MAY 2017

Risk

The business logic in debiasing

Debiasing business decision making has drawn board-level attention, as companies doing it are achieving marked performance improvements.

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A previous McKinsey article on the future of risk management in banking highlighted six structural trends that are expected to transform the risk function's role in the coming decade. Of these, the trends relating to regulation, costs, customer expectations, analytics, and digitization are familiar, to one degree or another, to most readers. One trend that is less familiar is *debiasing*, that is, using insights from the fields of psychology and behavioral economics to help organizations take bias as much as possible out of risk decisions.[1]

Biases are predispositions of a psychological, sociological, or even physiological nature that can influence our decision making. They often operate subconsciously and by definition are outside the logical process on which decisions are purportedly based. While we may readily acknowledge their existence, we often believe that we ourselves are not prone to bias. (This is actually a form of bias in itself, called overconfidence.)

The business world is scarcely immune, as executives have long suspected. In a survey of nearly 800 board members and chairpersons, McKinsey found that respondents ranked "reducing decision biases" as their number-one aspiration for improving performance.[2] As a consequence, we have seen increasing numbers of companies provide training in unconscious biases and how they affect management actions, such as gender bias in personnel decisions.

Bias is costly. Take the effect of one kind of bias, stability bias, in one dimension of business, capital allocation, as an example. McKinsey research has shown that companies that allocate capital dynamically—rebalancing regularly according to performance—return between 1.5 and 3.9 percent more to shareholders than companies with more static and routinized budgeting. The study suggests that companies with dynamic capital allocation could grow twice as fast as those without it. Yet in a classic example of stability bias, we found a 90 percent correlation in budget allocation year after year, for a 20-year period.[3] The latest McKinsey research only underscores the relevance of these findings. A 2016 survey of nearly 1,300 executives worldwide revealed that higher-performing companies more tightly link reallocation to performance and value creation, using rigorous bias-reducing principles.[4]

Sometimes companies question least the decisions affecting their core business, such as underwriting in banks and insurance companies. These decisions and their governing processes can be so deeply embedded in the institutional culture that they might not appear to be open to question—or even recognized as decisions. The failure to take debiasing actions in these areas means that most of the potential bottom-line impact from debiasing remains unaddressed. Yet companies can shape practical, targeted debiasing interventions and achieve tangible business benefits. These can be substantial. When debiasing high-frequency decisions such as those in credit or insurance underwriting, we have seen losses reduced by more than 25 percent.

Diverse biases and business priorities

Biases affect how we process information, make decisions, and construct strategies (see sidebar "An overview of business-relevant biases"). They do not, however, always work in the same direction nor are they equally distorting in all situations. Companies have so far tapped only a small part of the potential of debiasing in business contexts. One reason is that no ready formulas exist that address the many different biases and business contexts. But corporate efforts to diagnose biases and take debiasing actions can be very effective, especially when prioritized by business need. Prioritization involves zooming in on the handful of decisions with the greatest business impact and then, decision by decision, identifying the actions that will reduce or eliminate the biases that may be present.

No summary account can reveal the full complexity of biases, which originate in diverse human cultures, complex social interactions, and the depths of the human psyche. Biases can be predominantly psychological or social in origin. The social dimension of biases includes all cultural and organizational behavior. McKinsey research has highlighted "continuous improvement" as an important aspect of corporate culture at successful companies. Yet this advantage, which fosters internal competitiveness and rewards entrepreneurial creativity, can trigger action biases that can lead to unneeded or even harmful actions. Product launches, for example, are often the upshot of action biases. Yet three out of four launches fail to meet revenue expectations and many result in significant losses to the company.[5]

Group psychological behavior produces some of the most powerful biases in business settings. Group dynamics can cause managers to sacrifice reasonable dissent to enhance their associations, maintain the favorable perceptions of others, and keep competitors at bay. They may recognize but choose to ignore flaws in the analyses and proposals of their allies, so these kinds of biases are not cognitive in nature—they do not relate, in other words, to the acquisition and assimilation of knowledge. Rather, they are generated by the group setting itself, in which managers almost consciously relinquish good logic as they compare and evaluate options for action.

Approaching debiasing systematically

Many good executives are aware of individual and organizational biases—yet awareness alone cannot overcome some biases, which can be embedded deep in our thought processes, almost like a childhood

An overview of business-relevant biases

Business-relevant biases have been explored in the field of behavioral economics—the study of psychological and social influence on business decisions. It draws on the relationship defined in behavioral psychology between *heuristics* and *cognitive biases*. The former term describes obvious, practical methods of solving problems that yield expected results often enough for us to rely on them almost automatically. Heuristic methods are based on experience and tradition, and can lead to unwarranted biases, which are unsuitable or even damaging in complex, dynamic environments.

