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Betting on Success: exploring the intersection of Poker and Asset Management

Antonio Messina | Mathilde Ducoulombier

Under the supervision of Professor Itzhak Gilboa

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Abstract

This paper explores the intersection between poker skills and hedge fund management performance, focusing on how skills and strategies from the game of poker can enhance fund management performance. We conducted an experiment comparing hedge fund managers' stock-picking abilities against random stock selections from the S&P 500 for a period of 3 years. We achieved the following results: hedge fund managers, on average, outperform random selections with an average return of 58.6% compared to 51.2%, indicating that skill plays a crucial role in asset management. We reviewed empirical studies, such as the "Hold'em Poker" study, and found that hedge fund managers who excel in poker tournaments also tend to have better fund performance. This is because many skills are transferable from one field to the other: both domains require strategic thinking, risk assessment, and decision-making under uncertainty. The intersection of poker and asset management extends beyond theoretical similarities, as many financial firms are now incorporating poker-based training into their development programs for fund managers and actively seeking candidates with strong quantitative backgrounds and strategic skills similar to those found in poker.

1. Introduction

The connection between poker and hedge fund management has garnered significant attention recently. High-profile poker players have been recruited by prominent hedge funds, operating under the belief that the strategic skills developed at the poker table are strongly applicable to fund management. Conversely, several established fund managers have demonstrated considerable success in poker tournaments. The interplay between these two fields has also been vividly depicted in popular culture, such as in the "Wall Street Poker Night Tournament" featured in "The Quants" (Patterson, 2010), and in the portrayal of hedge fund managers in "Molly’s Game" (Sorkin, 2017).

For those unfamiliar with these realms, traders and poker players might seem to merely test their luck. However, upon closer examination, many similarities emerge. Both fields require strategic decision-making under uncertainty and managing significant risks. In poker, players must evaluate the risks and potential rewards of their hands before placing bets, akin to how traders assess the risk of an entry versus the potential profits and analyse market conditions before investing. Books like "Liar's Poker" have enshrined these comparisons, highlighting how both fields involve high stakes and quick judgment calls. Success in both disciplines often hinges on the ability to adapt to rapidly changing circumstances and maintain emotional composure while navigating the highs and lows of the game.

Why poker and not another game

While chess and bridge are also games of skill, poker’s blend of luck, skill, and incomplete information more closely mirrors the conditions faced by fund managers. As noted by Kevin Zollman, a game theorist and Professor of Philosophy at Carnegie Mellon “playing poker is the best off-time activity to improve investing skills... ‘Investing has a lot of the same features as poker... Poker is a game of incomplete information. In chess, I know where all the pieces are located. In theory, I could calculate all I need to know about chess. With poker, there's still randomness. Bridge lives between poker and chess. In bridge, all the cards are dealt out in the beginning. While you don't know where they are, you can make educated guesses”. Consequently, we believe that among all games, poker is the most analogous to investing. It requires decision-making under uncertainty, mirroring the inherent unpredictability and risk in financial markets.

Research objectives

This study aims to delve into the parallels and practical intersections between poker and hedge fund management. We focus on three pivotal questions: (1) Is success in asset management and poker driven by skill or by luck? (2) Is there a correlation between skill in poker and skill in hedge fund management? and finally (3) How do investors perceive and react to visible evidence of poker skills in fund managers?

To address the first question, we start by investigating how decision-making processes in poker and asset management are influenced by psychological factors, and we aim to understand where human reasoning encounters biases. Moreover, we examine whether success in these fields is primarily a result of skill or luck. This includes an experiment comparing hedge fund managers' stock-picking abilities with random stock selection from the S&P 500 over a 3-year period.

For the second question, we analyse how the strategic skills used in poker translate into successful fund management. This involves reviewing findings from the “Hold’em Poker” study to understand the practical implications and potential for skill transfer between the two disciplines.

The third question is addressed by examining real-world examples of individuals who excel in both poker and fund management and analysing how investors respond to the visible evidence of poker skills in fund managers, reflecting on how the financial industry has begun integrating poker-based strategies into its practices.

Finally, we conclude by outlining the overlapping skill sets essential for success in both poker and asset management. We define the characteristics of an ideal professional who can thrive in both areas, providing a comprehensive view of how these domains intersect and inform each other.

2. Decision-making in Poker and in the Asset Management field

Every day, humans face dozens of choices based on few incomplete pieces of information and uncertain outcomes. While many decisions are minor, such as choosing what clothes to wear during a normal day, others can have important personal or professional implications, such as deciding whether to trade a stock at a particular price. Other decisions can even be life-changing, such as undergoing a significant medical treatment. Understanding how these decisions are made is a key concern in behavioural economics and social and cognitive psychology. Notably, this understanding is essential for research on expertise and skill, as certain decisions foster experience through repeated practice, clear criteria for decision making, competitive settings and feedback. When making this type of decisions, individuals develop specific skills that enhance their chances of achieving positive outcomes compared to those without this expertise. This is why, people often rely on the competence of professional figures, such as portfolio managers, to make the right choices.

To fully understand expertise in risky decision-making in Poker and Asset Management, we must clearly analyse the types of decisions people face and the components involved. This includes identifying the psychological biases that influence choices and examining various decision-making strategies. By dissecting these elements, we can uncover the psychological mechanisms that underpin both the success and failure of decisions in complex, ambiguous, and intricate real-world settings. We will apply this approach to explore the intersection between poker and asset management skill, shedding light on how professionals in both fields navigate risk and uncertainty to achieve the best possible outcome.

2.1. Background on the decision-making process in Texas Hold’em Poker and Asset Management

Texas Hold'em is one of the most popular variants of poker, where the objective is to win a pot of chips wagered progressively by players during each round, or hand. A player can achieve this by either causing all opponents to fold their cards or by having the strongest combination of cards at the showdown. The showdown involves comparing the player’s two dealt cards, known as hole or pocket cards, with the five community cards visible to all players. The game progresses through three stages of dealing the community cards. Initially, three cards, called the flop, are revealed. This is followed by the turn, which is a single card, and finally the river, the last card. Players have four opportunities to bet: before the flop (pre-flop), after the flop, after the turn, and after the river. During these betting rounds, a player can choose to check, maintaining their stake without increasing or abandoning the pot; bet, by wagering a certain number of chips; call, by matching another player's bet; or raise, by betting more than the current highest wager. The game advances to the next stage once all players have matched the same number of chips in the pot.

A player's decisions are influenced not only by the strength of their cards in relation to the community cards but also by their position at the table. The player's position, determined by their proximity to the dealer, affects their strategy hold because acting later in the round provides more information based on the actions of preceding players. Therefore, the same hand can be played differently depending on where the player sits relative to the dealer. Additionally, players must decide the appropriate amount to bet based on the perceived strength of their hand. If they believe they have the strongest hand, they may bet or raise to entice others to follow and increase the pot size. Conversely, if they think their hand is weak, they might bet to bluff and induce opponents to fold, capitalizing on their uncertain position. Strategic choices in betting must also consider the player's chip stack relative to opponents and the current blind, which is the minimum bet required to see the flop and increase over time.

Frey, Albino, and Williams (2018) explored the dynamics of a three-variable system in poker, comprising two inputs and one output: the opponent's bet (public information) and the player’s own cards (private information) as inputs, and the player’s bet as the output. Their study utilized the framework of Partial Information Decomposition (PID) to dissect the total information into four distinct components:

- Unique Information from the First Input: Information solely derived from the opponent's bet.
- Unique Information from the Second Input: Information exclusively originating from the player's own cards.
- Redundant Information: Information redundantly available from both inputs, which could have been independently obtained from either.
- Synergy: Information generated through the interaction between the inputs that could not be derived from either input alone.

The concept of synergy, in particular, quantifies the intricate "integrative" information processing where the optimal use of information from one source depends on the condition of the other. This type of processing is essential in scenarios involving conditional reasoning and complex decision-making. In poker, synergy refers to the strategic employment of information about opponents in a manner contingent on the player's own cards, and vice versa.

