NBER WORKING PAPER SERIES

THE CLIMATE ADAPTATION FEEDBACK

Alexander C. Abajian
Tamma Carleton
Kyle C. Meng
Olivier Deschenes

Working Paper 33531
http://www.nber.org/papers/w33531

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2025

ACM are joint first authors. ACMD conceived of the project. ACM conducted the analysis. ACMD contributed to writing. The authors declare that they have no competing interests. We thank Max Auffhammer, Chris Costello, Ranjit Deshmukh, Kelsey Jack, Michael Oppenheimer, Andrew Plantinga, Ashwin Rode, Peter Sherman, and participants at the Bren School of Environmental Science & Management (UCSB) and Environmental Markets Lab (UCSB) seminars for helpful comments. This research was supported by funding from the Environmental Defense Fund. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The Climate Adaptation Feedback
Alexander C. Abajian, Tamma Carleton, Kyle C. Meng, and Olivier Deschenes
NBER Working Paper No. 33531
February 2025
JEL No. Q4, Q5

ABSTRACT

Many behavioral responses to climate change are carbon-intensive, raising concerns that adaptation may cause additional warming. The sign and magnitude of this feedback depend on how increased emissions from cooling balance against reduced emissions from heating across space and time. We present an empirical approach that forecasts the effect of future adaptive energy use on global average temperature over the 21st century. We find energy-based adaptation will lower global mean surface temperature in 2099 by 0.12 degrees Celsius (0.07 degrees Celsius) relative to baseline projections under RCP8.5 (RCP4.5) and avoid 1.8 (0.6) trillion USD ($2019) in damages. Energy-based adaptation lowers business-as-usual emissions for 85% of countries, reducing the mitigation required to meet their unilateral Nationally Determined Contributions under the UNFCCC by 20% on average. These findings indicate that while business-as-usual adaptive energy use is unlikely to accelerate warming, it raises important implications for countries' existing mitigation commitments.

Alexander C. Abajian
Department of Economics
2127 North Hall
University of California, Santa Barbara
Santa Barbara, CA 93106-9215
xander.abajian@gmail.com

Tamma Carleton
Department of Agricultural and
Resource Economics
University of California, Berkeley
Berkeley, CA 94720
and NBER
tcarleton@berkeley.edu

Kyle C. Meng
Bren School of Environmental
Science and Management
Department of Economics
University of California, Santa Barbara
4416 Bren Hall
Santa Barbara, CA 93106
and NBER
kmeng@bren.ucsb.edu

Olivier Deschenes
Department of Economics
2127 North Hall
University of California, Santa Barbara
Santa Barbara, CA 93106
and NBER
olivier@econ.ucsb.edu

A Github repository is available at https://github.com/xabajian/ACDM_Climate_Adaptation_Feedback
A Data repository is available at https://doi.org/10.5281/zenodo.10476310.

1 Introduction

Human adaptation will be increasingly critical for moderating harms and exploiting opportunities under climate change (1). Recent studies highlight that climate adaptation requires significant changes in energy use; increased energy consumption has been shown to reduce excess mortality and protect well-being in homes, workplaces, and schools under extreme temperatures (2; 3; 4; 5; 6; 7; 8; 9; 10). Energy use is carbon-intensive: cooling demand alone comprised 10% of recent global electricity consumption and is expected to rise substantially during the 21st century (11). This raises the question of whether adaptation to climate change may itself induce additional warming, a phenomenon we call the Climate Adaptation Feedback (CAF). The CAF is the anthropogenic analogue to geophysical climate feedback mechanisms (e.g., declines in oceanic CO_2 uptake or albedo) that can amplify global climate change (12). It captures how behavioral responses to climate change may be maladaptive by ultimately increasing future global mean surface temperatures (GMST) (10; 13; 14).

This paper develops a framework for quantifying the CAF driven by adaptive energy consumption. We calculate the CAF over the course of the 21st century by combining high-resolution, subnational projections of energy consumption responses to anthropogenic climate change with country- and energy-specific CO_2 emissions intensities. Our calculation accounts for energy consumption implications of all behaviors and investments that individuals and firms undertake in response to temperature change across all non-transport sectors including residential, commercial, industrial, and agricultural sectors (8), covering $N = 142$ countries or nearly 80% of current global CO_2 emissions (15). It is built from state-of-the-art, globally-comprehensive, empirical estimates of how energy demand responds to changing temperatures (8). These estimates incorporate heterogeneous effects of a changing climate on energy consumption across fuels and locations (2; 3; 8; 9; 16; 17; 18; 19), as well as how income growth and climate change will alter these responses over time.

While our work is not the first to note the potential feedback between energy used for adaptation and the climate (16; 20; 21), it formalizes the notion of the CAF and provides a tractable framework for its calculation. Prior work has used a regional Integrated Assessment Model (IAM) to estimate the effects of energy-based adaptation on global warming (22). Through the lens of an IAM, the feedback in ref. (22) is modeled by allowing changing frequencies of regional temperature extremes to affect the productivity level of energy inputs in economic production. We instead adopt a data-driven approach that, relative to prior work, increases the spatial resolution of energy demand responses used to forecast changes in emissions, includes the response to the full distribution of daily temperature realizations rather than restricting inputs to realizations of local extremes, and accounts for country-level heterogeneity in emissions intensities, as well as their dynamics, for both electricity and other fuels.

The possibility that adaptation-induced energy consumption could influence the trajectory of future temperatures breaks the conventional separation between mitigation (actions that reduce emissions) and adaptation (protective efforts), with important implications for both climate policy and research. For example, global climate models estimate climate responses to exogenous radiative forcing, but omit behavioral responses. This will lead to inaccurate local temperature projections if the CAF is non-zero. Any error in projections then affects associated climate damage estimates, influencing key policy metrics like the social cost of carbon (23; 24). Additionally, the possibility of a *positive* CAF raises concerns that adaptation could exacerbate climate change inequities, since the indoor temperature control that is more accessible at higher incomes (4; 19) may accelerate climate change damages borne by lower-income regions (25; 26; 27; 28). While integrated assessment models have taken steps to account for geophysical feedbacks and nonlinearities in the climate system (29) as well as adaptive behavioral margins (30; 31; 32; 33; 22; 34), current models do not, to the best of our knowledge, account for how local changes in final energy consumption for adaptation directly alter global temperatures under a non-zero CAF.

2 The Climate Adaptation Feedback

Current research and media attention have predominantly focused on the risks posed by behavioral feedbacks that would lead to a positive CAF, such as increased demand for air conditioning raising emissions from the electricity sector (4; 11; 22; 21). While this specific channel will undoubtedly play an important role, Figure 1 illustrates that both the sign and magnitude of the CAF stemming from all forms of energy-based adaptation to climate change are unclear. While climate change will lead to warming of daily temperatures in all locations (Figure 1a-b), the resulting response in energy consumption will be highly heterogeneous. A higher frequency of realized hot days will increase electricity demanded by cooling services in locations that are already warm (Figure 1d), but warming will simultaneously lower demand for heating in locations that currently experience a large number of cold days (Figure 1c). This heterogeneity interacts with variation in the CO_2 intensities of electricity and other sources of energy, leading to substantial differences in the response of emissions from adaptation to temperature change across countries.

For example, Canada and Sweden will both likely experience declines in heating demand under climate change. However, Canada's electricity sector emits 15 times more CO_2 per GJ than does Sweden's, while its other fuels sector emits 2 times more. These differences lead to differential emissions responses to changing daily temperatures (Figure 1e). Similarly, energy-based adaptation in India and Brazil will lead to increased demand for electricity due to more energy being required for refrigeration and indoor temperature control, but the dominance of coal in India implies much larger increases in emissions than in Brazil, where hydropower is the primary source of electricity (Figure 1f). Thus, the change in future global CO_2 emissions due to energy-based adaptation, and by extension the sign and magnitude of the CAF, are *a priori* unknown. A positive CAF implies behavioral adaptations increase global CO_2 emissions on net (Figure 1g), raising projected rates of warming (Figure 1h). However, if future declines in emissions due to reduced demand for heat from other fuels dominate the additional future emissions due to higher electricity demand, the CAF will be negative.

We develop a framework to sign and quantify the net effects of the forces illustrated in Figure 1. Specifically, we define the CAF in any given year as the difference in global mean surface temperature (GMST) between a baseline value (e.g., projected warming under the Representative Concentration Pathway 8.5 (RCP8.5) emissions trajectory) and one accounting for future energy-based adaptation (e.g., projected warming under RCP8.5 plus the net change in emissions from adaptation) (see Methods Section 5.1). We note that while energy demand responses to warming in specific sectors and by specific energy sources will be heterogeneous, as illustrated in Figure 1, the sign and magnitude of the CAF depend only on the net change in resulting emissions across all sectors and sources. Therefore, we focus our analysis on the aggregate emissions changes resulting from all measurable energy-based adaptations.

We implement this framework by leveraging newly-available high-resolution projections of future energy changes in response to local temperature realizations from ref. (8). These causal "dose-response" functions represent the change in the use of final energy sources – electricity and all other fuels – in response to variations in daily temperature, pooling energy consumption across residential, commercial, industrial, and agricultural end-uses (excluding transportation). Any adaptive actions taken by individuals, firms, or public agencies across a broad spectrum of sectors, such as the use of air conditioning or space heating, are included in these estimates. The estimated dose-response functions vary across space and time, accounting for the fact that average incomes and baseline climates shape the sensitivity of energy use to temperature changes, for example through changing the adoption and efficiency of energy-intensive technologies. Accounting for such extensive margin adjustments in the energy sector has been shown to have first-order impacts on projected impacts of climate change on energy demand (4; 9; 16; 21). To account for uncertainty, we report estimates from multiple socioeconomic and emissions scenarios, while accounting for both statistical and climatological uncertainty (see Methods Section 5.1).

We combine these projections with country-level CO_2 emissions intensity factors for each final energy source constructed using data from the International Energy Agency's Emissions Intensities Report (see Methods Section 5.2). These granular data are critical for translating adaptive energy use into a global CAF, as the CO_2 intensity of energy use varies substantially across fuels and locations, as shown in Figures 2a-b. When combined with projections of energy consumption from ref. (8), these factors allow us to predict future changes in global CO_2 attributable to energy-based adaptation (see Equation (2)). As our forecasts for future energy consumption take an underlying emissions (RCP) and socioeconomic (Shared Socioeconomic Pathway; SSP) scenario as given, we fix emissions factors in our projection at historical 2010-18 levels. While this assumption is restrictive, it avoids the inconsistency that would result from changing emissions factors while maintaining an SSP-RCP that fixes baseline emissions. We discuss and evaluate the potential implications of this choice in Section 4.

