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Assessing and comparing the effects of public policies – a new approach

Xavier Fernández-i-Marín^a, Markus Hinterleitner^b, Christoph Knill^c and Yves Steinebach^d

^aFaculty of Law, Universitat de Barcelona, Barcelona, Spain; ^bSwiss Graduate School of Public Administration, University of Lausanne, Chavannes-près-Renens, Switzerland; ^cDepartment of Political Science, LMU Munich, Munich, Germany; ^dDepartment of Political Science, University of Oslo, Oslo, Norway


ABSTRACT

Assessing the effects of public policies is essential for academic and practical reasons. While existing approaches focus on the effects of individual policies or entire sectoral policy regimes, approaches that evaluate individual policies within the context of sectoral policy mixes are missing. This paper introduces a middle-ground approach called the Conditional Effects of Public Policies (CEPP) method. The CEPP approach uses a Bayesian-based procedure to (1) capture all policies in a specific area aimed at a particular outcome and (2) compare each policy's effect on that outcome. We demonstrate the analytical value of our approach for the 'Porter Hypothesis' in order to distinguish between environmental regulations that hinder or promote green innovations. Covering 21 OECD countries over two decades we show that while no environmental policy is universally 'good' or 'bad' in this regard, public investment programmes tend to be a driver of innovation. Hierarchical instruments by contrast show varied effects. Taken together, this paper not only provides a new method to assess policy effects in times of increasingly congested policy spaces, but also makes a clear contribution to a contested question in policy research, namely, whether and under which conditions environmental policies can offer benefits for the regulated companies.

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CONTACT Christoph Knill  christoph.knill@gsi.lmu.de  LMU Munich, Oettingenstraße 67, Munich 80538, Germany

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Introduction

Political analysts and policy-makers have a strong interest in assessing and comparing the consequences of governmental interventions. How strong is an environmental regulation's impact on a country's environmental performance? Does a specific social policy help to reduce economic inequality, or is another policy better suited for the job? Which governmental intervention promises to reduce the number of suicides in society? These questions animate scholarly research and guide debates among policy-makers in all policy areas, from social policy to environmental policy, climate policy, industrial policy, and migration policy.

The methodological approaches that have been developed to detect and compare 'policy effects' can be broadly clustered into two groups, both of which have their advantages but also display important shortcomings. For one, there is a plethora of approaches – from experimental to quasi-experimental to observational methods – that help to identify the effects of *individual policies* (Bennett & Checkel, 2015; Imbens & Lemieux, 2008). For example, randomised impact evaluations allow one to assess the social and employment outcomes of a community renewal programme (Glennerster & Takavarasha, 2013). While these approaches can identify different types of policy effects and quantify their exact size in particular settings, their results are difficult to generalise as the effect of a given policy might depend on the presence or absence of other policies in the 'mix' (Adam *et al.*, 2018). Although single-policy approaches of course aim at generalising their findings to other situations and contexts,¹ generalizability thus remains an untested assumption. Moreover, and even more important, single-policy analyses usually do *not* tell policy-makers how a policy's effect stacks up against (often very different) policy alternatives.

At the other end of the spectrum are aggregate approaches – such as regression analyses or macroeconomic models – that capture the effects of *a country's sectoral policy regime* in some area on various outcomes. Following this approach, scholars aggregate various policies into a single or composite index to provide a simplified yet comprehensive view of a country's sectoral policy regime (see, for example, the OECD Environmental Policy Stringency Index). These aggregated approaches can be used to identify relationships between 'macro-level' phenomena, such as the relationship between countries' migration regimes and international migration flows (De Haas *et al.*, 2019) or developments in CO₂ emissions based on the overall number of climate policies in place (Nachtigall *et al.*, 2024; Schaub *et al.*, 2022). While these approaches can identify the effect of the entirety of measures in place in a given policy area (Jochim & May, 2010; Wilson, 2000), it is often unclear which *parts* of a sectoral policy regime are mainly

responsible for certain effects, which parts are irrelevant, and which parts may even work in the opposite direction of the aggregated regime effect.

Hence, what is missing is a 'middle-ground' approach that can, first, discern and compare the impacts of the individual components while, second, taking into account and controlling for the influence of all other policies in a given sectoral policy regime on a predefined outcome. This paper introduces such a novel approach. We develop an analytical procedure that (i) succinctly captures all policies in a particular policy area that serve a predefined purpose, such as the improvement of air quality, the reduction of poverty, or the increase of education levels in society, and (ii) subsequently assesses each policy's association with the outcome dimension. This *Conditional Effects of Public Policies (CEPP) approach* – provides us with a concise overview of a particular policy regime and allows us to cluster its individual components into policies with positive, negative, and no association with the outcome dimension.

The CEPP approach structures a country's sectoral policy regime, i.e., the entire stock of policy arrangements in any particular area or subarea, by identifying all policy targets (who or what is addressed?) and all policy instruments (how are the targets addressed?) and arranging them in a two-dimensional space – where each 'box' represents a target-instrument combination. Subsequently, the CEPP approach draws on models developed in the area of genome-wide association studies (GWAS) and adapts them to the context of two-dimensional policy portfolios. GWAS models consecutively 'test hundreds of thousands of genetic variants across many genomes to find those statistically associated with a specific trait or disease' (Uffelmann *et al.*, 2021, p. 1). GWAS models can thus identify the associations of a multitude of individual, 'micro-level' parameters (i.e., genes) with a 'macro-level' outcome (i.e., a disease). An important peculiarity of our research problem is that the effectiveness of policies strongly depends on the presence or absence of other policies (e.g., technical prescriptions may only induce innovation activity among firms if they are accompanied by subsidies for R&D); a situation that easily may lead to over-parameterization, i.e., too many variables to estimate in a single regression analysis. To address this complication, we complement the GWAS logic with a Bayesian procedure that controls for the simultaneous presence (or absence) of other policy measures in the policy portfolio, thus yielding the *conditional effect* of each policy instrument. The CEPP approach provides researchers and practitioners with valuable insights into the individual effects of each policy measure within a mix. It accomplishes this by controlling for the interactions between public policies and safeguarding against potential biases, including those that could result from overfitting.

The paper is structured as follows. The first part develops the CEPP approach step-by-step. The second part of the paper illustrates the approach

'in action' by applying it to an empirical situation in which policy-makers seek to identify the best possible intervention(s) for a particular policy objective: We demonstrate how the CEPP approach can help policy-makers to detect those environmental policies that boost environmental innovation in the economy. We conclude by summarising the strengths of our approach and pointing to potential advancements to tackle its limitations. Moreover, we outline several exemplary situations in which the CEPP approach can be applied in the future and promises to be most useful for political scientists and policy-makers. The R code provided with this article enables scholars to implement and enhance the CEPP approach in their respective areas of interest and expertise.