The authors' primary finding highlights that successful poker players demonstrate a higher degree of synergy: their information use from one source is significantly contingent on the current state of the other, as evidenced by a 99% high confidence interval. This suggests that the distinction between profitable and unprofitable online poker players lies not in the volume of information they extract from the game, but in how they integrate these sources. Specifically, a greater proportion of actions taken by winning players can be explained by the interaction between public and private signals, indicating that these players engage in more sophisticated integrative information processing. This finding provides a mechanistic insight into how players balance strategic and adaptable decision-making. In poker, adapting to opponents is vital for sustained success. However, reliance on observable inputs and outputs can lead to predictability.

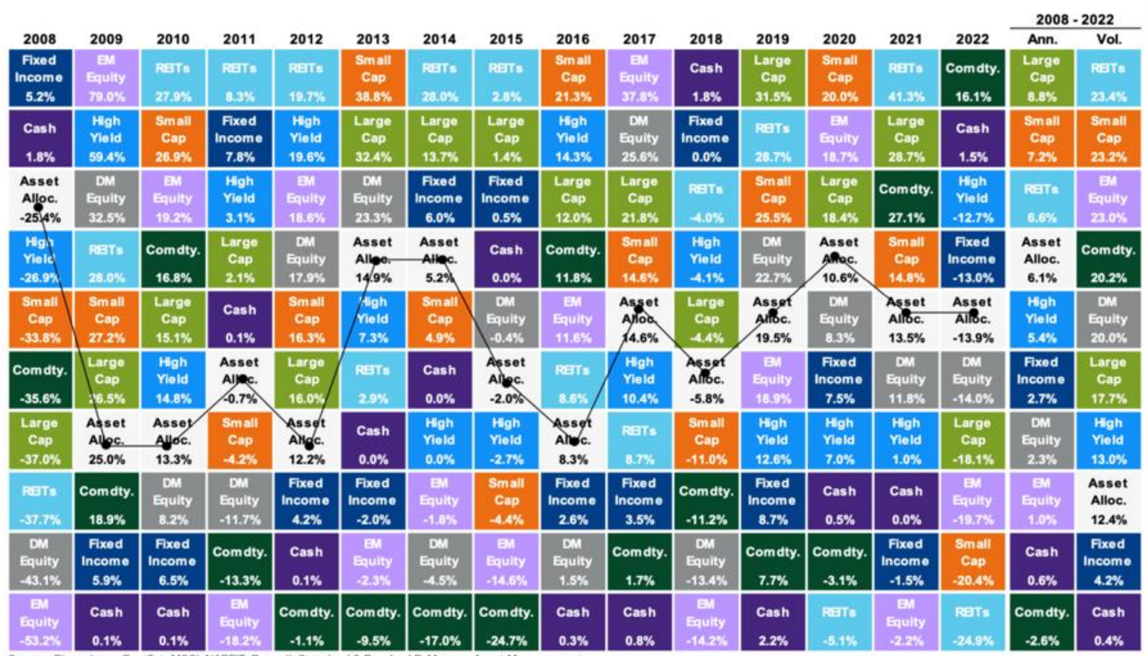
The study proposes that these characteristics become mutually exclusive only in the absence of synergy. Synergy enables players to leverage public signals without fully revealing their strategic approach. Because synergistic information is derived solely from the interplay between multiple inputs, an observer would need access to all these inputs to fully understand the outcomes of such processing. In poker, with one input being private, synergistic information remains concealed within the private channel. The study also notes that in Texas Hold'em, integrative information processing can be exposed in the 17% of cases where neither player folds, and the hand progresses to a showdown. During these showdowns, players reveal their cards, providing the only instance where all three information channels—public and private—are disclosed. In terms of the balance between exploitation and vulnerability, revealing one's cards is akin to disclosing one's strategic algorithm.

As David Sklansky, a mathematician and poker expert who authored the influential 1976 book "Hold'em Poker", asserts: “the goal for successful players is not to win every individual hand but to secure long-term gains through making superior mathematical and psychological decisions”. These decisions involve knowing when and how much to bet, raise, call, or fold. Winning players strive to influence their opponents' betting while maximizing their own expected gain on each betting round, thereby enhancing their overall long-term winnings.

As for the Fund Manager, his objective is to create the best portfolio composed of different financial instruments to secure the best risk-adjusted returns over the long-run, while avoiding excessive exposure to short-term market fluctuations.

As of 2019, approximately 61% of assets in U.S. mutual funds or ETFs were under active management. By maintaining diversified portfolios, investors can achieve comparable expected returns with reduced volatility (see Figure 1): diversification is key to make financial markets not seem like a casino.

Figure 1: Asset allocation achieves 4th bets returns but has the 3rd least volatility out of 9 asset classes.



2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2008 - 2022 Ann.	2008 - 2022 Vol.
Fixed Income 5.2%	EM Equity 79.0%	REITs 27.9%	REITs 8.3%	REITs 19.7%	Small Cap 38.8%	REITs 28.0%	REITs 2.8%	Small Cap 21.3%	EM Equity 37.8%	Cash 1.8%	Large Cap 31.5%	Small Cap 20.0%	REITs 41.3%	Comdty. 16.1%	Large Cap 8.8%	REITs 23.4%
Cash 1.8%	High Yield 59.4%	Small Cap 26.9%	Fixed Income 7.8%	High Yield 19.6%	Large Cap 32.4%	Large Cap 13.7%	Large Cap 1.4%	High Yield 14.3%	DM Equity 25.6%	Fixed Income 0.0%	REITs 28.7%	EM Equity 18.7%	Large Cap 28.7%	Cash 1.5%	Small Cap 7.2%	Small Cap 23.2%
Asset Alloc. -25.4%	DM Equity 32.5%	EM Equity 19.2%	High Yield 3.1%	EM Equity 18.6%	DM Equity 23.3%	Fixed Income 6.0%	Fixed Income 0.5%	Large Cap 12.0%	Large Cap 21.8%	REITs -4.0%	Small Cap 25.5%	Large Cap 18.4%	Comdty. 27.1%	High Yield -12.7%	REITs 6.6%	EM Equity 23.0%
High Yield -26.9%	REITs 28.0%	Comdty. 16.8%	Large Cap 2.1%	DM Equity 17.9%	Asset Alloc. 14.9%	Asset Alloc. 5.2%	Cash 0.0%	Comdty. 11.8%	Small Cap 14.6%	High Yield -4.1%	DM Equity 22.7%	Asset Alloc. 10.6%	Small Cap 14.8%	Fixed Income -13.0%	Asset Alloc. 6.1%	Comdty. 20.2%
Small Cap -33.8%	Small Cap 27.2%	Large Cap 15.1%	Cash 0.1%	Small Cap 16.3%	High Yield 7.3%	Small Cap 4.9%	DM Equity -0.4%	EM Equity 11.6%	Asset Alloc. 14.6%	Large Cap -4.4%	Asset Alloc. 19.5%	DM Equity 8.3%	Asset Alloc. 13.5%	Asset Alloc. -13.9%	High Yield 5.4%	DM Equity 20.0%
Comdty. -35.6%	Large Cap 26.5%	High Yield 14.8%	Asset Alloc. -0.7%	Large Cap 16.0%	REITs 2.9%	Cash 0.0%	Asset Alloc. -2.0%	REITs 8.6%	High Yield 10.4%	Asset Alloc. -5.8%	EM Equity 18.9%	Fixed Income 7.5%	DM Equity 11.8%	DM Equity -14.0%	Fixed Income 2.7%	Large Cap 17.7%
Large Cap -37.0%	Asset Alloc. 25.0%	Asset Alloc. 13.3%	Small Cap -4.2%	Asset Alloc. 12.2%	Cash 0.0%	High Yield 0.0%	High Yield -2.7%	Asset Alloc. 8.3%	REITs 8.7%	Small Cap -11.0%	High Yield 12.6%	High Yield 7.0%	High Yield 1.0%	Large Cap -18.1%	DM Equity 2.3%	High Yield 13.0%
REITs -37.7%	Comdty. 18.9%	DM Equity 8.2%	DM Equity -11.7%	Fixed Income 4.2%	Fixed Income -2.0%	EM Equity -1.8%	Small Cap -4.4%	Fixed Income 2.6%	Fixed Income 3.5%	Comdty. -11.2%	Fixed Income 8.7%	Cash 0.5%	Cash 0.0%	EM Equity -19.7%	EM Equity 1.0%	Asset Alloc. 12.4%
DM Equity -43.1%	Fixed Income 5.9%	Fixed Income 6.5%	Comdty. -13.3%	Cash 0.1%	EM Equity -2.3%	DM Equity -4.5%	EM Equity -14.6%	DM Equity 1.5%	Comdty. 1.7%	DM Equity -13.4%	Comdty. 7.7%	Comdty. -3.1%	Fixed Income -1.5%	Small Cap -20.4%	Cash 0.6%	Fixed Income 4.2%
EM Equity -53.2%	Cash 0.1%	Cash 0.1%	EM Equity -18.2%	Comdty. -1.1%	Comdty. -9.5%	Comdty. -17.0%	Comdty. -24.7%	Cash 0.3%	Cash 0.8%	EM Equity -14.2%	Cash 2.2%	REITs -5.1%	EM Equity -2.2%	REITs -24.9%	Comdty. -2.6%	Cash 0.4%

