Nudging and Boosting Financial Decisions

Nudge o Boost? Psicologia ed economia comportamentale: indirizzare o spingere buone decisioni finanziarie

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Increasingly, policymakers are using insights from psychology and behavioral economics into how people make decisions to inform nonregulatory and nonmonetary policy interventions. To date, much of the focus has been on nudges: interventions designed to steer people in a particular direction while preserving their freedom of choice. Yet behavioral science also provides support for a distinct kind of nonfiscal, noncoercive intervention: boosts. The objective of boosts is to foster people's competence to make their own choices. We explore how boosts differ from nudges, address possible misconceptions, provide a taxonomy of boosts, and outline possible boosts for financial literacy.

Sempre più spesso, i policymaker usano le conoscenze della psicologia e dell'economia comportamentale su come le persone prendono decisioni per definire politiche non normative e non monetarie. Finora, gran parte dell'attenzione è stata incentrata sui nudge: gli interventi pensati per orientare le persone in una particolare direzione preservandone la libertà di scelta. Eppure la scienza comportamentale fornisce anche il supporto per un altro tipo di intervento non fiscale, non coercitivo: il boost, ossia la spinta ad accrescere la competenza delle persone per compiere le proprie scelte. In questo articolo esploriamo come i boost differiscono dai nudge, affrontiamo possibili equivoci, forniamo una tassonomia delle spinte e valutiamo come possono favorire la competenza nelle decisioni finanziarie.

1. Behavioral Science and Politics

Numerous governments and international organizations such as the World Bank (2015) and the European Commission (Lourenco, Ciriolo, Almeida, & Troussard, 2016) have begun to acknowledge the enormous potential of behavioral science evidence in helping to design more effective and efficient public policies. For instance, behavioral science is now used or seriously considered as a policy tool in many of the 35 member countries of the Organisation for Economic Co-operation and Development (Oecd), whose mission it is to «promote policies that will improve the economic and social well-being of people around the world» (n.d.). In fact, the Oecd (2017) recently published a collection of over 100 case studies of applied behavioral insights. Drawing attention to the importance of behavioral science for policymaking is the outstanding achievement of the nudge approach, presented most prominently in Thaler and Sunstein (2008). Nudges are nonregulatory, nonmonetary interventions that steer people in a particular direction while preserving their freedom of choice (e.g., Alemanno & Sibony, 2015; Halpern, 2015). Paradigmatic examples include setting automatic enrollment in organ donation schemes and pension plans as the default option, where individuals must actively opt out (rather than having to actively opt in if they want to enroll); redesigning cafeterias to display healthier food at eye level; and using social norms (e.g., that many taxpayers pay on time; see Cialdini & Goldstein, 2004) to increase tax compliance. The nudge approach has also prompted critical and informative debates about its underlying political philosophy of liberta-

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rian paternalism (e.g., Rebonato, 2012), the ethics of nudging (e.g., Barton & Grüne-Yanoff, 2015; Bovens 2009), the empirical success of nudging policy interventions (e.g., House of Lords Science and Technology Select Committee, 2011), and the approach's starting proposition: that deficits in human decision-making competence are pervasive and difficult to alter (e.g., Grüne-Yanoff & Hertwig, 2016).

The current interest in behavioral science within governments, owed to the enormous impact of the nudge approach, offers psychology a new channel for informing and influencing public policy (Teachman, Norton, & Spellman, 2015). Yet it would be a mistake to equate all public policy-making informed by behavioral science evidence with nudging, or to assume that all such evidence ultimately points to nudge interventions. The scientific study of human behavior also provides support for a decidedly distinct kind of intervention, namely, boosts (Grüne-Yanoff & Hertwig, 2016). The objective of *boosts* is to improve people's competence to make their own choices. The focus of boosting is on interventions that make it easier for people to exercise their own agency by fostering existing competences or instilling new ones. Examples include the ability to understand statistical health information, the ability to make financial decisions on the basis of simple accounting rules, and the strategic use of automatic processes (we return to these examples below).

In this article, we distinguish between nudges and boosts on seven dimensions, summarized in table 1. Not all of these dimensions are independent of each other but we believe that they are sufficiently important to merit separate discussion. Our text is structured largely along these seven dimensions. After discussing the differences between nudges and boosts with respect to their immediate intervention targets (i.e., behavior vs. competences), their roots in different research programs, and the causal pathways through which they affect behavior, we provide an initial taxonomy of boosts. We then discuss the differences between nudging and boosting with respect to their assumptions about the human cognitive architecture, the reversibility of their effects, their programmatic ambitions, and their normative implications. We conclude by addressing some of the misconceptions about boosts that we have encountered in recent discussions and the literature, and by offering possible boosts for financial literacy.

Table 1

Seven Dimensions on Which the Nudging (Non-Educative) and Boosting (Long-Term) Approaches to Public Policy Can Be Distinguished

Dimension	Nudging	Boosting
Intervention target	Behavior	Competences
Roots in research programs and evidence	Show decision maker as systematically imperfect and subject to cognitive and motivational deficiencies	Acknowledge bounds but identify human competences and ways to foster them
Causal pathways	Harness cognitive and motivational deficiencies in tandem with changes in the external choice architecture	Foster competences through changes in skills, knowledge, decision tools, or environment
Assumptions about cognitive architecture	Dual-system architecture	Cognitive architectures are malleable
Empirical distinction criterion (reversibility)	Once intervention is removed, behavior reverts to preintervention state	Implied effects should persist once (successful) intervention is removed
Programmatic ambition	Correct momentous mistakes in specific contexts – «local repair»	Equip individuals with domain-specific or generalizable competences
Normative implications	Might violate autonomy and transparency	Necessarily transparent and require cooperation – an offer that may or may not be accepted

2. A Plurality of Views on How Real People Reason and Decide

We begin by briefly reviewing the plurality of views within the behavioral sciences on how and how well people make decisions. The goal is to illustrate the surprising range of views on the nature of human decision making and to show that the rich behavioral evidence available is indeed consistent with more than just nudging. We begin with the view on which nudging rests.

