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Synergies of interventions to promote pro-environmental behaviors – A meta-analysis of experimental studies

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ABSTRACT

Addressing the threat of climate change requires effective environmental regulation to induce pro-environmental behavior. While various policy interventions already exist, combining different policies may offer greater effectiveness in dealing with market failures, multiple environmental objectives, and mitigating the regressive effects of single policies. In this meta-study, we investigate the potential synergies between policy interventions by rigorously assessing their comparative effectiveness when used individually versus in combination. We focus on experimental studies providing comparable findings from controlled settings to facilitate an empirically grounded understanding of climate policy synergies. Our analysis reveals negative synergy effects, indicating that, on average, the analyzed policy mixes are less effective than the sum of their individual intervention effects. However, we also find that policy mixes can offset the negative effects of single policies. Notably, combinations involving nudges and monetary incentives prove particularly effective in promoting pro-environmental behavior. Lastly, behavioral changes induced by policy mixes tend to wane faster compared to single interventions once the policies are removed. Our study provides important scientific and policy-relevant insights regarding the performance of policy mixes.

1. Introduction

Addressing the environmental and societal challenges posed by climate change requires significant changes in human behavior and lifestyles (IPCC, 2022). Regulatory policies play a crucial role in driving these behavioral shifts, but the effectiveness of individual interventions can be limited. For instance, monetary incentives exhibit diminishing marginal returns (Layard et al., 2008), and single behavioral interventions can be ineffective and short-lived (Szaszi et al., 2022).

To effectively tackle environmental challenges, a wide set of policy tools is required. In this context, policy mixes that combine different interventions represent a promising approach. There are at least two reasons why different interventions are applied to influence the same behavior: the belief in their superior effectiveness compared to a single intervention and the alignment with various governance levels. In fact, overlapping governance competencies already lead to multiple interventions targeting the same behavior (Hawkins et al., 2016; Jordan et al., 2012; Feike and Henseler, 2017). For example, Belgian consumers buying a fridge or a washing machine can be entitled to a financial subsidy in the form of Ecocheques - small financial incentives for ecological products and services that are exempt from payroll taxes, based on national policy - and at the same time face European Union-legislated energy labels that highlight the energy efficiency of these appliances.

Policy mixes are well-established in practical regulatory environments, and policymakers rely on them due to their ability to simultaneously harness demand-driven and supply-driven effects (Herrmann and Savin, 2017), and to enhance acceptance, perceived fairness, and political feasibility (Maestre-Andrés et al., 2021). Policy mixes can also amplify the positive second-order effects of price interventions, such as taxation. When incentives prompt behavioral changes, peer effects gain traction, leading to the alteration of individuals' inherent preferences towards pro-environmental actions (Konc et al., 2021). Finally, policy mixes can alleviate market failures, address multiple environmental objectives, and mitigate unwanted side-effects that some single policies are prone to create (van den Bergh et al., 2021). For instance, combined behavioral interventions and economic incentives might be less likely to crowd out intrinsic motivation (Frey and Jegen, 2001) and pressure-

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induced lower performance resulting from monetary rewards (Ariely et al., 2009), be more appealing to paternalism-averse individuals (Sunstein et al., 2018), or ameliorate other shortcomings of single interventions (Falk and Kosfeld, 2006; Fuster and Meier, 2010; Gneezy et al., 2011; Damgaard and Gravert, 2018; Kocher et al., 2018).

Specifically in the realm of environmental policy, policy mixes can also correct shortcomings of single policies and be more effective when transaction costs for single policies are high, as is the case for pollution control (Lehmann, 2012). They also have the potential to mitigate adverse impacts arising from subsidies in the context of a carbon market, achieved by combining environmental taxes with renewable energy policies, especially in areas not directly covered by the tax (van den Bergh et al., 2021). Third, policy mixes can target behaviors across all phases of the product life cycle, thus advancing the circular economy of the European Union (Milios, 2018).

While recognized for their multiple benefits, a lack of quantitative analyses exists regarding the effectiveness of combined traditional and behavioral economic interventions based on existing experimental evidence. Our study aims to fill this gap by empirically evaluating the effect sizes of a large set of studies that apply policy mixes to induce pro-environmental behavior. We compare the effectiveness of combined interventions to their summed effects when implemented individually. Our investigation expands upon the extensive research on the effectiveness of individual interventions (Weersink et al., 1998; Shogren, 2012; Bergquist et al., 2019) and builds on meta-analyses revealing moderate impacts of monetary incentives (Maki et al., 2016) and variable effect sizes for behavioral interventions (Osbaldiston and Schott, 2012; Abrahamse and Steg, 2013; Niemiec et al., 2020; Mi et al., 2021) on pro-environmental behavior. We go beyond meta-analyses that compare the effectiveness of behavioral and monetary interventions (List et al., 2023), the effectiveness of behavioral interventions implemented in the lab vs. in the field (DellaVigna and Linos, 2022), and the cost-benefits of nudges compared to traditional policy tools (Benartzi et al., 2017). Notably, these studies primarily examine the effectiveness and costs of these interventions individually. For example, List et al. (2023) examine the welfare effects of policy mixes that combine nudges and taxes, but do not explicitly study reduced-form interaction effects of nudges and taxes. What sets our paper apart is our explicit focus on studying the reduced-form interaction effects when behavioral and monetary interventions are implemented simultaneously.

This meta-analysis relies on a taxonomy that outlines three possible synergy effects of combined interventions: positive, negative, and backfire effects (Drews et al., 2020). The former occurs when two interventions have a larger effect than the sum of their individual effects. A negative synergy exists when two interventions are at least as effective as a single intervention, but not as effective as the two single interventions. Backfiring occurs when the combined effect is less than that of an intervention on its own. In addition to our focus on the synergy effect, we investigate the role of intervention domains (traditional vs. behavioral economic interventions), mechanisms through which interventions affect behavior, characteristics of the targeted behavior (scrutiny and prevalence), and persistence of behavioral effects.

Our results reveal a negative synergy effect, suggesting that policy mixes are less effective than the sum of the single constituting interventions. However, policy mixes still outperform single interventions as they are more effective than the most effective single intervention contained in the policy mix. Additionally, our findings highlight the importance of considering the specific environmental behavior targeted by the intervention, as policy mixes indicate task-dependency. We also find that cross-domain policy mixes are more effective than single-domain policy mixes, primarily due to the detrimental effect of combining solely traditional economic interventions. We neither find convincing evidence that combining interventions influencing behavior through a certain mechanisms makes policy mixes particularly effective, nor do we find convincing evidence for the effect of prevalence and observability of the pro-environmental behavior on the effectiveness of policy mixes. We do, however, reveal a trade-off between effectiveness and persistence, as policy mixes tend to be more effective but less persistent in their effect once the intervention is removed.

This meta-analysis provides valuable insights for researchers and policymakers seeking to understand and design effective and efficient combinations of interventions for climate policy. It fills a critical gap in the literature by systematically synthesizing the effects of policy mixes, offering relevant guidance for policymakers striving to enhance pro-environmental behaviors and lifestyles.

2. Methods

2.1. Identification of studies

To conduct our meta-analysis, we utilized 'Scopus', the 'Web of Science Core Collection', and 'Google Scholar' to identify relevant papers. Our Google Scholar search was limited to the first 300 studies (30 pages). The search terms we employed are categorized in Table 1 based on relevant (1) interventions, (2) study design, (3) policy mix terms, and (4) environmentally related terms. These categories are linked to the PICOS elements (population, interventions, study design, comparator, and outcome variable) commonly used in systematic reviews (Amir-Behghadami and Janati, 2020).

