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Effective climate policies for 'all seasons': novel evidence from 40 countries

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ABSTRACT

As governmental climate policy efforts are expanding, evaluating their effectiveness has become increasingly challenging due to numerous coexisting policies that complicate isolating individual impacts. How can we assess the effectiveness of individual climate policies during periods of continuous policy expansion? This paper explores methodologies designed to explicitly model all climate 'policy parameters'. By integrating Bayesian priors, we regularize the estimation model, incorporating additional information to ensure that only policies meeting a certain threshold of evidence are considered. Applying our methodology to the analysis of 47 different climate policies in 40 countries over 32 years (1990–2022) in four policy sectors (1,737 individual policies), we identify those policies being consistently effective under various contextual conditions and examine their emission reduction potential in greater detail. Our findings provide decision-makers with insights into the most likely effective climate policies and offer scholars an innovative tool with which to evaluate policies within expanding policy mixes.

Key policy insights

- The paper introduces a new methodological toolkit that enables a comprehensive analysis of climate policies, adaptable to examine various policy areas amid policy growth.
- The paper presents a list of essential climate policy measures that effectively enhance climate ambitions across all mixes, serving as a guide for policymakers.
- The paper provides a country-specific overview identifying areas with the highest potential for additional climate action, offering policymakers a clear path to improve their country's climate performance.

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Climate policy; policy effectiveness; policy growth; policy evaluation

Introduction

Climate change is one of the greatest challenges of our time (IPCC, 2023). Given its scope and urgency, it is crucial to develop climate policies that effectively curb carbon dioxide (CO_2) emissions. We understand climate policies as the combination of specific policy targets (such as sectors, activities, or target groups) addressed by certain policy instruments (including regulatory interventions and market-based actions), with the objective to reduce CO_2 emissions. However, while governments have a wide array of policy options (i.e. potential combinations of targets/sectors and instruments) at their disposal, they face uncertainty regarding their effectiveness in emissions reduction. This uncertainty mainly results from the fact that individual policy

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effects can hardly be observed in isolation but instead interact with the effects of other policies in existing climate policy mixes.

The challenge of discerning the specific impact of individual policies has strongly increased over the past two decades, during which countries around the globe have significantly increased and expanded their climate policy mixes (Hoppe et al., 2023; Steinebach et al., 2024). Individual climate policies thus no longer operate in isolation (Adam et al., 2018). Instead, their effectiveness is increasingly influenced by the presence and configuration of other policies in this sector. A crucial question to address is thus: Which individual climate policies are most effective in reducing CO_2 emissions across diverse policy constellations?

To address this research question, we need an approach that (i) evaluates the individual effects of climate policies while (ii) simultaneously accounting for the influence of other climate policy measures. Such an approach, in turn, requires the incorporation of all relevant policy parameters into the analysis. However, a well-known practical challenge arising from this constellation is over-parameterization. Over-parameterization occurs when the model includes too many variables relative to the amount of available data. This paper explores different methodological approaches designed to address this challenge. These approaches work with different Bayesian priors to ensure that we only consider climate policies for which we can confidently conclude that they effectively lead to a reduction in emissions.

Our analysis of climate policies in 40 countries over a period of 32 years identifies these policies that are consistently effective under various conditions and examine their emission reduction potential in greater detail. What is 'effective' or not comprises two key components: the certainty with which effects can be achieved, and the strength a given policy has in reducing emissions. Typically, these aspects are correlated, as policies that exhibit stronger effects often also come with a higher level of certainty regarding their impact. However, it is possible for some policies to demonstrate significant effectiveness under certain conditions while still being associated with considerable uncertainty in general. In this paper, we consider policies as effective when there is a *high degree of confidence* in their ability to negatively impact emissions. While the exact magnitude of this effect is important, it is of secondary relevance to our analysis.

Importantly, our goal is not to identify the most effective *combinations* of climate policies but to pinpoint the *individual* policies that enhance any policy mix and that hence work for 'all seasons'. Using a sports analogy, we are not interested in identifying the best 'team' of policies but rather in finding the best 'players' that can reliably enhance any team they join.[1] In this way, our paper contributes to an expanding body of literature that seeks to assess the effectiveness of climate policies and attribute the adoption of certain policies to observed outcome changes.

The identified effective climate policies include a wide variety of instrument types, rather than being restricted to a single category. This breadth demonstrates that successful climate action does not hinge on one optimal measure; instead, there are numerous pathways to achieving meaningful climate goals. Nevertheless, the findings suggest that – regardless of the sectors or targets addressed – that some instruments may be more dependable than others. Notably, implementing carbon pricing and taxation, along with investing in renewable energy and research, stand out as particularly reliable strategies for attaining significant reductions in CO_2 emissions.

Our contribution is twofold. First, we provide scholars with a novel tool to evaluate policies within the context of broader policy mixes. Our approach enhances the understanding of how individual policies perform within complex, interrelated policy environments, thereby aiding in the development of more informed and impactful climate strategies. Building on this foundation, our second contribution is to provide decision-makers with new insights into policy options that promise effective and likely emission reductions. Together, these contributions enable a more comprehensive and strategic approach to effective climate action.

The article is structured as follows: In the next section, we examine the issue of climate policy expansion and the consequent challenges for policy evaluation. The third section introduces our new approach for assessing climate policy measures in times of continuous policy growth. The fourth section details our research design, and the fifth section presents the empirical analysis. The last section discusses our findings and presents conclusions.

Climate policy growth and the resulting challenges

Multiple datasets capture the development of climate policies across countries (Fankhauser et al., 2016; Nachtigall et al., 2024; Nascimento & Höhne, 2023; NewClimate Institute, 2023). These datasets vary in their temporal and spatial coverage, as well as in the specific policy sectors and policy instruments they consider (Steinebach et al., 2024). Despite these differences, all datasets consistently demonstrate a tremendous growth in the number of climate policies adopted. As shown in Figure A35 in the online appendix, the most conservative estimates indicate that the number of climate policies is now, on average, about four times higher than it was in the year 2000 (see OECD dataset). In the most extreme cases, the growth in climate policies reaches up to approximately fifteen times the 2000 levels (see Climate Change Laws of the World (CCLW) dataset).

While scholarly contributions unanimously agree that the current measures are still largely inadequate to meet countries' Paris Agreement commitments and to limit the global temperature increase to within the 1.5-degree Celsius target (Baker et al., 2025; UNEP, 2023), Figure A35 demonstrates that addressing climate change ranks high on countries' agendas and that significant climate actions and efforts have been undertaken over the last two decades.

In practice, all these policies work together, mutually influence each other, and jointly affect CO_2 emissions. This development challenges existing approaches to evaluate the effectiveness of the adopted policies. Existing approaches for assessing climate policies can be broadly categorized into three groups.