Dozens of biases have been identified in behavioral economics. For our purposes, it will be useful to discuss five groups of biases encountered in a business context.[1]

- ***Action-oriented biases*** prompt us to take action with less thought than is logically necessary (and prudent). These biases include *excessive optimism* about outcomes and the tendency to underestimate the likelihood of negative results, *overconfidence* in our own or the group's ability to affect the future, and *competitor neglect*—the tendency to disregard or underestimate the response of our competitors.

- ***Interest biases*** arise where incentives within an organization or project come in conflict—such as *misaligned individual incentives*, unwarranted *emotional attachments* to elements of the business (such as legacy products), or *differing perceptions of corporate goals*, such as misaligned weights assigned to different objectives.

- ***Pattern-recognition biases*** cause us to see nonexistent patterns in information. This set of biases includes *confirmation bias*, in which evidence in support of a favored belief is overvalued while evidence to the contrary is discounted; *management by example* (more accurately, subjective experience), is the tendency to overly rely on one's own recent or memorable experiences when making decisions; and *false analogies*, which are a form of faulty thinking based on incorrect perceptions and the mistaken treatment of dissimilar things as similar.

- ***Stability biases*** are the tendency toward inertia in an uncertain environment. These biases include *anchoring without sufficient adjustment,* which is the tying of actions to an initial value and failure to adjust to take new information into account; *loss aversion*, the familiar fear that makes us more risk averse than logic would dictate; the *sunk-cost fallacy*, which allows the unrecoverable costs of the past to determine future courses of action; and *status-quo bias*, which is the preference for keeping things as they are in the absence of immediate pressure to change.

- ***Social biases*** arise from our preferences for harmony over conflict or even constructive challenging and questioning. These biases include "groupthink," in which the desire for consensus disables a realistic appraisal of alternative courses of action, as well as "sunflower management"—the tendency for group members to align with the views of their leaders.

[1] For further discussion, see Dan Lovallo and Olivier Sibony, "A language to discuss biases," *McKinsey Quarterly*, McKinsey.com.

memory. Many would welcome a more systematic approach to debiasing business decisions, given prevailing levels of business and organizational complexity.

Executives concerned with improving the quality of decision making in key areas often turn to training. Training is helpful to create demand for debiasing, but by itself cannot solve the problem. The biases are often too strong to be overcome through training exercises alone. The solution lies in designing an alternate decision process and selecting an effective debiasing strategy. The most effective strategy may not be the most obvious candidate, however, or the easiest to implement.

The choice of debiasing approaches will differ based on the type and frequency of the decisions that are being debiased. Analytical tools can be very efficient in debiasing high-frequency decisions such as those involved in credit underwriting. Analytics play an important but different role in low-frequency decision processes, providing, for example, an objective fact base for committees making quarterly decisions on recalibrating credit-rating models. Finally, for some important but infrequent decisions—such as those relating to infrastructure spending, technology transformations, or M&A—there may be a lack of sufficient data for analytical tools to be applied. Here, debiasing can be conducted by imposing specific, structured elements in group discussions and group-based decisions (such as those in board committees) to detect and counter emerging biases.

A systematic approach also requires a cultural change within the organization—one that creates demand for debiasing measures and adherence to them. Part of the cultural change involves bringing informal decision-making processes into the open by appropriately formalizing them, so that they may be subject to debiasing through explicit procedural changes.

Debiasing high-frequency decisions

In many business sectors, high-frequency decisions are often governed by formal processes. One of the most powerful techniques for debiasing process-based decision-making are statistical decision systems. These are advanced models designed to discover patterns and probabilities in large data sets. For many process-based activities, decisions can be largely automated using statistical algorithms such as regression analysis, decision trees, and more advanced machine-learning algorithms. These can generate valuable insights—discovering attractive customer subsegments within otherwise less promising segments and geographies, for example.

