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BEHAVIORAL FINANCE AND WEALTH MANAGEMENT: MARKET ANOMALIES, INVESTORS' BEHAVIOR AND THE ROLE OF FINANCIAL ADVISORS

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名誉 良心 高貴

Meiyo *Ryoushin* *Kouki*
Honor *Conscience* *Nobility*

VIRTUS INTERPRESS

Published in Ukraine by Virtus Interpress

Virtus Interpress
Gagarina Str. 9, 311
Sumy, 40000
Ukraine
www.virtusinterpress.org

Cervellati, E. M., Angelini, N., & Stella, G. P. (2024). *Behavioral finance and wealth management: Market anomalies, investors' behavior and the role of financial advisors.* Virtus Interpress. https://doi.org/10.22495/bfwm

ISBN: 978-617-7309-26-9

DEDICATIONS

“A chi crede in me e mi dà la forza di affrontare anche le più folli sfide della mia vita”
(Enrico Maria Cervellati)

“A Ray, il raggio di luce che illumina la mia vita”
(Natascia Angelini)

“A Thea, per l’amore che mi trasmette”
(Gian Paolo Stella)

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FOREWORD

This book presents an examination of the intricate relationship between human behavior and financial decision-making, with particular regard to wealth management. It is built on a 2012 book by Enrico Maria Cervellati *"Finanza comportamentale e investimenti. Oltre l'approccio tradizionale per comprendere gli investitori"* ("Behavioral Finance and Investments. Beyond the Traditional Approach to Understanding Investors"). On one hand, the book was in Italian, limiting the possibility of being accessible to non-Italian readers. On the other, after 12 years, it needed to be updated. Thanks to the important contributions of Natascia Angelini and Gian Paolo Stella, this book not only updates the materials contained in the previous book but also adds new insights, expanding the topics from investments to wealth management.

The first chapter is dedicated to the behavioral foundations, delving into the origin and progression of behavioral economics and finance, it explores cognitive and emotional biases such as confirmation bias, hindsight bias, the illusion of knowledge and the illusion of control, overoptimism, and overconfidence, as well as status quo bias. The intricacies of heuristics like affect, anchoring, availability, familiarity, and representativeness are discussed. The chapter also covers framing effects, including loss aversion, aversion to a sure loss, and mental accounting, and concludes with a focus on debiasing techniques and choices under uncertainty, highlighting prospect theory.

The second chapter proposes key market anomalies and individual investors' behaviors. Among market anomalies, we consider calendar or seasonal anomalies, cross-section anomalies, event-based anomalies, momentum, and reversal. A deep dive into individual trading behaviors uncovers reasons for underperformance and phenomena such as the disposition effect and under-diversification. The chapter includes a section on evidence from Italy, discussing overconfidence in trading and attention-grabbing behaviors.

The third chapter focuses on the links between behavioral finance and wealth management. This pivotal part of the book integrates behavioral insights into practical wealth management and represents a major contribution compared to the 2012 book on behavioral finance and investments. It discusses motivational theory, the pitfalls of naive diversification, and the biased perception of risk-reward ratios. Behavioral portfolio theory, mental accounting in the context of investment pyramids, and behavioral goals-based wealth management are explored. The chapter examines behavioral profiling beyond risk tolerance, addressing aspects like overconfidence, the role of luck and competence, and the importance of trust and life satisfaction in financial decision-making.

By dissecting biases, market anomalies, and investors' behaviors, the book provides valuable insights for investors, financial advisors, and anyone interested in the intersection of behavioral finance and wealth management.

Enrico Maria Cervellati,
Natascia Angelini,
Gian Paolo Stella

CHAPTER 1: BEHAVIORAL FOUNDATIONS

1.1. The birth and evolution of behavioral economics and behavioral finance

The inception of behavioral economics, and specifically behavioral finance, as a distinct field, can be traced back to the groundbreaking research of pioneer psychologists Daniel Kahneman and Amos Tversky. The significance of this research was acknowledged when the Nobel Prize in Economics was awarded to Kahneman in 2002. The Nobel committee underscored the pivotal role of biases, heuristics, and framing effects in real people's decision-making processes, in contrast to the assumed perfect rationality of economic "agents" in traditional economics.

These cornerstones of behavioral finance — biases, heuristics, and framing effects — are elaborated on below. We highlight the most impactful cognitive and emotional biases, decision heuristics, and framing effects, at least from our subjective perspective.

Traditional economic models have long overlooked the psychological underpinnings of individual decision-making, which this section aims to address. The prevailing hypothesis of perfect rationality in individuals and the foundational axioms of expected utility theory (von Neumann & Morgenstern, 1947) historically left little scope for the potential errors individuals might make.

Even though classical economists like Adam Smith, Irving Fisher, and John Maynard Keynes — the concept of "animal spirits", taken up as the title of a recent book by Akerlof and Shiller (2009) — acknowledged the profound significance of the psychological component in economics, by the mid-20th century, particularly the 1970s, psychology had all but vanished from orthodox economic theories, overshadowed by the dominance of rational expectations within the discipline.

Herbert Simon presented a notable exception by introducing the concept of "limited rationality" (Simon, 1955). This theory posits that individuals have bounded cognitive capabilities and, when making choices, they tend to simplify problems to reduce the complexity inherent in decision-making.

It was during this time, somewhat paradoxically, that the pioneering work of psychologists Daniel Kahneman and Amos Tversky — but also others, e.g., Paul Slovic — began to seep into economic science. This cross-pollination laid the groundwork for the advent of behavioral economics.

Two seminal contributions that defined the behavioral approach in economic science are the concepts of "heuristics and biases" (Tversky & Kahneman, 1974) and "prospect theory" (Kahneman & Tversky, 1979). The latter, in particular, caught the attention of economists, notably Richard H. Thaler, who is credited with pioneering work in behavioral economics (Thaler, 1980), that later received the Nobel Prize in Economics in 2017.

Slovic (1972) is regarded by many as the seminal piece on behavioral finance — distinct from broader behavioral economics — penned by a psychologist. It highlights how the glut of information in financial markets compels investors to navigate a situation burdened by information overload. The challenge lies not only in the volume but also in the quality and pertinence of the information: the rise of mass media — and more recently, social media — has made data and news readily accessible, yet it burdens individuals with the formidable task of assessing its significance. Thus, it showed how crucial it is to dissect how agents process, value, and utilize information to make investment choices.

The mid-1980s heralded other significant contributions to the behavioral approach. The inaugural piece on behavioral finance authored by economists tackled the enigmatic "dividend puzzle" (Shefrin & Statman, 1984), succeeded by two seminal papers on the "disposition effect" (Shefrin & Statman, 1985) and the "winner-loser effect" (De Bondt & Thaler, 1985).

Traditional economists initially met these early behavioral finance works with skepticism, criticizing the behavioral approach for merely narrating "stories" or failing to offer a cohesive and robust alternative to the efficient market theory. However, nearly three decades on, the behavioral perspective has not only gained traction but is so ingrained in finance that it permeates virtually all research domains.

While the 1980s were marked by debates between traditionalists and behaviorists, and the late 1990s saw the first comprehensive symposiums on this emerging viewpoint, it was Kahneman's Nobel Prize in Economics in 2002 that accorded behavioral finance its deserved acknowledgment. The volume of research in behavioral finance has surged since its inception.

The contention between advocates of the traditional and behavioral paradigms remains intense, particularly among those who misconstrue the latter as being antithetical to the former. In reality, they are not at odds because the traditional approach is normative, outlining how individuals ought to act ideally, whereas the behavioral approach is descriptive, capturing how people actually behave. These perspectives exist on distinct epistemological tiers (Rigoni, 2006). Notwithstanding, behavioral finance does offer normative advice, as in the recommendations of "nudges" (Thaler & Sunstein, 2008).

Bridging finance with psychology, the behavioral method strives to elucidate how individuals apprehend, process, and apply information in decision-making.

Real individuals are neither perfectly rational nor all-knowing, and they commit cognitive and emotional errors. While traditional finance acknowledges the existence of less-than-rational actors, labeled unsophisticated or naive investors, or "noise traders", it generally postulates efficient markets with boundless arbitrage opportunities that correct prices to their equilibrium. The behavioral school contests these assumptions, addressing both the presence of irrational investors and the nature of arbitrage — seen as risky and finite in reality — and posits that departures from the rational conduct posited by economists are not erratic but rather systematic and recurrent.

As for market efficiency, behaviorists contend that institutional investors cannot always engineer riskless arbitrage, as the influence of irrational agents may not diminish over time but can grow, perpetuating anomalies and price misalignments from true values (mispricing). The concept of risk associated with noise traders constrains arbitrage opportunities (Shleifer & Vishny, 1997), which are theoretically supposed to offer risk-free profits. Traditional theorists often label these deviations from market efficiency as "anomalies". In contrast, behavioral economists refer to them as "regularities" due to their persistence. Market practitioners have long acknowledged the critical role of "market psychology". Investor psychology is frequently simplified to the emotions of greed and fear. Yet, it appears the primary factors in individual financial behavior are the fear of losing money and the hope (more than greed) of accruing wealth over time (Lopes, 1987). Beyond hope and fear, other emotions and psychological factors also impact financial decisions. A principal aim of behavioral finance is to prove that these elements are categorizable and analyzable. To lay the groundwork, it is vital to introduce the three pillars underpinning this discipline (Shefrin, 2002): the first involves behavioral biases arising from heuristic decision-making; the second pertains to frame dependency, that is, the context in which problems are presented; the third concerns the observed anomalies or regularities in financial markets. Several findings suggest that despite the diversity among individual investors, many exhibit common behavioral patterns leading to systematic errors, with predictable impacts on the markets. Ignoring these behavioral elements and their market effects severely narrows the scope of financial analysis.

1.2. Cognitive and emotional biases

While the paper that initially caught economists' attention was the one on "prospect theory", the other one on heuristics and biases probably represents the origin of the behavioral revolution in economics and finance. The word "bias" in English often connotes "error", but it more accurately refers to a "predisposition" towards error. Thus, it is sometimes equated with "prejudice", in the literal sense of something that precedes judgment (pre-judgment). However, due to the generally negative implication of "prejudice", we choose to retain the term "bias", which has become ingrained in financial terminology. It is a common mistake to conflate cognitive aspects with emotional ones. Behavioral finance is frequently misconceived as a field concerned with managing investors' emotions. While it does account for emotional influences, behavioral finance primarily investigates cognitive processes, distinguishing it from the so-called "emotional economics", which is more concerned with the emotional responses of individuals. These aspects are distinct; cognitive aspects involve how individuals access and process information, while emotional aspects pertain to the feelings experienced during the mental processing of that information. Cognitive and emotional factors collectively influence decision-making, yet they operate on different levels and can lead to distinct behavioral outcomes.

The following subsections will discuss the most recognized cognitive biases in the literature. Some emotional biases, such as regret and affect, will be addressed in subsequent sections.

1.2.1. Confirmation bias

Confirmation bias is a cognitive phenomenon where individuals tend to favor information that confirms their existing beliefs or hypotheses while giving disproportionately less consideration to alternative possibilities. This bias can lead to errors in judgment as it results in a skewed evaluation of information, impacting decision-making processes across various domains, including finance, science, and everyday life.

In the realm of finance, confirmation bias can significantly impact investment decisions and market behavior. Investors might selectively seek out information or interpret market data in a way that reinforces their existing investment strategies or market predictions. For example, a trader holding a specific stock might focus on positive news regarding the company and ignore warning signs of potential financial trouble, leading to suboptimal investment decisions. The role of confirmation bias in financial markets has been highlighted in various studies, such as Rabin and Schrag (1999), who discuss how investors might misinterpret evidence to support their beliefs, leading to market inefficiencies.

In scientific research, the aim is to objectively test hypotheses rather than seek evidence to support them. This is crucial for the integrity of the scientific method. Scientists define a null hypothesis and an alternative hypothesis and use statistical tests to potentially refute the null hypothesis. The principle of falsifiability, as introduced by philosopher Karl Popper, emphasizes the importance of being able to disprove a hypothesis. Scientific advancement often hinges on the ability to challenge and falsify existing theories, not just to confirm them. This approach helps to mitigate the influence of confirmation bias in scientific research.

In everyday decision-making, confirmation bias can lead to a range of problems, from trivial misunderstandings to serious misjudgments. People tend to seek out information that aligns with their existing beliefs and interpret ambiguous information in a way that supports these beliefs. This bias can affect various aspects of life, including political views, social interactions, and personal beliefs. A study by Nickerson (1998) provides a comprehensive review of the psychological mechanisms behind confirmation bias and its effects on reasoning and decision-making.

To counteract confirmation bias, individuals and organizations can adopt strategies such as actively seeking out contradictory information, engaging in critical thinking, and considering alternative viewpoints. In the context of investment, diversification of sources and types of information can help investors make more balanced decisions. In scientific research, rigorous peer review processes and replication studies are essential for ensuring objectivity and reliability.

In summary, confirmation bias is a pervasive cognitive bias that affects decision-making in various fields. Awareness and strategies to mitigate its influence are essential for objective analysis and sound decision-making.

1.2.2. Hindsight bias

Hindsight bias, also known as the "knew-it-all-along" effect, is a common cognitive bias where individuals believe after an event has occurred, that they had accurately predicted or expected the outcome. This bias distorts one's memory of past events and leads to an overestimation of one's predictive abilities. Hindsight bias has significant implications in various fields, including finance, psychology, and decision-making.

In finance, hindsight bias can lead to overconfidence in investment decisions. Investors may believe they predicted past market movements or investment outcomes and, therefore, overestimate their ability to predict future market trends. This can result in risky investment behaviors, inadequate diversification, and poor portfolio management.

Research by Fischhoff (1975) and Roese and Vohs (2012) highlights the impact of hindsight bias on financial decision-making, showing how investors often reconstruct their memories of past investment decisions to align with current outcomes, leading to a skewed perception of their investment skills.

In psychology, hindsight bias affects how individuals recall their past judgments and decisions. People often reconstruct their memories to fit with current knowledge, believing that they “knew it all along”. This bias can impact personal relationships, legal judgments, and medical decisions. Studies by Blank et al. (2007) and Guilbault et al. (2004) explore the psychological underpinnings of hindsight bias, emphasizing how it arises from a need for cognitive consistency and the desire to see the world as predictable and controllable.

In decision-making, hindsight bias can lead to inappropriate blame or credit assignment. For instance, in organizational settings or legal environments, individuals might be unfairly judged for decisions made under uncertainty, with the benefit of hindsight. Research studies by Hawkins and Hastie (1990) discuss the implications of hindsight bias in legal judgments and organizational decision-making, stressing the importance of considering the context and information available at the time of the decision.

To mitigate hindsight bias, it is essential to maintain accurate records of decisions and the rationale behind them, practice humility in judgments, and be aware of this cognitive bias. Decision-makers should focus on forward-looking strategies, considering the uncertainty and unpredictability of future events. Engaging in critical thinking, seeking diverse perspectives, and reflecting on the limits of one's knowledge can also help reduce the impact of hindsight bias.

1.2.3. Illusion of knowledge and illusion of control

The illusion of knowledge and the illusion of control are closely related cognitive biases that significantly impact decision-making, particularly in the field of finance and investing.

The illusion of knowledge occurs when individuals believe they understand or know more than they actually do. It often results from the misinterpretation or overestimation of the amount and relevance of information they possess. Contrary to the assumption that more information leads to better decision-making, Slovic’s (1973) seminal work indicates that an excess of information can actually lead to overconfidence and poor decisions. This phenomenon is not limited to amateur investors; professional traders and analysts are also susceptible. Guiso and Jappelli (2006) further corroborated this by showing that well-informed investors often demonstrate overconfidence, leading to poorly diversified investment portfolios.

Recent studies have continued to explore this bias. For instance, research by Odean (1998) on individual investors’ trading behaviors found that increased access to information often led to excessive trading and reduced net returns. Similarly, Barber and Odean (2008) demonstrated that investors who traded more frequently, possibly due to having more information, actually earned lower returns than those who traded less.

The illusion of control is the tendency to overestimate one’s ability to control or influence outcomes, especially when the actual degree of control is low or nonexistent. Lopes (1987) identified this illusion as stemming from a basic human desire to exert control over one’s environment. This bias is particularly pronounced in situations where chance plays a significant role, such as in financial markets. People often mistakenly believe that their personal skills or strategies can significantly influence market outcomes.

This cognitive bias has been further explored in studies like Henslin (1967), which found that people tend to believe they can influence the results of a chance game, and Thompson et al. (1998), which showed that people overestimate their control in various situations, including financial decision-making.

The interplay between the illusion of knowledge and the illusion of control significantly impacts financial decision-making. These biases can lead to overtrading, under-diversification, and herding behavior, as demonstrated in the research by Bikhchandani et al. (1992), which explored how investors often mimic the actions of others rather than relying on their independent analysis.

Additionally, the self-attribution bias plays a critical role in these illusions. People tend to attribute successful outcomes to their abilities and decisions, while failures are often blamed on external factors. This attribution style is highlighted in research by Miller and Ross (1975), which discusses how individuals attribute success to internal factors and failure to external circumstances.

To mitigate these biases, investors and decision-makers must be aware of these psychological tendencies and practice critical thinking.

This includes questioning the relevance and source of information and recognizing the limits of personal control in uncertain environments. Future research in this area could focus on developing tools and strategies to help investors and professionals better assess the quality of information and understand the probabilistic nature of financial markets.

1.2.4. Overoptimism and overconfidence

Overconfidence and overoptimism stand out as two significant behavioral biases, each with distinct impacts. Thus, we devote more space to describe them in detail.

Overconfidence is frequently mistaken for overoptimism, yet these are separate constructs, though they may co-occur. The former pertains to self-perception, while the latter to the outlook on external circumstances. Thus, it is entirely feasible to be overconfident while also being pessimistic.

In the context of overoptimism, the definitions within behavioral finance and psychology are quite aligned. Shefrin (2007) describes “excessive optimism” as the propensity to overestimate the likelihood of favorable events and to underestimate the possibility of unfavorable outcomes. Here, overoptimism refers specifically to “unrealistic optimism” as defined by Weinstein (1980), which pertains to biased expectations in specific areas, rather than to “dispositional optimism,” a generally positive outlook on the future as conceptualized by Scheier and Carver (1985). Overoptimism generally causes individuals to overrate the probability of positive events and underrate the likelihood of negative ones (Weinstein, 1980; Kahneman & Lovallo, 1993). People tend to envision the future through an unduly positive lens.

While optimism can have beneficial effects — with optimistic people often generating positive externalities (Puri & Robinson, 2005) and excelling in personal and professional spheres — excessive optimism can lead to unpleasant outcomes, particularly in financial and entrepreneurial endeavors. Investors who are too optimistic may assume their selected securities will perform better than what the associated risks would suggest. Similarly, overly optimistic managers are prone to project inflated expectations for future ventures.

Several variables are used in the behavioral finance literature to proxy for overoptimism. The variable termed “Rose-Colored Glasses” gauges dispositional optimism, drawing on the works of Dawson and Henley (2012) and Lovallo and Kahneman (2003). This measure often stems from survey questions asking people whether they anticipate more positive occurrences in life than negative ones. Other variables delve into unrealistic optimism. Hoelzl and Rustichini (2005, p. 305) underscore the prevalence of unrealistic optimism, especially when individuals assess their own risk of experiencing adverse life events in comparison to the average population, an observation supported by Perloff and Fetzer (1986) and Hoorens and Buunk (1993). These variables are often derived from survey questions crafted to evaluate “comparative optimism” (Weinstein, 1980), reflecting the belief in experiencing more positive events than others.

Unrealistic optimism can skew judgments, leading to poor assessments and suboptimal outcomes (de Meza & Dawson, 2021). Erroneous judgments can precipitate not just systematic decision errors but also impulsive behaviors (de Meza et al., 2019) and insufficient precautionary actions.

Armor and Taylor (1998, p. 332) observe that people who underestimate negative events or their consequences may place themselves in real danger due to inadequate precautions.

Overconfidence, instead, is a personal trait where people believe they are more competent or informed than they truly are. These individuals are often highly capable but hold an exaggerated view of their capabilities. Thus, overconfidence represents a perceptual error, not incompetence.

Statistically, overconfidence manifests when people set "too narrow a range" (the so-called "confidence interval") for the probable answer to a query, resulting in a lack of "calibration" in their judgments (miscalibration). Therefore, the correct answer often lies outside the overly restrictive range they choose.

Psychological research offers various interpretations of overconfidence, as highlighted by Fischhoff et al. (1977) and Moore and Healy (2008). Specifically, Moore and Healy (2008) categorize overconfidence into three distinct types:

1) Overestimation, where individuals have an inflated perception of their capabilities, achievements, control, or likelihood of success.
2) Overplacement, which is the belief of being superior to others.
3) Overprecision, characterized by unwarranted certainty in the correctness of one's beliefs.

In behavioral finance, instead, a common distinction is made between "overconfidence in one's abilities" and "overconfidence in one's knowledge or beliefs" (Shefrin, 2007). The former is when individuals believe they are more capable or effective than they truly are, and the latter is when they assume their knowledge is more extensive than it is. Therefore, "overconfidence in abilities" aligns with overestimation and overplacement, while "overconfidence in knowledge and beliefs" corresponds to overprecision. This latter form is thought to contribute to the underestimation of risk.

Although the link between risk underestimation and "overconfidence in knowledge and beliefs" is generally accepted in behavioral finance, it is less so in psychology. Thus, it is important to elaborate further; extreme certainty in the accuracy of one's knowledge or beliefs results in overly narrow estimation intervals for future outcomes. Given that these estimation intervals relate to standard deviation, the narrower the interval, the lower the perceived volatility. In behavioral corporate finance — the application of the behavioral approach to corporate finance — there is a significant focus on overconfidence in executive decision-making. Malmendier and Tate (2005) claim that CEOs with a high propensity to heavily invest in their own company's stock exhibit overconfidence. Overconfident chief executive officers (CEOs) display overestimation and overplacement, as well as under-diversification, leading to bearing an overly amount of idiosyncratic risk.

This is particularly relevant as both groups' compensation and human capital are significantly tied to their company's performance, meaning negative outcomes can adversely affect their personal wealth and future job prospects. CEOs of large corporations are frequently compensated through stock options, creating a unique incentive structure. These options encourage CEOs to boost their company's stock volatility, enhancing the value of their options (Malmendier & Tate, 2005). Consequently, CEOs face a balancing act between the risks of under-diversification and the potential gains from their stock options. Overconfidence may skew this balance by leading them to overestimate their ability to control future returns, which often results in delaying the exercise of their options. Malmendier and Tate's (2005) theory primarily considers the overestimation of CEOs' skills and self-attribution bias rather than overprecision. They note, however, that their framework might not fully apply in scenarios where CEOs overestimate the precision of their beliefs, as such miscalibration could actually lead to reduced expected stock volatility, thereby diminishing the value of their stock options.

While overconfidence (comprising overestimation and overplacement) and overoptimism are often used interchangeably in the literature, they are distinct concepts and should be treated as such. Echoing this distinction, Shefrin (2007) points out that overconfidence and excessive optimism, despite their interconnection, are not identical. A person could, for instance, be pessimistic yet exhibit overconfidence. Åstebro et al. (2007) further elaborate on this differentiation, noting that optimism is a feeling of anticipating positive life outcomes, whereas overconfidence is more individual-centric, relating to one's self-assessed ability and knowledge. Overconfidence implies that individual investors are unaware of their informational disadvantages relative to professional investors. A further ramification is that individuals tend to overtrade in their securities portfolios, thereby diminishing performance after accounting for transaction costs (Odean, 1998; Barber & Odean, 2000a). In exploring overconfidence within behavioral finance, various indicators have been utilized.