The first group focuses on *individual* climate policy evaluation (see e.g. Bayer & Aklin, 2020; Cui et al., 2021). This method excels at isolating the effects of specific policies within a given context, providing detailed insights into their immediate impacts. However, this approach struggles with generalizability. The results obtained from one context may not apply to another due to the myriads of other policies that can influence the effectiveness of a given policy or impact the same outcome dimensions.

The second group focuses on the effectiveness of entire climate policy 'regimes' (Bergquist & Warshaw, 2023; Nachtigall et al., 2024; Schaub et al., 2022). These analyses typically rely on aggregated indices or simply count the number of the measures adopted, assessing the effectiveness of the policies in their entirety. A key challenge of this approach is that it becomes difficult to discern which exact components of the broader policy mix primarily drive specific effects and which are less relevant, ineffective, or even counterproductive.

The third group of studies includes a recent contribution from Stechemesser et al. (2024). This paper addresses the identified shortcomings by analyzing the effects of multiple policies while refining the 'candidate pool of effective policy interventions' (p. 884). This refinement is achieved by 'identifying large reductions in emissions and subsequently attributing them to potential policy interventions' (ibid.). While the approach is systematic and robust in its application, the selection criteria predominantly emphasize statistically identifiable large emission trend breaks. Consequently, this methodology may overlook policies that, although they do not result in immediate sharp emissions reductions, produce gradual yet significant effects over time.

We conclude from this overview that an approach that evaluates the individual effects of climate policies while simultaneously accounting for the presence of other climate policies is still needed. Additionally, this approach should avoid making assumptions about how abrupt (or gradual) emission changes should be for climate policies to be considered effective.

Assessing the effects of climate policies in the context of growing policy mixes

If we aim to explicitly model the effects of all policies *without* ex-ante restrictions on which policies to consider, the main challenge is that statistical models can quickly become excessively complex. This complexity arises from having too many parameters relative to the number of observations, which can lead to overfitting and reduce the model's accuracy.

We address this issue by employing different priors in Bayesian statistical modelling. By incorporating these priors, we can regularize the model, effectively introducing additional information to ensure that we only consider those climate policies meeting a specific threshold of certainty. This prevents the model from becoming overly complex and allows us to focus on those policies that are very likely to constitute effective interventions.

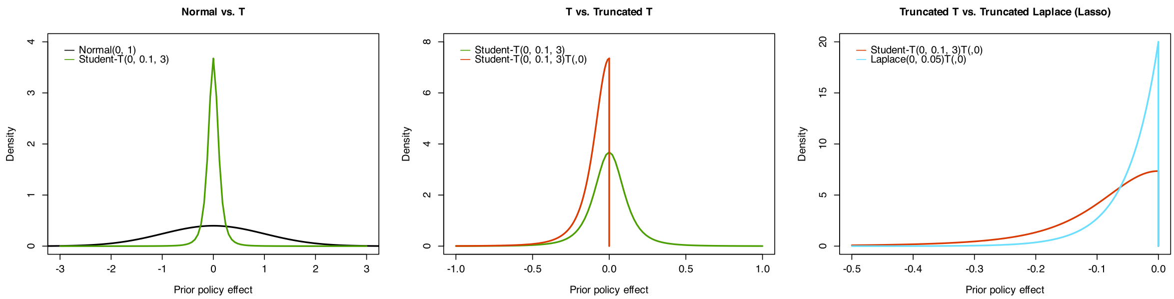

Figure 1. Illustration of different priors.

Note: The figure compares different prior distributions. On the upper left, Student-t priors are used instead of normal priors, offering a sharper peak and heavier tails when degrees of freedom are low. The figure on the upper right contrasts a two-sided prior (allowing both positive and negative policy effects) with a truncated prior (restricting effects to only CO_2 reductions). In the lower middle figure, a Laplace prior is shown, which has a more peaked shape than the t-distribution, with flatter shoulders and longer tails.

We employ three families of priors, each with different properties and assumptions on the underlying data generation process, which can be understood as 'filters' with increasingly strict benchmarks for differentiating between effective and ineffective policies. These filters are illustrated in Figure 1. The first family of priors involves using Student-t priors instead of normal priors (*upper left-hand illustration*). Compared to a Gaussian distribution (weakly informative prior), the T distribution is characterized by a more pronounced peak around the mean while allowing for larger tails when the degrees of freedom are low (we set them at 3). With this modification, we essentially ask the model to include only those parameters (policies) that provide a clear indication of making a significant difference for policy impacts. This helps to filter out 'noise' and focus on the most impactful policies.

The first figure shows that compared to the default standard normal prior, which is the baseline reference for a weakly informative prior, the T prior with a standard deviation of 0.1 and 3 degrees of freedom is less likely to produce posteriors that signal a policy effect. In the next step, we compare this two-sided prior (allowing for both positive and negative effects of policies on CO_2 emissions) to a truncated prior where the effects of the policy can only reduce CO_2 emissions. This allows us to discard potential false positive effects. In the third figure, we compare this Truncated T with a prior corresponding to a Lasso regression, which puts even more density closer to zero, making it harder to find false negatives (policies that signal a reduction of CO_2 emissions when, in fact, they do not reduce them). The second prior considers the fact that climate policies should, optimally, *not* result in increased CO_2 emissions (*upper right-hand illustration*). While some climate policies might be poorly designed and, therefore, largely ineffective, it is reasonable to assume that they will not result in the exact opposite of their intention, namely, exacerbate emissions. This prior helps us further constrain the model to consider only those policies that either reduce emissions or have a neutral impact. Lastly, we utilize a Laplace prior (*lower middle illustration*). Compared to the t-distribution, the Laplace distribution is (even) more peaked and characterized by flatter shoulders but longer tails. This means we further constrain the information, creating a sharper distinction between significant and insignificant coefficients.[2]

Each of these priors has distinct effects on our model and tends to 'filter out' different policies. Consequently, we do not favour one approach over the others; instead, we aim to observe where the various selection methods converge regarding policies. While this approach may be viewed as vague or even arbitrary, we believe that an 'open' methodology is more justified, particularly as we are promoting a novel approach. This openness allows for a more comprehensive understanding of which policies are consistently identified as effective across different modelling choices, ultimately enhancing the robustness and credibility of our findings.

Research design

To identify individual policy effects, our dependent variable is CO_2 emissions by sectors. The sectors considered are buildings, energy, industry, and transport. The sectoral emissions are divided by the population in millions and logged and standardized to facilitate cross-sectoral interpretation. Our key independent variables are individual climate policies. We analyze how individual policies affect CO_2 emissions in a context of diverse policy mixes, with varying other climate policies in place. As discussed above, multiple datasets nowadays provide information on climate policies (Steinebach et al., 2024). In this paper, we rely on the OECD Climate Actions and Policies Measurement Framework as it is the only existing dataset that not only provides information on the existence or absence of policies but also details their exact stringency (Nachtigall et al., 2024). Stringency refers to the specific level of governmental intervention, such as the precise emission limit to be met or the carbon tax to be paid. The stringency of a particular instrument can vary significantly – it may be high or low and often changes after a certain policy is introduced. The dataset is categorized into sector-specific (buildings, energy, industry, and transport) and cross-sectional policies. While sector-specific policies are anticipated to impact emissions within their respective sectors, cross-sectional policies are expected to influence emissions across all sectors. Overall, the dataset encompasses 1,737 individual policies adopted in 40 countries over a period of 32 years (1990 until 2022), which can be classified into 47 different policies (target-instrument combinations).[3] We use this full sample in our analysis.