For this meta-analysis, we specifically focused on controlled experiments involving human subjects, excluding agent-based models (Savin et al., 2023; Chersoni et al., 2022) and theoretical and numerical approaches (Bénabou and Tirole, 2006; Konc et al., 2021), even though we recognize their potential in investigating policy mixes. By narrowing our scope, we were able to compare standardized effect sizes of single and

Table 1
Search Terms employed to identify relevant studies.

PICOS Elements	Search Terms	
Population		
Interventions	1	price*based*, incent*, mone*induce*, reward*, price*instrum*, sanction*, penal*, tax, taxes, charg*, surcharg*, punish*, price*based*, incent*, mone*induce*, reward*, nudg*, choice architect*, label*, priming*, prime*, prompt*, remind*, feedback, feed-back, default*, commit*, boost*, norm*, intrins*incent*, tailed*infmation*, infmation*intervene*, tailed*recommendation*, recommendation*interv*, prais*, non-monetary*, price*instrum*, sanction*, penal*, tax, taxes, charg*, surcharg*, punish*, nudg*, choice architect*, label*, priming*, prime*, prompt*, remind*, feedback, feed-back, default*, commit*, boost*, nm*, intrins*incent*, tailed*infmation*, infmation*intervene*, tailed*recommendation*, recommendation*interv*, prais*, non-monetary*
Study design	2	experiment*, RCT, controlled*trial
Comparator		
Outcome	3	joint*, interaction*, mutual*, combin*, synerg*, mix*, common*, together*, unit*, both, adhere*, bundle*, addi*
	4	pro-environment*, proenvironment*, sustainab*, unsustainab*, nonsustainab*, non-sustainab*, eco*, environment*, climate, energy, electric*, renewable*, water, recycl*, car, cars, bus, car-shar*, carshar*, car-pool*, carpool*, public transpt*, bicycle*, cycle cycling temperature conserv*, preserve preserving, pre-serve, pre-serving, donat*, volunteer*, litter*, organic, food, vegan, vegetarian, meat, (green*, NEAR/2, (product*, consum*, purchas*, buy*, power, behavio*, attitud*, intention*)), insulat*, solar, wind, power, buying, used, second, hand, secondhand, buying, pre-owned, reus*, re-us*, emission*, carbon*, single-use, disposable*, compost*, travel*, airplane*, plane*, turn-off, turnoff, switch-off, pollut*, CO2

Note: The search terms to target environmental studies (Outcome, 4) were adopted from Geiger et al., 2021. For the search via Google Scholar, a simplified version of the search terms were used (see Table 5 of the Supplementary Material).

combined interventions on individual behavior.

To ensure comprehensive coverage, we also examined the reference lists of two relevant meta-analyses (Geiger et al., 2021; Buckley, 2020).

Moreover, through dissemination within the experimental economics research community, we acquired seven additional articles that were included in the meta-analysis in January and August 2023. The initial search was conducted in February 2022 and repeated in May 2022 with no additional articles of relevance found. In total, we identified 5,069 articles.

2.2. Screening and inclusion of studies

Fig. 1 depicts the process of including articles. While additional records identified via Google Scholar, screening reference lists of relevant studies, and reaching out to the scientific community were all screened manually, the database search including the majority of 4756 articles followed a different process partially supported by Artificial Intelligence (see more info below). After removing 969 duplicates, we screened the titles and abstracts of the 3,787 studies according to the following inclusion criteria: (1) the language of the article had to be either English, French, Spanish, or German to account for potentially relevant non-English publications based on researchers' language competencies; (2) the study had to be a published article, preprint, conference paper, dissertation, or master's thesis, to minimize the risk of missing null findings that are less likely to be published (Franco et al., 2014); (3) the behavior assessed in the study (i.e., the outcome variable) had to be related to environmental behavior, including emission reduction activities, green consumption, pollution control, donations to environmental charities, and pro-environmental computer tasks. This selection was based on previous meta-analyses on the topic (Geiger et al., 2021; Maki et al., 2019). The related search terms can be found in Table 1; (4) the study had to apply experimental methods; (5) we excluded all fractional factorial designs with a missing control or unusable single interventions. The experiment had to include a full factorial design measuring the outcome variable in the control treatment, the single intervention treatments, and the policy mix treatment. This design allows us to identify the standardized effect size for the synergy effect, which is defined as:

$$\text{SynergyEffect} = (\text{PEB}_{\text{Policymixintervention}} - \text{PEB}_{\text{Control}}) - [(\text{PEB}_{\text{InterventionA}} - \text{PEB}_{\text{Control}}) + (\text{PEB}_{\text{InterventionB}} - \text{PEB}_{\text{Control}})]$$

In this equation, PEB refers to the pro-environmental behavior of participants in the experiment and the subsets indicate the treatment interventions. The control treatment includes no intervention, interventions A and B each include one intervention, while the policy mix intervention includes both interventions A and B. We also included and adequately marked studies with a fractional factorial design, where one of the single interventions had not been tested; (6) the experiment had to involve a human sample; (7) the experimental design had to include a policy mix treatment, i.e., we excluded all fractional factorial designs with no policy mix treatment; (8) the reported data had to allow for the calculation of standardized effect sizes or be made available by authors on request; (9) the study had to be available in digital format. The same criteria were used to screen the additional records.

We used 'AS-Review' to assist in the screening of the articles obtained through the database search in the identification stage according to the above criteria. 'AS-Review' employs an active machine-learning algorithm, using word-level data from the abstracts to rank articles based on relevance (van de Schoot et al., 2021). The naïve Bayes classifier uses the term frequency-inverse document frequency of abstracts. The algorithm ranks articles by relevance based on an initial set of articles manually marked as relevant. This set of articles consisted of Drews et al. (2020); Mizobuchi and Takeuchi, 2013; Panzone et al., 2021; Pellerano et al., 2017 and Schall et al. (2016). Based on this ranking the researcher makes inclusion and exclusion decisions manually, receiving the abstracts and titles of the articles by their relevance ranking, which updates concurrently based on user decisions. Out of the 1,000 manual decisions, none of the latter 200 studies met the inclusion criteria. For the purpose of a robustness check, we assessed another 500 articles suggested by the algorithm, where only one article was included. Consequently, the remaining studies were classified as irrelevant.