Nudging's starting point is a drastically different view of the real-world decision maker from that of the stylized, hyperrational *Homo economicus* or the Olympian model of rationality, which according to Simon (1990), «serves, perhaps, as a model of the mind of God, but certainly not as a model of the mind of man» (p. 34). Thaler and Sunstein (2008) put it this way: «If you look at economics textbooks, you will learn that homo economicus can think like Albert Einstein, store as much memory as Ibm's Big Blue [sic], and exercise the willpower of Mahatma Gandhi» (p. 6). Proponents of the nudge approach argue that real and boundedly rational people not only lack these heroic qualities – they are fallible, inconsistent, ill-informed, unrealistically optimistic, and myopic, and they suffer from inertia and self-control problems (Sunstein, 2014; Thaler & Sunstein, 2008; see also Halpern, 2015). This dismal portrayal of people's decision-making competence has its roots in the *heuristics-and-biases program* (e.g., Kahneman, 2003, 2011; Kahneman, Slovic, & Tversky, 1982). This program has, over more than four decades, cataloged a large set of «cognitive illusions,» that is, systematic violations of norms of reasoning and decision making (e.g., logic, probability theory, axioms of rational choice models). The underlying idea is that due to their inherent cognitive limitations, humans are unable to perform rational calculations and instead rely on heuristics. These heuristics are «highly economical and usually effective, but they lead to systematic and predictable errors» (Tversky & Kahneman, 1974, p. 1124). The cumulative weight of these errors has thus «raised serious questions about the rationality of many judgments and decisions that people make» (Thaler & Sunstein, 2008, p. 7) and necessitates as well as enables a new approach to public policy.

The innovative core of nudging is the insight that policymakers can harness individuals' cognitive and motivational deficiencies rather than having to yield to them as insurmountable obstacles to good decisions and welfare. By enlisting these deficiencies, policymakers can steer (nudge) individuals' behavior toward behaviors that are consistent with their ultimate goals or preferences – and that result in better outcomes than would otherwise be obtained (Rebonato, 2012; Thaler & Sunstein, 2008). Take, for illustration, defaults as one paradigmatic nudge. Default rules establish what will automatically happen if a person does nothing – and «nothing is what many people will do» (Sunstein, 2014, p. 9). Betting on this inertia, a policymaker can put in place a default that brings people closer to a desired behavioral outcome (Beshears, Choi, Laibson, & Madrian, 2010). For example, automatic enrollment in employer-sponsored savings plans increases employees' retirement income. Because people tend to keep the default option, automatic enrollment raises participation rates in retirement savings plans (but not necessarily contribution rates; see Butrica & Karamcheva, 2015).

Although undoubtedly influential, the heuristics-and-biases program is not the only view about human decision makers and their competence, and its conclusions have been questioned. What some perceived as «the message that man is a "cognitive cripple"» (Edwards, 1983, p. 508) was by no means unanimously endorsed – as illustrated by one early conceptual criticism of the heuristics-and-biases program that far preceded the more contentious discussions of the 1990s (e.g., Gigerenzer, 1996; Kahneman & Tversky, 1996): «In the research literature [on heuristics and biases], subjects are almost never given feedback about the logical implications of their judgements, never shown their inconsistencies and invited to resolve them, rarely asked for redundant judgements so that inconsistency can be utilised as part of the assessment process, and almost never asked to make judgements in a group setting. […] It is perfectly possible that many people, given the right tasks in the right circumstances, could make precise, reliable, accurate assessments of probability […]» (Phillips, 1983; p. 536).

Phillips (1983) argued that «research on heuristics and biases has become a psychology of first impressions» (p. 538) and that there is more to human decision making and problem solving than this first response. Indeed, let us briefly consider five other research programs concerned with human decision making and problem solving that suggest different views and conclusions. Preceding the heuristics-and biases program, a research program often referred to as *man as an intuitive statistician* (Peterson & Beach, 1967) reached a very different conclusion on how people make decisions. Reviewing studies conducted in the 1950s and 1960s that, like the heuristics-and-biases program, used probability and statistics as a benchmark against which people's intuitive statistical inferences and predictions (e.g., about proportions, means, variances, and sample sizes) were evaluated, Peterson and Beach (1967) concluded that «the normative model provides a good first approximation for a psychological theory of inference» (p. 42). Although this view of intuitive inference and prediction did not deny the existence of discrepancies between norm and intuition (e.g., probability updating being too conservative), the premise was that people «cannot help but to gamble in an ecology that is of essence only partly accessible to their foresight» and that the individual «gambles well» (Brunswik cited in Peterson & Beach, 1967, p. 29).

Since the mid-1980s, a research program with roots in social psychology has been concerned with the dynamics of social influence and persuasion (see, e.g., Cialdini, 2001; Cialdini & Goldstein 2004; Sherman, Gawronski, & Trope, 2014). This research shares with the heuristics-and-biases program the assumption that people are «cognitive misers» who, owing to their limited mental processing resources, aim to save time and effort when navigating the social world (Fiske & Taylor, 1991). Yet – and this is crucial – even cognitive misers can be motivated and enabled to allocate more cognitive resources and to engage more extensively with arguments. Take, for instance, two influential models of persuasion: the heuristic-systematic model (Chaiken, 1987) and the elaboration-likelihood model (Petty & Cacioppo, 1986). In the former, an argument is processed *systematically* or *heuristically*; in the latter, information processing takes either the *central* or the *peripheral* processing route. Simply put, the models' core notion is that the quality of an argument will be systematically processed (central route) only if it has high relevance or if the listener is highly motivated. If, in contrast, listeners are on «autopilot» and do not devote mental capacities to systematically poring over arguments (see Booth-Butterfield & Welbourne, 2002; Todorov, Chaiken, & Henderson, 2002), their attitudes will be shaped by peripheral cues (e.g., the expertise of an argument's source rather than the quality of the argument).

Originating in the late 1980s, the research program on naturalistic decision making (Klein, 1999; Lipshitz, Klein, Orasanu, & Salas, 2001) has studied how people make decisions in complex, high-stakes, real-world settings such as firefighting, nursing, and commercial aviation. This program started from the premise that norms of rational choice are not suitable for the typically ill-defined and challenging tasks encountered by, for instance, fireground commanders, in which conditions of uncertainty and time pressure preclude any effort to generate and comprehensively evaluate sets of options and then pick the best one. Instead, «when people need to make a decision they can quickly match the situation to the patterns they have learned. If they find a clear match, they can carry out the most typical course of action. In that way, people can successfully make extremely rapid decisions. The Rpd [recognition-primed decision-making] model explains how people can make good decisions without comparing options» (Klein, 2008, p. 457). This research program has been committed to revealing the mechanisms behind the often impressive performance of experts, without denying that failures may occur (see also Kahneman & Klein, 2009).

