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Behavioral

Finance for
Private Banking

*From the Art of Advice
to the Science of Advice*

Second Edition

KREMENA BACHMANN
ENRICO G. DE GIORGI
THORSTEN HENS

WILEY

Behavioral Finance for Private Banking

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Contents

CHAPTER 1		
Introduction		1
CHAPTER 2		
Behavioral Biases		5
2.1	Information Selection Biases	6
2.2	Information Processing Biases	11
2.3	Biases after Receiving Feedback	31
2.4	Are More Heads Smarter Than One?	33
2.5	Summary of Biases	35
2.6	Conclusion	39
CHAPTER 3		
Cultural Differences in Investors' Behavior		41
3.1	What Is Financial Culture?	41
3.2	The INTRA Study	43
3.3	Conclusion	46
CHAPTER 4		
Neurological Foundations and Biases' Moderation		47
4.1	The Human Brain	47
4.2	Insights for Behavioral Finance	48
4.3	Moderation of Biases	49
4.4	Conclusion	50
CHAPTER 5		
Diagnostic Tests for Investment Personality		51
5.1	A Case Study	51
5.2	Design of Diagnostic Questionnaires	52
5.3	Knowledge and Investment Experience	53
5.4	Psychology and Emotions	59
5.5	Client's Diagnostic Profile	65
CHAPTER 6		
Decision Theory		69
6.1	Introduction	69
6.2	A (Very) Short History of Decision Theory	70
6.3	Expected Utility	73

6.4	Mean-Variance Analysis	76
6.5	Prospect Theory	78
6.6	Rationality of Mean-Variance and Prospect Theory	87
6.7	The Optimal Asset Allocation	91
6.8	Comparing the Decision Theories	102
6.9	Conclusion	103
CHAPTER 7		
Product Design		105
7.1	Introduction	105
7.2	Case Study	107
7.3	Theory of Product Design	114
7.4	Structured Products Designed by Customers	120
7.5	Conclusion	123
CHAPTER 8		
Dynamic Asset Allocation		125
8.1	Time Diversification	126
8.2	Rebalancing	129
8.3	Conclusion	134
CHAPTER 9		
Life-Cycle Planning		137
9.1	Case Study	137
9.2	Case Study Werner Bruni	139
9.3	Consumption Smoothing	140
9.4	The Life-Cycle Hypothesis	141
9.5	The Behavioral Life-Cycle Hypothesis	143
9.6	Conclusion	146
CHAPTER 10		
Risk Profiling		147
10.1	Risk-Profiling Methodologies	148
10.2	Comparing Risk-Profiling Methodologies	151
10.3	A Case Study	152
10.4	The Risk Dimensions	153
10.5	Behavioral Risk Profiler	155
10.6	Risk Profiling and Its Regulation	166
10.7	Conclusion	167

CHAPTER 11	
Structured Wealth Management Process	169
11.1 Benefits	172
11.2 Implementation	173
11.3 Regulatory Requirements	174
11.4 Structuring the Wealth Management Process	177
11.5 Relevance of Different Theories	196
11.6 Complying with the Regulatory Requirements	197
11.7 Information Technology in Client Advisory Services	197
CHAPTER 12	
Fintech	201
12.1 History of Fintech	201
12.2 Current State of Fintech	201
12.3 Assessment of Fintech Solutions	202
CHAPTER 13	
Case Studies	203
13.1 Case Study 1: Structured Wealth Management	204
13.2 Case Study 2: Experience Sampling	209
13.3 Case Study 3: Goal-based Approach	210
CHAPTER 14	
Conclusions	219
CHAPTER 15	
Appendix: Mathematical Arguments	221
15.1 Proof that Expected Utility Satisfies the Axioms of Rational Choice	221
15.2 Derivation of the Fourfold Pattern of Risk Taking	222
15.3 Mean-Variance as a Special Case of Prospect Theory	222
15.4 Prospect Theory Optimal Asset Allocation	224
15.5 No Time Diversification Theorem	225
References	227
Index	235

Behavioral Finance for Private Banking

Introduction

Behavioral finance is an interdisciplinary research area that combines insights from psychology with finance to better understand investors' behavior and asset prices. It has managed to bridge the gap between theory and practice. Moreover, the psychological research that behavioral finance is based on recently got a foundation in biological differences found in the brain.

