C O M M E N T

OPTIMIZING NUDGES FOR CLIMATE CHANGE: INSIGHTS FROM BEHAVIORAL AND ENVIRONMENTAL ECONOMICS

by Anjali Narang

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Prof. Felix Mormann's *Climate Choice Architecture* comprehensively catalogs and classifies different types of nudge interventions that can be used to combat climate change. He argues that choice architecture can complement command-and-control mandates, market-based incentives, and other forms of regulation while also acknowledging its limitations. Despite choice architecture's shortcomings, I wholeheartedly concur that it is an underutilized tool in the environmental policymaker's toolbox. This underutilization is evident in the fact that the Intergovernmental Panel on Climate Change in 2022 reported that sociocultural factors and behavioral change could rapidly reduce greenhouse gas emissions by at least 5%,[1] but the share of research funding related to climate change awarded to the social sciences was only 0.12%.[2]

In this Comment, I make two recommendations drawn from the academic behavioral and environmental economics literature to supplement Professor Mormann's article. First, I urge researchers and practitioners interested in using insights from behavioral economics to mitigate climate change to consider which behavioral barriers are relevant to tackling the particular problem of interest and to apply that understanding of behavioral mechanisms to design and target behavioral interventions. Second, based on the behavioral welfare economics literature on optimal nudges and the environmental economics literature on environmental policy instruments, I advocate that choice architecture's role in climate change mitigation be jointly considered with those of other environmental policy tools. This consideration of the optimal climate change policy mix should be informed by a cost-benefit analysis of the alternative policy options.

I. Identify Behavioral Barriers and Target Nudges

To the author's point that there are different taxonomies of choice architecture, for context, it is first worth noting that behavioral economists tend to use a taxonomy of choice architectural interventions that is based on the "internalities" choice architecture aims to reduce. Individuals generate "internalities" when they make a choice that is not welfare-maximizing, or, in other words, in their best interest. While nudges from the perspective of behavioral economics usually aim to reduce an internality and improve an individual's welfare, climate change nudges can both reduce internalities *and* reduce negative environmental externalities if decisionmakers internalize the environmental costs of their actions.

My first recommendation is that choice architects identify the relevant internalities and behavioral barriers to a desired behavior and then use that information to refine nudge design. Implementing this recommendation requires more exploratory work upfront. On a deeper level, this work would involve developing an evidence-based theory of change and identifying sources of heterogeneity across people in the target population in their behavioral barriers, internalities, the levels of externalities generated by their actions, and their responsiveness to behavioral interventions.

The rationale for this recommendation is that choice architecture that accounts for heterogeneity and distributional impacts is more likely to improve welfare.[3] This

1. Intergovernmental Panel on Climate Change, *Climate Change 2022: Mitigation of Climate Change, Summary for Policymakers*, *in* Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (P.R. Shukla et al. eds., 2022).
2. "Only 0.12% of all research funding was spent on the social science of climate mitigation, spent instead on the natural and technical sciences," Kent D. Messer et al., *Applications of Behavioral Economics to Climate Change*, Nat'l Acads. of Scis., Eng'g, and Med. 4 (2023) (quoting I. Overland & B.K. Sovacool, 2020).
3. Cass R. Sunstein, *The Distributional Effects of Nudges*, Nature Hum. Behav. 6 (2022).

is because heterogeneity is inefficient; it creates a wedge between who responds to a behavioral intervention and who benefits from it the most, hampering individuals from sorting into the behavior that is the most beneficial for them.[4] Targeted nudges, however, could address the inefficiencies of heterogeneity. Indeed, "one-size-fits-all solutions . . . provide very weak generalizations"[5] because human decisionmaking is not homogeneous or predictably (ir)rational.[6] It is additionally worth asking not only whether a nudge needs to be targeted, but also whether it is "'well-targeted': does it primarily affect individuals subject to relatively large [market] distortions?"[7] Well-targeted nudges are those that create large benefits for those who make errors or mistakes while imposing small consequences on the rational, welfare-maximizing individuals. Calorie labels are examples of nudges that are not well-targeted.[8] Calorie labels lead to greater reductions in calorie consumption among people with more self-control than less self-control and are also valued more by those with more than less self-control.[9]