Another research program, initiated in the mid-1990s (and to which one of the present authors has contributed), has studied which *simple heuristics* (or fast-and-frugal heuristics) people use to make decisions and how good those decisions are. The starting premise of this program is that individuals and organizations cannot help but rely on simple heuristics in conditions of uncertainty, lack of knowledge, and time pressure. Rather than conceptualizing heuristics as inherently error-prone, however, the program has provided evidence that less information, computation, and time – conditions embodied by heuristics – can help *improve* inferential and predictive accuracy (but may violate norms of coherence; see Arkes, Gigerenzer, & Hertwig, 2016). This program views the cognitive system as relying on an «adaptive toolbox» of simple strategies, with the key to good performance residing in the ability to select and match the mind's tools to the current social or nonsocial environment (ecological rationality; Gigerenzer, Hertwig, & Pachur, 2011; Gigerenzer, Todd, & the ABC Research Group, 1999; Hertwig, Hoffrage, & the ABC Research Group, 2013). Of course, heuristics may still fail (e.g., when applied in the wrong environment), but this approach emphasizes that, relative to resource-intensive and general-purpose normative strategies, heuristics can be surprisingly efficient and robust (Gigerenzer et al., 2011).

Most recently, an approach sometimes referred to as *Bayesian rationality* (Oaksford & Chater, 2009) or the *probabilistic mind* (Griffiths, Chater, Kemp, Perfors, & Tenenbaum, 2010) has suggested that many of the reasoning problems used in studies that have purportedly found irrational behaviors are in fact better understood as probabilistic problems. From this perspective, human rationality and higher-level cognition are best defined not by logic but by probability theory. Human thought thus conceptualized has been found to be «sensitive to subtle patterns of qualitative Bayesian, probabilistic reasoning» (Oaksford & Chater, 2009, p. 69).

The goal of this short history of psychological theorizing and evidence on how people reason and make decisions was to demonstrate that the nudge approach's portrayal of the human decision maker as systematically imperfect is not the only legitimate conception. Several others exist, and their conclusions about human decision-making competences tend to be less disquieting. Our objective here is not to champion one idea over the other. Yet if behavioral science insights into how people make decisions are to inform public policy, it is vital to acknowledge the existence of different views and findings – particularly as these different approaches may suggest different types of policy interventions, including measures that foster existing competences or build new ones.

3. Boosts and Nudges: Definitions and Causal Pathways to Behavior

Thaler and Sunstein (2008) defined a nudge 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» and where this intervention is «easy and cheap to avoid» (p. 6). Nudging thus defined includes all behavioral policies that do not coerce people or substantially change their financial incentives and whose point of entry is the choice architecture – that is, the external context within which individuals make decisions. Within this extensive category, nudges often come in the form of either «non-educative» or «educative» nudges (Sunstein, 2016). We first focus on non-educative nudges – the innovative core of nudging and libertarian paternalism – and return to educative nudges below when discussing boosts aimed to improve performance in the short term.

The intervention target of non-educative nudges is behavior (table 1). To causally steer behavior, non-educative nudges harness cognitive or motivational deficiencies (e.g., inertia, procrastination, loss aversion; see also Rebonato, 2012) and effect corresponding changes in the choice architecture in order to steer behavior in the desired direction. In so doing, policymakers do not target features over which people have explicit preferences (e.g., money, convenience, taste, status, etc.) but rather exogenous properties of the choice architecture that people typically claim not to care about (e.g., position in a list, default settings, formulation of semantically equivalent statements). Furthermore, the behavior change brought about has to be easily reversible, permitting the chooser to act otherwise. Because this easy reversibility preserves individuals' freedom of choice, this kind of paternalism has been described as «libertarian» in nature (Thaler & Sunstein, 2008).

For illustration, consider the Save More Tomorrow (Smt) nudge. It was designed to boost retirement savings (Thaler

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& Benartzi, 2004) and works as follows: Unless people actively choose to opt out of the retirement savings plan, they commit to allocating a portion of their future salary increases toward retirement savings. The intervention target of Smt is behavior. To steer behavior, Smt exploits specific cognitive and motivational deficiencies, which it enlists to increase employees' contributions to retirement savings accounts. One deficiency is the present bias, a strong preference for present over future rewards, which causes people to save less for their old age than they should. This bias decreases when a present reward is projected into the near future (Loewenstein & Prelec, 1992) – a change in preference that would not be expected if people discounted the future consistently. Smt harnesses this inconsistency in discounting by not asking people to choose between consumption now versus consumption later. Instead, it offers a choice between consumption in the near future (e.g., a year from now) and consumption later: Participants commit today to a series of increases in contributions that are timed to coincide with salary increases in the future. Because the plan is tied to salary increases, people may never see their nominal take-home pay go down, thus decreasing the influence of loss aversion. A second deficiency that Smt enlists is inertia. As a consequence of it, people typically will not opt out of a program they are enrolled in, even when future contributions escalate with every pay raise. In a nutshell, Smt does not aim to foster people's competences. Instead, it skillfully designs an external choice architecture – involving automatic enrollment, projection of the choice into the near future, and dynamic adjustment of savings rates – that harnesses decisional deficiencies (without correcting them) to prompt behavior change.

Building on Grüne-Yanoff and Hertwig (2016), we define boosts as interventions that target competences rather than immediate behavior (table 1). The targeted competences can be specific to a single domain (e.g., financial accounting; Drexler, Fischer, & Schoar, 2014) or generalize across domains (e.g., statistical literacy). A boost may enlist human cognition (e.g., decision strategies, procedural routines, motivational competences, strategic use of automatic processes), the environment (e.g., information representation or physical environment), or both. By fostering existing competences or developing new ones, boosts are designed to enable specific behaviors. Furthermore, they have the goal of preserving personal agency and enabling individuals to exercise that agency. Consequently, if people endorse the objectives of a boost – say, risk literacy, financial planning, healthy food choices, or implementing goals – they can choose to adopt it; if not, they can decline to engage with it. To this end, a boost's objective must be transparent to the boosted individual. People can then harness the new or «boosted» competence to make choices for themselves (e.g., whether to undergo a medical test or consume a particular food).

