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Behavioral instruments in renewable energy and the role of big data: A policy perspective

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ABSTRACT

There has been a surge in the application of behavioral insights for environmental policymaking. It is often presented as an easy and low-cost intervention to alter individual behavior. However, there is limited insight into the cost effectiveness of these attempts and the impact of inserting behavioral policy instruments into an existing mix of traditional tools in a particular policy sector. Furthermore, there has been little focus on the intersection of large behavioral datasets and how they could complement behavioral insights. We present a conceptual overview of how the intersection of big data and behavioral knowledge would work in the renewable energy sector. We indicate that inserting behavioral insights into the energy instrument mix is complex due to technological trajectories, path dependencies and resistance from incumbent industries to change production patterns. We also highlight the underutilized role of large behavioral datasets that can inform not only policy implementation, but also policy design and evaluation efforts. Drawing on these findings, we introduce future research streams of government capacity in combining behavioral insights and data, the compatibility of this information with existing policy instruments and how this affects policy change.

1. Introduction

Many policy tools have behavioral assumptions as their foundation in order 'to get people to do things they might not otherwise do or enable people to do things that they might not have done otherwise' (Schneider and Ingram, 1990, 513). These behavioral assumptions have increasingly dominated the policy research agenda as well as policy-making domains under the label of 'nudging'. Nudging however is only one aspect of the broader range of behavioral interventions (BIs) that aim to modify people's actions in a predictable way. The application of behavioral economics to policy stems from the idea that people deviate from the axioms and assumptions of standard economic theory and these behavioral economic phenomena can be used as a toolbox to improve effectiveness of policy interventions (Simon, 1987; Oliver, 2015). BIs can thereby constitute stand-alone policy instruments, such as modifying default options, or inform traditional interventions, such as regulatory initiatives (Lourenco et al., 2016). This idea builds on a long history of behavioral economic observations in individual decision making where rather than scaling up microeconomic and financial incentives in the market, psychological characteristics, such as automatic or sub-conscious processes are taken into account (Chatterton and Wilson, 2014). For example, 'gains and losses around some specific reference point, which is usually assumed to be the status quo but is susceptible to manipulation, is more important than what one finally ends up with, and that losses matter more than gains' (Oliver, 2015, 701; Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). These findings are not unified, there are various models and theories for understanding behavior and 'the validity of a particular model depends on the problem as defined, or the question being asked' (Chatterton and Wilson, 2014, 42).

In accordance with the multitude of such models, behavioral insights have inspired a plethora of policy instruments. These tools have been defined differently depending on whether researchers take on the more narrow view of nudging or the wider scope of BIs. In the context of the latter perspective, Lourenco et al. (2016) classify existing behavioral policy initiatives along the lines of 'behaviorally-tested (i.e. initiatives based on an ad-hoc test, or scaled out after an initial experiment), behaviorally-informed (i.e. initiatives designed explicitly on previously existing behavioral evidence), or behaviorally-aligned (initiatives that, at least a posteriori, can be found to be in line with behavioral evidence)' (Ibid, 6). Nudging falls into the last category of behaviorally-*aligned* initiatives and mainly consists of four different types of policy instruments: 1) simplification and framing of information; 2) changes to the physical environment; 3) changes to the default policy; and 4) the use of social norms (Mont et al., 2014). Thereby, nudging is defined as ‘any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives’ (Thaler and Sunstein, 2008, 6). It is often presented as an easy and low-cost intervention to alter behavior, which focuses predominantly on the choice architecture in different contexts of human behavior while preserving the range of choice options. In contrast, behavioral insights include a broader repertoire of instruments, since they can be integrated with or inform traditional forms of intervention (Lourenco et al., 2016). It is in this context that data and specifically behavioral data can contribute to both developing new policy tools as well as optimizing existing ones, since there is a lack of evidence at population level. Many studies work with small samples and few provide evidence of cost effectiveness or long-term impact of policy initiatives (Mont et al., 2014).