Source: Bloomberg, FactSet, MSCI, NAREIT, Russell, Standard & Poor's, J.P. Morgan Asset Management.
Large cap: S&P 500, Small cap: Russell 2000, EM Equity: MSCI EME, DM Equity: MSCI EAFE, Comdty: Bloomberg Commodity Index, High Yield: Bloomberg Global HY Index, Fixed Income: Bloomberg US Aggregate, REITs: NAREIT Equity REIT Index, Cash: Bloomberg 1-3m Treasury. The "Asset Allocation" portfolio assumes the following weights: 25% in the S&P 500, 10% in the Russell 2000, 15% in the MSCI EAFE, 5% in the MSCI EME, 25% in the Bloomberg US Aggregate, 5% in the Bloomberg 1-3m Treasury, 5% in the Bloomberg Global High Yield Index, 5% in the Bloomberg Commodity Index and 5% in the NAREIT Equity REIT Index. Balanced portfolio assumes annual rebalancing. Annualized (Ann.) return and volatility (Vol.) represents period from 12/31/2007 to 12/31/2022. Please see disclosure page at end for index definitions. All data represents total return for stated period. The "Asset Allocation" portfolio is for illustrative purposes only. Past performance is not indicative of future returns.
Guide to the Markets – U.S. Data are as of December 31, 2022.

J.P.Morgan
ASSET MANAGEMENT

Asset managers employ a variety of methods to guide their decision-making process, they face the dual challenge of leveraging historical insights while adapting to evolving market conditions. Investors typically engage in three main types of inquiry:

- Retrospective: analyse past market events to understand their causes, which helps in making sense of historical performance and learning from previous trends
- Counterfactuals: explore how different scenarios, policies, or economic conditions, might have altered outcomes

- Policy/ Investing advice: focus on how to build portfolios for the future by factoring in current economic conditions (e.g., business cycles, credit cycles, long-term macroeconomic trends)

However, the complexity of financial markets, makes retrospective and counterfactual analyses hard to do without a structured approach. Ideally, one would conduct scientific experiments to test hypotheses, but it is impractical to run all parameters influencing the market, such as changes in the FED policies. Consequently, asset managers rely on models, for which data is a crucial input. These models are crucial for making sense of data and guiding decisions, but they are not without limitations:

- The signal-to-noise ratio in financial and economic data is extremely low, making it easy to overfit models to irrelevant fluctuations rather than true underlying patterns. Markets are also dynamic, so data that is useful today might just be noise tomorrow.
- It is difficult or impossible to conduct large-scale experiments across entire economies or financial markets to understand how fundamental changes might impact outcomes.
- Finance does not qualify as a "big data" field in the conventional sense, as it is constrained by the inability to generate an infinitely large dataset at a minimal cost. This limitation is fundamentally tied to temporal factors; it is not possible to artificially create additional trajectories for an economy or stock market beyond what historical and real-time data provide.
- Sampling error is a critical issue, as decisions are based on limited data samples rather than entire populations. This is particularly important in asset allocation, where errors in estimating means and variances can significantly impact portfolio decisions.

Despite all this, economic models are indispensable for making informed decisions. While sophisticated models can be tempting, it is often more practical to use simpler approaches. Unless there is significant concern about tail events, it is typically advisable to assume that the returns of a portfolio follow a normal distribution. This simplification means that only one random variable needs to be modelled for each asset allocation, reducing the complexity of the analysis.

At the core of mean-variance optimization process is the Monte Carlo simulation, a versatile tool used to assess portfolio performance under various scenarios. Monte Carlo methods have long been used in pricing complex derivatives, computing “Greeks” and managing risk through measures like Value at Risk (VaR). These same techniques can be applied to portfolio management to evaluate risks such as shortfall, maximum drawdown, and the probability of meeting investment objectives. One of the most useful applications of Monte Carlo simulation is to use it to evaluate how an asset allocation strategy is performing in normal or stressed markets and what are the chances of maintaining real purchasing power, but one has to be careful here, as these portfolio properties will always be driven by the initial simulation assumptions.

During financial crises, many VaR-based models failed to anticipate the heightened risks, often due to their reliance on strict assumptions about wealth distributions. As an alternative, stress testing emerged as a method to evaluate the impact of large shocks (e.g., increase in interest rates, increased volatility in equity markets) on portfolios by introducing significant changes to the simulation model. While this approach can provide valuable insights, it is somewhat ad-hoc, as the scenarios chosen are ultimately proxies for equilibrium market outcomes.

For Mean-Variance Optimization (MVO), three forecasts are needed: expected returns (arithmetic mean return), expected risks (standard deviation), and correlations (pair-wise correlation). But using historical data leads to very weird portfolios typically not well-diversified and concentrated, with extreme portfolio positions not implementable. However, MVO can lead to unstable portfolios when based solely on historical data, often resulting in concentrated holdings (around three or less asset classes) and drastic changes in allocation with minor shifts in forecasts. To address these issues, alternative strategies have been developed.

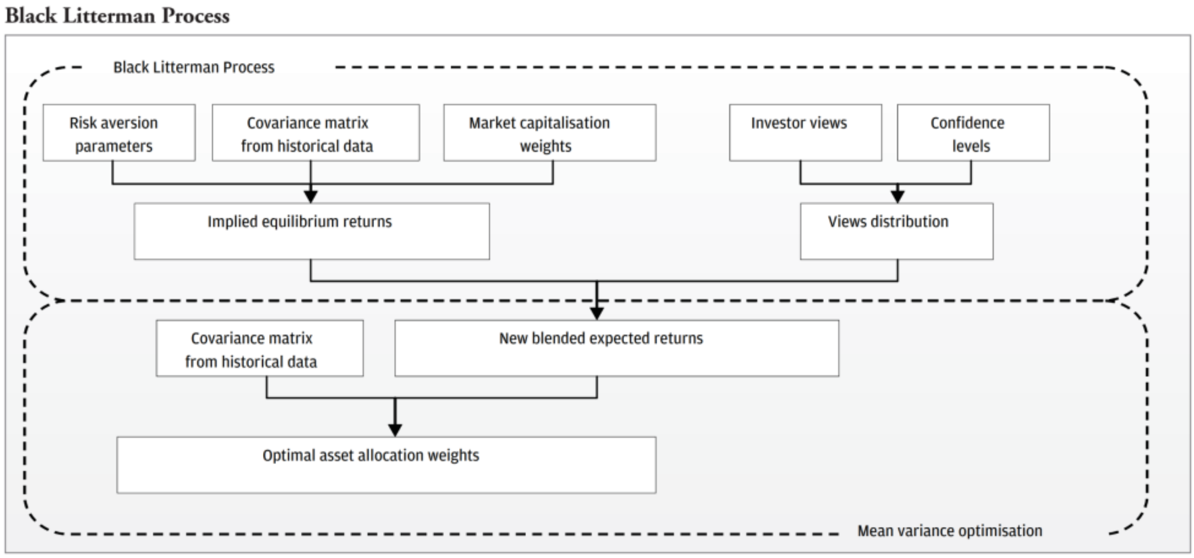
Risk parity-based asset allocation strategies rely on risk-based diversification and aims to equalize the risk contributions from different assets. This approach assumes that the Sharpe ratios across asset classes are roughly equal, making it particularly effective when diversifying across assets that respond differently to economic conditions. For instance:

- Equities generally do well in high growth and low inflation environments
- Bonds generally do well in deflationary or recessionary environments
- Commodities tend to perform well during inflationary environments.