To obtain the CAF, we calculate the annual cumulative change in global CO_2 emissions due to energy-based adaptation for horizons from 2020 to 2099 (Figure 2c and Equation (6)). We then translate these cumulative emissions into a change in global temperatures (ΔGMST) using an empirically-derived relationship that leverages simulated warming from an ensemble of Global Climate Models for the two emissions pathways we consider (Figure 2d; see Methods Section 5.3).

3 Results

We find that the CAF is negative at all horizons and decreasing monotonically over time. Figure 3a plots point estimates (solid green line) and 90% confidence intervals (shaded green area) for the annual CAF over the 2020-2099 horizon under our baseline SSP2-RCP8.5 scenario. In 2099, under RCP8.5 (RCP4.5) the CAF is -0.12°C (-0.07°C); changes in energy consumption driven by adaptation lead to a 0.12°C (0.07°C) lower GMST relative to baseline.

This projected reduction in warming in 2099 alone is equivalent to six (four) years of recent warming at the observed 0.018°C/yr rate between 1981-2019 (35) and is 25 times larger than that implied by a back-of-the-envelope calculation in ref. (8). Under the SSP2-RCP8.5 scenario, our estimated CAF implies that adaptive energy consumption is predicted to lower the change in GMST in 2099 from 4.27°C to 4.15°C, relative to the pre-industrial climate. Using the Data-driven Spatial Climate Impact Model (DSCIM) built by the Climate Impact Lab, we estimate that the decrease in warming due to the CAF lowers the present value of cumulative damages from climate change between 2020 and 2099 by 1.8 (0.6) trillion (2019 USD) (see Methods Section 5.1). Accounting for both climatological and statistical uncertainty in 2099 yields a 90% confidence interval for the CAF of -0.35 to 0.073°C, and the CAF is robust to iteratively leaving out the adaptation of individual countries when forecasting cumulative emissions reductions in 2099 (Supplementary Information Section 5).

A limitation of our benchmark approach is that it implicitly assumes the effects of adaptive emissions on the GMST pathway do not themselves affect future adaptation. Paths for future changes in energy consumption are fixed in the sense that the demand responses generated by temperature trajectories under each SSP-RCP are determined before we calculate the CAF at a given horizon. We relax this assumption in Methods Section 5.4 to construct a dynamic version of the CAF, which allows for historical adaptation to affect our projections for adaptive energy use from that point forward. Allowing for such dynamic linkages leads to a negligible difference, as shown by the dashed green line in Figure 3a; the two CAFs are indistinguishable given the degree of statistical uncertainty. Our point estimates imply that accounting for dynamic adaptation effects decreases the magnitude of the CAF in 2099 by 0.8%.

We also recalculate the CAF relaxing assumptions over fixed emissions factors. The long dashed lime green line in Figure 3a shows the CAF under the assumption that historical global trends in emissions intensity for both fuels between 2000 and 2018 continue for all countries through 2099, an assumption taken in prior related work on global climate damages

(36; 37). Allowing each sector to continue to decarbonize at historical rates lowers the CAF to -0.13°C under SSP2-RCP8.5. As emissions from other fuels have remained relatively unchanged on a unit basis when compared to the substantial reduction in the emissions intensity of electricity generation over the past two decades, extrapolation of this trend lowers emissions from the electricity sector and amplifies the mechanisms leading to a negative CAF (Supplementary Information Section 3).

Figure 3b displays how several factors contribute to the sign and magnitude of the benchmark CAF (first bar). First, adaptation-induced changes in electricity consumption, which are largely driven by increased demand for cooling under rising temperatures (4; 38; 8), lead to a positive value of 0.06°C (second bar). This electricity effect has been the focus of prior discussions of energy-based adaptation (11; 21). However, a negative CAF emerges when we add changes in demand for other fuels, whose value of -0.18°C (third bar) more than offsets the positive component from electricity, due to substantial projected declines in demand for heating under climate change. These findings highlight the importance of accounting for all forms of energy demand that will change in response to climate change. Moreover, they reinforce results in the previous literature demonstrating that energy demand responses to climate change differ in sign and magnitude across distinct sectors and fuel sources (16).

Heterogeneity in CO_2 emissions intensity also plays an important role. Using a constant global CO_2 emissions intensity – a simple average across countries and fuels (fourth bar) – results in a CAF that's 37% smaller in magnitude than our benchmark estimate, which allows CO_2 emissions intensities to vary across countries and fuels. This result implies that emissions are higher per unit of energy in countries with larger energy-based adaptive responses to climate change.

Our estimates of the CAF are largely invariant across socioeconomic scenarios, but depend heavily on the magnitude of baseline greenhouse gas emissions. Figure 3c shows point estimates for the 2099 CAF under alternative SSP-RCP scenarios, demonstrating that the CAF under RCP8.5 is roughly double that under RCP4.5, due to greater baseline warming leading to larger energy savings from fewer cold days. Although SSP scenarios change total population and levels of income across countries, which can shape the total energy response to daily temperatures (8), we find that within an RCP, global CAF values differ little across SSP scenarios. This is likely due to the fact that income and population levels vary most across SSPs within low-income countries (39), and yet, as we show below, the CAF is driven primarily by adaptive responses in higher-income, high-emissions countries.

There is substantial heterogeneity in the magnitude of adaptation-induced CO_2 emission changes across countries. Figure 4a shows both a map and histogram of country-level cumulative adaptation-induced CO_2 emissions changes by 2099 under SSP2-RCP8.5 (this is denoted as $\mathcal{E}_{2099}$ in Equation (3)). While 85% of countries experience CO_2 emissions reductions, of those countries, the 5th and 95th percentiles of cumulative adaptation-induced emission changes by 2099 are -0.027 and -6.24 $GtCO_2$, respectively. For the remaining 15% of countries that experience increases in emissions, magnitudes are small, with the 5th and 95th percentile range estimated at 0.0024 to 0.5 $GtCO_2$. These net changes in emissions can be decomposed into country-level changes in emissions from electricity, which are positive in most countries (Supplementary Figure S1), and in emissions from other fuels, which are negative in virtually all countries (Supplementary Figure S2). The case of India is particularly striking, as it exhibits large adaptation-induced declines in CO_2 emissions by end-of-century, despite facing substantial increases in exposure to extreme heat in future years (40). This result is driven partially by the demand responses from ref. (8), which estimate that electricity demand will increase by 4.1 Exajoules (EJs) by 2099, while cumulative demand for other energy will fall by 7.0 EJs, due to electricity-temperature demand responses being very low for lower-income populations. This result is also influenced by heterogeneous emissions intensities: other fuels in India are substantially more emissions-intensive, implying that demand responses translate into an increase of only 0.9 $GTCO_2$ emissions from electricity compared to a decline of 2.7 $GTCO_2$ from other fuels. This decomposition is detailed in Supplementary Information Section 4.

One interpretation of reduced CO_2 emissions from energy-based adaptation is the accrual of "free" abatement. Unlike typical CO_2 abatement, which results from climate mitigation policies designed to directly curtail emissions, this abatement emerges solely as a consequence of behavioral adjustments unprompted by mitigation policies. However, the resulting emissions reductions from these adaptations have global benefits identical to those induced by environmental policy and can influence international negotiations and country-level mitigation benchmarks. The magnitude and distribution of this free abatement has two important features relevant for climate policy design.

First, Figure 4b shows that for the $N = 121$ countries projected to experience adaptation-induced CO_2 declines, the magnitude of cumulative abatement by 2099 is strongly correlated with historical emissions. For example, while Eritrea is responsible for less than 0.03 billion tons of CO_2 emissions cumulatively since 1970, we project that it will accrue only 0.14 billion tons of free abatement in the coming century. In contrast, the U.S. is responsible for more historical emissions than any other nation on earth, but is projected to benefit from over 10 billion tons of adaptation-induced abatement without any mitigation policy. This correlation implies that while the countries responsible for most greenhouse gas emissions to date are often targeted for aggressive mitigation in international climate negotiations (41), they are projected to receive substantially more free CO_2 abatement during the 21^{st} century, relative to today's developing economies.

Second, we find that the magnitude of adaptation-induced abatement is large relative to existing mitigation targets. To illustrate this, we report each country's cumulative adaptation-induced abatement in 2050 as a fraction of that country's cumulative required abatement in 2050 under its Nationally Determined Contribution (NDC) from the Paris Agreement of the United Nations Framework Convention on Climate Change (UNFCCC) (42; 43; 44). When this ratio takes a value of one, the entirety of a country's obligations under its NDC will be met without any mitigation policy; that is, the projected gap between a country's baseline emissions and its NDC is met entirely by our estimate of adaptation-induced abatement. Figure 4c shows a histogram of these values, displaying the share of mitigation stipulated under each country's NDC that is realized through adaptation-induced abatement for each of the 63 countries with long-term commitments catalogued by ref. (44). Similar to the the full sample, 82% of the countries in this subsample are projected to experience adaptation-induced abatement. For these 52 countries, adaptation-induced abatement will on average reduce gaps between baseline emissions and their NDCs by 20% in 2050. Several countries are projected to undergo emissions reductions from adaptation that are larger than the mitigation commitments implied by their NDCs, as shown by share values that exceed 1. This highlights that NDC commitments, which already have been shown to be insufficient to meet the Paris Agreement goal of no more than 2°C increase in global average temperatures relative to pre-industrial (45), are even weaker than previously assessed: once the CAF is accounted for, many countries need to undertake little mitigation policy to achieve their targets.

4 Discussion

We develop a framework for quantifying the feedback between energy-based adaptation and anthropogenic climate change, a phenomenon we label the Climate Adaptation Feedback. Our methodology combines high-resolution projections of future energy consumption responses to climate change with country- and energy-specific CO_2 intensities to quantify cumulative emissions changes due to adaptation. Under several benchmark pathways for future emissions and socioeconomic development, we consistently find a negative CAF – i.e., that declines in energy use from adapting to fewer cold temperatures overpower increases in energy use from adapting to warmer temperatures. This result is driven in part by the finding that much of the global population is projected to face income constraints that prevent substantial increases in energy demand in response to rising temperatures (8). Our central estimate implies that adaptive energy use attenuates warming by 0.12°C in 2099, roughly equivalent to six years of warming at recent rates. This moderation of GMST change between 2020 and 2099 avoids 1.8 (0.6) trillion of damages (in 2019 USD) in present value terms, an amount equivalent to roughly 2 percent of 2019 global output. When accounting for statistical and climatological uncertainty, our results suggest it is unlikely that the CAF is positive, limiting concerns that energy-based adaptation will exacerbate future warming.