The OECD researchers did their coding based on reviewing laws, programmes, and other relevant documents to identify the measures contained within them. A single law or programme could contain multiple policies. For instance, the same law might prescribe an emission standard while also imposing a tax on carbon emissions from the transportation sector. In the next step, policies adopted by different countries that shared the same key features – such as the targets they addressed and the instruments they applied – were merged into distinct policy categories. This explains why there are more individual policies than consolidated policy categories. Beyond the OECD dataset, we coded the EU Emission Trading Scheme (ETS) as a distinct policy, with its stringency defined by the emission coverage and price, and incorporated this into each country's policy mixes being part of the ETS (27 EU member states plus Liechtenstein, Iceland, and Norway).

When analyzing the influence of climate policies on changes in CO_2 emissions, it is crucial to control for various external factors that may also impact emission levels. In addition to the implementation of climate policies, several economic and structural variables can significantly affect emissions. Therefore, we incorporate a set of control variables in our analysis to better isolate the effects of climate policies. These control variables include, first, GDP per capita, which serves as an indicator of the economic wealth and consumption patterns of a country. Wealthier countries can be expected to produce more CO_2 emissions in view of higher levels of industrialization, higher standards of living, and more widespread use of energy-intensive technologies (e.g. cars, air conditioning, heating) and tend to consume more goods and services overall. Second, GDP growth captures the overall economic dynamic of a country. Economic growth can be expected to lead to higher emissions because it typically increases industrial activity, energy consumption, and transportation, all of which are carbon-intensive processes relying on fossil fuels. Third, the fossil fuel energy share highlights a country's dependence on carbon-intensive energy sources. Fourth, industry share represents the industrial sector's contribution to the national economy. Both higher fossil and industry share can be expected to positively affect the level of CO_2 emissions. Fifth, we consider trade openness as it may influence emissions through the import and export of goods. Trade openness drives CO_2 emissions by increasing the movement of goods across borders, often leading to higher production and transportation emissions, particularly when goods are manufactured in countries with less stringent environmental regulations. Sixth, we consider state capacity to control for the government's ability to enforce policies effectively. Finally, overall climate policy activity is included in the analysis to account for the possibility that it may not only be the specific policies adopted and their combinations that affect emissions, but also the sheer volume of policies in place. To control for this overall policy activity, we sum up the total *number* (count) of policies in place. The economic and structural variables are sourced from the World Bank, with the industry share data coming from the OECD. Data on subnational carbon pricing schemes is obtained from the World Bank's Carbon Pricing Dashboard. The state capacity measure is derived from research by Hanson and Sigman (2021). *Section F* in the Online Appendix summarizes the description, measurement, and data sources of the various variables used in this study.

One challenge for our analysis is that adopting a certain instrument is not random, as governments might tend to 'self-select' into treatment (Stechemesser et al., 2024, p. 8). This can affect the assessment of the effectiveness of policies, as governments may only opt for policies they expect to perform relatively well within their specific contexts. To address this issue, we employ Propensity Score Analysis using the control variables considered. There are essentially two methods for conducting propensity score analyses. The first approach involves using the propensity score to create treatment and control groups that are well-balanced across all confounding variables. The second approach, which we implement in this paper, is to calculate the likelihood of a country adopting a specific policy based on its covariates and incorporate this likelihood parameter into our model. The underlying assumption is that countries that are more inclined to adopt certain policies are also more likely to achieve stronger effects from those policies in their specific contexts. We accordingly conduct this analysis for *each* of the 47 policies under consideration. This approach helps to level out biases and ensures that our analysis more accurately reflects the effectiveness of the policies across different contexts.

The formal model is based on a linear model with various additional features that provide several layers of robustness. First, the stochastic component accounts for country-clustered errors. Second, there are varying intercepts that remove between-country variation not accounted for by potentially omitted variables. Third, the temporal dynamic is accounted for by both (a) employing varying intercepts that are smoothed using a state-space Kalman filter and (b) an autoregressive component (AR1). Fourth, the model includes an explicit control for causal identification in the form of propensity scores, estimated with a complementary model assessing the likelihood of adoption of each of the policies considered. The equation is as follows:

$Y_{c,y}$	$\mathcal{N}(\mu_{c,y}, \sigma_c)$	Main data component
$\mu_{c,y}$	$\delta_c + \gamma_y + CV*\beta + X*\theta + PS*\lambda + \rho_c*(Y_{c,y-1} - \mu_{c,y-1})$	Main linear model
σ_c	$\mathcal{U}(0, 10)$	Error component
γy	$\mathcal{N}(\gamma_{y-1} + \kappa, \sigma_\gamma)$	Time dynamics
σ_γ	$\mathcal{U}(0, 10)$	Prior for state noise
$\delta_c, \beta_{cv}, \kappa, \lambda$	$\mathcal{N}(0, 1)$	Auxiliary priors
ρ_c	$\mathcal{U}(-1, 1)$	Prior for the AR(1) process
$\theta_{i,t}$	$\mathcal{T}(0, 0.1, 3)T(, 0)$	Truncated T Priors for main effects

Where:

- c: Country
- y: Year
- cv: Control variables
- i: Instrument
- t: Target
- $Y_{c,y}$: Continuous variable with CO_2 equivalent per capita emmisions (in T) for a specific country (c) and year (y).
- CV: Matrix with the control variables and covariates.
- X Matrix with the policies.
- PS Matrix with the propensity scores for the policies.
- σ: Standard deviation of the model.
- δ: Country effects.
- γ: Year effects.
- ρ_c: AR(1) parameter.
- σ: Standard deviation of the state-space component.
- κ: State transition coefficient.
- β: Effects of control variables.
- λ: Propensity score matching controls.
- θ: Effects of portfolio spaces. Main parameters of interest.