The Black-Litterman model, on the other hand, integrates market expectations with investor views. In this approach, first, the asset manager decides on what asset classes to invest in and find market- cap weights. Then, he estimates a “risk model” (the variance-covariance matrix) for the asset classes. Using an estimate of market risk aversion, he then computes

CAPM-implied expected asset class returns using the market- cap weights plus the risk model. The asset manager incorporates any investor views about asset class expected returns with the CAPM-implied expected return. Such views can be expressed either as absolute views (asset class X will have a return of 8%) or as relative views (asset class X will outperform asset class Y by 2%). One doesn't have to construct a view on every asset class since the market weight picks that up for us. This process results in adjusted or "posterior" expected returns and an updated variance-covariance matrix, and the asset manager finally determines the optimal asset allocation.

Figure 2: Illustration of the Black-Litterman process by Idzorek



Source: Idzorek (2005).

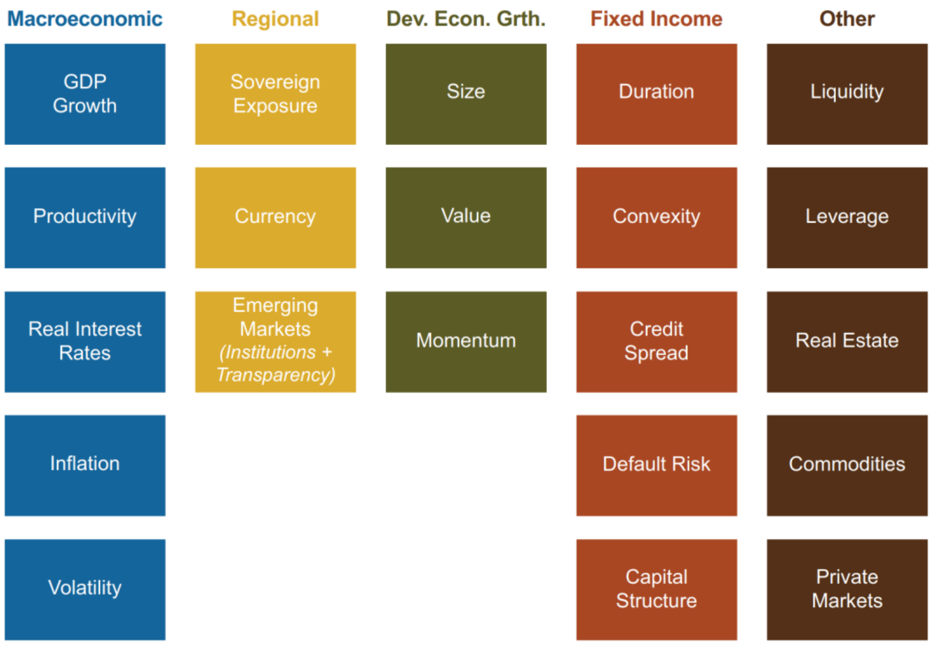
It is widely recognized that modern portfolio theory encounters significant challenges due to the noise inherent in estimating expected returns and risk models. Pedersen, Babu, and Levine (2020) identify the asset classes where this estimation noise has the greatest impact, often resulting in disproportionately large or "crazy" portfolio weights. To address this issue, they introduce a method called Enhanced Portfolio Optimization, which effectively reduces the influence of asset classes where estimation noise is most pronounced.

Their approach also extends to integrate the Black-Litterman model, allowing for the incorporation of investor views into the optimization process. Crucially, the authors demonstrate that their method performs robustly in out-of-sample tests. Although there are more sophisticated variations of their approach, the authors emphasize the practicality and simplicity of the Simple Enhanced Portfolio Optimization. This method adjusts the risk model (specifically the variance-covariance matrix) by applying a shrinkage factor, modifying the values by multiplying them by $(1 - s)$, where s represents the shrinkage parameter. In their applications, they find that a shrinkage parameter of 0.75 yields effective results.

The Arbitrage Pricing Theory (APT) is a method to assess risk-return trade-offs based on the principles of no arbitrage and the law of one price. Unlike the equilibrium-focused CAPM, APT is a multi-factor model that relies on statistical relationships to explain returns. By assuming that diversified portfolios can be constructed by some investor in the economy, the APT uses simple no arbitrage arguments to derive a multi- factor security market line (SML). The theory breaks down asset returns into a few key factors, asserting that these returns are driven by the premiums associated with these factors, multiplied by the asset's exposure to each factor.

Factor-based investing leverages this decomposition to focus more on risk management than on predicting exact returns, building better portfolios by understanding these factor exposures. As Podkaminer (2013) puts it and with the help of Figure 3: “Factors are the basic building blocks of asset classes and a source of common risk exposures across asset classes. Factors are the smallest systematic (or non-idiosyncratic) units that influence investment return and risk characteristics. They include such elements as inflation, GDP growth, currency, and convexity of returns. In a chemistry analogy: If asset classes are molecules, then factors are atoms. Thus, factors help explain the high level of internal correlation between asset classes”.

Figure 3: Podkaminer lists potential factors



Lastly, asset managers employ two main styles of allocation: strategic and tactical. Strategic asset allocation involves setting fixed portfolio weights across asset classes and regularly rebalancing them (monthly, quarterly, or annually) to maintain these proportions. This method, used in approaches like mean-variance optimization, risk parity, Black-Litterman without views, and factor-based investing, provides a stable long-term investment framework. Alternatively, tactical asset allocation allows for occasional adjustments, or "tilts," toward or away from certain asset classes, styles, or factors. This flexibility helps address concerns about potential mid-term underperformance or capitalize on expected overperformance, adapting the strategic allocation to changing market conditions.

2.2. Analysis of cognitive and psychological factors influencing decision-making in Asset Management

Behavioural finance acknowledges that not all investors and managers operate with complete rationality. Instead, it considers psychological influences and biases that lead to systematic deviations from rational behaviour and affect investors' investment decision-making process.

The main theory of behavioral finance, Prospect Theory, developed by Kahneman and Tversky, offers a descriptive model of how people make decisions under risk and uncertainty. Unlike traditional economic theories, which assume that investors think and behave "rationally" within an efficient market framework, Prospect Theory acknowledges that psychological factors significantly influence decision-making. Proponents of the efficient market hypothesis (EMH) maintain their argument that the market rapidly incorporates any new information relevant to a company's value, leading to random future price changes due to the complete integration of available information, both public and non-public, into current values.

Investors, including asset managers, are significantly influenced by psychological biases. They tend to exhibit loss aversion (Odean, 1998), demonstrate overconfidence (Odean, 1999) and have under-diversified portfolios (Benartzi and Thaler, 2001). These biases lead to systematic deviations from rational behavior, resulting in market inefficiencies that can be observed through phenomena like the equity premium puzzle and price trends following news announcements. For many investors, these biases can hinder decision-making, causing suboptimal investment strategies, such as holding onto losing stocks for too long or selling winning stocks too quickly (Barber and Odean, 2000). Following Barberies and Thaler (2003), we can classify psychological biases into two types: biases in beliefs and biases in preferences.