Our analysis has several limitations. First, we define the CAF relative to a fixed SSP for socioeconomic conditions and fixed RCP for baseline global emissions. The advantage of this approach is that SSPs and RCPs are widely used in climate projections and do not already account for emissions arising from energy-based adaptation (46). As discussed above and in Methods Section 5.4, this abstracts from a full characterization of the dynamic interplay between changing adaptive energy demand and climate change. One existing study used computational general equilibrium methods to endogenize the dynamic relationship between climate change and energy demand (22). The authors find, in contrast to our results, evidence of a positive climate feedback from adaptation. This prior study is complementary to our analysis in that it computes the CAF under future conditions in which a global social planner optimally balances benefits and costs of mitigating climate change, while our data-driven CAF represents the climate feedback that emerges under plausible, but exogenous, future emissions trajectories. However, results from ref. (22) also depend on earlier empirical estimates of energy demand responses from ref. (16), which differ strongly from those employed here. For example, our CAF is built from 24,378 heterogeneous empirically-derived fuel-specific energy demand responses representing subnational units across the globe, while there are just two aggregate fuel-specific demand responses in ref. (22) representing two large global regions. Similarly, our estimates include demand responses to the full distribution of daily temperature realizations, instead of only the effects of temperature events in the tails of the distribution in ref. (22). Finally, we account for country-level heterogeneity in emissions intensities, as opposed to heterogeneity across only 17 global macro-regions. Notwithstanding, our sensitivity analysis outlined in Methods Section 5.4 computes a dynamic version of the CAF, finding a nearly identical result to the baseline estimate shown in Figure 3.

The use of a fixed SSP-RCP baseline prohibits us from examining the CAF in tandem with decarbonization scenarios more sophisticated than extrapolating historical trends. Any decarbonization assumptions we might employ to alter current CO_2 intensities of energy consumption into the future would be inconsistent with modeling assumptions built into these exogenous scenarios; a fully coupled approach in which behavioral adaptations are built directly into climate and socioeconomic modeling would be required to comprehensively assess the implications of decarbonization for the CAF. However, as long as CO_2 intensities associated with other fuels do not decline dramatically relative to those for electricity, our estimate should serve as an upper bound on the magnitude of the CAF. For example, if the electricity sector continues to decarbonize faster than other fuels (47), there will be fewer additional emissions from increased electricity consumption to offset the decreased emissions from other fuels, implying a more negative CAF than the value we have uncovered here.

Second, relying on a fixed SSP-RCP baseline further omits other general equilibrium channels associated with energy-based climate adaptation. For example, recent integrated assessment models of climate change illustrate the importance of price effects from energy-based adaptation in altering the social cost of carbon (17; 22; 34). While some state-of-the-art, multi-region macroeconomic models do incorporate some heterogeneity in demand for energy across space (22; 37; 48), these models do not yet capture how adaptation may directly alter how energy enters final consumption worldwide. Incorporating both behavioral responses to climate change through energy use and allowing for these changes to affect prices, expectations, and investment will be essential moving forward in establishing a unified modeling framework whereby socioeconomic conditions and emissions pathways interact dynamically.

Third, our analysis is somewhat limited in its coverage of energy-based adaptations. We omit possible feedbacks arising from transportation-based adaptation due to a paucity of empirical estimates for how transportation-related GHG emissions respond to a warming climate (e.g., ref. (49) provide such estimates, but only for the United States). Our estimates may also fail to account for long-run changes in the response of energy demand driven by shifts in preferences or technological change, leading us to not fully capture some facets of the extensive margin for adaptation (9; 20; 21). If the price of electricity falls drastically in the future relative to that of other energy, we may underestimate electricity demand responses which would bias our CAF estimate downward. Conversely, if end-uses for electricity become more efficient in a way previously unexplained by income growth, our CAF will overstate future emissions from electricity. More generally, our estimates of the CAF will not capture future energy demand responses to climate change driven by factors that are not captured by the two-factor model in ref. (8). This omits the potential for government policy or technological breakthroughs to cause structural shifts in how energy use responds to temperature changes. Additionally, our calculation includes all direct energy consumption responses to daily variations in temperature, but omits any indirect effects on energy demand that may arise under climate change. For example, declining agricultural yields due to climate change may induce more fertilizer use, which could alter GHG emissions from the agriculture sector even if it uses the same level of direct energy inputs (50; 51). Such indirect channels of energy-based adaptation have, to our knowledge, not been systematically quantified globally. When these adaptive behaviors are better characterized in the scientific literature, they too may be incorporated into the CAF using the framework developed here.

Even within the non-transportation energy sector, we face two primary data limitations. First, our measure of CO_2 emissions intensity corresponds to a country's average emissions intensity, whereas a more appropriate measure would be the CO_2 intensities of marginal energy sources that will experience increasing (or decreasing) demand due to variation in local temperatures. Unfortunately, the data for calculating marginal CO_2 intensities for every country is not readily available, nor is it clear whether the average CO_2 intensities we use systematically under- or overstate true marginal intensities. Second, the absence of non-CO_2 GHG emissions intensities prevent us from directly quantifying corresponding changes in non-CO_2 emissions due to adaptation. While our empirical estimate of the relationship between GMST changes and global cumulative CO_2 emissions implicitly includes non-CO_2 GHG emissions (see Figure 2d and Methods Section 5.3), our analysis does not capture any geographical heterogeneity in the covariance of these emissions and CO_2. For example, because phase-out rates of hydrofluorocarbons (HFCs) vary by country under the Kigali Amendments to the Montreal Protocol, some countries may see decreased CO_2 from air conditioning coincide with declines in HFC emissions larger than those captured in our estimated global temperature response relationship. Lastly, by definition, the CAF only quantifies the GMST consequences due to GHG emissions caused by energy-based adaptation. In practice, fossil energy consumption for heating and cooling leads to additional local ambient air pollution from power plants and the direct combustion of fossil fuels (e.g., natural gas furnaces). In the case of electricity generation, those local ambient air pollutants (e.g., PM2.5, SO_2, and NO_x) have been shown to have large effects on human health outcomes (52; 53; 54). Therefore, the declines in energy consumption due to adaptation that we study here may lead to additional local environmental benefits not considered in this analysis.

Our finding that energy-based adaptation may lower global CO_2 emissions necessitates a reevaluation of existing mitigation commitments. Projections of "business-as-usual" CO_2 emissions that fail to account for declining energy use on net due to adaptive behaviors (that occur even regardless of policy changes) may lead to a false measure of policy stringency. As we show by comparing cumulative adaptation-induced CO_2 abatement with mitigation commitments under existing NDCs, energy-based adaptation alone may account for a substantial share of NDC abatement for many countries. For a more accurate measure of climate policy stringency, measures of business-as-usual or baseline emissions must incorporate GHG emissions changes due to adaptive behaviors.

More broadly, a negative CAF highlights the inherent link between climate mitigation and adaptation that is beginning to be employed in policy and research (21). Advocates and policy makers have long argued that mitigation and adaptation should be considered separately, in part to isolate the objectives within each domain. With a non-zero CAF, those objectives are inherently linked; mitigation goals must take into account the consequences of adaptive behavior, and climate adaptation must be viewed as an additional channel for mitigation. Our results further emphasize the importance of interdisciplinary research quantifying the future effects of climate change. With both Earth System Models and Integrated Assessment Models increasing in complexity, coupling projections of the climate system with the dynamic responses of human behavior is critical in order to appropriately inform each class of models. Our finding suggests that adjusting existing models to allow for this interaction will play an important role in forming more accurate projections and prescriptions of the human response to anthropogenic climate change going forward.

Figures

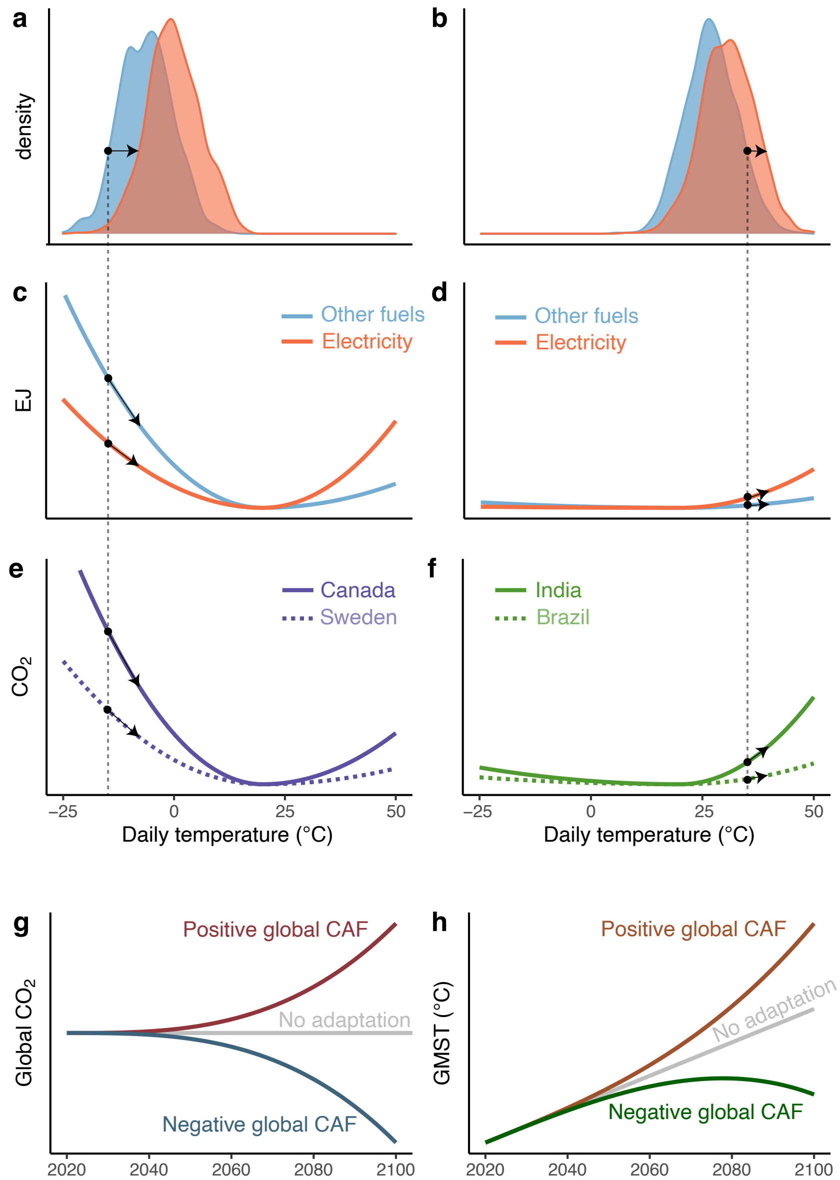

Figure 1: The ambiguous effects of energy-based adaptation on global CO_2 emissions and global mean surface temperature. The Climate Adaptation Feedback (CAF) is the net effect of adaptation-induced energy use on global mean surface temperatures (GMST); its sign is theoretically ambiguous. Climate change generates a rightward shift across heterogeneous baseline climate distributions for (a) colder and (b) warmer locations. This leads to (c) declines in energy consumption in cold locations and (d) increases in energy consumption in hot locations. Country-specific emissions intensities of electricity and other fuels result in different impacts of changing energy consumption on CO_2 emissions in (e) cold locations and (f) hot locations. (g) Increases in emissions from elevated cooling demand on hot days balance against decreases in emissions from declining heating demand on cold days, making the net effect on global CO_2 emissions ambiguous. (h) When increased emissions from cooling outweigh decreased emissions from heating, a positive CAF increases GMST compared to a baseline rate of warming; when the opposite is true and emissions reductions from decreased heating demand outweigh decreased emissions from cooling, the CAF is negative. Only with no energy-based adaptation is there no feedback on GMST.