The choices people make increasingly involve the use of information technology, which means that data generated from this usage becomes a resource for policy-makers to decide on instruments while the technology itself can be a tool to create customized behaviorally-driven choice architectures (Mont et al., 2014). In fact, much of this policy-relevant data is behavioral data, which allows for the application of a combination of data-based predictive analytics and behavioral economics in policy domains such as renewable energy development. Thereby, the technological aspect is one sub-dimension in the larger context of behavioral economics. Chatterton and Wilson (2014) identify four dimensions including actors, domain, durability, and scope. As part of the domain aspect of behavior, which asks what shapes or influences behavior, technical considerations focus on the psychological dimension and can be separated into ‘automatic and reflective systems (Thaler and Sunstein, 2008) or fast and slow thinking (Kahneman, 2011), and also disaggregated cognitions such as attitudes, opinions and values (Bergman, 1998; Chatterton and Wilson, 2014, 46). In short, technology can influence behavior and raise questions about how people interact with certain devices, and at the same time technology can itself become a source of vast amounts of behavioral data.

In the environmental and energy policy domain, policymakers have struggled to motivate citizens to take action against climate change, in this light, the use of behavioral incentives based on data has become a prominent mechanism for addressing this challenge. Research has increasingly advocated the use of behavioral interventions in designing climate policies (Allcott and Mullainathan, 2010; Vandenbergh et al., 2011; Truelove et al., 2014). In fact, some of the longstanding puzzles in environmental policy can be explained by looking at the behavioral biases driving limited output. In short, current priorities in the environmental policy domain, such as energy efficiency improvement, ‘require behaviorally motivated policy solutions since their attainment fundamentally rests on behavioral change’ (OECD, 2017b, 46). Research has shown that from a behavioral economics perspective, the most powerful cognitive biases and anomalies in energy consumption include the status quo bias, loss and risk aversion, sunk-cost effects, temporal and spatial discounting, and the availability bias (Frederiks et al., 2015). Introducing new technologies to potentially offset harmful behavior can further lead to a ‘rebound effect’. This effect describes that an increase in energy efficiency in goods can lead to increasing levels of energy services and ultimately result in more energy being consumed (Wigley, 1997; Greening et al., 2000).

Once this rebound effect surpasses a hundred percent, it is called the Jevons paradox. The erosion of technology efficiency gains raises questions around the sources and size of such an effect. High rebound estimates would lead to technology policies reinforcing higher energy prices to achieve original carbon and energy savings. The behavioral responses embedded in this effect have only been explored to a limited extent due to the lack of dynamic micro-level and time-panel data (Greening et al., 2000). New and bigger data sources can potentially provide the basis for establishing policy action by being able to capture policy-target sub-groups and their real-time behavior (Ruggeri et al., 2017). As Greening et al. (2000) point out, rebound effects are based on the application of economic theory in a static situation, whereas aggregated, more dynamic micro-behaviors combined with paths of technological change could reveal transformational effects in preferences.

While the complementary nature of the two resources – a behavioral framework and the support of data – is evident, there are several obstacles that government encounters when merging the two. Firstly, any government intervention has to work within an established policy instrument mix. This means that instead of new instruments being created, existing tools of government will predominantly be tweaked or adjusted (Howlett and Rayner, 2013; John, 2018). Secondly, any behavioral intervention is, more generally, part of a complex system with moving parts that might affect both government action as well as individual environmental behavior (Spotswood, 2016). In the energy field, policy goals are further challenged by existing technological trajectories, path dependencies and resistance to change towards new, often renewable technologies from incumbent industries and investors.

