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## Long-lasting heuristics principles for efficient investment decisions

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### Abstract

**Purpose** – Behavioral solutions to our cognitive biases have long been studied in the literature. However, there is still ample evidence of behavioral biases in decision-making, with only limited improvement in the medium/long term even when debiasing methods are applied. The purpose of this paper is to describe how financial investors could benefit from a proactive management of emotions combined with a set of learning and decision-making heuristics to make more efficient investments in the long run.

**Design/methodology/approach** – First, the authors offer a classification of the appropriate quantitative and qualitative methodologies to use in different ecological environments. Then, the authors offer a list of detailed heuristics to be implemented as behavioral principles intended to induce more long-lasting changes than the original rules offered by the adaptive toolbox literature. Finally, the authors provide guidelines on how to embed artificial intelligence and cognitive diversity within the investment decision architecture.

**Findings** – Improvements in decision skills involve changes that rarely succeed through a single event but through a succession of steps that must be habitualized. This paper argues that implementing a more conscious set of personal and group principles is necessary for long-lasting changes and provides guidelines on how to minimize systematic errors with adaptive heuristics. To maximize their positive effects, the principles outlined in this paper should be embedded in an architecture that fosters cognitively diverse teams. Moreover, when using artificial intelligence, the authors advise to maximize the interpretability/accuracy ratio in building decision support systems.

**Originality/value** – The paper proposes a theoretical reflection on the field of behavioral research and decision-making in finance, where the chief goal is to offer practical advices to investors. The literature on debiasing cognitive biases is limited to the detection and correction of immediate effects. The authors go beyond the traditional three building blocks developed by the behavioral finance literature (search rules, stopping rules and decision rules) and aim at helping investors who are interested in finding long-term solutions to their cognitive biases.

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**Keywords** Heuristics, Principles, System 1-2, Decision-making under uncertainty, Asset management, Decision support systems, Cognitive diversity

**Paper type** Conceptual paper

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### 1. Introduction

Financial investing usually starts with a specific objective, e.g. growing people's wealth by X% per year. Practically speaking, the investment manager is confronted with an objective function and some constraints, which are inherent to each individual client. To achieve that

objective, the managers can use computational methods, like for instance maximizing the Sharpe ratio. However, for many professional investors, the use of “optimization” methods is probably too sophisticated for what they consider relevant for achieving a satisfactory performance. Rather, passive solutions have become the strategy of choice of millions of investors who are satisfied with duplicating benchmark returns instead of trying to beat it. Moreover, numerous studies (Pastor and Stambaugh, 2002) have consistently reported the underperformance of a vast majority of professional investors versus the market portfolio, or as described by Richards (2012): the average investor underperforms the average investment [1]. Contrary to passive systematic investment, discretionary active investing implies subjective human decisions; the relative underperformance of active investors can be then seen as the result of one structural factor, the “behavior gap penalty” (Richards, 2012) [2], defined as the contribution of the human factor to a biased perception of reality caused by cognitive dissonances. Filling this gap and achieving long-lasting improvements in investment decisions involve the search of solutions to a wide array of cognitive limitations. We argue that these investigations should include the study of heuristics.

Heuristics can be viewed as decisions rules that provide good and fast solutions for complex problems; they are conceptually simple, and implementing them rarely requires high levels of mathematical sophistication or programming skills. Good heuristics are fast and frugal as they rely on “a minimum of time, knowledge and computation to make adaptive choices” (Gigerenzer *et al.*, 1999), not necessarily subject to a tradeoff. However, other scholars consider that heuristics can never be more accurate than a “rational choice” (Tversky and Kahneman, 1974).

