Original Research Article

Pattern Discovery for Climate and Environmental Policy Indicators

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Abstract: Quantitative environmental policy indicators are useful for modeling the impact of environmental policy on the economy. They can be important tools for policy-makers, companies, investors, and researchers alike. The most highly regarded environmental policies lead to cleaner environments whilst encouraging innovative behavior to stimulate green growth and 'win-wins' for the economy and the environment. Such win-win policies are sought out by policymakers, as seen recently with growing interest in green 'new deals' and net zero carbon emissions pledges at a national level. But there is a gap between the needs for environmental policy data and the supply of reliable indicators and indexes. What are the effects of these policies? This disconnect has negative consequences for policy feedback as well as the inducement of potential innovators of environmental technologies. While there are now a wide range of indexes, these largely remain inadequate for various reasons. This is disappointing considering the immense progress that has been made in machine learning and pattern discovery methods—methods that are already fully deployed in other research disciplines. Such automated techniques can limit human biases which currently plague the environmental indicator's scholarship. The main objective of this paper is to highlight how researchers can carefully collect these data, and then to suggest how machine-aided methods can enhance the veracity of environmental policy indicators and indexes. This is an important research area that, apart from a handful of studies, is not sufficiently developed.

Keywords: machine learning; pattern discovery; PCA; environmental policy indicators; environmental policy indicators; climate change

1. Introduction

How environmental regulations impact businesses and the economy has been an open and contentious question since at least the 1970s. Statistical analysis in this field was spearheaded by the OECD (Organisation for Economic Cooperation and Development) and the IEA (International Energy Agency) because OECD countries needed an effective response to the Oil Crises—saving energy and inventing new energy production technologies being two main solutions (Kozluk and Zipperer, 2015; Popp, 2010). In the intervening years environmental and now climate change policies have become commonplace throughout the globe. Indeed the IEA, in collaboration with IRENA (the International Renewable Energy Agency), lists 5,659 climate and environmental policies, covering nearly every country in the world.

To understand the effects of these policies, efforts have been made to create indexes that proxy the stringency and impact of these policies, but results have so far been suboptimal (Brunel & Levinson, 2013; Galeotti et al., 2020).). In general, environmental policy indicators should be able to 'simplify, quantify, analyze and communicate the complex and complicated information' that underlies policy decisions and their constituent effects on the ground (Singh et al., 2012: 282). This is not always the case, however. In this paper we use indexes, indicators, and proxies interchangeably to refer to a quantitative estimate of a country-level environmental policy at a certain point in time. We delimit our analysis to country-level environmental proxies for the sake of simplicity and also because several 'off-the-shelf' indicators, for example those that are supplied by the OECD, WEF (World Economic Forum), and Yale University, provide country-level, yearly indicators that are useful as examples.

While environmental indexes and indicators attempt to assess first the stringency and timing of policies and second the ancillary effects on society, the economy and the environment, persistent problems remain during the development and transformation stages (Brunel & Levinson, 2013). Consequently, although environmental and climate policies are evidently very important, especially as green 'new deals' gain traction around the world, we still do not have an analytical grasp on how firms and economies react to such policies (Henderson & Millimet, 2007; Popp, 2019). At the same time, whilst pattern recognition has been widely deployed in other research literature (Jain et al., 2000; Wright et al., 2010), it is not deployed in the extant literature on environmental policies; this could be one reason why, so far, the latter tend to fall short. However, many of the shortcomings can be attributed to human bias, high-dimensionality, or otherwise latent complexity. As a corollary, therefore, we suggest that these shortcomings can be mitigated by machine learning and pattern discovery tools. This is the main argument of our paper. To this end, this paper makes a substantive contribution to environmental and climate policy index creation and transformation literature (Sing et al., 2012).

This paper is structured as follows: in the next Section 2, we introduce the main reasons that more reliable indicators are needed and demonstrate the common errors often made during the upstream construction, followed by the downstream transformation of these. Section 3 introduces several studies that have made inroads into transformation and calibration of 'off-the shelf' indicators. Section 4 introduces specific machine learning and pattern discovery tools that could be very useful to this research field. Section 5 provides a conclusion and suggestions for future research.

2. Background

Due to the sheer number and diverse scope of environmental policies across different countries, indexes also vary widely (Singh et al., 2012). This makes empirical approaches to test their impacts on the ground exceedingly difficult. Following the formulation of an index, scaling, normalisation, weighting, and aggregation is realised. These involve important decisions, such as the appropriate transformation strategy to be applied according to each specific research question and scope. As such, indicator transformation can help to enhance and calibrate an indicator to fit a specific research or policy question. But first the development and construction of indicators must be addressed.

Developing a suitable indicator is an instrumental part of the process, but this step often succumbs to human bias. Indeed, much of the empirical literature on environmental policy and the economy leads to equivocal results, largely due to this reason (Cohen & Tubb, 2018). In order to confront these issues, we propose that environmental indicators should be divided into two constituent parts: development, followed by transformation and application. We unpack these issue dimensions in Sections 2.2 and 2.3. First, however, we discuss the essential background for environmental policies--specifically, why it is important to develop these methods and literature..

2.1 Why do we need reliable environmental policy indicators?

Green Growth

How to achieve green growth is becoming an important policy question throughout a number of different countries (Meckling & Allan, 2020). Indeed, a renewed call for green recovery has arisen in 2020 in response to COVID-19 (Agrawala et al., 2020; Kuzemko et al., 2020). While increasing interest in green growth is promising, little is known about how these policies impact the economy and the environment (Barbier, 2010; Fankhauser et al., 2013). What might be the effects of 'green new deals', green industrial and 'green Keynesian' policies? How should such policies be rolled out, and later re-calibrated, to produce win-wins for the economy and the environment?

As a consequence, green industrial policies, while not synonymous with green growth, are becoming more commonplace in countries throughout the world (Barbier, 2010). For example, after the 2008 global financial crisis, 16% of $2.8 trillion was dedicated to green industrial policy in the U.S., while South Korea attributed 79% of their $59 billion stimulus to environmental policy (Jacobs, 2012; Robins et al., 2009). In addition, China's green industrial policy is often cited as highly successful in building up a powerful domestic solar technology industry (Groba & Cao, 2015). More recently, the European Union has formally introduced Green New Deal legislation (see EC 2019/640). Likewise, President-elect Biden has vowed to put the US on a path to carbon neutrality by the year 2050, with the explicit goal of driving economic growth and competitiveness through invention and trade in clean technologies (https://joebiden.com/climate-plan/). Similar plans were announced by Japan, China, and South Korea.