Some boosts are *short-term*. They foster a competence, but the improvement in performance is limited to a specific context. Others are *long-term*. Ideally, these permanently change the cognitive and behavioral repertoire by adding a new competence or enhancing an existing one, creating a «capital stock» (Sunstein, 2016, p. 32) that can be engaged at will and across situations.

To appreciate this distinction, consider psychologists' work on conditional probabilities, natural frequencies, and Bayesian inferences[1]. In the 1970s and 1980s, researchers within the heuristics-and-biases program (Kahneman, 2011) concluded that people systematically neglect base rates in Bayesian inference: «The genuineness, the robustness, and the generality of the base-rate fallacy are matters of established fact» (Bar-Hillel, 1980, p. 215). In the 1990s, others suggested that the mind's statistical reasoning processes evolved to operate on natural frequencies and that Bayesian computations are simpler to perform with natural frequencies than with probabilities (the information format used in the base-rate fallacy studies)[2]. Consistent with this hypothesis, Gigerenzer and Hoffrage (1995) and Hoffrage, Lindsey, Hertwig, and Gigerenzer (2000) showed that statistics expressed in terms of natural frequencies improved the Bayesian inferences of students, patients, doctors, and lawyers. The improvement was achieved not by explicit instruction,

1 Bayesian inferences are statistical inferences that in the simplest case encompass two exclusive hypotheses (e.g., having or not having breast cancer) and a datum such as the outcome of a medical test (e.g., a mammography). Bayes' theorem is a mathematical formula that combines pieces of probability information – that is, the base rate of the hypothesis (e.g., breast cancer is present), likelihood information (e.g., the true-positive rate and the false-positive rate of the test), and a new datum (e.g., a positive test result) – to arrive at the posterior probability (e.g., the probability that someone with a positive mammogram result actually has breast cancer).

2 Natural frequencies refer to the outcomes of natural sampling – that is, the acquisition of information by updating event frequencies without artificially fixing the marginal frequencies. Unlike probabilities and relative frequencies, natural frequencies are raw observations that have not been normalized with respect to the base rates of the event in question.

but by changing the information format in probabilistic reasoning problems from probabilities to natural frequencies. This boost was a short-term, context-specific fix, with no aspiration to improve Bayesian reasoning beyond the given set of problems.

A long-term boost of Bayesian reasoning, in contrast, could foster people's competence to actively translate any probabilities they encounter into frequencies and thereby simplify the Bayesian computations. Using a computerized tutorial program, Sedlmeier and Gigerenzer (2001) taught people to actively construct frequency from probability representations, and found this newly developed competence to be robust after 15 weeks, with no drop in performance.

Recently, Sunstein (2016) introduced the notion of educative nudges, citing reminders, warnings, and information such as nutrition labels as examples. In our view, educative nudges and short-terms boosts largely overlap. Both represent local fixes to a given problem and require – in contrast to classic nudges, such as defaults – a modicum of motivation and cognitive skill. Yet even local fixes, if they are to be successful, require psychological knowledge on the part of the booster; merely providing information is often not enough. Health statistics or nutritional information, for instance, bring no benefits if they are opaque (e.g., reliant on conditional probabilities), overwhelming (e.g., software license agreements), or misleading (e.g., expressed as relative risk information; Gigerenzer, Gaissmaier, Kurz-Milcke, Schwartz, & Woloshin, 2007). In the following, we present a taxonomy of long-term boosts and compare non-educative nudges and long-term boosts in terms of the assumptions they make about the human cognitive architecture, the reversibility of their effects, their programmatic ambitions, and their normative implications (table 1).

4. A First Taxonomy of Long-Term Boosts

Our goal is not to provide an exhaustive account of long-term boosts but to show just how rich this class already is (even when limiting the scope of our brief review to recent work)[3]. One dimension on which boosts can be classified is the competence that is boosted.

Risk literacy boosts establish or foster the competence to understand statistical information in domains such as health, weather, and finances. This competence can be achieved through (a) graphical representations (e.g., Lusardi et al., 2014; Spiegelhalter, Person, & Short, 2011; Stephens, Edwards, & Demeritt, 2012), (b) experienced-based (as opposed to purely description-based) representations (e.g., Hogarth & Soyer, 2015; Kaufmann, Weber, & Haisley, 2013), (c) representations that avoid biasing framing effects (e.g., absolute instead of relative frequencies; Gigerenzer et al, 2007; Spiegelhalter et al., 2011), (d) brief training in transforming opaque representations (e.g., single-event probabilities) into transparent ones (e.g., frequency-based representations; Sedlmeier & Gigerenzer, 2001), and (e) training of general math skills (e.g., during story time with parents; Berkowitz et al., 2015). Boosts targeting risk literacy work as long as people have access to actuarial information about risks. Often, however, people need to make decisions under uncertainty, with no explicit risk information available. In this case, they need other mental tools.

Uncertainty management boosts establish or foster procedural rules for making good decisions, predictions, and assessments under uncertain conditions with the help of (a) simple actuarial inferential methods (e.g., Dawes, Faust, & Meehl, 1989; Swets, Dawes, & Monahan, 2000), (b) simple rules of collective intelligence (e.g., Kurvers, Krause, Argenziano, Zalaudek, & Wolf, 2015; Kurvers et al., 2016; Wolf, Krause, Carney, Bogart, & Kurvers, 2015; see also Herzog & Hertwig, 2014), or (c) fast and frugal decision trees, simple heuristics, and procedural routines (e.g., Drexler et al., 2014; Gigerenzer et al., 2011, see chapters 29, 31, 32, 34, 36, 39; Hertwig & Herzog, 2009; Jenny, Pachur, Williams, Becker, & Margraf, 2013).

