4A) and (ii) a range of outcomes are possible due to uncertainty in the unique ENSO sequence going forward (Fig. 4, B and C) together imply that emissions reductions alone are insufficient to protect economies from El Niño. While mitigation remains critical to blunt the catastrophic impacts of anthropogenic warming (*47*), our findings also raise the priority of climate adaptation and resilience efforts. Improved disaster risk management and ENSO early warning could reduce ENSO-driven damages (*48*), and scientific investments in decadal climate prediction could reduce the uncertainty in projections of these damages.

Conclusion

Our finding that El Niño has a persistent effect on economic growth has four key implications. First, it demonstrates that growth is highly sensitive to climate variability independent of warming. Our findings demonstrate that the local extreme conditions associated with ENSO integrate into a globally persistent macroeconomic effect, implying large and underestimated costs of historical El Niño events. Secondly, our results demonstrate that future changes to ENSO may increase the macroeconomic costs of warming. Previous climate-economy studies have not incorporated changes in climate variability, and we show that this omission has hidden a potentially major cost of rising temperatures. Thirdly, stochastic variation in ENSO could result in either losses or benefits from warming, emphasizing the importance of investing in ENSO prediction, particularly on decadal time scales (*41*). Lastly, these findings together suggest that while climate mitigation is essential to reduce accumulating damages from warming, it is imperative to devote more resources to adapting to El Niño in the present day.

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SUPPLEMENTARY MATERIALS

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Materials and Methods
Supplementary Text
Figs. S1 to S17
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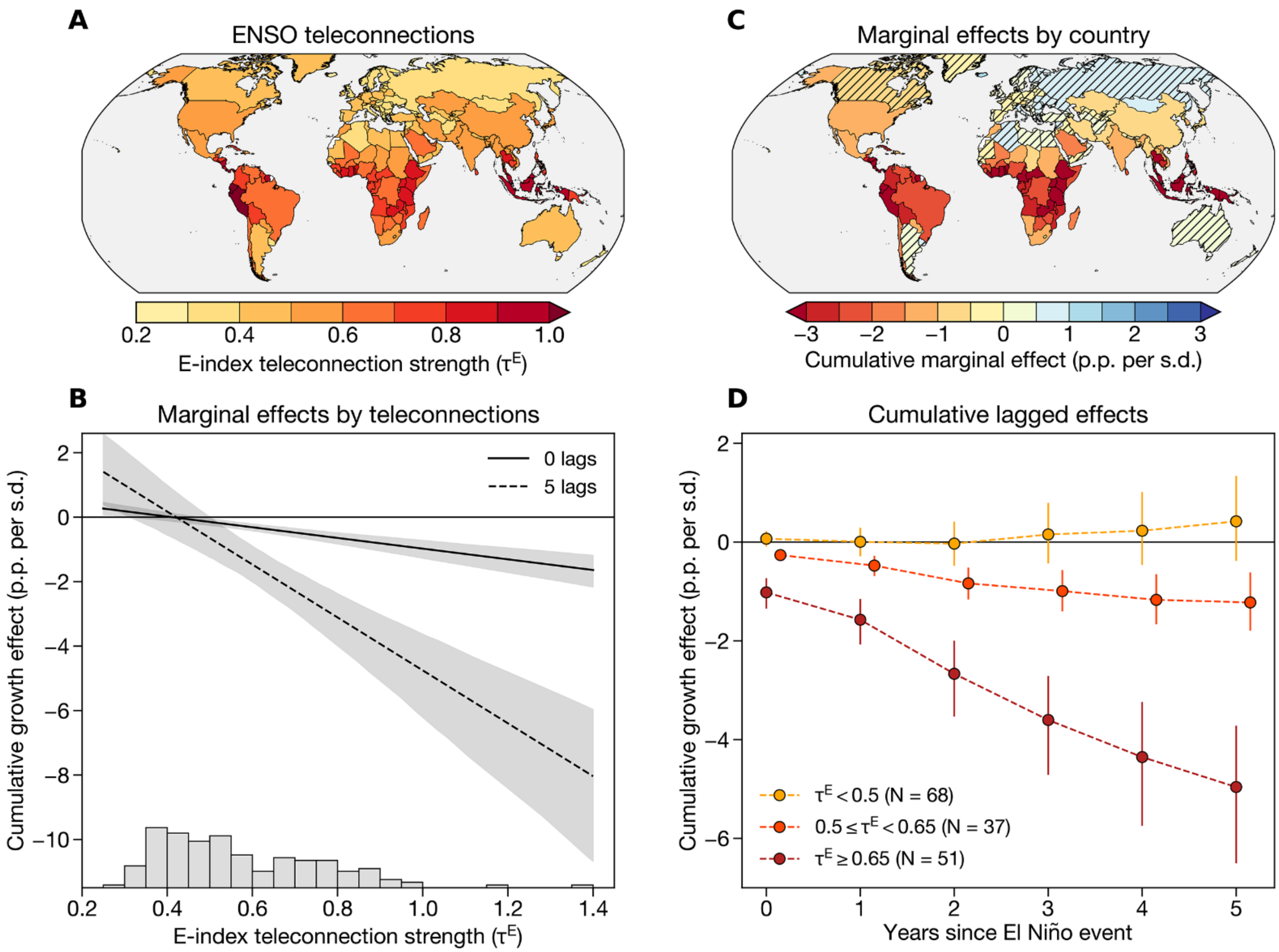