The "Better-than-Average" effect is a prevalent measure used to identify overplacement, as highlighted by Alicke (1985), Alicke et al. (1995), Alicke and Govorun (2005), and Kruger (1999). This effect is a key metric in assessing overconfidence, particularly in the context of overplacement. Other variables are often generalized to overconfidence without specifically addressing overestimation, overplacement, or overprecision. The variable "gender" is employed to address the well-documented observation that men are generally more overconfident than women, a finding supported by Barber and Odean (2001) and Hansemark (2003). This gender disparity in overconfidence is task-dependent, as demonstrated by Lundeberg et al. (1994), and is more pronounced in tasks traditionally viewed as masculine (Beyer & Bowden, 1997; Bönte & Piegeler, 2013; Deaux & Emswiller, 1974; Deaux & Farris, 1977; Lenney, 1977). Other authors observe that male executives are more prone to issue debt, engage in acquisitions, provide narrower earnings estimates, and delay stock option exercises than their female counterparts. These findings suggest a higher degree of overconfidence in men regarding critical corporate decisions.

Companies led by male CEOs typically have higher debt ratios compared to those headed by female CEOs. Faccio et al. (2016) further contribute to this discourse, revealing that firms with female CEOs tend to exhibit lower leverage, less volatile earnings, and reduced corporate risk-taking than their male-led counterparts.

The investigation of people's height aims to unravel its correlation with overconfidence. Height's importance transcends various domains, as seen in studies highlighting the "height gap". This concept points to the advantages taller individuals often enjoy including superior wages, profits, job positions, and overall happiness, compared to shorter individuals, as evidenced by research from Case and Paxson (2008, 2009), Deaton and Arora (2009), and Persico et al. (2004).

The disparity in earnings linked to height is comparable in scale to that associated with gender (Deaton & Arora, 2009; Persico et al., 2004). One plausible interpretation is that height plays a crucial role in fostering confidence, particularly during adolescence, which could later manifest as wage differences. This body of work implies that height could be a valid indicator of overconfidence.

Overconfident CEOs, particularly those who are taller and younger, are inclined towards riskier decisions and are more likely to steer growth-oriented companies. Overconfidence bolsters ambition, morale, perseverance, and determination (Bernoster et al., 2018; Johnson & Fowler, 2011).

Overestimation often arises from unrealistic expectations about task completion speed, leading to commitments beyond feasible limits (Moore, 2023). Bitler et al. (2005) use working hours as a metric for effort. Everett and Fairchild (2015) propose evaluating the entrepreneurial effort level or changes therein as a surrogate for overconfidence, arguing that entrepreneurs exert effort only if confident in the positive impact on their venture's success prospects. Otherwise, it would equate to knowingly squandering effort (Everett & Fairchild, 2015).

To comprehensively understand people's decision-making processes, it is vital to consider both overconfidence and overoptimism jointly not in isolation, integrating these biases concurrently, to provide a more holistic understanding of entrepreneurial behavior.

While the two biases are distinct, it is important to consider them jointly. Approaches that only consider one bias or treat them independently may not capture the entire scenario, potentially leading to flawed conclusions (J. S. Chen et al., 2018).

In financial matters, for example, overconfidence tends to make people underestimate the risks involved, whereas overoptimism leads them to overestimate the expected returns.
In another field, Åstebro et al. (2007) conducted a study on the inventors' persistence in the face of discouragement, uncovering that optimism plays a beneficial role, while overconfidence seemingly has no impact.

This finding was acknowledged by the authors as surprising, considering the extensive evidence of overconfidence effects documented in the literature (Burson et al., 2006; Kruger, 1999; Kruger & Dunning, 1999; Yates, 1990).

They differentiated two predominant forms of overconfidence identified in earlier research: "confidence in judgment" (termed as "overconfidence in knowledge and beliefs" by Shefrin, 2007, and "overprecision" by Moore and Healy, 2008), and "confidence in ability" (similar to the concept in Shefrin, 2007, and referred to as "overestimation and overplacement" by Moore and Healy, 2008). Åstebro et al. (2007) emphasized that their study primarily measured the first type, suggesting that the persistence of inventors might be more closely linked to the second type of overconfidence, which their study might not fully capture. Perseverance, the unyielding determination to continue despite obstacles, appears to align with what Åstebro et al. (2007) describe as “confidence in ability”, involving overestimation and overplacement. Nevertheless, our approach does not overlook the possibility that this trait might also be connected to overprecision. This link could enhance the entrepreneurs’ illusion of control, potentially skewing their perception of success likelihood and inadvertently leading them to underestimate risks.

1.2.5. Status quo bias and endowment effect

The concept of “status quo bias” plays a pivotal role in understanding human behavior, especially in the context of financial decision-making. Originating from the seminal work of Samuelson and Zeckhauser (1988), this bias describes an individual’s propensity to prefer their current situation over potential changes, even if the latter could lead to better outcomes. This resistance to change is not just a matter of comfort with the familiar but is deeply rooted in the fear of potential loss or deterioration of one’s situation. Tversky and Kahneman (1991) further elaborated on this by linking it to loss aversion, a foundational principle of their prospect theory. Loss aversion implies that the pain of losing is psychologically about twice as powerful as the pleasure of gaining, making the avoidance of losses a more significant driver than the pursuit of equivalent gains.

Status quo bias often manifests in decision-making as inertia or paralysis, where individuals avoid making choices that could disrupt their current state, leading to procrastination or complete inaction. This bias is evident in various real-world scenarios, such as investors sticking to a particular investment strategy despite changing market conditions or consumers remaining with their current service providers despite better alternatives. This behavior is often reinforced by default options that cater to the status quo bias, leading individuals to accept these defaults without actively seeking out potentially superior alternatives.

The “endowment effect” (Kahneman et al., 1990) is closely related to status quo bias and is another manifestation of loss aversion. The endowment effect posits that individuals tend to ascribe higher value to objects they own compared to those they do not, simply because of their ownership. This effect leads to an overvaluation of one’s assets, often irrationally so.

The underlying mechanism is believed to be an individual’s inclination to focus more on the loss of relinquishing an owned item rather than the gains from acquiring something new. This perspective on loss aversion is crucial for understanding why people might refuse profitable exchanges or sales.

Both the status quo bias and the endowment effect are influenced by a range of factors, some rational and others behavioral. On the rational side, factors like transaction costs and the effort involved in making a change can justify a preference for the status quo. However, behavioral factors often play a more significant role. These include not just loss aversion, but also the desire to avoid regret, cognitive biases like the familiarity heuristic (favoring the known over the unknown), and the sunk cost fallacy (continuing a behavior or endeavor as a result of previously invested resources).

Recent studies have continued to explore these phenomena. Morewedge and Giblin (2015) delving into how this effect varies across different cultures and contexts, indicating that it might not be as universally prevalent as once thought.

Understanding these biases is crucial, especially in fields like behavioral finance, where they can significantly impact investment decisions, market dynamics, and financial planning. Recognizing the influence of status quo bias and the endowment effect helps investors, policymakers, and financial advisors make more informed, rational decisions that account for these often subconscious biases.

1.3. Heuristics

Heuristics are cognitive shortcuts or “rules of thumb” that facilitate decision-making. They are particularly useful in everyday situations where quick, intuitive judgments are required. However, when these heuristics are applied to areas that demand rigorous technical and scientific analysis, such as finance or business, they can lead to high error rates. Heuristics are deeply rooted in cognitive biases. The terminology describing various heuristics often stems from the specific cognitive errors they are associated with. This forms a logical sequence: individuals have an inherent bias that predisposes them to a certain mistake, they then apply a heuristic to simplify their decision-making process, and the use of this heuristic leads them to commit the predicted error. To delve deeper into heuristic processes, we present well-known heuristics in literature such as availability, representativeness, anchoring, ambiguity aversion, and the affect heuristic.

1.3.1. Affect heuristics

Decision-making is often guided by instinct or emotion (Loewenstein et al., 2001; Slovic et al., 2002). Psychologically, the appraisal of a stimulus is not determined by precise mathematical rules but through an affective value that ranges from very positive to very negative. While intuition can be initially beneficial, judging something like an investment project requires a transition to more quantitative and rigorous analyses.

Relying on memories of past experiences, which may not be repeated, can lead to erroneous conclusions (Kahneman & Riepe, 1998). It is important to differentiate between “affect” — an involuntary emotional response to a stimulus — and “affect heuristics”, that is how these emotions can sway the decision-making process, prompting intuitive rather than logical choices. Studies from the early 1980s on affect heuristics (Zajonc, 1980) suggested that affective responses are the brain’s initial automatic reactions, subsequently influencing cognitive processes and judgments. More recent research (Finucane et al., 2000) has indicated that a positive sentiment towards a situation leads to a distorted perception that underplays risks and exaggerates potential benefits. The affect heuristic’s influence is so potent that it often preserves the initial impression, even in the face of contrary cognitive evidence. This heuristic pervades numerous decision-making scenarios. In finance, it fosters misconceptions about the risk-return dynamic, making people wrongly assume that risk and return are inversely related, contrary to traditional finance which posits a direct proportionality between risk and expected returns.

1.3.2. Anchoring

The concept of “anchoring” originates from the term “anchoring and adjustment”. It illustrates how individuals, in decision-making, tend to cling to an initial reference point — the “anchor” — and adjust based on new information, usually inadequately. An example in finance is an investor using the purchase price of a stock or its historical high as a mental anchor, which then becomes the yardstick for assessing gains and losses. These mental anchors restrict our perspective, permitting only minor deviations from the established reference value. The prominence of the anchor determines its influence on the individual, often resulting in insufficient adjustments to the reference point when weighing gains and losses, thus affecting probability estimation. For instance, when setting a confidence interval for an answer, anchoring can lead to overly narrow intervals due to an overreliance on the initial value provided (narrow framing).

This bias extends to the misperception of probabilities for joint or separate events. Using the probability of a base event as a reference often leads to an overestimation of the likelihood of combined events, even though the probability of a joint occurrence is inherently less than that of any single event. Conversely, there is an underestimation of disjoint events.

Kahneman et al. (1982) illustrate this with a nuclear reactor’s risk assessment, where the low probability of failure for each component might lead to underestimating the overall risk of catastrophe given the multitude of components in a reactor.

An anchor, such as the failure probability of individual components, may lead a proponent of nuclear energy to underestimate the aggregate risk of an accident.

1.3.3. Availability

The availability heuristic influences decision-making based on the most readily recallable information. For instance, when asked to choose the more common cause of death between “murder” and “heart attack”, individuals may opt for “murder” due to its frequent, sensational coverage in the media. In contrast, heart attack cases, which typically receive less media attention, might not come to mind as readily. This leads to the “availability bias” (Tversky & Kahneman, 1973), where people overlook the statistical evidence that heart attacks are significantly more common than homicides. From a statistical standpoint, people often overlook foundational data (such as the frequency of heart attacks compared to homicides) in favor of more recent and readily accessible information (like the extensive media coverage of homicides). Availability bias is the inclination to recall and thus prioritize easily retrievable information, while the associated heuristic leads one to erroneously infer that death frequencies are dictated solely by the number of remembered incidents. Proclaiming homicides as the leading cause of death over heart attacks exemplifies this error. A key factor reinforcing availability bias is memory's tendency to favor the recollection of recent events (recency effect) and personal experiences over statistical data, due to their emotional resonance. Personal experiences often carry twice the influence of statistical facts, which lack an emotional component.

The emotional impact is significant not only in the sourcing of information but also in assessing its importance. However, the most accessible information is not always the most pertinent. A rational person should discern the true significance of available data.

Psychological research indicates that it is the frequency of information presentation, rather than its relevance, that people commonly use as a benchmark. Information possesses two qualities: strength and weight. Confusion between these can lead to either overreaction or underreaction to the information, depending on its perceived significance. Griffin and Tversky (1992) suggest that high-strength, low-weight information prompts overreaction, whereas the opposite triggers underreaction.

The media’s influence is pivotal, as evidenced by research on news that grabs the attention of both individual and institutional investors. Barber and Odean (2008) observed that the prominence given to a news story alters public perception of its frequency or importance. Thus, company visibility in the news can sway investors, regardless of whether the coverage pertains to fundamental company values. This effect is observed even when the news does not concern company fundamentals. Similar behaviors have been documented in the Italian market regarding investors' reactions to press-reported information (Cervellati et al., 2014).

1.3.4. Familiarity

Familiarity is a shortcut that people use when making decisions or judgments, relying on familiarity or recognition as a guide. This heuristic is often used when individuals face complex decisions and need to simplify the process. It describes the tendency for people to favor the familiar when making choices. This is grounded in the theory that familiar items are perceived as safer or better. Familiarity also plays a significant role in areas like marketing, consumer behavior, and investment decisions. When individuals are presented with familiar brands or products, they are more likely to choose them over unfamiliar ones. While familiarity simplifies decision-making, it also has limitations and can lead to suboptimal outcomes. Overreliance on familiar information can result in neglect of novel or superior options (Gilovich et al., 2002). The influence of the familiarity heuristic may vary across different cultural contexts. Research in cross-cultural psychology highlights how cultural upbringing can affect reliance on familiarity in decision-making (Nisbett & Miyamoto, 2005). The ongoing research continues to explore the nuances of familiarity, particularly in the digital age where information overload is common. Emerging studies focus on how the internet and social media influence the reliance on familiarity (Thorson, 2016). Familiarity leads to “home bias”, which is the evidence of investors’ tendency to favor investments in companies that feel more familiar, whether due to geographical proximity (national or local companies) emotional connections (a sense of belonging), or an illusion of knowledge, such as investing in one’s employer (Huberman, 2001). This bias leads to the under-diversification of portfolios, increasing exposure to specific risks.

1.3.5. Representativeness

The traditional finance paradigm posits that individuals are rational and capable of efficiently assimilating and processing information. Classical theory suggests that, when presented with new data, one should engage in “Bayesian updating” to make decisions. Bayesian statistics involves appropriately balancing the significance of new information against pre-existing data (often referred to as “base” or a priori information). Thus, individuals should theoretically update their existing knowledge base, assigning proper weight to both new and old information. However, in practice, people do not typically engage in such rigorous probabilistic thinking. Instead, they often default to using the representativeness heuristic in their information update processes. Representativeness is a heuristic where decision-making is driven by analogies or how closely a situation aligns with a specific stereotype in one’s mind. The perceived probability of an event is influenced by how “representative” the event seems of a certain category or how similar one situation is to another that is familiar.

Consider the following example: You are tasked with guessing the occupation of Linda, a thirty-year-old, single, outspoken, and intelligent woman who was deeply involved in social justice during her college years. Although Linda’s friends, who claim to have good knowledge of her, have not provided current details about her interests or career, you are given eight possible occupations to choose from. The options suggest that Linda could be:

a) a primary school teacher;
b) a bookstore manager with a passion for Yoga;
c) an activist in feminist movements;
d) a social worker;
e) a member of the Association of Women Voters;
f) an insurance company employee;
g) a bank teller;
h) a bank teller and an activist in feminist movements.

What does Linda do? Commonly, people deduce that Linda is likely to be involved in feminist movements or work as an elementary school teacher or social worker, while fewer envision her as a bank teller or clerk. Consider this: does Linda epitomize the typical bank teller, or does she resonate more with someone active in feminist movements? The latter seems more representative. Yet, this is contrary to the rational process advocated by classical economic theory, where representativeness often leads to overemphasis on new information at the expense of basic data. For Linda, the base information is that more women in their thirties work in banking or insurance than as teachers or activists. While Linda’s characteristics are relevant, representativeness errs by assigning them too much weight.

The so-called “conjunction fallacy” associated with representativeness involves violating probability laws. Many might say Linda is more likely to be a bank teller active in feminist movements than merely a teller. Probabilistically, this is flawed since the word “and” in the phrase “a bank teller and an activist in feminist movements” denotes a joint event’s likelihood, combining “Linda is a bank teller” and “Linda is an activist in feminist movements”, which is misconstrued by the conjunction fallacy.

The “small sample bias” reflects overvaluing evidence from small samples inadequate for inferential purposes. Contrarily, the “law of large numbers” suggests that averages from repeated, independent trials converge on the expected value over time.

Moreover, individuals often overlook the principle of reversion to the mean, confusing it with alternating sequences of above or below-average values. Reversion to the mean indicates that values gravitate back towards the average, not that a sequence below the average necessarily predicts subsequent above-average results.

These misconceptions give rise to the “gambler’s fallacy”, where individuals expect a reversal in deviations from expected behavior in random processes, mistakenly assuming a negative correlation between successive trials, such as anticipating a run of tails after a streak of heads, despite the constant 50% probability for each flip.

1.4. Framing effects

1.4.1. Loss aversion and aversion to a sure loss

A "frame" refers to the context or method in which a decision-making problem is presented to an individual.

While traditional finance promotes frame independence, where only the substance of the decision should matter, behavioral finance posits that the framing of information is also critical. Loss aversion illustrates that the pain of a loss exceeds the pleasure derived from an equivalent gain. In practical terms, losing $100 is significantly more distressing than the satisfaction of gaining $100.

Psychological studies have quantified that losses are weighted roughly 2–2.5 times more heavily than equivalent gains. Therefore, the displeasure from losing €100 might only be offset by a gain of about €200–250.

"Aversion to a sure loss", however, describes a propensity to take on more risk following a loss in hopes of recuperation or breaking even. This leads to an asymmetrical approach to potential gains versus losses. To illustrate, consider having to choose between a definite loss of €75 or a 75% chance of losing €100 (with a 25% chance of no loss at all). Many people will gamble to avoid the sure loss. Similarly, if one has already lost €74, given the option to accept the loss or risk losing €100 with a 75% probability, the inclination is again towards the risky choice, despite unfavorable odds.

The underlying motivation is the hope of overcoming the odds or breaking even. However, this drive can compel investors to take unnecessary risks to avoid recognizing losses, which can verge on becoming pathological, a condition termed "get-even-it is".

1.4.2. Mental accounting

Mental accounting (Thaler 1985, 1989) refers to the cognitive process where individuals categorize their finances into distinct "mental accounts". These accounts represent separate pools of money, each earmarked for different purposes, contradicting the traditional finance notion that money is fungible.

Finances are often divided into two major categories reflecting consumption tendencies: current and future income. The "current income" mental account encompasses funds meant for immediate spending, like cash on hand, checking and savings accounts, and even short-term bonds. Conversely, the "future income" account is allocated for long-term objectives, such as retirement savings, and is usually associated with a much lower consumption propensity.

The creation, management, and closure of these mental accounts are not always executed logically but are often influenced by heuristics from past decisions, leading to potential errors. For instance, after incurring substantial losses in a specific mental account, one might be inclined to undertake more risk to recoup the losses.

An illustrative scenario of mental accounting is proposed by Thaler and Johnson (1990). Consider the following simultaneous choices, where one must decide on a "package" of options:

1) Choose from:
   A. a guaranteed gain of €2,400, or
   B. a 25% chance to gain €10,000, with a 75% chance of gaining nothing.
2) Choose from:
   C. a guaranteed loss of €7,500, or
   D. a 75% chance to lose €10,000, with a 25% chance of no loss at all.

In making these choices, mental accounting can significantly sway one's preference for each option. Analyzing responses provides insight into decision-making processes.

Suppose you chose A in the first scenario, opting for the risk-free option. Although the certain gain of €2,400 from this option is less than the expected value of alternative B (€2,500), many choose the certain option over the riskier one, especially when the expected gain is not substantially greater. Conversely, experimental results indicate that about 90% select D in the second scenario, demonstrating an aversion to sure loss. Despite these decisions forming a combined "package", individuals often segment them into separate mental accounts.

Mental accounting can lead to errors due to frame dependence within the decision context. The clarity of the presentation of options matters; transparent framing simplifies decision-making, whereas opacity complicates it. Now, consider these choices:

E. 75% chance to lose €7,600 and a 25% chance to gain €2,400, or
F. Option E with an additional €100 in both outcomes.

Rationally, one should select F, as it offers an extra €100 in all scenarios. The discerning reader will recognize this as the same decision presented in the original "package". Specifically, F yields a 25% chance of gaining €2,500 and a 75% chance of losing €7,500. However, while the framing in question two is transparent, in the first scenario (the dual decision package), it is opaque, making the choice more challenging. Thus, most people end up selecting options A and D together, coinciding with the result of E. Alternatively, choosing B and C could result in a more favorable outcome: a 25% chance of winning €2,500 and a 75% chance of losing €7,500, mirroring the result of option F. In conclusion, through an opaque frame, many fail to choose the more rational option.

1.4.3. Hedonic editing

Reflect on these two scenarios (Thaler & Johnson, 1990):

I. Receive €1,500 for certain or engage in a game where a coin flip decides a win of €1,950 for heads or €1,050 for tails.

II. Accept a sure loss of €750, or take a gamble where heads result in a loss of €525 and tails in a loss of €975.

Typically, individuals opt for the guaranteed €1,500 in the first case due to risk aversion, but prefer to gamble in the second case, demonstrating risk-seeking behavior to avoid a sure loss. This aligns with prospect theory (see section 1.6), which suggests that risk attitudes vary when assessing gains versus losses. Further insights emerge from these examples:

i. You have won €1,500 in a lottery and have a chance to enter a second lottery based on a coin flip, winning €450 for heads and losing €450 for tails. Would you participate in the second lottery after the first win?

ii. Now, imagine losing €750 in a lottery, but you can enter another lottery where heads win you €225, and tails lose you €225. Would you join this second lottery after the initial loss?

Comparing option i with option I, though monetarily equivalent, often yields different choices, challenging the classical financial theory. Data indicates an average of 25% are more risk-inclined in option i than in option I, attributed to hedonic editing, which is how individuals arrange their mental accounts to maximize pleasure.

In option i, a potential €450 loss is mentally aggregated with a €1,500 gain, netting €1,050, similar to option I. However, wins are typically savored individually.

People show a preference for risk in option i over option I because the chance to enjoy two separate gains is appealing. Regarding options II and ii, evidence shows over 75% risk the gamble over accepting a sure €750 loss in the former. Yet, despite their monetary equivalence, nearly half of the participants switch from risk-taking in option II to risk-aversion in option ii. This suggests that losses tend to be mentally "pooled", amplifying the "pain" of a €225 loss following a previous €750 loss.

1.4.4. Cognitive and emotional aspects in framing effects

Addiction to frames is influenced by both cognitive and emotional biases. The cognitive side concerns how individuals process information, while emotional biases are related to the feelings elicited during this process (Shefrin, 2002). In the context of the previous example i, the cognitive aspect involves considering or dismissing the initial win of €1,500 when deciding whether to engage in a new gamble.

These cognitive biases often work in tandem with emotional reactions. Some may disregard the €1,500, feeling a loss of €450 and the associated negative emotions; others may factor in the initial win, perceiving not a loss but a reduced win of €1,050.

This distinction significantly influences behavior, with those overlooking the initial win likely being more risk-averse compared to those who feel they are already ahead by €1,500.

Typically, people are risk-averse with potential gains but become risk-seeking in the face of losses, a phenomenon that forms the basis of prospect theory outlined in section 1.6. This behavior is identified as the "house money effect" (Thaler & Johnson, 1990), named after a casino term. "House money" refers to funds provided by casinos to patrons, which are to be used only for gambling. This incentivizes customers to gamble more since they perceive they are not risking their own money, but rather a "gift". However, after quickly losing the initial sum, patrons often feel at a loss and become prone to risking their own funds. Rationally, this should not feel like a personal loss, yet due to the endowment effect, once the game begins, any loss becomes personal (Kahneman et al., 1990).

Individuals often grapple with self-control in various aspects of life. Consider the challenge of forgoing a dessert while dieting or resisting a cigarette when trying to quit smoking. Commonly, self-control issues arise when decisions affect the future; people tend to forsake long-term objectives for immediate satisfaction, failing to fully consider the future impact of present choices. The bias of self-control is thus the tendency to overvalue immediate outcomes at the expense of future benefits, leading to insufficient savings, neglecting insurance or pension plans, or abandoning advantageous long-term investment strategies due to an inability to appreciate future gains from present decisions.

Those aware of their willpower limits may set rules to enforce self-discipline. "Limited willpower" acknowledges the human tendency to favor short-term benefits over more significant long-term rewards (Mullainathan & Thaler, 2000). For instance, faced with a future tax payment of €6,000, one might save €500 monthly in an account or opt for a direct monthly deduction from their salary. While rationality favors savings to accrue interest, many choose direct deduction to avoid the risk of self-control lapses.

