CLIMATE POLICY

Climate policies that achieved major emission reductions: Global evidence from two decades

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Meeting the Paris Agreement's climate targets necessitates better knowledge about which climate policies work in reducing emissions at the necessary scale. We provide a global, systematic ex post evaluation to identify policy combinations that have led to large emission reductions out of 1500 climate policies implemented between 1998 and 2022 across 41 countries from six continents. Our approach integrates a comprehensive climate policy database with a machine learning–based extension of the common difference-in-differences approach. We identified 63 successful policy interventions with total emission reductions between 0.6 billion and 1.8 billion metric tonnes CO_2. Our insights on effective but rarely studied policy combinations highlight the important role of price-based instruments in well-designed policy mixes and the policy efforts necessary for closing the emissions gap.

Meeting the Paris Agreement's climate objectives necessitates decisive policy action (*1*). Although the agreement seeks to limit global average temperature increase to "well below 2°C above preindustrial levels and pursuing efforts to limit the temperature increase to 1.5°C," its success critically hinges on the implementation of effective climate policies at the national level. However, scenarios from global integrated assessment models suggest that the aggregated mitigation efforts communicated through nationally determined contributions (NDCs) fall short of the required emission reductions (*2*), and the United Nations (UN) estimates quantify a median emission gap of 23 billion metric tonnes (Gt) carbon dioxide equivalent (CO_2-eq) by 2030 (*3*). The persistence of this emissions gap is not only caused by an ambition gap but also a gap in the outcomes that adopted policies achieve in terms of emission reductions (*4*). This raises the fundamental question as to which types of policy measures are successfully causing meaningful emission reductions. Despite more than two decades of experience with thousands of diverse climate policy measures gained around the world, there is consensus in neither science nor policy on this question (*5*–*7*). This highlights the need for a fine-grained global assessment of climate policy interventions that pays careful attention to the diversity among policy instruments and their mutual complementarity.

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Assembling such a global stocktake of effective climate policy interventions is so far hampered by two main obstacles: First, even though there is a plethora of data on legislative frameworks and pledged national emission reductions (*8*–*10*), systematic and cross-nationally comparable data about the specific types and mixes of implemented policy instruments are lacking. Second, empirical tools are typically tailored to isolate the effect of single policy instruments and are predominantly applied to policies that researchers subjectively deem particularly relevant. Consequently, only a few headline policy instruments receive much attention. For example, carbon pricing is well-studied in high-income countries (*11*–*13*), whereas countless alternative policy instruments such as standards remain sparsely evaluated, specifically in lower-income countries. Last but not least, there are few tools to empirically evaluate mixes of multiple, simultaneously combined policy instruments. Thus, although policymakers heavily rely on policy mixes (*14*–*16*), assessing which combinations of policies effectively unfold complementarities and can deliver stronger emission reductions is poorly understood. For all these reasons, the emission gap is intertwined with an equally notable knowledge gap on effective climate policies. This also hampers learning in Intergovernmental Panel on Climate Change (IPCC) assessments that can only draw on descriptive reviews of selected studies and instruments (*17*) rather than systematic evidence for the entire spectrum of diverse climate policy instruments at the global scale (*18*).

Here, we provide a global, data-driven causal impact assessment to identify effective policies that have led to large emission reductions out of a universe of about 1500 climate policy measures implemented over the past 2 decades across 41 countries from six continents, whose emissions altogether account for 81% of total global emissions in 2019 (*19*). The aim of this large-scale, cross-country assessment is to guide societies and decision-makers in effectively ratcheting up NDCs under the Paris Agreement by providing tangible evidence on which policy instruments have the potential to achieve large emission reductions. At the heart of our analysis is a meticulously collated climate policy database from the Organisation for Economic Co-operation and Development (OECD), which constitutes the most comprehensive, internationally harmonized policy inventory to date and addresses important prior data limitations. It is global, disaggregated by relevant economic sectors (buildings, electricity, industry, and transport), covers both policy adoptions and the tightening of existing policies, and is of high quality, ensured by drawing on official data verified by countries. Its consistent, theory-based categorization of 48 distinct climate policy instrument types enables systematic assessments of synergies between different instruments.

The empirical challenge is that the candidate pool of effective policy interventions is too large to tackle for standard evaluation tools with their focus on single, known interventions. For example, controlling for all possible policies from the OECD database in a conventional policy evaluation setting would label all countries as treated and leave us with very few degrees of freedom and little if any statistical power. Rather than resorting to a subjective selection of particular policies to analyze, we aimed to identify large reductions in emissions and subsequently attribute them to potential policy interventions. We did so by applying a machine learning–based extension of the standard difference-in-differences (DID) approach to evaluate policy.

First, we exploited methods of break detection from the time series literature in a generalized DID setting using well-established variable selection tools from the machine learning literature to generate data-driven hypotheses about previously known or unknown policy interventions with meaningful emission reduction effects. In comparison with the standard DID approach, which requires a priori knowledge about where and when a small subset of policies was implemented, we neither made any assumptions about which country is treated at which point in time, nor did we restrict the number of potential interventions. Allowing for any country to be potentially treated at any point in time permits us to identify large reductions and reduces concerns around omitting potentially influential policy interventions.