Fig. 1. Teleconnections mediate the effect of El Niño on economic growth. (**A**) Country-level ENSO teleconnections, calculated as the sum of the absolute value of the correlation coefficients between the E-index and monthly country-level temperature and precipitation (methods). (**B**) Marginal effects of El Niño on economic growth across teleconnection values in year of the event (0 lags, solid line) and the fifth year after the event (5 lags, dashed line). Black line shows the mean and shading shows 95% confidence intervals from bootstrap resampling (methods). Lower histogram shows the density of teleconnection values in the sample. (**C**) Cumulative 5-lag effect of El Niño on economic growth for each country. Hatching denotes countries whose effects are not distinguishable from zero (i.e., they fall on a location on the x-axis in (B) where the shading includes zero). (**D**) Cumulative effects of El Niño over time, beginning with the year of the event (year 0) and accumulating to the fifth year after the event (year 5). Countries are grouped into three bins according to their teleconnection strength, with "N" denoting the number of countries in each bin. Dots show averages and bars show 95% confidence intervals.

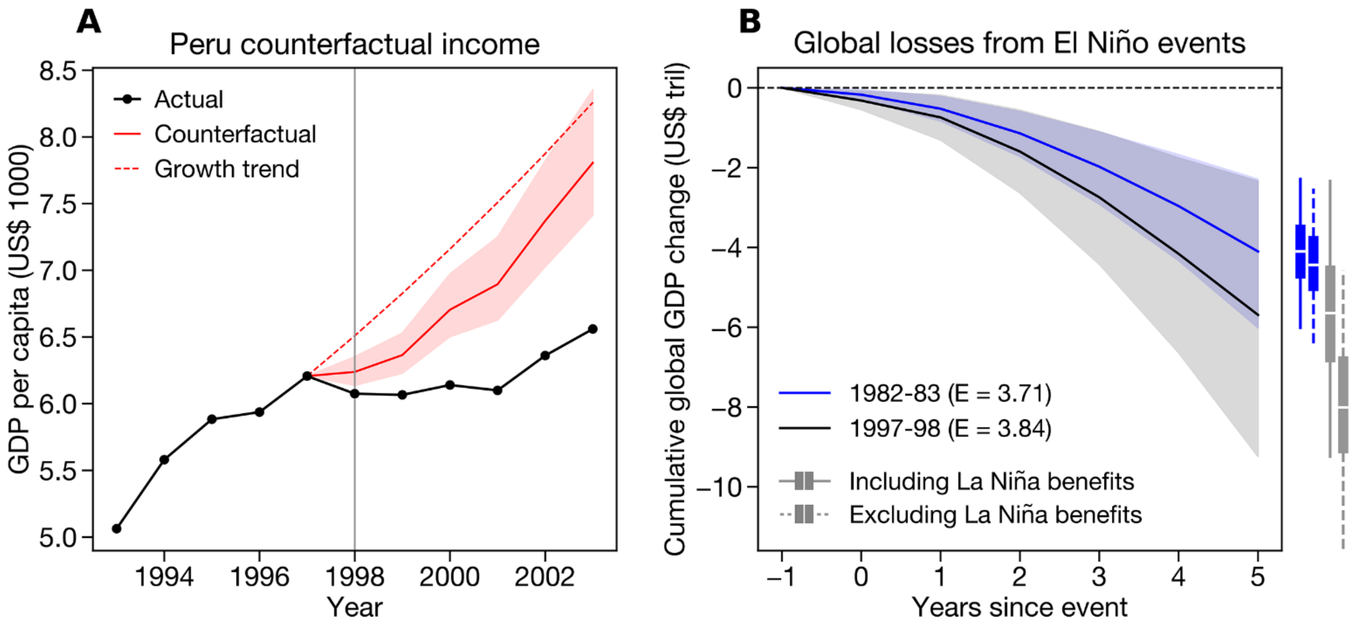

Fig. 2. Damages from extreme El Niño events. (**A**) GDP per capita (GDPpc) in Peru before and after the 1997–98 El Niño event. Black line shows actual GDPpc, red line shows the average counterfactual GDPpc across regression bootstrap samples (methods), and red shading shows 95% confidence interval. Dashed line shows GDPpc if Peru had maintained its average growth rate from the 5 years preceding the event. (**B**) Cumulative global GDP change for the 5 years after the 1982–83 (blue) and 1997–98 (black) El Niño events. Center line shows the mean and shading shows the 95% confidence intervals across regression bootstrap samples. Global GDP change is only calculated for countries with statistically significant marginal effects (Fig. 1C). Text in legends denotes the DJF-average E-index in the corresponding years. Boxplots at right show cumulative global GDP change when including the benefits of the following La Niña events (solid lines) and excluding those benefits (dashed lines). All dollar values are in constant 2017 prices.