The Necessity for Reliable Indicators

In much of the empirical literature on green growth, policies and innovation, the explanatory variable of interest is the environmental policy under analysis (Ambec et al., 2013). Hence, the main explanatory variable is typically an environmental policy proxy. A common technique is to designate environmental technology patents as the dependent variable, regressed on environmental policy (Johnstone et al., 2010b), total factor productivity (Rubashkina et al., 2015; Wang et al., 2019; Janicke, 2012), or multi-factor productivity (Albrizio et al., 2017), among others. The question is how policy can benefit the economy and the environment, drive innovation and productivity The question tests whether green growth lives up to 'The promise that technological change and substitution will improve the ecological efficiency of the economy, and that governments can speed this process with the right regulations and incentives' (Hickel & Kallis, 2020: 470).

Under this interpretation of green growth, not only can domestic firms react innovatively, but they can also gain 'first-mover' competitive advantages with respect to firms in other countries (Tews et al., 2003; Söderholm & Klaassen, 2007; Herman & Xiang, 2020). Yet, despite the important contributions of previous empirical research, because the main explanatory variable of interest is usually environmental policy stringency—and these indicators remain problematic (Brunel & Levinson, 2016)--much of the research stands on shaky foundations. Consequently, policy-makers might not be receiving accurate and timely feedback. The same applies to innovators, firms, and investors. For these reasons, it is critical to carefully compile, transform, and apply environmental policy indicators.

Measuring Environmental Policies

There are two main components of environmental policy indicators. The upstream component relates to measurement, data collection and construction. Particular care must be taken to articulate the environmental policy being measured. The downstream component involves calibration, transformation and empirical application. In general, upstream issues often arise from temporal and geographical differences, which render measurement quite difficult. The downstream problems, meanwhile, arise from the layers and dimensions of environmental policy that are either not well articulated, or otherwise occur if the index is not properly transformed in order to align with the policy or research question.

As a main consequence these upstream and downstream issues, if not resolved, lead to the statistical and mathematical issues incongruities which, although inherent in high dimensional data, tend to inhibit the indicator transformation. More detrimentally, this can lead to spurious application of indicators downstream. One negative consequence is to render empirical modeling too complex or, even worse, completely insufficient to undertake the task at hand (e.g. measuring environmental policy effects on green growth, the economy and the environment). Figure 1 below is a depiction of the upstream and downstream components of environmental policy construction and transformation.

Figure 1. The Construction and application of environmental policy indexes

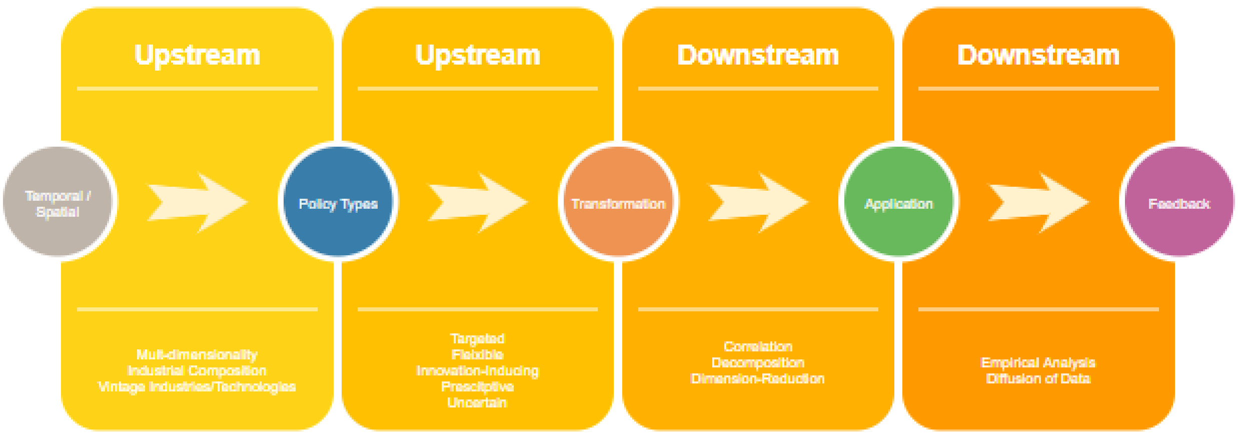

Figure 1. Authors' depiction of 'upstream' and 'downstream' components involved in construction, transformation and application of environmental policy indexes.

In the remainder of this section, we unpack the integral upstream components that frequently cause issues during the construction phase of environmental policy indicators. Importantly, on a more granular level, both upstream and downstream measurement and transformational components are at risk of human bias and high-dimensionality, hence the recommendations throughout this paper for concerted efforts to deploy pattern discovery methods to effectively mitigate against these issues.

2.2 Common measurement problems: Upstream

The timing and geographical point of incidence are rather consequential for environmental policies. Against this backdrop, Brunel and Levinson (2016) identify four temporal and spatial measurement issues that can arise during the upstream compilation of environmental policy indicators. These are: (1) multidimensionality, (2) simultaneity, (3) industrial composition and (4) capital vintage. Immediately below we introduce these concepts, with examples, in order to convey important considerations during the construction of indicators.

Multidimensionality

Multidimensionality implies that the scale and scope of a regulation leads to diverse on-the-ground effects. In other words, breadth and depth are important concerns, especially when contrasting two different policies. The failure to account for these differences leads to poor proxies and spurious empirical results. The U.S. Clean Air Act, for example, imposes uniform regulations on every county in the United States; yet, due to natural environmental endowments (such as mountains next to cities that trap pollution in contrast to coastal cities that do not), the regulatory burden is unevenly distributed (Brunel & Levinson, 2016). For example, Hawaii expends little effort meeting the requirements as trade winds blow the pollution immediately offshore. Contrarily, cities such as Los Angeles and Salt Lake City expend a much greater effort to reduce air pollution due to geographical endowments. Thus, the frequently used 'pollution abatement costs' (PACE)--often deployed as a main explanatory variable in the extant literature (Ambec & Lanoie, 2008)--is a poor environmental policy proxy since it does not account for uneven costs of meeting new regulations (Rubashkina et al., 2015).