We then merged the articles from the database search and the additional records, removing eight duplicates. Two researchers assessed the full texts of 92 articles for eligibility using the criteria above, leading

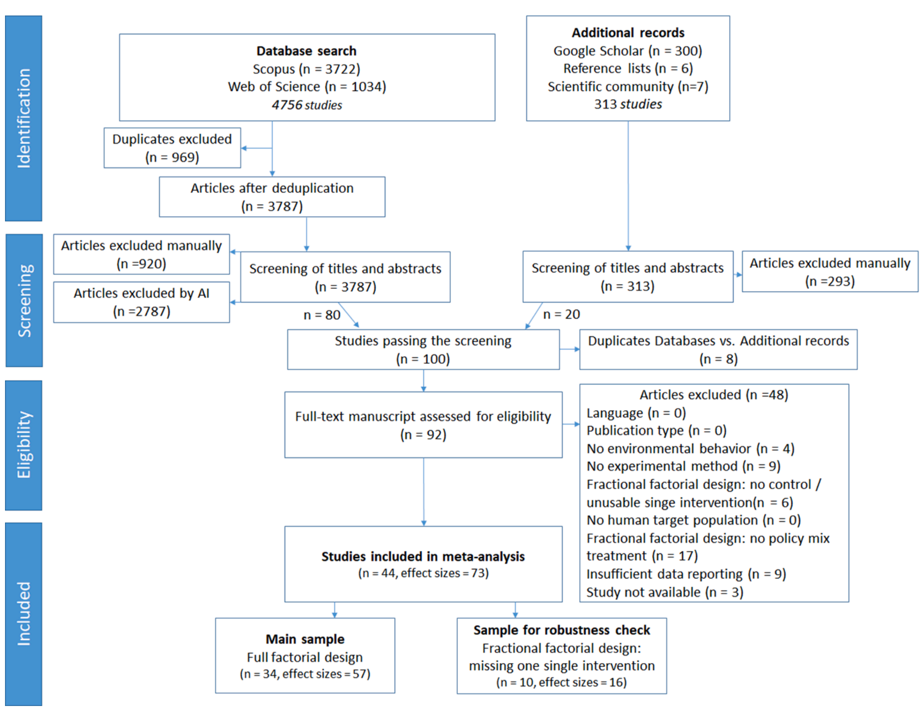

Fig. 1. Prisma flow-diagram.

to the inclusion of 44 articles. Among these, 34 articles had a full factorial design and entered the main sample, comprising 57 studies with 342 effect sizes and 520,766 participants (Fig. 1). Additionally, we included 10 articles (16 studies, 64 effect sizes) with a fractional factorial design, where one of the two single interventions had not been tested. We use this extended data set to assess the robustness of the policy mix's effect sizes to the inclusion of these additional studies.

2.3. Assessed study characteristics

We coded various characteristics of the included studies. In total, we assessed 71 criteria, with 35 providing information about the article, such as title, publication year, number of treatments, age and gender of study participants, and type of experimental analysis. The remaining 36 criteria included metrics extracted, such as relevant means, standard deviations, and calculated standardized effect sizes. An overview of the categories and criteria can be found in Section 6 of the Supplementary Material.

We classified the type of interventions as presented in Table 2 based on existing classifications (Loewenstein and Chater, 2017; Luo et al., 2021). We differentiate between the "behavioral" and the "traditional" economic domain (Loewenstein and Chater, 2017). The behavioral economic domain includes nudges and boosts. Nudges aim to systematically change behavior by altering the choice architecture, without changing the incentive structure (Thaler and Sunstein, 2008). Boosts are non-fiscal and non-coercive behavioral interventions that empower individuals to make their own choices by fostering their competencies and agency (Hertwig, 2017). Examples of boosts include decision-support tools (Blasch et al., 2022) and training to increase energy literacy (DellaValle and Sareen, 2020). The main difference between boosts and nudges is that the former mitigates the (negative) effects of biases and heuristics on decisions rather than exploiting them. While the traditional economic domain encompasses monetary incentives like taxes and subsidies, and command-and-control measures, we did not include studies on the latter. We exclude command-and-control because they impact people's choice set (Loewenstein and Chater, 2017), excluding certain options instead of changing incentives or choice architecture. Comparing interventions with different choice sets statistically is not possible without either confounding the treatment effect with differences in the choice sets between treatments or reducing the choice set to the shared subset between treatments, with the latter effectively reducing the amount of information contained in the dependent variable (Falk and Kosfeld, 2006; Bruns and Perino, 2021). The latter would render comparisons between different studies using different choice sets largely uninformative.

We also differentiate interventions based on the mechanism through which they influence behavior, notably if they do so by affecting people's cognitive processes, their (perceived) effort, or their non-monetary, or monetary motives. Information and feedback provision, reminders and other forms of communication mainly affect cognition and memory, in turn influencing behavior. Boosts and default values impact behavior by changing the (perceived) effort of pro-environmental choices. Norm and motivation-based interventions, primes, goal settings, and scrutiny influence individuals' non-monetary motives, such as intrinsic (Deci et al., 1981) and altruistic motives (Becker, 1974; Andreoni, 1989), identity (Akerlof and Kranton, 2000), personal (Bašić and Verrina, 2021) and social norms (Bicchieri, 2005), and other-regarding preferences including reputation (Bénabou and Tirole, 2006) and inequality (Fehr and Schmidt, 1999) concerns. Taxes and subsidies influence behavior by changing the costs of certain actions and choices, thus appealing to individuals' monetary motives.

This categorization serves as a prototype to shed light on the mechanisms underlying the synergies between different interventions. However, we acknowledge it may not fully capture all complex intervention interactions and mechanisms due to potential multi-mechanism impacts and subjective category allocation.

In addition to categorizing the interventions as described above, we also assessed whether the interventions in a study were of the same or different types, the type of experimental study (lab, online, or field), how behavior was assessed (hypothetical, self-reported, or incentivized behavior), the specific behavior assessed (e.g., recycling, car driving, energy conservation), the "scrutiny" of behavior in the experiment (i.e. how visible to and examinable by others was the behavior), and the prevalence of the behavior within society. Moreover, we assessed the quality of a study, with relevant criteria indicating low sample size ($n<30$), no clear baseline treatment, no clean intervention treatments, other interfering treatments, no clean laboratory/ field conditions hypothetical answer, behavior only remotely related to the environment, no statistical sound analysis, and within-subject treatment variation. On top of that, sample characteristics such as type (general population, university students, etc.) and country where the experiment was conducted were assessed.

The coding framework and guidance regarding the criteria were approved by all authors and preregistered (see https://osf.io/85xb9). Two researchers independently collected and coded the data, resolving discrepancies through discussion. The inter-rater agreement was 96.84 percent, with the largest disagreement when coding the scrutiny and the prevalence of the respective pro-environmental behavior. There was 82 percent agreement in these categories, mainly due to the challenge of evaluating scrutiny and prevalence in a categorical format with three options. To address this, we paid closer attention to comparing and discussing these variables.

Table 2
Categorization of interventions according to domain and main mechanism through which they impact pro-environmental behavior.

Behavioral Economic Domain			Traditional economic domain
Cognitive	**Effort**	**Non-monetary motives**	**Monetary motives**
Information Feedback Reminder Communication	Boost Default	Norm Motivational intervention Prime Goal Scrutiny	Tax Subsidy

Note: The first row indicates the domain and the second row indicates the "mechanism" through which the interventions affect behavior, and the remaining rows show the type of the interventions.

2.4. Meta-analytical strategy

To calculate the required effect sizes for identifying synergy effects, we utilized R-package "esc". If the data was only provided graphically, we applied the R-program "metaDigitise" to extract the necessary data to calculate effect sizes.

We obtained a maximum of six effect sizes per study, which included (1) one effect size for the combined application of interventions compared to no intervention; (2) two effect sizes comparing each single intervention to no intervention; (3) two effect sizes comparing the combined intervention to each of the single interventions; (4) one calculated effect size for the sum of the single intervention treatments inferred under (2). To account for the non-linearity of Cohen's d when calculating the sums of single interventions, we first transformed them to Fisher's z-values, then derived Cohen's d from the obtained z-value (Cohen, 2013).