Motivational boosts foster the competence to autonomously adjust one's motivation, cognitive control, and self-control through interventions such as expressive writing (e.g., Beilock & Maloney, 2015), growth-mindset or sense-of-purpose exercises (e.g., Paunesku et al., 2015; Rattan, Savani,

3 Comprehensive frameworks for the classification of evidence-informed behavioral change interventions already exist (e.g., Michie, von Stralen, & West, 2011). Because frameworks such as the behavior change wheel (Michie et al., 2011) include interventions that go far beyond those targeted by the nudging and boosting approach (e.g., coercion, incentivization, and restriction of choice) we will not consider them further here. Within the behavior change wheel, the boost interventions we consider here would be classified under «education», «training», «environmental restructuring», «modeling», and «enablement».

Chugh, & Dweck, 2015), attention and attention-state training (e.g., Tang & Posner, 2009; Tang, Tang, & Posner, 2013; see also Moffitt et al., 2011), psychological connectedness training (Hershfield et al., 2011), reward-bundling exercises (Ainslie, 1992, 2012), the strategic use of automatic processes (e.g., harnessing simple implementation intentions; Gollwitzer, 1999), and training in precommitment strategies (Schelling, 1984) and self-control strategies (e.g., see table 30.1 in Fishbach & Shen, 2014).

Another dimension on which boosts could be classified is the target audience. Some boosts target specific developmental periods (e.g., childhood); others are applicable across the adult life span (e.g., risk literacy boosts). Some boosts target the population at large (e.g., Spiegelhalter, Person, & Short, 2011); others target subsets of the population, such as smokers (Tang et al., 2013), general practitioners (Jenny et al., 2013), or diagnosticians (Kurvers et al., 2015).

5. Nudges Versus Boosts: Which Cognitive Architecture Is Assumed?

Nudges and boosts differ in the target of intervention and the causal pathways taken to prompt behavior change (table 1). Nudges co-opt the decision maker's (internal) cognitive and motivational processes and design the (external) choice architecture such that it, in tandem with the (untouched) functional processes, produces a change in behavior. Nudges target behavior directly. Boosts, in contrast, target individual competences to bring about behavior change. Their goal is to train the functional processes or adapt the external world (e.g., representation of information), or both, to improve decision making and its outcomes.

To appreciate these distinct pathways, let us first clarify the concept of functional processes. A construct often used in cognitive science, artificial intelligence, and other disciplines is that of the *cognitive architecture*. It specifies the «infrastructure» of an artificial or naturally evolved information-processing system, including mental hardware such as memory structures for the storage of beliefs, goals, and knowledge, and the functional processes operating on that hardware, such as cognitive algorithms, heuristics, and reasoning processes (e.g., Langley, Laird, & Rogers, 2009). Although psychologists agree that the human mind is a natural information-processing system, there is much debate about the nature of its architecture and especially about the mind's functional processes and their rationality. Some proposals for a cognitive architecture of the human mind are rooted in neuroscientific findings (e.g., Anderson & Lebiere, 1998; McClelland, Rumelhart, & the PDP research group, 1986; Rumelhart, McClelland, & the PDP research group, 1986); others are more metaphorical, with the function of generating new research hypotheses (e.g., the mind as a Swiss army knife; Cosmides & Tooby, 1994) or summarizing existing data (Kahneman, 2011). Differing assumptions about the mind's functional processes also represent important distinguishing criteria between nudging and boosting.

Nudging. The nudge approach has its roots in the dual-system view of the human cognitive architecture. According to Kahneman (2003, 2011), the mind can be divided into two processing systems: System 1 (the automatic system), which is fast, intuitive, and emotional, and System 2 (the effortful system), which gives rise to slow, rule-governed, and deliberate reasoning and is emotionally neutral. System 1 is an efficient first-response system but its speed and automatic processes render it susceptible to systematic biases («cognitive illusions»). System 2 could, in principle, supervise System 1's mental products and conclusions as well as rectify biases – but it is often too sluggish to do so.

Attempts to change behavior can thus take one of two routes: One is to engage System 2 and foster it, the other is to harness System 1's deficiencies. Nudging, at least in Thaler and Sunstein (2008; but see Jung & Mellers, 2016), predominantly takes the latter approach. Attempts to strengthen System 2 are rare for at least two reasons. One is conceptual (Kahneman, 2011, p. 28). According to the dual-process view, people's cognitive and motivational deficiencies are robust, often difficult to prevent, and largely impervious to change; debiasing attempts are often seen as futile. The fact that even experts – in business, medicine, and politics (e.g., Bornstein & Emler, 2001; Heath, Larrick, & Klayman, 1998;

Kahneman & Renshon, 2007; Malmendier & Tate, 2005; Norman & Eva, 2010) – fall prey to cognitive illusions suggests that even rich learning opportunities do not equip people to escape them.

The second reason System 2 nudges are rare relates to another unique selling point of nudges: their cost efficiency. By implementing simple nudges with a large scope (e.g., mass default rules, automatic enrollment), policymakers can effect substantial behavior changes at relatively low costs. Indeed, cost efficiency in combination with large-scale impact – creating maximum net benefits – has often been highlighted as a key advantage of nudging relative to educating the public or, indeed, traditional economic policies (e.g., Weber & Johnson, 2009, p. 75).

Boosting. Unlike proponents of nudging, proponents of boosting do not share a single view of the human cognitive architecture as in the dual-system view (see also the section «A Plurality of Views on How Real People Reason and Decide»). Nevertheless, proponents of boosting necessarily agree that human functional cognitive processes and motivational processes are malleable and worth developing. Specifically, existing mental tools can be enhanced or a person can learn to employ new procedural rules. Despite its focus on boosting the mind's competences, this policy approach is not introversive. On the contrary, competences are often best fostered by redesigning aspects of an external environment or by teaching people how to redesign them.

What are the theoretical foundations of boosting? In Grüne-Yanoff and Hertwig (2016), we discussed to what extent the necessary assumptions of nudging and boosting are implied by a theoretical commitment to the heuristics-and-biases program and to the simple heuristics (and ecological rationality) program (Gigerenzer et al., 2011), respectively. Our analysis of what we called policy–theory coherence could be read to imply that boosting's view of the mind is that of an adaptive toolbox of ecologically rational heuristics. In fact, we argue that boosts include – but also go beyond – simple and ecologically rational heuristics. For instance, because boosts include motivational interventions, their development could benefit greatly from links with programs on mindset (Dweck, 2012) and lay theory interventions (Yeager et al., 2016), cognitive control and attention state training (Tang & Posner, 2009), the strategic use of automatic processes (Gollwitzer, 1999), and knowledge of how people process arguments (in particular, factors that prompt them to invest cognitive effort in evaluating arguments; for reviews, see Booth-Butterfield & Welbourne, 2002; Todorov et al., 2002).