Nonetheless, if financial markets are complex, adaptive systems driven by a large number of heterogeneous market participants with imperfect information who decide under bounded rationality (Lo, 2017), heuristics may be a better solution than one that adds and weights all relevant (and non-relevant) data (Artinger *et al.*, 2015). These limitations on knowledge and computational capability constrain the ability of decision makers to identify optimal choices; seeking adequate (satisficing) solutions turn out to be a better option (Simon, 1957). Particularly, Neth and Gigerenzer (2015) argue that heuristics may simply be a better way to make decisions in a world characterized by uncertainty and frequent changes in underlying financial market conditions. In short, less can be more.

Meanwhile, heuristics can be more than simple rules. Massironi and Chesini (2016) made use of heuristics-like daily conceptual operations, when the authors analyzed Kenneth Fisher decision-making tools to invest by “knowing what others do not.” Jones (2014) gives several recipes on how people can process data to make better investment decisions. Dalio (2017) offers a comprehensive list of principles to “maximize the probability of being right in investing,” by circumventing individual inherent weaknesses such as ego, emotions and blind spots.

In this paper, we build upon Dalio (2017) and discuss some heuristics-based principles for improving decision-making in the long run, with specific suggestions on when and how investors might apply them to their own decisions. This article is structured as follows. First, we take an historical perspective on the evolution of the concept of man as a decision maker, from *homo oeconomicus* to *homo heuristicus*. We continue with a detailed classification of the appropriate methodologies to use in different ecological environments. Finally, we offer a list of heuristics to be implemented as behavioral principles intended to create more long-lasting changes than the original rules offered by the adaptive toolbox literature.

## **2. From homo sapiens to homo oeconomicus to homo heuristicus**

The basic concept of the capital market theory (CMT) has been developed in the 1950s and 1960s by the pioneering work of Henry Markowitz (1952), James Tobin (1958), William

Sharpe (1964), Eugene Fama (1965), among others. At first, inspired by the Chicago School of Economics and its conception of man as homo oeconomicus, the first generation of portfolio optimization methods such as modern portfolio theory (Markowitz, 1952) and CAPM (Sharpe, 1964) were only driven by mathematical optimization. The efficient market hypothesis (Fama, 1965), a contextual framework for a rationality-driven world, completed the triumvirate of Modern Portfolio Theory - Capital Asset Pricing Model - Efficient Market Hypothesis (MPT-CAPM-EMH) that laid the theoretical foundations for several generations of asset allocation strategies.

However, the fundamental weakness of these theories (i.e. assuming market participants as homo oeconomicus rational agents) can be traced back to selective interpretations of previous literature by Milton Friedman and other researchers at the Chicago School of Economics. The Scottish philosopher and father of modern economics, Adam Smith described market participants in his two main publications (Smith, 1759, 1776) as civilized persons, willing to sacrifice beyond self-interest and capable of altruism. Keynes (1936) and Hayek (1952), among others, viewed market participants as social beings with limited cognitive capacity, whose market choices arise from social and reflexive interactions. For instance, Hayek (1952) considers the market as a complex social system, whereas the complexity has its origin in the constructivist perception of the brain, which interprets any information subjectively and converts it into heterogeneous expectations. As early as in the 1960s though, Benoit Mandelbrot, the father of fractals and creator of the chaos theory, criticized the MPT by explaining why the simplifying assumptions make them out of relevance to the real world. Philip Anderson (1997), a Nobel prize-winning physicist, summarized this view as: "much of the real world is controlled as much by the 'tails' of distributions as by averages: by the exceptional, not the mean; by the catastrophe, not the steady drip."

Efforts to make sense of the deviating-from-average behavior involved an increasing employment of psychological insights. The academic foundations of a behavioral approach accumulated through a body of work that had its first peak in the 1970s, with the contribution of researchers such as Jensen, 1978; Kahneman and Tversky, 1979; and continued with Shiller (1981), documenting market phenomena, which could not be explainable by the established classical theories, and mostly caused by the cognitive biases of market participants. These studies laid the foundation for subsequent research in detecting and isolating dozens of biases since (Shefrin, 2000). Andrew Lo's combination of cognitive neuroscience and evolution theory gave rise to the adaptive market hypothesis (AMH) (Lo, 2004). Lo (2004) defines market efficiency from an evolutionary perspective, arguing that market participants optimize their satisfaction while oscillating between greed and fear. Following the same route, Lo (2017) defined capital markets as complex, adaptive systems with a high level of endogenous dynamic, driven by a large number of heterogeneous market participants with imperfect information and bounded rationality.