Traditional finance has focused on the ideal scenario of thoroughly rational investors in efficient markets. According to this standard paradigm in finance, individuals rationally search for information and know all available actions that serve their preferences. The latter are stable over time and robust to the occurrence of unanticipated events. As a result, rational investors searching for superior returns detect and eliminate any predictability in the asset prices—the market is efficient. According to traditional finance, the market remains efficient even if some investors behave irrationally. Indeed, rational investors will detect any mispricing generated by irrational investors and exploit it with the use of arbitrage strategies, which are assumed to be unlimited.¹ Consequently, any mispricing will very quickly be corrected, irrational investors will be driven out of the market, and the market will again quickly become efficient. A statistical consequence of prices being unpredictable is that returns are (log)-normally distributed—which is the content of the central limit theorem—a cornerstone of statistics. Consequently, optimal decisions can be taken based on the two parameters of a normal distribution: the mean and the variance. Thus, the *mean-variance optimization* and the efficient markets hypothesis are logical consequences of the rationality assumption.

In practice, however, we observe that even professional investors behave irrationally. Moreover, there is empirical evidence that the use of arbitrage strategies to exploit observed mispricing is limited (e.g., implementing an arbitrage strategy could be expensive and typically not at zero risk).

¹An arbitrage strategy is a strategy that generates positive returns at no risk. The assumption that arbitrage is unlimited means that arbitrage strategies can be implemented in the real-world and their costs is low.

The consequence of irrational investors and limited arbitrage is *inefficient markets*. As we will discuss in detail, investors are not always able to make rational decisions so that market prices show anomalies. For example, investors tend to adopt the behavior of other investors, and this herding behavior causes short-term predictability that leads ultimately to market crashes. Consequently, asset returns are no longer normally distributed. For example, they have *fat tails* (i.e., too many very bad returns)—which Taleb (2007) called *black swans*. Moreover, in inefficient markets, the mean-variance optimization is no longer rational. Thus, ignoring the insights from behavioral finance can be costly for investors adhering to traditional finance.

Behavioral finance emerged when Nobel laureate Daniel Kahneman and his colleague Amos Tversky conducted psychological research to question the assumptions of rationality—a cornerstone of the classical decision theory. Kahneman & Tversky (1979) developed a new theory, which they called *prospect theory*. Prospect theory has two phases: an editing phase and an evaluation phase. In the first phase, Kahneman and Tversky show how choice alternatives are mentally coded and transformed to be evaluated in the second phase. The editing phase has developed into a rich knowledge of behavioral biases—the topic of the next section. In the evaluation phase, Kahneman and Tversky develop a new decision model, which is the main content of our section on decision theory. The knowledge of behavioral biases is very valuable for a better understanding of clients in wealth management. Prospect theory also offers a risk measure that is consistent with the client's experience. With this measure one can construct asset allocations that better suit the clients than the asset allocations based on the volatility used in traditional finance. Prospect theory states that investors dislike losses more than volatility. In fact, investors react more to losses than they react to gains. Unlike volatility, the psychological risk measure is not the same for all investors, but is a characteristic of the individual. For this reason and others, the advantages of having a quality risk profiling procedure are numerous.

In this book, we apply these insights from behavioral finance to truly identify the client's situation from a holistic standpoint. With discoveries in the way people deal with information and respond to it in investment risk taking, it is reasonable to say that behavioral finance gives more attention to the investor's behavior. A more realistic investor, as described in behavioral finance, has a different perception and a different understanding of risk than the theoretical investor in the traditional decision theory. Consequently, this investor will need to invest differently than the theoretical investor in the traditional decision theory.

The book combines new research results with practical applications. It draws on the rich research body of behavioral finance and on profound

experience in the practice of wealth management. The book starts with the behavioral biases—the mistakes that people make when dealing with information and making financial decisions. The chapter describes the biases, discusses their implications for financial decisions, and suggests strategies with a proven success in moderating the biases. The following four chapters discuss the cultural dimensions of the biases and their biological foundation as well as their moderation and suggest how advisors could proceed in assessing the biases of their clients.