Regret, the emotional response to past actions or inactions, can be more intense for missed opportunities than for actions taken. Deviating from the conventional can heighten vulnerability to regret if outcomes are unfavorable (Kahneman et al., 1982). This feeling can lead to cognitive dissonance, a psychological conflict that arises from the realization of incorrect beliefs. To mitigate dissonance, people may avoid new information that exacerbates their error, preferring to find justifications, even flawed ones, that sustain their initial beliefs. Regret theory examines the relationship with negative events (Loomes & Sugden, 1982). Regret is often quantified as "difference regret", the gap between the actual outcome and what could have been, or as "ratio regret", comparing the actual result with the optimal one.

1.5. Debiasing

In behavioral finance, a crucial challenge is debiasing, that is the rectification of biases' detrimental effects. This corrective process demands considerable effort and utilizes various techniques, each tailored to the specific bias at hand but generally reliant on repetitive, defined procedures. Overcoming ingrained behavioral errors is strenuous as they are deeply embedded in the brain and resistant to change. While recognizing an error is the initial step toward rectification, debiasing necessitates more deliberate and systematic actions. Effective learning occurs most readily when decisions yield immediate and discernible outcomes. If feedback on choices is instead belated or unclear, the learning process wanes. Regrettably, financial decision outcomes are often delayed and ambiguous, influenced not just by the investor's actions but by external factors outside their control. Success in investments may be attributed to personal acumen or favorable market conditions, while negative results may be blamed on poor choices or market shocks. Investors frequently credit themselves for gains (self-attribution bias) and fault external factors for losses (attribution bias). Consequently, learning in the financial realm is typically sluggish and ineffectual, underscoring the need for debiasing methods where conventional learning falters.

As noted, errors can be cognitive or emotional. While the latter are harder to eliminate, the former may be addressed initially through financial education. However, the effectiveness of financial education programs is contentious: while their importance is acknowledged, they are not alone sufficient in remedying investors' mistakes.

Elevating financial literacy is crucial, but educational efforts must account for the behavioral issues highlighted. Cognitive limitations and information management errors can thwart proper learning. The debate is ongoing about the responsibility for initiating financial education, that is whether it should fall to individuals, financial regulatory bodies, or governments.

In conjunction with financial education, disclosure rules attuned to behavioral finance findings are essential. Merely obliging financial intermediaries to inundate clients with information is not sufficient. Such an approach incurs high costs for the savings industry and does not necessarily benefit investors. What matters more is the relevance of the information and the manner of its presentation. Hence, both informed financial education and carefully crafted disclosure rules are needed to counteract the adverse effects of behavioral biases.

Furthermore, devising a system that encourages financial advisors to assist clients with debiasing procedures is prudent. Given the difficulty individuals face in correcting their biases, the expertise of financial professionals is invaluable, not only for technical advice but also for applying debiasing techniques effectively. Individuals are prone to narrow framing, focusing too intently on the immediate decision at hand, often at the expense of the bigger picture.

An external expert, such as a financial advisor, when well-qualified, can aid the investor in regaining a comprehensive perspective. Advisors must establish clear communication regarding expectations, investment goals, and the strategies to achieve them (see section 3.1 describing the motivational theory, also called "SP/A" by Lopes, 1987).

Simultaneously, they should educate clients about the psychological traps that may arise during the investment journey. The advisor should adopt the approach of a "financial physician", a concept introduced by Statman (2002). Like a family doctor who may not be a specialist but knows the patient's history, personality, and how they might respond to treatments, a financial advisor needs not to be a specialist, like a fund manager. Instead, the advisor requires sufficient technical knowledge to guide the client, understanding their financial literacy, investment history, and risk tolerance to anticipate their reaction to market fluctuations. This insight allows advisors to gauge whether their clients will adhere to the investment plan or stray from it.

Before advisors can aid their clients, however, they must first be capable of recognizing and amending their own biases. Overconfidence, often stemming from illusions of control and knowledge and exacerbated by confirmation bias, requires critical evaluation of supporting evidence and openness to contrary viewpoints as a debiasing method. Regularly practicing this exercise proves valuable. To mitigate anchoring effects, for example, it is important to periodically reassess and validate one's mental anchors to ensure their continued relevance. Moreover, overcoming the bias of aversion to certain losses involves redefining reference parameters to treat past costs as sunk and irrelevant, enabling individuals to move past previous losses without lingering influence.

1.6. Choices under uncertainty

Risk is a cornerstone in financial decision-making. Generally, risk is distinguished from uncertainty, with risk seen as objective and quantifiable, and uncertainty as more elusive and subjective (Knight, 1921). Traditional finance, employing classical statistics and probabilistic calculus, has developed variables to measure risk and determine expected return by assigning probabilities to future states of the world. Volatility is the traditional statistical measure of an equity security's total risk, accounting for both negative and positive deviations from the mean. However, people often perceive only negative events as risky, making semi-variance a more suitable risk measure.

Markowitz (1959) evaluated various risk measures' strengths and weaknesses. Statistical measures imply that risk is objectively quantifiable, but in reality, risk perception is multi-faceted — encompassing risk tolerance, capacity, and knowledge — and varies with the situation and the individual's state of mind.

Emotional factors can also sway risk perception, which fluctuates with our emotions (Loewenstein et al., 2001).

Behavioral finance primarily examines how cognitive distortions affect risk perception. Behavioral theories argue that risk is inherently subjective and attempts to measure it are merely rationalization efforts that fail to capture its many facets (Slovic, 2000). For instance, risk appetite varies depending on whether evaluating gains or losses, common or rare events, and individual aspirations and goals. Risk tolerance shifts with objectives, challenging the definition of a singular risk profile for each person. The behavioral biases, decision-making heuristics, and framing effects distort risk perception not just for retail investors but also for professionals like portfolio managers, financial analysts, managers, and entrepreneurs.

In traditional finance, decisions under uncertainty are based on the theory of expected utility, but behavioral finance highlights that decisions are actually influenced by prospect theory. Prospect theory, a descriptive rather than prescriptive theory, is founded on three main characteristics identified through experimental evidence, showing that actual human behavior often contradicts the rationality assumed in expected utility theory. These characteristics are the “isolation effect”, the “reflection effect”, and the “certainty effect”. However, before delving into these effects, it is crucial to acknowledge the core premise of prospect theory, namely frame dependence, which manifests in two stages: editing and evaluation. The editing stage involves framing the decision-making problem, aiming to simplify the representation of various options to ease the subsequent evaluation process. During this phase, outcomes are categorized in terms of gains or losses relative to a reference point, which could be an individual’s current situation (status quo), such as their level of wealth. In the context of selling a security, the reference point often becomes the security’s purchase price. It is noteworthy that the reference point can be shaped by the framing itself, as well as by individual expectations. The editing phase involves not just the categorization of gains and losses but also other crucial processes such as combining probabilities of options with identical outcomes, eliminating certain parts of lotteries, and discarding elements common to multiple options. This final operation, known as the isolation effect, highlights individuals’ tendency to disregard elements common to various choice options, focusing instead on differential issues. This involves disregarding unlikely events, identifying dominant choices, and eliminating dominated ones. However, overly emphasizing differential elements at the expense of common ones can lead to judgment errors. The reflection effect relates to how people respond to potential gains or losses. Experimental findings indicate stark differences in behavior for these scenarios. When faced with potential gains, individuals generally exhibit risk aversion, preferring a “certain equivalent” over a risky gamble. Conversely, when potential losses are involved, people are more likely to opt for a risky bet than accept a certain loss.

This decision-making occurs in the evaluation stage of prospect theory, where the central element is the “value function”, a behavioral parallel to the utility function in traditional approaches. This function is influenced not by absolute wealth levels but by changes relative to a pre-established reference point. It is widely recognized that individuals’ perceptual and judgment systems are geared towards assessing changes against a reference point, rather than focusing on absolute wealth levels. This does not imply total wealth is irrelevant, but its inclusion in prospect theory could have overcomplicated the framework. Omitting this detail simplified the theoretical model without altering the core concept of evaluating gains and losses relative to the reference point.

Prospect theory contrasts with traditional finance’s assumption that individual preferences are expressed in terms of absolute wealth levels and that risk attitudes remain constant. Traditional finance categorizes individuals as risk-averse, neutral, or risk-seeking, but not as varying between risk-averse and risk-seeking depending on the situation.

The value function in prospect theory is distinguished by its intersection with the axes, marking the reference point against which gains and losses are evaluated. In the gain domain, to the right of this point, the function exhibits concavity due to individuals' risk aversion. In the loss domain, to the left of the axis intersection, it shows convexity, reflecting their appetite for risk.

Although the evaluation phase follows the editing phase, it is evident that framing significantly influences individual choices. How the choice is framed, either as achieving gains or avoiding losses, affects the final decision. Consequently, the value function is characterized by a distinct asymmetrical S shape, with a transition from convexity to concavity at the reference point.

It is conceivable that the value function in prospect theory may not perfectly mirror reality: there could be intervals of convexity within the gain area and concavity within the loss domain. Nonetheless, experimental evidence suggests that prospect theory accurately represents the behavior of most people.

Another key aspect of prospect theory is the framing effects. Among these, the theory highlights loss aversion and aversion to certain losses. Generally, individuals are loss-averse, assigning about two and a half times more weight to losses than to gains of equivalent magnitude. Graphically, this manifests as the value function being steeper in the loss domain than in the gain domain. For example, a change of 100 impacts value differently depending on whether it is a gain or a loss. In the case of a gain, the value increases by 100, whereas a loss results in a value decrease of 250, precisely 2.5 times the change in the gain scenario. Loss aversion is evident in people's reluctance to accept a loss, often leading them to take on more risk to "break-even". Geometrically, this effect causes the value function's convexity in the loss area, indicating individuals' risk appetite.

Value changes are also influenced by an individual's wealth level. In the earnings domain, for example, the value function is concave: value increases with earnings, but less than proportionally. The "true" preferences of individuals may diverge from prospect theory's value function, with discontinuities reflecting cognitive process limits.

The certainty effect is the tendency for individuals to overly weight the probabilities of events deemed almost certain or almost impossible. For instance, if the likelihood of an event is perceived to be over 90%, it is often regarded as certain. Conversely, an extremely unlikely event is perceived as impossible. The psychological impact of an event is thus greater if it is seen as certain (or impossible), rather than just probable. In essence, individuals overly focus on events with extreme probabilities and underemphasize those with intermediate probabilities. Even slight variations in probability, which push an event into the realm of certainty or impossibility, are overemphasized. The shift from a 10% to a 20% probability level is not the same as from 90% to 100%, as the latter shift signifies event certainty. However, the value function alone cannot explain why individuals buy lottery tickets or insurance policies, despite the expected loss. The probability weighting function, accompanying the value function in prospect theory, effectively explains behaviors under the sub-certainty property. This necessitates replacing the traditional linear probability function with a nonlinear probability weighting function. This function, not the original from 1979 but from Tversky and Kahneman's (1992) cumulative prospect theory, adjusts event probabilities to account for the certainty effect. The positioning of probabilities reflects individual preferences, with the slope of the weighting function measuring preference sensitivity to probability changes. The curve's initial concavity and subsequent convexity mirror the earlier mentioned subadditivity and over-additivity. Moving away from certainty and impossibility, the curve flattens and diverges from the bisector, deviating from the expected utility theory's linear probability preferences.

This phenomenon, known as "sub-certainty", means that in situations where an event is merely "probable" and not certain, the sum of the weighting function values for that event and its complement does not equal one, failing to represent a certain event.

While the prospect theory weighting function might not perfectly match individuals' "true" preferences, with potential discontinuities reflecting cognitive limitations, its value lies in explaining decisions swayed by the emotional impact of events perceived as unlikely yet associated with significant gains or losses.

For instance, people buy lottery tickets despite the low winning probability (yielding an expected value below the ticket cost) because the substantial prize pool captivates them, fulfilling desires for victory and wealth. Conversely, the fear of catastrophic outcomes from an accident can lead many to oppose nuclear energy use. Thus, the certainty effect sheds light on why people purchase insurance policies, often at actuarially unfair premiums, to avoid potentially large payments in the case of highly negative, albeit extremely unlikely, events. Ambiguity aversion, or uncertainty aversion, highlights a preference for known risks over unknown ones. This is not merely risk aversion, as the acceptance or rejection of risk here is grounded in their certainty or uncertainty, not their magnitude. Beyond the certainty effect and ambiguity aversion, another intriguing concept is "source dependence", which indicates that people prefer to engage in games with familiar themes and uncertain outcomes, rather than gamble on unknown topics, even with known success or failure probabilities (Heath & Tversky, 1991).

While the value function can order individual preferences, it does not accurately represent the scale of evaluation. This complexity arises in prospect theory because the weighting function does not adhere to probability axioms like in expected utility theory, complicating preference level measurement.

CHAPTER 2: MARKET ANOMALIES AND INDIVIDUAL INVESTORS

2.1. Market anomalies

Equity markets periodically undergo phases of widespread over-optimism or euphoria, exemplified by the dot-com bubble of the late 1990s and early 2000s, as well as periods of fear or even panic, vividly demonstrated by the financial crisis of 2007–2009 or the one that followed the COVID-19 pandemic. Historical market crashes have also revealed that markets can incur substantial losses without clear reasons tied to underlying fundamentals. Post the 1987 crash, for instance, the observed market volatility far exceeded what the available information at the time would have justified (Shiller, 2000).

The behavioral perspective asserts that these price deviations from equilibrium are partly due to cognitive mistakes made by individuals, the decision-making heuristics they employ, and framing effects. However, before delving into the 'inefficiencies' of the market, it is essential to clarify what economists understand by efficiency.

There are various interpretations of efficiency, but this discussion focuses on the concept of “informational” efficiency, specifically the well-known efficient market hypothesis (EMH) proposed by Eugene Fama in 1970. EMH has been the cornerstone of traditional finance since the 1970s and remains a fundamental tenet of the neoclassical viewpoint. Literature typically categorizes informational efficiency in markets into three forms: weak, semi-strong, and strong. The weak form asserts that current prices reflect all historical information; the semi-strong form suggests that markets integrate not only past but also all current publicly available information; and finally, the strong form hypothesizes that even private information is reflected in market prices. Under the tenet of strong efficiency, insider trading activities should not yield profits. The available evidence shows otherwise.

In the 1960s and 1970s, the evidence supported the market efficiency hypothesis — particularly in its semi-strong form — leading traditionalists to argue that a security’s market price mirrored its intrinsic value. They believed deviations from equilibrium prices were minor, rare, and temporary (Fama, 1965). Consequently, they posited that investors could not systematically achieve excess returns.

However, in the 1980s, emerging research began to challenge some core issues of the efficient market theory. Traditionalists labeled such findings as “anomalies”, conflicting with the market efficiency assumption. In contrast, behaviorists referred to them as “regularities”, highlighting their persistence without necessarily implying market inefficiency.

The 1990s saw the debate escalate to a new level. As market anomalies (regularities) became undeniable, the discussion shifted towards the causation of these market behaviors.

Traditionalists maintained that these phenomena could be explained by risk factors.

This notion, coupled with the observation that the traditional asset pricing model such as the capital asset pricing model (CAPM) was no longer fully accounting for observed market returns, led to the development of alternative pricing models. One notable example is the “three-factor” model (Fama & French, 1992, 1993). This model suggested that securities from smaller companies and “value” securities (those with a high book-to-market ratio) tended to outperform stocks from larger companies and “growth” stocks (with a low book-to-market ratio).

Behaviorists, instead, claim that market regularities cannot be explained by referring to risk factors, but by behavioral factors.

We classify market anomalies whether they are dependent on:

1) Calendar-based factors or seasonal trends (calendar or seasonal);
2) Fundamental characteristics of the issuers (cross-sectional);
3) Occurrence of specific corporate events (event-based);
4) Autocorrelation of short and medium-to-long-term returns (momentum and reversal).

Notably, while the first three types of regularities challenge the semi-strong efficiency hypothesis, underscoring the potential to predict future security returns based on current and publicly available information, the fourth type starkly contrasts with the weak form of efficiency, given its reliance on return autocorrelation, suggesting the possibility of achieving excess returns based on historical data.

2.1.1. Calendar or seasonal anomalies

Seasonal and calendar-based anomalies encompass regularities tied to specific times of the year, days of the week, or even climatic variations, often referred to as "weather-related anomalies".

Traditionally, the size effect has been predominantly observed in January, a month where listed companies, especially smaller ones, have tended to yield higher returns than the broader market and other months. This convergence of the size effect with January indicates that companies experiencing abnormal returns during this period are typically smaller in scale. Acknowledged by both traditional and behavioral finance theories, the explanations offered differ considerably. Traditionalists have pointed to the potentially greater risk associated with small caps relative to blue chips and a tax-based rationale. The increased returns of small companies in January are attributed to individual investors who often sell these stocks in December for tax loss harvesting, only to repurchase them in January (Ritter, 1988). This end-of-year selling pressure leads to an undervaluation of these stocks in December, with the positive abnormal returns in January being seen as a market correction, realigning the prices of small company stocks with their true value. This argument is also supported by analyses that have shown that the January effect is concentrated in the first weeks of the month (Haugen & Lakonishok, 1988).

The demand surge for small caps would lead to a diminishing and eventual disappearance of anomalous yields. The "January effect", prominent until the 1990s, saw a resurgence in the 2000s, as noted by Siegel (2007). This effect, while predominantly affecting smaller companies, extends more broadly. An additional explanation is the beginning of the year, an opportune time for markets due to new capital inflows. Individual investors often have more funds for stock market investments due to year-end bonuses, while institutional investors, planning annual management and potentially rebalancing portfolios, might use liquidity from closing positions at the previous year's end.

Another notable seasonal regularity is the so-called "Sell in May and go away" strategy (Bouman & Jacobsen, 2002), based on historical patterns of higher equity market returns in early months, followed by a decline from May. This trend might largely stem from the January effect.

Calendar regularities also include the well-known "Weekend effect", or "Monday effect", characterized by historically lower average returns on Mondays, compared to other days of the week. The traditional explanation attributes this to the release of bad news when markets are closed, typically over weekends, with Monday's downturn reflecting reactions to such news. The behavioral explanation, instead, links this evidence to investors' moods, often lower on Mondays as they return to work, leading to a selling tendency that depresses stock markets. This mood-based interpretation also accounts for the "Friday effect", where returns on Fridays tend to be higher than on other days, driven by the anticipation of the weekend and resulting optimism among market participants.

The third category of seasonal regularities encompasses climate-related anomalies. Research indicates that stock markets usually fare better on sunny days compared to gloomy weather, attributing this trend to the impact of weather on people's moods. A positive mood is thought to heighten individuals' risk tolerance, thus increasing buying activity in the stock market.

Broadly, these mood-based studies could also explain other regularities, like the weekend effect or the observed underperformance during autumn months, a period marked by shorter days and reduced daylight.

2.1.2. Cross-section anomalies

Cross-section regularity pertains to findings across multiple companies over the same observation period, with no variation in the observed phenomena over time. For a more detailed examination of the regularities observed in international financial markets, consult the works of Daniel et al. (1998) and Fama (1998).

Traders commonly utilize price-to-earnings ratios and price-to-book ratios to differentiate between growth and value stocks. Value stocks, typically marked by lower indices, have historically outperformed growth stocks, which are often identified by higher values of the said ratios.

Alongside the size effect, these are the most explored cross-section regularities in literature, contributing to the development of the Fama and French three-factor model. The book-to-market ratio compares a company's net asset book value to its market price value (equity). Generally, a stock's market value exceeds its book value as it reflects the company's future growth prospects. The historical trend shows that value stocks, prevalent in mature industries like utilities, exhibit higher book-to-market ratios than growth stocks, which are common in emerging sectors such as new technologies. Consequently, this implies that value stocks usually have a lower market-to-book ratio (inverse of book-to-market). In essence, growth stocks' market-to-book ratio is higher as they belong to more growth-driven companies, with market prices reflecting greater growth expectations compared to those tagged as value.

The observation that value stocks have historically outperformed growth stocks might seem counterintuitive, as the latter are often perceived as more lucrative. This perception could be a result of representative-based judgment: growth stocks, being associated with growth-oriented companies, are presumed to yield better returns than those in mature sectors. Yet, it is crucial to remember that a stock's overall expected return primarily hinges on two elements: the anticipated dividend rate and the expected change in the "capital account". Value stocks, common in mature industries, generally offer high dividend rates. On the contrary, growth companies typically distribute lower dividends, if any, preferring to reinvest most profits to fuel future growth. Thus, the aforementioned evidence suggests that historically, this reinvestment has not sufficiently compensated for the lower dividend yields.

More broadly, within the classical approach, the only feasible way to rationalize higher returns is by linking them to increased risk. One plausible reason behind the superior performance of value stocks could be that many are priced below their book value, indicating potential issues. This pricing could reflect an additional risk factor, which the market recognizes and accounts for.

The enduring debate over the relative performance of value versus growth stocks forms the cornerstone of the value investing strategy, an approach rooted in the seminal work of Benjamin Graham and David Dodd (Graham & Dodd, 1996), and later popularized by Warren Buffett through his management of the Berkshire Hathaway fund. Conventionally, it is posited that small and valuable stocks carry a higher likelihood of financial distress. Yet, this rationale falls short as numerous value stocks do not trade at market values lower than their book values. Rather, their price-to-book ratios are not as elevated as those of growth stocks. Many of these value stocks are part of industries known for their stability over the medium to long term, often exhibiting relatively low-risk levels. Supporting this view, Daniel and Titman (1997) found that the size and price-to-book ratio of a security do not necessarily correlate with traditional risk metrics. Intriguingly, the three-factor model suggests that investors should anticipate higher returns from small and value stocks, considering them riskier than larger and growth-oriented stocks.

Contrarily, not just individual investors but also professionals, such as financial analysts, generally expect growth stocks to outperform value stocks on average.

2.1.3. Event-based anomalies

Event-based regularities relate to corporate activities, both routine and extraordinary. The literature has examined numerous event types. For simplicity, these can be categorized based on long-term performance relative to peers — companies similar in nature but not impacted by the analyzed event. Primarily, there are events linked to lower medium to long-term performance compared to peers. This includes Initial Public Offerings (IPOs), Seasoned Equity Offerings (SEOs), general listings, and mergers.

An IPO represents a company's first share offering to the public market. Three typical phenomena related to IPOs are the hot issue market, initial underpricing, and long-term underperformance. A hot issue market occurs when the new equity issue market is active, usually during economic expansion phases. Initial underpricing is seen when IPOs experience significant first-day trading gains, suggesting the offering price was too low compared to the first closing price. Lastly, long-term underperformance indicates that new issues, on average, yield lower returns than shares of comparable companies, for instance, in terms of size and the book-to-market value ratio.

The long-term underperformance relative to peers is also seen in SEOs and the aftermath of mergers or acquisitions (M&As). Usually, the acquiring company tends to underperform post-merger, while the acquired company, or the target, often sees gains.

Conversely, certain events lead to medium to long-term outperformance of the involved companies' stocks compared to their peers. Notably, this includes stock splits and the repurchase of treasury shares.

Concerning stock splits, the traditional view expects no change in market equity value. However, splits are associated with medium to long-term outperformance, with average excess returns of 7.93% in the first year and 12.15% over three years. For instance, a 1-to-2 split of a €10 share results in two €5 shares (Ikenberry et al., 1996).

Interestingly, sell-side equity analysts often have pessimistic earnings estimates post-split, although these companies typically face less likelihood of future earnings decline compared to peers.

Share buybacks serve various purposes, such as financial structure reorganization towards an optimal debt ratio or management's belief in the undervaluation of the company's securities. Evidence shows that buybacks strongly signal the market, with an average immediate reaction of 3.5%. This is not the end, as companies undertaking buybacks generally see a price uptrend, yielding long-term excess returns of 45.3% over four years, particularly for low book-to-market ratio firms. This equates to an average annual abnormal return of 12.2% (Shefrin, 2007).