Thus, in a non-trivial system like capital markets, market participants are then constantly exposed to the risk of being overwhelmed. In response, they tend to be ambiguity- and complexity-averse. Ambiguity aversion, highlighted as the Ellsberg paradox (Ellsberg, 1961), suggests that decision makers prefer risky situations with given objective probabilities over ambiguous situations where the probabilities are not known, as it is typical in financial markets (Epstein and Schneider, 2010). Complexity aversion describes the preference of decision makers for less complex options (Conlisk, 1989). Ambiguity and complexity aversion lead to other cognitive biases such as anchoring, herding and representativeness, which are thoroughly studied in the literature. These biases

often lead to bad decision-making in asset allocation that may in turn lead to mispricing in financial markets (Shiller, 1998).

These phenomena can be explained through the lens of the division between “System 1” and “System 2” mental processes (Kahneman, 2011). If the situation is complex, System 2, namely, slow, effortful, infrequent, logical, calculating mind, is given limited chance to provide an answer. As a result, System 1, namely, fast, automatic, frequent, emotional, stereotypic, has a bigger impact on decisions (Kahneman, 2011). Using System 2 is physically demanding; hence, by default, the brain operates in System 1, or in other words, by relying on cognitive shortcuts (Roth, 2003). While System 1 works well for energy-efficient routine decisions that provide fast and unambiguous responses, it presents a second best when most rational decisions in a complex environment are needed (Jones, 2014).

However, the understanding of heuristics being a predominantly negative phenomenon for rational decisions is slowly changing (Forbes *et al.*, 2015; Mousavi and Gigerenzer, 2014). Gerd Gigerenzer and his team have long argued that most of us regularly use heuristics, because they often produce better decisions (Gigerenzer and Brighton, 2009; Gigerenzer, 2011). The consideration of the context turns a heuristic from a phenomenon to be avoided to a tool to be used for making more rational decisions, as long as the heuristic is aligned with its ecological rationality (Artinger and Gigerenzer, 2016). The criticism posed by Gigerenzer on Kahneman is that the latter has ignored the relevance of the context, blaming an individual to act sub-optimally, when being trapped (Mousavi and Gigerenzer, 2017) in heuristics-based cognitive biases, while ignoring the relevance of heuristics in the context of uncertainty.

### 3. Homo heuristicus: a better answer to the uncertain world

In his seminal article, Knight (1921) broadly distinguished between two conceptually distinct scenarios: situations of risk vs situations of uncertainty. Several decades later, Donald Rumsfeld helped in popularizing the differentiation in the now famous:

[T]here are known knowns; they are things we know, we know (**category 1**). We also know there are known unknowns (**category 2**); that is to say we know there are some things we do not know. But there are also unknown unknowns (**category 3**) – there are things we do not know we don't know.

Taleb (2012) names these scenarios differently, but comes to the same conclusion when categorizing risk and uncertainty [3]:

White swans (= known knowns/Category 1);  
Grey swans (= known unknowns/Category 2); and  
Black swans (= unknown unknowns/Category 3).

Neth and Gigerenzer (2015) points to three contexts, defined by the availability of data and information, where heuristics based decision-making might be appealing. We go one step beyond these authors and now elaborate on four main environments of risk and uncertainty that a professional investor might face during her decision process and provide details on which methods are the most appropriate for each case:

- Options are known and available (white swan or reducible risk)

In this context risk, it is well defined, i.e. there is a known probability distribution of outcomes, even though the actual outcome is not yet known. We argue that when those conditions are met, i.e. when there is an objective basis to derive outcome probabilities, probabilistic models should be applied. As a matter of fact, a long list of articles showed that statistical algorithms produced better decisions than clinical experts and their cognitive biases when both have access to the same data (Grove *et al.*, 2000).