Thereafter, we explain decision theory (rational and behavioral) as a foundation of finance and show how it can be used in the construction of clients' portfolios and for the design of structured products. The question of how optimal portfolios should be adjusted over time is discussed in the following two chapters. The last chapters show how the new insights that behavioral finance has generated can be applied to client advisory, to designing behaviorally founded risk profiles, and to structuring the wealth management process. Thus, our books give a scientific foundation to financial advice given in private banking, which in practice is seen more as an art than a science. We believe that practitioners find some useful foundation for their work and that the transition from the art of advice to the science of advice is not disruptive but smooth.

This book is the second edition of the book *Behavioral Finance for Private Banking* that was published in the middle of the financial crisis. Many banks and financial advisors used the existing body of knowledge to improve their products and advisory services. A tool that we have developed demonstrates how this can be done.² In addition, this book benefits from insights of new areas of research such as cultural finance, neurofinance, and fintech. Finally, it compares the insights behavioral finance has gained with the new regulatory requirements in Europe (MiFID II) and in Switzerland (FIDLEG).

We are grateful to Mei Wang and Marc Oliver Rieger for their collaboration in the assessment of the cultural dimensions of investors' behavior. Moreover, this work greatly benefited from BhFS Behavioral Finance Solutions, a spinoff firm of the University of Zurich and the University of St. Gallen, which allowed us to present their tools. Last but not least we are grateful to the Wiley team and to Marie Hardelauf for their patience and help in editing our book.

²Access to a demo version of the tool can be requested from info@bhfs.ch.

Behavioral Biases

Behavioral finance research is driven by observations suggesting that individuals' decisions can be irrational and different from what previous theories assume. In this chapter, we will see that individuals' decisions can be systematically wrong because people's decisions are driven by emotions or misunderstandings or because people use inappropriate rules of thumb, also called *heuristics*, to handle information and make decisions. Certainly, financial markets are very complex so that optimization can lead to fragile results and good heuristics are preferable.¹ But what is typically observed is that people apply successful heuristics from other domains without properly assessing their effect in the investment domain. One example for the latter is *adaptive learning*, which is very successful in many day-to-day situations like choosing food: One tries out a new wine. If one likes it, one buys it again. However, in finance it leads to buying assets when they are expensive and selling them when they are cheap, as the *roller coaster* in Figure 2.01 illustrates.

To more deeply understand why we may observe such behavior, we consider a typical decision-making process and discuss how each stage of the process can be biased. First, decision makers select the information that appears to be relevant for their decisions. Then, they process the selected information to form beliefs and to compare alternatives. After deciding, individuals receive new information as a feedback. This feedback influences, in return, the way the decision makers search for more data, that is, the loop is closed.

The chapter provides evidence that certain mistakes can occur in each of these steps. It discusses the relevance of these mistakes for investors and suggests strategies to avoid the mistakes.

¹A good example is the superiority of the equal weights asset allocation (1/N) over mean-variance optimization, as DeMiguel, Garlappi, & Uppal (2009) have shown.

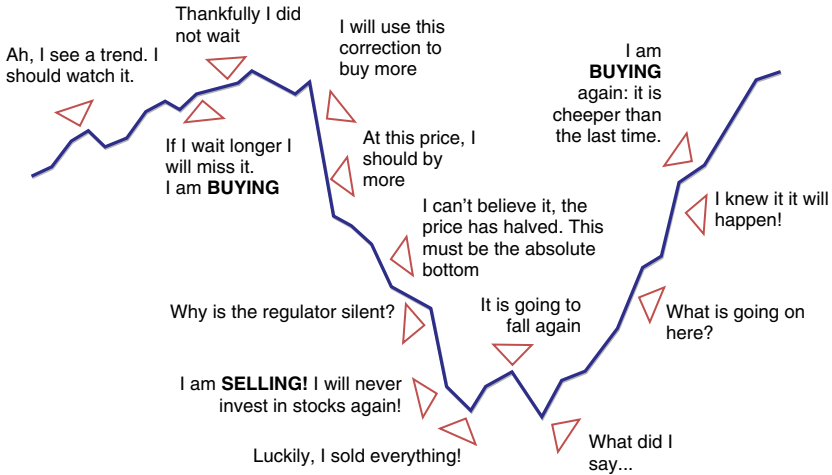


FIGURE 2.01 Market dynamics and decision behavior of a typical investor

2.1 INFORMATION SELECTION BIASES

When confronted with information, individuals need to judge how relevant it is for the task they need to handle. Thereby individuals seem to consider only particular information while disregarding other that might be relevant as well. For investment decisions, such information filtering can be dangerous since there is uncertainty about the relative importance of economic factors for the future—investment rules that have worked in the past do not always work in the future. So, are there any patterns in the way people select relevant information, and why should we expect that their impact is systematic?