At the extreme end of targeted nudges are individually personalized nudges. Personalized nudges might be even more effective than nudges targeted to coarser divisions of people like population subgroups. Opower's customized home energy reports are one prominent successful example of personalized nudges.[10] Big data, machine learning, and artificial intelligence create even more opportunities to personalize nudges at scale, as they can be leveraged to develop predictive models of nudge effectiveness that can generalize and replicate over large and heterogeneous populations.[11]

This recommendation of identifying behavioral barriers for the purpose of targeting nudges can be illustratively applied to the issue of political divide over climate change issues. For example, Democrats might be more receptive to science communication because they lack but value scientific knowledge about anthropogenic climate change.[12] Republicans might be more receptive to neutral framings of policy labels like "fee" or "offset" instead of "tax"[13] because they are averse to references to government intervention.[14]

Despite the benefits of personalizing nudges, it is also worth noting that personalization is costly. One interesting approach to decrease the cost of personalization is to offer a menu of policy choices that allows the decisionmaker to self-select into different nudging interventions.[15] This approach reduces costs by avoiding making decisions ex-ante about personalization. This alternative is especially attractive when data on individual preferences and behavior that could be used as predictors of the outcome of interest are lacking.

II. Evaluate Nudges as a Component of an Optimal Climate Change Policy Bundle

As Professor Mormann pointed out, choice architecture is not a panacea for addressing climate change. While climate choice architecture might be justified by multiple market distortions, including environmental externalities, imperfect information, and "behavioral" biases such as inattention to energy costs, there are likely behavioral and non-behavioral explanations for the gap between actual and "rational" levels of climate change mitigation. Non-behavioral problems might require non-behavioral solutions.[16] A multi-pronged, holistic approach to climate change mitigation that considers both positive and negative interactions between non-pecuniary behavioral and traditional pecuniary approaches like taxes and subsidies is likely needed. For this reason, my second recommendation is that nudges and traditional environmental policy tools be jointly evaluated.

An optimal policy bundle should not only involve decisions about which tools to include in the mix, but also decisions about the optimal level of those tools. The optimal nudge is one that perfectly corrects decisionmaking biases. The optimal level of a nudge should depend on the "nudgeability" of decisionmakers, defined as the ability of the nudge to affect the perceived ("decision") utility from a good.[17] Examples of nudges high in nudgeability include public anti-cigarette campaigns and public pro-recycling campaigns. Heterogeneous internalities in the form of price misperceptions and heterogeneous nudgeability imply that both corrective price policies and nudges are

4. Dmitry Taubinsky & Alex Rees-Jones, *Attention Variation and Welfare: Theory and Evidence From a Tax Salience Experiment*, 85 Rev. Econ. Stud. 2462 (2018).
5. Emir Hrnjic & Nikodem Tomczak, *Machine Learning and Behavioral Economics for Personalized Choice Architecture* (July 3, 2019) (unpublished manuscript), *available at* https://arxiv.org/abs/1907.02100.
6. *Id.*
7. Hunt Allcott et al., *Tagging and Targeting of Energy Efficiency Subsidies*, 105 Am. Econ. Rev. 187 (2015).
8. Sunstein, *supra* note 3.
9. Linda Thunström, *Judgment and Decision Making*, 14 J. Judgm. & Decis. Mak. 11 (2019).
10. Matthew E. Kahn & Peng Liu, *Utilizing "Big Data" to Improve the Hotel Sector's Energy Efficiency: Lessons From Recent Economics Research*, 57 Cornell Hosp. Q. 202, 202-10 (2016).
11. Hrnjic & Tomczak, *supra* note 5.
12. Pew Research Center, *How Americans See Climate Change and the Environment in 7 Charts*, (Apr. 21, 2020), https://www.pewresearch.org/short-reads/2020/04/21/how-americans-see-climate-change-and-the-environment-in-7-charts/.
13. Elke U. Weber & Paul C. Stern, Public *Understanding of Climate Change in the United States*, 66 Am. Psych. 322 (2011) (citing David J. Hardisty et al., *A Dirty Word or a Dirty World? Attribute Framing, Political Affiliation, and Query Theory*, 21 Psych. Sci. 86 (2010)).
14. Gracia Perino et al., *Motivation Crowding in Real Consumption Decisions: Who Is Messing With My Groceries?*, 52 Econ. Inquiry 593 (2014) (citing Edward L. Deci & Richard M. Ryan, *Intrinsic Motivation and Self-Determination in Human Behavior*, Springer Sci. & Bus. Media (1985)).
15. Rebecca Dizon-Ross & Ariel Zucker, *Mechanism Design for Personalized Policy: A Field Experiment Incentivizing Exercise* (2023) (unpublished working paper, University of Chicago).
16. Hunt Allcott & Sendhil Mullainathan, *Behavior and Energy Policy*, 327 Sci. 1204 (2010) (arguing that people are not taking straightforward measures to reduce energy consumption even though it would result in a 23% reduction).
17. Fredrik Carlsson et al., *The Use of Green Nudges as an Environmental Policy Instrument*, 15 Rev. Env't Econ. & Pol'y 225 (2021).