Simultaneity

The issue of simultaneity mainly refers to the timing and time period covered by the environmental policy. These temporal components are particularly salient for comparison of policies across countries, as well as across industries. Due to temporal differences, however, simultaneity often leads to acute measurement problems in multi-country and multi-sector analyses (Brunel & Levinson, 2013). At the same time, making comparisons is one way policymakers can learn about the effectiveness of green growth policies—what does and doesn't work. Furthermore, one important pillar of the Paris Climate Change agreement—the so-called Nationally Determined Contributions (NDCs)--seems to rest on an ability to compare and contrast the green growth of countries over time. However, due in part to the simultaneity problem, if not rectified, determining how countries' environmental policies measure up against one another remains perplexing, and can lead to 'race to the bottom' policies that create competition for inward investment of polluting industries (Woods, 2006).

Capital Vintage and Industrial Composition

Since the 1970s, governments around the world have introduced increasingly stricter emissions standards on automobiles. However, these standards largely apply to new vehicles. Thus, vintage vehicles are not subject to new regulations. This is the 'capital vintage' and 'industrial composition' environmental policy measurement problem. There is no straightforward way to measure how policies impact vintage versus newly manufactured technologies.

To take another example, if heavy industry is intrinsic to a country's DNA, it is likely that policy-makers will enact quite stringent regulations to curtail runaway emissions and negative impacts on human health; following the introduction of such regulations, improvements will appear greater since the starting point was quite low. Another country in a more advanced stage of economic development that relies more on service-oriented industries would likely not be hindered by the same regulatory burden. Consequently, the impacts would be much smaller in comparison to the higher polluting country (Esty & Porter, 2005). The counterintuitive result, sometimes, is that stringent policies prolong the life of vintage equipment, resulting in a net increase in emissions in comparison to business as usual (Stavins et al., 2003). Indeed, the same effect is seen in energy production: new policies adversely penalise vintage power-plants built decades ago during a time of more lax environmental regulations, but wrongly constructed policies only prolong the life of vintage power-plants.

2.3 Types and Typologies of Environmental Policies

Beyond the sectoral, temporal, and qualitative differences germane to the heterogeneous impacts of environmental regulations—differences which are important to model whilst constructing indicators—there are also specific vectors of influence such regulations can induce. The vector of policy influence is referred to as the point of 'incidence,' and is where targeted policy addresses the environmental harm. Once identified, the point of incidence draws in innovators (Jaffe et al., 2002). The aim is to encourage environmental-economic win-wins through innovation and industrial upgrading.

Environmental policy measures that address the point of incidence are, among others, performance standards, environmental taxes, or tradable permits. These are frequently used for climate change policies to encourage renewable energy innovation and deployment, for example (Polzin et al., 2015). Indeed, the state has a vital role to play to induce radical and incremental environmental technology innovations and disruptive clean energy transitions (Egli et al., 2015; Johnstone & Newell, 2018; Johnstone et al., 2020). Well-crafted environmental regulations can signal resource inefficiencies, reduce uncertainty, pressure firms to innovate, level the playing field, and reduce costs of innovation-based learning (Porter & van der Linde, 1995). In this sense, environmental regulations can become 'a tool for competitive advantage […] for minimizing ecological impacts of economic production while enhancing the competitiveness of firms' (Shrivastava, 1995: 183). There is growing evidence for such win-wins that stem from flexible and timely policy interventions (Esty & Winston, 2009; Sarkar, 2013; Ambec, 2017).

Policy Flexibility and Innovation

In the extant literature on green growth, policy-induced innovation follows the seminal work by Rosenberg's (1966): 'focusing devices'. A well-crafted environmental policy provides a 'focusing device' for potential innovators (Jaffe et al., 2002). It illuminates a prominent problem that, if solved by an innovator or firm, can lead to sustained profits. The policy highlights the negative externality (e.g. the environmental harm that could be resolved with a new technology). Flexible environmental policies are seen as the most capable for creating focusing devices.

Environmental regulatory flexibility is therefore a key tool for policy-makers because it can induce green-growth and local innovations (Haščič et al., 2009). At the same time, it can increase the competitiveness of domestic firms, underscoring the rewards of well-crafted green-growth policies (Herman & Xiang, 2019). New environmental technologies are costly and difficult to produce. In the absence of stable but flexible policy, innovators are less likely to take on risks.

Policy Uncertainty and Prescriptive Regulations

Prescriptive regulations can often be the opposite of flexible regulations. They demand a specific standard or technology, which can lead to bottlenecks and typically stifles the search for innovative solutions (Van Leeuwen & Mohnen, 2017). They also can lead to end-of-pipe, non-innovative solutions (Johnstone et al., 2010b). Hence, the provision of win-wins for the economy and environment are less likely under policy uncertainty in contrast to flexible environmental policies. With the former, investments will be postponed until the 'policy dust' settles (Johnstone et al., 2010b). Policy uncertainty, likewise, can have significant negative consequences for would-be innovators looking for sustained government support (Jaffe et al., 2002; Fischer & Reuber, 2003).

Unstable policies effectively serve as a break on innovation (Haščič et al., 2009). For example, the US, Canada, and Australia have had unstable climate change policies—that is, these countries at first introduced stringent climate policy regulations, only to have these repealed by successive governments—with negative consequences on green innovation. This reverses the benefits of green growth and green industrial policies and indeed might be more harmful than if no policies were enacted in the first place (Rodrik, 2014; Fankhauser et al., 2013).

In this section, we reviewed how spatial, temporal, geographical and qualitative differences can lead to widely differentiated effects of environmental policies on the ground. These are the upstream issues to be aware of during construction of indicators. Likewise, issues related to the many different types and typologies of policies, if not properly accounted for, can cause error in construction of environmental policy indicators. These issues are likewise relevant during indicator transformation and application. In the following section, we present some transformation and application techniques previously deployed in the extant literature with an eye on how these upstream effects inform the downstream processes.

3. Application and Transformation: Downstream

In this section we explore some of the environmental policy indicators that are widely deployed and transformed throughout the extant literature. We climb inside the 'black box' of policy proxy normalisation, transformation and application to further understand the nuances of the upstream and downstream issues raised in the previous section (multidimensionality, simultaneity, industrial composition, capital vintage, policy flexibility, innovation policy uncertainty, prescriptive regulation).