To analyze the effect sizes, we employed a random effects hierarchical Bayesian model, which allowed for full parameter uncertainty, inclusion of other relevant information, and accommodating more complex yet realistic scenarios (Sutton and Abrams, 2001). The model considered the interdependence of effect sizes from the same study by defining two levels: the "article level" as the first and the "study level" as the second level (Cheung, 2019). Additionally, we introduced a second hierarchical structure to account for variations in pro-environmental behavior types. The first level is given by the pro-environmental behavior and the second level is provided by the effect sizes of the individual studies.

To estimate the model, we used priors for the effect sizes of the policy mixes and the sum of single interventions based on clues from the literature on the effectiveness of interventions such as nudges and monetary incentives (Osbaldiston and Schott, 2012; Maki et al., 2016; Niemiec et al., 2020; Mi et al., 2021). The moments and distributions of the remaining priors, most importantly for the synergy effect, were chosen according to our hypotheses. All priors are reported in Table 8 of the Supplementary Material.

We estimated the effects using an iterative Markov Chain Monte Carlo (MCMC) sampling procedure with 5,000 iterations and 1,000 warm-up iterations using the R-packages “brms” (Bürkner, 2017) and “RStan” (StanDevelopmentTeam, 2017). Below is an example of the basic model, which we used to identify the synergy effects of policy mixes:

$$y_i = \beta_R + T_i\beta_t + X_i\beta_c + u_i + v_i + e_i$$
$$u_i \sim N(0, \tau^2)$$
$$v_i \sim N(0, \tau^2)$$
$$e_i \sim N(0, s_i^2)$$

In this model, β_R depicts the average effect size of the sum of the single interventions, and β_t the synergy effect, i.e., the difference in effect sizes between the sum of single interventions and the policy mix interventions. The term $X_i\beta_c$ controls for the influence of other covariates on the effect sizes. Included control variables comprise the type of experiment, the prevalence and observability of the environmental behavior, and the quality indicators. u_i and v_i are random effects parameters, measuring the within-article variation of studies’ effect sizes and the within pro-environmental behavior variation of effect sizes (DuMouchel, 1994). Lastly, e_i denotes the error term.

To evaluate and report the strength of evidence for the alternative relative to the null hypothesis, we used the Bayes Factor (BF). We interpret a $BF > 100$ as extreme, $BF = 30 - 100$ as very strong, $BF = 10 - 30$ as strong, $BF = 3 - 10$ as moderate, and $BF = 1 - 3$ as weak evidence for the alternative hypothesis. $BF < 1$ suggests evidence for the null hypothesis (Rouder et al., 2009; Schmalz et al., 2021).

3. Hypotheses

To address the effectiveness of policy mixes compared to the sum of single interventions and to identify which types of interventions generate the most significant synergies when combined in policy mixes, our meta-analysis is structured around four preregistered hypotheses (see https://osf.io/85xb9). The hypotheses were formulated following a systematic and evidence-based approach, akin to established practices in previous meta-analyses within the field (Nguyen-Van et al., 2021; Buckley, 2020). The process involved a review of the existing literature, including peer-reviewed studies and theoretical frameworks related to pro-environmental behavior and the effectiveness of interventions.

Hypothesis 1. *Policy mixes are more effective in promoting pro-environmental behavior than the corresponding single interventions, but their effectiveness remains below the sum of the single intervention effects, resulting in a negative synergy effect.*

We base this hypothesis on the reasonable assumption that the utility of consumption is concave (Gossen, 1983; Tversky and Kahneman, 1989; Rabin, 2000). For environmental policies, this implies that the marginal utility of consumption decreases in units of consumption of an environmentally beneficial good or increases with every unit of reduced consumption of an environmentally harmful good. Thus, changing individual behavior becomes more difficult for every additional unit of foregone consumption of the harming good and with every unit of consumption of the environmentally beneficial good (Horowitz et al., 2007). Consequently, adding interventions targeting the same behavior will render each additional intervention less effective than applied in isolation. Therefore, we predict that a combined intervention is less effective than the sum of the respective single interventions. Other reasons for negative synergies are policy mixes causing information overload (Persson, 2018), ceiling effects (McCalley et al., 2006), or adverse responses to high pressure (Ariely et al., 2009).

Hypothesis 2. *Combined traditional and behavioral economic interventions create larger synergy effects than combined interventions from the same domain.*

We base this hypothesis on two possible mechanisms. First, cross-domain policy mixes may be more effective in mitigating the diminishing marginal utility of consumption. Applying policy mixes with interventions from the same domain might decrease effectiveness since both interventions lower the marginal utility of income in the case of monetary incentives (Ariely et al., 2009). Instead, cross-domain policy mixes where, for instance, monetary incentives are paired with a social comparison nudge often address the utility of two different goods, i.e., the utility of income and the utility of conformity (Bernheim, 1994).

Second, interventions to enhance pro-environmental behavior suffer from various shortcomings, which reduce their effectiveness (Ariely et al., 2009; Kocher et al., 2018; Werthschulte and Löschel, 2021). Combinations of interventions leveraging more than one approach to affect behavior could be more likely to provide a remedy for the other intervention’s shortcomings than interventions that rely on a single approach. Thereby, the mechanisms of cross-domain policy mixes can act complementary to each other. For example, if an external incentive renders the reasoning of performing a task from a moral framing to an economic framing, a motivational nudge (Czap et al., 2015) could reframe the decision as being morally motivated, thus offsetting the crowding out effect of the monetary incentive (Ling and Xu, 2021).

Hypothesis 3. *The effectiveness of combined interventions depends on the prevalence and scrutiny of pro-environmental behavior.*

Two potential moderators of policy mixes’ effectiveness are the prevalence (commonness) and scrutiny (observability) of the targeted behavior. Prevalence captures how common or established a specific pro-environmental behavior is in society, while scrutiny depicts its observability in a specific setting. We expect both to interact differently with policy mixes. More specifically, we expect the following:

First, according to Bénabou and Tirole, 2006 the effectiveness of interventions varies depending on the prevalence of the addressed behavior, i.e., (i) if the behavior is uncommon, interventions can curtail social recognition benefits and thereby crowd out a motivational aspect of engaging in this behavior, and (ii) if the behavior is very common, interventions are less effective as the remaining non-adopters are likely to have high marginal costs to switch. We expect this dependence to also apply to policy mixes. Whether they become more or less effective with increasing prevalence remains an empirical question.

Second, the effectiveness of policy mixes depends on the observability of pro-environmental behavior. Observability affects behavior as it amplifies social norms (Vesely and Klöckner, 2018) and bolsters compliance (Anderson and Dunning, 2014; Vesely et al., 2020; Lacetera and Macis, 2010; Bicchieri and Dimant, 2022). However, it might also undermine intervention efficacy, particularly for individuals driven by motivations beyond social recognition (Bolton et al., 2021). Thus, since there exists evidence for the dependence of interventions on observability, we expect it to also moderate the effectiveness of policy mixes. Since there is evidence for both observability rendering interventions less or more effective, we leave the direction of the change to the empirical analysis.