Second, we estimated the effect size for the agnostically detected country-specific interventions using two popular estimators from the

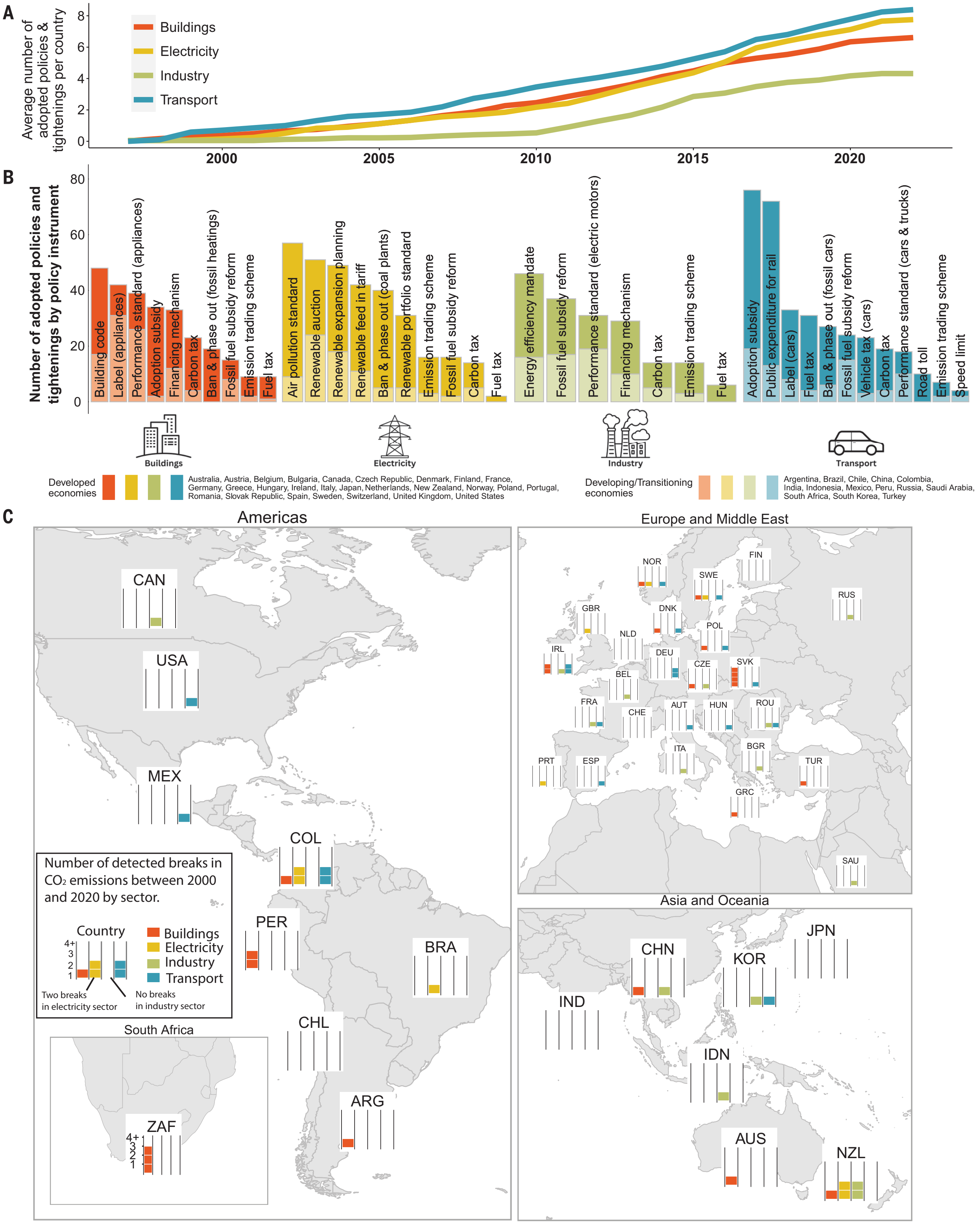
A
Average number of adopted policies & tightenings per country
Buildings
Electricity
Industry
Transport
2000
2005
2010
2015
2020
B
Number of adopted policies and tightenings by policy instrument
Building code
Label (appliances)
Performance standard (appliances)
Adoption subsidy
Financing mechanism
Carbon tax
Ban & phase out (fossil heatings)
Fossil fuel subsidy reform
Emission trading scheme
Fuel tax
Air pollution standard
Renewable auction
Renewable expansion planning
Renewable feed in tariff
Ban & phase out (coal plants)
Renewable portfolio standard
Emission trading scheme
Fossil fuel subsidy reform
Carbon tax
Fuel tax
Energy efficiency mandate
Fossil fuel subsidy reform
Performance standard (electric motors)
Financing mechanism
Carbon tax
Emission trading scheme
Fuel tax
Adoption subsidy
Public expenditure for rail
Label (cars)
Fuel tax
Ban & phase out (fossil cars)
Fossil fuel subsidy reform
Vehicle tax (cars)
Carbon tax
Performance standard (cars & trucks)
Road toll
Emission trading scheme
Speed limit
Buildings
Electricity
Industry
Transport
Developed economies
Australia, Austria, Belgium, Bulgaria, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Slovak Republic, Spain, Switzerland, United Kingdom, United States
Developing/Transitioning economies
Argentina, Brazil, Chile, China, Colombia, India, Indonesia, Mexico, Peru, Russia, Saudi Arabia, South Africa, South Korea, Turkey
C
Americas
CAN
USA
MEX
COL
PER
BRA
CHL
ARG
Number of detected breaks in CO2 emissions between 2000 and 2020 by sector.
Country
Buildings
Electricity
Industry
Transport
Two breaks in electricity sector
No breaks in industry sector
South Africa
ZAF
Europe and Middle East
NOR
FIN
SWE
RUS
GBR
DNK
NLD
POL
IRL
DEU
SVK
CZE
BEL
FRA
CHE
AUT
HUN
ROU
ITA
BGR
PRT
ESP
TUR
GRC
SAU
Asia and Oceania
CHN
JPN
KOR
IND
IDN
AUS
NZL

Fig. 1.