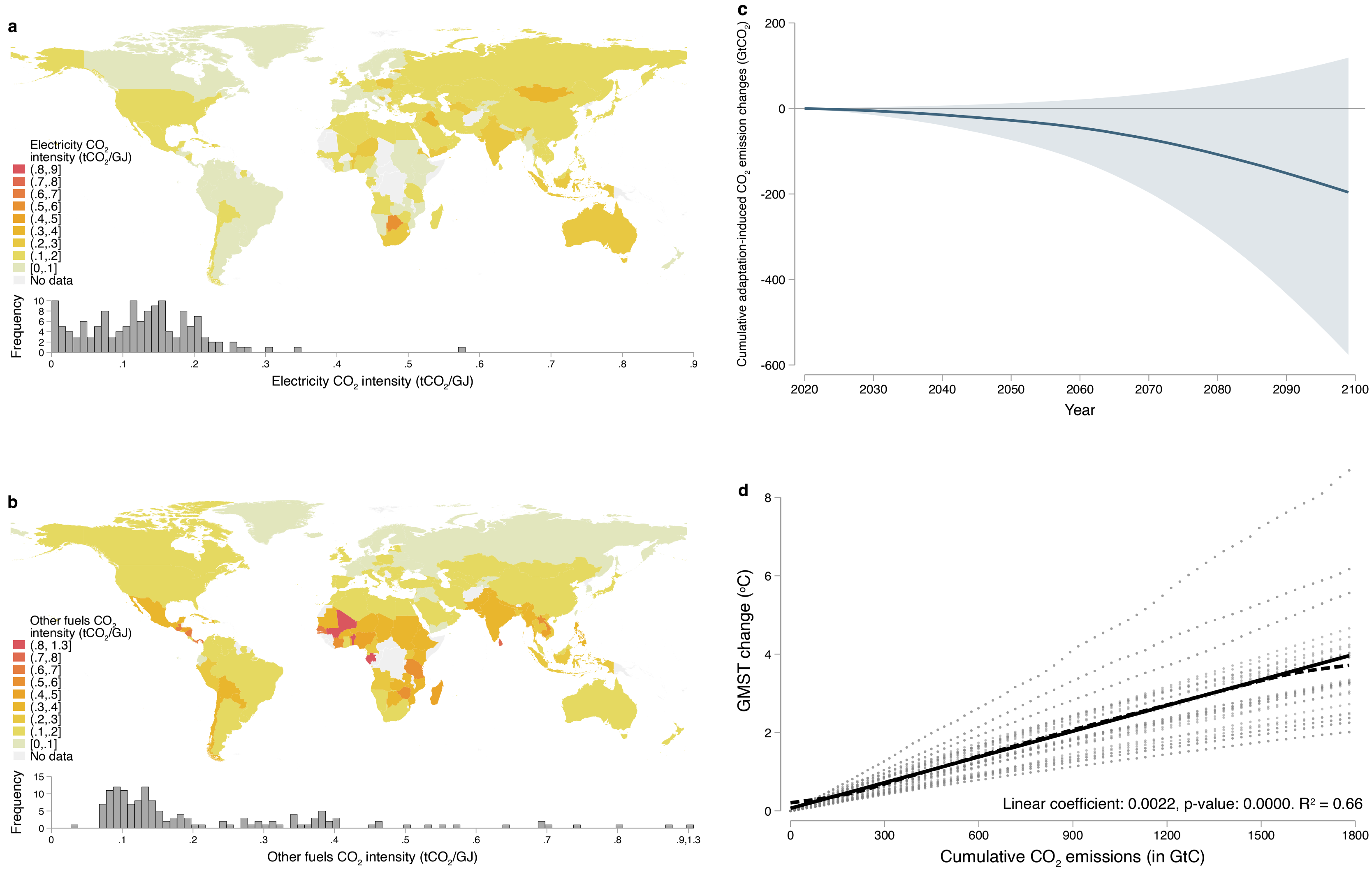

Figure 2: Constructing the Climate Adaptation Feedback (CAF). The CAF is constructed by combining high-resolution projections of climate change impacts on energy consumption from ref. (8) with the following emissions factors: (a) country-level CO_2 intensities for electricity (2010-2018 average, tCO_2/GJ); and (b) country-level CO_2 intensities for all other fuels combined (2010-2018 average, tCO_2/GJ). Together, these data allow us to compute (c) cumulative adaptation-induced CO_2 emission changes (in $GtCO_2$) for 2020-2099 under SSP2-RCP8.5. Finally, we estimate (d) the relationship between projected GMST change (in °C) and cumulative CO_2 (in GtC) across RCPs and GCMs over 2020-2099 (see Methods Section 5.3 for details). This plot shows a fitted linear model (solid line) with 90% confidence intervals (shaded area) and point estimate and p-value of the linear coefficient, as well as a local polynomial fit (dashed line) using an Epanechnikov kernel with a rule-of-thumb bandwidth (55) ($N = 5,200$).

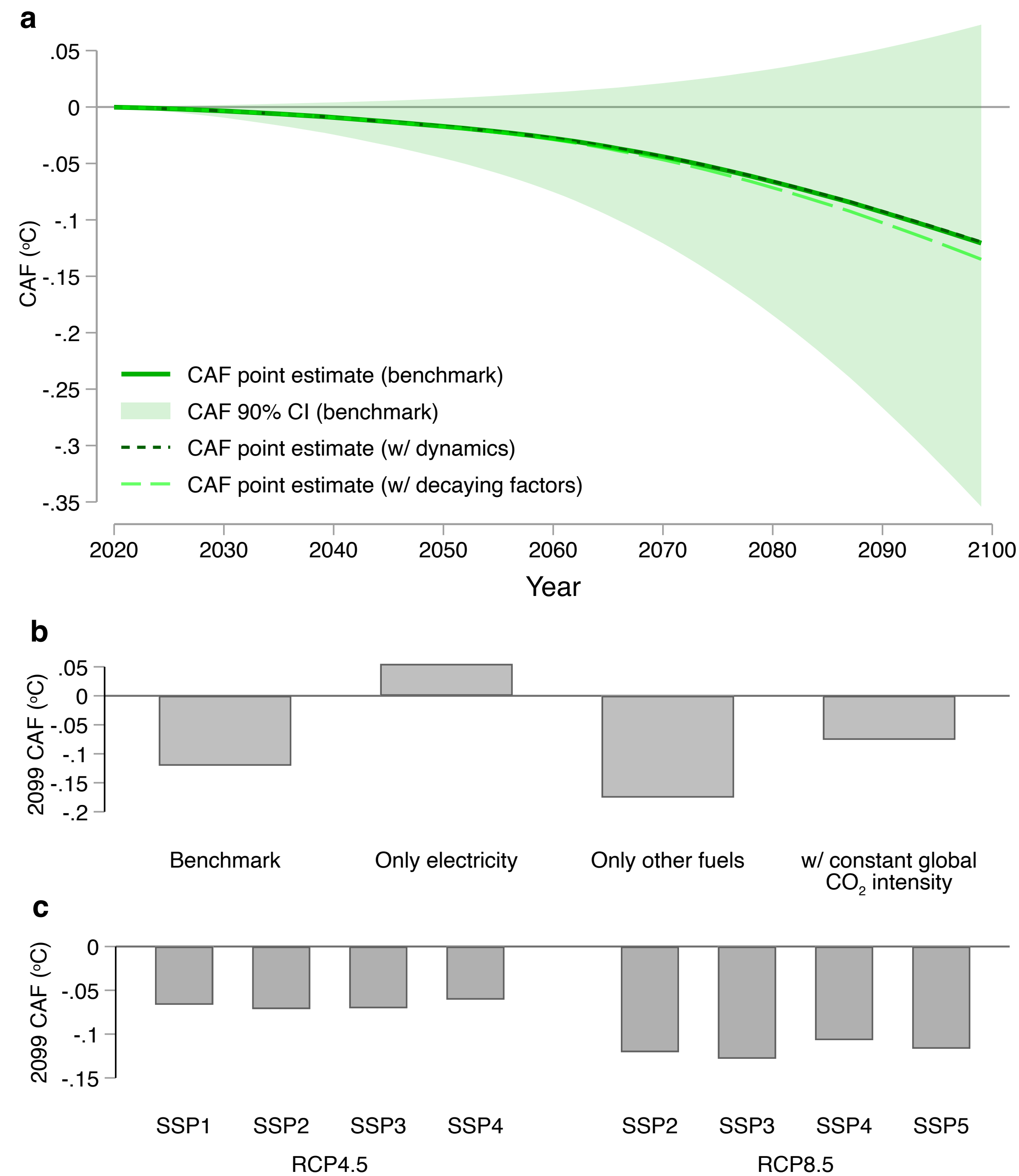

Figure 3: The Climate Adaptation Feedback. (a) Solid green line and shaded green area show point estimates and 90% confidence intervals for the Climate Adaptation Feedback (in °C), for 2020-2099 under SSP2-RCP8.5 using our benchmark approach. The darker dashed line shows the dynamic CAF, which accounts for how additional climate change from adaptation feeds back into future adaptation, as detailed in Methods Section 5.4. The lighter dashed line shows the CAF recalculated using emissions factors that follow historical trends between 2000 and 2018, as detailed in Supplementary Information Section 3. (b) Components of the benchmark CAF in 2099 under SSP2-RCP8.5. The first bar is the full CAF (consistent with panel (a) for 2099). The second bar shows the CAF component derived from electricity consumption alone. The third bar shows the CAF component derived from only other fuels consumption. The fourth bar shows the CAF component derived using a globally constant CO_2 emissions intensity, ignoring heterogeneity both across space and across fuel times in emissions intensity of energy-based adaptation. (c) The last set of bar graphs show point estimates for the CAF in 2099 under different SSP-RCP combinations.