Hypothesis 4. *Combined traditional and behavioral economic* *interventions reduce negative spillovers induced by traditional economic interventions.*

Spillovers are unintended effects of an intervention affecting other related behaviors (Blanken et al., 2015; Dolan and Galizzi, 2015; Maki et al., 2019). When an intervention-induced behavior spills over into other untargeted behaviors, a *behavioral spillover* occurs, and the direction (negative or positive) of such spillovers depends on how the intervention affects individuals' pre-existing motives to engage in the target behavior, such as identity (Bénabou and Tirole, 2011; Torren Peraire et al., 2023) or altruism (d'Adda, 2011). Focusing on spillovers influencing behavior at a different time, we assess whether policy mixes affect the post-intervention behavior differently than single interventions. Prior evidence suggests that policies exerting high levels of control on individuals are prone to induce negative spillover, whereas autonomy-supportive measures are likely to induce positive spillover (Geiger et al., 2021). Assuming that traditional policies are perceived as more autonomy-threatening than behavioral interventions (Bruns and Perino, 2023), we expect a combination of interventions from both domains to induce less negative spillover than single traditional economic interventions.

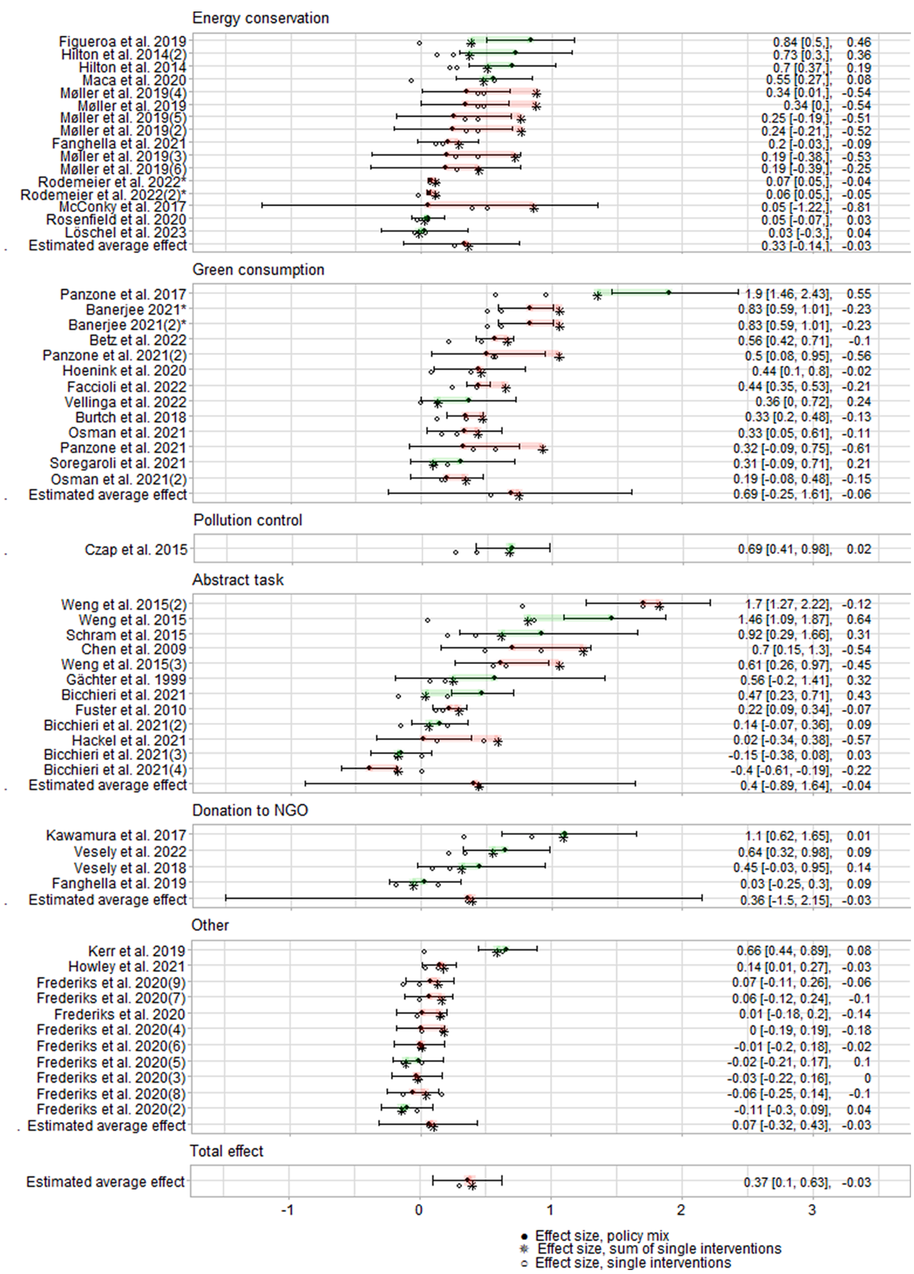

Fig. 2. Forest plot of different effect sizes of studies by pro-environmental behavior. *Note*: Mean and 95% confidence intervals (in parentheses) of the policy mix and the mean of the synergy effect reported on the right of the graph. The forest plot is sorted by the effect size of the studies' policy mix. The effect of the policy mix is given by the effect size of the joint application of both interventions. The sum of single interventions is obtained by adding the Fisher's z-values of both single intervention effect sizes of each observation. The synergy effect is the difference between the policy mix's effect size and the sum of both single intervention effect sizes. Positive synergies are shown as a green line, negative synergies are shown in red. Studies marked with a star (*) at the end of their name are not peer-reviewed (See above mentioned references for further information).

Table 3
Main results.

Hypothesis			Effect size and Bayes factor for		
			Policy mix	Sum of individual effect	Synergy effect
1.	Synergy effects are negative.		0.365 (BF = 26.78)	0.395 (BF = 33.78)	-0.03 (BF = 8.59)
2.	Cross-domain combinations of interventions are more effective than within-domain combinations.	Within-domain	0.334 (BF = 17.87)	0.383 (BF = 26.03)	-0.049 (BF = 23.54)
		Across-domain	0.414 (BF = 21.10)	0.427 (BF = 24)	-0.013 (BF = 0.56)
		Difference	0.08 (BF = 2.04)	0.044 (BF = 1.46)	0.036 (BF = 6.27)
3	The synergy effects are not dependent on contextual factors.	Non-Prevalent	0.422 (BF = 29.08)	0.447 (BF = 32.06)	-0.0251 (BF = 0.14)
		Prevalent	0.424 (BF = 9.15)	0.446 (BF = 10.11)	-0.022 (BF = 0.41)
		Difference	0.003 (BF = 1.02)	-0.001 (BF = 1.00)	0.004 (BF = 1.18)
		No Scrutiny	0.383 (BF = 24.48)	0.419 (BF = 33.78)	-0.036 (BF = 12.16)
		Scrutiny	0.329 (BF = 5.16)	0.34 (BF = 5.48)	-0.011 (BF = 2.02)
		Difference	−0.054 (BF = 1.37)	-0.079 (BF = 1.60)	0.025 (BF = 2.73)
4.	The synergies regarding behavioral spillovers are negative.		0.439 (BF = 1.48)	0.493 (BF = 1.57)	-0.054 (BF = 6.29)

Note: Effects are reported in Cohen's d. The Bayes Factor (BF) quantifies evidence strength for the alternative relative to the null hypothesis Bayes factor in parentheses. We interpret a $BF > 100$ as extreme, 30–100 as very strong, 10–30 as strong, 3–10 as moderate, and 1–3 as weak evidence for the alternative hypothesis. A $BF < 1$ suggests evidence for the null hypothesis. Priors are reported in Table 8 of the Supplementary Material. The corresponding estimations are reported in Section 7 of the Supplementary Material. The results are re-estimated on a restricted sample including peer-reviewed articles only (see Supplementary Material, Section 8.1, Table 23).