Models are often designed to manage high-frequency process-based decisions. The decisions around calibrating the models, however, are low-frequency decisions and are not process based. Debiasing low-frequency decisions is discussed below, but it is important to remember that the development of algorithmic models entails many potentially idiosyncratic, bias-prone assumptions and decisions. Even well-constructed algorithms, when deployed on data sets full of biased observations and outcomes, can propagate and systematize biases. Designers and managers must therefore actively prevent their algorithmic models from becoming black boxes with baked-in biases. The models should be validated by an independent team and challenged in dialogue and discussions similar to those companies have when considering new policies. Their operation must be periodically observed and the output reviewed for bias: without such intervention, machine learning could perpetuate the biases we are trying to avoid or create new and unexpected distortions.[6]

Fortunately, analytics can also help diagnose the presence of biases. The presence of such biases as mental fatigue (sometimes called “ego depletion”) or anchoring can be tested statistically and the effectiveness of counterbalancing interventions validated. Simulation tools even allow this kind of debiasing to be conducted without experimenting with the "live object"—that is, without interfering with a company's actual risk decisions. In commercial lending, for example, such tools allow risk officers and relationship managers to participate in simulations of specific risk decisions and base real improvements on outcomes.

Not all high-frequency decisions can or should be automated by algorithms, however. To continue with the commercial-lending example, for larger commercial loans, a carefully debiased manual review of applications will add more value than a statistical algorithm. Algorithms cannot create an informed view on investment plans based on customer interviews or an analysis of regulatory changes pending in the legislature. The sidebar "The Qualitative Criteria Assessment" describes one approach to debiasing judgment in high-frequency decisions.

Debiasing low-frequency decisions

Low-frequency decisions, such as those governing large investments, M&A, or organizational and business transformations, are prone to many of the same biases as process-based high-frequency decisions. The debiasing of these high-stakes decisions proceeds along different lines, however.

The Qualitative Criteria Assessment

The Qualitative Criteria Assessment aims at debiasing subjective assessments, such as judgment-based credit underwriting, commercial insurance underwriting, and case prioritization by tax investigators. It replaces broad, fuzzy concepts with carefully chosen sets of specific, focused proxies from which more objective assessments can be developed. The approach uses statistical validation techniques optimized for the small sample sizes typically associated with manual data collection during the modeling stage. These techniques, which can derive generally valid results from limited data sets, were developed in scholarly disciplines such as the social sciences and have long been used in model validation.

Explicit psychological guardrails are deployed to debias qualitative assessment processes. One effective guardrail is to construct a detailed timeline for pertinent data points to help assessors reconstruct the past more accurately. In assessing a builder, for example, an insurance company might want the full list of the general contractors the company has used, along with their tenures of service. By requesting the information be provided in the form of a timeline, the insurer eliminates availability or selection bias and can be more confident of the reliability of the builder's response. Likewise, a potentially significant marker for credit risk for a small or medium-size company is the number of chief financial officers (CFOs) it has had in the past several years. If asked informally, assessors might fail to recall one or two past CFOs, thus underreporting the number of CFO changes; if a timeline is provided, gaps in tenure become immediately apparent. The Qualitative Criteria Assessment is thus a means to support deeper insights and better risk assessment, through the more complete recovery of past performance.

The techniques employed must first of all take place in an environment where decision makers readily recognize their own as well as others' biases. Often enough, senior executives are prone to overconfidence when it comes to their own biases—they can see the bias in the actions of others but not in their own. Executives who learn to accept the signals of their own biases and correct for them make better and more effective decisions.

On an organization-wide level, the very data that underlie a decision process can be flawed. Without conscious, systematic probing, data selection is prone to confirmation bias—the selection of information that would tend to confirm our own expectations and business goals. Data that contradict our intentions is prone to rejection as faulty. To understand the importance of selecting bias-free data—and indeed, of debiasing generally—we need only recall the failure of value-at-risk models in the financial crisis. Damage assessments often revealed that the assumptions and inputs for these models served to disguise rather than reveal portfolio risk. The rare model that—presciently—assigned hefty capital requirements to mortgage exposures was rejected as faulty.

Pragmatic solutions

The good news is that pragmatic solutions exist. Carefully chosen interventions can achieve a real difference in decision making. The use of a neutral fact base, for example, can anchor decisions in objective reference points. Mental processes can be reset to a bias-free state, using such techniques as destressing exercises and initial anonymous voting to reveal concerns without the impediment of groupthink effects. Another powerful approach is the premortem analysis: for important business decisions, alternative scenarios are thereby fully explored to reveal potential implications. (French law schools were pioneers of this technique, having for decades required students to write full briefs of equal length on both sides of a case.)

Another debiasing technique is the formal challenger role, by which a devil's advocate or independent observer confronts biasing behavior actively and explicitly. In some institutions, a formal devil's advocate role is played by a team designated to challenge the main findings competitively. The effectiveness of this approach is however dependent on the alertness and competence of the chosen advocates. Confidential voting—often with the aid of commercially available tools—is a way to empower every participant to challenge the group free of any social pressure.