This paper adds to the discussion of the intersection of data analytics and the use of behavioral interventions in the energy domain by focusing on the main categories of policy instruments in this sector. Recent research has shown that rather than being stand-alone instruments, BIs facilitate a more empirical approach to designing policies based on, for example, experiments or random control trials. This trend has led to a combination of available and new data that would support behavioral frameworks and re-visit existing, traditional policy tools (Mont et al., 2014; Benartzi et al., 2017). To contribute to this research perspective, we illustrate the potential for behavioral economics and big data to complement each other in policy instrument mixes, by looking at the energy policy domain and the growing role of renewable energy therein, as it allows policymakers to customize interventions (Lim, 2016). The discussion is based on the question ‘how have big data and behavioral insights complemented each other for reaching renewable energy goals within energy programs’. To tackle this question, the paper first looks at the complementary nature of basing these frameworks on big data and then identifies behavioral programs in the renewable energy domain to exemplify the types of policy instruments that they work with.

2. Behavioral policy instruments and the use of (big) data

In general, increased data use has the ability to impact both procedural and substantive policy instruments in a given policy domain. These two types of instrument categories capture the collection of information to enhance evidence-based policymaking and public institutions communicating information to citizens (substantive), as well as the activities by government to regulate information based on legislation for its release (procedural) (Howlett, 2011). In this context, government is both producer and consumer of data by storing a vast amount of administrative information in addition to tapping into more (real-time) data originating from sensors or social media. A combination of these types of data allows government to track individual treatment effects of policy initiatives, which can in turn be used to customize policy instruments rather than base design decisions on average treatment effects. In addition, this creates new opportunities to conduct and evaluate randomized experiments (Einav and Levin, 2014). In the energy policy domain specifically, data analytics provide opportunities to refine design by providing decision support for regulators based on improved tracking of, for example, carbon emissions or household energy consumption (Zhou et al., 2016). For behavioral insights, there is a high demand for linking existing data as well as utilizing new sources of data. So far, there is a lack of evidence at the population level as well as on the effectiveness and long-term effects of behavioral instruments. However, new technologies allow for generating bigger datasets without breaching data privacy. For example, smart meters installed in many households as well as the use of social media give opportunities to learn about individual energy behaviors (Mont et al., 2014; Lourenco et al., 2016). Data science techniques further allow for more advanced analyses of over-time developments and the effectiveness of instruments. This applies to the calculation of potential rebound effects linked to technological advancement and energy consumption. Greening et al. (2000) find that a lack of consumption data for end use results in overestimating rebound effects. Similarly, 'measurements of the take-back or direct rebound effect of commercial or industrial firms are extremely limited' (Greening et al., 2000, 396)

These opportunities lead to three main research considerations that are imperative for furthering the theoretical and practical knowledge regarding the use of behavioral insights in policy mixes. First, there is a methodological dimension to using big data in the behavioral framework used for policy instruments and the compatibility of the two. This refers to the granular data available to policymakers that can move beyond average treatment effects by setting-up tailored incentives and potentially reducing process-level uncertainty by eliminating some of the trial and error procedures observed in the setting of popular behavioral instruments, such as nudges. In other words, this entails moving past some of the context-specific results produced in behavioral experiments. This also speaks to a change in evaluation tools and how they themselves can change in the process. A second aspect is the capacity of government to tackle the complexity of environmental programs with the combination of big data and behavioral insights. And finally, a third consideration is the effect that these developments and new behavioral inputs can have on existing notions and models of policy change. These three emerging research concerns are further elaborated below.

2.1. *Methodological compatibility of behavioral initiatives and big data*

Contemporary research on behavioral interventions struggles with the type and the size of samples. Often, results rely on study populations where size rather than quality is a criterion. While large samples are relevant to generalizing findings, government is also interested in subpopulations. Larger, but more granular datasets help to see 'how cultural preferences, attitudes and economic outcomes may differently affect low-income groups' (Maddix, 2017, 1). Enlarging N in these settings includes, for example, utilizing real-world intervention data. The collection of this type of massive dataset allows researchers to track interventions over-time and variation within an individual. This addresses the issue of testing intervention in uncontrolled settings, which is often raised in the nudging research domain. In addition, it addresses concerns around control groups in experimental settings.