2.1.1 Attention Bias

The first observation on individuals' selection of information is that it can be biased due to a specific task. People gather information that they think is relevant for dealing with the problem and disregard others, which they would otherwise notice. This is demonstrated in an experiment, where participants have been asked to watch a video with two basketball teams: one team wearing black shirts and another one wearing white shirts (Simons & Chabris, 1999). The task was to count the passes of the white team. Afterward, participants have been asked whether they have observed something unusual. Some participants spotted that there was a second ball. But only a

few noticed a big black gorilla walking slowly through the picture, stopping in the middle, winking, and passing slowly away. The reason for not seeing the gorilla is the *attention bias*. Due to the limited attention that people have, they can get only the information they consider important for solving a specific task. All other information remains disregarded, independent of how extreme it is. Hence, when people focus too much on one task, something unexpected can happen that they might not notice. Moreover, related experiments show that even when people know that something unexpected might happen (e.g., that a gorilla would appear), this doesn't help them notice other unexpected things.

Relevance for Investors and Moderation The attention bias is relevant for investors because all investors use media to inform themselves. But the media process follows certain patterns. Some media set the agenda, other media follow, and for some time all media report the same story. In these times, other investment relevant information is not seen—like the gorilla in the experiment just mentioned. For example, in summer 2011 we observed a global stock market downturn: From the end of July to the end of August, the DJIA fell from 12,700 to 10,700, the Euro Stoxxs 50 fell from 2,800 to 2,200, and the Nikkei from 10,000 to 8,750 (i.e., stock markets plunged by 16%, 21% and 12.5%, respectively). Looking at the words Internet users searched in Google² during summer 2011, we see that the public attention mainly focused on the US debt ceiling debate that was positively resolved by August 1st. So why did stocks decline after the showdown in the US Congress was resolved? One explanation is that the gorilla “US recession” was not seen in July, so the attention for a possible recession in the United States was hidden behind the budget ceiling debate while after that debate was over the recession attracted the attention of the public. Indeed, the search for the words “US debt” peaked in July 2011 while the words “US recession” peaked in August 2011. And indeed, the US business cycle slowed down considerably during the summer of 2011.

The best moderation of the attention bias is to agree on certain key information (e.g., macroeconomics, politics, valuation levels, sentiment of the market) that one always discusses with the investors irrespectively of whether it is topical or not.

2.1.2 Selective Perception Based on Experience

Perception of information is, by its nature, always selective. But in many situations people might not be able to see things just because they do not

²See www.google.com/insights.

expect them to occur given their experience. This has been demonstrated in an experiment with playing cards (Bruner & Postman, 1949). Participants were shown five playing cards and asked what they have seen. What researchers were testing is whether the participants would recognize doctored cards (e.g., a *black* three of a heart). They found out that, on average, participants needed four times longer to recognize a doctored card than a normal card. Most of the people were very sure that the doctored card was a normal card. Even when participants recognized that something was wrong, they sometimes misperceived the *incongruity* (e.g., people who were shown a black four of hearts declared that the spades were “turned the wrong way”). This experiment shows that experience can influence the way people look at new evidence. When people have enough experience with a specific situation, they often see what they expect to see based on their experience. Hence, in some cases, experience may lower performance.

Relevance for Investors and Moderation To give an example of how selective perception can affect investments, recall the stock market crash in the years 2007–2008. From the summer of 2007 to the beginning of 2009, the DJIA fell from 14,100 to 6,525, the Euro Stoxx 50 from 4,500 to 1,800 and the Nikkei from 18,250 to 7,125—that is, stock markets plunged between 50% and 60% around the world. Unfortunately, none of the standard indicators could predict this decline. The P/E ratios and the Fed measure that could predict for example the crash of the dot-com bubble signaled no risk during the summer of 2007. Investors who used those risk measures because of the positive experience with them were caught by surprise during the stock market crash of 2007–2008. Indeed, that stock market crash did not come from overvaluation of stocks but from a bubble in the housing market in the United States, the United Kingdom, and Spain. This housing bubble resulted in a financial crisis, which then slowed down the global economy. Thus, experience with some indicators might seduce investors to stop thinking transversally.