Empirical findings

Figure 2 summarizes our results. The colours on the y-axis indicate the policy sector affected. The colours in the cells showcase the direction of the effect, while the boldness of the letters denotes the level of evidence that the posterior values deviate from zero. Please note that the interpretation of a high level of evidence – presence

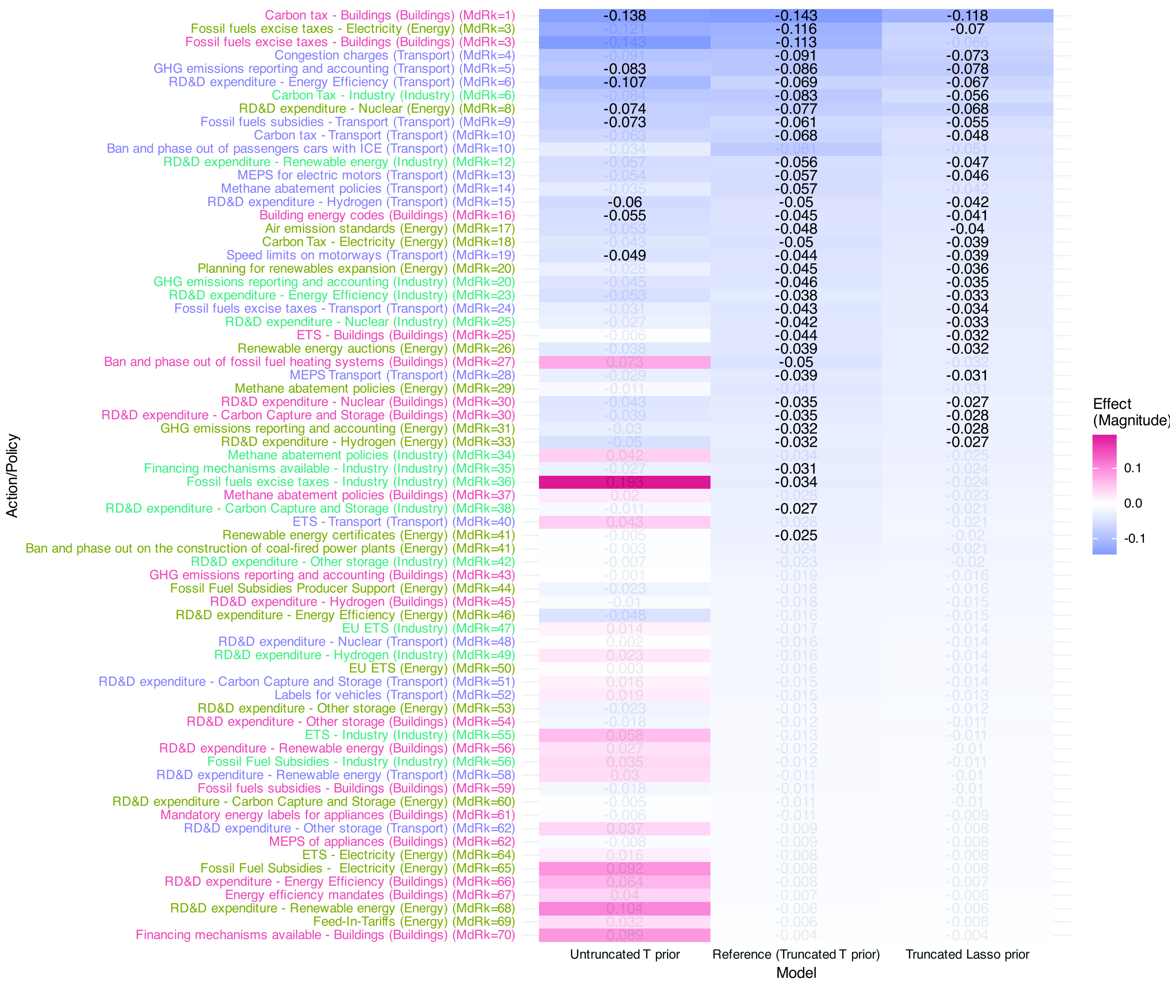

Figure 2. The effectiveness of climate policy measures.

Note: Figure 2 presents our results on the effectiveness of different climate policies. The y-axis colours represent different policy sectors: Industry is marked in green, Building in red, Energy in yellow, and Transport in blue. Each cell's colour indicates the direction of the effect, while the boldness of the letters within the cells reflects the confidence level. Policy measures are sorted by their level of effectiveness. The three columns present models using different priors. The 'fossil fuel subsidies' variable captures the impact of removing or lowering subsidies for fossil fuels. MdRK stands for Median Ranking, which reflects the average effect size ranking of the respective policy measures across the three models. A higher ranking generally indicates a stronger policy effect.

of 'significant effects' – varies slightly across the models. Specifically, in contexts where effects are primarily anticipated to be negative (i.e. aimed at reducing emissions), conventional measures using two-sided confidence intervals are not applicable. Instead, we identify evidence of an effect when the distance between the last 5 percent of the simulations (percentile 95 to percentile 100) is bigger than the distance between the previous 5 percent of the simulations (percentile 90 to percentile 95). This indicates that the parameter is actually deviating from zero and not 'sticked' to it. Additionally, a threshold value is applied to ensure that only substantive effects are considered significant, avoiding the inclusion of rather low effects. We provide a more detailed explanation of how we handle this challenge in the online appendix (Section E). The policies are sorted by their magnitude of effectiveness, as indicated by the number within the cells. The effect size can be interpreted as follows: It shows how emissions (in tons of CO_2-equivalent per capita) change with a one-standard-deviation increase in policy stringency. The truncated T-prior columns exhibit the policies with a high level of certainty regarding their effects (35), followed by the truncated Lasso prior model (28) and the untruncated T prior model (8), where we only consider policies with a reduction of emissions.

As discussed above, our primary focus is on the certainty with which a specific policy affects the impact dimension. Practically speaking, our analysis centres on the formatting of the numbers in Figure 2 – whether they are highlighted in green and bold – rather than the specific values within the cells. However, it is important to note that the two aspects are closely associated; a policy with a very minor effect is often more difficult to highlight as significant. None of the 'secure' effects listed in Figure 2 appear at the bottom of the table, which is ordered by effect magnitude.

Twenty-eight climate policies have been identified in at least two models as having significant effects. In Table 1, these policies are presented alongside the broader instrument types to which they can be assigned, as well as the corresponding policy sectors they apply to. Additionally, the table includes the percentage of country-years in which each respective policy is implemented, with values ranging from 2.5% to 56.6%. This essentially indicates that our results are *not* driven by the frequency of occurrence; that is, we do not have a higher level of evidence simply because some policies are more widely applied than others.

In the following, we focus on these policies. This 'conservative approach' might come with the downside of potentially overlooking some effective policies. However, given the cost and burden involved for policymakers, administrations, and companies to produce, execute, or follow potentially ineffective policies, we believe it is more appropriate to be cautious (see, e.g. Fernández-i-Marín et al., 2024). Overlooking some policies is preferable to recommending policy solutions whose effects primarily result from the model choice rather than actual effectiveness.

The effective policies identified span a range of instrument types rather than being confined to a single category. When we classify these policies into broader instrument categories, the distribution appears quite diverse. For 'Carbon Pricing and Taxation', there are eight policies. The 'Energy Efficiency and Standards' category encompasses five policies. Measures under 'Renewable Energy and Research' include eleven policies, and the 'Reporting and Accountability' category comprises three policies, while for the reduction of subsidies there is only one effective policy.

Table 1. List of effective policies by instrument type.