Fig. 1. Increase in climate policy and detected 69 success cases with large emission reductions across sectors and countries. (**A**) Increase in average number of adopted policies and policy tightenings per country between 1998 and 2022. A policy tightening is a substantial increase in stringency of an already existing policy instrument (SM section 3). (**B**) Visualization of the number of adopted policies and policy tightenings across the whole timeframe for each instrument type, highlighting the diverse number of instruments used. Developed and developing or transitioning economies are considered separately. (**C**) Number of large emission reductions for each country and sector as detected with the break detection DID analysis. Overall, we found 69 breaks.

causal inference literature that address different identification concerns. In the last step of our methodology, policy attribution, we combined these estimates with our comprehensive policy data from the OECD to draw systematic inference on the (differential) effectiveness of single policies and various policy mixes. The combination of conservatively controlling for the risk of spuriously identifying false positives, the use of control groups in a panel setting, and a cross validation with popular synthetic control methods and alternative selection algorithms give this reverse causal approach (*20*) credibility. Our policy data are publicly available to spur further research on ex post climate policy evaluation. Our statistical methodology is easily reproducible and allows for constant updating as new experiences with climate policies are gained (*21*).

Results

Increase in climate policies with diverse policy mixes over time

The OECD policy data reveal a consistent increase in the number of implemented climate policies across all sectors between 1998 and 2022 (Fig. 1A). By 2022, the average number of policy adoptions and tightenings ranged between four and eight policies per country. At the same time, there is substantial variation in the types of policy instruments used across sectors and countries (Fig. 1B). With 270 cases, command-and-control measures such as emission standards and technology mandates are the most frequently used policies in all sectors except transport. Market-based policies are primarily concentrated in developed economies and most prevalent in the transport sector. Among market-based policies, subsidies are popular, whereas carbon pricing (carbon taxes and emission trading schemes) remains limited, with a total of 116 cases (88 in developed economies).

Detecting structural breaks in sectoral emissions across the globe

Although we observed around 1500 policy adoptions and tightenings in our policy data, their impact on emissions has so far been highly uncertain. Our break detection DID analysis suggests that large emission reductions have materialized in only 69 cases (Fig. 1C). We identified these successful cases with a machine learning–based, data-driven search for structural breaks in sector-specific CO_2 emissions relative to a control group, separately for developed and developing or transitioning economies. The detected breaks identified large country-specific interventions without prior knowledge of their occurrence [supplementary materials (SM), materials and methods]. The realized emission breaks are unevenly distributed across sectors and countries (Fig. 1C). Most breaks occur in the buildings sector (24 cases), followed by transport (19 cases), industry (16 cases), and electricity (10 cases). A total of 48 and 21 breaks are identified in developed and developing or transitioning economies, respectively.

The reductions in emissions for each of the 69 breaks estimated with our preferred two-way fixed effects (TWFE) DID estimator (SM materials and methods) are shown in Figs. 2 and 3. They provide evidence that the detected breaks are credible and align with the timing of the adoption or tightening of meaningful climate policies. Visual comparison between the time series for observed emissions (Figs. 2 and 3, black lines) and predicted emissions (Figs. 2 and 3, blue lines) across countries and sectors suggests a good fit of our model for the log of CO_2 emissions as a function of socioeconomic developments [gross domestic product (GDP) and population], weather (cooling and heating days), and country-specific time trends. The comparison with the counterfactual emissions (Figs. 2 and 3, red lines), which would have occurred in the absence of the detected breaks and are derived from the control group in our DID setting, suggests strong country-level breaks in emissions. Our approach targets large emission reductions (which require a minimum effect size ranging from 4.5 to 13%) (SM section 6.1), and the average effect size across the detected large breaks is 19.4% (22.7% in buildings, 26% in electricity, 18.4% in industry, and 12.6% in transport). We report in tables S12 to S19 point estimates and standard errors for the country-level breaks in emissions. On the basis of an approximate 95% confidence interval (CI) of these estimates, we calculated equivalent total emission reductions between 0.6 and 1.8 Gt CO_2 (SM section 10). To ensure the robustness of our DID model against misspecification, which might lead to the detection of spurious breaks, we show in the SM that our results are robust to (i) the selection algorithm used for break detection (SM section 7.2), (ii) alternative model specifications (SM section 7.3), (iii) omitted variables (SM section 7.4), and (iv) the country sample composition (SM section 7.5). We obtained very similar results when we used generalized synthetic control methods rather than the TWFE DID model to estimate effect sizes of emission breaks conditional on their detection (SM section 8).

Association of breaks with known and unknown policies

The timing of the identified structural breaks matches well with newly adopted or tightened climate policies, which are visualized as squares along the time axes of Figs. 2 and 3. Of 69 breaks, 63 are associated with at least one policy adoption or tightening within a 2-year interval around the time of the break allowing for lagged or anticipatory policy effects (details on the policy attribution are available in the SM materials and methods). Of the matched breaks, four are associated with the heterogeneous effect of the introduction or tightening of a European Union (EU) policy that we control for (SM materials and methods). Most policies associated with our 21 breaks in developing economies have been rarely studied in the literature and highlight the benefit of our approach to detect hitherto insufficiently studied or unknown effective policy interventions that require more research. We show in fig. S45 how often each policy instrument coincides with a detected large emission reduction.

Most breaks are matched to two or more policies (70%). Before describing our systematic assessment of differential effects of policy mixes and stand-alone policies, we discuss here one prominent example for each country group that illustrates the power of our approach to identify both (i) known, headline policies for which some evidence already exists and (ii) previously unknown combinations of effective policies.

In the electricity sector, we detected two adjacent breaks for the United Kingdom in 2015 and 2016. These follow the mid-2013 introduction of a carbon price floor that imposed a minimum price for UK power producers in the EU emission trading system and has been shown to have reduced emissions considerably (*13*, *22*–*24*). Although the existing literature has attributed most of this effect to the carbon price floor, our attribution method, combined with the OECD policy database, reveals that the carbon price floor was part of a wide policy mix that included command-and-control measures (renewable portfolio standards, renewable expansion planning, stricter air pollution standards, and the announcement of a phase-out of coal power plants) and other market-based incentives (renewable feed-in tariff and auctions).