- Choices where many options are presented as available, requiring substantial search (light grey swan or partially reducible risk).

Having access to more data may result in more noise than good signals (Dawes, 1971), that is to say the probability distribution of outcomes is theoretically known, but the game is perverted with the uncertainty of finding the true probabilities. Therefore, when optimal solutions are difficult or impossible to solve because it is computationally intractable, one must then simplify them. A stream of literature that deals with such issues puts forth the use of so-called optimization heuristics. The idea is to drop constraints/observations in the optimization setup until the problem can be solved with standard numerical methods (Gilli and Schumann, 2012). Another way to simplify the problem at hand is to use heuristics in the selection of the hypotheses tested based on their economic plausibility, use statistics to verify them and algorithms to apply them (Jones, 2014).

- Choices where little information to the choice being made is available (dark grey swan or irreducible risk)

When information is scarce, there is no need to sweat much over getting the optimal weights of a complex algorithm. Dawes and Corrigan (1974) argue that it is far more important to identify the correct factors and causal directions than getting the weights right. In this case, a hypothetic-deductive model based on logic might be used, where experience and intuition are used to conjecture an explanation and deduce a prediction from that explanation. Scenario analysis, where the “model” is tested through worse-case situations via computer simulations should help confirm or adjust the initial logic. As argued by Hempel (1965), conjecture can also incorporate probabilities that may be updated as more information comes in.

- Highly uncertain choices, where risk based calculations seem forced (black swan or uncertainty)

When faced with significant uncertainty, i.e. in an “unknown unknown” situation, the robustness of the approach is more relevant to its future performance than its optimality. As Gigerenzer and Selten (2001) notes, in this case, this is not about computational tractability: a more uncertain environment requires a simpler approach, not a more complex one. In Gigerenzer’s words: “The optimization models performed better than the simple heuristic in data fitting but worse in predicting the future.” For Taleb (2012), outsourcing responsibilities to a mathematical formula or an econometric methodology is not only ethically wrong, but also epistemologically flawed. It suffers from the “garbage in, garbage out” syndrome. Taleb (2012) points on the danger of outsourcing this responsibility in case of a rare event:

Black Swans hijack our brains, making us feel we »sort of« or »almost« predicted them, because they are retrospectively explainable. [...] An annoying aspect of the Black Swan problem – in fact the central, and largely missed, point, is that the odds of rare events are simply not computable.

In the case of black swan events, presence of non-linearity and structural breaks are too strong challenges for a pure statistical view of the world. Logic and heuristics must complement or even substitute models when large, unbiased or representative data is not available.

Figure 1 summarizes the states of the world with the appropriate methods discussed above [4].

#### **4. Heuristics as long-term principles**

The previous section considers that the issue for active investors is not about finding an ontological truth, like an absolute algorithm, but in being able to interpret the cognitive map better than others. This implies the need of an investment process that responds to changes

in the configuration of the cognitive problem. Knowing which methodologies to use in which context is likely to lead to a competitive advantage. If active investing is about making the right decisions on a continuous basis, investors are then in need of tools to proactively manage their cognitive problem.