3.1 Correlation and Decomposition

The seminal work by Esty and Porter (2005) established the empirical grounding for country-level environmental policy indicator construction. Using their analysis as a baseline, we believe new techniques can create a reliable proxy with greater predictive power than existing methods, cited elsewhere as pertinent to more robust analysis (Ambec et al., 2013; Esty & Porter, 2002; Esty & Porter, 2005). Esty and Porter delineate the environmental regulatory regime into a series of more discrete variables to enable transformation: (1) stringency of environmental pollution standards; (2) sophistication of regulatory structure; (3) quality of the environmental information; (4) extent of subsidization of natural resources; (5) strictness of enforcement; (6) quality of environmental institutions (membership in intergovernmental environmental organizations, prevalence of ISO 14000). Their efforts, in part, led to the creation of Yale’s Environmental Performance Index (EPI), which remains one of the most comprehensive proxies for country-level environmental policies. However, as shown below, there is not much variation over time for this indicator. Therefore, comparisons across countries is quite difficult with this indicator due to the high correlations. Accordingly, Yale’s EPI might be an important starting point for transformation in future research.

Figure 2. Yale’s Environmental Performance Index is Highly Correlated Year-on-Year

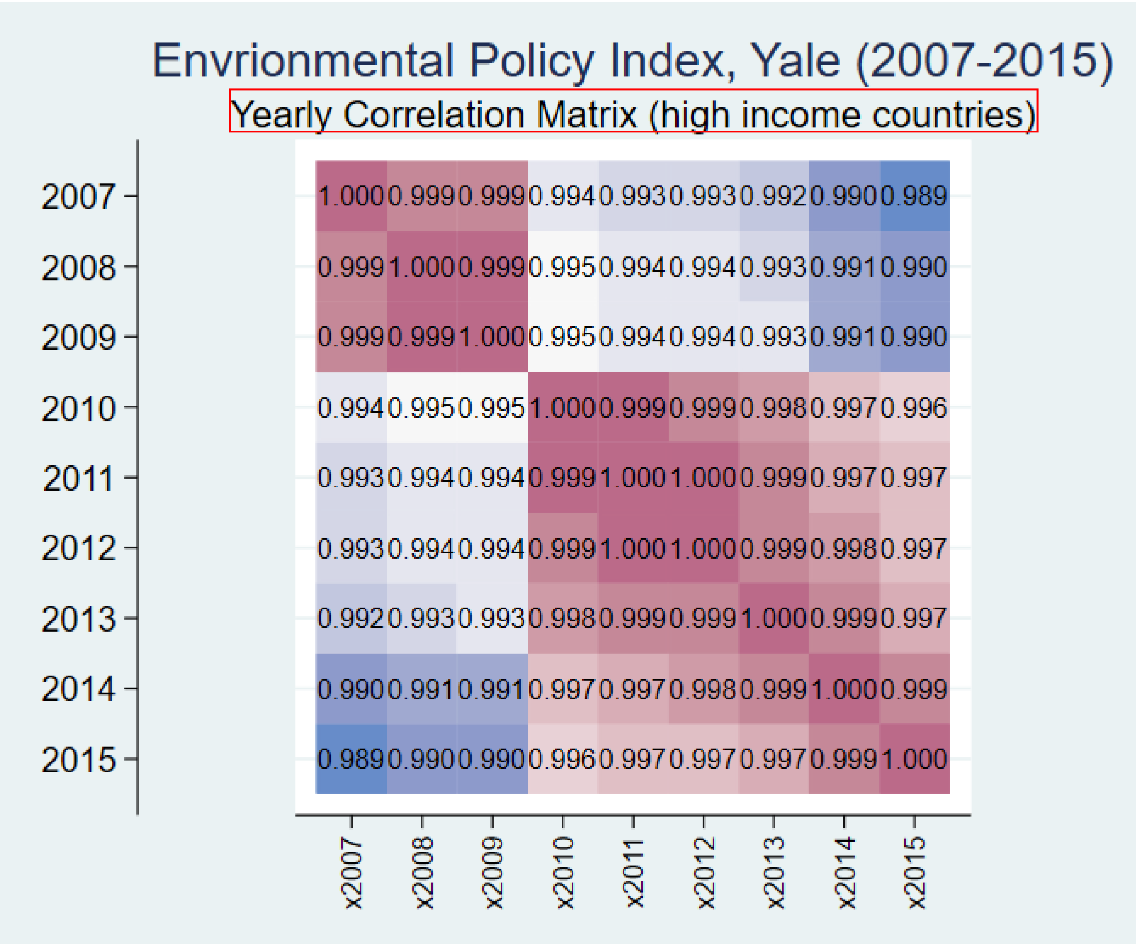

Figure 2. Heatmap correlation matrix: Yale's EPI from 2007-2015 years are highly correlated with one another; this is problematic for time series empirical testing, and therefore should be transformed. Analysis conducted by the authors. Source data can be found at www.EPI.Yale.edu

3.2 Dimensionality Reduction

High dimensionality in data and indicators has been recognized as a problem for some time (Andrews, 1972). With respect to environmental proxies, this issue continues to plague empirical research (Cohen & Tubb, 2018). To counter this, researchers can reduce the dimensions of the input variables that are used to create environmental proxies. For example, Costantini et al. (2013) develop a unique version of environmental policy stringency as the sum of three costs: PACE (as a percentage of GDP), environmental tax revenues per GDP, and public R&D investments for the environment (as a percentage of GDP). Further, they include the quantity of regulatory measures for renewable energy and energy efficiency throughout 100 countries, following Johnstone and Hascic (2008). Their findings show that the Kyoto Protocol led to higher rates of diffusion of climate and environmental technologies to lesser developed countries; this is important since the Protocol's Clean-Development Mechanism, as one of its primary policy goals, set out to enable clean technology transfers to developing countries from the Global North (Lema et al., 2015).

While Constantini et al. (2013) deploys a useful dimension-reduction technique, and indeed support Esty and Porter's (2001) claim that national competitiveness goes hand in hand with environmental regulatory stringency, its main weakness is to proxy environmental policy by costs. As stated elsewhere (Rubashkina et al., 2015; Dechezlepretre & Sato, 2017; Brunnermeier & Cohen, 2003; Galeotti et al., 2020), pollution abatement costs are a poor proxy due to upstream construction as well as downstream transformation of environmental policy proxies. Indeed, there has been a tendency to rely on cost proxies and neoclassical economics, an issue recently cited as the 'neoclassical monopoly over [environmental] policy options' (Meckling & Allan, 2020). One consequence of these incorrectly deployed proxies is to 'mak[e] dirty nations look clean' (Morse & Fraser, 2005). These nuances are important because we can expect, in the global competition among countries to determine who will win the 'green race' (Fankehauser et al., 2013)—and considering the evidence of cross-border policy-inducement effects (Herman & Xiang, 2020)—that much jockeying for clean-looking policy positions will ensue. However, one caveat is that, as done by Galeotti et al., (2020), costs proxies can be sufficient if first transformed with dimension reduction techniques.