Also, the medium-to-long-term market response to dividend events is notable. While stocks of dividend-paying companies outperform over time, those of non-dividend-paying companies underperform compared to their peers. Traditional finance posits that dividend decisions send significant signals to the market. Initiating a dividend is seen as a positive indicator of a company's confidence in its ability to sustain payments, whereas stopping dividends is often interpreted as a sign of potential future troubles. Market aversion to dividend cuts is well-documented, with a preference for a steady dividend trajectory, independent of fluctuations in company earnings. A deviation from market expectations, whether positive (initiation) or negative (omission), thus becomes a critical signal. Although this traditional explanation is now broadly embraced in academic circles, behavioral finance introduced the notion that the investor preference for dividends is also psychologically grounded. This is linked to mental accounting, where individuals categorize finances and the concept of hedonic editing.

Another intriguing regularity is the market response to corporate earnings announcements. Financial analysts' forecasts serve as a benchmark for investors. The average, or more precisely, the median of these predictions forms the analysts' consensus. Adhering to this consensus reduces the influence of individual analysts' estimates, likely providing a more reliable indicator since statistically, the forecast error associated with an average (the consensus) is smaller than that with individual forecasts. This makes the consensus more accurate. The potential conflicts of interest among analysts present an additional layer of potential bias, further reinforcing the rationale for relying on the consensus average. When reported profits exceed (fall short of) expectations, a positive (negative) "surprise" emerges, typically eliciting a corresponding positive (negative) market response. This reaction aligns with the efficient market hypothesis, which posits that market prices adjust to new information. The anomaly, however, lies in the persistence of excess returns for sixty days following the earnings announcement.

Termed "post-earnings-announcement-drift" in literature, this phenomenon reveals that stocks with a higher positive (negative) surprise yield a positive (negative) excess return of about 2% (-2%) over two months post-announcement, compared to similar companies without earnings surprises (Bernard & Thomas, 1989).

The cumulative anomalous returns (CARs) of U.S. listed companies from 1974 to 1986, based on their earnings surprises, further illustrate this. Ten portfolios are categorized by the magnitude of the earnings surprise: Portfolio 10 includes companies with the largest positive surprises, while Portfolio 1 contains those with the most negative. A strategy of buying Portfolio 10 and selling Portfolio 1 could yield an excess return of 4%. Since earnings data is publicly available, this post-earnings-announcement drift seemingly contradicts the semi-strong market efficiency hypothesis. A possible explanation is that investors do not immediately and fully react on the announcement day, possibly waiting for additional news to corroborate the earnings surprise before finalizing their stock positions.

Additionally, behavioral finance suggests that analysts tend to underreact to earnings announcement information, maintaining overly conservative estimates without sufficient adjustment based on new quarterly earnings information. Incorporating the information from announcements, one might expect to see a negative surprise follow a positive one and vice versa.

However, analysts often fail to adequately weigh this information, repeatedly expecting successive positive (negative) surprises to be followed by more of the same. This inertia is likely due to analysts consistently formulating estimates in the same direction in the short term. If high earnings are anticipated, they tend to discount opposing information that should prompt a downward revision in their estimates, an evidence displaying confirmation bias. Analysts eventually adjust their estimates, leading to the aforementioned reversal effect, but this often occurs too late, about a year post-earnings announcement.

It is also observed that small stocks exhibit abnormal returns more than double those of larger companies, a trend potentially aligning with the three-factor model proposed by Fama and French (1993).

2.1.4. Momentum and reversal

Regarding regularities based on return autocorrelation, there is a distinction between short-term momentum and medium- to long-term winner-loser effects.

In the short term, stocks demonstrate positive autocorrelation, or market inertia, known as the "momentum effect" (Jegadeesh & Titman, 1993), where historically a portfolio composed of stocks that performed well in the last six months, and shorting those that did not, can generate about a 10% positive excess return in the following year.

Three behavioral explanations for this effect exist. The first involves analysts and investors underreacting to news, leading to inertia. The second is overconfident investors overreacting to recent news and initial market movements. In positive news scenarios, market prices rise, and overconfident investors responding to this information create momentum. The third explanation stems from prospect theory: in positive news situations, risk aversion prompts investors to sell and secure gains, creating downward pressure on the stock and delaying its price rise. Thus, a full reaction is not immediate but persists over time. Conversely, with negative news, loss aversion leads investors to hold onto losing stocks, delaying their price decline, known as the disposition effect. The traditional momentum explanation suggests that past underperformers, being riskier, are likely to outperform subsequently.

However, this does not fully clarify why riskier stocks have to underperform initially, as higher risk should correlate with higher expected returns. The momentum evidence is so compelling that the "four-factor model" (Carhart, 1997), adding a "momentum" factor to the Fama-French model, is now the academic norm.

If short-term equity securities exhibit inertia, medium to long-term trends tend to reverse ("long-term reversal", Jegadeesh and Titman, 1993). A notable phenomenon here is the so-called "winner-loser effect" (De Bondt & Thaler, 1985). Consider the cumulative abnormal returns (CARs) of two portfolios: one comprising the worst performers over the past three years ("losers"), and the other, the best performers. Specifically, securities are divided into deciles based on their three-year historical performance. The winning stock portfolio consists of the first decile (the best), while the losing stocks are in the last decile. The subsequent five-year performance of these two portfolios is striking: the losers' portfolio records a CAR of approximately 30%, while the winners' CAR is around -10%. Engaging in a strategy of buying the losers and selling or shorting the winners results in an average excess return of 40% over five years. This medium- to long-term adjustment seems to correct the earlier mispricing of winning and losing securities. The winner-loser effect contradicts the weak form of market efficiency, as it leverages past information that should already be reflected in market prices. The traditional interpretation of this evidence argues that it is not a matter of misjudgment or investor overreaction, but rather that losing stocks are riskier and thus tend to outperform over the medium term.

According to Fama and French's (1993) three-factor model, past losers are likely small growth stocks, while past winners are typically value stocks from large companies. In efficient markets, at least in the medium term, it is improbable for the same stocks to underperform for three years and then overperform in the next five. The average return on these securities should align with risk and remain relatively stable over time. The behavioral explanation, however, points to representativeness leading investors to extrapolate past earnings trends ("extrapolation bias"), while the market generally exhibits mean reversion. This extrapolation leads to overreaction, undervaluing stocks that underperformed in the past (losers) and overvaluing past winners. Consequently, investors are often overly pessimistic about the prospects of losing stocks and overly optimistic about winning stocks.

Past losers then yield positive excess returns due to future earnings growth exceeding expectations, while past winners experience negative abnormal returns as their earnings growth falls short of anticipations. However, implementing contrarian strategies — buying past losers and selling past winners — is challenging in practice. This difficulty arises from hindsight bias and regret. Long-term reversal is an average phenomenon but not universal for all securities, meaning some past losers may continue their downward trajectory. If an investor buys these stocks hoping for a reversal that does not materialize, they may later believe it was obvious that the stock was a loser and regret the purchase.

Representativeness impacts not just individual investors but also professionals, as there appears to be a lack of full comprehension that many financial phenomena inherently exhibit mean reversion. Generally, mean reversion suggests that future returns gravitate towards the mean, not necessarily that above-average past returns must be followed by below-average future returns, or vice versa.

In this context, evidence indicates that financial analysts often deliver skewed earnings and long-term return forecasts due to representativeness, which leads them to extrapolate past trends and overreact. Their projections are more optimistic for stocks that have recently performed well than for those that have not (De Bondt, 1992). This tendency, referred to as the "gambler's fallacy", can be exemplified as follows. Consider flipping a coin five times, each time landing on "heads". Logically, the probability of "tails" appearing on the next flip remains 50%. Yet, many people believe that after a streak of "heads", a "tails" is almost "due". The error does not stem from ignorance about the 50% probability of landing heads or tails, as each flip is independent, but from the belief that this probability must hold true even in a short series of flips. Hence, they expect a "representative" series of coin tosses to contain roughly an equal number of heads and tails. Representativeness can lead to flawed conclusions as individuals tend to generalize based on limited evidence. This is known as the "law of small numbers" anomaly (Tversky & Kahneman, 1971), which contravenes the "law of large numbers" as people expect it to apply even to small samples. Behaviorally induced effects cause a delay in market price adjustments following news: the immediate market reaction exists but is partial, with the momentum effect and subsequent trend reversal merely reflecting the adjustment process towards fundamentals.

Regarding evidence of underestimation and overestimation, it is pertinent to mention Eugene Fama's critique of behavioral finance (Fama, 1998). Fama, a prominent figure and ardent advocate of the neoclassical approach, questioned both methods and interpretations of behavioral finance, suggesting it merely tries to explain empirical anomalies in financial markets. He specifically challenged the overreaction hypothesis for its temporal inconsistency, as it appears empirically valid in the medium to long term due to mean reversion, but not in the short term, where an under-reaction results in momentum. According to Fama and French (2006), occurrences of over-reaction are as frequent as under-reactions, thereby aligning on average with market efficiency and portraying anomalies as random. This critique would be valid if overreaction and underreaction occurred with equal frequency in both long and short terms.

However, evidence shows overreaction as a long-term phenomenon and underreaction as a short-term one, contradicting the supposed balance suggested by Fama's argument.

The insights from the anomalies (regularities) described should not give the impression that behavioral finance advocates believe market outperformance is straightforward. Recognizing that prices do not always efficiently mirror the fundamental value of a security does not necessarily mean these inefficiencies can be profitably exploited. In fact, due to the presence of less-than-rational agents, prices might stray from fundamentals for extended periods, and institutional traders might struggle to conduct arbitrage operations to restore market equilibrium. The risk posed by unsophisticated investors, known as "noise trader risk", suggests that mispricing might worsen before it improves, making arbitrage limited (Shleifer & Vishny, 1997) and risky, unable to realign market prices with fundamentals.

2.2. Individual trading behaviors

Traditional finance is predicated on the idea of rational and optimizing agents. In line with modern portfolio theory, investors are assumed to maximize a portfolio's expected return for a given level of risk or achieve a specific return while minimizing risk (Markowitz, 1952, 1959). They are expected to maintain diversified portfolios composed of risk-free securities and risky assets. Furthermore, the rational expectations theory, informed by information asymmetries, posits that while some individuals invest passively, others incur costs to acquire information, thus earning excess returns. Those with superior information can outperform unsophisticated investors (noise traders) who make nearly random transactions.

Contrastingly, behavioral finance reveals that investors are not perfectly rational or all-knowing. They do not invest optimally, exhibit varying risk tolerances depending on the specific mental account under consideration, and often have under-diversified portfolios and trade too aggressively due to overconfidence, adversely affecting their performance. When considered collectively, it is inaccurate to say individual investors behave randomly, as traditional models suggest. Instead, they tend to exhibit systematic, albeit frequently flawed, behaviors. However, it is not guaranteed that arbitrageurs can exploit these errors, as their persistence introduces a risk ("noise trader risk") that can endure for extended periods, thus constraining the arbitrage opportunities available to professional investors.

Individual investors are influenced by a variety of factors in their trading activities, leading them to be active in the market, but often resulting in errors detrimental to their performance.

Barber and Odean (2011) categorize the research on individual investor behavior into five broad themes:

1) Evidence and reasons for underperformance;
2) The disposition effect;
3) Under-diversification;
4) Attention capture and the influence of the past;
5) Learning from past actions.

This categorization provides a quite comprehensive overview of behavioral studies on individual investors, elucidating both the observed individual behaviors and their possible causes. However, a note of caution is warranted: despite the generalization of behaviors identified by the behavioral approach to the extent of defining a "category" of individual investors, existing studies reveal considerable heterogeneity among them.

This diversity does not undermine the value of behavioral theories; in fact, continuing to apply this approach is not only desirable but essential to unravel the complex web of variables influencing investor behavior.

2.2.1. The evidence and reasons for underperformance

While theoretical studies of individual investors date back to the mid-1980s, with concepts like the individual investors' preference for cash dividends (Shefrin & Statman, 1984) and the disposition effect (Shefrin & Statman, 1985), empirical research in this field is relatively recent. This delay is primarily due to the challenge of accessing data.

While research on professional operators thrived in the 1990s, thanks to abundant data, particularly on mutual funds, studies on individual investors were scarce. A driving force behind the focus on institutional investors was to seek indirect evidence supporting the efficient market hypothesis.

Many 1970s studies affirmed this hypothesis by demonstrating, for example, that mutual funds could not consistently outperform the market. However, in the late 1980s and the subsequent decade, pivotal studies revealed that some fund managers not only surpassed market returns but also demonstrated skill in investment selection, leading to above-average returns (Grinblatt & Titman, 1989; Daniel et al., 1997). It is crucial to note that this outperformance was before accounting for client fees, with net returns to clients falling below market returns. Yet, this contradicts the efficient market assumption. The fact that excess returns exist pre-fees does not confirm market efficiency; it simply implies beating the market is difficult, not impossible. These are fundamentally different ideas: if market outperformance is achievable by a subset of mutual funds, it implies the market is not entirely efficient. These findings, contradicting the efficient market hypothesis, further fueled the debate between traditionalists and behaviorists, heightening researchers' curiosity to validate behaviorists' theoretical propositions about individual investors.

Curiosity alone was not the only driver, but the realization that if the market cannot be consistently outperformed on average, yet some professional managers do succeed, it implies the existence of other investors who systematically underperform. The available data suggest that it is typically individual investors who fall into this category. This underperformance is not due to the efficient market hypothesis — which empirical evidence challenges — but rather a practical matter: in every transaction, there are two parties; if one outperforms, the other must underperform since the aggregate average expected return is the market's (before accounting for transaction costs). Terrance Odean is a notable figure in behavioral finance, both for validating many theoretical hypotheses from the eighties and for introducing and testing new ones. His work — often done together with Brad Barber — has made studies on individual investors a vibrant and promising area in behavioral finance. This advancement was facilitated by accessing databases on individual stock transactions, which form the basis of much empirical research.

While even top institutional investors struggle to ensure net performance that beats the market, individual investors seem to underperform not only net, but also before considering transaction costs like commissions, bid-ask spreads, and other trading-related expenses. Taxes are not included in these studies due to the absence of datasets with detailed information on the taxation of dividends and actual capital gains (Barber & Odean, 2011). Naturally, after-tax returns are lower than gross returns, which further exacerbates the issue of underperformance relative to the market.

When considering performance, the investment timeframe — whether long-term or short-term — plays a crucial role in understanding the sometimes-contradictory behaviors of individual investors. While some question findings about individuals' underperformance in light of evidence showing stocks that individual investors buy tend to outperform in the short term, and vice versa for those they sell, this trend does not hold in the long term. Individual investors may seem adept at selecting stocks for buying and selling in the immediate term (up to a few weeks), yet they incur significant losses over time, offsetting any initial gains (Barber et al., 2009a). Since the average investor typically holds stocks for more than a year, the underperformance documented in numerous studies emerges. In the U.S., for instance, individual investors' average stock holding period is around 16 months (Barber & Odean, 2000b).

Identifying non-rational attitudes is vital. To date, no study has established an optimal number of annual transactions or the factors influencing investors' trading activities. An interesting approach is Odean (1999), the first to empirically show that individuals err in selecting securities. Absent a model defining optimal trading, Odean (1999) posits rational behavior as that where the returns from purchased securities exceed those from sold ones. Logically, transactions should generate profit to be considered sensible. In his analysis of roughly 10,000 investors' transactions from 1987 to 1993, Odean found that securities purchased outperformed those sold by 3.3% in the year after the transaction. This finding holds true even when excluding transactions influenced by liquidity needs, portfolio rebalancing, or tax considerations.

Remarkably, this underperformance occurred before factoring in transaction costs. Yet, individuals frequently trade as if unaware of their losses. Another hypothesis for this high trading activity is that investors find enjoyment in stock market "gambling", similar to other forms of gambling.

Barber and Odean (2000a) expanded this research to a larger dataset covering about 78,000 households and over 158,000 accounts from 1991 to 1996. They analyzed overall investment choices, not just stock transactions, using data from a large discount broker. This broker processes customer orders without advisory services, at reduced fees, making the data ideal for studying individual investors' unfiltered decisions. The study's key revelation was that individual investors underperform a simple buy-and-hold strategy, such as purchasing Exchange Traded Funds (ETFs) mirroring the market portfolio. Active trading fails to outdo this passive approach, primarily due to transaction fees diminishing net returns. Investors were categorized into quintiles based on transaction frequency (monthly turnover).

The quintile with the most active traders achieved an average net annual return of 11.4%, whereas the least active, following a buy-and-hold strategy, saw returns as high as 18.5%. Transaction costs thus reduce net performance by a substantial 7% annually. Even after adjusting for risk, such as with Fama and French's (1993) three-factor model, the gap in performance against the buy-and-hold approach persists.

Barber and Odean (2000a) interpret excessive trading as an indication of individual investors' overconfidence: those who have more confidence in their investment abilities tend to excessively manage their portfolios, leading to detrimental effects on net performance. This finding seems to be broadly applicable, with most active investors underperforming compared to more passive ones but also lagging behind the market overall.

In a comparative analysis of the average performance of individual investors, investment clubs, and passive mutual funds that track the market index, it was observed that while the average individual investor might surpass market performance before considering transaction costs, their returns fall below a low-cost index fund's performance when these costs are accounted for (Barber & Odean, 2000b). Intriguingly, the performance of investment clubs, often touted in media as success stories, actually falls short of not just the market, but also the average individual investor. Thus, while investment clubs might serve educational and social functions, they appear to hinder financial performance.

This could be attributed to decision-making processes within groups, where collective biases, such as groupthink, can exacerbate the cognitive biases of individual members. This phenomenon often leads to decisions aligning with the leader's views, disregarding information that contradicts them.

The initial findings from the U.S. market have spurred research in other countries, including Taiwan. Barber et al. (2009a) analyzed the Taiwanese market between 1995–1999 and corroborated findings from other studies. They constructed portfolios replicating investors' trading decisions over periods ranging from a day to six months. It was observed that securities sold by individual investors and bought by institutional investors yielded high returns, whereas the reverse scenario resulted in lower returns.

Employing a long-short strategy that imitates individual investors' strategies over 140 days, it was possible to earn 0.75% monthly before transaction costs. Professional investors seem capable of securing positive excess returns at the expense of individual investors. The losses suffered by Taiwanese retail investors are significant, averaging 2.8% of their total personal income, including commissions and sales taxes. These investors underperform the market by approximately 3.8% annually, with their collective losses amounting to 2.2% of Taiwan's gross domestic product (GDP). Apart from transaction costs, individual investors also seem to lack the aptitude for selecting financial investments and often misjudge the timing for entering and exiting the stock market.

In the U.S., databases typically do not differentiate between individual and institutional investor transactions. Barber et al. (2009a) used the Trades and Quotes (TAQ) database, which helped distinguish between large and small transactions, the latter being a good proxy for individual investor transactions.

While individual investors underperform in the medium to long term, there is evidence that the securities they buy can yield excess returns in the very short term. Kaniel et al. (2008) discovered a positive correlation between individual investors' trading choices and short-term security performance. Using the Consolidated Audit Trail Data, with detailed transaction information on the New York Stock Exchange (NYSE), including the type of trader (individual or institutional), they analyzed order imbalances over nine weeks. Positive imbalances indicated more buying than selling, and vice versa. The top decile of most-bought stocks had the highest return in the month following the purchase, while the top decile of most-sold stocks had negative returns. The study concludes that individual investors can pick short-term high-performing stocks because they provide liquidity to companies in immediate need, rewarding investors who supply them.

Using the same dataset, Kaniel et al. (2012) demonstrated that the short-term trading of individual investors appears to be "informed trading", particularly in relation to earnings announcements. They found that, in the aggregate, securities purchased by these investors in the ten days leading up to earnings announcements outperformed those sold in the same period by 1.5% in the two days following the announcement. Individuals also seem capable of identifying companies that will produce positive or negative earnings surprises, thereby anticipating the market's reaction. The authors suggest that these excess returns are due not only to the increased information possessed by individual investors but also because these investors provide necessary liquidity to companies.

Barber et al. (2009a) arrived at similar conclusions, noting that order imbalances can meaningfully predict short-term returns. Stocks most frequently purchased by individuals outperform the market over the subsequent two weeks but then underperform for the rest of the year. They theorize that the positive short-term correlation is influenced by sentiment-based trading of individual investors rather than solely their role as liquidity providers. Market sentiment initially drives prices up (momentum effect), but long-term underperformance occurs as prices revert to the mean.

Kelley and Tetlock (2012) used data from brokers handling orders from retail brokers between 2003 and 2007 to differentiate between individual and institutional traders. They also found that daily order imbalances of retail traders could predict returns for the next 20 trading days.

These studies, although utilizing different databases, consistently indicate the ability of individual investors to select securities that outperform in the short term. The robustness of this finding across diverse data sources is notable. However, the exact cause of this phenomenon remains a topic of debate. It is unclear whether it can be attributed to individual investors' "predictive ability" to discern which companies need short-term liquidity, or whether it is influenced more broadly by market sentiment.

In the U.S. market, robust evidence indicates that individual investors often provide liquidity to companies and professional investors requiring short-term liquidity. This role as a liquidity provider often results in an individual investor achieving excess returns. However, the scenario is different in other countries.

For instance, Barber, Lee, et al. (2009) observed that in Taiwan, where individual investor transactions account for about 90% of total trading volumes, individuals incur short-term losses.

Andrade et al. (2008) found that stocks bought by individual traders tend to underperform in the week following the purchase, while the reverse is true for stocks they sell.

Kaniel et al. (2008) interpret this as indirect support for their liquidity provision hypothesis, indicating that in markets like Taiwan, individual investors do not earn excess returns typically associated with liquidity provision. The distinction between market and limit orders reveals mixed results. Market orders, known as "at best" orders, are executed immediately at the best available price, without specific price or time constraints. These orders are generally cheaper and often used in conditions of high volatility. Limit orders, conversely, are executed at a specified price or within a set timeframe and are typically more expensive. They are used for implementing strategies like stop-loss or stop-gain, especially during volatile market periods, and can limit the duration of a trade's validity.

Kelley and Tetlock (2012) suggest that while market orders from individual investors compile private information about the expected cash flows of companies, limit orders tend to provide liquidity to traders seeking immediate order execution.

In Finland, Linnainmaa (2010) notes that market orders yield positive short-term results, but limit orders do not, often incurring short-term losses. This discrepancy might occur because informed investors can exploit unmonitored limit orders placed by less informed or attentive traders. For example, consider a market with two types of investors: informed and uninformed. If uninformed investors place sell orders with a high price limit but fail to adequately monitor the stock's performance, informed investors might capitalize on this lack of vigilance. Informed investors, who might be privy to upcoming earnings releases expected to boost stock prices, could exploit the oversight of others by engaging as counterparties in their sell orders, thereby benefiting from subsequent price increases.

Between 1998 and 2001, investors experienced on average a loss of 0.51% the day after executing a limit order and 3.3% over the following three months. In contrast, market orders showed returns of 0.44% and 3.5% in the same periods, indicating that those who placed market orders earned almost exactly what was lost by those placing limit orders. However, this Finnish market data contrasts with findings from Taiwan, an electronic market primarily using limit orders rather than market orders.

Barber, Lee, et al. (2009) categorize limit orders as either aggressive or passive. Aggressive limit orders are buy orders priced above recent selling prices, while passive ones have a purchase price below the latest unexecuted limit order. Sell orders follow a similar classification. Aggressive limit orders mimic market orders in an electronic market like Taiwan's, where executing a limit order often requires setting an aggressive price, implying a readiness to buy high or sell low. In the ten days following their transactions, individual investors realize positive returns from passive limit orders, while their six-month performance generally shows no significant deviation from zero. Conversely, aggressive limit orders typically lead to negative returns in both the short and long term.

It is important to note that these findings represent the average performance of individual investors, which masks considerable heterogeneity. This variability is influenced by several identifiable factors, including the experience and skills of individual investors, their cognitive abilities, investment style, geographic location, and socio-demographic characteristics. Intriguingly, individuals exhibiting superior investment skills consistently generate excess returns.

Coval et al. (2005) show that investors who have previously achieved above-average returns continue to outperform in the very short term (one week) compared to those who have recently underperformed, albeit the extra performance is marginal. This finding does not account for transaction costs, which would likely negate the excess return.