Instrument type	Policy	Sector	Prevalence
Carbon pricing and taxation	Carbon tax – Buildings	Buildings	17.0%
	ETS – Buildings	Buildings	2.5%
	Carbon Tax – Electricity	Energy	6.6%
	Fossil fuels excise taxes – Electricity	Energy	4.9%
	Carbon Tax – Industry	Industry	5.8%
	Carbon tax – Transport	Transport	16.4%
	Congestion charges – Transport	Transport	4.7%
	Fossil fuels excise taxes – Transport	Transport	44.6%
Energy efficiency and standards	Building energy codes	Buildings	37.4%
	Air emission standards	Energy	29.7%
	MEPS Transport	Transport	29.7%
	MEPS for electric motors	Transport	32.6%
	Speed limits on motorways	Transport	56.6%
Renewable energy and research	RD&D expenditure – Carbon Capture and Storage	Buildings	20.1%
	RD&D expenditure – Nuclear	Buildings	39.5%
	Planning for renewables expansion	Energy	28.8%
	RD&D expenditure – Hydrogen	Energy	25.1%
	RD&D expenditure – Nuclear	Energy	39.5%
	Renewable energy auctions	Energy	6.6%
	RD&D expenditure – Energy Efficiency	Industry	43.6%
	RD&D expenditure – Nuclear	Industry	39.5%
	RD&D expenditure – Renewable energy	Industry	45.4%
	RD&D expenditure – Energy Efficiency	Transport	43.6%
	RD&D expenditure – Hydrogen	Transport	25.1%
Reporting and accountability	GHG emissions reporting and accounting	Energy	41.3%
	GHG emissions reporting and accounting	Industry	41.3%
	GHG emissions reporting and accounting	Transport	41.3%
Subsidies	Fossil fuels subsidies – Transport	Transport	31.0%

Note: The table lists various effective climate policies, categorized by instrument type, sector, and coverage (measured in country-years). A policy is considered to be effective when it shows evidence for a negative effect on emission developments in at least two of the three model specifications. Prevalence indicates the percent of country-year-observations with the policy in place.

This variety suggests that effective climate action does not rely on a single optimal policy but instead requires a comprehensive toolkit of diverse policies to reduce emissions effectively. However, the findings also indicate that some instruments may be more reliable than others. In particular, adopting carbon pricing and taxation, as well as investing in renewable energy and research, appear to be reliable ways to achieve CO_2 emission reductions.

The findings on carbon pricing are particularly intriguing. One common argument against the use of carbon taxes is that they are often set at insufficiently low levels due to political considerations. As a result, governments may introduce additional policies to offset the lower tax rates (Rosenbloom et al., 2020). The observed effects of carbon pricing, so the argument, often is due to the *combined* impact of various policy instruments. Our analysis reveals that carbon pricing still has a significant effect even when we simultaneously account for the influence of these other factors (for similar findings see Döbbeling-Hildebrandt et al., 2024).

To better illustrate the actual effect of these policies, Figure 3 plots the CO_2 emissions for Portugal across the four sectors under analysis. The black lines show the observed CO_2 emissions. In contrast, the grey lines indicate how the emissions would have developed since 2000 if the policies identified in Table 1 had been adopted with the greatest stringency. The grey bands display the uncertainty involved. In the building sector, we only include taxes, as it appears unlikely that governments would implement taxes and emission trading schemes simultaneously. Across all four sectors, the figures show a substantial 'gap' between the actual and the hypothetical 'what-if' emissions. The overall emission savings since 2000 in the four sectors considered would add up to 538 Mt CO_2eq in the counterfactual compared to the actual scenario. This is equivalent to an entire emission-free year in a country such as South Korea in the four sectors under scrutiny (567 Mt CO_2eq). Remarkably, in the energy sector, the counterfactual and actual scenarios converge at the end of the observation period. This is

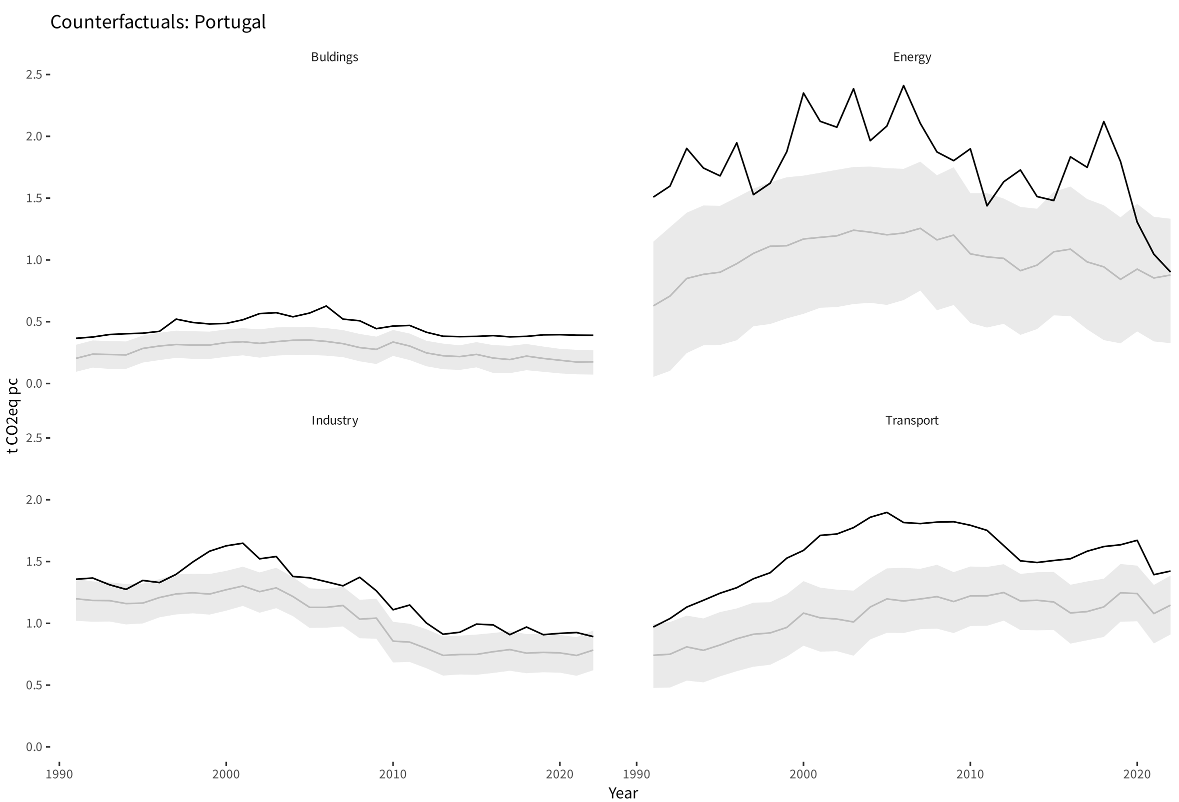

Figure 3. Emission trends with and without the most effective climate policies in four sectors.