6. Reversibility: An Empirical Criterion for Distinguishing Between Nudges and Boosts

In theory, the conceptual distinction between non-educative nudges and long-term boosts seems clear. But once concepts hit the messy world of real-life policy interventions, matters are rarely so simple. Let us therefore offer a pragmatic rule for distinguishing nudges from boosts. Boosts seek to foster people's cognitive and motivational competences, whereas nudges adapt a choice architecture to people's cognitive and motivational processes and leave them unaltered. This difference implies a different degree of reversibility in the behavioral effects induced (table 1): if, all else being equal, the policymaker eliminates an efficacious (nonmonetary and nonregulatory) behavioral intervention and behavior reverts to its pre-intervention state, then the policy is likely to be a nudge. If, all else being equal, behavior persists when an intervention is eliminated, then the policy is more likely to be a boost.

This criterion is based on the assumption that boosts ultimately change behavior (e.g., choosing healthier food, making better financial decisions, understanding health statistics) by enhancing existing competences or establishing new ones, and that those competences, once in place, remain stable over time. Consequently, the implied behavioral effects should persist once the intervention is removed and if the implied behavior is congruent with the person's value system. Nudges, in contrast, change behavior by adapting the choice architecture, leaving individual competences unchanged. Consequently, once the intervention is removed, behavior is likely to revert to the prenudging state[4].

4 Kelman (1961) proposed a valuable distinction between three processes of social influence, of which two are compliance and internalization. Although they cannot be mapped one-to-one onto nudging and boosting, Kelman's approach can provide a theoretical starting point for further analyzing the proposed empirical criterion for discerning between the two intervention types.

There is one important qualification to this criterion. As mentioned earlier, nudges that affect behavior repeatedly may produce behavioral routines through learning that persist even after the nudge has been removed from the choice architecture. In such cases, our empirical criterion indicates that the nudge intervention has a boosting «side effect»: By changing the choice context and harnessing cognitive and motivational deficiencies to affect behavior, the nudge inadvertently affects the cognitive and motivational processes themselves. The nudge thus turns into a boost, leaving lasting effects.

7. The Vision Behind Boosts

In response to our distinction between nudging and boosting (Grüne-Yanoff & Hertwig, 2016), Sunstein (2016) noted that «some of the best nudges are boosts» (p. 10). He described educative nudges (e.g., disclosure requirements, warnings, nutrition labels, reminders) as an attempt «to strengthen System 2 by improving the role of deliberation and people's considered judgments. One example is disclosure of relevant (statistical) information, framed in a way that people can understand it. These kinds of nudges, sometimes described as "boosts", attempt to improve people's capacity to make choices for themselves» (Sunstein, 2016, p. 52).

Given this description, one might indeed conclude that boosts are simply a special kind of nudge, even if their objectives and aspirations differ. Yet there are clear distinctions. Take, for illustration, the case of risk literacy, mentioned in our taxonomy of boosts. Thaler and Sunstein (2008) emphasized – and we believe rightly so – that «choice architecture is inevitable, and hence certain influences on choices are also inevitable» (p. 21). This means, however, that no governmental policymaker has full control over how, for instance, players in the medical marketplace – pharmaceutical companies, governments, doctors, patient groups, and so on – communicate health statistics. The vision behind boosting is to equip individuals with competences such as risk literacy that are applicable across a wide range of circumstances, including those that will not be reached by mandated disclosure requirements, warnings, and labels. The notion of educative nudges in Sunstein (2016) does not embrace this more encompassing goal of empowering people who will inevitably face commercially constructed choice architectures and industry nudges. Nor is such empowerment part of Thaler and Sunstein's (2008) vision of nudging. In fact, the notion of enhancing competences plays, if at all, a marginal role in their book – words such as «competence,» «knowledge,» «skills,» and «empowerment» do not even feature as entries in the index.

8. Nudges and Boosts and Their Normative Implications

It is important to consider efficiency, effectiveness, and welfare when choosing between the two kinds of policy interventions. In addition, nudges and boosts have different implications with respect to normative dimensions of policy interventions. We briefly discuss two such normative dimensions here: transparency and autonomy.

Hard paternalistic interventions such as laws (e.g., mandatory seatbelt use), bans (e.g., on smoking in public places), and financial disincentives (e.g., taxes on cigarettes) are visible and transparent (Glaeser, 2006). Citizens can scrutinize them and hold governments accountable. Some have argued that nudges are less transparent. Indeed, some nudges may operate behind the chooser's back and therefore appear manipulative (e.g., Conly, 2012; Wilkinson 2013). Default rules can be criticized on these grounds – they take advantage of people's assumed inertia and skirt conscious deliberation, meaning that they are perhaps not easily reversible and thus fail to meet the criterion of freedom of choice. Furthermore, even if default rules are completely transparent (and they often are – consider automatic enrollment in saving plans), a person's ability to discern an intervention as such (e.g., a default) is distinct from their ability to discern how it changes their behavior – particularly if the direction of the effect is counterintuitive. To the extent that people are unable to fathom the underlying mechanism that brings about the change in behavior, this reduces transparency.

Boosts, in comparison, require the individual's active cooperation. They therefore need to be explicit, visible, and transparent. The need for cooperation also implies individual judgment and engagement. This, in turn, implies – according to dominant notions of autonomy (Buss, 2014) – that boosts are more respectful of autonomy than nudges are. This holds in particular for those nudges that seek to bypass people's «capacity for reflection and deliberation» (Sunstein, 2016, p. 64)[5].

Individuals choose to engage or not to engage with a boost. The policymaker is therefore entitled to assume that a chosen boost reflects the individual's genuine motivation. A successful nudge does not necessarily reflect such genuine motivations. Of course, the hope is that policymakers, informed by data and the public discourse, aim to promote people's own ends, as they understand them (Sunstein, 2014). Genuine motivations are often seen as the proper evidential basis of welfare considerations (e.g., Hausman, 2012). Therefore, the distinction between boosts and nudges implies that boosts are more likely to respect such considerations. This, however, does not necessarily mean that boosts are as successful as or more successful than nudges in achieving a desired goal (e.g., higher contributions to retirement plans).