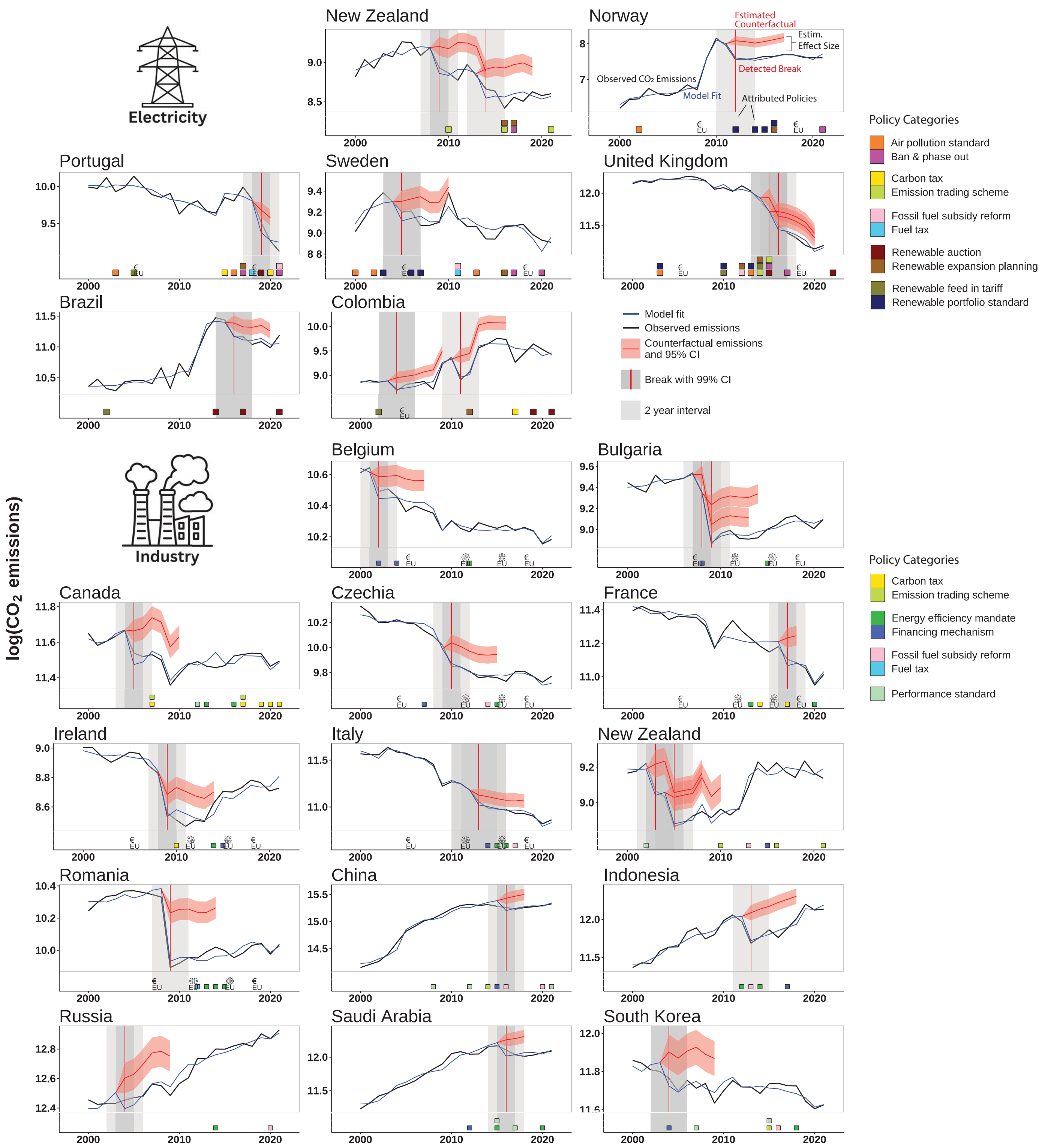

Fig. 2. Most emission breaks in the electricity and industry sectors can be associated with policy mixes. For each country and sector, the black line indicates the observed emissions over time, and the blue line indicates the model fit, which follows the true emissions closely. Detected emission breaks are indicated with vertical red lines, and counterfactual emissions are indicated in red. Each break is surrounded by a statistical CI (dark gray) and a 2-year CI (light gray), which in some cases overlap. The 2-year CI captures both the statistical uncertainty as well as leads and lags in the policy response. Each policy intervention is symbolized by a colored square along the *x* axis. Policy interventions include both newly adopted policies and tightened policies. The color of the boxes indicates the policy instrument. If a box falls into the 2-year CI around detected break dates, we attribute the given policy to an emission break. Adoptions and tightenings of EU labels, EU performance standards, and the EU emission trading scheme are indicated with symbols (tag, gear, and euro icons, respectively). For electricity and industry, 67 and 54% of the matched breaks, respectively, are associated with a policy mix.