Developing the CEPP approach

Our approach of assessing and comparing different policies within the context of a given sectoral policy regime involves two crucial steps: (i) a succinct overview of all policies within a policy sector; and (ii) an analytical procedure that allows one to identify the association of each policy with a predefined outcome dimension that is conditional on the existence of other policies.

Creation of the policy portfolio

The central challenge for assessing policy outputs is the need for an analytical concept that allows to compare policies of high substantive diversity. The public policy literature has developed various concepts in response to this problem, most prominently the classification by Hall (1993) which distinguishes between three 'components' of policies (or policy change events). According to this typology, a distinction is made between the broader goals that guide governments, the means they use, and the exact calibration of the instruments applied (see also Capano & Engeli, 2021; Howlett & Cashore, 2009). Our approach draws inspiration from this approach. We distinguish between the (1) policy targets addressed and the (2) policy instruments employed (Knill *et al.*, 2012). While policy targets are all of the issues addressed by the government, policy instruments are the means that governments have at their disposal to address the targets. While the instruments used vary across different policy areas, the literature typically distinguishes between command-and-control forms of governing (that attempt to change the behaviour of policy addressees by allowing or constraining certain choice opportunities, such as obligatory standards, prescriptions, entitlements, allowances, etc.), market-based instruments (that stimulate behavioural change via economic incentives, such as taxes or subsidies), and information-based instruments (that stimulate behavioural

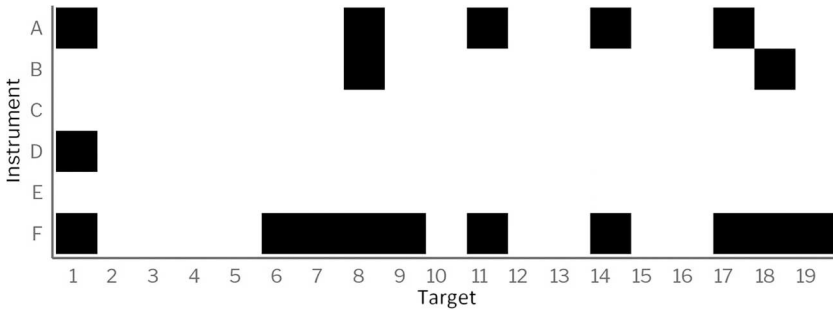


Figure 1. Example policy portfolio of a single country.

change by altering actors' beliefs and informational basis, such as campaigns, the provision of information access, or the communication of scientific evidence and data) (Hood & Margetts, 2007; Vedung, 2010).

The differentiation between policy targets and instruments creates a two-dimensional portfolio space (Fernandez-i-Marín *et al.*, 2021). Figure 1 illustrates this approach for a hypothetical policy domain. It shows a fictional policy portfolio consisting of policy targets (horizontal dimension) and policy instruments (vertical dimension). The policy portfolio changes whenever a target-instrument combination is added to or removed from the policy portfolio (i.e., a 'box' is added to or subtracted from the portfolio). This approach exhibits three advantages: (i) it can be applied to all kinds of policy sectors; (ii) it allows tracking the development of a policy portfolio over time; and (iii) it secures comparability between countries' policy portfolios. Together, these advantages create the basis for identifying the association of each policy (or 'box') contained in the portfolio with a predefined outcome variable.

The analytical procedure for the association of policies with the outcome variable

A challenge we face is that policy portfolios usually consist of many policies and that, in consequence, it is difficult to 'distil' which policy measures and combinations are ultimately associated with differences in the outcome dimension. Our proposed solution is inspired by GWAS, which confront a similar problem, i.e., to connect many micro-level factors or parameters (i.e., genes) to a macro-level outcome (i.e., a disease). The main idea of GWAS is to leverage advances in computational power and run individual regressions for hundreds of thousands of genes (while controlling for various health-relevant conditions). We adapt this idea for each box covered in the policy portfolio (see again Figure 1) while controlling for various factors that may likewise influence an outcome of interest.

An important peculiarity of our research problem is that the effectiveness of policies strongly depends on the presence or absence of other policies (Howlett & Rayner, 2013); a situation that easily may lead to over-parameterization, i.e., too many variables to estimate in a single regression analysis.

To address this complication, we complement the GWAS logic with a Bayesian procedure that controls for the simultaneous presence (or absence) of other policy measures in the policy portfolio, thus yielding the *conditional effect* of each policy instrument. Specifically, we employ a modified version of the GWAS approach that also considers all other boxes in the portfolio when conducting the regression for each policy contained in the portfolio. Mathematically, the difference between GWAS and our modified version of it can be expressed as follows. A GWAS unconditional analysis can be represented by a simple linear regression model running multiple times through different genes (g), defined by $\forall g \text{ in } G: Y_g = X_g\theta + \varepsilon$, where X_g would be a vector indicating each one of the genes, and the resulting θ set of unit vectors would be inferred from one regression at a time. Instead, our approach, where each association is conditional on all other policies contained in the portfolio, can be represented by $Y = X\theta + \varepsilon$, where X is a binary matrix indicating whether a specific policy is in place or not, and θ captures the association of a policy with a given outcome dimension, conditional on the whole set of extant policies.

Including all other existing policy measures into the analysis, however, comes with a distinct challenge. Even if one had several jurisdictions to compare over a larger time span, the high number of parameters to consider (here: policy target-instrument combinations) easily results in the problem of over-parameterization. Over-parameterization occurs when the analysis estimates too many parameters from a sample that is too small and that, in consequence, reaches ‘an upper limit to the complexity of the model that can be derived with any acceptable degree of uncertainty’ (Babyak, 2004). As Adam *et al.* (2018, p. 280) put it, ‘the combination of multiple independent variables in the form of policy parameters and limited sample sizes makes it highly unlikely to identify true effects, let alone true effect sizes for the individual components of the policy mix’.

To address this issue, we move from a frequentist to a Bayesian logic. Bayesian inference incorporates priors that enable inference and estimation when the data-to-parameters ratio is low. Setting priors allows us to consider pre-existing knowledge, beliefs, or assumptions about the parameters, which helps to constrain the potential parameter space and improves the accuracy of our estimates. This approach allows us to overcome the overparameterization problem and obtain more reliable estimates, even with limited data. We thus employ informative priors and initially set that the policies contained in the portfolio have no association at all with the outcome variable. The idea is that only policies overcoming this ‘hurdle’, i.e., those which show a strong

signal *despite* a prior of ‘zero’, will be estimated by the regression analysis. Those policies in the portfolio that do not clear this hurdle will not be estimated from the data and, in consequence, receive a value of zero. We thus filter out false positives and have numerical stability when estimating a model with few data points for each parameter. Overall, our modification of the GWAS approach (i) reduces the parameters to infer while (ii) still allowing us to consider the presence of ‘important’ other policies.