Note: The figure shows CO_2 emissions in Portugal across four sectors. The black lines represent observed emissions, while the grey lines illustrate the projected emissions since 2000 if the policies from Table 1 had been implemented at their highest stringency. The grey bands indicate the associated uncertainty.

primarily because Portugal adopted the policies we identified as effective in the energy sector, such as a carbon tax on fossil fuels.[4] As a result, it is only natural, and a confirmation of our approach, that there are no longer significant differences between the two scenarios.

Figure 4 provides a comprehensive view of the anticipated reduction in CO_2 emissions for the transport sector across various countries under the scenario where each country fully implements identified climate policies at maximum stringency. This reduction potential indicates the disparity between the current status quo and a hypothetical scenario where optimal policies are enforced. The left side of the figure depicts the expected reduction in CO_2 emissions, showing the difference between actual emissions (black line) and the counterfactual scenario (grey line) as illustrated previously in Figure 3 for each country. The right side of Figure 4, in turn, presents countries based on their existing policy stringency. Countries with significant scope to introduce more stringent policies are marked in brown, while those that have maximized their policy stringency are shown in green.

Several countries, as highlighted in the upper half of Figure 4, have relatively lenient policies when it comes to the most effective ones identified above (roughly from Poland to India). Yet, countries with otherwise quite ambitious climate policies also have some 'blind spots' when it comes to the effective policies identified. For instance, several countries, particularly Germany, could enhance their climate action by adopting stricter speed limits on motorways. Similarly, countries like Australia, Canada, and Japan could significantly improve their efforts by adopting higher fossil fuel excise taxes. The provided figures (see again Figure 4 and Figures A22 to A24 in the Online Appendix) enable national policymakers, citizens, and interest groups to identify areas where the government could take more effective policies to tackle CO_2 emissions.

Figure 4 also illustrates that some countries, such as Sweden and Norway, have successfully introduced all the policies, albeit with varying levels of stringency. This suggests that the approach of implementing all these policies simultaneously may be challenging, but appears politically feasible in practice.

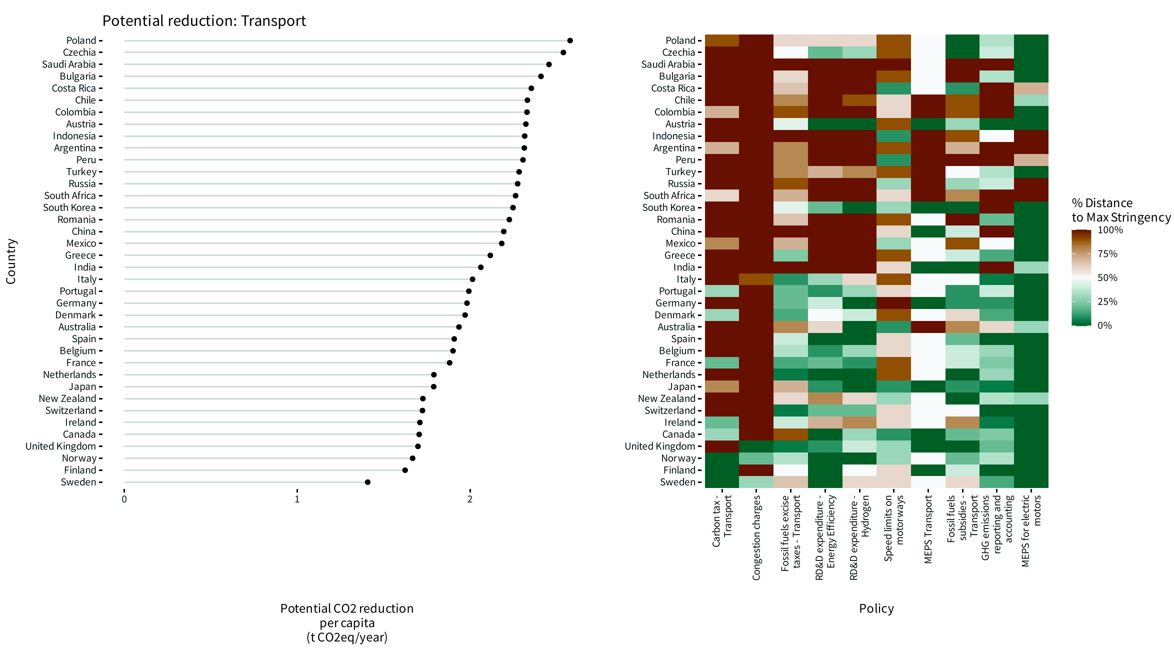

Figure 4. Emission reduction potential and policy options.

Note: Figure 4 illustrates the projected decrease in CO_2 emissions for the transport sector in different countries, assuming full implementation of identified climate policies at their highest stringency. The left side of the figure illustrates the expected reduction in CO_2 emissions if all identified effective climate policies are applied with maximum stringency. This visualization highlights the potential impact of fully leveraging these policies to mitigate emissions. The right side of the figure presents countries based on their current policy stringency. Countries marked in brown have not adopted the respective measures at all. Countries shown in green have already adopted the measures with full stringency, signifying they have maximized their policy efforts. Various shades in between brown and green represent intermediate states, where countries have adopted some measures to varying degrees of stringency.

We conduct various robustness checks. As shown in Figure A21 in the Online Appendix, our results remain unchanged even when we assume different lag structures and account for potential stringency outliers. Furthermore, the findings hold when we standardize stringency within the policy variables, enabling comparisons between policies with, e.g. stringency ranges of 0–10 and 0–5. This means we focus on the relative change within each policy rather than comparing absolute stringency levels across different policies. With this approach, we take account of the fact that stringency levels may not be directly comparable across different policies.

Additionally, we present a supplementary analysis in Online Appendix B that examines the effectiveness of policies in relation to time. In this section, we investigate three distinct time effects: first, we assess whether policies are more effective when adopted later; second, we analyze whether the effectiveness of policies increases the longer they remain in effect; and third, we explore whether policies become more effective with a greater time interval since the first country adopted them. The underlying logic here is that policies do not exhibit uniform effectiveness; rather, their impact may vary based on their timing and duration of implementation. Across these three additional model specifications, we identify ten policies which achieve statistical significance that are not observed in the baseline scenario. Notably, these policies are predominantly concentrated in the energy (see Figure A26 in the Online Appendix) and building sectors (see Figure A28 in the Online Appendix), while time appears to have a comparatively lesser influence in the transportation (see Figure A22 in the Online Appendix) and industrial sectors (see Figure A24 in the Online Appendix). In addition to the above-mentioned time effects, we investigated whether our results change when excluding the overall policy activity variable from our model. The inclusion of 'overall policy activity' may affect our findings due to its potential correlation with the primary independent variables (individual climate policies), raising potential multicollinearity issues. To address this, we ran our model without the policy activity variable (see Section B of the Online Appendix), and the results remained unchanged.