Barber et al. (2014) present a more substantial discovery among Taiwanese traders from 1992–2006. Day trading is prevalent in Taiwan, and the daily activities of the 300,000 individual investors studied during this period represented 17% of the total trading volume. The large number of investors and their active involvement in intraday trading allowed researchers to observe that the top 500 traders outperformed the thousands of others. Their average daily excess return of 0.5% is sufficient to cover transaction costs. This data supports the notion that some individual traders can, at least in the short term, systematically surpass the performance of the majority of other individual investors.

With access to the socio-demographic characteristics of investors, it becomes compelling to explore how these factors influence traders.

Behavioral finance suggests cognitive biases significantly impact investor performance. Korniotis and Kumar (2011) attempt to predict traders' cognitive abilities using socio-demographic variables like age, education level, and social networks. Consequently, investors deemed "smarter" outperform others by approximately 3.6% annually (before transaction costs). Their study also finds that performance inversely correlates with age, aligning with the notion of cognitive decline with increasing age.

Hallahan et al. (2003, 2004) indicate that risk tolerance diminishes with age, albeit not linearly, as earlier suggested by Riley and Chow (1992). Nonetheless, the impact of age on trading behavior remains a topic of ongoing debate.

Frijns et al. (2008) observe that older investors tend to invest more in riskier securities. Regarding the Italian context, Alemanni and Franzosi (2006) discover that older investors are among the most active on the stock market.

Additionally, it is widely recognized that as income increases, so does investors' risk tolerance (Morin & Suarez, 1983; Riley & Chow, 1992). There is also a near-unanimous agreement on the correlation between gender and attitudes towards risk (Frijns et al., 2008).

An essential study in this field is Barber and Odean (2001), comparing the performance of men and women under similar conditions to understand the impact of overconfidence on investors' net returns. Psychological research indicates that men generally exhibit more overconfidence than women (Deaux & Farris, 1977). Consequently, it is anticipated that men, under comparable conditions, engage in more transactions than women.

The results reveal that while women have an average annual turnover of 50%, men's is nearly double at 80%. It is important to note that some of the accounts in the study may be jointly owned by husbands and wives, making it unclear who makes the trading decisions. However, when focusing on single men, the data shows they conduct even more transactions, adversely affecting net performance. Among both men and women, there is a shared deficiency in investment selection skills, leading to subpar performance for both genders. Female influence tends to mitigate male overtrading and underperformance. Single men are prone to excessive portfolio movement, resulting in lower returns compared to those who trade less. It is crucial to remember that these are average figures; there could be exceptions where single men outperform their married counterparts.

Moreover, studies have explored how enhanced skills or knowledge can improve investor performance. Grinblatt et al. (2010) examined the link between intelligence quotient (IQ) and stock-picking abilities among Finnish investors. They found that investors with higher IQs outperform those with lower IQs by an annual margin of 2.2% and also demonstrate superior stock-picking skills.

Conversely, Ivkovic et al. (2008) focus not on individual skills but on the actual degree of information investors possess. In the U.S. market, well-informed investors concentrate their investments on a limited number of stocks where they have an informational edge, such as local companies not listed on the S&P 500 index. These investors outperform those with diversified portfolios by 0.16% monthly. This suggests that some investors indeed have better insights into geographically proximate companies. However, this should not be confused with the home bias phenomenon, where an individual's perceived familiarity with a company does not equate to actual informational advantage over other investors.

In summary, research on individual investors highlights three key observations. Firstly, while there is variation within this group, differences can often be attributed to socio-demographic factors, as well as individual abilities or access to information. Secondly, regardless of these disparities, it appears that individual investors generally lack effective stock-picking abilities and tend to hold onto portfolio securities for over a year, leading to long-term negative returns that offset any short-term gains. Finally, while some individual investors excel in outperforming their less skilled counterparts, their returns, though positive, do not surpass market performance after accounting for transaction costs.

Regarding the causes of individual investors' underperformance, explanations can be categorized as either rational or behavioral. From a rational perspective, it might be suggested that individual investors are cognizant of their informational disadvantage in markets dominated by professional traders. Consequently, they might engage in trading primarily when necessary, such as for funding current expenses, adjusting their portfolio's risk-return profile, or for tax considerations. However, this rationale seems inconsistent with the observed high turnover rates, which appear to be driven more by speculative activities.

Barber and Odean (2000a) report an annual turnover rate of 250% among the top 20% of most active investors in the U.S. Similarly, in the Taiwanese stock market, Barber, Lee, et al. (2009) noted a turnover rate of 300%, and in China, it even reaches 500% according to Gao (2002).

If trading decisions were predominantly influenced by the needs mentioned earlier, rather than speculative reasons, a more logical approach for these investors would be to opt for low-cost mutual funds, like passive funds that track the market index.

Traditional theories struggle to explain why many individual investors persist in actively investing in the stock market despite their average poor outcomes. A primary explanation from behavioral finance is overconfidence: an excessive belief in one's abilities leading to the underestimation of some relevant information and overemphasis on others (Moore & Healy, 2008). Confirmation bias and the illusion of knowledge (see Chapter 1) result in poorly calibrated judgments and excessive confidence in the accuracy of one's information. This form of overconfidence, known as miscalibration, leads to excessive trading and suboptimal net performance due to transaction costs (Odean, 1999; Barber & Odean, 2000b, 2001). Gervais and Odean (2001) present a multi-period market model demonstrating how learning about one's skills and biases can lead to overconfidence. Initially unaware of their skill levels, traders infer them from their transaction outcomes, often attributing success to their own actions and becoming more overconfident. Over time, as traders gain experience, their self-assessments become more accurate, and their overconfidence diminishes. Dorn and Huberman (2005) found that German investors who considered themselves above average tended to trade more frequently. Similar findings were reported by Grinblatt and Keloharju (2009) for Finnish investors. Graham et al. (2009) explored this effect among over 400 U.S. investors, finding that self-perceived skill level correlated with increased market activity.

Regarding the shift from traditional to online trading, Barber and Odean (2002) analyzed about 1600 online traders from 1991–1996 and found that those who switched from traditional channels (telephone, counter) to online increased their turnover compared to a control group who continued offline trading. Furthermore, these online traders tended to execute more trades and perform worse, with a marked decline in both cumulative gross and net returns following the transition to online trading. The first evidence demonstrates how the increased trading aggressiveness associated with moving to an online platform significantly deteriorates what was formerly a positive performance. The second one highlights the cumulative impact of transaction costs, leading to negative net returns for those who shifted to online trading. The authors propose that online traders may be influenced by self-attribution bias and an illusion of control. In summary, the presented research supports the notion that overconfidence affects trading behavior by increasing the frequency of transactions and diminishing the net performance of investors. The evidence for the "better-than-average" effect appears to be more robust than that for miscalibration, although this might be due to the challenges in accurately defining the latter, as determining the correct calibration is not straightforward.

Many studies (Dorn & Huberman, 2005; Dorn & Sengmueller, 2009; Glaser & Weber, 2007; Graham et al., 2009) have utilized field survey data to examine the trading activities of individual investors. These research efforts have focused on revealing the inconsistencies between the investors' decision-making processes, their actual choices, and the performance outcomes.

While these studies offer valuable insights, they are limited in scope as they primarily concentrate on one aspect of the trading decision-making process: the resulting performance.

Other research studies (Hoffmann et al., 2010; Hoffmann & Shefrin, 2011) have expanded on these earlier analyses. They not only consider the individual characteristics of investors but also delve into their trading objectives and strategies, as well as the impacts on both trading turnover and performance.

These studies utilize a database encompassing Dutch retail investors, comprising publicly available data and information based on personal characteristics. The authors employ a questionnaire that directly assesses the underlying behavioral tendencies of investors, rather than relying on proxies. They segment the population based on various criteria, including investment objectives and strategies, as well as individual investors' ambitions and risk profiles. Investor objectives are categorized into classes: capital growth, stock market gambling, retirement savings, speculation, and financial security achievement. The male demographic predominantly engages in stock market gambling or speculative activities. These individuals are typically the youngest and most active traders. In contrast, those seeking only financial security are less active. Investors focused on capital growth generally possess the most valuable portfolios, while those treating the stock market like a gambling venue allocate fewer funds. Speculators, who are more risk-averse than other trader types, exhibit a high transaction volume but also more experience.

Analysis reveals that investors targeting capital growth yield the best average monthly returns (0.68%), whereas speculators experience the poorest returns (-0.38%). Transaction costs further exacerbate speculators' losses (-2.22%) and marginally diminish the gains of growth-focused investors who trade less frequently (0.22%). Additionally, the most advantageous investment strategy on average involves leveraging financial news and intuition. Fundamental analysis ranks as the second most effective strategy, with technical analysis being the least profitable. Individuals engaging in speculation or gambling-oriented investments do not achieve the best performance. Factors such as experience, risk tolerance, ambition, speculative goals, and strategies reliant on intuition or technical analysis explain the high turnover among the most active investors, often to the detriment of their performance. The pursuit of intense sensations (Grinblatt & Keloharju, 2009) is not tied to the average risk of the portfolio but rather its constant activity. For some, online trading becomes akin to an addiction, comparable to gambling (Kumar, 2009a).

2.2.2. The disposition effect

The disposition effect refers to the tendency of investors to prematurely close positions that are profitable while holding onto those that are losing for an extended period.

In a study examining around 10,000 accounts at a U.S. discount broker from 1987 to 1993, Odean (1998) analyzed actual transactions versus "potential" ones, assessing the frequency at which investors sold "winning" stocks (realizing a profit) against the frequency of selling "losing" stocks (incurring a loss). The findings indicated that investors are 50% more likely to cash in gains relative to their opportunities to realize losses. This phenomenon might be explained by rational factors. One theory is "informed" trading, where investors might sell winning stocks more often than losers due to the information they possess, rather than loss aversion or other behavioral biases. Another theory suggests belief in mean reversion in the short term, leading investors to adopt contrarian investment strategies.

Additionally, portfolio rebalancing (Calvet et al., 2009) seems to be a factor influencing which securities are sold. Odean's analysis discounts these as primary causes, pointing instead to the disposition effect. Contrary to the assumption that the disposition effect only impacts retail investors, evidence shows that professional investors are also susceptible to this bias, often letting losses run while hastily closing profitable positions. The disposition effect has been substantiated by robust evidence spanning over two decades (1980 to 2002) in the context of U.S. mutual funds, as demonstrated by Frazzini (2006). This study evaluates the frequency at which these professional investors realize gains and losses relative to their total equity positions, either profitable or not. The findings indicate that fund managers liquidate profitable positions at a rate of 21% higher than losses. Particularly notable is that if a fund ranks in the bottom quartile based on the prior year's performance, this rate escalates to 72%. This pattern suggests that professional investors might be inclined to exhibit profitable positions in their new financial statements.

The disposition effect is not limited to the U.S., but it has been documented in various countries across different asset types and specific market scenarios.

Grinblatt and Keloharju (2001a), utilizing transaction data of Finnish investors from 1995 to 1996, discovered compelling evidence supporting the notion that investors tend to retain losing stocks in their portfolios for extended periods. Their study reveals that stocks with losses up to 30% are 21% less likely to be sold compared to those with gains, and for losses exceeding 30%, this likelihood increases to 32%. The implication is that the greater the loss, the more pronounced the reluctance to sell, leading to a higher probability of retaining the stock in the portfolio. Conversely, stocks that have realized substantial gains or are near their maximum monthly price are more likely to be sold.

Shapira and Venezia (2001) explored the trading behaviors of Israeli investors based on over 4,000 brokerage accounts, with 40% being self-managed and 60% professionally managed. They assessed the duration of "round-trip" transactions based on whether they concluded with a profit or a loss.

This approach serves as an indirect method to detect the disposition effect: if present, the holding period for profitable securities should be shorter than for losing ones, due to a tendency to sell winners early and hold onto losers for too long. Their findings confirm the disposition effect in both professionally managed and self-managed accounts, although it is less pronounced in the latter, which aligns with expectations.

Feng and Seasholes (2005) investigate the Chinese scenario. Scrutinizing the dealings of roughly 1,500 singular traders, they deduce these individuals demonstrate a heightened hesitation to part with stocks at a loss than at a profit (the likelihood of the former being 32% less than the latter). This data allowed the duo to substantiate that trading tenure — quantified as the span since the investor's market debut — can diminish the disposition effect.

Focusing on Finnish traders from 1995 to 2003, Seru et al. (2010) unveil that the impact of trading experience on lessening the disposal effect is more pronounced when gauged by transaction volume rather than mere years. Essentially, for accumulating expertise, it appears crucial to engage robustly in the market, rather than just lingering for extended periods with scarce activity.

In an expansive examination, Chen et al. (2007) scrutinized 50,000 Chinese investors from 1998 to 2002 and found a higher propensity to divest in profitable stocks over unprofitable ones: 67% more likely in the former scenario. This probability diminishes to 15% when focusing solely on institutional traders, despite their count being a mere 212.

Turning to Asian markets, specifically the Korean one, Choe and Eom (2009) highlight the manifestation of this effect in the index futures market, more pronounced among individual investors compared to professionals.

Parallel findings are observed in Taiwan. The Taiwanese Stock Exchange (TSE), one of the world's most vibrant markets, had a turnover of 292% in the studied period, dwarfing the NYSE's 69%.

Analyzing all transactions of Taiwanese investors between 1995 and 1999, Barber et al. (2007) discern a significant disposition effect among individual investors — the odds of offloading a profitable stock being quadruple that of a losing one — but a lesser effect among certain institutional investors like corporate investors and dealers, with foreign investors and Taiwanese mutual funds showing reluctance in selling losing securities. Yet, these traders represent a mere 5% of all market operations.

Typically, the disposition effect mirrors market trends: it amplifies with market ascents and diminishes during downturns. It is closely associated with cognitive misjudgments and a minimal grasp of financial literacy. Hence, its prevalence is higher among individual investors, particularly the less savvy, than among professional investors (Brown et al., 2006). Not just the latter, but also individual investors possessing greater financial resources (and acumen) (Dhar and Zhu, 2006 in the U.S.; Calvet et al., 2009 in Sweden) and those engaging in frequent daily trades (Kumar & Lim, 2008) appear less hesitant to accept losses. Conversely, the disposition effect intensifies with securities that are more challenging to evaluate (Kumar, 2009a).

This effect is flawed for two primary reasons. Firstly, selling winning stocks typically forfeits short-term positive returns, in light of the momentum effect (Jegadeesh & Titman, 1993). Secondly, it incurs tax inefficiencies: profits are taxed, whereas losses are not. Although tax considerations influence individual investment decisions, they do not completely justify the disposition effect, indicating suboptimal tax management: selling at a loss is preferable for delaying tax liabilities.

In the U.S., certain accounts are taxed immediately, others later. Analyzing over 400,000 households from January 1998 to June 1999, Barber and Odean (2004) observed that holders of immediately taxable accounts, recognizing the tax advantages of losses, readily sold unprofitable securities in December. However, those with deferred tax accounts exhibited the disposition effect.

Abundant empirical data confirms the disposition effect's existence, underscoring the need to comprehend its causes. Shefrin and Statman (1985) suggest it results from a mix of factors like prospect theory, regret avoidance, mental accounting, and self-control issues.

From a theoretical standpoint, numerous models have been formulated to decode how prospect theory impacts investment choices, especially concerning the disposition effect. Yet, the interpretations of these models currently remain inconclusive (Barberis & Xiong, 2009, 2012; Henderson, 2009; Kaustia, 2010; Frydman et al., 2011; Hens & Vlcek, 2011; Yao & Li, 2013). Summers and Duxbury (2007) explore the influence of emotions on the disposition effect. In a simulated market experiment, they discovered the effect is absent if individuals have not personally chosen the securities in their portfolio, but instead had them assigned. This indicates that if individuals do not feel accountable for selecting the securities yielding gains or losses, their aversion to selling at a loss diminishes. Thus, the disposition effect also appears tied to emotions: people sell winning securities to savor the gratification of a wise choice while delaying the unpleasantness of regret associated with a losing investment.

Furthermore, investors often repurchase stocks they have previously sold if these have subsequently declined (Strahilevitz et al., 2011). This behavior might be attributed to the joy derived from reacquiring a share at a lower rate than before. In experimental conditions, this tendency manifests only when individuals feel responsible for the earlier sale, underscoring the pivotal role of emotions in these decisions (Weber & Welfens, 2011). Conversely, if the stock's value has not dropped post-sale but risen, investors refrain from buying back to avoid the regret of having sold too soon, missing further price increases.

2.2.3. Under-diversification

The conventional finance paradigm suggests risk-averse investors should diversify their portfolios to minimize specific risks.

In his prominent speech at the Academy of Behavioral Finance's annual meeting (New York City, September 20, 2012), Nobel laureate Joseph Stiglitz highlighted that diversification is ideal when assuming investors' utility functions are concave, indicating risk aversion. Absent this foundational presumption of traditional models, diversification is not invariably the best approach. In times of high market volatility and risk appetite, diversification might propagate issues rather than mitigate them. Stiglitz analogized this to quarantining the sick rather than allowing them to spread infection. However, evidence shows individual investors often inadequately diversify, holding few securities without considering inter-correlations.

Barber and Odean (2000a) observed that their study's investors typically held just four stocks. Goetzmann and Kumar (2008) found investors favoring volatile, inter-correlated portfolios. Kumar (2009b) noted a preference for stocks with high idiosyncratic volatility or low prices. Mitton and Vorkink (2007) suggest the inclination for few-security portfolios might reflect a quest for asymmetric returns. Factors like home bias also contribute to under-diversification. This tendency towards domestic securities, while gradually diminishing, remains significant in many countries (Solnik & Zuo, 2011). It is costly, forgoing the diversification benefits of international portfolios, which benefit from lower inter-market correlations (French & Poterba, 1991; Cooper & Kaplanis, 1994; Tesar & Werner, 1995; Lewis, 1999).

Despite its waning prominence, the home bias persists, influenced by greater familiarity with local company stocks (Huberman, 2001; Ivkovic & Weisbenner, 2005; Seasholes & Zhu, 2010). Not just geographic proximity, but also shared cultural background with a CEO or language commonality intensify this familiarity, as shown in Finnish (Grinblatt & Keloharju, 2001b) and Chinese (Feng & Seasholes, 2004) contexts.

To be equitable, it is worth noting that some research indicates individual investors can achieve substantial returns from local equity investments (Ivkovic & Weisbenner, 2005; Seaholes & Zhu, 2010).

Yet, investing in local company securities, deemed more familiar and thus perceived as less risky, exacerbates the under-diversification issue for many individual investors. Consequently, any higher gains from such securities must be sufficient to outweigh the transaction costs and increased risk from a locally focused portfolio. More troubling is the tendency of employees to heavily invest in their own company's securities, tying their financial fate to its success. This exposes them to heightened specific risk. The most infamous example of the perils this poses is the Enron debacle. By December 2000, its employees had 62% of their pension plan assets in company stock. A year later, with Enron's bankruptcy, they not only lost their jobs but also saw substantial savings vanish.

Broadly, in the early 2000s, 44% of the defined contribution pension plans of the top twenty U.S. firms also invested in company stock (Poterba, 2003). Mitchell and Utkus (2003) estimate that five million Americans have over 60% of their pension plan assets in their employer's stocks.

Benartzi (2001) shows many employees voluntarily invest in their employer's securities, with the allocation to company stock growing if it yielded significant returns in the preceding decade. Fortunately, this trend has declined over the past decade, likely due to various scandals influencing public opinion.

The Employee Benefits Research Institute noted that in 1998, 60% of new hires invested in their company, but by 2009, this dropped to 36%. However, this proportion remains high; in 2009, 5% of employees had as much as 80% of their portfolios in their company's stock, indicating a near-total lack of diversification.

As highlighted earlier, there is evidence that investors focusing on a significant number of local bonds can achieve high returns. This might stem from a geographical proximity-based information advantage.

Massa and Simonov (2006) examined Swedish individual investors, noting a preference for companies linked to them either professionally or geographically. They argue that this familiarity grants an information edge, leading to higher returns.

Ivkovic and Weisbenner (2005) discovered similar trends in the U.S. Conversely, Døskeland and Hvide (2011) found that, despite investing in familiar sectors, Norwegian investors often face unusual negative returns due to under-diversification.

The debate on the home bias — whether it arises from a skewed perception of familiarity or from actual informational benefits about nearby companies — remains unresolved, as does its impact on performance. However, the resulting under-diversification of portfolios is clear. It is crucial to remember that assessing investors' diversification mistakes requires full portfolio data, not just equity investments.

This comprehensive analysis is challenging. Available information often pertains to specific brokerage accounts or stock market transactions, not encompassing all investment avenues. Investors might also engage in other markets or use multiple brokers.

An exception is Calvet et al. (2007), which analyzed a broad database of Swedish household portfolios. On average, these investors maintain diversified portfolios, aligning their returns with market averages. Nonetheless, a segment of investors (5%) incurs annual losses exceeding 5%.

Anderson (2008) highlights that investors with lesser incomes, the younger demographic, and those with limited education tend to allocate a substantial portion of their wealth to individual stocks, resulting in under-diversified portfolios, excessive trading, and underwhelming performance outcomes.

As previously noted, a fascinating area of study involves the effect of capturing individual investors' attention. It seems that these investors, particularly those less savvy, tend to execute transactions (primarily buys) following the allure of certain information. The concern, however, is that this information might not always be the most pertinent.

2.3. Evidence from Italy

2.3.1. Overconfidence and trading

The presence of individual investors in the markets has notably increased in recent years in Italy, similar to trends in other countries. Between 2003 and 2008, around three million families entered the stock market directly, without intermediaries. By 2008, internet trading was utilized by 12% of stock investors (Coraggio et al., 2008). The convenience of obtaining financial information and the widespread availability of online trading platforms have facilitated individual investors' access to the markets. Considering the significance of individual trading activities in Italy, it is pertinent to refer to some key analyses related to the Italian scenario.

Other studies employing a behavioral approach in the Italian context have been previously mentioned. These studies, addressing different themes from the current discussion, are referred back to. An early Italian contribution to this field is by Guiso and Jappelli (2006), focusing on how investors' access to information affects their overconfidence. Their study of transactions by clients of a major Italian bank revealed that more information leads to increased overconfidence in individuals, thus boosting transaction frequency. More information does not necessarily translate to better individual outcomes; in fact, even well-informed investors often see poor performances and fail to diversify their portfolios adequately. The abundance of information can heighten overconfidence due to an illusion of knowledge, but the quality of information is more critical than its quantity. Studies have also explored the connection between socio-demographic traits and individual investment behaviors.

While these studies are significant, research specific to Italy is sparse. Notable among these are the works of Alemanni and Franzosi (2006). Their 2006 study, based on telephone interviews, intricately examined the characteristics of online traders. Findings from the sampled group indicate that the typical Italian online trader differs socio-demographically from the general populace, being predominantly male, aged 35–45, self-employed, well-educated, and financially well-off. In the sample, 97% of online traders were male, compared to 49% in the broader Italian population.

Those aged 35–45 constituted 35% of the sample versus 22% of Italians in that age range. Self-employed and entrepreneurial participants made up 38%. Although these traits diverge from the typical Italian investor's profile, they align closely with those of online traders in other countries. The study leveraged data sourced from a collaboration between Borsa Italiana and five Italian online brokers. Each broker supplied transactional data for one hundred representative client accounts. These findings largely echo those of the earlier study but are grounded in actual data (covering the period from July 1 to December 31, 2005), not just interview responses. This distinction matters because questionnaire-derived data can be skewed by various biases.

One is selection bias: respondents might only include those who experienced successful investments, leaving out those embarrassed by their poor choices. Additionally, survey responses might not be entirely accurate; respondents could either intentionally misrepresent or, even with honest intentions, be misled by their self-awareness and recollection of events. For instance, an investor with hindsight bias might give inaccurate assessments of their past investment decisions.

2.3.2. Attention-grabbing

One limiting factor for agents' rationality is the level of attention they can allocate to gathering necessary information for decision-making.