generally needed; however, the more heterogeneity there is, the less desirable is the nudge.

There are also several scenarios in which nudges are potentially more desirable for achieving optimal behavior.[18] One scenario in which nudges might be favored is when traditional policy instruments imperfectly target externalities or internalities. Another scenario in which it might be beneficial to complement an optimal tax with a nudge is when a nudge affects people with a price misperception more than people without price misperceptions. Green nudges can also be useful policy complements to an optimal Pigouvian tax in scenarios in which green nudges generate "warm glow," a feeling of pride generated from consuming green goods. Warm glow might allow behavioral changes initiated in response to nudge-tax policy combinations to persist over time. Lastly, as Professor Mormann pointed out, nudges might be more desirable than taxes that aim to internalize environmental externalities because they are more politically feasible, as evident in the opposition to higher fuel taxes in many countries.

Cost-benefit analysis should also be used to identify the constituent components of the optimal environmental policy bundle. As commonly touted, nudges are often more cost-effective[19] than traditional tools, thought of as low-hanging fruit that can produce results relatively quickly and inexpensively. However, the cost of nudge research and testing is perhaps overlooked in claims about its cost-effectiveness. The context-specificity of nudge impact[20] implies that more research and iterative testing of nudges is needed to make generalizable claims.[21] If nudging requires policy experimentation to be effective at scale, and policy experimentation is expensive, then nudging at scale might become a more expensive endeavor than anticipated. On the other hand, one advantage of nudges over conventional policy instruments is that they *can* be tested on a smaller scale, which could, in turn, suggest that nudge compatibility with experimentation is a feature and not a bug, potentially saving money in the long run relative to untested interventions that are implemented en masse.[22]

III. Conclusion

The urgency, importance, and complexity of climate challenges require a battery of approaches to overcome, from low-cost, short-term solutions to high-cost and long-term ones. *Climate Choice Architecture* makes an important contribution to the discourse on climate change about the understated role of choice architecture in mitigation. My contribution to this discourse with this Comment is to highlight additional insights from behavioral and environmental economics that can be used to enhance the acceptance, efficacy, and prevalence of nudges for climate change. By underscoring the theoretical motivations for nudging from the behavioral welfare economics literature and appraising nudge cost-effectiveness from multiple perspectives, I hope that the original article and this Comment together make clear that governments should provide R&D funding for behavioral programs as part of their broader efforts to encourage energy and climate change-related innovation.[23]

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18. *Id.* at 225-27.
19. Shlomo Benartzi et al., *Should Governments Invest More in Nudging?*, 28 Psych. Sci. 1041 (2017).
20. Silvia Saccardo et al., *Assessing Nudge Scalability* (June 5, 2023), https://ssrn.com/abstract=3971192.
21. Allcott & Mullainathan, *supra* note 16, at 1204-05.
22. Carlsson et al., *supra* note 17, at 229.
23. Allcott & Mullainathan, *supra* note 16, at 1205.