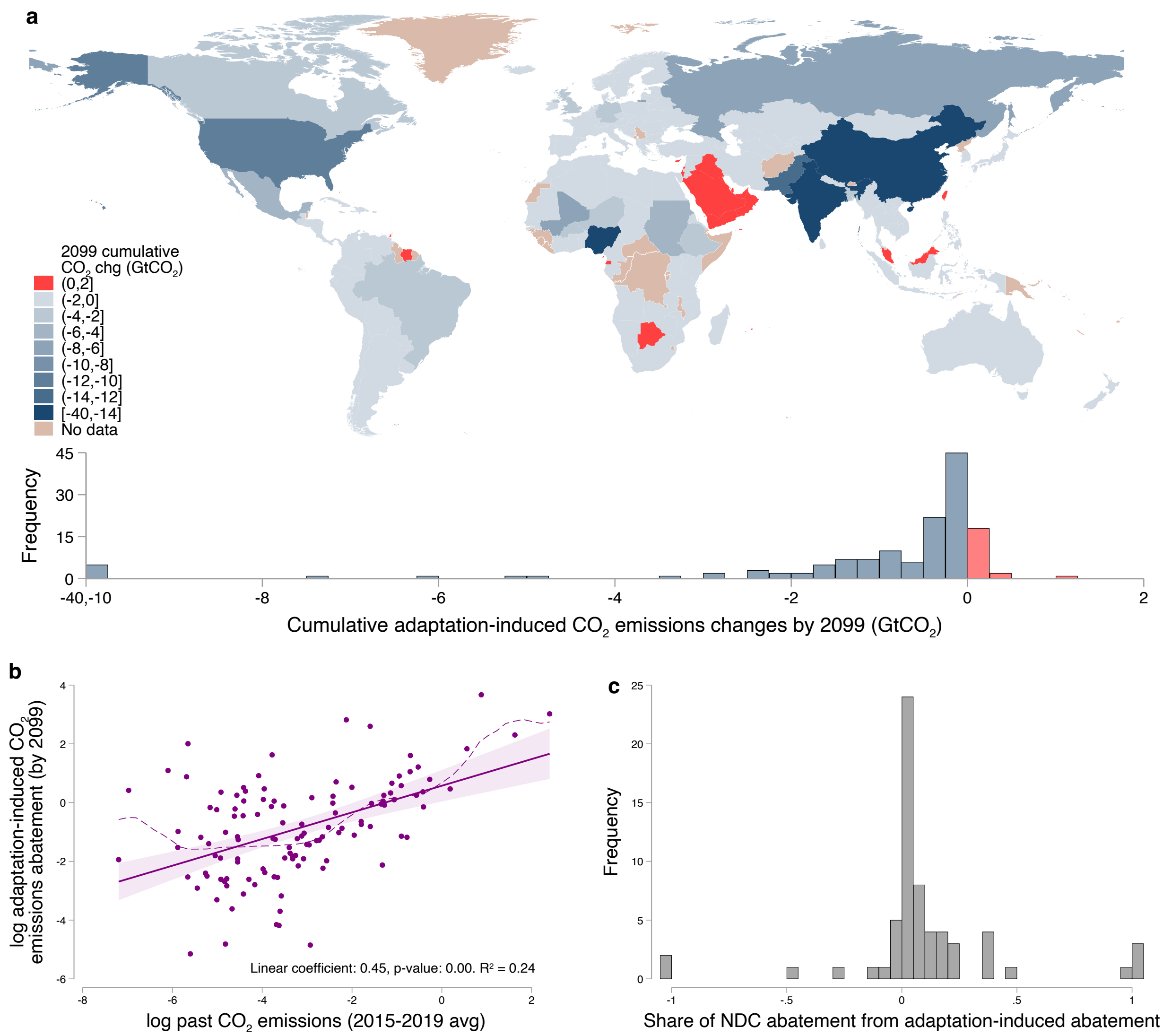

Figure 4: International heterogeneity in adaptation-induced cumulative CO_2 emissions. (a) The map and histogram display country-level cumulative adaptation-induced CO_2 emissions in 2099 measured in $GtCO_2$ ($\mathcal{E}_{2099}$ in Equation (3)). (b) The plot shows a country-level scatter plot of natural log cumulative adaptation-induced CO_2 emissions reductions by 2099 (y-axis) against natural log of present-day CO_2 emissions (x-axis; emissions averaged between 2015 and 2019). The plot also shows the linear model fit (solid line) with 90% confidence interval (shaded area) and point estimate and p-value of the linear coefficient. It also shows a local polynomial fit (dashed line) using an Epanechnikov kernel with a rule-of-thumb bandwidth (55) ($N = 121$). (c) Histogram shows the distribution of the country-level ratio of cumulative adaptation-induced CO_2 emissions reductions by 2050 to cumulative CO_2 emissions reduction commitments under Nationally Determined Contributions (NDC) taken from ref. (44). A value of 0.5 implies that 50% of NDC commitments are projected to be met by energy-based adaptation alone. Panels (a) and (b) show results for SSP2-RCP8.5, while panel (c) shows projected abatement for 63 countries under SSP5-RCP8.5 for consistency with ref. (44).

Acknowledgments

ACM are joint first authors. ACMD conceived of the project. ACM conducted the analysis. ACMD contributed to writing. The authors declare that they have no competing interests. We thank Max Auffhammer, Chris Costello, Ranjit Deshmukh, Kelsey Jack, Michael Oppenheimer, Andrew Plantinga, Ashwin Rode, Peter Sherman, and participants at the Bren School of Environmental Science & Management (UCSB) and Environmental Markets Lab (UCSB) seminars for helpful comments.

5 Methods

5.1 Constructing the Climate Adaptation Feedback

Our paper develops and implements a methodology to quantify the extent to which changes in future energy use driven by adaptation to anthropogenic climate change (ACC) will alter greenhouse gas (GHG) emissions and in turn affect climate change. We call the difference between global mean surface temperature (GMST) with versus without adaptation-induced energy consumption at time horizon τ the "Climate Adaptation Feedback", or CAF_τ. CAF_τ depends on the baseline scenario of emissions and socioeconomic conditions, defined for our purposes as a combination of a Representative Concentration Pathway (RCP) of global anthropogenic GHG emissions (56; 57; 58; 59; 60) and a Shared Socioeconomic Pathway (SSP) of projected national populations, incomes, and other socioeconomic characteristics (61; 62; 63). The following calculations fix our baseline SSP2-RCP8.5 scenario to avoid notational clutter, but we repeat the processes below for each SSP-RCP we consider (results for all scenarios are displayed in Figure 3).

Consider two projections of future warming, one that accounts for adaptive changes in energy use and one that does not. Denote projected GMST in period t as $\overline{T}_t^A$ when adaptive energy use is accounted for, and as $\overline{T}_t^N$ when it is not. Normalize time periods such that

$t = 0$ is the year 2020 and let Δ denote the time difference operator between period $t = 0$ and $t = \tau$. With this notation, we define the CAF at horizon τ as:

$$CAF_\tau \overset{def}{=} \Delta\overline{T}^A_\tau - \Delta\overline{T}^N_\tau. \tag{1}$$

Equation (1) is the difference in GMST change at horizon τ due to adaptive changes in energy use around the world. When the CAF is positive, adaptation exacerbates warming globally. When the CAF is negative, adaptation dampens warming.

To construct CAF_τ, we first calculate the change in global CO_2 emissions due to adaptation-induced energy use in each period through horizon τ. At the local scale, emissions from adaptive energy use depend on how ACC changes local temperature distributions as well as how different temperature realizations affect energy demand (see Figure 1). Because local temperature changes, energy use responses, and the CO_2 intensity of energy consumption vary substantially across space, we conduct this step at the country level before aggregating globally to compute the global CAF. Specifically, for each year t and country i, the CO_2 emissions generated by energy-based adaptation are:

$$E_{i,t} \;=\; \sum_h F_i^h \Delta J^h_{i,t} \;=\; \sum_h F_i^h \sum_{p\in i} \underbrace{\Big[J^h(\boldsymbol{T}^N_{p,t}, \boldsymbol{X}_{p,t}) - J^h(\boldsymbol{T}^N_{p,0}, \boldsymbol{X}_{p,t})\Big]}_{\substack{\text{Change in energy use due to} \\ \text{adaptation to temperature change}}}, \tag{2}$$

where h indicates final consumption of either electricity or an aggregate of consumption across all other fuels, including natural gas, oil shale and oil sands, biofuels, and others, as detailed in ref. (8), the source of our energy use projections. In this expression, p indicates one of ∼25,000 global subnational regions with approximately internally-homogeneous historical temperatures, which are defined by (8). Each F_i^h is the CO_2 emissions factor for a given energy type $h \in \{electricity, other\ fuels\}$ for country i, measured in units of in tCO_2 per gigajoule of fuel consumed. Construction of F_i^h is detailed in Methods Section 5.2 below. We fix F_i^h to the observed 2010-2018 averages for each country-fuel pair to avoid projecting future changes in CO_2 intensities while reflecting current differences in countries' energy mixes.

The underbraced object in Equation (2) represents the impact of climate change on adaptation-induced total energy use in region p. It is defined as the difference in total energy use (in gigajoules, GJ) between a future climate affected by ACC and a future with stable temperatures representative of the current ($t = 0$) climate. This projected change in energy consumption depends critically on the "dose-response" functions $J^h(\cdot)$, which are constructed by ref. (8) using historical energy consumption data and standard climate econometric tools. These functions relate energy consumption in each fuel category h to daily temperature, capturing the energy consumption that results from all behaviors and investments that individuals and firms undertake in response to local temperature variation across all sectors besides transportation.

As detailed in ref. (8), these energy demand response functions depend primarily on the realization of future daily temperatures within a given impact region, denoted by the vector $\boldsymbol{T}^N_{p,t}$, under a given RCP scenario. The dose-response functions also include higher-order terms of daily grid cell-level temperature realization along with a set of covariates summarized by $\boldsymbol{X}_{p,t}$, which include projections of GDP per capita and population specific to a SSP scenario and long-run averages of cooling and heating degree days under each temperature trajectory. These covariates allow for the response of energy consumption to daily temperature realizations to vary based on how the economic resources and climatology of a given location change in the future. This ensures the CAF calculation captures the extensive margin of adaptation that takes place over long periods and may be especially important in developing economies, where income growth is likely to lead to substantial increases in cooling and heating technology adoption (4; 8; 9). The empirical estimation of such extensive margin effects is conducted in ref. (8) by interacting short-run variation in weather with long-run variation in income and climate in a country-by-year panel regression. This model results in the estimation of heterogeneous dose-response functions in which energy demand sensitivity to daily realizations of temperature differs based on long-run average income and climate. The econometric procedure employed follows previously-developed methods (e.g., (64)) to recover nonlinear energy demand responses to temperature at a *grid cell-by-day* level, which can be applied to predict climate change impacts at the scale of ∼25,000 regions, even though more aggregated outcome data were employed (see Methods of ref. (8) for details). More generally, these interaction terms allow for the model to identify the heterogeneity in the response of local energy demand to temperature realizations caused by variation in income and climate over space and time. We show the quantitative importance of the extensive margin in shaping the CAF in Supplementary Information Section 2.