One way to implement this modification is to employ a Student’s *t*-distribution. This distribution can produce a prior with a strong density close to zero (mean zero and low standard deviation) but at the same time allows for long tails (low degrees of freedom), defined by $\theta \sim T(0, 0.1, 3)$. This specific prior helps us to set values close to zero as associations with ‘low’ signal, while (still) taking account of values away from zero as associations with a ‘strong’ signal. In [Figure 2](#), the red line represents a strongly informative prior while the black line represents a standard weakly informative prior with a normal distribution of a mean of zero and a standard deviation of one. Our main rationale behind employing such a strongly informative prior is to deal with weak signals in the association of a given policy with the outcome variable. In cases where the signal is weak, the prior acts to ‘pull’ the estimated value toward zero. As a result, we can estimate the associations of other policies with the outcome variable without being overly concerned about the noise introduced by the number of parameters that need to be estimated. This allows us to improve the overall robustness of our model.

Another advantage of Bayesian inference in our context is that we do *not* have to rely on arbitrary thresholds for *p*-values (Gill & Witko, 2013). Instead, we can quantify the degree of certainty that a particular parameter (policy measure) has a positive or negative association. To do so, we calculate the proportion of the posterior density that is either positive or negative. For parameters that have a clear signal (positive or negative), the value is close to one, whereas for policies with not enough signal, the value is close to 0.5,

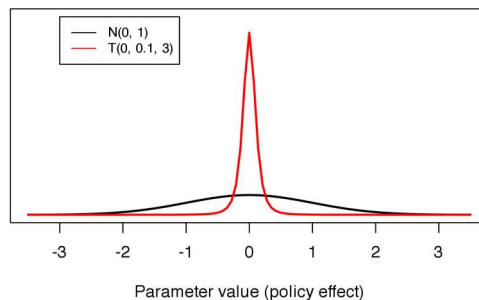


Figure 2. Comparison between a weakly informative prior (black) and a strongly informative prior (red).

implying that there is a 50:50 chance that the value is either positive (negative) or absent.

The results of the CEPP procedure can be illustrated by using the two-dimensional policy portfolio introduced in the previous section, where each 'box' represents a specific parameter (policy measure). We now fill these boxes with circles in different colours. Reddish circles indicate a positive association of a policy with a predefined outcome. Bluish circles signify a negative one. The stronger the colour and the larger the circle, the more likely it is that the association of a given policy is positive/negative. Boxes (target-instrument-combination) coloured in white have neither a strong positive nor negative association with the outcome dimension. Crossed-out fields have simply not been addressed (so far).

Figure 3 pictures this approach for the hypothetical policy portfolio presented in Figure 1. Of the 18 policies in the portfolio, five policies have a positive association with the predefined outcome (red boxes), four policies have a negative association (blue boxes), and nine policies have no association (blank boxes). Furthermore, the figure illustrates that the policies vary in their degree of certainty in having either a positive or negative association. For instance, the policies presented as B8 and F11 are much more likely to have a positive effect on the outcome than the policies in A8, F1, and F18. It is important to highlight that this approach also allows for the consideration of policies from different levels of government, i.e., policies originating from supranational, national, and even the subnational level.

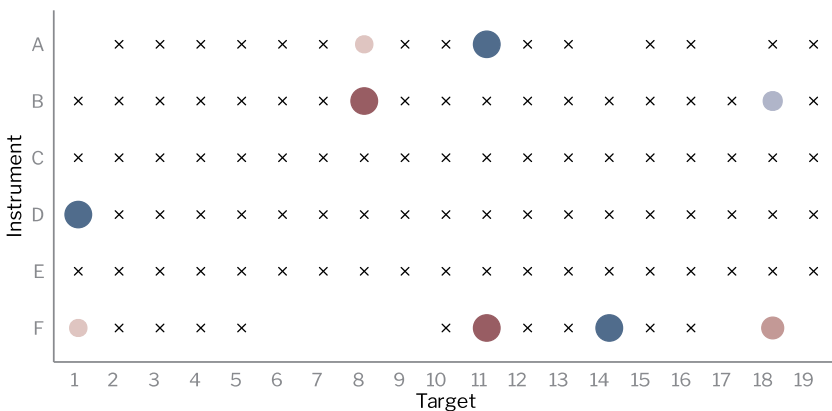


Figure 3. The CEPP approach applied to a hypothetical policy portfolio.

Note: Shades of red (blue) indicate a positive (negative) association of a target-instrument-combination with a predefined outcome. The stronger the colour, the more likely it is that there is an association. Boxes (target-instrument combinations) coloured in white have neither a strong positive nor negative association with the outcome dimension. Crossed-out spaces indicate that a (theoretically possible) target-instrument combination does not exist in a country's portfolio.

It is also possible to summarise the effect of policies by their instrument type. This representation allows us to quickly understand whether a particular instrument type, such as taxes or obligatory standards, generally has a positive or negative association with the outcome of interest, as well as the corresponding level of uncertainty. To do this, we simply take the mean probability of all red boxes contained in one row of the policy portfolio (e.g., the average positive association of the policies F1, F11, and F18 in Figure 4). The same can be done for all policies in the same row exhibiting a negative association, i.e., the blue boxes. By comparing the average association of each instrument type, we can determine whether they have no association, a positive association, a negative association, or an ambivalent association with the outcome dimension. Figure 4 summarises this idea: Instrument types that tend to be positively associated with the outcome dimension are located to the right of the diagonal ($CEPP > 0$, horizontal axis), while instrument types that tend to be negatively associated with the outcome dimension are located to the left of the diagonal ($CEPP < 0$, vertical axis). The further an instrument type is placed along the axes, the higher is the likelihood of positive/negative associations. Finally, instrument types with neither positive nor negative associations (lower left quadrant) and those

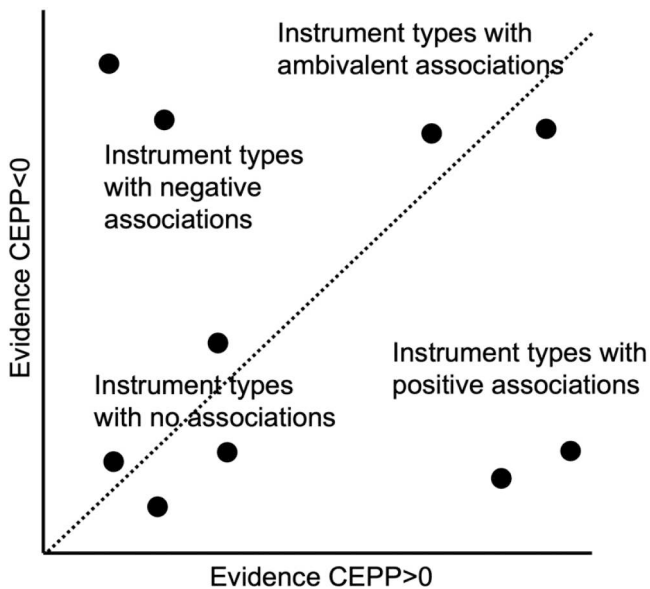


Figure 4. Mapping policy instruments based on their association with the outcome dimension.