> Control groups typically exist to account for systematic differences between participants in each group, as well as natural change over time. A within-person analysis is less subject to these concerns since each data point comes from the same person. (Carpenter et al., 2016, 14)

Researchers have further discovered that the big unstructured data available through social media interactions can provide insights into attitude and behaviors. This data provides information about posts, messages, searches and profile updates. In the health domain, for example, 'the analysis can provide insights about their likelihood of engaging in risky behaviors or contracting a disease, as well as inform public health policy and research' (Lourenco et al., 2016, 39; Young, 2014).

Another methodological aspect has to do with the trial-and-error procedures applied for these types of policy measures. Behavioral instruments are largely based on ongoing trial-and-error experimentation in real-world situations (Thierer, 2016). As Abdukadirov (2016) states, 'given the embryonic state of behavioral research and uncertainty that exists with regard to most behavioral interventions and mechanisms, nudge designers have to rely on a trial-and-error process to weed out bad ideas and refine promising nudges' (Ibid, 5). Based on these findings, government can then make decisions on how to re-calibrate certain policy instruments for them to produce the desired behavior. This 'learning by doing' approach to behavioral insights however has kept some governments from generating and using this knowledge in the first place, due to precautionary principle policymaking. Additionally, learning-by-doing brings about uncertainty around the interdependency of policy instruments, since policies might have intended and unintended effects that are not always recorded (Nauwelaers and Wintjes, 2008). Context specificity of trial runs also makes transfer of those findings to other policy domains impossible. Big data can counteract some of these challenges in several ways: (1) Data can offer predictive models that can be used to flag issues to which applying behavioral insights are valuable; (2) big data can capture sub-groups to create targeted interventions, and (3) 'instead of applying and re-applying nudges as 'best guesses', governments can tailor to very specific, personalized behavioral nudges to individuals and small groups' (Eggers et al., 2017, 1). Thereby, big data extends the evidence base for behavioral initiatives by relying on multiple sources, which creates more granularity, regulatory, consistency and flexibility (Ruggeri et al., 2017).

2.2. *Government capacity to combine behavioral insights and big data*

In order to utilize these opportunities that the combination of behavioral insights and big data can offer, government requires the capacity to apply them, especially in the environmental policy domain. In fact, while behavioral insights, and nudging in particular, have been treated as easy and low-cost interventions, they require quite extensive knowledge of existing evidence about human behavior in specific contexts (Mont et al., 2014). This further necessitates the allocation of resources to review available evidence and integrating it with existing knowledge of both the environmental policy domain and environmental policy instruments. A number of governments have formed so-called 'nudge units' to support the behavioral aspects of these efforts. These teams of behavioral science experts are tasked with 'designing behavioral interventions that have the potential to encourage desirable behavior without restricting choice, testing those interventions rapidly and inexpensively, and then widely implementing the strategies that prove most effective' (Benartzi et al., 2017, 10). However, there is often limited thought given to the data dimension of these studies. In other words, governments lack the expertise to match big data to draw on a broader foundation for designing some of these instruments in conjunction with traditional measures. In a report on BIs, the OECD (2017a) specifically outlines the importance of data by saying that 'good and reliable data is…required if behavioral insights are to become robust policy tools' (Ibid, 4). This lack of expertise also leads to, what the OECD (2017a) calls an 'implementation gap' where behavioral insights are largely used to fine-tune at a late stage of policymaking when instruments are already in place rather than facilitate the effectiveness of policy and regulation *before* designing the instrument.