The best way to deal with the selective perception bias is to ask yourself: What is my motivation to see things in a certain way? What expectations did I bring into the situation? Why do others not share my view?

2.1.3 Confirmation Bias

Previous experience influences the way we perceive information that we face, but it also affects the way we search for information. People tend to search for information that confirms one’s beliefs or hypotheses, while they give disproportionately less consideration to alternative possibilities. This bias

in information selection is known as the *confirmation bias*. It has been first discovered by Wason (1960). In his experiment, participants were asked to identify a rule applied to triples of numbers (e.g., 2, 4, and 6). To discover the rule, participants could decide on their own triples and receive a feedback on whether their numbers conform to the rule or not. While the true rule was “three numbers of increasing order of magnitude,” most participants tested a specific hypothesis as for example “increasing by 2.” However, those who test their rule can never discover that their rule is wrong because all examples that fit their rule fit also the true rule. Thus, to test the rule “increasing by 2,” it is critical to try, for example, 2, 4, and 7.

Although there are circumstances where searching for confirmatory evidence can be useful in testing a particular hypothesis (Klayman & Ha, 1987), it is unlikely that people are aware of them and adjust their test strategy. It is more likely that people use the same test strategy that can be useful in certain circumstances, but which, like any all-purpose heuristic, can lead to serious mistakes.

In another experiment, individuals were asked to decide whether the costs of alternative treatment methods should be covered by the mandatory insurance or not (Jonas, Schulz-Hardt, Frey, & Thelen, 2001). They have been offered different expert reports, each of them providing arguments why these costs should be covered by the mandatory insurance and why not as a preparation for a final decision. The participants showed a clear preference for reports that supported their initial opinion. Such biased information search can lead to the maintenance of the initial opinion, even if this position is not justified based on all available information.

Relevance for Investors and Moderation Like the experimental evidence already presented, different investors reading the same article discussing the future development of an asset may come to different conclusions regarding the prospects of the asset, depending on whether they hold the asset. As experiments suggest, it is more difficult to recognize news about a company as negative when holding shares of that company than when holding cash (Kuhnen & Knutson, 2011). Again, confirmation is sought but not information.

As a possible moderation, it is important to seek discussion with people who hold the opposite position. Thereby, one should try to avoid the natural impulse to seek for reasons why the opponent’s opinion is wrong. Instead, one should listen to the arguments and evaluate them as rationally as possible. To avoid the tendency to see evidence in support of previous investment decisions, one could ask: How would I decide in the face of the new evidence if I must decide again today?

2.1.4 Availability Bias

Finally, the perception of information is influenced by its properties. Concrete, imaginable, and exciting information is more easily perceived and stored than abstract or statistical data. Such kind of information is also more “available” and easy to retrieve when one tries to think of an instance. This is the reason, why there is a discrepancy between people’s judgment on the likelihood of an event and the statistical data. For example, most Americans think that homicide or car accidents kill more people than diabetes and stomach cancer and that tornados claim more lives than lightning, while the statistical evidence show that it is exactly other way around (Combs & Slovic, 1979). This bias in the perception is called *availability bias*. Because car accidents, tornadoes and murderers are on the headlines, they are more easily perceived and stored in memory than other information so that when people try to think of an instance this information influences the probability judgments because of its high availability. A close cousin to availability is *vividness*. It usually refers to how concrete and imaginable or how exciting some information is. Experiments show that decision makers are affected more strongly by vivid information than by abstract information.

Relevance for Investors and Moderation A famous study by Barber & Odean (2008) shows that individual investors are net buyers of attention-grabbing stocks. For example, they buy into stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns. Attention-driven buying results from the difficulty that investors have searching the thousands of stocks they can potentially buy. Individual investors do not face the same search problem when selling because they tend to sell only stocks they already own. Barber and Odean find that many investors consider purchasing only stocks that have first caught their attention. Thus, preferences determine choices after attention has determined the choice set. However, attention-driven investments do not generate superior returns.