Note: The axes indicate the probability that a certain instrument type has a positive (x-axis) and/or negative (y-axis) association with a predefined outcome. The black dots represent hypothetical policy instrument types.

with both positive and negative associations (upper right quadrant) are on or close to the diagonal.

In sum, the CEPP approach allows us to assess and compare the associations of individual policies with an outcome variable within the context of a larger sectoral policy regime. It provides a concise overview of a particular sectoral policy regime and clusters its components into policies with positive, negative, and no associations with the outcome dimension. The CEPP approach is not restricted to the assessment of specific outcomes but can be universally applied to *any* outcome dimension that is of analytical interest, including, for instance, the achievement of sectoral performance objectives (improvement of environmental quality or the reduction of poverty), but also any other potential consequences emerging from individual policies, such as effects on R&D investment, foreign direct investment, social equality, or innovation.

In the following, we illustrate the CEPP approach by showing how it can distinguish between environmental regulations that hamper and foster green innovations, thus illuminating a contested aspect of the 'Porter Hypothesis'.

Empirical application: the influence of environmental regulations on innovation

We show the CEPP approach 'in action' by assessing and comparing the associations of environmental policies with environmental innovation. There is a large interdisciplinary literature on the so-called 'Porter Hypothesis', which suggests that well-designed environmental regulations can actually boost environmental innovation in the economy (Porter & van der Linde, 1995a, 1995b). When the Porter Hypothesis was first formulated, it presented a sharp repudiation of conventional wisdom, which long assumed that environmental protection comes at an additional cost to firms and might thus erode their global competitiveness. The argument behind this conventional view is that environmental regulations, such as taxes or technological standards, force firms to allocate resources to environmental protection, thereby diverting capital away from more productive investments and activities. Porter and van der Linde (1995a, p. 98) challenged this view by suggesting that well-designed environmental regulations can 'trigger innovation that may partially or more than fully offset the costs of complying with them'. The reason is that 'pollution is often a waste of resources and that a reduction in pollution may lead to an improvement in the productivity with which resources are used' (Ambec *et al.*, 2013, p. 3).

The research programme that has developed in order to test and refine the Porter Hypothesis (for overviews, see e.g., Ambec *et al.*, 2013; Cohen & Tubb,

2018; Dechezleprêtre & Sato, 2017; Lankoski, 2009) constitutes an ideal background for illustrating the CEPP approach. First, and with regard to substantive reasons, the Porter Hypothesis claims that only *specific* environmental regulations have a positive impact on environmental innovation and, by extension, economic competitiveness; an aspect that turns the comparison of (very different) regulations and their effects into a major research focus. Second, there is a multitude of insights available that allow us to benchmark our results against those of previous studies to assess their reasonableness. And finally, this area of application allows us to demonstrate that even in the context of a well-developed and dense research programme, the CEPP approach can still create new (and more nuanced) knowledge than previous research efforts and thereby help to advance a research programme.

The existing literature distinguishes between three versions of the Porter Hypothesis (Ambec *et al.*, 2013; Jaffe & Palmer, 1997). The ‘weak’ version simply states that properly designed regulations can spur environmental innovation while leaving open the question of whether this innovation is actually good or bad for firms. The ‘strong’ version goes further in claiming that regulation-induced innovation often offsets firms’ additional regulatory costs and hence boosts their competitiveness. Finally, the ‘narrow’ version of the Porter Hypothesis argues that flexible regulations provide greater incentives to firms to innovate than prescriptive forms of regulation.

Our empirical focus in the following is on the weak and the narrow versions of the Porter Hypothesis, as they are centrally concerned with the *design* of environmental regulations and claim that only *specific types* of regulations have a positive influence on innovation while other types do not (or to a much lower extent). Porter and van der Linde (1995a, p. 110) state that innovation-enhancing environmental regulations should adhere to three principles:

First, they must create the maximum opportunity for innovation, leaving the approach to innovation to industry and not the standard-setting agency. Second, regulations should foster continuous improvement, rather than locking in any particular technology. Third, the regulatory process should leave as little room as possible for uncertainty at every stage.

It follows from these principles that market-based instruments such as emission taxes, auctioned emission permits, or subsidies are more conducive to innovation than command-and-control regulations such as performance standards or technology mandates ‘because they leave more freedom to firms to find a technological solution to minimize compliance costs’ (Ambec *et al.*, 2013, p. 13; Fischer *et al.*, 2003). However, the empirical evidence on the relative advantage of market-based over command-and-control regulations is mixed (Dechezleprêtre & Sato, 2017). While some studies suggest that market-based instruments lead to more innovation than command-and-control instruments (Driesen, 2005; Lanoie *et al.*, 2011), other studies show that also

command-and-control instruments can have innovation-enhancing effects and that a switch to market-based instruments can even lead to less innovation activity among firms (Popp, 2003; Taylor, 2012). In the following, we demonstrate how the CEPP approach can help to illuminate this contested aspect of the Porter Hypothesis and distinguish between ‘good’ and ‘bad’ environmental regulation (Ambec *et al.*, 2013, p. 12). In this context, ‘good’ environmental policies are those that spur innovation and green patenting, whereas ‘bad’ ones crowd out investment and thus hinder innovation.