Two sources of uncertainty enter into Equation (2). The first is climate model uncertainty: for a given emissions scenario, there is uncertainty over future local temperature realizations $\boldsymbol{T}_{p,t}^{N}$. We account for this uncertainty by utilizing all 33 Global Climate Model (GCM) projections included in the Surrogate Model Mixture Ensemble (SMME) employed by ref. (8) and built from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (65) climate models. The second is statistical uncertainty in the empirical estimates of the energy-temperature dose-response functions $J^h(\cdot)$; this uncertainty is captured by ref. (8) through application of the statistical Delta Method, creating a Gaussian distribution of predicted impacts for each of the 33 climate model projections. To combine both sources of uncertainties, we follow (8) in constructing the mixture distribution of these 33 Gaussian distributions using Newton's method.

There are multiple possible sources of empirically-based energy-temperature demand responses that we could have used to estimate Equation 2. In selecting a source, we sought to identify estimates that: (1) account for demand responses to changes across the entire temperature distribution, not just extreme temperatures; (2) are differentiated between electricity and other fuels, allowing for a different effect of temperature on the demand for both types of energy; (3) incorporate extensive margin responses of energy demand to changes in temperature over time; and (4) allow for different localities to have different responses to temperature change. While other multi-country energy-temperature demand estimates exist (e.g., ref. (16)), to our knowledge ref. (8) represents the only study meeting all four of these criteria.

Summing the results from Equation (2) over time and across space, we write the cumulative change in global CO_2 emissions between years 0 and τ caused by adaptation-induced energy use as:

$$\mathcal{E}_\tau = \sum_{t=0}^{\tau} \sum_i E_{i,t} \tag{3}$$

To convert cumulative emissions from adaptation, $\mathcal{E}_\tau$, to changes in future GMST, we estimate a relationship between projected future emissions and warming in the absence of adaptation using the forecasts generated by the 33 GCM projections described above. Methods Section 5.3 discusses this relationship in detail, how it relates with the transient climate response to cumulative carbon emissions (TCRE) in the climate science literature, and shows that it is well-approximated by a linear coefficient. We denote this linear relationship between emissions and GMST with the slope coefficient β. This implies that the GMST change between years 0 and τ due to adaptation is: $\Delta T_\tau^A = \Delta T_\tau^N + \beta\mathcal{E}_\tau$. Rewriting this expression in terms of the climate adaptation feedback definition in Equation (1) gives us:

$$CAF_\tau = \beta\mathcal{E}_\tau. \tag{4}$$

For each SSP-RCP combination, we obtain a point estimate for CAF_τ from Equation (4), as well as a 90% confidence interval that account for both climate uncertainty across GCMs and statistical uncertainty in the energy response functions, as discussed above.

Valuation To convert our estimates of the CAF into dollar value of avoided damages, we use the Climate Impact Lab's Data-driven Spatial Climate Impact Model (DSCIM). This model includes climate change damages to mortality, coastal storms and sea level rise, labor, energy, and agriculture. Mortality risk is monetized using the U.S. EPA VSL with a value of life years lost adjustment and an income elasticity of one, following ref. (28). Comprehensive documentation for the version of the DSCIM used by the U.S. Environmental Protection Agency as an input into its estimate of the social cost of greenhouse gases can be found here: `https://impactlab.org/wp-content/uploads/2020/10/CIL_DSCIM_User_Manual_092022-EPA.pdf`. DSCIM assigns a monetary value to the damages from global warming in every year along a baseline socioeconomic and climatic trajectory. Avoided damages due to the negative CAF are calculated as the difference between predicted damages in the baseline scenario and in the scenario inclusive of the CAF, for each year between 2020 and 2099. When discounting damages, the DSCIM model generates a stochastic discount factor (SDF) for all future periods based on the Ramsey rule calculated along the exogenous consumption pathway for a given socioeconomic scenario, and after incorporating consumption losses from baseline warming. Specifically, we use a coefficient of relative risk aversion equal to $\eta = 2$, and we discount future values using Ramsey discounting with $\eta = 2$ and a pure rate of time preference of $\rho = 0.0001$. We convert the avoided consumption losses due to the CAF into a present value in 2019 equivalents using this SDF.

5.2 Data

Projections of adaptation-induced energy use We obtain point estimates and 90% confidence intervals for projections of adaptation-induced energy use (i.e., the underbraced terms in Equation (2)) at the country-year-fuel level for two emissions scenarios and four socioeconomic scenarios directly from ref. (8).

Temperature projections We obtain projection-specific annual series of GMST between 2020 and 2099 under the RCP4.5 and RCP8.5 pathways directly from ref. (8). The SMME employed by (8) generates 33 projections of annual GMST under each RCP scenario. These global averages correspond directly with the impact-region specific daily temperature realizations that drive future $\Delta J^h_{i,t}$s under each model run in (8).

Socioeconomic projections We obtain five-year country-level GDP per capita and population projections for the 2020-2099 period under each SSP scenario from the International Institute for Applied Systems Analysis (IIASA) model (61; 62; 63) and from the Organisation for Economic Co-operation and Development (OECD) Env-Growth model. For projections under each SSP scenario, we take the average between these two model outputs.

Emissions intensities To convert adaptation-induced final energy consumption of energy source $h \in \{electricity, other\ fuels\}$ to CO_2 emissions, we need energy source-specific CO_2 emissions intensities that account for heterogeneity in the mix of primary fuels (e.g, coal, natural gas, and renewables) in each country. For example, electricity in Poland is mostly generated using coal, while in Costa Rica it comes almost exclusively from renewables, each with very different resulting CO_2 emissions intensities.

For each country i and year t, let $r \in \mathcal{H}^h_{i,t}$ index the primary fuels used to generate final consumption of energy source h. The final energy source CO_2 emissions intensity, F^h_i, is the weighted average of primary fuel CO_2 emissions intensities, $f^h_{i,r,t}$, across primary fuels r used to produce final energy source h where each weight, $\omega^h_{i,r,t}$, is the total amount of energy fuel r contributes to final consumption of h in year t. To account for year-to-year fluctuations in primary energy use, we take this average over 2010-2018 values. Country-level final energy source CO_2 emissions intensities are calculated as:

$$F^h_i \;=\; \frac{\sum_{t=2010}^{2018} \sum_{r\in\mathcal{H}^h} \; f^h_{i,r,t} \; \omega^h_{i,r,t}}{\sum_{t=2010}^{2018} \sum_{r\in\mathcal{H}^h} \; \omega^h_{i,r,t}}. \tag{5}$$

We obtain primary fuel CO_2 emissions intensities $f^h_{i,r,t}$ from the International Energy Agency (IEA) Emissions Intensities Report for each form of final use (66). We assign weights, $\omega^h_{i,r,t}$, based on consumption data from the IEA World Energy Balances (WEB) (67). The WEB catalogues country-level primary fuel consumption at the sector level which we aggregate to form our final energy use sectors. Electricity is one such sector (i.e. code ELOUTPUT). For other fuels, we follow (8) for consistency and pool together the industrial, residential, commercial and public services, agricultural, fishing, and other sectors not elsewhere specified (i.e., codes TOTIND, RESIDENT, COMMPUB, AGRICUL, FISHING, and ONONSPEC respectively).

To construct the globally constant emissions-weighted average CO_2 intensity across final energy sources and countries used in Figure 3b, we compute:

$$\overline{F} = \frac{\sum_{i=1}^{n} E_i^{2019} \sum_h F_i^h}{\sum_{i=1}^{n} E_i^{2019}}$$

where the weights E_i^{2019} are set equal to 2019 GHG emissions measured in CO_2-equivalents from ref. (68).

Baseline country-level emissions and Nationally Determined Contributions We obtain country-level baseline CO_2 emissions pathways and Nationally Determined Contributions (NDCs) from ref. (69). The repository is `https://zenodo.org/record/6383612#.Y4wnZC-B27c` and the version we use is dated February 14, 2022. Ref. (69) provide two sets of NDCs for most countries: a more stringent "conditional" NDC path (in the sense that the pathway is conditioned on action by other countries) and a "unconditional" NDC path, both available only under SSP1 and SSP5. We use the more stringent conditional NDCs along with baseline CO_2 emissions projections under the SSP5 scenario, both for the year 2050, to construct the ratio of cumulative adaptation-induced CO_2 emissions reduction over cumulative CO_2 emissions reduction under NDCs by 2050 in Figure 4c.

5.3 Estimating the GMST-cumulative CO_2 relationship

A key challenge to quantifying the CAF is that available emissions intensity data only apply to CO_2 emissions, while energy-based adaptation is likely to feed back into climate change via other greenhouse gases as well. Specifically, the IEA data detailed in Methods Section 5.2 does not contain emissions intensities for non-CO_2 greenhouse gas emissions from final consumption outside of the electricity and heat and power sectors. To address this data limitation, we construct an empirical relationship between GMST and cumulative CO_2 emissions that includes any changes in non-CO_2 emissions which covary with CO_2 emissions. Such a relationship is similar to, but not the same as, the transient climate response to cumulative emissions of CO_2 (TCRE), which is the direct (causal) effect of cumulative CO_2 emissions on GMST change and has been documented in the climate science literature and shown to be well-approximated by a linear relationship (70; 71; 72; 12). However, our empirical relationship additionally includes the effects of non-CO_2 greenhouse gases on GMST, to the extent that these gases correlate with CO_2 emissions in historical data.

To illustrate this approach, suppose the change in GMST over time horizon τ, $\Delta\overline{T}_\tau$, responds to cumulative CO_2 emissions, $\mathcal{E}_\tau^{CO2}$ and cumulative emissions of another GHG, $\mathcal{E}_\tau^{other}$, in the following manner:

$$\Delta\overline{T}_\tau = \rho\mathcal{E}_\tau^{CO2} + \alpha\mathcal{E}_\tau^{other}$$

In this expression, ρ is the TCRE – the direct effect of changing CO_2 emissions on GMST holding cumulative emissions of all other GHGs constant. However, due to IEA data limitations, we cannot estimated projected changes in $\mathcal{E}_\tau^{other}$ due to adaptative energy use. Instead, we can estimate the same regression omitting the effects of other GHG emissions:

$$\Delta\overline{T}_\tau = \beta\mathcal{E}_\tau^{CO2} + error_\tau$$

Since future emissions of CO_2 and other GHGs are likely to be positively correlated, β can be expressed as:

$$\beta = \rho + \alpha\frac{cov\left(\mathcal{E}_\tau^{CO2}, \mathcal{E}_\tau^{other}\right)}{var(\mathcal{E}_\tau^{CO2})} > \rho$$

The coefficient β is therefore our object of interest; it is the projected GMST change from an observed increase in cumulative carbon emissions. This coefficient combines the direct effect of a unit increase in cumulative CO_2 emissions and the indirect effect that accounts for the covariance between CO_2 and the other GHG emissions that are inputs into the SMME used to forecast future temperature pathways. When that covariance is positively correlated, one would expect β to exceed the TCRE, or ρ.