Discussion

As discussed above, our approach is among the first to assess climate measures' effectiveness comprehensively. One recent publication that has addressed the same issue is Stechemesser et al. (2024). Given that this paper received widespread academic and media attention, addresses the same broader research questions regarding the sorting of effective and ineffective policies, and utilizes the same dataset, we find it necessary to compare our results with those presented in this work. Table A5 in the online appendix thus compares our results with the findings of Stechemesser et al., using the Truncated T model as the reference. We distinguish between policies where our analysis aligns with that of Stechemesser et al. and cases where our analyses diverge. Within the latter category, we can further separate the cases into those where we identify an effect that Stechemesser does not, and those where the opposite applies. Overall, we have a quite high level of convergence (63 percent). However, the level of convergence varies significantly across different sectors. It is the highest (71 percent) in the transport sector and the lowest (56 percent) in the buildings sector. The divergence between our models mainly comes from 'false negatives', i.e. policy measures for which Stechemesser et al. find an effect but we do not.

At its core, these findings appear somewhat unexpected. Unlike Stechemesser et al., we do *not* have specific predictions about how changes in emissions will manifest, whether as abrupt shifts or more gradual adjustments in response to climate policies. Consequently, we would actually expect to observe more, rather than *fewer*, policies as effective. This suggests that the divergence must arise from the additional measures we employ to avoid false positives (see again Section E of the Online Appendix). When we relax these assumptions, the findings between the two studies converge more strongly, with approximately 83% agreement between the models. Overall, we consider these findings to strengthen the validity of both approaches. On one hand, these findings indicate that our approach is *not* at risk of recommending policies that ultimately prove ineffective; something that would be more likely if we identified a high number of effective policies that Stechemesser et al. did not identify as significant. On the other hand, high agreement between both approaches also suggests that, despite existing criticisms, Stechemesser et al. do not overlook a significant portion of effective policies.

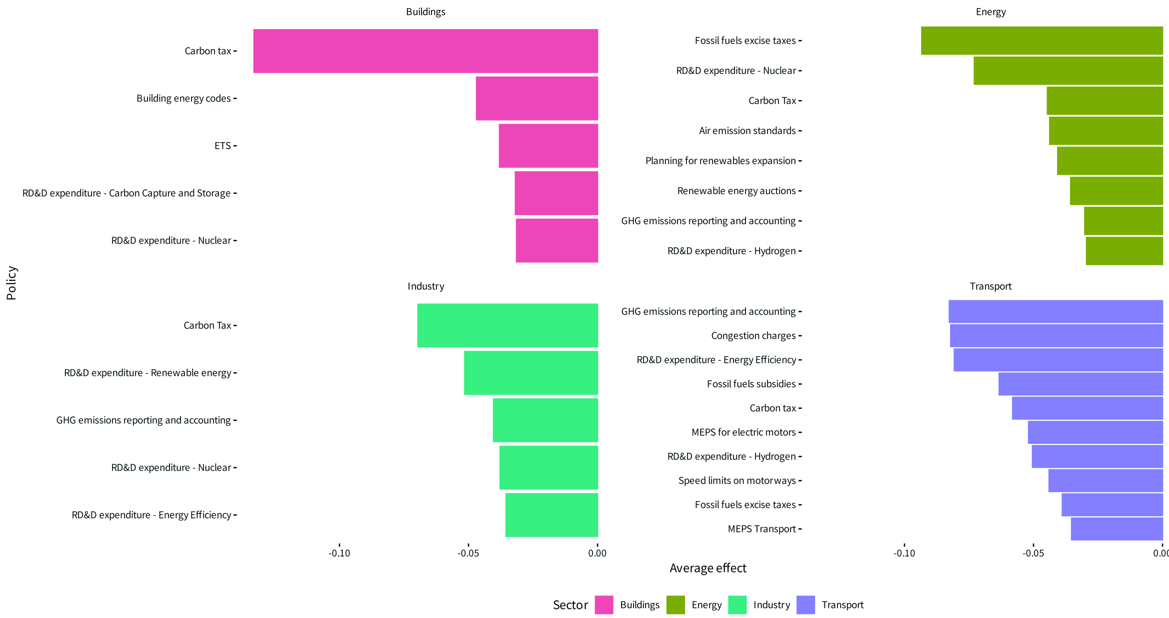

Figure 5. Figure of effective climate policies by sector.

Note: Effect size represents the change in emissions (t CO_2-equivalent per capita) for a one-standard-deviation increase in policy stringency with negative values indicating emission reductions.

Conclusion

Our results contribute to the discourse on climate policy in two primary ways. First, the findings of our study have important policy implications. Based on our analysis, we have compiled a comprehensive list of climate policies suitable for implementation 'across all seasons'. These policies demonstrate substantial effects on CO_2 emissions regardless of the policy context or specific conditions. In other words, if governments aim to ensure that their climate policies are effective, they should prioritize selecting from the list of policies presented in Figure 5. Measures are organized by sector and ranked by effect size.

Second, we have developed a novel approach for assessing the effectiveness of individual climate policies in the context of policy growth. This approach is easily adaptable and can be utilized in future analyses of climate policies. While we consider this method particularly relevant in climate policy – an area that has witnessed tremendous growth patterns over the past two decades – it can also inspire analyses in other policy areas. Recent publications have shown that policy growth and rising complexity are not restricted to relatively new and emerging policy areas such as climate policy but constitute a 'ubiquitous feature of modern democracies' (Limberg et al., 2023).

One aspect that may influence the results of this paper is the concern that focusing solely on climate policy could be too narrow. Recent research has highlighted the significant effects of industrial policies on carbon emissions and the detrimental impact of subsidies in various sectors (Bento et al., 2023). While this concern is valid, we argue that it actually *strengthens* our overall approach rather than undermining it. Our methodology is specifically designed to accommodate a broader range of policy data, enabling us to incorporate insights from different areas. Yet, available datasets on industrial policy are often limited in terms of time and geographic coverage (Evenett et al., 2024; Heinrich et al., 2025). Once more comprehensive industrial policy data becomes available, our analysis could be readily expanded to encompass other policies that may not be directly categorized as climate policy.

Notes

1. It might well be the case that some climate policies are only fully effective when accompanied by complementary policies specifically designed to suppress rebound effects of these policies; e.g., where energy or carbon efficiency improvements may lead to increased demand and emissions. Yet, our goal is to identify those policies that work effectively in every conceivable environment of other policies.
2. A Laplace prior enables us to perform a Lasso-like regression. Lasso (Least Absolute Shrinkage and Selection Operator) regression is a type of linear regression that includes an L1 penalty on the coefficients. Lasso regression prevents overfitting by introducing a penalty proportional to the sum of the absolute values of the model parameters (coefficients). This helps in identifying the most important variables and reducing the model's complexity.
3. We excluded all measures that aim to generally foster international cooperation in climate actions (e.g., participation in key trade agreements, engagement in climate initiatives agreements) and those that focus on broader capacity building (e.g., establishing an independent climate advisory board). This resulted in a refined selection of 47 concrete policy measures (from an initial 56) for our analysis.
4. Until 2020, the carbon tax rate was linked to the CO_2 prices of the European Union Emissions Trading System (EU ETS). However, due to a sharp rise in fuel prices, the government 'froze' the tax in 2022, opting to suspend the usual surcharge updates on CO_2 emissions. This decision effectively maintained the 2021 carbon tax rate throughout 2022. The freeze was lifted in 2023, restoring the regular update process for the carbon tax.