Having said that, numerous studies show that simply being aware of biases is not enough to overcome them. People with higher cognitive capacities do not necessarily behave with fewer biases (Oechssler, 2009). In fact, people that are more intelligent often excel at fitting discordant data into their internal narratives, rationalizing irrational beliefs and justifying poor decisions (Gottschall, 2012). The less personal the bias is, the lower the resistance in changing irrational behaviors. On the opposite, the highest resistance level lies when the process relates directly to the individual decider. For example, changes related to fees, tax structures or the implementation regulatory changes meets relatively little resistance from the investors. Thus, one should distinguish between individual changes that induce no paradigm shift of academic and professional backgrounds and changes that move the individual beyond its current state of knowledge. For example, a Chief Investment Officer (CIO) trained in the modern portfolio theory that apply the mean variance optimization in her job will show little resistance to change from Sharpe ratio maximizing toward minimum variance optimization. However, if the same person is asked to switch from one paradigm, e.g. mean variance allocation, to another, the behavioral prospect theory (Shefrin and Statman, 2000), a significantly increased level of resistance can be expected, as it goes beyond her background. In sum, human beings unconsciously create and maintain an internal narrative of events and then interpret, endorse or ignore information to protect those narratives. Following the same logic, the emotional finance hypothesis (Tuckett, and Nikolic, 2017) states that individuals gain conviction by creating narratives constructed socially with interactions. Through these interactions, narratives are created and disseminated, implying for instance the well-known phenomenon of “herd behavior.”

Against this background, the literature on debiasing cognitive biases has shown that long-lasting improvements involve changes that rarely succeed through a single event but instead through a succession of steps that must be habitualized (Croskerry *et al.*, 2013a, 2013b). Larrick (2004) classified debiasing techniques into four main approaches: motivational, cognitive, structural and technological. Heifetz *et al.* (2009) distinguished between “technical” and “adaptive” biases. Overall, a common feature of these solutions involves a conscious shift from System 1 reasoning to System 2 analytical processing so that judgments and narratives can be submitted to verification on a regular basis. This regime shift appears to be the critical feature of cognitive debiasing.

BLACK SWAN	DARK GREY SWAN	LIGHT GREY SWAN	WHITE SWAN
UNCERTAINTY	IRREDUCIBLE RISK	PARTIALLY REDUCIBLE RISK	REDUCIBLE RISK
UNKNOWN UNKNOWN	KNOWN UNKNOWN	KNOWN UNKNOWN	KNOWN KNOWN
HEURISTICS LOGIC	HEURISTICS LOGIC STATISTICS	STATISTICS OPTIMIZED HEURISTICS	STATISTICS PROBABILISTIC MODELS

**Figure 1.**  
Risk vs uncertainty and best methodologies

We now describe our heuristics principles for long-term debiasing, which go beyond the three blocks (search rules, stopping rules and decision rules) proposed by Gigerenzer and Selten (2001). We argue these enduring debiasing techniques are necessary conditions to navigate more efficiently through the different environments described above and avoid systematic errors of judgment. We break down these heuristics in the following three categories: “Harnessing Emotions,” “Learning Consciously” and “Triggering Rational Decisions.” Finally, we discuss additional principles to foster the positive effects of the previous heuristics, namely, the automated tools, that humans can use in conjunction (decision support systems) and the ecological culture that needs to be put in place (choice architecture).

#### *4.1 Harnessing emotions*

One should recognize that the biggest threat to good decision-making is harmful emotions and weaknesses. This is what Kenneth Fisher would state as “What is my brain doing to mislead and misguide me now” (Massironi and Chesini, 2016). One principle that Ray Dalio uses as his first heuristic comes from his daily trading work. Before taking any trading positions, Dalio would write down precisely the criteria that guided his decision and would do a thorough review of the outcome ex-post, highlighting the successes and the flaws of that decision. The process became part of the optimization of daily work routines where experiences and reflections are condensed in a structured manner. As a matter of fact, proper documentation has long been studied in the literature and has shown its power to reduce reliance on the availability bias (Plous, 1993). The ability to refer back to documentation to understand the empirical basis prevents the blind acceptance of anecdotal evidence (Poole and Lamb, 1998).