Table 4
Synergy effects by type of pro-environmental behavior.

	Estimate	Est.Error	CI.Lower	CI.Upper	Evid.Ratio	Observations
Energy conservation	−0.034	0.04	−0.10	0.03	0.82	16
Green consumption	−0.061	0.03	−0.11	0	36.74	13
Pollution control			no model convergence due to small n			1
Abstract	−0.037	0.04	−0.12	0.04	0.83	12
Donation to NGO	−0.025	0.04	−0.11	0.06	0.72	4
Other	−0.033	0.03	−0.1	0.03	0.89	11

Note: Effects are reported in Cohen's d. The Bayes Factor (BF) quantifies evidence strength for the alternative relative to the null hypothesis. We interpret a $BF > 100$ as extreme, 30–100 as very strong, 10–30 as strong, 3–10 as moderate, and 1–3 as weak evidence for the alternative hypothesis. A $BF < 1$ suggests evidence for the null hypothesis. Priors are reported in Table 8 of the Supplementary Material.

Table 5
Effectiveness of combining interventions compared to single application.

			combined with	
			Nudge	MonInc
Intervention in combination vs. single effect	Nudge	Δ in effect size	−0.038	−0.022
		BF	4.41	4.44
		n	14	39
	MonInc	Δ in effect size	−0.02	−0.055
		BF	4.98	7.60
		n	39	4

Note: The table reports the change (Δ) in effectiveness of nudges and monetary incentives being applied in a policy mix compared to being applied alone, varying whether the other intervention in the policy mix is given by a nudge or a monetary incentive. Effects are reported in Cohen's d. The Bayes Factor (BF) quantifies evidence strength for the alternative relative to the null hypothesis. We interpret a $BF > 100$ as extreme, 30–100 as very strong, 10–30 as strong, 3–10 as moderate, and 1–3 as weak evidence for the alternative hypothesis. A $BF < 1$ suggests evidence for the null hypothesis. Priors are reported in Table 8 of the Supplementary Material. The corresponding estimations are reported in Section 7 of the Supplementary Material.

Table 6
Effectiveness of nudges and monetary incentives within policy mixes by mechanism of nudges

Mechanism		Effect. Nudges in policy mix	Effect. Mon. Inc. in policy mix
non-monetary	Δ in effect size	−0.027	−0.02
	BF	5.05	0.82
cognitive	Δ in effect size	−0.01	−0.02
	BF	2.25	0.75
effort	Δ in effect size	−0.024	−0.03
	BF	3.98	5.11

Note: The first column presents the difference (Δ) in the effectiveness of nudges when combined with monetary incentives compared to being applied alone, considering the specific nudge mechanisms employed. The second column presents the change (Δ) in the effectiveness of monetary incentives when combined with nudges of different mechanisms compared to being applied alone. Effects are reported in Cohen's d. The Bayes Factor (BF) quantifies evidence strength for the alternative relative to the null hypothesis. We interpret a $BF >$ 100 as extreme, 30–100 as very strong, 10–30 as strong, 3–10 as moderate, and 1–3 as weak evidence for the alternative hypothesis. A $BF < 1$ suggests evidence for the null hypothesis. Priors are reported in Table 8 of the Supplementary Material. The corresponding estimations are reported in Section 7 of the Supplementary Material.

4. Results

4.1. Descriptive overview

Fig. 2 shows effect size distributions of policy mixes (depicted as black dots), sums of single intervention effects (indicated by asterisks), and single intervention effects (represented by white dots) across studies, categorized by environmental behavior. The figure also highlights synergy effects, indicating the difference between policy mix and sum of single interventions effect sizes. Negative synergy effects are shown in red and positive effects in green. The effect sizes of policy mixes range from −0.4 to 1.9.

Fig. 2 also shows the overall average estimated effect of policy mixes, as determined by the Bayesian model ($d = 0.365, BF = 26.78$). In the case of the different environmental behaviors, we observe that the effect size distributions vary substantially, with the largest effect sizes occurring in changing green consumption ($d = 0.69, BF = 7.16$), and the smallest occurring for other environmental behavior ($d = 0.07, BF = 2.2$). Compared to the remaining environmental behaviors, we observe wider confidence intervals for the effects of policy mixes on 'abstract tasks' and 'donations to NGOs'.

Overall, the Bayes factor suggests strong evidence for the positive meta-analytic effect of policy mixes ($d = 0.365, BF = 26.78$, Table 3). However, the average effect size for the sum of single interventions ($d = 0.395, BF = 33.78$, Table 3) is slightly larger than the average effect size of the policy mixes.

On average, our calculations indicate that studies are well-powered to identify the effectiveness of jointly applied interventions with an average statistical ad hoc power of 0.92. In total, 86 percent of studies indicated a statistical power of above 0.8. However, since the Egger's test has a significant intercept (Eggers test: $p = 0.0291$), we cannot rule out publication bias in our sample (see Supplementary Material, Section 10.3) (Buckley, 2020; Blanken et al., 2015; Li et al., 2021). Moreover, two of 34 scientific articles are not peer-reviewed (marked with "*" in Fig. 2). A robustness analysis reveals a negligible variation in the estimations when re-estimating the results including peer-reviewed articles only (see Supplementary Material, Section 8.1, Table 23).

4.2. Confirmatory hypothesis testing

Table 3 provides a summary of the results from the confirmatory hypothesis tests, encompassing three types of effect sizes: effect sizes of policy mixes, the corresponding sum of single interventions, and the synergy effect (the difference between these two effects, as explained in Section 2.1).

To evaluate the hypotheses, we employ a random effects hierarchical Bayesian model, considering Cohen's d effect sizes and their respective Bayes factors. We consider a hypothesis supported when the effect size aligns with the expected direction, and the Bayes factor exceeds three, indicating at least moderate evidence. To account for heterogeneities across studies, each estimation contains control variables for the type of experiment, the assessed environmental behavior, and the quality of the methodology.

Finding 1: *There is moderate evidence for a negative synergy effect of policy mixes.*

To assess Hypothesis 1, we calculated the synergy effect by subtracting the effect size of the policy mix from that of the sum of individual effects. The resulting analysis reveals moderate evidence for a negative meta-analytical synergy effect ($d = -0.03$, $BF = 8.59$, Table 3). However, policy mixes remain more effective than the most effective single intervention within the policy mixes' constituents ($d = 0.051$, $BF = 43.94$), indicating that, on average, policy mixes do not backfire.

This negative synergy effect remains robust to a leave-one-out analysis and when accounting for variations in study quality (Section 10, Supplementary Material). It only slightly increases when analyzing a subset of the methodologically most rigorous studies ($d = -0.017$, $BF = 1.86$, Table 25, Supplementary Material).

Finally, we analyze whether synergy effects exhibit variations when distinguishing between different environmental behaviors addressed by the policy mixes. The results of this analysis are reported in Table 4. For almost all types of pro-environmental behavior, we find no evidence for synergy effects with Bayes factors below one, although the sizes of the synergy effects are within range of the average synergy effect across pro-environmental behaviors. As an exception, we observe very strong evidence for negative synergy effects of -0.062 in the case of green consumption (BF $= 36.74$). The results indicate that the negative synergy effect across pro-environmental behaviors is largely driven by the corresponding effects on green consumption behavior.