Textual analysis can be a more systematic approach. It involves the review and often scoring of all evaluations pertinent to the topic and has been used

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in a variety of settings, including to evaluate gender bias. Many companies have introduced this (along with other debiasing procedures) into personnel decision making.

Benchmarks are another means to promote neutral evaluations. For financial analysis of proposals, for example, a requirement that financial ratios be presented with peer comparisons can foster unbiased perspectives. As discussed in the sidebar on the Qualitative Criteria Assessment, suitably complete historical data can be an effective debiasing requirement for overcoming availability bias—the tendency to base judgments on only the most memorable or available details.

In decision-making processes, several conflicting biases may arise. It will be important, therefore, to take the time to diagnose bias profiles and prioritize debiasing measures for implementation. A large utility company seeking to debias a megainvestment decision recently encountered competing biases that acted on each other, amplifying the distorting effects of each bias. Investment proposals often reflected action-oriented biases, while social and stability biases limited the degree to which the proposals were challenged in meetings. The company addressed the action bias with a vigorous premortem analysis as a mandatory element of investment proposals, while establishing a formal devil's advocate role in committee discussions to counteract groupthink.[7]

Debiasing in action

A typical debiasing process is a learning exercise for an organization. It can take many shapes and forms but has the following actions in common:

- *Diagnose.* The actual biases affecting business decisions are discovered by analyzing recent and past individual or group decisions, especially those that have been criticized in hindsight as biased. A decision-conduct survey is taken to discover how decisions have been made: concerned individuals are interviewed by experts in behavioral science, who match the evidence with markers of specific biases.

- *Design.* In the design phase, the key biases are matched with the best debiasing strategies in light of the organizational and process context. Many interventions are available for every kind of bias and bias combination. The selection of specific measures and how they should be tailored to fit the particular decision-making context can be worked out in an off-site event with executives, committee members, and experts. The special setting also helps build awareness for cultural change. In solution design, simplicity will be an important factor for success. Better decisions emerge from a small number of carefully targeted interventions against the most critical biases, rather than a grab-bag of "nice to have" best practices.

- *Implement.* This phase involves pilots and other mechanisms that are designed to maintain debiasing momentum. Change champions can be established, possibly on a permanent basis, to lead this work across the organization and to develop the approach to measuring and monitoring outcomes and impact.

In such areas as gender bias and hiring, many major organizations have already seen impact from debiasing. In certain settings, companies have begun to address the distorting effects of biases in business. In the financial sector, for example, regulatory concerns have inspired systematic debiasing, resulting in the three-lines-of-defense principle, model-validation exercises, and new accounting standards.

Above all, debiasing has a compelling business logic. For some high-frequency decisions, its bottom-line impact is substantial and easily measured. In financial services, for example, 25 to 35 percent credit-loss reductions have been achieved. The effects of debiasing on low-frequency decisions are not as easily measured, but executives in every sector should be aware of the value in more deeply probing such actions as M&A decisions and large investments. Ultimately, the best measure of debiasing's effectiveness may be the greater confidence leadership develops in rejecting, modifying, or endorsing the company's most important strategic choices. In a world of increasing volatility, where nimble decision making under uncertainty will increasingly become the main determinant of success, the value of such confidence is hard to overestimate. ■

1 Philipp Härle, Andras Havas, and Hamid Samandari, "The future of bank risk management," July 2016, McKinsey.com.
2 Chinta Bhagat and Conor Kehoe, "High-performing boards: What's on their agenda?," *McKinsey Quarterly*, April 2014, McKinsey.com.
3 The study was conducted by McKinsey's Corporate Strategy Practice and included 1,509 US companies for the period spanning 1990 to 2010. It covered all capital expenditures except M&A costs and revenues.
4 Tim Koller, Dan Lovallo, and Zane Williams, "The finer points of linking resource allocation to value creation," March 2017, McKinsey.com.
5 See, for example, Julie Hall and Joan Schneider, "Why most product launches fail," *Harvard Business Review*, April 2011, hbr.org. A degree of trial and error is of course to be expected in all business decisions—the point is about how informed and bias-free the trial is.
6 For more, see Nanette Byrnes, "Why we should expect algorithms to be biased," *MIT Technology Review*, June 24, 2016, technologyreview.com.
7 For a more detailed discussion of this experience, see "The debiasing advantage: How one company is gaining it," *McKinsey on Risk*, June 2017.

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