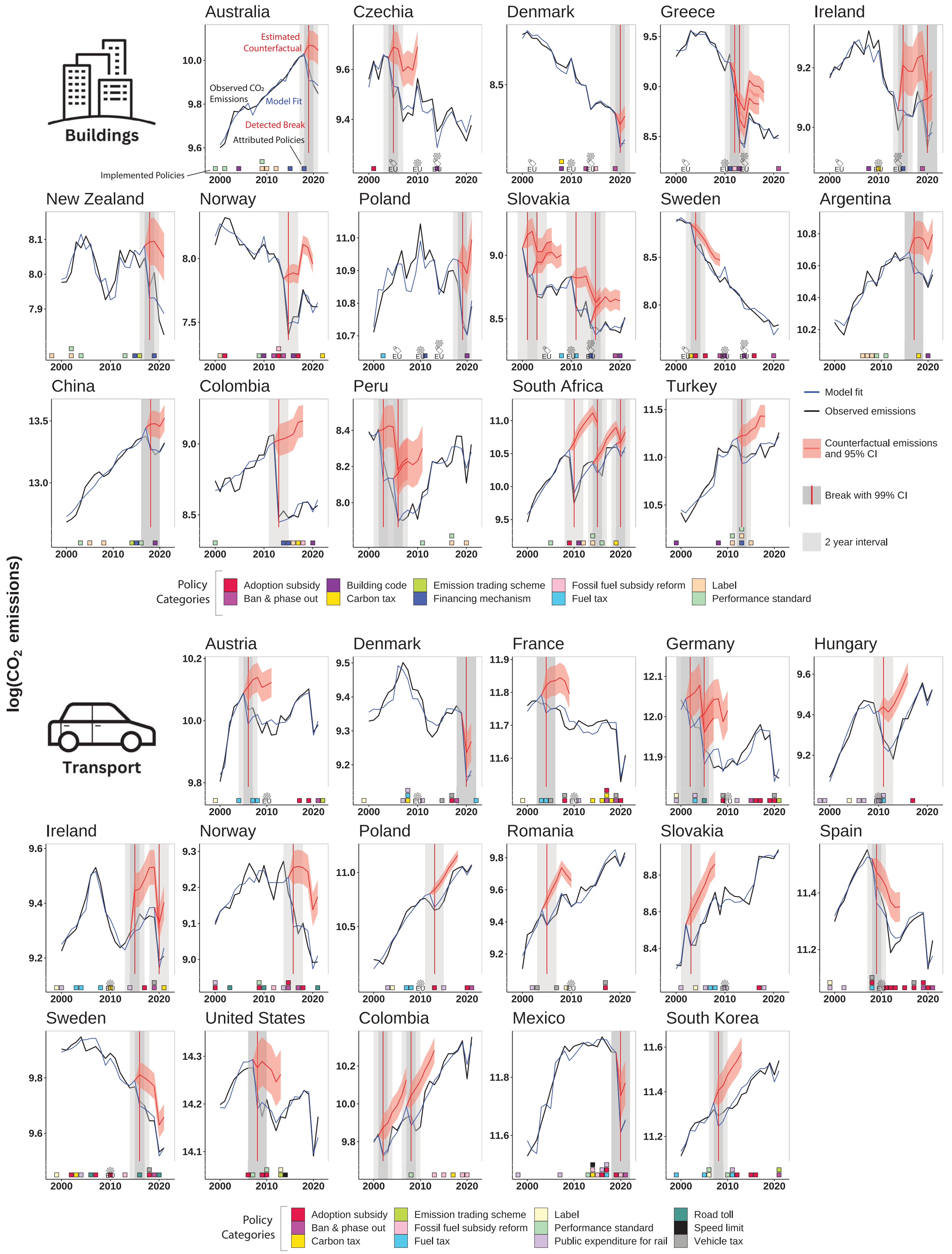

Fig. 3. Most emission breaks in the buildings and transport sectors can be associated with policy mixes. For each country and sector, the black line indicates the observed emissions over time, and the blue line indicates the model fit, which follows the true emissions closely. Detected emission breaks are indicated

with vertical red lines, and counterfactual emissions are also indicated in red. Each break is surrounded by a statistical CI (dark gray) and a 2-year CI (light gray), which in some cases overlap. The 2-year CI captures both the statistical uncertainty as well as leads and lags in the policy response. Each policy intervention is indicated with a colored square along the *x* axis. Policy interventions include both newly adopted policies and tightened policies. The color indicates the policy instrument. If a box falls into the 2-year CI around detected break dates, we attribute the given policy to an emission break. Adoptions and tightenings of EU labels, EU performance standards, and the EU emission trading scheme are indicated with symbols (tag, gear, and euro icons, respectively). For buildings and transport, 60 and 94% of the matched breaks, respectively, are associated with a policy mix.

In the industry sector, the break in China in 2016 occurs with some lag after the launch of seven pilot emission trading schemes beginning in 2013. Again, prior literature has shown that the carbon price reduced emissions (*23*, *25*), but these studies frequently do not consider the role of the simultaneous reduction of fossil fuel subsidies in 2016 and the strengthening of financing mechanisms for energy efficiency investments in 2015.

Identification of effective policy mixes

The major benefit of conducting policy evaluation for many policy instruments in one integrated approach is that we can systematically compare the effectiveness of these policy instruments both when implemented individually and when used as part of a mix. To this end, we aggregated instruments with equivalent economic mechanisms (such as emission trading and carbon and fuel taxes to "taxation") (SM section 9.1) and in Fig. 4A compared the average effect sizes of emission breaks by policy instrument for the case of a stand-alone implementation and an implementation in a policy mix. For non–price-based policies, we also show the average effect sizes of a mix with pricing.

In most cases, we found that effect sizes are larger if a policy instrument is part of a mix rather than implemented alone. Some policies—for example, labels and fossil fuel subsidy reforms—are only ever associated with large emission breaks in a mix, which suggests that these types of policy intervention are either never implemented as a stand-alone policy or do not cause major emission reductions by themselves. Several popular instruments—such as bans, building codes, energy efficiency mandates, and subsidies—are either also only ever detected in policy mixes or have smaller average effect sizes if they are associated as stand-alone policy with emission breaks. For example, the mean effect size of all breaks associated with ban and phase-out policies implemented in the buildings sector as part of a policy mix is around –32%, whereas it is only around –13% if ban and phase-out policies were stand-alone policies. By contrast, taxation is a notable exception in effectively causing large emission breaks alone. It stands out as the only policy instrument that achieves near equal or larger effect size as a stand-alone policy across all sectors.