Finding 2: *There is moderate evidence that combined traditional and behavioral economic interventions create larger synergy effects than combined interventions from the same domain.*

There is strong evidence that implementing two interventions from the same domain, i.e., either exclusively behavioral or exclusively traditional economic interventions, leads to negative synergy effects ($d = -0.049$, BF $= 23.54$, Table 3). However, when combining behavioral and traditional economic interventions, we find no evidence for negative synergy effects ($d = -0.013$, BF $= 0.56$, Table 3). Consequently, the overall negative synergy effect appears to be driven by within-intervention domain applications of policy mixes ($d = 0.026$, BF $= 6.87$, Table 3).

To delve deeper into the examination of synergy effects, we extend our investigation by conducting a decomposition analysis of the difference between within-domain and across-domain policy mixes. In Table 5, we present this decomposed analysis, showing how the effectiveness of an intervention changes when implemented within a policy mix as opposed to its individual application. Our analysis involves quantifying the difference in effect size between the policy mix and an intervention (A) used in isolation. This allows us to approximate the additive impact of another intervention (B) when combined with intervention A in a policy mix. We then compare this to the effectiveness of intervention B when applied individually, enabling us to assess the extent of its contribution within the policy mix context. More specifically, we first compare the effect of nudges in policy mixes with the effect of nudges in single applications (the first row of Table 5). Subsequently, we apply a similar approach by using monetary incentives in single application as a comparison (second row).

The analysis indicates that there is weak to moderate evidence that all interventions are less effective in policy mixes. In cross-domain policy mixes, the effectiveness of nudges and monetary incentives are reduced by 0.02 (BF $= 4.98$, Table 5) and 0.022 (BF $= 4.44$, Table 5), whereas in within-domain policy mixes, the effectiveness of nudges and monetary incentives decreases by an effect size of 0.038 (BF $= 4.41$, Table 5) and 0.055 (BF $= 7.60$, Table 5). Thus, cross-domain policy mixes tend to be more effective (or less ineffective) and particularly monetary incentives are less effective when combined with other monetary incentives.

In a next step, we focus on the mechanisms through which nudges and monetary incentives affect behavior (presented in Table 6). We find

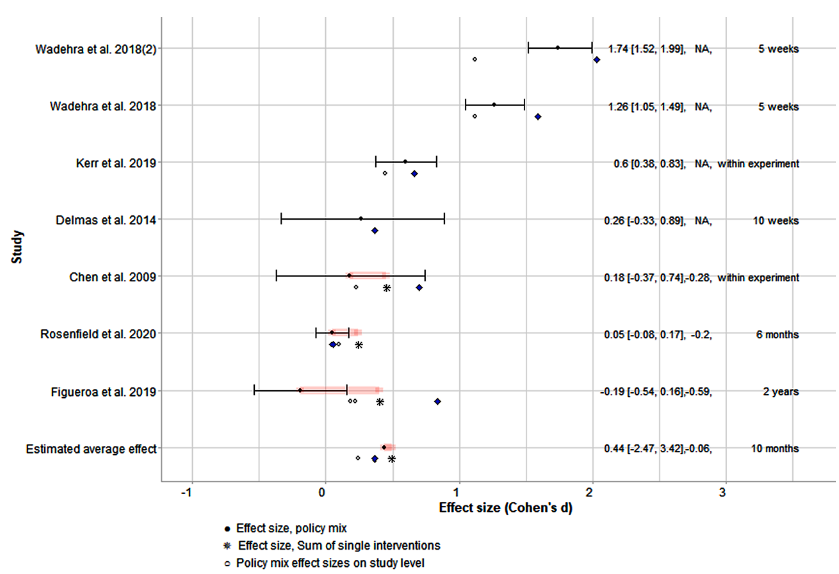

Fig. 3. Forest Plot of the spillovers' effect sizes by study. *Note:* Mean and 95% confidence intervals (in parentheses) of spillovers of policy mixes, the mean of the synergy effect, and the length of the post-intervention period reported on the right of the graph. The persistence of the sum of single interventions is obtained by adding the Fisher's z-values of both single intervention persistences' effect sizes of each observation. The persistence of the policy mix is given by the effect size of the joint application of both interventions compared to the control treatment in the post-intervention period. We calculate the persistence's synergy effect by the difference between the policy mix's effect size and the sum of single interventions' effect size. The confidence intervals of the estimated average effect are not displayed due to the wide range for the purpose of readability.

only weak evidence in support of the benefits of combining different mechanisms. This is shown in Table 6 which presents the change in effectiveness of an intervention in a policy mix compared to its effectiveness in single applications. In Column 3 (Effect. Nudges in policy mix), we assess the change in the effectiveness of nudges when affecting behavior through either mechanism (non-monetary motives, cognitive, or effort) with monetary incentives (always monetary motives) compared to the respective nudge applied alone. Column 4 (Effect. Mon. Inc. in policy mix) indicates the change in effectiveness of monetary incentives combined with nudges from the respective mechanism compared to monetary incentives applied alone. Both columns exhibit relatively low inter-column variation in values, indicating weak evidence for a significant difference in the changes of effectiveness brought about by the distinct mechanisms of nudges.

There is no evidence for a different change in effect size of nudges in policy mixes compared to a single application depending on whether the nudge uses a non-monetary mechanism or an effort-mechanism (BF $= 0.8$). Similarly, we find no evidence for a respective change in comparing nudges with a cognitive mechanism and nudges with an effort-mechanism (BF $= 0.69$). The same is the case for the change in effectiveness of monetary incentives in policy mixes given they are paired with nudges of different mechanism. We observe only weak evidence for a difference in the change of the effectiveness of monetary incentives when being paired with a nudge using a non-monetary mechanism or an effort-mechanism (BF $= 1.42$). The same is given for the effectiveness of monetary incentives when being paired with a nudge using a cognitive-mechanism or an effort-mechanism (BF $= 2.01$).

This indicates that all three investigated mechanisms of nudges exhibit comparable effectiveness when combined with a monetary incentive, as compared to their single applications. Consequently, it appears that the diverse mechanisms may not be the primary drivers of policy mix effectiveness when nudges and monetary incentives are combined.

This pattern is confirmed by an analysis of the different types of nudges (see Table 22, Supplementary Material), which also does not provide evidence indicating differences in the effectiveness of nudges within policy mixes in dependence on the particular type of nudges applied in the policy mix.

Lastly, we test whether taxes and subsidies induce different changes in effectiveness of monetary incentives when being applied in combination with nudges in policy mixes (see Table 22, Supplementary Material). Also in this case, we find only weak evidence for differences, suggesting that our initial finding that combined monetary incentives and nudges are in general more effective than policy mixes of two nudges or two monetary incentives is robust.

Finding 3: *There is weak evidence that contextual factors of the pro-environmental task, i.e., prevalence and scrutiny of a behavior, influence synergy effects of different interventions within policy mixes.*

We assess Hypothesis 3, which examines the role of contextual factors, specifically the prevalence and scrutiny of pro-environmental behavior, in influencing the effectiveness of combined interventions.