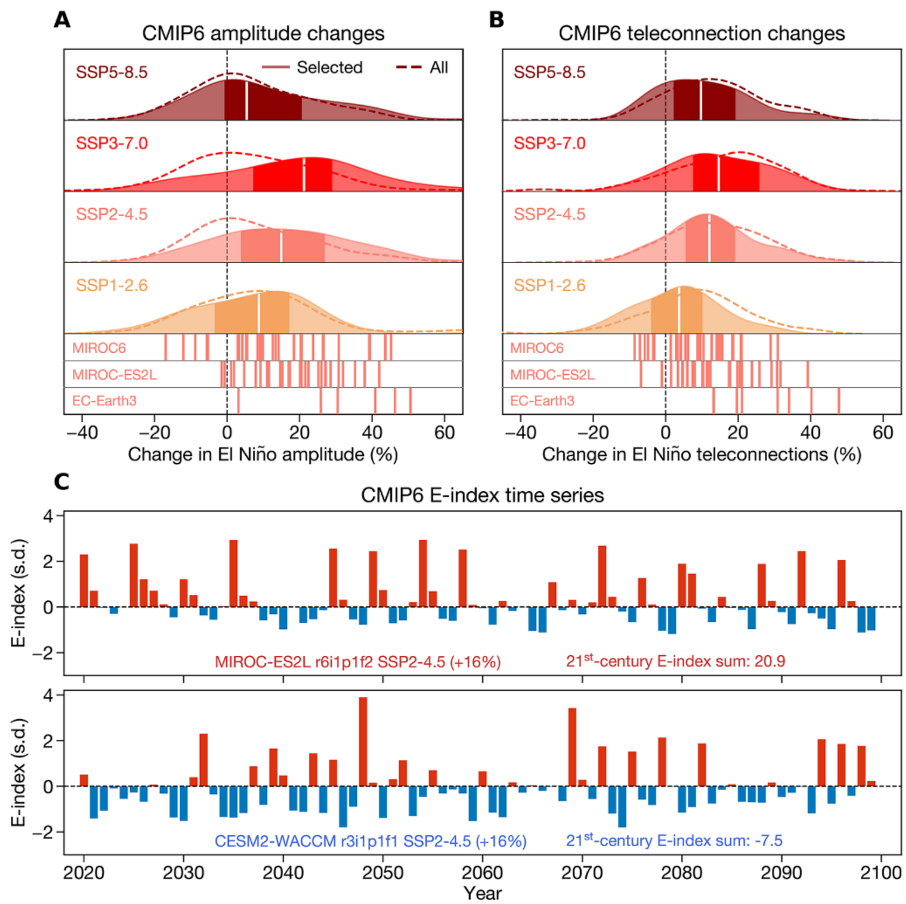

Fig. 3. Climate model projections of ENSO. Change in ENSO amplitude (**A**) and global mean teleconnection strength (**B**) between 1940–2019 and 2020–2099 for an ensemble of CMIP6 simulations from four SSP experiments. In both panels, dashed density lines show changes from all simulations and solid density plots show amplitude changes from selected high-skill simulations used in the analysis (methods). Vertical lines below density plots denote amplitude changes from the individual realizations of three models (MIROC6, MIROC-ES2L, and EC-Earth3), all drawn from the SSP2-4.5 experiment, illustrating the wide range of amplitude and teleconnection changes possible from internal variability alone. (**C**) E-index time series from two example simulations with similar amplitude increases: MIROC-ES2L r6i1p1f2 (top) and CESM2-WACCM r3i1p1f1 (bottom), both from the SSP2-4.5 experiment. Red bars denote eastern Pacific El Niño (E > 0) and blue bars denote eastern Pacific La Niña (E < 0). Left inset text in each panel denotes the model information and amplitude change. Right inset text denotes the sum of each E-index time series over the 21st century (2020–99), with positive values indicating that the time series contains more El Niños than La Niñas and negative values indicating the opposite.