Overall, the information selection biases make investors use either a subset of evidence or evidence that is inappropriate for the decision problem. This motivates the development of erroneous beliefs and hinders learning. One approach to correct these developments is to compare explicitly over- and underestimated dangers with evidence for the opposite view. Advisors should, however, be cautious not to induce the opposite effect—that is, motivate clients who previously overestimated some risks to underestimate them. It is best is to show long-term empirical evidence for similar cases.

2.2 INFORMATION PROCESSING BIASES

Selected information needs to be evaluated. What does the evidence say about the likelihood of events? Which alternative is now more attractive? Some rules of thumb cause systematic misperceptions.

2.2.1 Representativeness Bias

When making judgments, people often rely on the degree to which their observations represent known characteristics. This rule of thumb is called *representativeness bias*.

To give an example of tasks where the representativeness bias can affect decisions, suppose that one observes A and needs to judge whether it comes from B or from C, where B and C are samples of observations with different characteristics. For example, A might be a person (e.g., a fund manager) and B might be a group (e.g., fund managers with skills) and C might be another group (e.g., fund managers without any skills). The judgment task is to estimate the probability that the person is a member of the group B (e.g., that the fund manager is skilled). Similarly, A could be an event and B might be a process. For example, B might be the process of flipping a fair coin and A might be the event of getting six tails in a row. The judgment task could then concern the estimation of the likelihood for observing the event with an unbiased coin.

Let us now consider some examples of how the representativeness bias can affect decisions. Suppose that a fund manager is known to beat the market in two of three years. Let B mean that the manager beats the market and F mean that the manager fails to beat the market. Now consider the following protocols of the success of the manager: (a) BFBBB; (b) FBFBBB; and (c) FBBBBB. Which of the three protocols is most likely?

Most of the people answering this question consider protocol (b) as most likely. The reason for their judgment is that if the manager beats the market in two of three years, the probability for success is two-thirds. Hence, a protocol is considered as most likely if the protocol's realizations match this probability. In protocol (a) the manager beats the market in four of five years, but in protocol (b) the manager beats the market in four of six years. Comparing the success rate in the protocols with the expected probability for success given in the description of the problem, people looking for a closer match judge protocol (b) as more likely. However, protocol (b) is in fact equivalent to protocol (a) but it has the additional condition that in the first year the manager fails to beat the market. By the properties

of conjunct probabilities, it is less likely to observe protocol (b) than protocol (a).³

The observation that people fail to apply the conjunction rule correctly is known as the *conjunction fallacy*. It describes the tendency to overestimate the probability of conjunctive events. For example, suppose that you can build a complex machine consisting of 500 independent parts. Suppose also that each part were 99% reliable when used the very first time. What are the chances that the system would work on its first attempt? The answer is less than 1%, which surprises many people. In the example with the fund managers, the fallacy emerges due to the representativeness bias.

The representativeness bias emerges very often when people deal with *small samples*. People start to believe that a sample randomly drawn from a population should resemble other samples drawn randomly from the same population more closely than statistical sampling theory would predict. However, randomly drawn small samples may look quite different than larger samples drawn from the same population.

To demonstrate this, one could draw random numbers from 0 to 100 and order them in 10 equally large bins. The relative frequency of the numbers in each bin should be 10% as each number is equally likely to be drawn. This is true for a sample with 10,000 observations. However, a smaller sample with 10 observations, for example, may look quite different—that is, some bins may contain more than 10% of the observations; other bins may be empty. The smaller sample should, however, be considered as random as the sample with 10,000 observations, although each distribution looks different.

In some instances, the reliance on stereotypes leads people to ignore the relative frequency with which events occur (base rates). This has been demonstrated in an experiment where participants were told that psychologists have been interviewed and administered personality tests of engineers and lawyers (Kahneman & Tversky, 1973). Based on this information, the psychologists have written thumbnail descriptions. For example, a description of an engineer was:

Jack is a 45-year-old man. He is married and has four children. He is generally conservative, careful, and ambitious. He shows no interest in political and social issues and spends most of his free time on his many hobbies, which include home carpentry, sailing, and mathematical puzzles.