9. Addressing Potential Misconceptions About Boosts

Various misconceptions and oversimplifications exist about nudging as a policy intervention, and boosting is also subject to misconceptions. We next address some of them.

Boosting is not the same as school education. Boosting, as we conceptualize it, is not identical to school education, although some boosts (e.g., representation training, growth mindset interventions) could easily be included in school curricula. Schools have the task of providing students with knowledge and competences and thus *do* boost individuals; however, the policy interventions we have in mind differ from school education in several respects. First, the primary goal of boosts is not to offer accurate declarative knowledge and cultural skills such as reading, writing, and algebra. Instead, boosts offer competences in domains that are not typically addressed in school curricula, such as good financial decision making, accurate risk assessment, healthy food choices, informed medical decisions, and effective self-regulation. Second, boosts, like nudges, should be informed by evidence from behavioral science. This is not necessarily the case for what is being taught in schools. Third, boosts aim to foster or develop new competences under conditions of limited time and resources (on the part of the target audience and the policymakers) and typically in an adult citizenry that cannot be subjected to years of additional schooling. Fourth, the focus of boosts is typically on actionable motivational and decisional competences (e.g., procedural routines, heuristics, goal implementation skills) and not on information per se. Fifth, boosts often are «just-in-time» interventions, whereas school education provides knowledge and competences on a schedule. In all likelihood, people are most motivated to develop a new competence when they experience a specific need for it. Finally, boosts, as understood here, are interventions that preserve and enable individuals' personal agency and autonomy. Admittedly, if boosts were included in a mandatory school curriculum, the autonomy of the students would be curtailed.

Boosts need not be costly. Nudges are envisioned to be inexpensive policy measures. Indeed, some modifications of the choice architecture can be made at low cost. They scale up and promise immediate results. A default rule can, for instance, be changed by government mandate (e.g., from opting in to opting out). Changes in default rules also require minimal effort on the part of the nudged individual; in fact, sometimes the nudge rests on the very assumption that individuals will do nothing. In contrast, boosts often require investments in time, effort, and motivation on the part of both the individual and the policymaker. Yet, although boosts are rarely no-cost interventions, many of them are low cost. The necessary time investment can be as little as a few minutes (e.g., expressive writing, Beilock & Maloney, 2015), or no more than a few hours (growth min-

5 Boosted competences can, however, be employed to restrain other people's autonomy. For example, by coaching parents to engage in playful bedtime math with their children (Berkowitz et al., 2015), one might boost parents' ability to steer their children's behavior. Parents then, without loss of autonomy, participate in a routine that may curtail their children's autonomy.

dset and sense-of-purpose interventions, Paunesku et al., 2015; representation training, Drexler et al., 2014; Sedlmeier & Gigerenzer, 2001). Admittedly, the policymaker faces the costs of setting up learning opportunities for such interventions to be offered.

The domains of boosts are not completely orthogonal to those of nudging. Boosts and nudges are not perfect substitutes for each other. For instance, no nudge has been implemented to reduce math anxiety (Beilock & Maloney, 2015; Maloney & Beilock, 2012) or foster transparent communication of health risks (Gigerenzer et al., 2007). In these cases, policymakers have only one choice. Yet there are domains in which either nudges or boosts or both could be used, such as food choices, financial decisions, and self-control problems. The domain of financial decision making, to which we turn shortly, is a good example of a domain that is conducive to more than one policy intervention. As we have emphasized, which of the two interventions is more efficient is an empirical issue. Our goal is not to champion one over the other but to highlight the need for an analysis of the respective circumstances and goals, allowing policymakers to select the more appropriate intervention (Grüne-Yanoff et al., 2016). Hertwig (2016) has discussed in detail the rules that policymakers can apply to determine under what conditions boosts, relative to nudges, are the preferable form of intervention.

10. Boosting Towards Better Financial Decisions

Let us now introduce two possible interventions that can be used to boost people's ability to make sound financial decisions. One boost rests on rules of thumb that were designed to improve the accounting skills of micro-entrepreneurs. Drexler et al. (2014) equipped micro-entrepreneurs in the Dominican Republic with basic accounting heuristics in order to empower them to make better financial decisions. This heuristic-based training is not the same as standard accounting training programs, which teach small business owners the basics of double-entry accounting and the importance of keeping business and personal accounts separate, along with concepts such as inventory management, calculating cash profits, and investment planning. The heuristic-based, or rule-of-thumb, training instead used a hands-on approach to teach micro-entrepreneurs to keep their business and personal accounts separate. This approach offered participants «a physical rule to keep their money in two separate drawers (or purses) and to only transfer money from one drawer to the other with an explicit "Iou" note between the business and the household. At the end of the month they could then count how much money was in the business drawer and know what their profits were» (Drexler et al., 2014, p. 3). Drexler et al. (2014) compared the micro-entrepreneurs' behavior before and after they took part in the heuristic-based training with the effects of a standard accounting training program. They found that participants of the heuristic-based training «were more likely to keep accounting records, calculate monthly revenues, and separate their books for the business and the home» but they «did not find any significant changes for those in the standard accounting training» (p. 3). The beneficial effects of the heuristics training were particularly pronounced (and statistically significant) for the group of small business owners who had lower skills or displayed poorer financial practices.

Our second example of a financial decision-making boost concerns the representation and understanding of financial risks when making investment decisions. Financial institutions that offer investment products are required to provide key information about their significant properties (e.g., risks, costs, past performance history). Information about the risk of financial products can be presented to clients in different ways, with financial professionals often having a lot of leeway concerning how they actually present it. One way of presenting the information is in terms of numerical symbolic descriptions (e.g., historical returns in fact sheets); another way is in terms of what Kaufmann, Weber, and Haisley (2013) called «experience sampling» (inspired by work on the description–experience gap; Hertwig, Barron, Weber & Erev, 2004; Hertwig & Erev, 2009). Experience sampling has clients interactively sample possible outcomes for an investment, where each sampled outcome contributes to the buildup of the distribution; the entire distribution of outcomes is then displayed at the end of the sampling process. To implement this form of experience sampling, the authors designed a simple «risk tool» that allowed undergraduate students at a German university to experience and compile the distribution of a risky financial product.