In the realm of financial investments, the attention individuals pay is relatively minimal, even though these decisions are critically important. Investors may err in two ways: overvaluing outdated or irrelevant information or undervaluing crucial information. The former leads to an overreaction to minor information, while the latter typically results in an under-reaction, or delayed reaction, to vital data.

Barber and Odean (2008) illustrate that attention plays a key role in the decision-making process. The challenge is dual: selecting stocks to buy and to sell. Yet, in the latter case, individual investors tend to simplify the problem by opting to sell stocks they already possess, with few engaging in short selling. As a result, the pool of stocks to sell remains relatively small, posing a less daunting decision-making challenge. Conversely, when choosing stocks to buy, given the option to invest across international markets, the selection spans thousands of financial instruments, substantially complicating the process. Here, individuals often resort to heuristics to simplify these complex decisions. A common heuristic is purchasing attention-grabbing stocks.

Barber and Odean (2008) employ three proxies to pinpoint stocks that draw investors' attention: trade volume, the prior day's return, and media coverage of the stock. Their findings indicate a higher frequency of purchase orders for stocks that garner more attention.

Attention deficits, as well as attention itself, significantly skew investors' decision-making, leading to delayed responses to critical information or a failure to recognize its significance. Dellavigna and Pollet (2009), for instance, observed that market reactions are less pronounced for earnings announcements made on Fridays. Distracted by the upcoming weekend, individual investors tend to under-react to such news, causing a lag in market response, evidenced by a subsequent drift. Hirshleifer et al. (2009) found that when earnings announcements from multiple companies coincide, the immediate market reaction to surprises in earnings is subdued, while the post-earnings announcement drift — indicating the market's adjustment to the initial under-reaction — intensifies. This happens because concurrent announcements create a battle for investors' attention. However, Hirshleifer et al. (2008) could not directly link this drift to individual investor transactions, who appear to buy stocks with the most significant earnings surprises, regardless of their nature.

Seasholes and Wu (2007) studied around six million accounts on the Shanghai Stock Exchange, noticing a positive order imbalance (more buying than selling) for stocks hitting upper price limits. Such a limit breach is a common buy indicator for investors applying technical analysis. This kind of event effectively grabs the attention of numerous investors. This effect was more pronounced when few stocks reached their upper limits, facing less competition in attracting institutional investor attention. Even those who had never owned stocks were lured by these events. Interestingly, the authors demonstrate that more rational investors consistently capitalize on these scenarios, to the detriment of those swayed by attention-catching stocks.

Engelberg and Parsons (2010) demonstrate that individual investors tend to engage more in buying or selling S&P 500 index stocks if their earnings announcements receive local press coverage. In such instances, while both buying and selling activities increase, purchases escalate more, highlighting attention-capturing effects. The authors explore the market's overnight response to buy or sell recommendations on the TV show *Mad Money*. They observe a positive link between audience size and market reaction, more so with buy recommendations. The influence on investors is not confined to print media and television; the internet's impact is growing. Da et al. (2011) employ Google search frequency as an indicator of investor attention to assess if such attention impacts market prices. Their findings affirm that an uptick in searches for a stock predicts its price rise in the following two weeks, followed by a normalization over the next year.

In Italy, Cervellati et al. (2014) examine market responses to the dissemination of second-hand information. This research belongs to a body of work investigating whether previously known information can affect investor decisions merely due to its re-publication or media coverage. This area of study features an ongoing debate between two competing theories. The first posits that even second-hand news can sway prices without substantive new information (price pressure hypothesis). The alternative theory argues that the market reaction is driven by the dissemination of information genuinely valuable to investors (information dissemination hypothesis). Although online information is gaining traction in Italy, the printed press undeniably remains crucial for news dissemination. A primary source for many investors is *Il Sole 24 Ore*, known for its financial insights and investment advice. The paper features numerous columns, with its Saturday supplement being particularly popular for its comprehensive weekly analysis. Thus, even if a column lacks groundbreaking news, readers might interpret it as an implicit investment cue or perceive its data as valuable. The column's tone is generally neutral, albeit including summaries of financial analysts' opinions. Its format is consistent: authored by the same writer, each piece focuses on an Italian stock market-listed company, spanning two pages that cover the company's sector, financial figures, stock performance charts, management perspectives, and analysts' recommendations and forecasts.

Analysts' consensus and comparable companies' price/earnings ratios are often, but not always, included. The column's fixed attributes mean that variation lies in the number of analysts cited and their recommendation tones. The cited analysts do not encompass all those covering the featured company, but their number could signify heightened investor interest. The tone, averaging the column's recommendations, ranges from positive and neutral to negative. The study examines 165 columns about Italian firms from January 2005 to June 2009. This focus on Italian companies is due to the typical Italian investor's propensity to invest domestically (home bias) and the column's Italian language, making it unlikely for foreign investors to be readers or influenced by it.

The study concluded in 2009 due to subsequent changes in the column's format, renamed *"The Stocks of the Week"*, highlighting a shift from featuring a single company to comparing two typically sector-aligned companies. The column's length was reduced to one page, and it was no longer penned by the original journalist but managed by the Plus 24 editorial team. Although similar in content, the revised format introduced a comparative element, potentially influencing readers towards one of the two listed companies. This change, alongside the earlier described uniformity, led the authors to omit these columns from their analysis. Excluding companies lacking crucial analysis elements like analysts' recommendations, the final sample comprised 144 companies. The authors gathered data including each company's market capitalization, book-to-market ratio, price and volume movements pre- and post-column publication, and pertinent analyst numbers and recommendations, including average consensus when available.

This data calculated the market's abnormal returns post-publication, using the four-factor model by Carhart (1997), which considers company size and book-to-market ratio. The number of analysts indicates the mentioned company's market prominence.

The 144 columns discussed 83 different companies, with some featured multiple times (but not within the same year). Predominantly medium-sized firms, the most represented market segments were Star (54.2%) and Standard (33.3%), with fewer mentions of blue-chip companies, except during 2006–2007, where they accounted for about 20% of cases. The sample's diversity extended across 17 sectors.

The study period intentionally selected, spanned two contrasting market phases, one bullish (January 2005–May 2007 and mid-March 2009–end June 2009) and the other bearish, each of equal length. The columns under review predominantly fall within 2007–2008, accounting for more than half of the sample. This is because, during 2004–2005, many columns focused on foreign firms, excluded from the sample for previously stated reasons. Nonetheless, exactly half of the columns appeared during the bear market phase (June 1, 2007–March 10, 2009), with the remaining published in bullish periods. Central to the analysis is the sentiment of analysts' recommendations in each column. The authors attribute numerical values to recommendation types: 2 for "buy", 1 for "overweight", 0 for "hold, neutral", -1 for "underweight", and -2 for "sell". These values facilitate the computation of the average and median recommendation for each column, thereby establishing the consensus among cited analysts.

The study distinguishes between positive and non-positive consensus. The latter group encompasses negative and neutral recommendations (37 and 15 instances, respectively). Previous research indicates that the market often interprets neutral recommendations as negative (Davies &

Canes, 1978; Beneish, 1991), partly due to analysts' pervasive over-optimism and conflict of interest, leading to reluctance in conveying negative market information (Piras et al., 2012). This predisposes them towards issuing neutral instead of negative recommendations. Furthermore, the attention-capture effect appears to influence buying decisions than selling more significantly. Thus, differentiating positive recommendations from the rest is logical.

To gauge the market's response to the column's release, the authors employed a conventional event study approach (Fama et al., 1969), identifying abnormal returns (Campbell et al., 1997) and abnormal volumes (Ajinkya & Jain, 1989) post-event. They calculated abnormal returns using three models (the market model, CAPM, and the four-factor model), yielding comparable results. The 16-day event window [-5; +10] enabled analyzing market reactions during the trading week before (day 0) and the two weeks following the event. For estimation, the authors considered 250 trading days before the event window [-255; -6] for model coefficient calculations, utilizing the previous year's data to avoid overlap with the event-adjacent days that could skew coefficient estimations. The study found a positive average market reaction on the first trading day following the column's publication, typically the Monday after its Saturday appearance in Plus 24 (barring holidays). The abnormal return, per the four-factor model, stood at 0.9%, with trading volumes 33% above the norm. Notably, abnormal returns were also recorded the preceding Friday, which the authors explain in two ways. Firstly, although the column is published on Saturday, it is finalized in the editorial office by Thursday. This could lead to information leaks or insider trading affecting Friday's market. Potential insiders include the mentioned company's managers or the column's author. However, given the journalist's reputation and strict insider trading regulations in Italy, the authors largely dismiss this possibility, though they consider it methodologically. Secondly, the research accounts for the likelihood of concurrent events distorting market reactions before the event. The authors examined various sources, including company press releases, news articles, specialized websites, and analyst reports, to identify market-influencing (price-sensitive) news published on the event day or the preceding Friday.

Disregarding 29 columns due to overlapping events, the findings are largely unchanged in terms of both abnormal returns and abnormal volumes (20% above the norm) on the event day, with no further anomalies on the previous Friday.

Focusing solely on columns with positive analyst consensus, minus those with potential competing events, yields a 20% higher market reaction, resulting in a 1.16% abnormal return and volumes 36% above average.

Conversely, columns with non-positive consensus show no abnormal returns or volumes, aligning with the attention capture hypothesis, where positive market reactions are evident only for columns suggesting stock purchases.

To confirm this hypothesis, positive and negative cases are differentiated. In positive cases, a reduction in cumulative abnormal return to near zero is observed, hinting at the price pressure hypothesis: the column may not offer real investor value but initially captures attention. With negative consensus, no anomalies are noted post-event, supporting the attention capture hypothesis in the absence of any abnormal market reaction. For exploring the asymmetric market reaction's causes, the authors employed two distinct regressions, analyzing abnormal returns and volumes on the event day for positive consensus columns. Independent variables include the number of analysts cited, pre-event stock performance, presence of earnings estimates in the column, concurrent events, sector and annual dummies for fixed effects, company market capitalization, and price-to-book ratio. The last two, parts of the four-factor model, are not significant, as are the sector and annual dummies. This indicates constant abnormal returns and volumes over time, suggesting the market's reaction to the column's publication does not fade or lessen in intensity. This finding counters the expectation of market learning processes, as no such trend is evident. The key variables in this analysis are the number of analysts mentioned in the column and the inclusion of earnings estimates. The number of analysts serves as an indicator of the company's popularity among analysts or more broadly among investors, as well as the volume of information available in the market. A high analyst following might suggest abundant market information, possibly minimizing the marginal impact of the column. Hence, one might anticipate a negative correlation between the number of analysts and market reaction. However, the findings show a positive and significant influence in both regressions, contradicting the information dissemination theory and endorsing the attention capture hypothesis. This suggests the column heightens interest in already well-known stocks. It is important to note that there is no clear consensus in the literature regarding the expected pattern of cumulative abnormal returns following an attention-capture event. The incorporation of earnings estimates, conversely, seems to diminish the observed abnormal returns. This reduction is likely because the inclusion of estimates often comes with a consensus, enhancing the column's technical content and information level. This increased complexity might lessen the column's attention-grabbing impact, which is partly driven by emotional factors. Furthermore, advice from *Il Sole 24 Ore* experts in the column *"The expert advises"* does not always align with traditional financial theory (Cavezzali et al., 2011). Experts often recommend older savers invest in Italian company securities, contrary to traditional advice favoring international investment for better diversification. The authors suggest these experts are not subject to home bias but rather accommodate the cognitive biases of older readers, guiding them towards investments perceived as less risky. The advice highlighted by Cavezzali and Rigoni (2011) in *Il Sole 24 Ore* reflects a tendency to cater to the biases of the readership, which may not always align with optimal investment strategies. Financial advisors need to recognize and address these biases while providing guidance that truly aligns with the best interests and goals of their clients.

CHAPTER 3: A BEHAVIORAL APPROACH TO WEALTH MANAGEMENT

3.1. Motivational theory (SP/A)

Another cornerstone of behavioral finance is motivational theory, which asserts that emotions significantly influence individuals' decision-making processes, linking choices and objectives (Lopes, 1987).

Decision-making is shaped by two factors: the goals pursued, and the aspirations held. The primary goals individuals strive for are "security" and "potential" (gain), while aspirations relate to the choice of these goals, which can also be wealth-centric. Hence, this approach is termed SP/A theory, where S signifies Safety, P for Potential, and A for Aspiration. The SP/A theory provides a nuanced framework to comprehend how investors balance their desires for safety and potential gains. This theory particularly resonates in the field of behavioral finance, where emotional and psychological factors are as influential as rational considerations.

Security represents the desire to avoid low wealth levels that might compromise one's lifestyle, whereas the pursuit of potential is about maximizing wealth. Though these goals are diametrically opposed, each individual harbors both, in varying degrees. When the desire for security dominates, an individual tends towards risk aversion. Conversely, if the pursuit of potential is paramount, there is an inclination towards risk-taking. In this scenario, an investor's readiness to take risks is influenced by two conflicting emotions: fear and hope. Fear plays a crucial role as it often leads to overestimating the likelihood of negative outcomes, thus undervaluing potential success. This can lead individuals to lessen the chance of maximizing expected wealth levels. The goal of security is not just about avoiding risk; it is about the preservation of current wealth status and ensuring a certain standard of living. This aspect of SP/A theory is closely aligned with the concept of loss aversion found in prospect theory, where the pain of losing is psychologically about twice as powerful as the pleasure of gaining. Individuals with a higher inclination towards safety are likely to prefer investments with lower volatility and more predictable outcomes, such as bonds or fixed deposits.

The pursuit of potential, on the other hand, aligns with the desire for wealth maximization. This aspect often mirrors the traditional utility maximization approach in finance. However, unlike the traditional approach that assumes rationality and risk tolerance based solely on expected returns, SP/A theory acknowledges that this pursuit is also emotionally driven. For instance, the joy of achieving a significant gain or the status that comes with successful investments can heavily influence decision-making. Hope can cause people to perceive the probability of achieving desired wealth levels as higher than it is. This suggests that the weighting function is asymmetric, overemphasizing the probability of negative events for those more focused on safety, and the opposite for those prioritizing potential.

Aspirations vary among individuals, as the same wealth level can represent different aspiration levels, influenced significantly (though not exclusively) by varying initial wealth. Aspiration level serves as a natural reference point in individual decision-making and is crucial in setting the threshold for subjective and varies among individuals. For example, an investor with a modest financial background might set a lower aspiration level compared to someone from a wealthier background.

Aspirations are not static and can shift over time due to personal experiences, social comparisons, and changes in financial circumstances. An investor might raise their aspiration level after a period of successful investments or lower it following losses.

Aspiration levels significantly impact risk behavior. Individuals whose wealth levels are close to their aspiration levels may exhibit risk-seeking behavior to reach their goals. Conversely, those who have exceeded their aspiration levels might become risk-averse to protect their gains.

Understanding how individuals balance safety and potential is key to explaining investment choices. For instance, during market downturns, the safety goal might dominate, leading to a widespread sell-off. Conversely, in a booming market, the potential goal might take precedence, resulting in bullish behavior.

The interesting aspect of SP/A theory is the inherent conflict between the goals of safety and potential. This conflict often results in internal dilemmas for investors, as they grapple with the trade-off between securing what they have and striving for more. Behavioral finance recognizes this conflict as a central aspect of investor psychology.

The theory also underscores the importance of emotional regulation in investment decisions. Investors who can balance their fear and hope effectively are more likely to make decisions that align with their long-term financial goals.

In conclusion, the SP/A theory offers a comprehensive framework for understanding the complex interplay of safety, potential, and aspiration in financial decision-making. By acknowledging the emotional and psychological underpinnings of investor behavior, this theory provides valuable insights into the anomalies and irregularities observed in financial markets.

3.2. Naive diversification and biased perceived risk-reward ratio

In prospect theory, as observed, gains and losses are evaluated relative to a reference point, which can differ from the status quo and align instead with a specific level of contingent aspiration. While risk aversion or propensity is temperamental, aspirations hinge on current situations and thus change over time. Unlike in prospect theory where risk-taking is inherent in the value function (with convexity in the loss domain), aspirations depend on three key elements: the (subjective) assessment of achievable goals; the nature of available alternatives; and the influence of external factors on an individual’s overall circumstances.

Motivational theory suggests that risk appetite can shift when evaluating scenarios leading to a certain aspiration level. Individuals often encounter conflicts, such as in financial investments where there is a clash between the desire for security, which comes with lower returns, and the pursuit of potential, necessitating higher risk. Personality initially guides the choice towards security or potential but does not entirely eliminate other options, leading to regret over missed opportunities.

The relationship between an individual’s “structural” behavior and aspirations is not fixed, as choices can be swayed by the immediate likelihood of achieving a specific goal. This explains why typically risk-averse individuals might behave riskily in certain situations if it aids in attaining a desired aspiration level. For instance, if an investment brings one closer to purchasing a dream home, the reference point might shift from initial wealth to the new aspiration level, altering the attitude from risk-averse (in the domain of gains) to risk-seeking. This shift occurs because, compared to the new reference point of a higher aspiration level, current wealth feels insufficient, placing one in the domain of losses.

Prospect theory reveals that individuals are risk-averse when dealing with gains and risk-seeking in the loss domain, with the value impact of a loss being more significant than that of a gain. Consequently, people typically view risk negatively.

Generally, the risk-return relationship perceived by investors in financial investments contrasts with traditional finance’s assumption of a positive correlation (riskier stocks yield higher future returns). Instead, evidence suggests individuals may perceive this relationship as negative, expecting higher returns from less risky securities (Duxbury & Summers, 2004). Investors often fall into the trap of equating company performance with stock performance. This misalignment between perceived and actual risk can lead to a skewed risk-reward perception, where less risky investments are erroneously expected to yield higher returns. This phenomenon is particularly evident in how investors view blue-chip stocks versus high-growth potential stocks. This perception largely stems from the representativeness heuristic, where investors view "good companies" as "good stocks" (Shefrin, 2002), thus anticipating higher returns from safer companies. Though flawed, this reasoning is psychologically understandable given the negative connotation often associated with risk, making it difficult to link it with positive outcomes like high returns.

The perception of risk and reward can also be highly influenced by prevailing market conditions. In bull markets, investors might underestimate the risk due to the general optimism, and vice versa in bear markets, leading to a cyclical pattern of risk perception that does not necessarily align with actual risk levels.

Not just erroneous risk perception, but other factors also lead to mistakes in constructing investment portfolios. Despite diversification's known advantages, many individual investors hold too few stocks in their portfolios. Those who do diversify often do so suboptimally, not considering securities' return correlations but merely splitting their investment equally among all options (Benartzi & Thaler, 2007). This decision-making heuristic, known as the "1/n rule" or "naive" diversification, underscores the importance of framing — how investment alternatives are structured and presented.

The 1/n rule demonstrates a simplistic approach to diversification. Investors often adopt this rule not because it is optimal, but because it reduces the complexity of decision-making. This heuristic bypasses the need for extensive research and analysis on the individual securities, making the investment process less daunting but potentially less effective. A notable example of this is seen in the investment choices of some U.S. workers regarding their company's supplemental pension plans.

Madrian and Shea (2001) observed that when workers had to choose between a bond line and an equity line, they often split their contributions evenly between the two. However, when the options were one active line and another mixed (comprising half shares and half bonds), they continued to distribute their funds equally between the two available lines. In this latter scenario, workers ended up with three-quarters of their portfolio in shares and only one-quarter in bonds. Thus, the number and presentation of investment options significantly impact asset allocation and the associated risk level. Investors might not differentiate sufficiently between options, inadvertently assuming excessive risk. A limited understanding of how different options contribute to overall portfolio risk can lead to unintentional overexposure to certain asset classes. This underscores the importance of clear and comprehensive financial education for investors.

Another example of incorrect diversification in portfolio asset allocation is home bias — introduced in Chapter 1 — that is the tendency to invest predominantly in domestic markets (French & Poterba, 1991). This approach is flawed because yield correlations are typically lower than within domestic markets, making it more beneficial to diversify across multiple markets, not just sectors within one's own country. Traditional explanations cite higher costs and information-gathering challenges for foreign securities trading. While this was true historically, today's lower explicit costs and easier information access, thanks to online platforms, render this justification less valid. The behavioral approach offers an alternative explanation rooted in the familiarity heuristic and ambiguity aversion. Foreign company securities are less familiar than those of domestically listed companies, and due to individuals' aversion to ambiguity and uncertainty, they tend to prefer investing in the latter. The preference for domestic investments shows how investors feel more comfortable with well-known local markets. This comfort is often mistaken for lower risk. Furthermore, familiarity should not be mistaken for knowledge.

A specific type of home bias, where people invest in their employer's company or those in their region (local home bias), warrants attention. Investing heavily in local or employer-related stocks is a prime example of the illusion of knowledge. Investors may believe they have better insights into these companies, but this often leads to an overconcentration of risk. Except for managers or high-level employees, this often leads to a dangerous illusion of knowledge, resulting in an equity portfolio concentrated in a few stocks, reducing diversification opportunities and making returns dependent on a single source (the employer).

In cases of employer bankruptcy, this risk concentration can have catastrophic consequences, as evidenced by Enron employees who lost not only their salaries but also health insurance, pension savings, and investments in company securities. The collapse of Enron is a stark reminder of the dangers of this bias.

Another important issue in individual investors' portfolio choices is "time diversification" (Fisher & Statman, 1997). Understanding the investment time horizon is as critical as defining investment goals. Conventional wisdom recommends a younger focus on equities and a shift towards less risk with age. This approach, however, overlooks individual needs over mere age. For example, a young investor planning to buy a house soon would find investing heavily in stocks unwise due to their inherent volatility. Thus, a one-size-fits-all approach based on age does not account for personal risk tolerance and specific financial objectives. Investors should regularly reassess their investment horizons and adjust their portfolios accordingly. This is particularly important for investors approaching major life events, such as retirement or purchasing a home, where liquidity needs and risk tolerance may change significantly.

The naive perceived risk-reward ratio and diversification practices highlight the profound impact of behavioral biases in financial decision-making. Understanding these biases and their implications is essential for both individual investors and financial advisors to foster more effective and tailored investment strategies. Educating investors about the principles of risk, reward, and diversification is crucial. An informed investor is more likely to make decisions that are aligned with their long-term financial health, rather than being swayed by prevailing market sentiments or cognitive biases.

3.3. Behavioral portfolio theory

Modern portfolio theory (Markowitz, 1952a), a cornerstone of conventional finance, operates on the mean-variance principle, defining each security by its expected return-risk duo. Central to this is the two-fund separation theorem, suggesting investors allocate wealth solely between a risk-optimized market portfolio and a risk-free asset. Asset distribution hinges on risk appetite, yet the risk-optimized portfolio remains universally optimal, maximizing market risk premium per risk unit. Risk, if defined by volatility (a security's return standard deviation), aligns with the Sharpe ratio. A fundamental assumption is that rational investors assess the portfolio in totality, factoring in the interplays between securities (or funds) and positioning on the efficient frontier, where the efficient portfolios reside, which, for a given expected return, minimize risk. However, traditional theory remains silent on what investors intend to do with their money, specifically their objectives and the strategies they employ to achieve them. Consequently, mean-variance theory is merely an intermediary step in grasping how investors work towards their goals.

Interestingly, in the same year as his groundbreaking work on modern portfolio theory was published, another of his articles, lesser-known (Markowitz, 1952b), established the groundwork for behavioral portfolio theory. This paper broadened the framework first introduced by Friedman and Savage (1948) that posited that key investor goals are wealth protection and the aspiration to enrich oneself. Their concept, dubbed "insurance lottery", hinges on the idea that people are risk-averse when it comes to insurance purchases for protection, yet risk-seeking when buying lottery tickets. Markowitz (1952b) elaborated that even typically risk-averse individuals might opt for higher risks if it meant a significant improvement in life quality.

In 1979, as mentioned, psychologists Daniel Kahneman and Amos Tversky furthered this notion, introducing the now-famous prospect theory — earning Kahneman a Nobel Prize in Economics in 2002 — named for its focus on decision-making under uncertainty and facing alternative choice "prospects" (Kahneman & Tversky, 1979). A central tenet of the theory is that personal utility is not solely based on absolute wealth; instead, decisions are made by comparing gains or losses relative to a specific reference point. Kahneman and Tversky (1979) found that people tend to be risk-averse when considering potential gains but risk-seeking when facing potential losses. This phenomenon, termed "loss aversion" in behavioral finance, highlights a general aversion to losses, where individuals faced with past losses are more likely to embrace risk to return to even.