Overall, these comparisons of relative effect sizes provide suggestive evidence that some of the most widely used regulatory instruments and subsidy schemes may require complementary instruments to enable substantial emission reductions. The effect sizes of policy mixes that combine these non–price-based instruments with taxation or reduced fossil fuel subsidies (Fig. 4A, thick black lines) suggest that in most cases pricing is the complement that enables effective emission reductions. For example, in the electricity sector all mixes that were associated with large emission reductions have pricing elements (fig. S46). However, we cannot rule out whether a single policy dominates the combined effect of a mix or whether any policy instrument in the mix is weakening the overall effect. In this regard, we offer in Fig. 4A a starting point toward understanding interaction effects among policy instruments, but empirical challenges remain.

Next, we assessed which specific combinations of policy instruments caused large emission breaks. To this end, we categorized instruments into four groups of policy types (Fig. 4A, *x* axis, and SM section 9.1), whose role is at the center of high-level political discussions about optimal policy design: information, pricing, regulation, and subsidy. We show in Fig. 4B how often each distinct policy combination or single policy is associated with a break as a percentage share of all successful interventions (an alternative pairwise clustering approach that uses less aggregated policy categories is provided in SM section 9.5).

Our findings suggest that the combinations of policy instruments that are complementary vary across sectors and country groups. Transport is generally the sector with the most potential for complementarities. However, the dominant sectoral policy differs across country groups. In developed economies, pricing stands out individually, with 20% out of all successful detected interventions being associated with pricing individually. Yet subsidies are the most complementary instrument, especially in combination with pricing (33%). By contrast, in developing economies regulation is the most powerful policy. It is highly effective as an individual policy (33%) but also in combination with the duo of subsidies and pricing (33%) and information (33%). The electricity sector of developing economies shows no detected complementarities. In this study, subsidies alone are the most powerful policy tool (67%). By contrast, in developed economies we never found successful stand-alone subsidies. Instead, regulation is the most effective stand-alone policy (33%), but pricing is an equally important element of effective policy mixes because 50% out of all successful policy mixes include pricing. In the industry sector, pricing plays a prominent role. It is most effective individually in developed economies (43%) and shows the most synergy with other policies in developing economies (50%). However, subsidies can be effective complements in both contexts. In buildings, across countries, our findings suggest that a broad set of instruments can be similarly powerful, but subsidies slightly dominate (individually and in combinations) in developed economies and regulations in developing economies.

Discussion

Identifying effective policies is crucial to guide policy-makers in designing the most meaningful interventions. We sought to narrow the policy evaluation gap by applying a machine learning–based extension of the DID approach to identify effective policies that have led to strong emission reductions. We considered the universe of about 1500 observed policies documented in a comprehensive, high-quality, OECD climate policy database. Across four sectors, 41 countries, and 2 decades, we found 63 successful policy interventions with large effects that reduced total emissions between 0.6 and 1.8 Gt CO_2.

Our results inform contentious policy debates in three main ways. First, we contribute empirical evidence for the effectiveness of policy mixes. Although the assertion is widespread that policy mixes can be beneficial and unfold positive synergies (*17*), controversies remain because critics argue that policy mixes may instead be subject to overlapping instruments and perform no better than a single instrument, which is partly backed by theoretical studies in economics (*26*, *27*). Even though we cannot generally rule out such negative synergies owing to empirical constraints, we identified a number of policy instruments for which the empirical evidence suggests complementary effects. These include popular subsidy schemes and regulatory instruments such as bans, building codes, energy efficiency mandates, and labels, for which we found larger reduction effects in policy mixes as compared with the case of a stand-alone implementation. This suggests that some of these most widely used policy instruments are complementary or even reinforcing in policy mixes,