Composite Indicators

Composite indicators can effectively mitigate the multidimensionality issues raised in Section 2 above. They are indeed commonly deployed to deal with the multidimensionality problems (Brunel & Levinson, 2013; Booysen, 2002; OECD, 2004; Nardo et al., 2005). The method incorporates a weighting system over a set of variables (Booysen, 2002). Prior to that, however, the method first requires if a composite indicator is appropriate (Nardo et al., 2005; Galeotti et al., 2018). The benefits are to reduce dimensionality and enable longer time series analysis—useful for cross-country analysis.

These methods are widely deployed to analyse global environmental treaties such as the UNFCCC. For instance Battig et al. (2008) and Bernauer and Bohmelt (2013) create composite climate policy cooperation indexes, which use global environmental treaty data to rank countries according to their participation in the Kyoto Protocol. Likewise, Li et al. (2014) proxy national environmental regulatory stringency by the number of international environmental treaties and ENGOs (Environmental Non-Governmental Organizations). Johnstone et al. (2010) employ World Economic Forum (WEF) survey data from business executives to proxy domestic policy stringency. Finally, Fankhauser et al. (2013) create a global green competitiveness index to determine which countries are most likely to 'win the green race.'

However, the multidimensionality issue that composite indicators explicitly aim to mitigate can also be their main weak point: there is no straightforward econometric technique to deal with multidimensionality without imparting some sort of strong human bias. Therefore, composite indicators beg for transformational techniques via machine-enhanced applications. These are discussed further in Section 4.

3.3 Transformation and Application

The downstream transformation and application of already-created environmental policy proxies is an important avenue for future researchers. Apart from a handful of attempts to transform the OECD's Environmental Policy Stringency index, there is a dearth of research on the transformation of the hundreds of other indicators. One starting point could be to transform Yale's EPI or WEF's Global Competitiveness index.

Several general econometric techniques can be deployed to gain insight into high dimensional data: factor analysis and polychoric correlation, PCA based on Spearman correlations, and pre-cleaning methods such as using Cronbach's alpha to determine the reliability of input values. Before the index transformation stage, therefore, we can decompose the indicator to determine its underlying strengths and weaknesses. For instance, few would predict that emissions limits for Nox, Sox and PMx 'Standards', one of many components of the OECD's EPS, are highly correlated with the main OECD EPS indicator. Yet, as shown in Graph 2 below, these three input variables (emissions standards) correlate highly with the overall EPS indicator. This is not, on its own, problematic; however, during transformation or the OECD's index, researchers must be aware of underlying correlations.

Figure 3. Patterns within the OECD's Environmental Policy Stringency Index

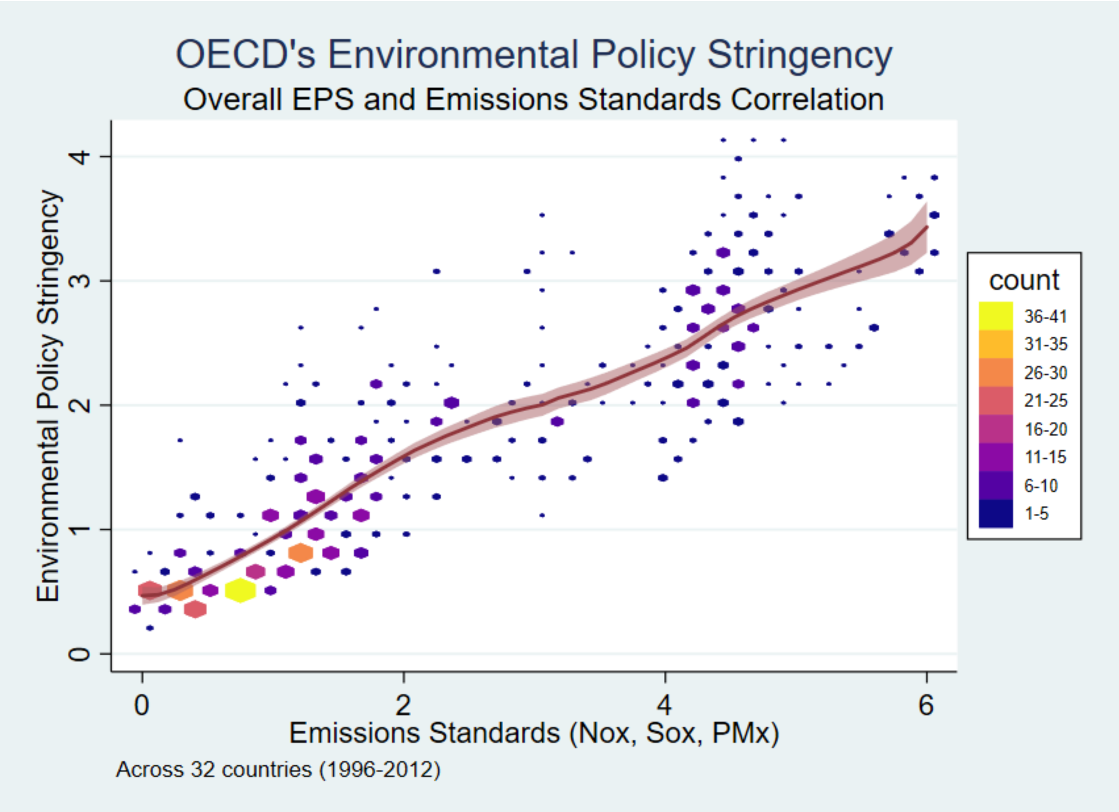

Figure 3. Author's depiction of OECD data**.** Preliminary analysis shows that one of the six main inputs (emissions standard's limits) for the Environmental Policy Stringency (EPS) index correlates highly with the overall index measure.

Decomposition: Principal Component Analysis and Climate Policies

Recognising the need to address how different types and typologies of policies coexist within an economy—and how such policy differences can impart widely differing environmental innovation inducement effects—Johnstone et al. (2012) cluster climate policies by the 'points of incidence' and targeted dimensions. They delineate among price-based, voluntary programs and quantity-based policies. The main benefit of transforming policy proxies, therefore, is a more complete picture of how a suite of climate and environmental policies impacts the economy. Rather than singling out one potentially weak policy, for example, all are accounted for (Johnstone et al., 2012). Furthermore, by using this technique, underlying correlations among the data can be reduced, which allows for more meaningful empirical analysis.