Biases in Beliefs

Beliefs form as market makers interpret private signals related to order flow. The success and profitability of their trades rely not only on the accuracy of their interpretation of these signals but also on an element of luck. However, when market makers consistently misinterpret these signals throughout the trading day, biases in beliefs emerge. These biases can arise from various factors and typically fall into five key categories.

- Mental accounting: involves the tendency of individuals to assign their funds for specific purposes.
- Emotional gap: decision-making can be significantly influenced by strong emotions such as anxiety, anger, fear, or excitement. These intense emotions often hinder rational decision-making
- Anchoring: refers to linking spending or valuation decisions to specific reference points. For example, individuals might consistently adhere to a particular budget or justify expenditures, regardless of broader financial context or changing circumstances.
- Self-attribution: refers to the tendency of making choices driven by an inflated sense of one's own knowledge or expertise. Within this category, individuals tend to credit themselves for past successes and blame bad luck for past failures. Moreover, investors tend to rate their expertise higher than others, even if objective measures suggest otherwise. This can explain why securities markets have so much trading volume, something that the efficient market hypothesis does not predict.
- Herd behaviour: suggests that people often imitate the financial actions of the majority, leading to instances of collective behaviour in the stock market. Herding behaviour is notably responsible for significant market surges and declines, as word-of-mouth enthusiasm and the media then can produce an environment in which even more investors think stock prices will rise in the future. The result is then a so-called positive feedback loop in which prices continue to rise, producing a speculative bubble, which finally crashes when prices get too far out of line with fundamentals.

Behavioural finance has shown that investors often place too much emphasis on decisions based on limited data or single sources, causing them to either overestimate or underestimate new information compared to their existing beliefs. For example, investors frequently credit an analyst's success in picking a winning stock to skill rather than chance. Conversely, once an opinion is formed, it tends to be stubbornly held. A case in point is the widespread belief in the late 1990s that any sudden market drop was a good buying opportunity, a "buy-the-dip" mentality that still persists today. Investors often have undue confidence in their judgments and focus intensely on isolated, seemingly significant details, rather than viewing the overall trends. This narrow perspective prevents them from understanding the broader market context.

Confirmation bias happens when investors prefer information that supports their existing beliefs about an investment. Even if this information is inaccurate, they accept it to justify their prior decisions.

Experiential bias, also known as recency or availability bias, occurs when investors' memories of recent events skew their judgment, making them believe such events are more likely to repeat. For example, after the financial crisis of 2008 and 2009, many investors exited the stock market. This negative experience reinforced their bias, causing them to overestimate the chances of another similar crisis, even though the economy eventually recovered, and the market rebounded in the following years.

Familiarity bias is evident when investors prefer to put their money into investments they know well, such as domestic companies or local ventures. This tendency leads to a lack of diversification in their portfolios, limiting exposure to different sectors and types of investments, and potentially increasing risk. Investors often opt for investments with which they have some prior experience or a sense of familiarity.

Biases in Preference

There are also preference-based deviations from rationality, most of them rooted in the prospect theory of Kahneman and Tversky (1979). One of the most notable aspects of this theory is the concept of loss aversion. Loss aversion refers to the tendency of investors to give more weight to the fear of losses than the satisfaction from market gains. In simpler terms, they prioritize avoiding losses over making gains from investments. Consequently, some investors may demand higher returns to compensate for potential losses. If these larger returns are unlikely, they might avoid losses altogether, even if the investment's risk is reasonable from a logical standpoint. When applied to investing, loss aversion leads to the disposition effect, where investors sell their winning assets quickly but hold onto their losing ones. This behaviour stems from the different attitudes people have towards risk after gains versus losses. Specifically, individuals exhibit greater risk aversion when considering gains, preferring to secure and realise profits quickly. However, when an investment starts losing money, they hold onto it and become more risk-seeking in the hope of recovering their initial investment. Investors often quickly acknowledge their correctness when a gain is realized while they hesitate to admit their investment mistake when facing losses. This bias is flawed as it ties the investment's performance too closely to the initial entry price, anchoring it at the reference point and disregarding changes in the investment's fundamentals or attributes.

Frazzini (2006) proposes that the disposition effect contributes to an initial underreaction to news, thereby creating return predictability and a subsequent price drift following announcements. This observed price behaviour is influenced by two pivotal factors: the informational content of the news and the investor's reference price in relation to the current stock price. Specifically, stocks exhibiting significant unrealized gains tend to underreact solely to positive news, while those with substantial unrealized losses show a similar underreaction exclusively to negative news. This asymmetric response is consistent with the disposition effect's predictions, which foresee order flows based on the gap between the present and reference prices. When faced with capital losses, investors influenced by the disposition effect are typically hesitant to realize these losses, leading to an underreaction to adverse news. Conversely, their propensity to sell prevents a stock's price from immediately adjusting to its new equilibrium following favourable news. The degree of this post-event drift is most pronounced in circumstances where the disposition effect predicts a notable underreaction. The magnitude of the post-earnings announcement drift is directly linked to the unrealized capital gains or losses experienced by shareholders at the time of the event. Thus, stocks with significant unrealized capital gains underreact to positive news, while those with substantial unrealized capital losses underreact to negative news.

In his 1998 study, Odean formally examined whether investors exhibit a stronger reluctance to realize losses compared to gains, positing that loss aversion is a fundamental driver of the disposition effect. This theory suggests that investors' reluctance to sell at a loss is motivated by an unwillingness to admit that their initial investment decisions were misguided. Odean's analysis, based on transaction data from U.S. discount brokerage accounts between 1987 and 1993, reveals that, on average, investors actualize a significantly higher proportion of gains than losses.

This tendency remains consistent even after adjusting for factors such as portfolio rebalancing, the influence of low-priced and low-return stocks, and the rational contrarian investment strategy, which anticipates that today's losing stocks will become tomorrow's winners and vice versa. An exception to this loss aversion behaviour is observed in December, when a greater proportion of losses are realized compared to gains, likely due to tax-loss selling practices prevalent in the U.S. market. Furthermore, Odean's findings indicate that the disposition effect is evident among both frequent and infrequent traders, although it is less pronounced among those who trade more frequently.

Building upon the insights of Brooks and Zank (2005), it is evident that gender significantly influences the degree of loss aversion, with women demonstrating higher levels of loss aversion compared to men. Additionally, an investor's age appears to correlate with their propensity for loss aversion, with older investors showing a greater tendency toward this behaviour relative to their younger counterparts. Research by Frino, Lepone, and Wright (2014) in the Australian market reveals that loss aversion also varies by ethnicity. Specifically, investors of Chinese heritage are more likely to liquidate their winning investments rather than their losing ones, compared to non-Chinese investors. This disposition bias remains significant even after adjusting for other investor characteristics such as age and gender, with Chinese-background investors exhibiting a 5.01% higher propensity for this bias than the overall sample.

These findings lend further credence to the concept that two biases—overconfidence and loss aversion—act in opposition within the investment decision-making process. For instance, investors who consistently trade in round sizes are 3.42% more likely to realize gains rather than losses. Trading in round sizes serves as a cognitive shortcut and heuristic simplification, where individuals who routinely engage in such trading are more likely to bypass detailed analyses of expected returns. Instead, they rely on simplifications and existing or historical market conditions, rather than forward-looking expectations, thus reinforcing the presence of the disposition effect.

It is worth considering whether these studies can empower investors to consistently outperform the market. In theory, recognizing rational shortcomings should create lucrative opportunities for astute investors. However, in practice, very few, if any, value investors systematically apply behavioural principles to identify undervalued stocks that consistently yield returns exceeding market norms. The impact of behavioural finance research remains more pronounced in academic settings than in practical money management. Although these theories elucidate various rational deficiencies, they offer limited guidance for capitalizing on market exuberance. For instance, Robert Shiller, in his seminal work "Irrational Exuberance" (2000), highlighted the existence of a market bubble in the late 1990s but could not predict the precise moment of its collapse. Similarly, contemporary behavioural economists find it challenging to pinpoint exact market peaks or troughs, as evidenced by their inability to foresee the market's bottom following the 2007-2008 financial crisis. Nonetheless, they excel in describing the characteristics that signal significant turning points in the market.