Patent applications as a measure of innovation activity

To relate our results to previous findings, we follow established conventions and use the number of environment-related patent applications to measure the dependent variable, i.e., the level of green innovation activity in the economy (Brunnermeier & Cohen, 2003; Jaffe & Palmer, 1997). The innovation process can be divided into three stages. The first stage involves the birth of an idea, which is the spark that ignites the entire innovation process. At the second stage, the idea is developed and transformed into a commercially viable product through patent registration. Finally, for the innovation to have a real impact, it must spread across the economy, reaching a wider audience and generating significant benefits. In line with previous research, our empirical research concentrates on the second stage of the innovation process, which involves converting an invention into a patent for commercial gains (Lim & Prakash, 2023). As an indicator of environmental innovation, we thus use the number of annual patent applications in domains that are classified as environmental-related or green innovation. The patent statistics are sourced from the OECD Database on ‘Science, Technology and Patents’, and the year of the application is based on the priority date, which corresponds to the first filing worldwide and is, therefore, closest to the invention date. We do not distinguish between patent applications filed at the European Patent Office (EPO) or the US Patent and Trademark Office (USPTO), as both offices are major players in the global patent landscape. The patent statistics are available from 1999 onwards and thus determine the length of our investigation period (1999–2020).

Creating an environmental policy portfolio

There are generally two approaches for gathering information on policy portfolios. The ‘inductive’ approach implies to identify all policy targets and instruments while coding. This means that the data collection is *not* restrained by predefined categories, allowing a comprehensive overview of all policy targets and instruments as specified within national legislation. Alternatively, one can opt for a ‘deductive’ approach. In this approach,

researchers establish a predefined set of significant policy targets and instruments based on prior literature and insights. The principal advantage of the deductive method is its superior efficiency in terms of data collection and the better comparability of coding categories both across countries and over time. In this paper, we rely on the second approach. In other words, we use a predefined set of environmental policies for which effects on green innovation can be reasonably expected. Specifically, we rely on data collected in the context of the CONSENSUS and ACCUPOL sprojects. We identified all environmental policies adopted in 23 OECD countries over approximately two decades (1999–2020), leading to a total of 506 country-year observations.

The countries analysed are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Mexico, Portugal, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States of America. Changes in policy targets (*what exactly is being addressed?*) and policy instruments (*how is it addressed?*) over time were assessed through a content analysis of all relevant national legislation adopted throughout the observation period. We collected national legislation through national legal repositories and other legal databases such as ECOLEX. Additional checks on data reliability were carried out using legal commentaries and secondary literature. A detailed coding manual helped to systematically extract relevant information (policy targets and instruments) from the legal documents. Policies stemming from EU Directives are involved in the analysis as they need to be transposed at the national level. EU regulations that immediately enter into force, by contrast, are not part of the dataset used.

We identified the 48 most addressed policy targets across three policy subfields that make up environmental policy: clean air, water conservation, and nature conservation policies (see Online Appendix Part A). Moreover, we distinguished between 10 types of policy instruments (plus one residual category). These instruments cover command-and-control (obligatory standards, prohibitions, permits, etc.), market-based (subsidies, public investments, taxes, etc.), and information-based forms of governmental intervention. [Table 1](#) lists all policy instruments considered.

Overall, the combination of 46 policy targets and 10 policy instruments provides us with a policy portfolio that can contain up to 480 target-instrument-combinations whose association with the number of successful environment-related patent applications could be theoretically identified (see [Figure 5](#)). Out of the 480 policies that can theoretically be adopted, 336 have actually been adopted in at least one country-year observation in our data. These binary indicators observed (target-instrument combinations yes/no) for each country and year constitute the primary source of explanatory variables in the X matrix.

Table 1. Policy instruments under analysis.

Instrument type	Description
Obligatory standard	A legally enforceable numerical standard, typically involving a measurement unit, e.g., mg/l or mg/km
Prohibition/ ban	Total or partial prohibition/ ban on certain emissions, activities, products etc.
Technological prescription	A measure prescribing the use of a specific technique or technology
Tax/ levy	A tax or levy for a certain polluting product or activity
Subsidy/ tax reduction	A measure by which governments grant a financial advantage to a certain product or activity
Liability scheme	A measure that allocates the costs of climate damage to those who have caused the damage. In our case, this includes emission trading schemes.
Public investments programmes	Specific public investment; investment in research and development
Information-based instrument	The dissemination of information and knowledge to achieve its intended objectives
Permits	Permit to pollute the atmosphere or to produce/import/export/sell climate harmful products
Voluntary instrument	Voluntary agreements or commitments (focus on sectoral or umbrella organisations)

Model specification

We assess the association between distinct target-instrument combinations and green innovation against several confounders. Independently of the specific policy measures adopted, it likely makes a difference how much (or little) a government does in environmental matters. Higher portfolio sizes should – irrespective of the concrete policies applied – signal a stronger governmental commitment to foster environmental policy which in turn should affect the innovation orientation in the economy. Second, we control for the population size (logged) and the level of economic prosperity (GDP per capita). Third, we control for labour costs and the government’s tax revenues. Both aspects can be expected to have an indirect impact on the innovation

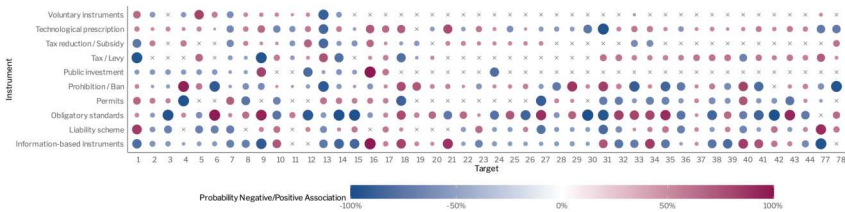


Figure 5. Probability of associations between environmental policies and green innovations for different target-instrument combinations.

Note: Shades of red (blue) indicate a positive (negative) association between environmental policies and green innovations for different target-instrument combinations. The stronger the colour and the larger the circle, the more likely it is that the corresponding association occurs. Boxes (target-instrument combinations) that are only very weakly coloured have neither a strong positive nor negative association with the outcome dimension. Crossed-out spaces indicate target-instrument combinations that do not exist in the country sample. Tabular results for this figure can be found in Online Appendix Part B2.

level as they determine the money left for firms' investment in innovation. Fourth, we control for the share of large firms (above 250 employees) in a country's economy. Existing research indicates that factors that hamper innovation are often more striking in small firms (Andries & Stephan, 2019). Moreover, large firms typically dominate R&D investment in most countries. Another factor that may vary across countries and affect the level of green innovation is the innovation capacity within the population/workforce. We measure this aspect by tertiary enrolment rates, i.e., the percentage of high school graduates successfully enrolling into university. Lastly, we control for trade openness. There is ample evidence that trade openness generates an increase in foreign direct investment. In consequence, countries that are more open to international business tend to attract larger amounts of investment from abroad that encourage innovation and technological transfer. Trade openness can be measured as the sum of a country's exports and imports as a share of that country's GDP. The additional data required to measure the control variables is made readily available by the OECD or the World Bank. In our notation, the control variables are captured in the CV matrix. In addition to these control variables, our final model includes a non-nested set of varying intercepts by country (δ_c) and year (γ_y). Moreover, it controls for temporal and spatial dynamics in the error term by adding an auto-regressive component (AR1, captured by ρ_c) and country-clustered standard error (σ_c). Our final model can be summarised as follows:

$Y_{c,y} \sim$	$\mathcal{N}(\mu_{c,y}, \sigma_c)$	Main data component
$\mu_{c,y} =$	$\delta_c + \gamma_y + CV * \beta + X_{i,t} * \theta_{i,t} + \rho_c * (Y_{c,y-1} - \mu_{c,y-1})$	Main linear model
$\sigma_c \sim$	$\mathcal{U}(0, 10)$	Error component
$\delta_c, \gamma_y, \beta_{cv} \sim$	$\mathcal{N}(0, 1)$	Priors for varying intercepts and explanatory variables
$\rho_c \sim$	$\mathcal{U}(-1, 1)$	Prior for the AR(1) process
$\theta_{i,t} \sim$	$\mathcal{T}(0, 0.1, 3)$	Priors for main effects of portfolio spaces

Where:

- c : Country
- y : Year
- cv : Control variables
- i : Instrument
- t : Target
- $y_{c,y}$: Continuous variable with the number of patents for a specific country

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- CV : Matrix with the control variables and covariates.
- $X_{i,t}$: Matrix with the explanatory values for each covariate (v).
- σ : Standard deviation of the model.
- δ : Country effects.
- γ : Year effects.
- β : Effects of control variables.
- ρ_c : AR(1) parameter.
- θ : Effects of portfolio spaces. Main parameters of interest.

Figure 5 presents the main results of our analysis. Boxes filled with red circles indicate a positive association of a different target-instrument-combination with the number of patent applications. Blue circles, by contrast, indicate a negative association. The colour intensity and size of the circle capture the

probability (certainty) that the identified association is positive or negative. Boxes that are only weakly coloured with a small circle thus indicate an association that is neither clearly positive nor clearly negative. Crossed-out boxes represent target-instrument-combinations that were never adopted in our country sample.

The figure reveals strong variation in the observed associations not only across different instruments but also with regard to the association of the same instrument type with different targets. Yet, despite this variation, two important initial observations can be made. First, it becomes apparent that for some instrument types, the probability of a negative or positive association is generally much higher than for other types. For instance, it seems far more likely that obligatory standards make a significant difference compared to voluntary instruments. Second, certain instrument types are characterised by the dominance of more positive associations (such as public investments), while for others (tax/levy or permits) the negative associations with innovation are more pronounced.

In order to gain a better understanding of the observed patterns, we summarise our findings for different types of policy instruments. As described in the theoretical section, we calculate the average probability values for each policy instrument (column), considering all targets. For each instrument type, this analysis is conducted separately for target-instrument combinations that have positive and those that have negative associations with green patent applications. By presenting this information separately, we can distinguish between instrument types that, in the aggregate, have (i) no/a weak, (ii) a positive, (iii) a negative, or (iv) a rather ambivalent association with the outcome dimension.

Figure 6 pictures the results. This figure is based on the two-dimensional graph presented in Figure 4 where the x-axis represents the probability that the observed positive associations are actually positive, while the y-axis displays the same probability for negative associations. Overall, we can identify three distinct clusters of policy instruments based on their association with a country's number of environmental patent applications. These clusters exhibit significant differences in the likelihood that certain types of instruments are positively or negatively correlated with green innovation.

The lower-left area of the graph shows several instrument types with weak associations. These instruments seem unlikely to have either a significant positive or negative impact on environmental patenting. Public investments are located in the lower-right corner of the graph, suggesting a high probability of a *positive* association with environmental patent applications. The likelihood of a negative association, by contrast, is relatively low for public investments. Similarly, information-based instruments are likely to have a positive association with environmental patenting but with a slightly higher chance of also involving negative consequences. Obligatory standards

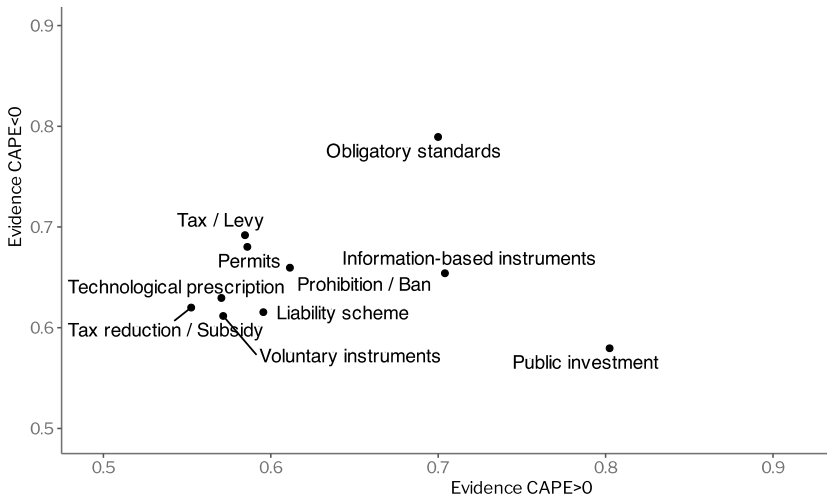


Figure 6. Probability of associations between environmental policies and green innovations per instrument type.

Note: The axes indicate the probability that a certain instrument type has a positive (x-axis) and/or negative (y-axis) association with a predefined outcome.

are located in the upper-right corner. This implies that they tend to have more ambivalent associations. While obligatory standards seem to promote environmental patenting in some cases (policy targets), they might hamper innovation in others. Remarkably, there are no policy instruments in the upper-left corner, implying that there are *no* environmental policies that seem to generally stifle innovation.

Our empirical findings are consistent with the existing literature on the Porter hypothesis. First, we find no evidence suggesting that environmental policy generally hamper innovation. This is in line with the (core) assumption that environmental protection can promote innovation *without* negatively impacting firms' innovation capacity or performance. Second, also our findings on the quite ambivalent nature of obligatory standards align with the current state-of-the-art. Previous research has shown that the effectiveness of hierarchical interventions varies depending on the exact policy and area being analysed. While our findings reflect this mixed evidence, the CEPP approach provides indications in which areas (policy targets) regulation may help to foster innovation and where it may hinder it. Third, while the effects of public investment programmes have not yet been addressed extensively in the literature on the Porter hypothesis, recent scholarly contributions on 'green growth' and stimulus packages have found that public investments are a powerful tool to boost green innovation (Böhringer *et al.*, 2012; O'Callaghan *et al.*, 2022). A remarkable difference from previous studies is that we actually find *no* association between patent applications and more

market-based instruments, such as taxes and liability schemes (see e.g., Lim & Prakash, 2023). This may be because these instruments ‘lose’ effectiveness once the (simultaneous) impact of additional policy measures is considered, as done by the CEPP approach.