After clustering the climate policies according to their specific point of incidence, Johnstone et al. (2012) apply Principal Component Analysis (PCA). PCA involves identifying the directions of variables—referred to as principal components (PCs) or orthogonal sub-indices—which explain most of the variance in the data. The PCs make up linear combinations of the broader policy variables and are particularly well suited to deal with variation in the index data. Therefore, otherwise inconsequential input data can be removed. This is achieved by creating a covariance matrix of the data and performing eigen-decomposition on the covariance matrix, then sorting the eigenvectors from largest to smallest corresponding eigenvectors. In other words, PCA finds a solution that 'transforms a given set of variables into a composite set of components that are orthogonal to, i.e., totally uncorrelated with, each other [and requires] no particular assumptions' (Morzuch, 1980: 81). There is one important limitation, however: 'components with small eigenvalues may be correlated very highly with the dependent variable. Thus, a structural norm which simultaneously considers the amount of variability accounted for by a particular component and its correlation with the dependent variable has greater appeal' (Morzuch, 1980: 82).

Thus PCA enables the discovery of key patterns as well as latent variables which explain the underlying distribution in multivariate data (Vona & Nicolli, 2014; Nesta et al., 2014; Botta & Kozluk; Tubi et al., 2012). If, however, the 'normality assumption' is violated (due to skewness and kurtosis of the distribution), the pairwise correlations that build the PCs will become biased. This can be mitigated via a maximum likelihood estimator to fit the data to a continuous, normal distribution before calculating the correlation matrix. Building a large dataset of climate policy stringency often incorporates non-normally distributed data due to the temporal, spatial, and geographical heterogeneity issues addressed in Section 2. For this reason, PCA can be an 'ad hoc' factor analysis approach, the latter relying on factor loadings to transform the data into acceptable 'solutions' to the problem of dimensionality and correlation.

Transformation: The OECD's Environmental Policy Index

The OECD's Environmental Policy Stringency Index (EPS) (Botta & Kozluk, 2014) has been widely used as a proxy in the literature on policy-induced innovation for environmental technologies (Vona & Nicolli, 2014; Kozluk & Zipperer, 2015; Popp, 2019; Herman & Xiang, 2019; Herman & Xiang, 2020). The EPS is divided into Non-Market Based (NMB) and Market Based (MB) instruments. NMB policies include emissions standard's limits (for SOx, NOx, Particulate Matters and Sulphur Content of Diesel) and Government energy-related R&D expenditures as a percentage of GDP. Market-Based policies include feed in tariffs (solar and wind energy), taxes (on CO_2, SOx, NOx and Diesel), certificates (White, Green and CO_2) and the presence of deposit and refund schemes (DRS). All variables are continuous, except DRS which are dichotomous. It covers 32 countries (OECD countries and the 'BRICS'). However, while widely deployed in the literature, researchers often do not first transform the EPS, which is recommended due to underlying correlations among years and constituent variables included in the index. As shown below, this can become problematic as several of the input variables are highly correlated among one another, which could lead to spurious results in empirical models.

Figure 4. Correlation Heatmap of the OECD's Environmental Policy Stringency Index

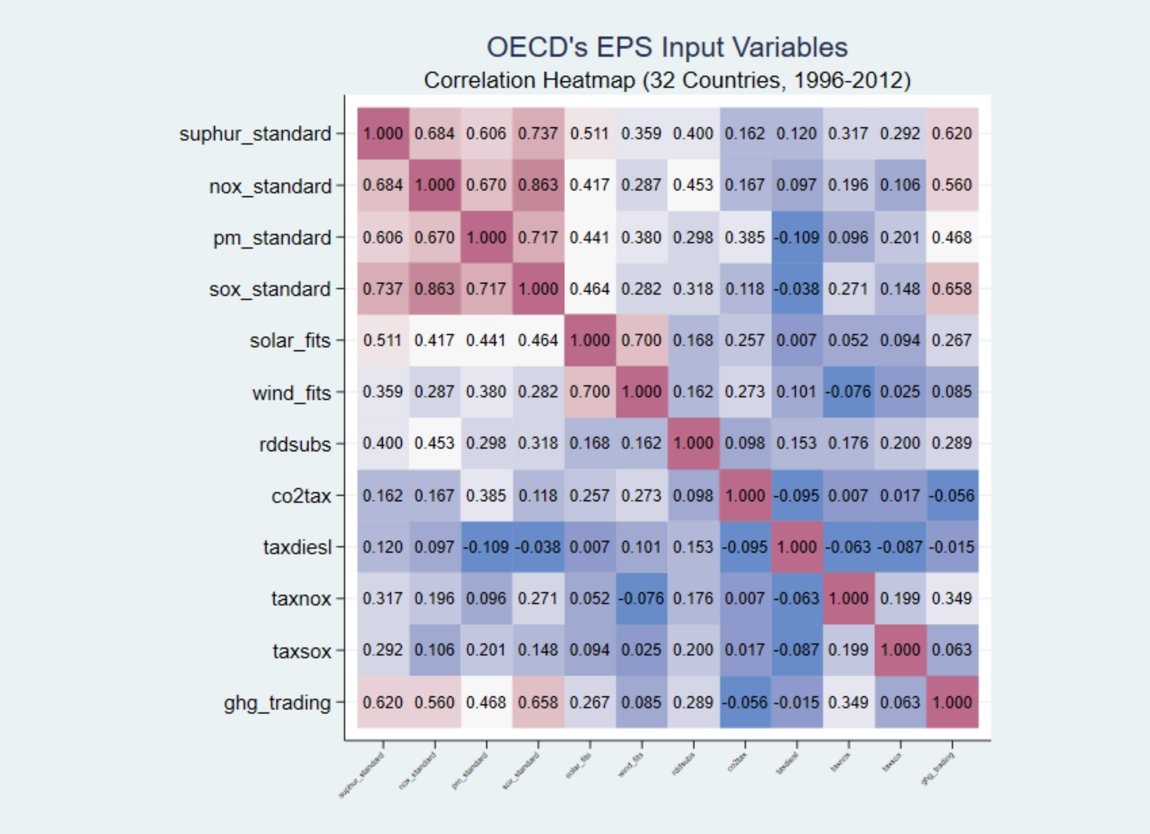

Figure 4. Author's depiction of OECD data. OECD EPS overall correlation shows that some the input variables are highly correlated. Data source available at OECD's website.