Transitioning seamlessly from subconscious biases to rational thinking is not always feasible. Thus, recognizing and understanding these heuristics and psychological tendencies is imperative to manage them effectively. Chad Slater, the founder of a global long-short equity portfolio at Morphic Asset Management, underscores the importance of self-awareness in the investment industry. He argues that understanding one's strengths, fears, and common errors is crucial for achieving success. For instance, investors often succumb to the temptation to quickly move on to new ideas, yet discipline is essential to pass on unsuitable opportunities and focus on the most promising ones. Likewise, holding onto positions out of mere hope or doubling down after losses are pitfalls that can undermine long-term returns.

In essence, profound self-awareness is foundational to making profitable decisions in the financial world. Without a deep understanding of one's own behavioural tendencies and decision-making patterns, achieving consistent financial success becomes a formidable challenge.

2.3. Analysis of behavioural factors influencing decision-making in Poker

Previous sociological field studies, such as Browne (1989), suggest that effectively managing one's emotions during gameplay, including enduring critical remarks from peers, is a significant determinant of success in poker. Therefore, it is reasonable to assert that individual poker strategies are influenced by both long-term considerations, such as maintaining reputation and player identity, and short-term awareness of opponents' actions at the table, such as betting patterns. This dual influence is particularly salient given the constant observation by adversaries during the game.

The concept of "tilting" refers to a player's loss of emotional control in response to adverse outcomes, which often leads to aggressive behaviour and poor decision-making. This state is frequently accompanied by "chasing" behaviour, where the player impulsively attempts to recover lost funds. Many players find that making suboptimal decisions under social and emotional pressure, including the inability to manage tilting, not only jeopardizes their financial assets but also undermines their perceived status as skilled poker players.

Research by Corless and Dickerson (1989) highlights a link between self-perceptions of patience and emotional stability and the propensity to lose control during poker. Moreover, Golder and Donath (2004) note that the avatars used in online poker may influence the gaming experience. It is plausible that external social information, beyond the in-game mechanics, such as players' reputations or perceived personal attributes, modulates the interaction between emotions and decision-making.

Laakasuo, Palomaki and Salmela (2014) conducted an experiment in which participants were randomly assigned to two conditions following the reading of a narrative. Both conditions involved engagement in five separate hypothetical online poker decision-making scenarios presented in text format. In the social identity manipulation condition, participants were exposed to a pair of animated human eyes that tracked the movement of their mouse cursor during the tasks. These eyes could be either male or female, with the gender randomized for each participant. In the control condition, a black box was displayed, responding to mouse movements by tilting left or right depending on the cursor's position. The dimensions and positioning of the black box were identical to those of the animated eyes. As hypothesized, participants in the anger prime condition exhibited poorer mathematical decision-making performance compared to those in the control group. This effect was especially pronounced when a set of eyes followed the participants' mouse cursor movements on the screen. Additionally, participants with greater poker experience demonstrated more accurate mathematical decision-making skills.

Decisions should be made based on the potential benefits and costs that lie ahead, without considering previous gains or losses. In poker, each hand stands alone, independent from the ones before it. However, in real-world scenarios, historical context is important because players might adjust their view of their abilities and strategies, and the results can have emotional impacts. Revised evaluations align with a Bayesian viewpoint where players use wins and losses to gauge their skill. For seasoned players, a few hands should minimally impact their judgment of their abilities. However, humans are not detached Bayesian statisticians; they frequently make judgments based on scant data that ought to be unconvincing (Kahneman and Tversky, 1972). If significant losses undermine poker players' confidence, they might doubt their ability to assess probabilities and opt for a more cautious approach in their gameplay. Conversely, substantial wins could boost players' confidence in their probability evaluations, leading them to adopt a less cautious playing style. Consequently, we might anticipate that major losses lead to more conservative play, while major wins prompt more aggressive play.

- The value function has an S-shape, being convex for losses and concave for gains. This reflects people's tendency to be risk-averse with moderate probability gains (for instance, preferring a guaranteed $50 over a 50% chance of winning $100) and risk-seeking with moderate probability losses (such as preferring a 50% chance of losing $100 over a certain loss of $50).
- The value function shows a sharp bend at the origin, emphasizing losses more than equivalent gains, because most people avoid bets that offer a 50/50 chance of either winning or losing $100.
- The decision weight function treats very improbable events as if they were impossible and very probable events as if they were certain. For probabilities that are not as extreme, it tends to overestimate small probabilities and underestimate medium to large probabilities.

Kahneman and Tversky (1979) note that a person who has not reconciled with their losses is likely to engage in gambles that they would normally find unacceptable.

- Research suggests that mood influences risk-taking behaviours; notably, individuals are more optimistic when in a good mood (Isen et al. 1982, Wright and Bower 1992). Similarly, studies have found that stock markets tend to perform better on sunny days compared to cloudy ones (Saunders 1993, Hirshleifer and Shumway 2003). In poker, the thrill of winning a big hand or the disappointment of losing one can affect subsequent decisions. Players might be prone to taking unwarranted risks after a win and become more cautious after a loss. This indicates that mood swings could lead even seasoned poker players to alter their play style following significant wins or losses.
- Thaler and Johnson (1990) have suggested that gamblers who win bets often feel as they are playing with "house money," leading them to be less cautious since they perceive it as playing with someone else's money. Following a substantial win, players might be less worried about losing money that they originally did not possess.

Conversely, after a significant loss, they may become more cautious, perceiving that they are now gambling with their own funds.

- Poker players often express beliefs like being "due for aces" or certain that they "will hit their next flush." Those who subscribe to the gambler's fallacy might be hesitant to place bets after winning, thinking luck is not in their favour, while they might be more inclined to bet after losses, believing that their chances of winning are due to improve.
- Conversely, some players believe in the concept of "hot" or "cold" cards. Extensively, research on regression to the mean shows that people often downplay the role of randomness when interpreting data to evaluate underlying phenomena. For instance, many investors erroneously view short-term fluctuations in a company’s earnings as indicative of lasting changes in profitability (Lakonishok et al. 1994, La Porta 1996). In poker, those who subscribe to the idea of hot and cold streaks tend to bet more aggressively after wins, believing the streak will continue, and become more cautious after losses, fearing the streak might worsen.
- Poker players often adjust their playing style for strategic reasons. Doyle Brunson, a two-time World Series of Poker main event champion, intentionally alters his approach after significant wins. In his highly regarded poker strategy book, "Super System" (2003), Brunson advocates for a loose-aggressive style—playing a wide range of hands and betting aggressively—to dominate opponents. He refers to the successful application of this strategy as experiencing a "rush." Brunson humorously critiques scepticism towards this concept in the book, stating, "Scientists don't believe in rushes, but sometimes rushes can make you a fortune. There's only one world-class poker player that I know of who doesn't believe in rushes. Well, he's wrong, and so are the scientists. Besides, how many of them can play poker anyway?" (Brunson, 2003).

Texas Hold‘em is revered as a strategic game due to its multiple betting rounds and the visibility of five community cards to all players, which adds layers of complexity and strategy. The immediate outcome of each hand hinges on the draw; for instance, a player with two aces ("aces in the hole") could still lose to someone with two 3s if another 3 appears among the community cards. However, sustained success in the game relies more on sound betting decisions—essentially, knowing when to hold and when to fold. Online Texas Hold‘em offers significant advantages, such as convenience, faster gameplay due to quicker dealing, and reduced costs compared to physical venues. A notable drawback, however, is the lack of physical tells, which can be crucial in reading opponents' intentions and strength of hands.