Moreover, the “documentation” heuristic also reduces attribution bias. Managers and investors have a tendency to take greater responsibility for successes rather than failures. Meanwhile, they are easily impressed by big results like large returns, nice success stories, unchecked strong patterns, to name a few. These halo effects are likely to make an erroneous long-lasting impression on one’s mind and control the executive function System 2. Thus, documenting properly investment decisions is also helpful to untangle skills from luck.

Likewise, in the field of financial advising, Kahneman and Riepe (1998) offers a “checklist “for financial advisors to measure their effectiveness at dealing with emotional and cognitive biases. The frequent assessment of risk-taking and regret aversion, with an emphasis on the difference between long and short views as well as small and big bets, is a good step toward mitigating the harmful effects of emotional biases.

#### *4.2 Learning consciously*

One must recognize that learning is an iterative process. Humans learn by associating new and unknown information with old and known information, and by building new information on top of old information. However, a series of decision-making experiments shows that individuals disproportionately stick with the status quo (Samuelson and Zeckhauser, 1988). Worse, money managers seek information that supports or confirms their beliefs while discounting information that contradicts them, the so-called confirmation bias. One way to mitigate the belief perseverance bias, or challenge the status quo, involves putting more weight on contradictory information than one typically does. Devil’s advocate should be institutionalized within a management team so that each course of action implies that an open, free and frank discussion could ensue. Notably, brainstorming in search of potential alternatives has been shown to be effective at reducing group thinking and confirmation bias (Heuer, 1999). Specifically, “quantity should be emphasized over quality,



every option should be documented, negativity should be avoided during the brainstorming process, and the generated options should not be “owned” by any one person” (Adams *et al.*, 2009). The use of contradictory thinking may be the most effective strategy studied in the literature, reducing confirmation, hindsight and overconfidence biases (Pohl, 2017). Finally, one should recall the words of Popper (1959): “scientists are men with bold ideas, but highly critical of their own ideas; they try to find whether their ideas are right by trying first to find whether they are not perhaps wrong.” The falsification theory, or how to think critically, is a necessary first step to ensure that learning is done consciously and efficiently.

#### *4.3 Triggering rational decisions*

As discussed previously, the level of confidence about a decision is often related with the coherence of internal narratives, not the quality of the evidence used, leading human beings to be overconfident and overestimate the accuracy of their beliefs: the so-called overconfident bias. As described by Taleb (2012), investors have a tendency to get married to positions, changing their story to fit their narrative. Likewise, human beings tend to disregard objective probabilities, and even more so under uncertainty, violating the normative rules for decision-making. Dreadful possibilities stimulate strong emotional responses, such as fear and anxiety, obscuring rational judgments. Probability neglect implies that small risks are either neglected entirely or hugely overrated (Sunstein, 2003). The best response to this excessive fear or greed is to put the issue of probability in front of people’s eyes, i.e. directly and explicitly. Some mechanisms, referred to as cognitive forcing functions, exist to anticipate the pitfall of not changing one’s course of action and/or to engage people in finding more objective information.

Cognitive forcing functions are designed interventions to prevent human beings from taking an action without consciously considering information, thus triggering them to use more analytical thinking. For instance, such forcing functions in finance are stopping rules (the equivalent of time-outs in medicine). Kaminski and Lo (2014) shows the value-added of stop loss rules and its impact on portfolio’s cumulative losses. Those predefined triggers force conscious attention upon something, triggering System 2, and thus deliberately prompt reconsideration of the initial investing assumptions, therefore reducing anchoring bias. In sum, forcing functions ensure that the cost of being wrong is limited by optimizing the cost–benefit tradeoff.