While the OECD's EPS does well to disaggregate different types of policies, and therefore effectively deals with some upstream problems identified in this paper, downstream it does not perform as well. As such, before being applied to empirical models, it should be transformed. High levels of correlation among the different input variables can be problematic if not properly identified and transformed. Secondly, the index is high-dimensional and composed of both continuous and discrete input variables. Therefore, PCA transformation is a reasonable method due to its underlying correlation among the input variables.

Consequently, researchers have applied PCA to transform the OECD's EPS index (Galeotti et al., 2020; Nesta et al., 2013; Nicolli & Vona, 2019). The technique takes high dimensional data—the OECD's EPS is composed of 15 separate environmental policies at country-level—and compresses the dimensions to deliver more meaningful, and less correlated, environmental policy proxies. For example, Vona and Nicolli (2014) extract PCs, then build three sub-indices using PCA from feed-in-tariffs (FITs) for renewable energy generation, renewable energy certificates (RECs), and R&D credits. They then build three PCA sub-indices: (1) price-based policies (2) quantity-based (3) and innovation-based (R&D) policies.

Likewise, Galeotti et al. (2020) perform a transformation of the OECD's EPS with PCA, following the procedure used by Nesta et al. (2014). They set out to test how environmentally stringent policy countries induce innovations across OECD countries from 1995-2009. They assign '1' when a country first implements an environmental policy; then the sum of the different dummy indicators is used for each country and year, based on the OECD's EPS. The first indicator employs 15 such dichotomous variables; the second is composed of six categorical aggregates. Overall, these environmental policy indicators capture the 'diversification of the environmental policy portfolio' (Galeotti et al., 2020).

Thereafter, they use PCA to reconstruct emissions-based indicators (which in our graphic above are the most highly correlated at the start). Finally, they reduce the number of correlated variables to smaller, latent variables (PCs) to reconstruct and enhance the empirical veracity of existing indicators.

However, despite the aforementioned developments in the literature, there remains little agreement on the proper development, timing and usage of such indicators and proxies, and transformation (Brunel & Levinson, 2016; Galeotti et al., 2020). While some important contributions to the literature are enumerated above, there remains much work to be done. To mitigate these issues, we suggest employing novel pattern discovery and machine learning methods to enhance the veracity of these indicators—how they are constructed, empirically deployed, and calibrated—to provide real-time updates as data become available and policies are adjusted accordingly.

Importantly, not only do indicators provide policy feedback and improve quantitative empirics, but they also help to induce innovation from companies and allow investors to decipher complex environmental regulations. Therefore such proxies, on their own, can act as independent catalysts for the low-carbon technology transition paradigm (Köhler et al., 2019). Thus, this exercise is not merely academic. Reliable indicators, indexes, and proxies can have serious consequences for green growth.

4. How to Leverage Pattern Discovery for Environmental Policy Indicators

In the previous section, we addressed some transformations of environmental policy proxies which have been met with some moderate success in the literature. However, upstream and downstream issues continue to impede the creation, transformation, and application of environmental policy proxies. Therefore, in this section, we offer some suggestions to address these perennial problems—and to further provide policy-makers with accurate and timely policy feedback—by leveraging some widely accessible machine learning pattern discovery tools. However, as mapped out in the previous sections, should the tools in this section be deployed, great care must be taken during the collection of data, compilation of the indicator with respect to spatial and temporal considerations, imputation and transformation of the index, and finally the application of the indicator to the proper empirical question.

4.1 Enhancement of Data Collection

Automated data collection techniques exist to scrape data from distant and varied sources that can be useful to construct environmental policy indicators. Keeping in mind the salient upstream issues outlined in Section 2 (simultaneity and multi-dimensionality), researchers can deploy these techniques to quickly compile and clean data. Temporal and spatial effects of environmental policy must be carefully calibrated while using automated data collection, however. If not careful, the construction of environmental policy proxies through automated data-scraping could be rendered useless.

Many of these tools are open source and free to use (e.g. Scrapy, Apify SDK, Cheerio, PySpider, UiPath). These needs can also be met through an integration of well-established open source programs such as data and pattern mining algorithms (e.g. Rapidminer, KNIME and WEKA, TraMineR), data transformation tools, (e.g. Grafter and OpenRefine), visualisation services and toolkits (e.g. Google charts API, Gephi). This is also important to revise and update data since policies are changing at a rapid rate. Indeed, shown by the example of the OECD's EPS, much of the policy proxy data is seriously out of date. For example, much of the latest country-level data are from 2012.

4.2 Decomposition and Calibration

Using rather straightforward statistical machine learning (i.e. correlation clustering, decision trees, support vector machines) researchers can reduce bias that is inherently introduced during the construction of indicators. Indicators therefore might perform very well in this regard by, for instance, reducing dimensions without necessitating biased selection (e.g. selecting which particular input variables should be dropped or kept). Both tools effectively confront multidimensionality issues head-on. For example, matrix decomposition breaks down complex and high-dimensional matrices into simpler ones, in effect reducing the high dimensionality that has been identified as a primary impediment. Using these refined data, calibration of the environmental policy indicator can align to the research question at hand.

Support Vector Machines (SVMs)

SVMs could be very useful to classify the different types and typologies of environmental policies (downstream components outlined in Section 2.2). This could be a preliminary step to find 'flexible' and 'stable' policies to conduct further analysis. Indeed, as pointed out by Johnstone et al., (2012), green growth policies should be flexible in order to stimulate innovation, while prescriptive and unstable policies often 'put a break on innovation'. Therefore, SVMs can be used as a first approach to discard proxies that approximate unstable and otherwise unproductive green growth policies, which would save time by eliminating from the start the policies that are unlikely to provide win-win co-benefits to the environment and the economy.

Neural Networks and Support Vector Machines (SVMs)

Neural networks are opaque function approximators that perform successive computations on signals through a biologically-inspired architecture of layers and nodes. They are similar to Support Vector Machines (SVMs) in the sense that both 'black box' models are very good at regressing data in high dimensions (Fall et al., 2003). However, while SVMs are considered easier to implement and are also able to model data that are not linearly separable, neural nets are typically harder to configure and debug due to the high number of hyperparameters required for fine-tuning.