In the analysis, Smith et al. consider a hand where a player's gain or loss is $1,000—equivalent to 20 times the big blind—as a significant event. To understand the impact of such wins or losses on player behaviour, we observe the player's actions over the next 12 hands, which span two cycles around a six-player table. This duration is chosen because it is common for experienced players to make no voluntary bets during this period, and 12 hands remain within a close timeframe to the significant win or loss, allowing the authors to gauge any immediate strategic or psychological adjustments. Their observations indicate that players tend to play less aggressively after a significant win than they do after a significant loss. Notably, this tendency to adopt a more aggressive strategy following a large loss is most pronounced at two-player tables. This behaviour is logical because, in a heads-up scenario, a player only needs to defeat one opponent to win the entire pot. In contrast, at a six-player table, the likelihood increases that someone will call a raise, making a lucky flop a more viable strategy to recover from an earlier loss.

The data the authors obtained does not support most of the theories outlined in Annex 1. For instance, the house-money hypothesis suggests that individuals become less cautious after a gain and more cautious after a loss. However, Thaler and Johnson (1990) in their seminal work on the house-money effect, introduce the concept of the break-even effect, which might supersede the house-money effect. They note that "when prior losses are present, gambles which offer the prospect of changing the sign of the status of the current account will be treated differently from those which do not." They concur with Kahneman and Tversky (1979) that an initial loss may drive risk aversion in some cases, yet other types of gambles that provide a chance to break even are considered acceptable. The gambler's fallacy, which suggests players expect outcomes to reverse after a series of losses or wins, loosely aligns with our findings but is more relevant to a sequence of outcomes rather than a single large pot. In contrast, prospect theory's break-even hypothesis, which anticipates similar reactions following a single large win or loss and a recent significant cumulative win or loss, seems to better explain our results. The fact that poker players are more likely to alter their play following a single substantial win or loss, rather than after a series of wins or losses, suggests that the break-even hypothesis provides a more accurate framework for understanding their behaviour.

Smith and the other authors' analysis supports the break-even hypothesis, suggesting that a poker player who has lost a significant pot might consider the most cost-effective strategy to recover their losses as taking a chance on a long-shot flop with a weak hand. For instance, they might continue with a pair of deuces, hoping to catch another deuce on the flop. This observed change in poker behaviour might also apply to other decision-making contexts. Ken Warren, a respected poker writer, emphasized the importance of adherence to a sound strategy in Texas Hold'em, stating, "More money is lost by players who know what the right thing to do is, but don't do it, than for any other reason. Having a strategy, a game plan, and the discipline to stick to it are, along with a sufficient bankroll, the four most important things that a player needs to be a winner."

David Nelson (2003), Senior Vice President of Legg Mason Funds, echoed this sentiment for investing, highlighting the parallels between poker and financial decision-making. Brett Steenbarger (2007) also draws connections between poker and investing, pointing out key differences such as investing not being a zero-sum game and the centrality of deception in poker. If investors behave like poker players, their decision-making might be influenced by significant gains and losses, potentially leading them to make risky, long-shot investments in hopes of quickly offsetting earlier losses.

There is evidence supporting this behaviour in financial markets as well. Research by Covai and Shumway (2005) found that Treasury bond futures traders are more likely to take greater risks in the afternoon following morning losses. Similarly, Locke and Mann (2004) observed that futures floor traders on the Chicago Mercantile Exchange increase their risk exposure after experiencing losses. Garvey et al. (2007) discovered that professional day traders who incur losses in the morning tend to trade more aggressively in the afternoon. Additionally, Crum et al. (1981) argued that major mutual funds and portfolio managers not meeting their targets exhibit risk-seeking behaviour to enhance their returns and reach their goals. Kumar (2009) noted that in economically challenging times, there is an increase in the sales of lottery tickets and investments in 'lottery stocks'—low-cost, typically unprofitable stocks with a slim chance of a significant return.

These findings were highlighted in a February 2009 Wall Street Journal article, which reported that many investors, in response to stock market losses, were pursuing increasingly risky investments described as the financial equivalent of a 'Hail Mary pass'—a desperate, last-minute attempt to recover their losses with a high-risk action (Zweig 2009). All these behaviours align with the "break-even" mentality observed in poker players and further suggest that this mindset might be a broader psychological phenomenon affecting various types of high-stakes decision-making.

3. Skill vs Luck

3.1. Evaluating Hedge Fund Manager's Stock-picking abilities

Discussion

There is a widespread opinion across economists and researchers in which beating the stock market is impossible over the long term. Economist Burton Malkiel famously argued in his 1973 book, "A Random Walk Down Wall Street," that even a blindfolded monkey randomly throwing darts at a newspaper's financial pages could achieve results on par with professional investors. This analogy underscores the belief that much of the market's performance is driven by chance rather than skill.

Our study seeks to examine whether Malkiel's assertion holds true in the short-term, more specifically, over three years. We intend to address the question: Do hedge fund managers possess genuine stock-picking skills, or is their success largely attributable to luck? To explore this, we compare two distinct approaches: (1) a random selection of three stocks from the S&P 500, held for three years, versus (2) an active investment strategy from Hedge Fund Managers in the US. By analysing the returns generated through these methods, we seek to determine if hedge fund managers truly have the skill or if their performance can be matched by a random selection.

Data

Approach (1): Random stock selection

Our analysis is based on historical data from the S&P 500, specifically focusing on monthly open prices and volatility metrics for all included stocks. We selected the top 150 stocks by market capitalization as of December 31st, 2012, which are likely of most interest to individual, non-sophisticated investors. Our dataset spans three years, from December 31, 2012, to December 31, 2015, as it is also the average Hedge Fund age in the US (Exact value: 3.02 years – Annex 2). The total return for each stock, expressed as a percentage, compares its price in 2015 to historical price in 2012, including all dividends distributed during that period. Volatility, a key measure of investment risk, is calculated as the standard deviation of daily logarithmic price changes over the selected timeframe. All data are sourced from the Bloomberg Terminal.

Approach (2): Active Hedge Fund Investment

For information on Hedge Funds in the US we retrieve the data from the study “Hedge Fund Hold’em”, which uses a sample starting in 2001 and ending in 2015. They exclude funds if the main strategy is ‘fund of funds’, and end with a final sample composed of 3,237 funds. They obtain data on hedge fund characteristics, returns and assets under management from Lipper TASS database.

Methodology

To simulate the decision-making process of an individual investor, we assigned numbers from 1 to 150 to each of the selected stocks. Based on research indicating that non-sophisticated investors typically choose three stocks to invest in (a figure derived from a “Investor characteristics and the disposition effect” study based in Equity Market in Australia), we constructed all possible combinations of three-stock portfolios from these 150 stocks using Python txt file. This resulted in a total of 551,300 unique portfolio combinations. This large number of portfolios allows for a robust analysis, ensuring that the findings are statistically significant and reflective of the overall potential distribution in the market.

For each portfolio, we calculated the average return by averaging the returns of the three stocks over the 3-year investment period, assuming equal weighting (one-third) for each. The portfolio's standard deviation was computed using the following formula, which incorporates the individual volatilities and the pairwise correlations between the stocks:

$$\sigma_p = \sqrt{w_1^2 \times \sigma_1^2 + w_2^2 \times \sigma_2^2 + w_3^2 \times \sigma_3^2 + 2 \times \rho_{1,2} \times \sigma_1 \times \sigma_2 + 2 \times \rho_{1,3} \times \sigma_1 \times \sigma_3 + 2 \times \rho_{2,3} \times \sigma_2 \times \sigma_3}$$

where w represents the weights (all equal to 1/3 in this case), σ are the volatilities of each stock, and ρ are the correlation coefficients between each pair of stocks (for instance, correlation between stock x and y, correlation between stock x and z, and correlation between stock y and z), calculated using historical price data.

Summary Statistics

Our analysis yielded the following summary statistics for the 551,300 portfolios:

Table 1: Summary Statistics of Portfolio Returns

Time series data	Values
N (portfolios)	551,300
Average 3y Return	**51.19%**
Minimum 3y Return	-64.09%
25^{th} Percentile	31.20%
Median	50.58%
75^{th} Percentile	70.56%
Maximum 3y Return	184.49%

This table provides a detailed overview of the performance of 551,300 randomly generated portfolios over a three-year period. The average monthly return across all portfolios was 51.19%, very close to the median return of 50.58%, suggesting a balanced distribution of returns. The minimum return observed was a significant loss of 64.09%, highlighting the risks associated with random stock choices, however, the maximum reached 184.49%, which means the investor could at most almost triple its initial investment.