³To see that this is true, assume that realizations are independent from each other and compute the probabilities of the three protocols. Rounding to full percentages for a) we get $\left(\frac{2}{3}\right)^4 \frac{1}{3} = 7\%$, for b) we get $\left(\frac{2}{3}\right)^4 \left(\frac{1}{3}\right)^2 = 2\%$, for c) we get $\left(\frac{2}{3}\right)^5 \frac{1}{3} = 4\%$.

One group of participants was told that there were 30 engineers and 70 lawyers. Another group was told that there were 70 engineers and 30 lawyers. When asked to estimate the probability that someone randomly selected from the pool of 100 descriptions would be an engineer, the average estimate in the first group was 30% and in the second group 70%. In other words, participants in both groups used the base rates given in the problem. However, when participants were provided with descriptive information as shown about Jack, they tended to ignore the base rates. The average estimate in both groups was the same. Thereby, it did not matter whether the information was informative or not. Even provided with information that is equally descriptive for an engineer or a lawyer, participants ignored on average the base rates and gave a median probability estimate of 50%. Hence, participants ignored the base rate information and simply judged the description as equally representative of an engineer and a lawyer. This observation remained in the literature as the *base rate fallacy*.

When do people tend to neglect base rates? People appear to use base rates when they are consistent with their intuitive theories on cause and effect. In one experiment, participants were asked to predict the average grade points of a student based on either causal factors (such as the number of hours in a week spent for preparation) or noncausal information (such as student's income). Participants were told that noncausal factors have the same predictive power as causal factors but on average participants used base rates more often when the information was causal.

Relevance for Investors and Moderation The representativeness bias has important implications for investors looking for price patterns that they could exploit. After a short sequence of positive returns, they might develop the belief that the economics producing them has turned in favor of good returns, even though this might not be true. Indeed, De Bondt & Thaler (1985) showed that portfolios of prior losers (stocks with recent negative performance) outperformed portfolios of past winners (stocks with recent positive performance). That is, representativeness bias led investors to overreact to positive (negative) information relative to prior winners, as these appeared more representative for the recently observed good (bad) returns. The best moderation to address this fallacy is to reveal it by statistical evidence.

2.2.2 Conservatism

There are also circumstances where people overweight the base rates and ignore new information. This is called *conservatism*.

The famous Monty Hall problem (derived from the TV show *Let's Make a Deal*) is one example. In this problem, there are three doors; two have a

goat and one a car behind it. You are asked to choose one of the doors—not knowing which door hides which object. Then, before you can open it someone who knows what is behind the doors opens one of the doors you have not chosen that hides a goat. The question is whether observing this action you need to swap away from your door to the other door that is still closed. Many people answer “no,” because at that point there are two doors and one car and one goat left. So, they assume that the chance of getting the car when sticking to the originally chosen door is 50%. However, this is wrong, since the action of opening a door that you have not chosen and behind which there is a goat reveals important information. Indeed, comparing the two strategies “sticking to your door” and “swapping with the other door” shows that following the latter you win in two out of three cases, while the former is only successful half that often.

Another example that shows the effect of conservatism has been proposed by Edwards (1968):

There are two urns; each one contains 10 balls. Urn A contains 7 red and 3 blue balls, while urn B contains 3 red and 7 blue balls. One urn is randomly chosen by flipping a fair coin. 12 balls are now drawn from this urn with replacement. The result is the following: 8 red and 4 blue balls were drawn. What is the probability that the randomly drawn urn is urn A when observing this result (8 red and 4 blue balls)?

People answered the question with probabilities very close to the base rate of 50%. However, in this example the information that 8 of the 12 balls drawn from the urn are red and only 4 are blue is very important, because statistical rules would imply a probability of urn A of 97% (i.e., close to 100%).

Representativeness bias (see Subsection 2.2.1) and conservatism seem to generate opposite effects of information processing on beliefs. Griffin & Tversky (1992) suggest that people update beliefs based on the strength and weight of new evidence. Strength refers to how salient and extreme new information is, while weight is its statistical content (i.e., its relevance from a statistical point of view). Griffin & Tversky (1992) argue that people tend to focus too much on strength and too less on weight, that is, when information seems salient and extreme, people tend to focus on it and update beliefs accordantly, while if information does not appear relevant and important, people tend to ignore it. Therefore, when strength is high but weight is low, new information is overweighed and the representativeness bias arises. By contrast, when strength is low but weight is high, new information is underweighed and conservatism arises.