2.3. *Behavioral inputs and policy change*

Finally, there are two aspects relevant for making the connection between behaviorally-based policy tools and larger policy change. First, there are limited efforts in policy circles to assess the cost effectiveness of these types of instruments. This makes it difficult to estimate whether a tool 'increases engagement in a desired behavior by a larger amount per dollar spent than a traditional intervention' (Benartzi et al., 2017, 10). And second, small experiments with limited generalization ability can rarely serve as a justification to expand behavioral instruments in other policy areas. Results so far show that the effects for tangible policy change in OECD countries are mixed (OECD, 2017a):

> Countries that have been dealing with behavioral insights for longer

have largely focused on changes mostly on improving implementation (e.g. letter to tax payers, access to information, default options, etc.)…there was hardly any information in the survey about examples where insights-related initiatives had been transferred to policy thinking generally, and whether there had been an evaluation of its success. (Ibid, 44)

Concrete examples of policy change however do exist. Based on findings from the transport sector where experiments in retail settings were conducted with regards to the labeling of car fuel efficiency, showed that 'translating fuel efficiency indicators into expected fuel costs throughout a period of multiple years can be highly effective in driving consumers towards the purchase of more fuel efficient vehicles' (EPOC, 2017, 31). The applications of behavioral insights around simplifying and framing information, in order to increase the effectiveness of fuel efficiency labels and their role in car choice led the United States Environmental Protection Agency (US-EPA) to mandate a change in the framing of fuel efficiency labels in 2011 to include information on the fuel costs associated with car use (EPOC, 2017). Additional (linked) data can support these efforts by providing potential insights beyond specific policy sectors and further compare different mixes of policy instruments and their effectiveness.

To summarize, an increased awareness and focus on the data dimension of behavioral insights can shed light on the interaction between behavioral and traditional environmental policy instruments and ultimately offer evidence for their effectiveness to support governments in both the early stages of policy design as well as during the evaluation steps of policymaking (OECD, 2017b). The following section analyses the intersection of behavioral insights and new data sources in the renewable energy domain by mapping existing categories of policy instruments.

3. Behavioral programs in the renewable energy domain

To date, the main instruments that have been deployed by governments seeking to proliferate renewable energy and energy efficiency technologies have fallen under two categories: regulatory policies and financial or fiscal policies (REN21, 2018) (Table 1). The expanded use of these instruments has resulted in policy directives that seek to directly address renewable energy proliferation by increasing its supply and public demand from a market or regulatory perspective. While financial incentives and regulatory compliance have been important factors affecting low-carbon energy behaviors, these behaviors have also been influenced profoundly by other cognitive determinants such as general beliefs about the importance of environmental sustainability (Bang et al., 2000); values favoring 'green' products and choices (Wang et al., 2014) that can often trump knowledge of low-carbon energy benefits as a major reason behind green energy choices (Wolsink, 2007); and adherence to social norms and isomorphic behavior with regards to reference groups (Welsch and Kühling, 2009). As a result, while the main categories of policy instruments used in the renewable energy domain rely on the influence of financial or regulatory markers, behavioral interventions have been employed in order to address long term sustainability of renewable energy use and production behaviors.

In terms of regulatory policies, mandatory renewable energy quotas or renewable portfolio standards (also known as RPS in the United States) are the most common policy directives for enhancing renewable energy use. This policy instrument mandates a specific percentage of electricity to be derived from renewable energy sources such as solar, wind, biomass or geothermal. In the United States, for example, 'the deployment mandate is gradual over time [eg. 15% of electricity production from renewables by 2025, with incremental goals along the way], and compliance typically incorporates traditional command and control mechanisms, such as monitoring and sanctioning, along with the trading of credits in order to increase flexibility for implementing jurisdictions' (Carley et al., 2017, 439). While portfolio standards and quotas can be set in several ways, most processes rely on the analysis of big data related to energy demand and supply in order to calculate baselines and estimate business as usual (BAU) and alternate future energy scenarios (IRENA, 2015). However, supporting programs to understand the social behavioral response for such standards have also

Table 1
Renewable Energy and Energy Efficiency Policy Tools and Supporting Behavioral Programs.