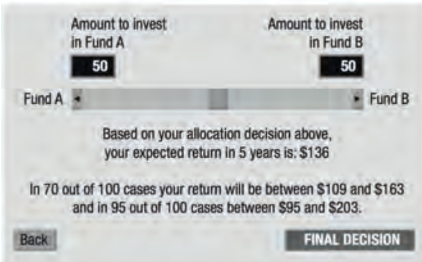
Figure 1 represents the description condition and the risk tool condition that Kaufmann et al. (2013) examined (they also studied two others that will not be addressed here). In each condition, participants were asked to make a number of allocations between two investment options, a risk-free asset and a risky asset. The behavior of the experimental investors in each condition was then compared on several dimensions. Investors in the risk tool condition allocated a larger percentage of their initial endowment to the risky fund than did the investors in the description condition. In addition, investors in the risk tool condition were more accurate when answering on recall questions that probed their understanding of the options' expected return and, importantly, the probability of a loss. Last but not least, investors in the risk tool condition did not report a greater dissatisfaction with losses than investors in the description condition, taking similar levels of risk in subsequent allocations. Based on these results, the authors concluded: «the use of experience sampling and the distribution function in financial simulations may be a fruitful strategy for banks to improve the quality of the information they provide about their investment products. With the help of a risk tool, it is possible to ensure that clients are informed, committed to, and confident about the amount of risk they are prepared to take» (Kaufmann et al., 2013, p. 336).

The empowering effects of simulated experience can be enormous (see Hertwig, Hogarth & Lejarraga, 2018, for a conceptual discussion of experience). Many professionals

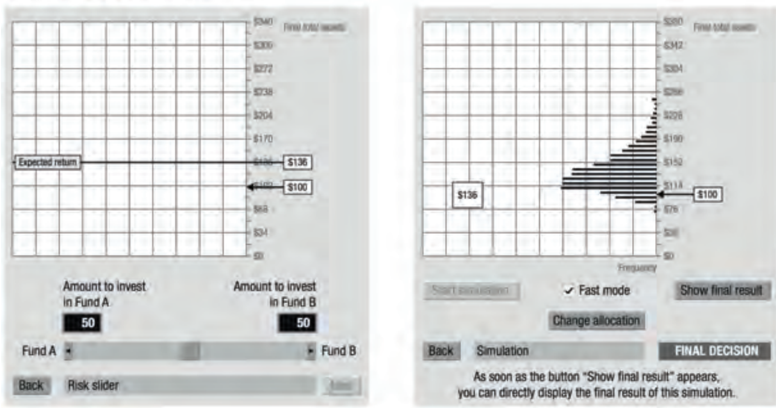
Figure 1

Two ways of representing and understanding financial risks

Description Condition



Risk Tool Condition



The description condition and the risk tool condition, as examined by Kaufmann, Weber, and Haisley (2013). Participants were asked to allocate an endowment of $100 between two funds: the risk-free fund A and the risky fund B. In the description condition, participants were given a numeric description stating the expected return. Participants read the description after entering an allocation (in percentages) with the risk slider, being allowed to try different allocations (and read about their effects) before deciding on a final one. In the risk tool condition, participants entered an allocation with the risk slider and saw the simulated expected returns of their investment on a graphical interface. To simulate experience sampling, participants used the tool to draw potential returns randomly from a distribution based on historical data. Each random draw contributed to a sampling distribution function that was displayed gradually on the screen. Participants were allowed to sample for as long as they wanted with the risk tool, but were required to sample at least eight draws. After sampling, the simulation displayed another eight draws and then built up the entire distribution. Participants were able to adjust their allocation with the risk slider and repeat the simulation until they decided on a final allocation. Adapted from «The Role of Experience Sampling and Graphical Displays on One's Investment Risk Appetite», by C. Kaufmann, M. Weber, and E. Haisley, 2013, in *Management Science*, 59, p. 337-338. Copyright 2013 by Informs.

learn to deal with complex situations by training in simulated conditions – especially when real experience would be costly or dangerous. Training pilots, for example, relies heavily on simulation, and some universities use simulated hospitals to teach medical students about surgical procedures. The crucial factor in the investment simulation is that it trains investors to deal with uncertainty. Investors need to experience the range of possible outcomes and the potential frequencies of their occurrence: When events are frequent, they need to experience that frequency; when events are rare, their scarcity must be noted. Kaufmann et al.'s (2013) results suggest that simulated experience can be more effective than mere descriptions in boosting investors' ability to judge the risk of investment options (for related results see Bradbury, Hens & Zeisberger, 2015). This, in turn, appears to increase investors' appetite for risk – an effect that could be helpful in countries like Germany, where citizens often view shares with suspicion and refuse to buy them.

Let us conclude with a crucial point. We do not suggest that these and other financial decision-making boosts are necessarily more effective than nudges (e.g., automatic enrollment). This is ultimately an empirical question, and we hope that the debate on the effectiveness of financial education versus automatic enrollment (e.g., Fernandes, Lynch, & Netemeyer, 2014; Willis, 2011) will be extended to include boosts based on simple heuristics and simulated experience. However, we do want to highlight that behavioral science evidence informs boosts as well as nudges, and that different kinds of interventions – for instance, in the domain of financial decision making – can complement each other. This raises an important question that is likely to receive more attention in the future: Under what circumstances is a particular intervention – boosting or nudging – more desirable (see Grüne-Yanoff, Marchionni, & Feufel, 2016; Hertwig, 2017)?

11. The Public Policymaker's Choice

Conceptual clarity is the key to understanding the toolbox available to public policymakers and to appreciating the pros and cons of each tool. Although two tools may aim to bring about the same behavioral effects, they can do so via different causal pathways. For instance, Thaler and Sunstein (2008) have strictly distinguished nudges from measures that change behavior through economic incentives. Aiming for the same kind of conceptual clarity, we have argued for distinguishing (at least) two kinds of evidence-informed nonregulatory and nonmonetary interventions: nudging and boosting, which represent different causal pathways to behavior change. Making this distinction explicit contributes to the normative debate on behavioral policies and offers policymakers a choice.

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