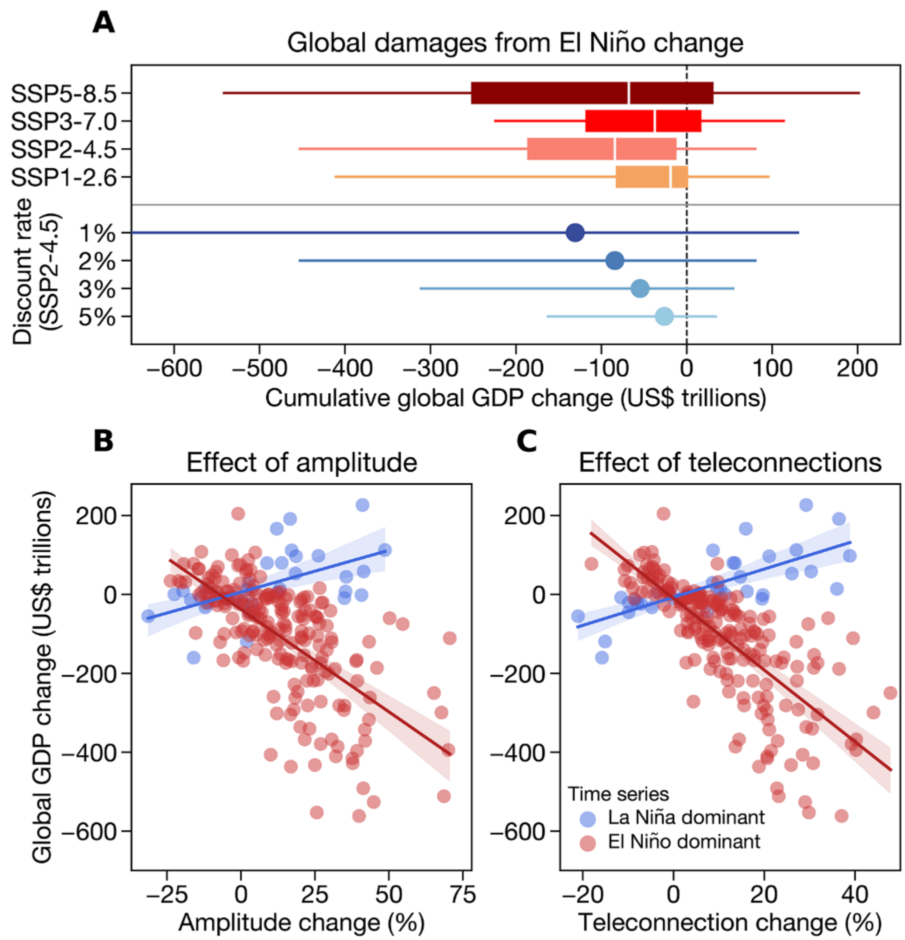

Fig. 4. Global economic impacts of changes in El Niño amplitude and teleconnections. (**A**) Boxplots show the cumulative global GDP change in each scenario under a 2% constant discount rate. Colors correspond to the scenario colors in Fig. 3. In each boxplot, white line denotes the median, box spans the first and third quartiles, and whiskers span the 95% range. Lower blue lines denote global economic losses under SSP2-4.5 and a range of discount rates. Dot denotes the median and lines span the 95% range. (**B** and **C**) Cumulative global GDP change due to changes in ENSO amplitude (B) and teleconnections (C) with a 2% discount rate, with each dot corresponding to one climate model simulation. Simulations are pooled across all four scenarios. Red dots denote simulations in which the 21st-century E-index sum is greater than 0 (El Niño–dominated time series), while blue dots denote simulations in which the sum is less than 0 (La Niña–dominated time series). Red and blue regression lines and 95% CIs are drawn separately for each subset of simulations.

Persistent effect of El Niño on global economic growth

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