#### *4.4 Combining human and artificial intelligence*

Nowadays, the machines’ capabilities to search, store, filter, summarize and analyze data are no longer commensurate to what humans can do. Meanwhile, according to several studies (Cowan, 2001), human beings find it difficult to consider more than four variables simultaneously when making decisions. Thus, human beings tend to substitute complex decision-making processes with easier ones, preferring either to blindly trust the machines solution, or to rely on their gut feelings (Gigerenzer and Brighton, 2009). In both cases, solutions are sub-optimal achieving either accuracy or interpretability, but never a satisfactory level for both dimensions. However, decision-making tools, which maximize robustness over complex overfitting methods, do exist. Decision support systems (DSS) development is defined “as the area of the information systems discipline that is devoted to supporting and improving human decision-making” (Arnott, 2002). Bhandari, Hassanein and Deaves (2008) showed that DSS was useful in reducing representative and ambiguity aversion biases. One necessary condition though is that the DSS system needs to suggest several options, ensuring that decision makers are aware of them, rather than “pulling” the decision maker in a particular direction (Kessel, 2003). In sum, DSS helps to overcome

cognitive biases mainly because it forces consideration of alternative and/or contradictory views. Therefore, DDS is not a one-size-fits-all solution: other conditions must be met to ensure efficiency. Arnott (2002) argues that a debiasing approach can be successful if DSS targets a specific bias. Moreover, DSS, as a systematic tool, remains dependent on the validity of evidence. This is the “garbage in-garbage out” principle: the results are only as good as the data upon which the conclusions are based. Davis (1989) argues that analytic decision-making is most appropriate when the environment changes slowly and goals are fully defined. Within more uncertain or time-pressured environments, naturalistic decision-making like fast and frugal trees seems to be more effective (Keller *et al.*, 2010).

In conclusion, in the quest for robustness, one might then want to build the decision-making architecture around one philosophy: start with “white-box” human-friendly models, and then if not satisfied, combine them with more sophisticated machine learning-based models, thus maximizing the interpretability/accuracy ratio.

#### *4.5 A culture made in diversity*

The success of long-lasting heuristics may also be challenged by the ecological rationality, i.e. they are likely to work only if there is a match between the environment, the strategy and the skills (Artinger and Gigerenzer, 2016). Hence, if established heuristics that support more rational decision-making ought to last, they have to be synchronized with the choice architecture of the investment process. The choice architecture is a combination of cultural and procedural patterns (Thaler and Sunstein, 2009). The awareness of investors regarding the relevance of the choice architecture arrangement is slowly rising, supported by further research in that field (Lo, 2014). Dalio (2017) describes team culture that encourages the willingness to constructively challenge oneself in search for blind spots, to reach better explanation in a debate. The goal is to create “group level accountability mechanisms” (Johnson, 2001) to ensure that individuals feel responsible for group decisions. As discussed previously, by challenging the status quo, the teams will be incentivized to go beyond traditional norms, with the ability to generate innovative ideas and discover what individual learners could not achieved single-handedly.

Investment professionals increasingly recognize the potential benefits of allowing diverse ways of thinking into their teams. Larry Fink, CEO of BlackRock pointed that having groupthink was to make sure that firms fail, and that diversity of mind lies at the foundation of good management, leadership and stewardship (Fink, 2018). As a matter of fact, recent research points to the significant positive contributions of cognitively diverse teams regarding a wide range of tasks, such as problem-solving (Reynolds and Lewis, 2017), creativity and innovation (Aggarwal and Williams Woolley, 2019). Therefore, if both team/individual- and process/culture-level are synchronized, active investors are more likely to develop and maintain a competitive advantage over their peers.

Table 1 summarizes the main adaptive tools discussed above, to minimize cognitive biases.

## **5. Conclusions**

In finance, market participants are exposed to a certain configuration of capital markets: they are complex, adaptive systems with a high level of endogenous dynamic, driven by a large number of heterogeneous market participants with imperfect information and bounded rationality (Lo, 2017). Against this background, this article proposes a theoretical reflection on the literature regarding the improvement of decision processes and offers practical advices to investors, for the average investor to outperform the average investment, or as Dalio put it: “raising the probability of being right is valuable no matter what your probability of being right already is.”