Renewable energy / energy efficiency support policies	Examples of supporting behavioral instruments and considerations	Type of data used for instrument design	Indicative literature
REGULATORY POLICIES			
Renewable portfolio standards (RPS); Electricity quota obligations	Stakeholder participation programs to improve accountability and sense of 'co-ownership' of RPS targets.	Energy supply, demand and energy mix composition data for:	REN21 (2018), IRENA (2015)
Tradeable Renewable Energy Certificates (RECs) or Green Certificates	Negotiation and consultation committees; hearings on goal setting Promotion campaigns and workshops for garnering public support and buy-in	• Target setting • Baseline analysis • Business-as-usual (BAU) estimates	
Transport sector fuel obligations	Consumer 'eco-driving' training	Randomized Control Trials (RCTs) Small-n case studies	Stillwater and Kurani (2013), Barkenbus (2010)
Net Metering / Smart Grids	Community-Based Social Marketing (CBSM)	Public Opinion and End-User survey data on: • Long term energy use and consumption • Consumer awareness and degree of concern • Willingness to Pay • End-user motivation • Barriers and risks to uptake • Market segmentation • Socio-economic analysis	McKenzie-Mohr (2000), Anda and Temmens (2014);
FINANCIAL AND FISCAL POLICIES			
Feed-in Tariffs and Renewable Energy Premium Payments	Consumer Engagement	User surveys and interviews Diverse incentives for varying FITs	IRENA (2015), REN21 (2018), Richler (2017), Stokes (2013)
Production tax credits, or tax reductions	Power Purchase Agreements (PPA) negotiations and contracts Federal or state level RPS mandates Green-consumer programs	Risk-management information such as: • Investor credit status • Corporate guarantees • Insurance cover	Barradale (2010), Wiser et al. (2007), Williams (2006), Steineger (2005)

been necessary during their formulation, evaluation and adjustment phases. In the EU, for example, such programs have included committees to facilitate public negotiation and consultation with stakeholders and promotion campaigns to garner public buy-in to the goals set by the RPS policy (IRENA, 2015).

A popular policy instrument that has been used to support renewable energy portfolio standards are tradable renewable energy certificates (RECs), often also known as 'green certificates'. These certificates are issued once a quota for renewable energy use is set by a regulatory body, whereby a 'cap-and-trade' mechanism can follow thereafter. In this instance, a certificate is issued by the regulator for each MWh of renewable energy supplied by the energy generator, who is then able to sell this certificate to a power utility company that is required to supply a certain percentage of its electricity from renewable sources (Coulon et al., 2015). These required percentages or shares can also specify a particular type of renewable technology (such as solar). Albeit largely successful, markets of tradable certificates that are based on such set quotas or caps have been known to be susceptible to price volatilities and investor behaviors have been shown to be influenced by factors other than certificate prices, such as *a priori* beliefs regarding technology effectiveness (Berry, 2002; Marchenko, 2008; Masini and Menichetti, 2012). Furthermore, time limitations of some REC schemes may fuel investor pessimism, especially in the case of large projects that may not get completed in time to be able to sell their certificates (Linnerud and Simonsen, 2017).

Technical mandates and obligations in transportation are another category of policy tools that are employed by jurisdictions to reduce transport sector or heating emissions. However, it has also been shown how such regulatory standards have often increased emissions instead of reducing them (Alamand Aonghus, 2014). Supporting behavioral interventions have been suggested, especially in the case of the United States and the EU, that look to reducing short-term vehicular emissions by addressing 'aggressive' driving and adapting 'eco-driving' techniques to enhance fuel economy (Stillwater and Kenneth, 2013; Barkenbus, 2010).