The reference point in prospect theory is often the current status (status quo) of the decision-maker. For many investors, this reference is a potent mental anchor, like the purchase price, which then informs their decisions. This "anchoring" effect means that decisions are influenced more by past experiences than future expectations. This mindset is risky in general, but more so because it changes how investors approach risk.

The reference could also be an investor's aspirational level, as suggested by the already mentioned "motivational theory" (Lopes, 1987). This theory forms another cornerstone of behavioral finance, also referred to as SP/A, representing Security, Potential — the primary goals of investors — and Aspirations. Under this theory, a typically risk-averse investor might embrace higher risks if the potential reward enables a likely attainment of their aspirational level. This concept partly revisits the "insurance-lottery" framework by Friedman and Savage (1948) and Markowitz (1952b). This perspective helps understand why lotteries appeal to lower-income groups, while their saving rates are negligible or negative, especially under substantial debt. The rationale is that the less affluent might save, but the amount is usually minimal and, even when invested, unlikely to elevate their social status. Hence, saving seems futile, prompting expenditures on immediate needs and lottery tickets, hoping for substantial wealth and a leap in social standing, unachievable through mere saving. Intriguingly, this approach implies that people may feel in a "negative zone" even when not losing money, like being below their aspiration level.

The development of behavioral portfolio theory is credited to pioneers Hersh Shefrin and Meir Statman, particularly in their work *"Behavioral Portfolio Theory"* (BPT, henceforth) (Shefrin & Statman, 2000).

To succinctly delineate BPT from traditional theory, one must consider the concept of mental accounting. Behavioral finance proposes that people segregate funds into distinct mental partitions or accounts, based on the money's origin and intended purpose. For instance, money earned through hard work is valued differently than winnings or funds allocated for discretionary spending versus necessities. The issue with mental accounting is its potential to obscure the comprehensive view of one's finances. In investment terms, this translates to ignoring correlations across various asset classes. BPT exists in two forms, "Single Account BPT" (BPT/SA) and "Multiple Accounts BPT" (BPT/MA).

BPT/SA somehow parallels traditional theory, assuming decision-making is based on a single mental account. The mean-variance theory's central concept is the "efficiency frontier", delineating all combinations that yield the highest expected return for a given risk or, alternatively, the lowest volatility for a specified return. Risk assessment in BPT diverges from the conventional model. Rather than relying on volatility, it assesses the probability of failing to meet a specific threshold in a particular mental account. Many investors find the concept of volatility ambiguous, perceiving risk not as a variance from an expected value but as the chance of "loss" or failing to achieve a specific goal. Thus, in BPT/SA theory, the counterpart is an efficiency frontier in the expected wealth-probability domain. This differs from the traditional approach as it aims to prevent wealth from dipping below a predetermined aspiration target. In both scenarios, investors seek high returns or elevated expected wealth levels, coupled with low volatility and minimal risk of failing to meet their aspiration levels. However, the optimal portfolios in BPT diverge from those in modern portfolio theory. While efficient portfolios blend a risk-free asset with a market portfolio, BPT investors distribute their wealth across securities and "lottery tickets", which are investments that, although currently unfair, present an opportunity to reach their aspirational goals. BPT/MA, instead, suggests that individuals, operating with multiple mental accounts, overlook correlations between these accounts and thus between different asset classes. BPT/MA is deemed the authentic version of behavioral portfolio theory, aligning more closely with the thought processes of actual individuals who often lack an understanding of correlation. Going forward, this theory will be the primary focus. Thus, we will refer to it as just BPT, but meaning BPT/MA. BPT suggests that investors operate within separate efficient frontiers, one for each mental account, unlike traditional finance which proposes a singular efficient frontier. It further contends that investors may exhibit risk aversion in certain mental accounts while being risk-seeking in others, aligning with the principles of prospect theory. This methodology mirrors the psychological and behavioral patterns of individuals who usually categorize their investments by different goals and risk tolerance levels. Thus, BPT provides a more comprehensive and tailored investment perspective, acknowledging the diverse psychological and behavioral aspects influencing financial decisions.

3.4. BPT, mental accounting, and investment pyramid

BPT's foundation in motivational theory underscores the significant role of emotions in investment decisions. Understanding how emotions like hope, which drives expectations, and fear, leading to anxiety, panic, and subsequent regret, as well as biases such as self-attribution bias, and overconfidence, impact investors' choices is crucial.

In evaluating investments, individuals consider the likelihood of reaching a desired aspiration level rather than choosing securities solely based on the risk-return dynamic proposed by the mean-variance approach.

Often, their selection is influenced more by their emotional response to the characteristics of a security. Underlying the fear of loss is the quest for downside protection, while the aspiration for gain underscores the pursuit of upside potential. This interplay of emotions shapes investors' risk tolerance, guiding investment choices that fulfill both economic and emotional needs.

The so-called "reward pyramid" (Wall, 1993) encapsulates this dual-need investment approach, offering a more realistic representation of real-world investment decisions than traditional portfolio theory and aligning closely with prevalent financial advisory practices. This approach, often called "portfolio pyramid" or "investment pyramid" underscores the fluctuating nature of risk tolerance across different "mental accounts" in which wealth is categorized. It introduces an added tier named "pseudo-safe-haven assets", highlighting their perceived low risk which masks underlying high risks.

Mental accounts thus become a pivotal element in this pyramid structure. The pyramid's tiered design mirrors the escalating need for security.

At its base, a significant portion of financial resources is dedicated to protection. As one ascends the pyramid, progressively smaller sums are allocated to riskier ventures and the pursuit of upside potential.

To guarantee security, perceived as a paramount need, investments are channeled into risk-free vehicles like certificates of deposit, savings accounts, or short-term government bonds for vital goals, such as covering rent, mortgage payments, and routine expenses. Following this, government and corporate bonds offering attractive yields with minimal risk, typically investment-grade, are chosen.

An additional advantage of bonds is their periodic interest payments, which are often mentally categorized as "current income". This income is perceived as readily available and hence expendable. Consequently, individuals progressively allocate smaller portions of their assets to riskier investments like stocks or high-yield bonds to fulfill their aspiration for portfolio value appreciation. These high-yield bonds, often termed "junk bonds", are acknowledged for their heightened risk. This distinction between high risk and high returns can sway less sophisticated investors, exemplifying framing effects.

At the apex of the investment pyramid lie extremely high-risk investments. These include derivatives employed for speculative purposes (as opposed to hedging) or other ventures that, although actuarially unsound, fulfill the "hope" for an enhanced standard of living. The proportion of funds allocated to each investment within the pyramid's different levels varies according to each individual's risk tolerance.

It is also critical to recognize that people's perceptions of risk do not always align with the actual risk. Take real estate investment, for example. It shares similarities with equity investment in tying up a substantial sum for long-term asset appreciation. Yet, real estate, is often viewed as a safe-haven asset, perceived as low-risk. Some do not even regard it as an investment per se, as it meets a basic need such as housing.

Securities that offer safety resonate with investors driven by fear, while those promising high returns appeal to those seeking potential. Most investors, however, are motivated by both emotions and adopt a "sequential" approach, prioritizing safety before seeking potential gains.

This approach contradicts the simultaneous portfolio optimization prescribed by traditional theory. Activities that satisfy both safety and potential become particularly appealing in this context. For instance, some bonds issued in the UK with monthly lottery tickets as prizes instead of interest payments exemplify this concept. These bonds were highly successful as they addressed both the need for downside protection and the aspiration for upside potential. Lottery tickets, in this case, represent a unique form of "investment" offering high potential earnings albeit with low winning odds. Typically, lotteries are not perceived as genuine investments but rather as a form of wagering that fulfills the dream of wealth.

The concept of mental accounts is often illustrated through what is known as the Layered Investment Pyramid, where each layer symbolizes a separate mental account. There are several interpretations of this pyramid, with the "goal-oriented" and "instrument-based" versions being particularly prevalent.

In the "goal-oriented" pyramid, each tier is associated with a specific investment objective. To illustrate, consider a simplified version with just three objectives: the foundational layer focuses on capital protection and stability; the middle layer caters to investments with a balanced risk-return profile; and the apex layer targets high-risk investments with the potential for substantial returns.

In the realm of BPT, the ideal securities resemble call options, characterized by their asymmetrical return distributions. This suggests the possibility of notable gains but also carries a heightened risk of losses.

Consequently, BPT advocates for a diversified investment approach, not merely across different asset classes but also aligning with the investor's diverse objectives and risk tolerance. This approach is visually encapsulated in the various levels of the investment pyramid. In each investment objective, a distinct approach to risk is apparent. This suggests that investors do not possess a singular risk attitude; rather, they exhibit as many risk attitudes as the mental accounts they deploy.

This concept of differentiating between mental accounts (objectives) and linking them to specific risk tolerances is crucial, as it enables financial advisors to tailor asset allocation to the behavioral needs of their clients, considering each client's unique objectives and limitations. Furthermore, advisors can organize the client's assets into sub-portfolios, each aligned with a particular mental account/objective, details of which will be discussed later. Identifying the objectives is the first step, followed by selecting appropriate instruments to achieve them. The subsequent illustration displays a common investment pyramid, organized by instrument types.

This mental account-based pyramidal structure, which separates safety-oriented goals from those seeking upside potential, is consistent with the "core" and "satellite" portfolio distinction widely adopted by financial consultants. In the pyramid's foundation, focusing on safety, one finds low-risk options like government securities or bank savings. The middle tiers of the pyramid might encompass goals such as achieving steady income or moderate capital growth, typically through investments in corporate bonds or balanced funds. The pinnacle of the pyramid, aimed at upside potential, is reserved for higher-risk ventures like growth equities or hedge funds. This structured approach offers a comprehensive and methodical perspective on investment, simplifying the portfolio management process in line with clients' diverse risk and return expectations and requirements.

Security, being a fundamental necessity, is why at the pyramid's base are placed secure investment tools (cash, checking accounts, deposit certificates, money funds), aimed at fulfilling essential needs like rent or mortgage payments, daily expenses, and more. On the left side, we identify instruments that offer higher income at a similar risk level but with reduced liquidity, whereas the right side presents the converse. Advancing to the upper tier, one encounters government securities with short, medium, and long maturities, along with corporate bonds, also generally regarded as secure. Riskier ventures such as equities or high-yield bonds — bearing a high risk, thus sometimes disparagingly called "junk bonds" — receive progressively smaller portions of an investor's assets, targeting the sought-after upside potential or portfolio value increase. At the pyramid's pinnacle lie the exceptionally high-risk investments like speculative derivatives, catering to the “hope” of a better life quality or simply higher yields (akin to a casino’s allure). This layout aids investors in conceptualizing their risk management and asset distribution, harmonizing the need for security with the potential for financial growth, all while considering their individual financial needs and goals.

Harry Markowitz himself acknowledged this in a 2011 paper co-authored with colleagues including Meir Statman, a trailblazer in behavioral finance (Das et al., 2011).

On a psychological level, many investors tend to conflate their desired objectives, such as security, with the means of attaining them within a defined time frame. To illustrate how the portfolio theory by mental accounts works, let us examine a hypothetical investor scenario, adapted from Das et al. (2011).

We envision a fifty-year-old investor endowed with €1 million, aiming to allocate it across three distinct objectives: bequest, education (for his children), and retirement. More in detail, imagine the following data, related to each objective.

- Bequest: the investor aspires to leave approximately €850,000 as an inheritance in 25 years, requiring an initial investment of €50,000 today.
- Education: to support his children’s educational pursuits, he anticipates a need for €190,000 in 3 years, with €150,000 already at his disposal.
- Retirement: planning to retire in 15 years, he aims for a retirement fund of €1.9 million, commencing with the existing €800,000.

For simplicity, we assume the consultant is investing in just three funds, each with the following attributes:

- Bond Fund: expected return of 2%, volatility at 5%.
- Defensive Equity Fund: the anticipated return of 8%, with a volatility of 20%.
- Aggressive Equity Fund: the expected return of 15%, characterized by a volatility of 40%.

Additionally, let us assume that the bond fund does not correlate with the equity funds, while the two equity funds exhibit a 25% correlation with each other.

To accommodate his client’s specific goals (mental accounts), the advisor divides the available portfolio (€1 million) into three sub-portfolios (SP, henceforth):

- Retirement SP: a €800,000 investment with an expected 6% return over 15 years, aiming for €1.9 million.
- Education SP: allocating €150,000 with an expected return of 8% over 3 years, targeting approximately €190,000.
- Inheritance SP: a €50,000 investment with an expected 12% return over 25 years, aspiring to reach around €850,000.

The investor’s financial advisor is calculating the anticipated returns needed to meet your objectives within the given timeframe.

The overall portfolio’s expected return is calculated as a weighted average of the SP returns. However, the standard deviation is not, as it is crucial to consider the 25% correlation between the two equity funds. Although individuals thinking in terms of mental accounts may not account for correlations, the advisor must take this into consideration.

The bond allocation is higher in the Retirement SP due to its lower risk tolerance. Conversely, for the Bequest objective, the bond allocation even becomes negative to overweight the equity component.

For the typical investor, thinking about expected returns comes naturally, but grasping the concept of volatility (standard deviations) can be a bit challenging.

However, when it comes to the SPs, it is a more straightforward task compared to handling the entire portfolio.

Dealing with the full portfolio would entail considering correlations between various funds and performing complex calculations, which might be beyond the capabilities of the average investor due to a lack of expertise. Conversely, it is simpler to align objectives with risk tolerances as follows: Pension for low tolerance, Education for medium tolerance, and Bequest for high tolerance.

All three SPs are considered efficient because the consultant optimizes the risk-return balance for each objective or mental account.

The Overall Portfolio is positioned close to the Retirement SP, as most of the client's wealth is allocated toward this goal. It is essential to highlight that the SPs associated with the client's objectives do not necessarily need to exist as separate entities in reality; they can remain "virtual". In other words, the advisor does not have to construct them as distinct sub-portfolios; instead, they calculate the asset allocation for each of them. The sole "real" portfolio can be the comprehensive one, avoiding the multiplication of management costs.

However, the advisor may choose to create the sub-portfolios if they wish. Irrespective of the decision to physically implement the sub-portfolios, the differentiation in asset allocation for mental accounts and objectives enables the consultant to provide the client with dual sets of statistics: the first based on the overall portfolio and the second on the SPs.

This allows the client to see how the individual sub-portfolios are progressing, even if only virtually, and where they stand in terms of achieving different objectives. In practice, this approach helps the consultant focus the client's attention on their specific goals and effectively manage their emotions, especially during periods of high market volatility. From the client's perspective, it is easier to monitor portfolio performance when it can be associated with individual objectives.

Furthermore, since each objective or mental account is linked to a distinct risk tolerance, the client can better handle market fluctuations on accounts tied to long-term goals, which typically include riskier asset classes. For objectives with time horizons of 15 or 25 years, short-term fluctuations will be of less concern compared to the funds designated for a three-year goal. Given the client's varying timeframes and objectives, the asset allocations of the sub-portfolios will also differ.

As previously mentioned, understanding the concept of volatility can be challenging for many individual investors who lack a specific background in finance or statistics. While they recognize it as a measure of risk, only a few truly grasp its intricacies. Behavioral finance has revealed that the perception of risk, in general, is subjective, in contrast to the traditional objective perspective.

Moreover, investors are not primarily averse to risk in its classical form, which involves deviations from the expected value, but rather to potential losses.

To bridge the gap between investors' mindset and traditional measures of risk like volatility, it becomes essential to shift the focus towards a concept that not only considers potential losses but also the likelihood of experiencing them.

Negative returns are indicative of potential losses relative to the established threshold for each SP. The shaded cells highlight the probabilities of losing 10%, which is 6.28% in the Retirement SP, 5% corresponding to 19.67% in the Education SP, and 15% amounting to 14.27% in the Legacy SP.

The objective is to illustrate how the volatilities of the SPs correspond to these loss probabilities. For example, the volatility of the Retirement SP (at 10.45%) equates to a probability not exceeding 6.28% of losing more than 10% of their funds in that SP in the coming year. Employing the same reasoning, the advisor can engage the client in discussions regarding the other SPs and the overall portfolio. The use of the table, therefore, offers the client deeper insights into the risk exposure of the sub-portfolios and translates the statistical concept of volatility into loss probabilities.

Nevertheless, "real" investors do not adhere to the notion of perfect rationality, at least not in the strict confines of "economic rationality". Their primary concern is not merely the efficiency of their portfolios; instead, they prioritize the attainment of specific goals, like securing a stable retirement, funding their children's college education, or ensuring a particular inheritance.

Traditional financial theory, while rational and pragmatic, overlooks these ultimate objectives of investors. These objectives take center stage in behavioral portfolio theory, although this theory is not notably "practical". To maintain simplicity, we will not delve into the intricate mathematical details of behavioral portfolio theory but refer readers to Shefrin and Statman (2000) for a more comprehensive understanding. It is essential to underscore that the mathematical modeling involved in this theory is considerably more intricate than Markowitz's (1952a) mean-variance approach, which accounts for why behavioral theory is often regarded as less "practical".

The concept of mental account portfolios aims to bridge these two approaches by leveraging their strengths. It adopts the mental account structure characteristic of the behavioral approach while demonstrating the feasibility of constructing efficient sub-portfolios. Beyond the efficiency of sub-portfolios and the overall portfolio, which may not align with the genuine concerns of "real" investors, the key insight lies in recognizing that risk tolerance varies depending on the objective and time horizon in question. Building upon this foundation, one can assess adjustments to the asset allocation of sub-portfolios, thereby facilitating investors in achieving their specific objectives. Another intriguing aspect is aligning with the mindset of "real" investors, considering not only volatility but also the probability of incurring losses, even if it means falling short of their desired wealth level.

The combined utilization of the behavioral approach and the fundamental concept of mental accounting has the potential to equip financial advisors and their clients with a method to effectively navigate "behavioral traps" and manage their asset allocation in a satisfying manner. While the resulting allocation may not adhere to perfect rationality, it will certainly represent the "best achievable in practice" (Pompian, 2012). The role of the financial advisor is pivotal, encompassing not only technical portfolio management but also assisting clients in addressing these behavioral errors to enhance their asset allocation along the path known as the "journey toward optimality" (Brunel, 2015).

3.5. Behavioral Goals-Based Wealth Management

Goals-Based Wealth Management (GBWM) is an approach to personal financial planning and investment management that focuses on aligning an individual's financial resources with their life goals (Brunel, 2015) and represents a paradigm shift from traditional wealth management techniques, emphasizing the client's objectives rather than solely concentrating on maximizing financial returns.

It is a client-centric approach since it puts the client's life goals at the forefront of financial planning. It involves a deep understanding of the client's aspirations, life stages, and risk tolerance. Unlike traditional models that prioritize market benchmarks, GBWM measures success by how well clients meet their individual financial goals, which are categorized as essential needs, lifestyle wants, and legacy aspirations.

Each category receives a different investment strategy. For instance, essential needs might be funded with low-risk investments, while lifestyle wants may allow for more risk-taking. In this approach, risk is not just viewed in terms of portfolio volatility but also in the context of failing to achieve specific goals.

This approach leads to more personalized risk management strategies that are closely aligned with individual goal timelines and significance. GBWM encourages a dynamic approach to portfolio management: as personal circumstances or market conditions change, the investment strategies for different goals are adjusted accordingly. This flexibility is key to responding effectively to life's uncertainties.

By focusing on personal goals, advisors can create a more engaging and meaningful relationship with clients. Customizing investment strategies based on specific goals can lead to better financial outcomes for clients.

GBWM has gained considerable traction in recent years, spurred by advancements in technology and a greater focus on personalized financial advice.

GBWM represents a significant evolution in the way individuals approach their financial planning and investment strategies. Its growing popularity suggests a shift towards more holistic, client-centered financial advice. Future research may delve deeper into the long-term effectiveness of GBWM strategies, the integration of technological advancements, and the exploration of sustainable investing within this framework.

Recently, GBWM integrated insights from behavioral finance to understand and mitigate cognitive biases such as loss aversion or overconfidence. This helps in making more rational investment decisions aligned with long-term goals. This integrated approach known as Behavioral Goals-Based Wealth Management (BGBWM) helps in aligning investment decisions with the client's behavioral tendencies, potentially leading to more disciplined and long-term focused investing.

More in detail, this method acknowledges that individual investors have unique financial goals and psychological traits that influence their investment decisions. The key elements of BGBWM include understanding client behavior, focusing on personal goals, and managing behavioral biases. A key feature is behavioral bias management which starts from recognizing clients' behavioral biases and eventually addressing them, to mitigate their negative effects on clients' portfolios. Behavioral risk profiling is also fundamental, involving a deep understanding of each client's risk tolerance, not only from a financial standpoint but also considering their emotional responses to market changes, as well as distinct risk tolerances depending on different mental accounts. Another way in which financial advisors may help their clients is through behavioral financial education and communication. Educating clients about market realities and the psychological factors that can impact decision-making is key. Personalized communication also helps in aligning investments with goals and adjusting strategies as life circumstances change.

While using mental accounting, this approach uses a holistic view of clients' financial situation, including non-investment aspects like estate planning, tax strategies, and life insurance needs.

BGBWM is still an evolving field, continuously incorporating new research from behavioral finance to better serve the diverse needs of investors. In this respect, the use of technology, including robo-advisors and artificial intelligence (AI), to assist in understanding client behavior and automating parts of the investment process while maintaining a personalized approach is nowadays fundamental (Baker & Ricciardi, 2014).

3.6. Behavioral profiling: Beyond risk tolerance

Clarification in the terminology regarding the various facets of risk is necessary, particularly in differentiating risk aversion/appetite from risk tolerance. Risk tolerance is commonly defined as the amount of risk an individual is ready to undertake, interpreted as the quantity they are willing to risk for potential gains (Pan & Statman, 2012).

This subjective dimension stands in stark contrast to the notion of risk appetite as understood in traditional finance (Linciano & Soccorso, 2012). Typically, younger people display a higher risk tolerance compared to their older counterparts, though this correlation is not strictly linear. Diverse socio-demographic characteristics, such as gender, also influence variations in risk tolerance. For example, men generally demonstrate a greater risk tolerance than women (Barsky et al., 1997), a disparity that remains evident among professional fund managers (Beckmann & Menkhoff, 2008), irrespective of educational or professional backgrounds. This is in opposition to traditional finance theories that do not differentiate in risk aversion or appetite based on gender. Comprehending the nuances between risk propensity and tolerance necessitates an understanding of concepts like risk attitude, capacity, and knowledge. While risk tolerance is a psychological attribute and challenging to quantify, risk capacity pertains to the tangible ability to assume risk and risk knowledge concerns the comprehension of financial risks.

An investor's economic and financial status significantly dictates their risk capacity, thus shaping their risk perception. Wealthier investors typically perceive lower risk in smaller investments, whereas less affluent individuals, even if inherently risk-tolerant, perceive higher risks due to limited resources. The financial stakes involved in decisions impact risk perception, subsequently influencing risk tolerance. As the value of money in consideration escalates, risk tolerance tends to diminish (Holt & Laury, 2002). An individual who might be comfortable betting €10,000 could become reluctant at the prospect of risking €100,000 or their total portfolio, even if the potential gains or losses are proportionately larger.

While using transaction frequency as a marker for overconfidence is a common approach, Hoffman and Shefrin (2011) indicate that not all frequent traders are overconfident; some are merely adept and experienced, achieving superior results. Given that the concepts of classical risk aversion and appetite are extensively examined, it is advised to consult standard finance textbooks for a comprehensive understanding of the premises underpinning utility functions and methods to measure risk aversion coefficients (both absolute and relative).

3.6.1. Questionnaires for risk profiling

The previous discussion underscores that accurately defining an investor's risk profile is a complex task, yet it is of considerable practical importance. This has led to numerous methodologies aimed at measuring or profiling investor risk. Among these methods, certain tools, when correctly applied, can yield fairly accurate assessments. Particularly noteworthy are questionnaires.