In summary, our findings indicate that our approach strikes a good balance between sectoral regime approaches and those focused on individual policy measures (see e.g., Lim & Prakash, 2023). An essential highlight of our analysis is the finding that environmental policies are not inherently ‘good’ or ‘bad’ in terms of driving green innovation, but rather have different impacts depending on the policy target addressed (see Figure 5) and the instrument type used (see Figure 6).

Moreover, by controlling for the existence of various policy measures, we address a critical limitation of analyses that focus solely on the functioning of single instrument types. For instance, market-based instruments appear to have a much weaker effect on innovation when considering the parallel influence of other policy measures. Such ‘narrow’ analyses often fail to account for the influence of other policies within the mix. In contrast, our approach ensures a more comprehensive understanding of how certain instruments might function across different contexts. We can thus be confident that the instruments and target-instrument combinations we have identified as effective will deliver similar outcomes when applied in other policy environments.

Our empirical application of the CEPP approach can be subjected to at least five potential critiques. The first critique pertains to the timing of the government’s adoption of policies to promote green innovation. It is possible to argue that the impact of policies depends not only on whether or not they are adopted but rather on when governments choose to regulate a certain issue. Policies may be more effective in fostering innovation when they are introduced to address a particular issue for the first time. In countries that are considered ‘late-movers’, companies may opt to acquire innovations developed in ‘first-mover’ countries rather than investing in their own innovation efforts. As a result, these companies may rely on purchasing or licensing existing innovations instead of actively engaging in the process of developing new ideas themselves. To address the potential impact of a government’s timing in adopting policies to promote green innovation, we replicated our previous analysis and introduced a ‘premium’ (dummy) for leaders whenever a government is the first to adopt a target-instrument combination. As illustrated in Figures 6 and 7 in the Online Appendix, our key results remain unchanged.

A second concern is that the analysis does not adequately take into account differences in the *setting* of policy instruments. Emission trading schemes, for example, might only have a significant impact on emission levels once a certain CO₂ price level has been reached. Incorporating the

setting in our analysis is generally difficult as we are interested in the differences across instruments. In other words, we need some assumptions about how to compare the stringency of different instrument types. For instance, we must determine whether the emission limit of 95 g/CO₂ per km for a passenger car is more or less stringent than e.g., a taxation of 50 Dollars per ton CO₂.² In our study, we tackle this issue by examining the average correlation between a policy tool and its resulting outcome. While the effectiveness of a policy may fluctuate depending on its exact stringency or setting, on average, the effects likely correspond to what we observe. Despite this approach, however, there is still the potential that our findings are influenced by countries adopting *exceptionally* ambitious environmental policies. To address this issue, we replicated our study, this time controlling for the environmental regulatory stringency as provided by the OECD. Even though this metric covers fewer instruments than we originally considered and combines individual measures into an aggregate stringency index, it still offers insights into the overall ambitiousness of the policy measures taken. As demonstrated in Figures 12 and 13 in the Online Appendix, the inclusion of stringency in our analysis does not affect our key results.

A third concern could be that whether or not certain policy instruments have a positive or negative association with green innovation is endogenous to a country's political economy. For instance, governments may be inclined to simply prioritise investments in technologies that align with the strengths of their domestic industries. In consequence, governments may finance the development of technologies that would also be developed in the absence of public investment programmes. Likewise, the selection of certain policy measures (instruments) can reveal specific power structures within a given context, with the choice of instruments often reflecting what is feasible in that particular environment (Lascoumes & Le Galès, 2007). To tackle this potential shortcoming of our analysis, we employ propensity score matching. This technique involves estimating the probability of a 'treatment' (the existence/adoption of a certain target-instrument-combination) based on observable covariates and matching treated and control units with similar propensity scores. By using propensity score matching, the association between policy measures and outcomes can be estimated more accurately, as the comparison groups are more similar regarding observable characteristics, reducing the impact of confounding variables and selection bias. As common in the literature, we match our cases based on those variables we identified as important in the previous analysis to estimate our outcome of interest, i.e., the number of green patents at the national level. As shown in Figures 8 and 9 in the Online Appendix, this procedure slightly alters our findings. Most importantly, public investments move from the lower right corner towards the diagonal. This implies that once we consider the unique

economic and political characteristics of the countries being studied, public investments are no longer exclusively a good thing but – just as obligatory standards – must be treated with caution as they might both promote and hamper innovation. The latter might be the case if, for example, governments overinvest in certain technologies or branches and, through this, crowd out innovation in other areas. Or, if public investment programmes are too prescriptive in terms of the types of projects they support, they may limit the range of innovative ideas that are pursued.

A fourth issue to consider is policy instruments may show heterogeneous effects depending on the level of economic development. Figure 14 in the online appendix illustrates this by plotting the main effects of these instruments against the interaction effects moderated by the level of economic development. The figure suggests that for hierarchical forms of intervention, such as regulations, there is no systematic variation in their effects. In contrast, the innovation-stimulating function of market-based and particularly soft instruments, like information dissemination, appears to be influenced by the level of economic development. In the context of low economic development, the effects of these instruments are stronger while in the context of high economic development they are weaker. One possible explanation for this phenomenon is a ‘ceiling effect’ on innovation. In highly developed economies, industries may have already achieved high levels of innovation and efficiency. Consequently, these industries may be less strongly stimulated by ‘softer’ forms of governmental intervention, such as information measures.

A last concern of our approach is the risk of false positives. With a large number of analyses being performed, there is a certain chance of finding significant associations by chance alone, even when there is no true underlying association between environmental policies and green innovation. To address this issue, researchers using the GWAS approach apply statistical methods to ‘correct’ for the large number of statistical tests performed, such as the Bonferroni correction or the false discovery rate (FDR) correction. As shown in Table 9 in the Online Appendix, our use of a Student’s *t*-distribution with highly informative priors addresses this concern. With our approach, we have been able to reduce the share of statistically significant results to approximately 4 per cent at the 95 per cent confidence level. When we combine our CEPP approach with propensity score matching (see discussion above), this value even drops to approximately 1 per cent. In comparison to this, a plain frequentist unconditional approach would lead to about 46 per cent of statistically significant results by mere chance. The FDR correction would decrease this to 38 per cent, and the Bonferroni correction to 19 per cent. Our approach has thus proven to be effective not only in dealing with the issue of overparameterization but also in reducing the risk of detecting associations when there is actually *no* true effect.