Categories	Biases	Heuristics/principles
Harnessing emotions	<ul style="list-style-type: none"> <li>• Availability bias</li> <li>• Attribution bias</li> <li>• Halo effect</li> <li>• Recency bias</li> <li>• Regret aversion</li> </ul>	<ul style="list-style-type: none"> <li>• Proper documentation (Plous, 1993)</li> <li>• Feedback loop analysis (Poole and Lamb, 1998)</li> <li>• Checklists (Kahneman and Riepe, 1998)</li> <li>• Playbooks</li> </ul>
Learning consciously	<ul style="list-style-type: none"> <li>• Confirmation bias</li> <li>• Belief perseverance</li> <li>• Hindsight bias</li> <li>• Congruence bias</li> </ul>	<ul style="list-style-type: none"> <li>• Role-playing (Heuer, 1999)</li> <li>• Devil's advocate (contrarian thinking) (Pohl, 2017)</li> <li>• Falsification (Popper, 1959)</li> </ul>
Triggering rational decisions	<ul style="list-style-type: none"> <li>• Overconfidence bias</li> <li>• Probability neglect</li> <li>• Anchoring bias</li> </ul>	<ul style="list-style-type: none"> <li>• Cognitive forcing functions</li> <li>• Stopping rules (Kaminski and Lo, 2014)</li> <li>• Cost-benefit analysis</li> </ul>
Combining human and artificial intelligence	<ul style="list-style-type: none"> <li>• Automation bias</li> <li>• Automation complacency</li> </ul>	<ul style="list-style-type: none"> <li>• Targeted DSS (Arnott, 2002)</li> <li>• Fast and frugal trees (Keller <i>et al.</i>, 2010)</li> <li>• Optimizing interpretability/accuracy ratio</li> </ul>
A Culture made in diversity	<ul style="list-style-type: none"> <li>• Status quo bias</li> <li>• Group thinking</li> </ul>	<ul style="list-style-type: none"> <li>• Challenging the status quo (Dalio, 2017)</li> <li>• Group-level accountability mechanisms (Johnson, 2001)</li> <li>• Building cognitively diverse teams (Reynolds and Lewis, 2017)</li> </ul>

**Table 1.**  
Summary of cognitive biases and best principles/heuristics

Managing assets may be more an art than a science; however, the mechanism behind the growth of the finance industry is the result of a process closely resembling what Darwin called “natural selection”: the remaining firms have shown their fitness by surviving in their struggle for existence, a competitive struggle that eliminates those who are unfit. Fair enough that financial firms must have skillful teams to survive; but to develop and maintain their competitive edge, we argue in this article that a consistent set of heuristics principles together with a robust choice architecture is a necessary condition.

We are aware that behavioral solutions to our cognitive in/abilities have long been studied in the literature (see Zahera and Bansal, 2018). However, there exists only a few published managerial articles on long-term debiasing. The existing literature on cognitive biases has shown that improvements in decision skills involve changes that rarely succeed through a single event (see Aczel *et al.*, 2015). It would be useful if future research were not limited to the detection of immediate debiasing effects, but were more thoroughly exploring the endurance of the corrections. The task is not easy, but not impossible; we hope that this article has laid out the necessary principles to achieve that objective, and that their long-term validity will be tested empirically in more studies.

## Notes

1. Overconfidence in their ability to “pick” stocks that perform better than the average. Richards (2012) argues that investors could just own an average fund, and if they behave correctly, will outperform 99% of their peers.
2. Active investing using a systematic approach is less prone to behavioral biases.
3. The psychoanalytical philosopher Slavoj Žižek extrapolated a fourth category out of the first three: “unknown knowns” (Žižek, 2006), referring to those refuse to acknowledge epistemological realities and pretend not to know them like US mortgage lending practices during the last cycle.

4. Lo and Mueller (2010) list different regimes of uncertainties, which go from black swan (fully reducible uncertainty) to radical uncertainty (irreducible uncertainty).

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