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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

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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