Discussion

In the previous section, we demonstrated the application of the CEPP approach in the context of environmental regulation, i.e., we analysed which policy measures foster or hamper green innovation. Moreover, we showed that the CEPP approach can be refined in important dimensions so that it more comprehensively captures the specificities of a particular research situation (i.e., first-mover advantages; jurisdiction-specific policy adoption logics; elimination of false positives; 'effect sizes'). But can the CEPP approach also be applied in other contexts, and if so, what does it take to make it work?

In essence, our approach can be applied in *all* contexts and policy areas as long as researchers have the following ingredients at hand: First, they need information about policy targets and instruments across different jurisdictions. Whether these jurisdictions are municipalities, states, or countries does *not* play a role as long as there is some variation in the policy instruments used. Likewise, it does not make a difference whether a policy area is characterised by many or only a few policy targets and instruments. This also implies that it does not matter whether the conceptualisation of policy sectors or regimes is rather broad (e.g., environmental policy) or narrow (e.g., water or clean air policy). Yet, the CEPP approach seems most suitable when the number of policies exceeds what can be easily handled with careful examination or cogitation (May, 1991). There are, by contrast, no 'upper limits' of policy complexity that can be handled by the CEPP approach. However, more policy targets and instruments require stronger priors to filter out the most relevant target-instrument combinations. In consequence, with a growing number of policy targets and instruments, the final results increasingly depend on the methodological choices made. [Table 2](#) provides a brief overview of available datasets that could be used to apply the CEPP approach. This list is *not* exhaustive but covers databases from different policy areas.

Conclusion

Assessing the effects of public policies is a central concern for political science. While a plethora of approaches exist, they usually focus on the effects of single policies or of entire sectoral policy regimes. This article complemented the existing literature through an approach that covers the 'middle-ground', i.e., situations where scholars and policy-makers are interested in comparing the effects of all relevant policies on a predefined outcome. As we have shown in our empirical application, the CEPP approach allows us to identify constellations in which certain policy instruments no

Table 2. Available databases suitable for the CEPP approach.

Policy Areas	Dataset	Nr of Policy Targets and Instruments	Jurisdiction	Potential Outcome Variables
<i>Climate Policy</i>	CLIMATE POLICY database	9 policy targets; 9 policy instruments	198 countries (national and subnational level)	Reduction in CO2 emissions
<i>Gun Control Policy</i>	MORAPOL database	1 policy target (gun owners); 11 policy instruments	16 countries (national level)	Homicide rate
<i>Plastic Regulation</i>	REGCRIC database	23 policy targets; 17 policy instruments	12 countries (national level)	Plastic waste produced Recycling rates
<i>Migration Policy</i>	DEMIG POLICY database	14 policy targets (migrant categories); 28 policy instruments	45 countries (national level)	Migration flows
<i>Social Policy</i>	SPIN database	7 policy targets; 16 policy instruments	40 countries (national level)	Child or poverty rate

longer exhibit positive effects on a certain outcome once the effects of other instruments are considered.

The CEPP approach consists of two crucial steps: (i) a succinct overview of all policies within a policy sector that structures them in terms of instruments used and policy targets addressed; and (ii) a GWAS-inspired Bayesian procedure that allows one to identify the average association of each policy with an outcome variable while considering other policies that are present in the policy sector. The application of the CEPP approach to the case of green innovation suggests that this approach yields valid results and can contribute new insights that may inform future and more targeted in-depth investigations of specific policies and their effects. Moreover, the CEPP approach can be refined in important dimensions to gear it towards specific research contexts.

The CEPP approach offers several benefits when applied. First, it enhances the understanding of policy portfolios and their potential consequences. This is particularly crucial during periods of policy growth, which often lead to numerous interaction effects between policies, making it increasingly challenging to develop a comprehensive perspective on what a jurisdiction is doing in a specific area and the related effects (Adam *et al.*, 2018, p. 3; Hinterleitner *et al.*, 2024; Steinebach *et al.*, 2024). Second, the CEPP approach can assist in identifying alternative policy options that could help improve a predetermined outcome. This is especially relevant in polarised political environments where comprehensive policy changes are challenging to implement, and incremental additions to policy portfolios are the only feasible option for policymakers (Barber & McCarty,

2015). In such contexts, the CEPP approach can help identify other, potentially less controversial yet equally effective policy solutions. Third, the approach can also contribute to discussions on administrative overburdening and associated deregulation efforts. As policy growth risks overwhelming public administrations tasked with implementing policies, many countries have introduced 'regulatory offsetting schemes', requiring governments to abolish existing policies simultaneously while drafting new ones (Steinebach *et al.*, 2024). The CEPP approach can inform these offsetting schemes by identifying policy measures that could be terminated *without* negatively impacting specific outcomes. This can lead to smaller policy portfolios and fewer policies, without compromising the desired results.

To be sure, the CEPP approach also comes with certain potential limitations and analytical challenges with regard to its application and interpretation, in particular with regard to capturing not only different instrument types, but also the calibration of different instruments. Yet, we have also demonstrated that these challenges can be overcome by careful research design and statistical testing. Moreover, we are confident that these limitations are outweighed by a range of unique advantages discussed above.

While the CEPP approach can theoretically be applied in all contexts and policy areas where there is information about policy targets and instruments across different jurisdictions in combination with valid measurements of an outcome dimension, it is also possible to further develop the approach. For example, a modified version of the CEPP approach could help to better understand goal conflicts, i.e., situations where policies may improve one outcome (e.g., firm competitiveness) but worsen another (e.g., pollution). In such a scenario, the CEPP approach could be used to categorise relevant policies into three groups: those exhibiting positive associations with both outcome variables, those showing no or negative associations with both outcomes, and finally those displaying a positive correlation with one outcome and a negative correlation with the other. In general, approaches that can capture policy complexity in a structured way and identify policy effects *in spite of* this complexity offer great potential to better understand government activity and its effects.

Notes

1. Experimental and quasi-experimental approaches aim at generalizability by selecting a population sample that is representative of that population. Observational approaches aim at generalizability by selecting cases that allow one to make inferences about other types of cases.

2. With a consumption of 95 gr/CO₂ per driven km, this equals a taxation of 0.475 Cent per driven km.

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Notes on contributors

Xavier Fernández-i-Marín is a Ramón Cajal Fellow at the University of Barcelona, Spain.

Markus Hinterleitner is Professor of political science at the University of Lausanne, Switzerland.

Christoph Knill is Professor of political science at LMU Munich, Germany.

Yves Steinebach is Professor of political science at the University of Oslo, Norway.

Data availability statement

The data that support the findings of this study are openly available at <http://xavier-fim.net/publication/jepp-2025>.

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