For increasing the use of renewable energy, Feed-in-tariffs (FIT), or premiums are non-regulatory policy instruments whereby payments are extended to individual businesses or households that generate their own electricity through renewable sources. FITs offer financial benefits for the renewable energy generation, additional bonus payments for exporting such energy back to the grid and/or a discount on utility charges from the energy that is produced. By guaranteeing a market setting for energy generated through renewable sources, FIT programs help investors expand such technologies by setting a standard purchasing price and long-term contracts (Stokes, 2013). However, the challenges that these programs often run into, and seek to address using supporting BIs, surround issues of variable incentives and equity. For example, corporate investors seeking tax credits and write-offs can override local participation, regulators building flexibility into the pricing adjustment process may undermine investor confidence and higher FIT rates may mean that participating maybe more motivated by economic benefits than changing energy behaviors (Stokes, 2013; Richler, 2017). Similarly, for net-metering or smart grid schemes, community-based social marketing programs have been used to understand participant motivations and incentives. Public opinion and end-user survey data are used to understand target group behavior and give information on long-term energy use, consumer awareness and level of concern, willingness to pay and perceived barriers and risks (Mckenzie-Mohr, 2000; Anda and Temmen, 2014)

Another example of financial or fiscal policy tools are production tax credits (PTCs), that are issued to energy producers, within pre-set time frames, who generate power using renewable resources. The largest example of PTCs exists in the US to support the incorporation of wind energy into power production whereby producers are given tax credits for up to the first ten years of operation with the requirement that plants commence operation by the PTC expiration date. Since its inception, the PTC has been renewed several times, however the time frame between the expiry of one scheme and its renewal have often been considered to be too short resulting in the targets of this policy – investors and power companies – facing significant amounts of price uncertainty that has undermined investments (Wiser et al., 2007; Barradale, 2010). Despite this inherent volatility in price brought on by PTCs, evidence has shown that investor behavior favoring renewables can be guided by motivations other than economic cost, such as policy incentives forwarded by renewable energy mandates, heightened demand by consumers through green consumer programs, that work alongside PTCs (Williams, 2006; Steineger, 2005). Barradale (2010) provides significant evidence that in the face of price uncertainty brought on by PTCs, the contract negotiation dynamics between independent power producers and state utilities to set up power purchase agreements (PPAs) can be a significant factor in ramping up renewables. These PPA negotiation processes consider a variety of data such as pricing, development benchmarks, risk-profiling based on creditworthiness, corporate guarantees and insurance covers. Therefore, PPA negotiations and the behavioral implications from other policy signals like RPS need to be considered alongside PTCs to gauge the latter instrument's efficacy.

As is highlighted in the above discussion, strong political will, backed by enabling policy instruments and programs have been fundamental towards the growth of renewable energy technologies as states consciously choose to embark on energy transitions that decarbonize their economies. These transitions have required the interplay of multiple actors as technological advancements have co-evolved along with changing social values (Rogge et al., 2017; Grin et al., 2010; Markard et al., 2012). As a result, these transitions become apparent only over a few decades as they must overcome 'multiple barriers, including lock-in into high carbon, fossil fuel based technological trajectories, path dependencies and resistance to change from incumbent industries benefitting from the current socio-technical configurations' (Rogge et al., 2017, 1). Some scholars have argued that these lock-ins and path dependencies can have a strong cognitive component as industries tend to continue growing and maturing along conventional technological trajectories, stymying the space that is available for revolutionary new energy developments (Unruh, 2000). Lock-ins may also stem from institutional factors as prior organizational obligations, associations and conferred interests within energy industries can result in the perpetuation of inefficient, carbon-intensive technologies (Walker, 2000).

Energy analysts are in agreement that in order to meet the targets that countries have set to transition to low-carbon economic growth, huge additional investments are necessary over the short and long-term (Meyer et al., 2009). As reiterated by the examples given in this paper, gauging investor behaviors and preferences that influence investment decisions favoring technological development becomes an important priority to consider when designing policies to boost renewable energy. Masini and Menichetti (2012) for example, outline several beliefs previously held by investors (such as confidence in market efficiency and technology effectiveness), policy preferences (such as perceptions of the importance of policy types as well the level and duration of government support), and their individual attitudes towards technological risk. At the level of individuals, while motivations to adopt renewable and more efficient energy practices often involve addressing upfront cost considerations, sustaining low-carbon consumption behaviors beyond the uptake phase often requires policymakers to devise programs that support the deployment of traditional regulatory, financial and fiscal policy instruments by addressing behavioral considerations.