Author contributions

XFM, MH, CK and YS have made substantial contributions to the conception or design of the work or the acquisition, analysis, or interpretation of the data; drafted the work or revised it critically for important intellectual content; approved the completed version, and are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. XFM, MH, CK and YS have read and approved the final manuscript.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Adam, C., Steinebach, Y., & Knill, C. (2018). Neglected challenges to evidence-based policy-making: The problem of policy accumulation. *Policy Sciences*, *51*(3), 269–290. https://doi.org/10.1007/s11077-018-9318-4

Baker, J., Kammerer, M., Castro, P., & Ingold, K. (2025). The vertical policy harmonization indices: Assessing the gap between climate mitigation pledges and policies. *Climate Policy*, *25*, 1144–1159. https://doi.org/10.1080/14693062.2024.2443482

Bayer, P., & Aklin, M. (2020). The European Union emissions trading system reduced CO_2 emissions despite low prices. *Proceedings of the National Academy of Sciences*, *117*(16), 8804–8812. https://doi.org/10.1073/pnas.1918128117

Bento, A. M., Miller, N., Mookerjee, M., & Severnini, E. (2023). Incidental adaptation: The role of non-climate regulations. *Environmental and Resource Economics*, *86*(3), 305–343. https://doi.org/10.1007/s10640-023-00793-3

Bergquist, P., & Warshaw, C. (2023). How climate policy commitments influence energy systems and the economies of US states. *Nature Communications*, *14*(1), 4850. https://doi.org/10.1038/s41467-023-40560-y

IPCC. (2023). Climate change 2023: Synthesis report. In Core Writing Team, H. Lee, & J. Romero (Eds.), *Contribution of working groups I, II and III to the sixth assessment report of the intergovernmental panel on climate change* (pp. 35–115). IPCC.

Cui, J., Wang, C., Zhang, J., & Zheng, Y. (2021). The effectiveness of China's regional carbon market pilots in reducing firm emissions. *Proceedings of the National Academy of Sciences*, *118*(52), e2109912118. https://doi.org/10.1073/pnas.2109912118

Döbbeling-Hildebrandt, N., Miersch, K., Khanna, T. M., Bachelet, M., Bruns, S. B., Callaghan, M., Edenhofer, O., Flachsland, C., Forster, P. M., Kalkuhl, M., Koch, N., Lamb, W. F., Ohlendorf, N., Steckel, J. C., & Minx, J. C. (2024). Systematic review and meta-analysis of ex-post evaluations on the effectiveness of carbon pricing. *Nature Communications*, *15*(1), 4147. https://doi.org/10.1038/s41467-024-48512-w

Evenett, S., Jakubik, A., Martín, F., & Ruta, M. (2024). The return of industrial policy in data. *The World Economy*, *47*(7), 2762–2788. https://doi.org/10.1111/twec.13608

Fankhauser, S., Gennaioli, C., & Collins, M. (2016). Do international factors influence the passage of climate change legislation? *Climate Policy*, *16*(3), 318–331. https://doi.org/10.1080/14693062.2014.1000814

Fernández-i-Marín, X., Hinterleitner, M., Knill, C., & Steinebach, Y. (2024). Policy growth, implementation capacities, and the effect on policy performance. *Governance*, *37*(3), 927–945. https://doi.org/10.1111/gove.12816

Hanson, J. K., & Sigman, T. (2021). Leviathan's latent dimensions: Measuring state capacity for comparative political research. *The Journal of Politics*, *83*(4), 1495–1510. https://doi.org/10.1086/715066

Heinrich, C., Knill, C., & Steinebach, Y. (2025). Analyzing industrial policy portfolios. *Policy Sciences*, *58*(1), 87–109. https://doi.org/10.1007/s11077-024-09559-0

Hoppe, J., Hinder, B., Rafaty, R., Patt, A., & Grubb, M. (2023). Three decades of climate mitigation policy: What has it delivered? *Annual Review of Environment and Resources*, *48*(1), 615–650. https://doi.org/10.1146/annurev-environ-112321-103821

Limberg, J., Knill, C., & Steinebach, Y. (2023). Condemned to complexity? Growing state activity and complex policy systems. *Governance*, *36*(2), 575–608. https://doi.org/10.1111/gove.12684

Nachtigall, D., Lutz, L., Cárdenas Rodríguez, M., D'Arcangelo, F. M., Haščič, I., Kruse, T., & Pizarro, R. (2024). The climate actions and policies measurement framework: A database to monitor and assess countries' mitigation action. *Environmental and Resource Economics*, *87*(1), 191–217. https://doi.org/10.1007/s10640-023-00821-2

Nascimento, L., & Höhne, N. (2023). Expanding climate policy adoption improves national mitigation efforts. *npj Climate Action*, *2*(1), 12. https://doi.org/10.1038/s44168-023-00043-8

NewClimate Institute, Wageningen University and Research & PBL Netherlands Environmental Assessment Agency. (2023). Climate policy database. https://doi.org/10.5281/zenodo.10869734

Rosenbloom, D., Markard, J., Geels, F. W., & Fuenfschilling, L. (2020). Why carbon pricing is not sufficient to mitigate climate change—and how "sustainability transition policy" can help. *Proceedings of the National Academy of Sciences*, *117*(16), 8664–8668. https://doi.org/10.1073/pnas.2004093117

Schaub, S., Tosun, J., Jordan, A., & Enguer, J. (2022). Climate policy ambition: Exploring a policy density perspective. *Politics and Governance*, *10*(3), 226–238. https://doi.org/10.17645/pag.v10i3.5347

Stechemesser, A., Koch, N., Mark, E., Dilger, E., Klösel, P., Menicacci, L., Nachtigall, D., Pretis, F., Ritter, N., Schwarz, M., Vossen, H., & Wenzel, A. (2024). Climate policies that achieved major emission reductions: Global evidence from two decades. *Science*, *385*(6711), 884–892. https://doi.org/10.1126/science.adl6547

Steinebach, Y., Hinterleitner, M., Knill, C., & Fernández-i-Marín, X. (2024). A review of national climate policies via existing databases. *Nature Climate Action, 3*(80), 1–11..

UNEP. (2023). Emissions gap report 2023: Broken Record – Temperatures hit new highs, yet world fails to cut emissions (again). https://www.unep.org/resources/emissions-gap-report-2023