In practice, to estimate β, we use variation in GMST and cumulative CO_2 emissions (in the absence of adaptation) across RCP4.5 and RCP8.5 and the 33 GCM predictions drawn from the SMME based on CMIP5. Letting s index the 66 RCP-GCM combinations, we estimate:

$$\Delta\overline{T}^{N}_{\tau,s} = \beta\mathcal{E}^{N}_{\tau,s} + error_{\tau,s} \tag{6}$$

using the temperature and emissions time series generated by the ensemble of models in CMIP5 ($N = 5,200$). Our estimate of β is $2.2e - 3$ $C^{\circ} \times GTC^{-1}$ ($p(|T| > |t|) < 0.01$). To examine whether our linearity assumption is valid, Figure 2d shows a scatter plot between $\Delta T^{N}_{\tau,s}$ and $\mathcal{E}^{N}_{\tau,s}$ along with a flexible relationship estimated using a local polynomial function with an Epanechnikov kernel and a rule-of-thumb bandwidth (55) that reveals any data-driven nonlinearities. We do not detect any nonlinearities. As a point of comparison, our estimate for β is 1.4 times the median estimate for the TCRE (or ρ) detected in the literature, although well within confidence intervals for the TCRE (72). This is consistent with cumulative emissions of CO_2 and other GHGs being positively correlated.

5.4 A Dynamic Climate Adaptation Feedback

As discussed in Section 3, our baseline estimate for the CAF takes projected changes in emissions from adaptation as given by the calculations in ref. (8). That is, we assume that the additional climate change due to the CAF does not itself lead to additional adaptive energy demand. In doing so, the estimated CAF in Methods Section 5.1 implicitly assumes adaptive changes in emissions have no concurrent effects on the GMST pathway that determines *future* adaptation. This is a strong assumption if emissions changes due to adaptation have large immediate effects on the GMST path each year after they enter the atmosphere. In this section, we develop a dynamic version of the CAF and show that, in practice, the result is nearly identical to the approximated value we center in our analysis in Methods Section 5.1.

Specifically, we account for the dynamics of energy-based adaptation by updating the original projections of $E_{i,t}$ from Equation (2) at each time horizon to account for how historical adaptive emissions through time $t-1$ will have affected the GMST pathway that year. This is implemented by iteratively updating the temperature pathway at each horizon relative to a given RCP baseline to account for temperature change due to the CAF, and then using this distance from the baseline to adjust projected adaptive energy use from that point forward. Starting in 2021 (the second projection year from the (8) data we use), we adjust the baseline projected temperature pathway each year to account for the cumulative effects of emissions from adaptation. We then update each country-year-fuel emissions tuple in that year to account for the adjusted GMST pathway. We repeat this procedure out to 2099 and recalculate the cumulative emissions changes to form an estimate of the CAF that accounts for concurrent dynamics between adaptation use and GMST change.

Specifically, we begin with the set of 66 projected time series of emissions changes computed under our baseline SSP2-RCP8.5 scenario from Equation (2). These forecasts are country-level changes in emissions for each climate model m:

$$E^h_{i,t,m} = F^h_i \sum_{p\in i} \left[J^h(\boldsymbol{T}^N_{p,m,t}, \boldsymbol{X}_{p,t}) - J^h(\boldsymbol{T}^N_{p,m,0}, \boldsymbol{X}_{p,t}) \right] \tag{7}$$

in year t for fuel h in country i under climate model m. We use these country-level sets of projected horizon-t emissions changes to estimate, for each country-fuel-year combination, the following reduced form response function:

$$E^h_{i,t,m} = \alpha^h_{i,t} \Delta GMST_{t,m} + \gamma^h_{i,t} \Delta GMST^2_{t,m} + \varepsilon^h_{i,t,m} \tag{8}$$

Equation (8) captures the additional emissions due to adaptation for each i, t, and h, as a quadratic function of changes in GMST. We estimate Equation (8) separately for each (i, t, h) tuple under the SSP2-RCP8.5 combination to form a time series of estimated $\hat{\alpha}_{i,t}^h$ and $\hat{\gamma}_{i,t}^h$ coefficients for each country-fuel combination. From these estimates we construct time-country-fuel impulse response functions (IRFs): each IRF (for an i, t, h pair) gives the estimated additional change in emissions from energy-based adaptation induced by marginal changes in projected GMST derived from fuel h and country i at the time horizon t. This object is the derivative of Equation (8) with respect to $\Delta GMST$:

$$\widehat{\Theta}_{i,t}^h \stackrel{def}{=} \frac{\partial \widehat{E_{i,t}^h}}{\partial \Delta GMST_t} = \hat{\alpha}_{i,t}^h + 2\hat{\gamma}_{i,t}^h \Delta GMST_t \tag{9}$$

These impulse responses give, by fuel-horizon-country, the *local* effects on concurrent emissions from adaptive energy use due to additional warming. We use this to project how prior temperature changes from adaptation will affect *contemporary* adaptive energy use relative to the baseline pathway. Starting in 2021, we update the values of emissions from energy-based adaptation using a first-order Taylor expansion around their baseline levels. For each country-fuel-year, we define a new series of emissions by:

$$\widetilde{E_{i,t}^h} = \underbrace{\bar{E}_{i,t}^h}_{\text{baseline emissions}} + \underbrace{\left(\underbrace{\hat{\Theta}_{i,t}^h}_{\text{response functions}} \times \underbrace{\hat{\beta}\ \widetilde{\Delta\mathcal{E}_{t-1}}}_{\text{horizon } \tau-1 \text{ CAF}} \right)}_{\text{dynamic effect}} \tag{10}$$

where $\widetilde{\Delta\mathcal{E}}$ is the cumulative emissions change due to energy-based adaptation between 2021 and year $t-1$ accounting for the dynamic effects of adaptation:

$$\widetilde{\Delta\mathcal{E}_{t-1}} = \sum_{s=2021}^{t-1} \sum_i \sum_h \widetilde{E_{i,s}^h}, \tag{11}$$

and $\hat{\beta}$ is our mapping between emissions and temperature as described in Equation (6) in Methods Section 5.3. Starting in 2021, we calculate the cumulative change in emissions due to adaptation while accounting for how adaptive emissions in turn affect future use for adaptation through the GMST channel. The first term in Equation (10) captures baseline emissions from adaptation as calculated in Equation 2 and used in the main text. The second term accounts for how the effects of past emissions from adaptation on the pathway of GMST in turn affect emissions in that year.

We iterate over the process in equation (10) over all country-fuel pairs at each horizon through 2099, updating the series for cumulative emissions and temperature each period. The iterative procedure ensures the baseline temperature path (under RCP8.5) is adjusted to reflect the cumulative level of adaptive emissions changes each year. We then recalculate the CAF with concurrent dynamics using the updated energy changes due to adaptation through year 2099. We track the dynamic CAF each year as follows:

$$CAF_{\tau}^{dyn} \stackrel{def}{=} \hat{\beta} \sum_{i} \sum_{h} \sum_{t}^{\tau} \widetilde{E_{i,t}^{h}}. \tag{12}$$

The dashed line in Figure 3a displays the time series of our baseline CAF_{τ} without dynamic emissions-temperature linkages and the dynamic version CAF_{τ}^{dyn} incorporating concurrent emissions-GMST linkages over the 2021-2099 period under the baseline SSP2-RCP8.5 scenario.

The concurrent emissions-GMST linkages channel decreases cumulative emissions and temperature changes (in magnitude) attributable to adaptation. This occurs because of the negative nature of the CAF: lower emissions from declines in heating use outweigh additional emissions from increased cooling at each horizon. This in turn lowers cumulative emissions relative to baseline each year and with it our forecast for $\Delta GMST$. These lower temperature levels in turn result in smaller future changes in emissions from adaptation through the IRFs, as declines in temperature lead to smaller declines in consumption of other fuels and smaller increases in emissions from electricity. This is indicated by an increasing gap between CAF_{τ} and CAF_{τ}^{dyn} over time; the larger the cumulative negative effect from the CAF, the lower the updated temperature series is relative to baseline. This further decreases emissions changes from adaptation (in magnitude) each year, further lowering the temperature. However, empirically, we find that this gap between CAF_τ and CAF_τ^{dyn} is small in magnitude. By 2099, CAF_{2099} is -0.1206 while CAF_{2099}^{dyn} is -0.1196. Given the minor consequence played by such dynamic emissions-GMST linkages, in our main text we emphasize CAF_τ over CAF_τ^{dyn}.

Data and code availability Upon acceptance, all code needed to replicate the results will be made publicly available on GitHub (`https://github.com/xabajian/ACDM_Climate_Adaptation_Feedback`). Emissions intensity data are non-publicly provided by the International Energy Agency Emissions Intensities Report and cannot be publicly shared. All other data will be hosted publicly in Zenodo upon acceptance at `https://doi.org/10.5281/zenodo.10476310`.

References

[1] Pörtner, H.-O. *et al.* Climate change 2022: Impacts, adaptation and vulnerability. *IPCC Sixth Assessment Report* (2022).

[2] Deschênes, O. & Greenstone, M. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the us. *American Economic Journal: Applied Economics* **3**, 152–185 (2011).

[3] Auffhammer, M. & Aroonruengsawat, A. Simulating the impacts of climate change, prices and population on californiaâs residential electricity consumption. *Climatic change* **109**, 191–210 (2011).

[4] Davis, L. W. & Gertler, P. J. Contribution of air conditioning adoption to future energy use under global warming. *Proceedings of the National Academy of Sciences* **112**, 5962–5967 (2015).

[5] Barreca, A., Clay, K., Deschenes, O., Greenstone, M. & Shapiro, J. S. Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy* **124**, 105–159 (2016).

[6] Wenz, L., Levermann, A. & Auffhammer, M. North–south polarization of european electricity consumption under future warming. *Proceedings of the National Academy of Sciences* **114**, E7910–E7918 (2017).