In contrast to Hypothesis 3, our analysis finds weak evidence for the reliance of policy mix's effectiveness on whether the behavior is prevalent or not, as the difference in effect sizes between the cumulative impact of individual interventions and the effect sizes of interventions within policy mixes, based on whether the behavior is prevalent or not, is minimal ($d = 0.004, BF = 1.18$, Table 3). Similarly, in the context of scrutiny, the difference between the effect sizes of interventions within policy mixes and the combined effect sizes of individual interventions is marginal for scrutable vs. non-scrutable behavior ($d = 0.025, BF = 2.73$, Table 3).

Finding 4: *There is moderate evidence supporting that combined traditional and behavioral economic interventions induce smaller spillovers than the sum of their constituents.*

We analyze temporal spillover effects as persistence effects (d'Adda et al., 2017), meaning that we assess the impact of policy mixes on behavior after some time has passed since the intervention was removed. We determine the effect by comparing the level of pro-environmental behavior in the treatment and the control group in the post-intervention period. The resulting effects are illustrated in Fig. 3, along with the effects of single interventions (white dots) and their cumulative impact (asterisks). For the purpose of comparability with the main direct effects, we depict the effect of a policy mix on the targeted behavior immediately after its implementation (blue rhombus). The studies vary in their post-intervention period in a range from measuring the persistence within the same session of an experiment to two years.

Overall, the effect sizes of spillover effects range from −0.19 to 1.74. The Bayesian model provides moderate evidence that the persistence of policy mixes is on average 0.054 smaller than the summed persistence of the single interventions ($d = -0.054, BF = 6.29$, Table 3). However, these results need to be cautiously interpreted due to the low sample size involved in the estimation. Particularly, the limited number of observations raises concerns about the reliability and generalizability of the findings (see Supplementary Material, Section 10.2). Further, the scarce number of observations does not allow us to distinguish whether combining monetary incentives with nudges leads to increased persistence of the intervention compared to a single application of monetary incentives as conjectured in Hypothesis 4.

5. Conclusions

This meta-analysis addresses the scarcity of empirical evidence on the interaction between behavioral and traditional economic policy interventions to promote pro-environmental behavior. Although behavioral and traditional economic policy interventions are frequently applied together, prior meta-analyses primarily focused on synthesizing evidence of individual interventions.

Analyzing 57 effect sizes from 34 articles that investigate synergy effects of various pro-environmental interventions provides moderate evidence that policy mixes are less effective than the sum of their constituents. Yet, this difference is small, which is particularly striking considering that changing individual behavior becomes more difficult for every additional unit of foregone consumption, which diminishes the potential of policy mixes. Policy mixes are still more effective than the most effective single intervention of their constituents, indicating that combined policies are unlikely to backfire.

Notably, there is some variation in the effectiveness of policy mixes with respect to the type of environmental behavior and there is moderate evidence suggesting that combining traditional with behavioral economic interventions creates larger synergy effects than combining interventions from the same domain. Combinations of monetary incentives entail the largest loss of effectiveness within policy mixes compared to its single effect, while the corresponding loss for the remaining combinations is only half in size.

We also investigated the impact of prevalence and scrutiny of behavior on intervention effectiveness. However, in the realm of synergies of policy mixes, we find no convincing evidence for their influence.

Lastly, we provide moderate evidence in support of combined traditional and behavioral economic interventions leading to less positive spillovers than the sum of their constituents.

Our findings contrast with our conjecture that the higher effectiveness of cross-domain policy mixes originates from alleviating shortcomings of single interventions. In this case, we would have observed certain combinations to be more effective than others, depending on the combined mechanisms or type of intervention. The evolution of research in this area, accompanied by the availability of a more extensive and diverse dataset, could provide the opportunity to validate and gain deeper insights into this outcome. At the same time, we observe policy mixes consisting of two monetary incentives to drive the low performance of within-domain policy mixes. This suggests the decreasing marginal utility of income as one cause behind the difference between within and cross-domain policy mixes' effectiveness and points to possible complementarities between measures that adhere to extrinsic and intrinsic motivation of individuals.

Our study reveals that negative synergies of policy mixes are particularly driven by their comparably pronounced negative effect on green consumption behavior. One reason could be that it is more challenging to induce people to "green" their consumption than to reduce their energy use or donate to a pro-environmental NGO, because green consumption usually involves having to assess, compare and consider a multitude of product characteristics. Another reason could be that combinations of different interventions might be more challenging for people to comprehend and account for in their behavioral reactions when the decision context is complex.

Finally, although policy mixes appear to effectively change individual behavior while in place, they are less prone to generate positive spillovers, i.e., to persist in the post-intervention period. This evidence, however, is based on a small sample of studies, leading to non-robust findings and limiting the possibility of testing if combining monetary incentives and nudges leads to increased persistence compared to single monetary incentives.

Our findings have important implications for policymakers in the realm of environmental interventions. Firstly, our results underscore the effectiveness of combining two different interventions to enhance pro-environmental behavior. By employing traditional and behavioral interventions simultaneously, policymakers can leverage synergistic effects, leading to more significant and positive outcomes. This indicates that policy measures that work in tandem are more likely to succeed in fostering sustainable behaviors compared to relying solely on a single intervention and that policymakers at national, regional, and local governance levels can address the same environmental behavior collaboratively.

Secondly, our study highlights the value of integrating both traditional economic policies and behavioral economic interventions. Traditional economic policies, such as carbon taxes or subsidies, can complement behavioral economic approaches, which involve nudges or boosts to empower decision-making. Combining these strategies allows policymakers to address environmental challenges from various angles, catering to both monetary and non-monetary motives.

Thirdly, policymakers should consider the specific environmental behavior they intend to address through policy mixes. For instance, encouraging individuals to increase their consumption of sustainable and green products might be better achieved through a single intervention, given the notable negative synergies observed in this particular type of environmental behavior.

Lastly, policymakers should carefully consider the implications of policy mixes in case they are aiming for a behavioral change which also strongly persists once the policy has been removed. While policy mixes might be effective in achieving immediate objectives, our findings suggest that they may not be as conducive to generating broader positive temporal spillover effects.

This initial meta-analysis faces some limitations, primarily due to a relatively low number of relevant studies and a focus limited to experimental studies and a specific set of interventions. Despite this, it lays the groundwork for future research and encourages transparency in terms of data provision. We invite further studies to better understand synergistic intervention impacts by also drawing on evidence from agent-based modeling, which offers a computational approach to explore complex societal dynamics and enhance policy recommendations for sustainable behaviors (Bertoni et al., 2023). This integration of methodologies can lead to more robust and nuanced policy recommendations, guiding the development of synergistic strategies to foster sustainable behaviors.

Pre-registration

This meta-study had been conceived in narrow guidance of the PRISMA guidelines to assure a rigorous and reproducible procedure (Moher et al., 2015; Rethlefsen et al., 2021). The respective pre-registration can be obtained from https://osf.io/298h6.

Data availability

The data that support the findings of this study are openly available through OSF at https://osf.io/298h6, reference number 298h6.

Code availability

The code for data cleaning, calculation of effect sizes, and analysis is available from the corresponding author, M.A., upon reasonable request.

CRediT authorship contribution statement

Marius Alt: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Hendrik Bruns:** Writing – review & editing. **Nives DellaValle:** Conceptualization, Supervision, Writing – review & editing, Project administration. **Ingrida Murauskaite-Bull:** Validation, review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.gloenvcha.2023.102776.

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