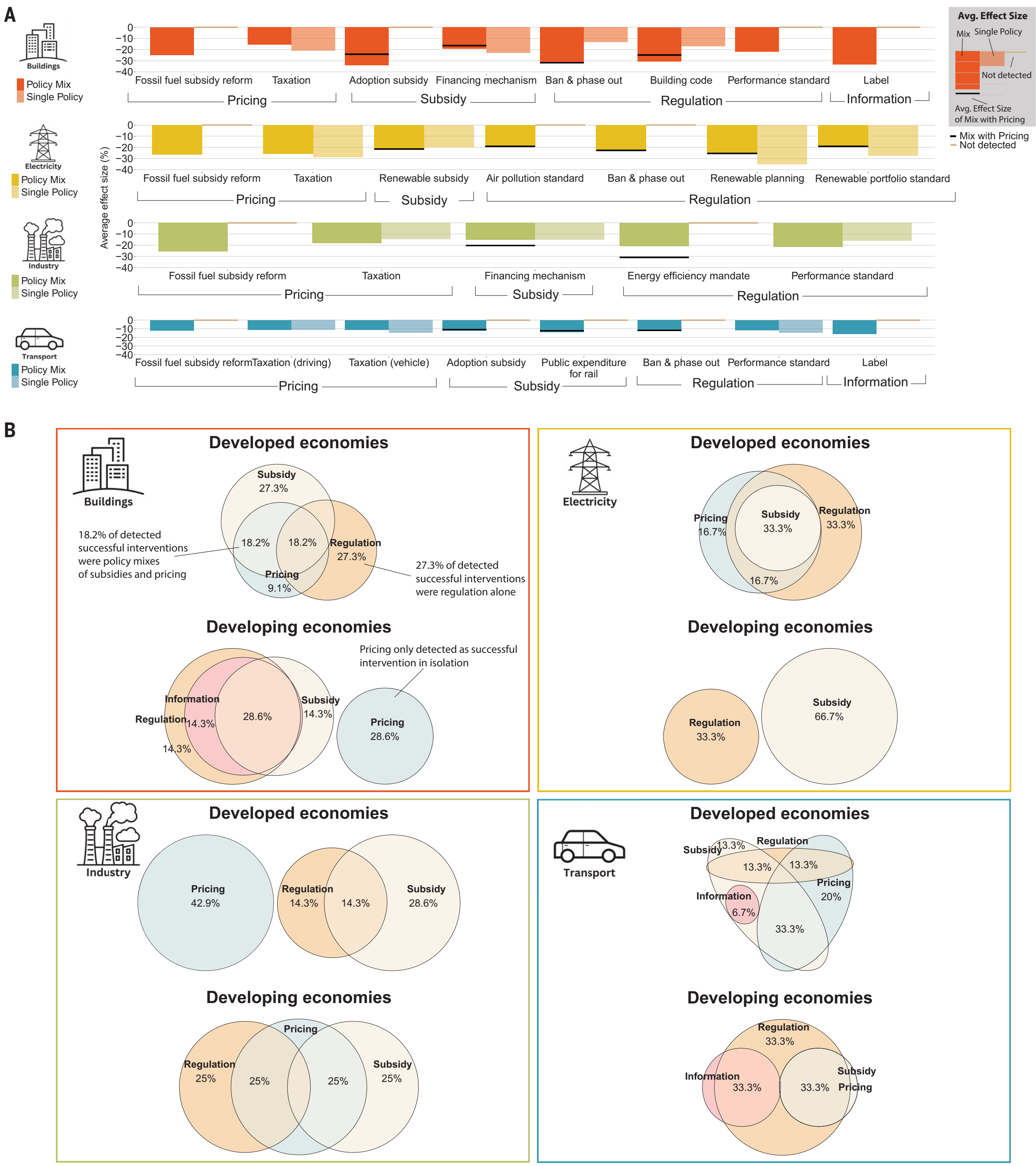

Fig. 4. Effective policies and policy mixes. (**A**) On the basis of point estimates for country-specific breaks in emissions (tables S12 to S19), we compared the average effect sizes of all breaks in which a policy instrument appears individually with that of all breaks in which this policy instrument appears in a mix. For non–price-based policies, the black thick line also indicates the average effect size of a mix with a given policy instrument and pricing (through taxation or reduced fossil fuel subsidies). (**B**) Euler diagrams (SM materials and methods) show which combinations of policy types [definitions of categories are provided in (A), *x* axis] are effective in each sector separately for developed and developing economies. For each circle area, the percentage indicates which share of successful interventions in this sector was made up by a specific individual policy type or a specific combination of policy types. An individual policy type encompasses breaks that match a single policy instrument (for example, one subsidy scheme) or a combination of policy instruments of the same type (for example, two or more different subsidy schemes).

which is in line with the theoretical understanding that these specific instruments alone often have a limited scope (for example, only new cars or new appliances) and are subject to rebound effects (*28*). Additional instruments such as pricing can effectively address both factors and thus generate positive synergy (*15*, *29*). Further explanations for the complementarities include that policy mixes can address a multitude of market failures (*7*) and may be more successful in increasing the overall policy stringency (*30*) and maximizing policy credibility, which shapes the expectations of consumers and investors (*31*).

Second, our findings highlight that successful policy mixes vary across sectors and that policy-makers should focus on sector-specific best practices when designing climate policy rather than following a one-size-fits-all approach. In line with theoretical expectations, we have identified pricing as a particularly effective policy in those sectors dominated by profit-maximizing firms—namely, industry—but also the electricity sector in developed economies. By contrast, for the building and partly also the transport sectors, which both include a large share of private consumers subject to documented behavioral factors such as myopia (*32*, *33*), we found most potential for complementarities between policy instruments. This is consistent with the hypothesis that broad incentives with a particular focus on adoption decisions (such as renewal of heating systems or cars) are needed in these sectors (*34*).

Third, our results stress that effective policies vary with economic development. For example, in sharp contrast to that of developed economies, we did not find any successful pricing intervention with large emission reductions in the electricity sector of developing economies, even though around 13% of policy adoptions or tightenings are pricing interventions. This finding is consistent with claims that the lack of liberalized markets and existence of other price distortions can limit the effectiveness of price-based instruments (*35*). It is also in line with the theory of policy sequencing, which states that in a first stage of climate policy-making, regulations and subsidies are effective in building economic interest in green technology and reducing the cost of technologies (*36*). In this respect, the observed differences in effective policies may partly reflect the climate policy stage. We may not observe some policies because they are not implemented owing to interest group opposition or limited state capacity in developing countries (*37*). However, for interpretation it is important to consider that our analysis for developing countries is based on a small set of estimates given the limited number of policies detected, particularly in the electricity sector.

Our approach identifies country-specific policy interventions that have led to large emission reductions. Thus, we are unable to quantify the effect of policies with minor effects (a discussion on minimum effect size is available in SM section 6.1). However, regarding the size of the emissions gap and the commitment to the Paris Agreement, it is arguably most important to identify combinations of policy instruments that have large effects. In addition to the detected effects of national climate policies, there might also exist impacts of international or regional policies that are only controlled for in this analysis. Furthermore, even though we are able to provide an analysis for 41 countries on 6 continents, our analysis still suffers from regional imbalance. This is largely caused by a sparsity of data for developing countries, especially in Africa and Asia. Last, the ex post analysis identifies past cases of successful policy interventions (2000 to 2020). If policy-makers focused more on the identified best practices, we can plausibly expect more substantial emission reductions in the future. However, we also acknowledge that the workings of policies can be context specific. Therefore, we caution against generalizing our country-specific effect estimates to average treatments effects for particular policy instruments or mixes. In addition, a better understanding of the optimal design of climate policy mixes in a sound welfare framework that accounts for additional dimensions than environmental effectiveness remains a major research need to guide policy-making.

Our results provide a clear yet sobering perspective on the policy effort necessary for closing the remaining emissions gap of 23 Gt CO_2-eq by 2030 (*3*). Using the average (or highest) effect sizes of the detected breaks, we computed a hypothetical scenario in which all 41 countries in our sample achieve emission reductions the size of the average (as well as highest) detected sectoral effect size once before 2030 (SM section 10). We estimate that this would close the emissions gap by 26% (or by 41% for the highest effects). Thus, scaling up good-practice policies identified in this study to each sector of other parts of the world can in the short term be a powerful climate mitigation strategy. However, even if all countries in our sample were able to replicate past success, more than four times (one and a half times) the effort witnessed so far would have to be exerted to close the emissions gap. This also highlights the need for research providing systematic evidence on which climate policy mixes are most powerful in spurring the necessary deployment and development of low-carbon technologies for a future net-zero economy (*38*).