[7] Park, R. J., Goodman, J., Hurwitz, M. & Smith, J. Heat and learning. *American Economic Journal: Economic Policy* **12**, 306–39 (2020).

[8] Rode, A. *et al.* Estimating a social cost of carbon for global energy consumption. *Nature* **598**, 308–314 (2021).

[9] Auffhammer, M. Climate adaptive response estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption. *Journal of Environmental Economics and Management* **114**, 102669 (2022).

[10] He, G. & Tanaka, T. Energy saving may kill: Evidence from the fukushima nuclear accident. *American Economic Journal: Applied Economics* (2023).

[11] IEA. The future of cooling, 2020. Tech. Rep., International Energy Agency (IEA) (2018). URL `https://www.iea.org/reports/the-future-of-cooling`.

[12] Masson-Delmotte V., A. P. e. a., P. Zhai. Ipcc, 2021: Summary for policymakers. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (2021).

[13] Barnett, J. & Oâneill, S. Maladaptation. *Global Environmental Change* **2**, 211–213 (2010).

[14] Schipper, E. L. F. Maladaptation: When adaptation to climate change goes very wrong. *One Earth* **3**, 409–414 (2020).

[15] IEA. Global co2 emissions by sector, 2019-2022. Tech. Rep., International Energy Agency (IEA) (2022). URL `https://www.iea.org/data-and-statistics/charts/global-co2-emissions-by-sector-2019-2022`.

[16] De Cian, E. & Sue Wing, I. Global energy consumption in a warming climate. *Environmental and resource economics* **72**, 365–410 (2019).

[17] Van Ruijven, B. J., De Cian, E. & Sue Wing, I. Amplification of future energy demand growth due to climate change. *Nature communications* **10**, 2762 (2019).

[18] Yalew, S. G. *et al.* Impacts of climate change on energy systems in global and regional scenarios. *Nature Energy* **5**, 794–802 (2020).

[19] Davis, L., Gertler, P., Jarvis, S. & Wolfram, C. Air conditioning and global inequality. *Global Environmental Change* **69**, 102299 (2021).

[20] Viguié, V. *et al.* When adaptation increases energy demand: A systematic map of the literature. *Environmental research letters* **16**, 033004 (2021).

[21] Colelli, F. P., Wing, I. S. & Cian, E. D. Air-conditioning adoption and electricity demand highlight climate change mitigation–adaptation tradeoffs. *Scientific Reports* **13**, 4413 (2023).

[22] Colelli, F. P., Emmerling, J., Marangoni, G., Mistry, M. N. & De Cian, E. Increased energy use for adaptation significantly impacts mitigation pathways. *Nature Communications* **13**, 4964 (2022).

[23] Greenstone, M., Kopits, E. & Wolverton, A. Developing a social cost of carbon for us regulatory analysis: A methodology and interpretation. *Review of environmental economics and policy* (2013).

[24] Carleton, T. & Greenstone, M. A guide to updating the us governmentâs social cost of carbon. *Review of Environmental Economics and Policy* **16**, 196–218 (2022).

[25] Burke, M., Hsiang, S. M. & Miguel, E. Global non-linear effect of temperature on economic production. *Nature* **527**, 235–239 (2015).

[26] Kalkuhl, M. & Wenz, L. The impact of climate conditions on economic production. evidence from a global panel of regions. *Journal of Environmental Economics and Management* **103**, 102360 (2020).

[27] Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G. & Lobell, D. B. Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change* **11**, 306–312 (2021).

[28] Carleton, T. *et al.* Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics* **137**, 2037–2105 (2022).

[29] Dietz, S., van der Ploeg, F., Rezai, A. & Venmans, F. Are economists getting climate dynamics right and does it matter? *Journal of the Association of Environmental and Resource Economists* **8**, 895–921 (2021).

[30] De Bruin, K. C., Dellink, R. B. & Tol, R. S. Ad-dice: an implementation of adaptation in the dice model. *Climatic Change* **95**, 63–81 (2009).

[31] Patt, A. G. *et al.* Adaptation in integrated assessment modeling: where do we stand? *Climatic Change* **99**, 383–402 (2010).

[32] Chambwera, M. *et al.* Economics of adaptation (2014).

[33] Benveniste, H., Oppenheimer, M. & Fleurbaey, M. Effect of border policy on exposure and vulnerability to climate change. *Proceedings of the National Academy of Sciences* **117**, 26692–26702 (2020).

[34] Jeon, W. Pricing externalities in the presence of adaptation (2022).

[35] Lenssen, N. J. *et al.* Improvements in the gistemp uncertainty model. *Journal of Geophysical Research: Atmospheres* **124**, 6307–6326 (2019).

[36] Barrage, L. & Nordhaus, W. Policies, projections, and the social cost of carbon: Results from the dice-2023 model. *Proceedings of the National Academy of Sciences* **121**, e2312030121 (2024).

[37] Krusell, P. & Smith, A. A. Climate change around the world. *NBER Working Paper* (2022).

[38] Auffhammer, M., Baylis, P. & Hausman, C. H. Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the united states. *Proceedings of the National Academy of Sciences* **114**, 1886–1891 (2017).

[39] Jones, B. & OâNeill, B. C. Spatially explicit global population scenarios consistent with the shared socioeconomic pathways. *Environmental Research Letters* **11**, 084003 (2016).

[40] Krishnan, R. *et al.* Introduction to climate change over the indian region. *Assessment of climate change over the indian region: a report of the ministry of earth sciences*

(MoES), Government of India 1–20 (2020).

[41] Del Ponte, A., Masiliūnas, A. & Lim, N. Information about historical emissions drives the division of climate change mitigation costs. *Nature Communications* **14**, 1408 (2023).

[42] Rogelj, J. *et al.* Paris agreement climate proposals need a boost to keep warming well below 2° c. *Nature* **534**, 631–639 (2016).

[43] Ou, Y. *et al.* Can updated climate pledges limit warming well below 2° c? *Science* **374**, 693–695 (2021).

[44] Meinshausen, M. *et al.* Realization of paris agreement pledges may limit warming just below 2° c. *Nature* **604**, 304–309 (2022).

[45] Liu, P. R. & Raftery, A. E. Country-based rate of emissions reductions should increase by 80% beyond nationally determined contributions to meet the 2 c target. *Communications earth & environment* **2**, 29 (2021).

[46] Riahi, K. *et al.* The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global environmental change* **42**, 153–168 (2017).

[47] IEA. Renewables 2022. Tech. Rep., International Energy Agency (IEA) (2022). URL `https://www.iea.org/reports/renewables-2022`.

[48] Cruz, J.-L. & Rossi-Hansberg, E. The economic geography of global warming. *Review of Economic Studies* rdad042 (2023).

[49] Obradovich, N. & Rahwan, I. Risk of a feedback loop between climatic warming and human mobility. *Journal of the Royal Society Interface* **16**, 20190058 (2019).

[50] Zhang, X. *et al.* Managing nitrogen for sustainable development. *Nature* **528**, 51–59 (2015).

[51] Celikkol Erbas, B. & Guven Solakoglu, E. In the presence of climate change, the use of

fertilizers and the effect of income on agricultural emissions. *Sustainability* **9**, 1989 (2017).

[52] Deschenes, O., Greenstone, M. & Shapiro, J. S. Defensive investments and the demand for air quality: Evidence from the nox budget program. *American Economic Review* **107**, 2958–2989 (2017).

[53] Jarvis, S., Deschenes, O. & Jha, A. The private and external costs of germanyâs nuclear phase-out. *Journal of the European Economic Association* **20**, 1311–1346 (2022).

[54] Deschenes, O. The impact of climate change on mortality in the united states: Benefits and costs of adaptation. *Canadian Journal of Economics/Revue canadienne d'économique* **55**, 1227–1249 (2022).

[55] Fan, J. & Gijbels, I. *Local polynomial modelling and its applications: monographs on statistics and applied probability*, vol. 66 (CRC Press, 1996).

[56] Smith, S. J. & Wigley, T. Multi-gas forcing stabilization with minicam. *The Energy Journal* (2006).

[57] Clarke, L. E. *Scenarios of Greenhouse Gas Emissions and Atmospheric Concentrations: Report*, vol. 2 (US Climate Change Science Program, 2007).

[58] Riahi, K., Grübler, A. & Nakicenovic, N. Scenarios of long-term socio-economic and environmental development under climate stabilization. *Technological Forecasting and Social Change* **74**, 887–935 (2007).

[59] Wise, M. *et al.* Implications of limiting co2 concentrations for land use and energy. *Science* **324**, 1183–1186 (2009).

[60] Van Vuuren, D. P. *et al.* The representative concentration pathways: an overview. *Climatic change* **109**, 5–31 (2011).

[61] O'Neill, B. C. *et al.* A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climatic change* **122**, 387–400 (2014).

[62] Samir, K. & Lutz, W. The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. *Global Environmental Change* **42**, 181–192 (2017).

[63] Dellink, R., Chateau, J., Lanzi, E. & Magné, B. Long-term economic growth projections in the shared socioeconomic pathways. *Global Environmental Change* **42**, 200–214 (2017).

[64] Hsiang, S. Climate econometrics. *Annual Review of Resource Economics* **8**, 43–75 (2016).

[65] Taylor, K. E., Stouffer, R. J. & Meehl, G. A. An overview of cmip5 and the experiment design. *Bulletin of the American meteorological Society* **93**, 485–498 (2012).

[66] IEA. Emissions factors. Tech. Rep., International Energy Agency (IEA) (2021). URL `https://www.iea.org/data-and-statistics/data-product/emissions-factors-2021`.

[67] IEA. World energy balances 2021. Tech. Rep., International Energy Agency (IEA) (2022). URL `https://www.iea.org/data-and-statistics/data-product/world-energy-balances`.

[68] Minx, J. C. *et al.* A comprehensive and synthetic dataset for global, regional, and national greenhouse gas emissions by sector 1970–2018 with an extension to 2019. *Earth System Science Data* **13**, 5213–5252 (2021).

[69] Meinshausen, M. *et al.* Data for study "realization of paris agreement pledges may limit warming just below 2° c". *Nature* (2022). URL `https://doi.org/10.5281/zenodo.5886866`.

[70] Matthews, H. D., Gillett, N. P., Stott, P. A. & Zickfeld, K. The proportionality of global warming to cumulative carbon emissions. *Nature* **459**, 829–832 (2009).

[71] Stocker, T. F. *et al.* Climate change 2013: the physical science basis. intergovernmental panel on climate change, working group i contribution to the ipcc fifth assessment

report (ar5). *New York* (2013).

[72] Matthews, H. D., Zickfeld, K., Knutti, R. & Allen, M. R. Focus on cumulative emissions, global carbon budgets and the implications for climate mitigation targets. *Environmental Research Letters* **13**, 010201 (2018).