One of the many recent applications of neural networks is in natural language processing (NLP), where patterns in textual data such as Twitter streams can be used to infer public sentiment (Reyes-Menendez et al., 2018). In addition, in contrast to SVMs, neural nets can be updated online, allowing real-time inference with minimal model training time. This could be particularly important for identifying and analysing swift changes to environmental policies and constituent effects across different sectors of an economy. Such semi-automated techniques could also be quite useful to refine and re-calibrate environmental proxies as countries alter their policy strategies as a result of political changes. Or, they could be used to gauge public sentiment on new green growth policies to avoid costly 'NIMBY' counteractions (Devine-Wright, 2014) which might otherwise impede the introduction of green growth policies. For example, more germane to political economy analyses, Gründler and Krieger (2016) have leveraged SVM to create a democracy index covering over 50 years and over a hundred countries.

4.3 Pattern Recognition, Transformation and Application

Whilst pattern recognition has been widely deployed in other research literature (Jain et al., 2000; Wright et al., 2010), it is largely not used in the extant literature on environmental policies. Pattern recognition can effectively help to identify, classify, and cluster environmental proxies such as public sentiments in Twitter streams mentioned above. Likewise, satellite imagery can also be transformed to assess the UN's Sustainable Development Goals (SDGs) (Kussul et al., 2019) or to automate the progress on emissions reductions of Greenhouse Gases covered by the Kyoto Protocol (Xu et al., 2018). Another usage could be to recognise similarities and differences among countries' NDCs under the Paris Agreement, as suggested recently by Franke et al. (2020).

t-distributed stochastic neighbor embedding (t-SNE)

Similar to PCA, t-distributed stochastic neighbor embedding, or t-SNE, transforms data with many input variables to distinctively reveal which variables are furthest apart. In contrast to PCA, however, t-SNE preserves small pairwise distances to reduce, rather than maximise, variance. This provides an excellent tool for visualisations (Maaten & Hinton, 2008). With high-dimensional data, such as is found in environmental policies, t-SNE can reduce to three dimensions in order to visualise, for example, the key differences among country-level green growth policies. Since it does not preserve distances or densities, however, it is primarily a visualisation tool and less relevant for analysis or clustering.

4.4 Simulation and Policy Feedback

Finally, if researchers can create machine learning and real time policy indexes, flexible policies could be calibrated ever so carefully over time. This could serve as a basis for an entirely new realm of forward-looking, semi-automated, 'anticipatory governance' (Maffe et al., 2020). While minor adjustments to environmental policy could enhance their veracity—and subsequent innovation-inducing prospects—there is also the potential for real-time feedback between firms and government, economy and the environment, investors and entrepreneurs, who are all critical to the success of an environmental policy with respect to the economy. There are now methods to weight and aggregate the numerous sustainability indicators, which might be one way to provide real-time monitoring and feedback for environmental regulations (Kong et al., 2020). Likewise, energy indexes can properly measure equally important needs such as energy security and energy sustainability, which points to another way machine learning tools can be coupled with policy flexibility (Narula and Reddy, 2015). Real-time feedback on energy usage and policy is already deployed in China, for instance (Kong et al., 2020).

Policy Simulation

Environmental policy simulation could be an immensely important tool to develop and roll-out green growth policies carefully. Before introducing a policy, for example, simulations could be run to determine how it might impact the economy, its firms and innovators: will it induce them to create innovative new environmental technologies? Or will it lead to end-of-pipe environmental technology solutions? While there is much research on estimating effects of climate policy on the economy--for example, Integrated Assessment Models in use during the UNFCCC climate negotiations for several decades--to the best of our knowledge, IAMs and related modelling does not deploy machine learning to predict policy outcomes, nor do IAMs focus explicitly on green growth, but rather climate and emissions.

As a corollary, simulation could allow careful calibration at the local level, which often suffers from the simultaneity problem because federal environmental policies impact smaller jurisdictions in multifarious ways. The scenarios can be repeated hundreds of times and provide predictions of different policy interventions (Androutsopoulou & Charalabidis, 2018). In this manner, policy-makers could compare across the different results and 'collaboratively distinguish the best solutions for tackling the situation under investigation [...] propagated with big data [...] Impact assessment could be [both] *ex ante* policy (phase of preparation) and *ex poste* (phase of implementation)' (Androutsopoulou & Charalabidis, 2018: 580). Open source tools such as Rapidminer, KNIME and WEKA can provide solutions here. Additionally, although some simulations have indeed been carried out for climate change policies (such as the Integrated Assessment Models), these have not, as yet, fully incorporated machine tools to update predictions the instant new data is available.

5. Conclusion

In this paper, we explored the issue of environmental regulatory indicators as a tool for empirical researchers and policy-makers. Evidently, researchers have faced an uphill battle to build, maintain, and transform reliable indicators, with some negative consequences for robust and consistent research output. These problems also extend to the transformation of existing indicators and indexes. The result is that policy-makers are unable to readily know the impacts of environmental policy on the economy, which is a salient issue especially in the era of widespread green growth policies. Environmental regulatory stringency proxies should ideally be easy to calculate, produced annually, cardinal, and available to a large array of different pollutants (Brunel & Levinson, 2013). Further, these indicators should not only be confined to certain sectors or industries, but rather extend to broader parts of the economy and across countries (Brunel & Levinson, 2016; Galeotti et al., 2020). Finally, more peripheral issues are the sensitivity to data revisions, variability in the data, and small sample issues (Nardo et al., 2005). However, the complexities and array of environmental policies in place worldwide make indicator construction and transformation an arduous yet wholly important task.

We have proposed to follow recent success using PCA to construct reliable indicators, and going one step further, to deploy new machine learning and deep learning techniques. Caution should be taken, however, with machine enhanced tools. For this reason we provided an exhaustive discussion on the topical issues that tend to inhibit upstream construction, followed by the downstream transformation and application, of environmental policy indicators.

The exponential increases in data collection in recent years enable researchers to deploy powerful statistical and machine-aided tools. These tools could be invaluable to construct environmental and climate policy indicators. But without adequate compilation and transformation of these data, they are at risk of being rendered useless. While machine learning and deep-learning techniques have some limitations and must be deployed with extreme care, these methods can lead to important pattern discovery for the environment; this is critical in light of the Paris Agreement, buttressed by a renewed interest in green growth policies worldwide. Much needed policy-economy-environment feedback loops could then deal with the inherently complex and fragmented arena that has troubled researchers, policymakers, and businesses for several decades.

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