Financial intermediaries utilize a range of questionnaires to determine the risk profiles of their clients, collecting data on investors' characteristics and investment objectives.

These questionnaires typically strive to jointly assess an investor's risk tolerance and capacity, thereby aiding in devising suitable asset allocation strategies. For example, an investor risk profiling questionnaire may include questions aimed at evaluating both risk capacity and tolerance.

A typical question to measure risk tolerance in the financial realm may be the following: "Imagine you have the option to swap your current portfolio for a new one with a 50% chance of boosting your standard of living by 50% annually for life, and a 50% chance of reducing it by X%. Specify the highest X% reduction in the standard of living you are willing to accept".

Barsky et al. (1997) propose a shift in the focus of risk profiling questionnaires, suggesting a greater emphasis on the occupational sphere rather than financial investments. This recommendation stems from the observation that earned income is often mentally separated from investment income, leading to differing risk tolerances in these two domains.

Specifically, younger individuals tend to exhibit higher risk tolerance when it comes to financial investments, but their risk appetite is lower when it concerns their careers. Conversely, older individuals tend to display the opposite pattern.

The underlying rationale behind these findings is that employment provides a safety net against downside risks during one's working years, while financial investments offer the allure of upside potential. In contrast, during retirement, financial security relies on sources such as social security and financial investments, rather than income from work. Consequently, young individuals in their working years often favor equity-heavy portfolios, aligning with their greater appetite for risk, as compared to older or retired individuals who may lean towards bonds and more conservative investment strategies.

An alternative to the above-mentioned question to measure risk tolerance, alternatively framed in the occupational context, could be: "Assume you are the sole breadwinner with a job securing your current lifelong income. You are offered a similarly stable job with a 50% chance to double your income and a 50% chance to reduce it by a third. Would you accept this new job?" If affirmative, the question is repeated, but with the potential income reduction being half. If negative, inquire if a possible 40% reduction would be acceptable, and so forth. Alternatively, ask for the maximum income reduction percentage tolerable for the chance to double the current income.

Barsky et al.'s (1997) responses revealed that younger people generally have the high-risk tolerance, not decreasing linearly with age. Pan and Statman (2012) suggest focusing on living standards rather than income, as people can envision a 50% improvement in living standards more easily than a doubling. Therefore, they propose the alternative question: "Suppose you are the family's sole earner with a job ensuring your current lifelong income. You are offered a job with a 50% chance of enhancing your living standard by 50% for life but also a 50% chance of reducing it by X%. What is the highest X% reduction in living standard you would accept?" The downside loss values range from 3% to 30% in 3% increments for investors to choose from.

More in general, Pan and Statman (2012) pinpoint five key shortcomings in risk profiling questionnaires:

1) Investors usually possess various risk tolerances, each corresponding to different mental accounts.

2) The correlation between answers in these questionnaires and the portfolio allocations they suggest often relies on heuristic rules rather than being grounded in a solid theoretical framework.

3) Risk tolerance is not a constant but changes in response to market trends (whether bullish or bearish) and emotional states.

4) The evaluation of risk tolerance varies if it's done looking backward (retrospective) or forward (prospective), as retrospective assessments tend to heighten feelings of regret.

5) Important elements like the investor's confidence in their advisor and their own level of overconfidence are not typically accounted for but are essential.

These issues necessitate a detailed review. The primary problem with many questionnaires is their inability to account for the array of risk tolerances, each linked to different objectives and mental accounts. This approach of estimating a singular, aggregate risk tolerance neglects the nuances of diverse tolerances associated with each mental account. Behavioral portfolio theory, as proposed by Shefrin and Statman (2000), argues that individuals do not perceive their wealth as a unified portfolio. Instead, they segregate it into distinct accounts, each earmarked for a specific goal. These goals could range from purchasing a home, ensuring sufficient retirement savings, supporting children's future, planning for inheritance, or engaging in philanthropy, with each goal influencing the corresponding risk tolerance. For example, an individual might exhibit low-risk tolerance in retirement or inheritance accounts to protect those specific goals, while demonstrating high tolerance in accounts aimed at realizing higher gains or achieving wealth. The second flaw concerns the obscure link between risk tolerance as deduced from questionnaires and the resulting asset allocation advice. Frequently, there is no apparent direct relationship between questionnaire results and the asset allocation advised, or the connection is not clearly defined and seems to depend on heuristic rather than analytical reasoning. Thus, the same individual might receive varying portfolio recommendations based on which questionnaire they complete. The third limitation is that current questionnaires do not adequately consider the variable nature of risk tolerance, which can be influenced by market conditions and emotional states. This oversight can lead to skewed evaluations of an individual's risk tolerance. For instance, in the aftermath of a bull market, investors generally show a heightened risk tolerance, potentially leading to an overestimation in standard questionnaires. Conversely, during bear markets, risk tolerance often decreases due to fear, risking an underestimation of the risk tolerance of a temporarily anxious client.

The fourth challenge in risk profiling questionnaires concerns the variability in risk tolerance when it is retrospectively or prospectively evaluated.

The hindsight bias can intensify feelings of regret, leading to situations where an investor, in retrospect, might criticize their advisor for overestimating their willingness to take risks, especially if the chosen investments were aggressive. This temporal or path-dependent nature of risk perception is influenced by past financial experiences. For instance, an individual who has recently gained from investments may be more inclined to risk-taking compared to someone who has recently faced a loss. Furthermore, the tendency to avoid losses can sometimes encourage greater risk-taking as a means to recuperate previous losses. Therefore, it is critical to consider how past emotional responses impact current risk tolerance, not just future expectations. The fifth limitation highlights the importance of considering factors beyond mere risk tolerance for a comprehensive understanding of an investor's risk profile. Individual traits and tendencies are often intertwined, affecting risk tolerance collectively. The level of trust in one's financial advisor and the degree of overconfidence are particularly influential. An investor with overconfidence might appear to have a high tolerance for risk, but this perception could be inflated by their overconfidence, not accurately representing their actual risk preferences.

Pan and Statman (2012) advocate for the inclusion of behavioral queries in questionnaires to attain a deeper insight into investors' tendencies, beyond just their risk tolerance. This enhanced approach would encompass aspects like overconfidence, inclination to regret, reliance on advisors, and goals related to personal and financial aspirations.

In a 2007 study involving around 2,500 participants, they found that individuals with a higher risk tolerance typically also showed higher levels of overconfidence and a greater tendency to maximize returns, coupled with substantial trust levels. The study also underscored gender-specific trends: men generally showed higher risk tolerance, while women were more prone to regret, less overconfident, and less inclined to maximize returns. Additionally, younger investors were found to be more receptive to risk than older individuals.

3.6.2. Distinct risk tolerances for objectives and mental accounts

Recognizing the significance of acknowledging an investor's varied risk tolerances based on their individual mental accounts and unique objectives underscores the necessity of incorporating specific questions within risk profiling questionnaires capable of discerning these distinctions. When individuals are deliberating on choices tied to the lower tiers of the investment pyramid, emphasizing safety and guarding against losses, they will probably manifest a reduced risk tolerance. Conversely, when evaluating investments situated in the upper echelons of the pyramid, where the emphasis is on optimizing potential returns, they are more likely to exhibit a heightened capacity for risk. Diverse risk tolerances underpin the common practice of individuals acquiring both insurances to safeguard against potential losses and lottery tickets in pursuit of potential gains.

When contemplating their wealth allocation for retirement, supporting their children, and leaving an inheritance, investors must pose distinct inquiries to accurately gauge their separate risk thresholds. An apt questionnaire acknowledging these facets of mental accounting might resemble the following question: "If you had the opportunity to enhance your returns by assuming greater risks, which of the following options would you be more inclined to pursue:

1) take significantly more risks with all your wealth;
2) take significantly more risks with a portion of your wealth;
3) take slightly more risks with all your wealth;
4) take slightly more risks with a portion of your wealth;
5) not take any additional risks?"

Responses 1) and 3) indicate a perspective focused on the overall portfolio risk. Conversely, responses 2) and 4) align more closely with the layered investment pyramid model and its discrete layers, wherein investors are available to assume increased risk, be it significantly or slightly, but only with a fraction of their wealth.

Selections of options 1) or 3) reflect a unified risk disposition, while choices 2) or 4) reveal diverse risk attitudes across distinct pyramid strata. Each person harbors unique mental accounts, and no questionnaire can foresee them all. Nevertheless, it is conceivable to consider the most prevalent mental accounts employed by the majority.

3.6.3. Overconfidence and the propensity to maximization

Overconfidence exerts a substantial impact on the risk tolerance of investors. Notably, individuals with overconfidence tendencies tend to underestimate risks, viewing them as less significant compared to those who possess a more balanced outlook. This disparity implies that conventional questionnaires may potentially overstate the risk tolerance of overconfident investors. A proficient financial advisor should be adept at identifying and addressing the adverse consequences of a client's overconfidence, particularly in areas such as risk tolerance. Given that overconfidence often manifests in investors overestimating their proficiency in selecting stocks, a pertinent question to assess this characteristic might be: "Some people believe they can consistently select stocks with above-average returns, while others doubt their ability to do so. Express your belief on this matter, choosing a number on a scale from 'I firmly believe that I cannot pick stocks with above-average returns' to 'I firmly believe that I can pick stocks with above-average returns'". On a scale that spans from 1 to 10, where a rating of 10 signifies a robust conviction in one's capacity to choose stocks with returns above the average, Pan and Statman (2012) discovered that men tend to display more overconfidence than women and younger individuals tend to exhibit higher levels of overconfidence compared to their older counterparts.

Additionally, individuals who manifest greater overconfidence demonstrate markedly elevated levels of risk tolerance in contrast to those who exhibit less overconfidence.

The "propensity to maximization" represents another pivotal aspect in the design of questionnaires, as highlighted by Pan and Statman (2012). Investors who possess a pronounced propensity for maximization tend to be rather exacting in their expectations. This attribute correlates with risk tolerance, as such investors, driven by their pursuit of ambitious objectives, may present a seemingly heightened appetite for risk that may not necessarily reflect their actual risk tolerance.

Motivational theory posits that when individuals believe they are approaching a significant goal, such as a specific aspiration level, they might be more inclined to take on greater risks in order to attain it. Schwartz et al. (2002) assessed the propensity to maximize by evaluating respondents' agreement with thirteen statements like: "I am never satisfied with the second choice".

In subsequent research conducted by some of the same authors (Nenkov et al., 2008), these statements were categorized into three distinct groups. In their study, Pan and Statman (2012) opted to include two specific statements reflecting "high standards": "No matter what I do, I always want the highest standards for myself" and "I never settle for second choice" and merged them into a single question: "I always aim for the best and am not content with the second choice". The scoring for these responses is typically on a scale from 1 to 10, with higher scores denoting a more pronounced propensity to maximize. The results from their survey unveiled that men tend to exhibit a greater propensity to maximize than women and younger individuals tend to display this trait more prominently than their older counterparts. Moreover, a heightened propensity to maximize is associated with both an increased appetite for risk and elevated levels of overconfidence.

3.6.4. Regret, luck, and competence

In Chapter 1, we initially introduced the concept of regret. It is worth highlighting that as we delve deeper into this topic, it becomes evident that ascribing one's own errors to external factors can mitigate feelings of regret. From this standpoint, for an investor, having a financial advisor can be likened to possessing a psychological call option, as proposed by Shefrin (2002): when an investment performs admirably, the investor can attribute the success to themselves (a manifestation of self-attribution bias); conversely, if the investment performs poorly, they have the option to assign blame to the advisor. Although not directly tied to risk tolerance, the inclination towards experiencing regret holds significant sway over investment decisions, given the potential for future regret stemming from these choices. Schwartz et al. (2002) illustrate that individuals possessing a substantial propensity to maximize tend to grapple with pronounced feelings of regret. They frequently find themselves contemplating whether their choices were optimal or if superior alternatives were available (Nenkov et al., 2008).

In order to gauge one's inclination towards experiencing regret, Pan and Statman (2012) recommend the use of the following question: "Whenever I make an investment decision, I seek information about the performance of other options I did not choose and feel regret if one of those other discarded alternatives performs better than my selection" (p. 60). Scoring for this particular question typically falls within a range of 1 to 10, with higher scores indicating a heightened propensity to experience regret. Notably, the research conducted by the authors revealed that women tend to be more susceptible to regret than men, and younger individuals exhibit a greater propensity for regret in comparison to their older counterparts.

Remarkably, the propensity to experience regret does not appear to exhibit a significant correlation with either risk tolerance or overconfidence. Therefore, a robust correlation between risk tolerance, the inclination to experience regret, and overconfidence might suggest that overconfident investors who are less prone to regret tend to have a greater tolerance for risk.

An illustrative question aimed at delving into individuals' propensity for regret can be found in FinaMetrica's risk tolerance questionnaire, specifically in its 13th item. This question inquires whether investors would hesitate to repurchase a security they had previously sold at a loss: "Imagine you bought shares in a highly regarded company five years ago. That same year, the company suffered a steep sales decline due to poor management, causing the share price to plummet, and you sold at a considerable loss. The company has since undergone restructuring under new management, with many experts now predicting the shares to yield above-average returns. Given your adverse past experience with this company, would you consider buying its shares again?" Responses vary from "definitely yes" to "definitely no". Strahilevitz et al. (2011) discovered that investors tend to exhibit reluctance when it comes to repurchasing securities they have previously sold at a loss. They attribute this hesitancy to a fundamental desire to avoid experiencing regret. Pan and Statman's (2012) research aligns with this observation. Additionally, another strategy employed by certain investors to shield themselves from regret is to attribute their investment successes more to luck than to skill. By adopting this approach, they reduce their sense of responsibility for their decisions, thereby mitigating the potential for regret. To gauge the inclination to attribute investment success to either luck or skill, investors can be presented with the following statement and asked to express their level of agreement with it: "Some people believe that the ability to invest in above-average performing stocks is primarily a result of skill, while many others think luck plays the key role". In this context, the scoring system typically spans from 1 to 10, with higher scores indicating a stronger belief that achieving success in selecting winning stocks primarily results from luck rather than skill. Notably, women are more prone to attribute their success to luck compared to men, although there is no significant difference related to age.

Additionally, a pronounced tendency to credit success to luck is associated with a propensity for regret. This connection makes sense, as attributing success to luck reduces the sense of personal responsibility for decisions made, thus diminishing the potential for regret. Interestingly, attributing success to luck is linked to both higher risk tolerance and lower overconfidence, which may initially appear contradictory, given that both overconfidence and attributing success to luck are associated with a greater appetite for risk. One possible explanation for this seeming contradiction is that attributing success to luck serves as a protective "shield" against potential regret, while overconfidence bolsters risk tolerance by diminishing the perceived level of risk.

3.6.5. Trust and life satisfaction

Trust holds a paramount position, not solely within the dynamics of financial markets but also the relationship between financial advisors and their clients. Its importance extends beyond shaping investors' risk tolerance and plays a crucial role in cultivating a more fruitful partnership between these two stakeholders.

Pan and Statman (2012) gauge the inclination to trust by scrutinizing responses to a question adapted from the World Values Survey: "Generally, do you agree that most people are trustworthy, or do you feel you need to be cautious with others outside your family?" The response scale for assessing trust typically spans from 1 to 10, where lower scores reflect strong disagreement with the idea that most people can be trusted, and higher scores indicate strong agreement. Notably, older individuals tend to place more trust in others compared to their younger counterparts, with no significant gender-based disparities in trust levels. Additionally, individuals who exhibit higher levels of trust tend to be more risk-averse, more inclined to attribute success to luck, and less prone to experiencing regret.

Another facet that offers insights into an investor's character is their level of life satisfaction, often associated with their expectations. While economic and financial status certainly plays a role, it is important to acknowledge that even a wealthy investor can feel dissatisfied, particularly when making comparisons with individuals who possess even greater wealth. In recent times, some financial advisors have recognized that their role goes beyond mere financial planning and encompasses life planning as well. This shift does not entail delving into clients' personal lives but rather acknowledges that their work involves managing not just assets, but also the overall well-being of individuals. Hence, there is a transition from being solely wealth managers to becoming well-being managers. To ascertain an investor's level of life satisfaction, the following question can be posed: "How satisfied are you overall with your life? Rate your satisfaction level on a scale from 'not at all satisfied' to 'very satisfied'". The potential responses to gauge an individual's level of life satisfaction typically range from 1 to 10, where higher scores indicate a greater sense of life satisfaction.

According to Pan and Statman's (2012) research, there are no significant disparities in life satisfaction between men and women, but younger individuals tend to report lower levels of satisfaction compared to their older counterparts. This finding might initially appear counterintuitive, considering that older individuals often confront objectively more challenging circumstances, such as health issues or increased financial needs during their retirement years when income may be reduced compared to their working years. A plausible explanation for this paradox could be that older individuals have come to terms with their situations or have adjusted their expectations to align with their current reality. In contrast, younger people's expectations often surpass their actual circumstances, leading to feelings of frustration. In summary, individuals who report higher levels of life satisfaction tend to exhibit more overconfidence, experience regret more frequently, and display greater trust in others. However, there appears to be no significant correlation between life satisfaction and risk tolerance.

3.6.6. Emotions and risk tolerance

Investors' emotions wield a substantial influence over their risk tolerance. When markets are on an upswing, and optimism prevails, risk tolerance tends to rise, prompting individuals to allocate more of their investments into stocks. Conversely, during extended periods of market decline, fear tends to dominate, resulting in a decreased risk tolerance and reduced investment in the stock market. This, in turn, can potentially trigger waves of divestment and panic. By analyzing monthly data from the Gallup surveys conducted between 1998 and 2007, which included the following question: "Do you think now is a good time to invest in financial markets?", Pan and Statman's (2012) research unveiled a noteworthy correlation: high past equity returns are linked to a greater likelihood of investors responding affirmatively to the question, indicating a willingness to invest. Conversely, the opposite trend emerges after bear markets. This underscores the importance of acknowledging this dynamic when conducting questionnaires, as it becomes evident that risk tolerance is influenced by the path taken. It tends to ascend following bull markets and decline after bear markets. Hence, it becomes crucial to recognize that in bull market conditions, questionnaires may potentially overestimate an investor's true risk tolerance, while in bear market conditions, they may underestimate it. This underscores the importance of situational context in assessing and understanding an individual's actual risk tolerance.

CONCLUSION

The journey through *"Behavioral Finance and Wealth Management: Market Anomalies, Investors' Behavior and the Role of Financial Advisors"* reveals that at the heart of financial decision-making lies the complex and often unpredictable human nature. Traditional financial theories, assuming rational behavior, are insufficient in explaining real-world phenomena. This book bridges this gap by integrating psychological insights into finance, demonstrating that investors are not always rational, and their decisions are often influenced by cognitive and emotional biases.

We learned that cognitive biases like overconfidence, hindsight bias, and emotional biases significantly impact investment decisions. These biases can lead to systematic errors in judgment and decision-making. The understanding of heuristics and framing effects provides a foundation for recognizing and mitigating these biases.

The book showed that market anomalies are often the result of collective (sometimes irrational) human behaviors. Individual investors frequently underperform due to biases like the disposition effect and under-diversification. Additionally, evidence from specific markets, like Italy, underscores the influence of overconfidence and attention-driven decisions on trading behaviors.

The integration of behavioral insights into wealth management strategies is a crucial advancement. Behavioral portfolio theory and Behavioral Goals-Based Wealth Management offer new paradigms for understanding and catering to the diverse psychological profiles of investors. This approach goes beyond traditional risk tolerance assessments, incorporating factors like trust, life satisfaction, and the role of emotions in financial decision-making.

The insights from this book have profound implications for both investors and financial advisors. Investors can better understand their own decision-making processes, helping them avoid common pitfalls and make more informed choices. Financial advisors can use these insights to better understand their clients' needs, tailor advice, and develop more effective wealth management strategies.

As the field of behavioral finance continues to evolve, it is clear that the understanding of human psychology will play an increasingly vital role in financial decision-making. This book lays a foundation for further exploration and application of these concepts in real-world financial scenarios.

In conclusion, the book offers a thorough and insightful exploration of the psychological aspects of financial decision-making. It highlights the need for a more nuanced understanding of investor behavior, paving the way for more effective and personalized financial strategies. As we look towards the future, the integration of behavioral insights in finance promises to enhance our understanding and management of wealth in an ever-complex financial world.

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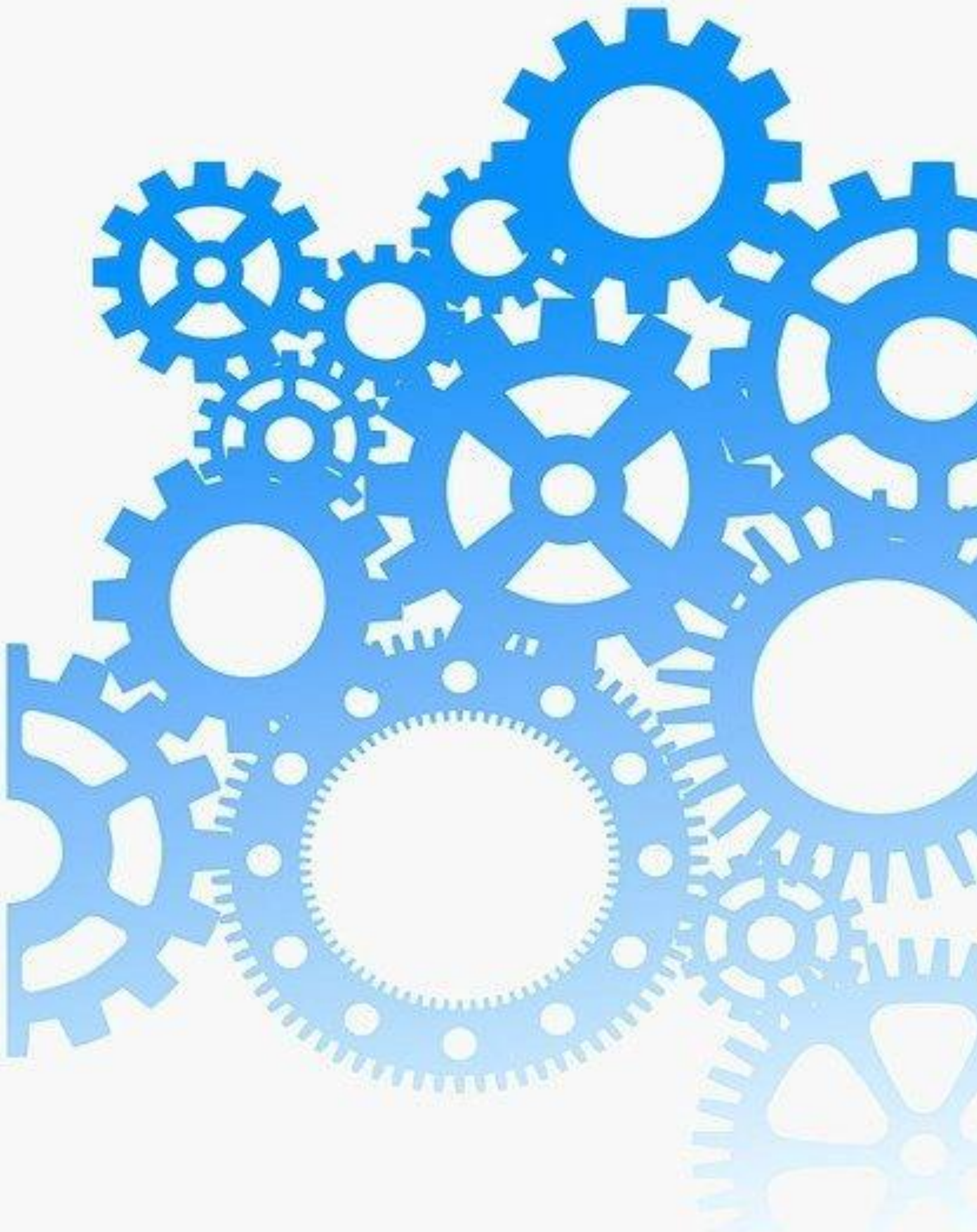

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