REFERENCES AND NOTES

1. H. D. Matthews, S. Wynes, *Science* **376**, 1404–1409 (2022).
2. M. Roelfsema *et al*., *Nat. Commun.* **11**, 2096 (2020).
3. UN Envrironment Programme (UNEP), Emissions Gap Report 2022, (2022); https://www.unep.org/resources/emissions-gap-report-2022 (accessed July 2023).
4. T. Fransen *et al*., *Nat. Clim. Chang.* **13**, 752–755 (2023).
5. T. Sterner *et al*., *Nat. Sustain.* **2**, 14–21 (2019).
6. D. Rosenbloom, J. Markard, F. W. Geels, L. Fuenfschilling, *Proc. Natl. Acad. Sci. U.S.A.* **117**, 8664–8668 (2020).
7. O. Blanchard, C. Gollier, J. Tirole, *Annu. Rev. Econ.* **15**, 689–722 (2023).
8. S. M. Eskander, S. Fankhauser, *Nat. Clim. Chang.* **10**, 750–756 (2020).
9. G. Martin, E. Saikawa, *Nat. Clim. Chang.* **7**, 912–919 (2017).
10. C. Le Quéré *et al*., *Nat. Clim. Chang.* **9**, 213–217 (2019).
11. P. Bayer, M. Aklin, *Proc. Natl. Acad. Sci. U.S.A.* **117**, 8804–8812 (2020).
12. J. J. Andersson, *Am. Econ. J. Econ. Policy* **11**, 1–30 (2019).
13. M. Leroutier, *J. Environ. Econ. Manage.* **111**, 102580 (2022).
14. M. Linsenmeier, A. Mohommad, G. Schwerhoff, *Nat. Clim. Chang.* **12**, 1107–1110 (2022).
15. J. van den Bergh *et al*., *Clim. Policy* **21**, 745–764 (2021).
16. N. Koch, L. Naumann, F. Pretis, N. Ritter, M. Schwarz, *Nat. Energy* **7**, 844–853 (2022).
17. J. Hoppe, B. Hinder, R. Rafaty, A. Patt, M. Grubb, *Annu. Rev. Environ. Resour.* **48**, 615–650 (2023).
18. J. C. Minx, M. Callaghan, W. F. Lamb, J. Garard, O. Edenhofer, *Environ. Sci. Policy* **77**, 252–259 (2017).
19. M. Crippa *et al*., CO_2 emissions of all world countries—2022 report (2022); https://publications.jrc.ec.europa.eu/repository/bitstream/JRC130363/co2_emissions_of_all_world_countries_online_final_2.pdf.
20. A. Gelman, G. Imbens, "Why ask Why? Forward Causal Inference and Reverse Causal Questions"(working paper 19614, National Bureau of Economic Research, 2013); https://www.nber.org/papers/w19614.
21. J. Elliott *et al*., *Nature* **600**, 383–385 (2021).
22. J. Abrell, M. Kosch, S. Rausch, *J. Environ. Econ. Manage.* **112**, 102589 (2022).
23. N. Döbbeling-Hildebrandt *et al*., *Nat. Commun.* **15**, 4147 (2024).
24. J. L. Castle, D. F. Hendry, *Found. Trends Econom.* **10**, 145–322 (2020).
25. J. Cui, C. Wang, J. Zhang, Y. Zheng, *Proc. Natl. Acad. Sci. U.S.A.* **118**, e2109912118 (2021).
26. S. Fankhauser, C. Hepburn, J. Park, *Clim. Change Econ. (Singap.)* **1**, 209–225 (2010).
27. G. Perino, R. A. Ritz, A. Van Benthem, "Overlapping climate policies," working paper 25643 (National Bureau of Economic Research, 2019); https://www.nber.org/papers/w25643.
28. K. Gillingham, M. J. Kotchen, D. S. Rapson, G. Wagner, *Nature* **493**, 475–476 (2013).
29. E. Dimanchev, C. R. Knittel, *Energy Econ.* **122**, 106697 (2023).
30. J. Meckling, N. Kelsey, E. Biber, J. Zysman, *Science* **349**, 1170–1171 (2015).
31. G. Dolphin, M. Pahle, D. Burtraw, M. Kosch, *Nat. Clim. Chang.* **13**, 1033 (2023).
32. K. T. Gillingham, S. Houde, A. A. van Benthem, *Am. Econ. J. Econ. Policy* **13**, 207–238 (2021).
33. E. Myers, *Am. Econ. J. Econ. Policy* **11**, 165–188 (2019).
34. S. T. Anderson, J. M. Sallee, *Annu. Rev. Resour. Econ.* **8**, 157–180 (2016).
35. F. Teng, F. Jotzo, X. Wang, Interactions between market reform and a carbon price in China's power sector, *Econ. Energ. Environment. Pol.* **6**, 39–54 (2017).
36. J. Meckling, T. Sterner, G. Wagner, *Nat. Energy* **2**, 918–922 (2017).
37. M. Jakob, J. C. Steckel, *The Political Economy of Coal: Obstacles to Clean Energy Transitions* (Taylor & Francis, 2022).
38. S. J. Davis *et al*., *Science* **360**, eaas9793 (2018).
39. OECD, Climate Actions and Policies Measurement Framework (CAPMF) (2023); http://oe.cd/dx/5if.
40. A. Stechemesser, Replication code and materials for "Climate policies that achieved major emission reductions: Global evidence from two decades". Zenodo (2023); https://zenodo.org/records/12773811.

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SUPPLEMENTARY MATERIALS

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