Due to these considerations, most major policy instruments for renewable energy development have had to increasingly acknowledge the behavioral components determining their success through supporting policy programs that can gauge target preferences and perceptions. However, this means that not only is behavioral change on the part of energy consumers a necessary factor in making the transition to clean energy, but that it is equally important to address technology investors and power producers as distinct policy target groups. In other words, the policy targets who are impacted by the above categories of policy tools, form a significantly heterogeneous community with a wide variety of behaviors that are relevant to ramping up renewable energy development. It therefore follows that for the successful design and implementation of a low-carbon growth trajectory, there can be strong demands on government's capacity to oversee the synergy between traditional data that is used to devise policy and behavioral data used to understand its impact.

4. Discussion and future research

To summarize, in the behavioral public policy domain (Oliver, 2013, 2017), a combination of behavioral research and the application of incentives in experimental settings have led to additional policy instruments largely focusing on citizens. A closer analysis of these developments however reveals that these attempts largely happen ad-hoc and in a trial-and-error setting, which creates uncertainty and limits the use of behavioral insights more generally, as well as possible cost-benefit analyses of the effects of these instruments. Furthermore, these efforts are part of a larger, mostly complex and path-dependent system, which might keep policy tools locked into existing routines (Spotswood, 2016; John, 2018). In the context of the renewable energy sector, we find that existing instruments have very limited systematic behavioral input and have to be tailored not only towards behavioral patterns of citizens, but also compliance behavior of companies and investors choices. In this setting, there can be hidden trade-offs among adding or changing instruments since they have an impact on the effects of existing policy tools.

Adding the data dimension to this discussion, it highlights that more information could possibly help identify and solve those trade-offs from a cost effectiveness perspective and also offer a more comparable way of looking at existing and new instruments. In addition, the analysis shows that extensive knowledge is required to design and inform instruments that pick up on both the data-driven and behavioral knowledge. This necessitates certain capacities within government to tackle the complexity of environmental programs with the combination of big data and behavioral insights. Looking at an established policy sector further raises the question whether this additional knowledge leads to actual policy change. So far, there has been insufficient evidence of that, which is partially connected to the limited efforts towards evaluating the behavioral implications of major categories of renewable energy policy.

In short, behavioral mechanisms can enrich the way policy instruments are mixed and set-up based on changes to the communication among government and stakeholders as well as the choice architecture. There are promising opportunities for enriching these insights with big data as 'there are still considerable gaps between existing theories in the behavioral sciences and evidence generated by big data' (Ruggeri et al., 2017, 1). However, a closer look at the renewable energy sector shows that its application is more complex than many of the policy recommendations from the behavioral side might suggest.

For future research, we pose the following questions that were raised by the analysis: First, to what extent are behavioral insights used to inform existing, traditional policy instruments in a systematic way? In other words, beyond creating new instruments and setting up nudge-based experiments, is there a knowledge base being established within government that policymakers in the environmental domain can tap into. Second, what are the trade-offs when new behavioral instruments are introduced into an existing mix of sustainability measures? Do they complement or enforce existing initiatives or are they potentially counter-acting parts of the regulatory set-up? And finally, is policy change happening based on these potentially new insights of behavior? Can we expect a larger shift in environmental policy due to additional knowledge and measures being taken? While diverse in scope, these questions fall within the three concerted and closely related research dimensions that we have identified in the paper. Firstly, they reflect a need to critically examine the methodological considerations of combining behavioral insights with big data for policy design, and the limitations therein. Secondly, and along the same vein, they call for an investigation of the different capacities of the government for effectively bringing together behavioral measures and big data analysis towards supporting the development of policy instruments. And lastly, they allude to a much-needed comparative focus on determining the mechanisms through which behavioral instruments can stimulate policy change.

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