Table 2: Portfolio Return Distribution Over 3 Years

Category	Number of Portfolios	Percentage of Total
Returns < 0%	20,482	3.7%
Returns < 50%	250,764	45.5%
Returns ≥ 50%	251,479	45.6%
Returns ≥ 100%	28,575	5.2%
Total	551,300	100%

In the portfolio distribution analysis, we used the PERCENTILE.INC function in Excel. We selected PERCENTILE.INC (inclusive) as it considers the entire range of the dataset, including the endpoints, to calculate the 25th and 75th percentiles of portfolio return. At the 25th percentile, portfolios returned 31.20%, indicating that a quarter of the portfolios earned less than this amount, reflecting the lower end of the performance spectrum. In contrast, the 75th percentile return was 70.56%, showing that a quarter of the portfolios achieved more than this, underscoring the potential for high returns even with random selection.

The table of portfolio return distribution reveals that the returns are fairly well distributed, aligning with what we would expect from a random selection process. Approximately half of the portfolios (45.5%) have returns below 50%, while the other half (45.6%) achieve returns of 50% or more. Despite the randomness, notably, there are more portfolios with returns exceeding 100% (5.2%) than those with negative returns (3.7%), highlighting a tendency for higher outliers.

Results

Finally, we compared the performance of our randomly selected portfolios against the average return of hedge funds over a three-year period. Based on the study "Hedge Fund Hold'em,", we calculated the returns by using a weighted average of funds managed by professional poker players and funds managed by non-poker players. We reached the following result: an average return for hedge funds from 2001 to 2015 equal to 58.6% over 3-year period of investment. We used this figure as a benchmark to evaluate how our randomly selected portfolios fared in comparison.

These results indicate that the average return of our random stock-picking strategy (51.19%) falls below the benchmark hedge fund return of 58.6%. This suggests that hedge fund managers may indeed possess stock-picking abilities, although it is worth nothing that fees associated to hedge funds are considerably higher and therefore may hinder the final return an investor actually achieves.

The fact that a significant number of randomly selected portfolios achieved high returns (50.8% of the portfolios achieved a return more or equal to 50%) suggests that luck plays a role in investment outcomes. However, Hedge funds likely employ sophisticated risk management techniques that mitigate losses and stabilize returns, which random portfolios do not benefit from. While hedge funds outperform random portfolios on average by 7.41%, the variation in random portfolio performance suggests that luck can lead to significant returns, though not as consistently as professional management.

A primary limitation of our study is the relatively short three-year investment horizon. Over a longer period, the performance dynamics might shift significantly: random stock selection could potentially align more closely with the returns of hedge funds. This limitation is particularly relevant given that long-term market returns are often driven by a few exceptional stocks, known as "superstocks," which significantly outperform the majority. This phenomenon illustrates the inherent difficulty in consistently picking winners. Therefore, future studies could investigate whether the observed trends persist or diverge as the time horizon lengthens, for a period of decades.

Additional Considerations

Additionally, we can compare our stock picking strategy with the currently most used alternative for unsophisticated investors: invest in the S&P500 or one of its ETFs. By computing the return on the S&P500 index over the period from 31/12/2012 to 31/12/2015 we obtain a return of 12.07%. This is probably because our return computed simply as a percentage change from the two dates does not include all the dividends distributed, which represent a big part of the gains obtained from stockholders of the companies within the index. For this reason, we rely more on the comparison with the SPDR S&P 500 ETF Trust (SPY) from State Street, which reinvests the dividends obtained. The SPY return is 51.97% across the same period, which is very similar to the average and median we obtained from the random stock picking process (respectively 51.19% and 50.58%).

At this point, it is possible to present two choices to the investor: pick the ETF, with a “sure” return of 51.97%, or pick three random stocks from the 150 most capitalized companies to obtain an average return of 51.19%, but with the possibility to lose money 3.7% of the times or double them 5.2% of the times.

Again, it is worth highlighting that this process should be repeated extensively across different time horizons and periods in order to better understand the level of correlation among the ETF and the stock picking strategy and provide unsophisticated investors that do not have access to hedge fund services with more evidence on which choice is worth pursuing.

3.2. Poker a game of skill

The emergence of a professional class of poker players, as highlighted by McCormack and Griffiths (2012) and Meng-Lewis et al. (2021), underscores the significant role that skill plays in poker. This involves a blend of mathematical prowess, self-discipline, and strategic acumen. In exploring the impact of skill differences among players, researchers have sought to determine whether these differences are "significant" — that is, sufficient to cause notable disparities in performance and earnings over time. Further research by van Loon et al. (2015) using online poker data showed that players who ranked in the top or bottom ten percent in earnings during the first half of a 12-month sample period were highly likely to remain in their respective performance deciles in the latter half, reinforcing the significance of skill in determining long-term success in poker.

In the realm of poker, the importance of self-control and strategic patience is also crucial. Poker players are often characterized by their 'tightness'—a style where players typically engage in no more than 20% of hands dealt to them (Smith et al., 2009). This approach emphasizes caution and selectivity, key traits of successful players. Supporting this, Siler (2010) conducted an extensive analysis of 27 million online poker hands and found a negative correlation between winning a high proportion of hands and overall profitability. This underscores the need for poker players to be disciplined and judicious in their play.

We therefore define our first proxy for skill in online poker:

- Skill 1: Self-Control. Successful poker players demonstrate patience by playing a smaller percentage of the hands dealt to them. They maximize the value of the hands they do play by adopting an aggressive style, often raising the stakes in more than 50% of these cases (Smith et al., 2009). This approach may seem counterintuitive since many players think it is better to hide strong hands early to keep opponents engaged (Sklansky and Miller, 2006). However, aggressive betting from the start can maximize winnings by compelling other players to either commit more to the pot or fold, thereby avoiding situations where opponents can stay in the game cheaply.
- Skill 2: Aggressive Betting. When skilful players choose to play a hand, they tend to bet assertively, frequently raising the current stakes. This aggressive approach pressures opponents and can lead to larger winnings when they have strong hands.
- Skill 3: Probability Calculations and Hand Selection. Skilled players focus their play on hands that have a higher potential for winning, known as hands with high expected

value. They not only choose these hands carefully but also bet on them aggressively, enhancing their chances of winning substantial pots.

Hergeux and Smagghue (2023) provide evince that the likelihood of investing some positive amount in any given hand, known as "looseness," diminishes significantly with experience. This probability drops from nearly 70% among beginners to around 25% among the most seasoned players, approaching the 20% benchmark typically associated with tight poker play. Concurrently, the average strength of the hands that players choose to engage with also increases with experience, rising from less than 2 (on a scale of 9) to about 4. Moreover, the probability that players will bet aggressively—that is, increase the stakes if they decide to invest—escalates from roughly 20% for beginners to 60% for veterans, a threefold increase, aligning more closely with expert-level play.

The analysis reveals considerable evidence of skill development across all four measures on a population-wide basis. However, it remains uncertain to what extent this improvement stems from actual skill acquisition versus the selective dropout of less committed players from the platform.

The pathway to expertise varies greatly among players, depending on their initial skill level. For instance, a novice starting in the lowest tenth of the skill distribution would need to play approximately 57,000 hands, or about 710 hours of practice—equivalent to 30 days—to reach the proficiency of the most experienced players on the platform. For someone able to dedicate an average of 5 effective playing hours per workday, achieving this level would require around 7 months of full-time engagement.

Linnet, Gebauer, Shaffer, Mouridsen, and Møller (2010) conducted an insightful study revealing significant differences in estimation bias between accepted and rejected gambles among experienced professional players (EPPs), a discrepancy not observed in less experienced players (IPPs). This suggests that estimation bias and decision bias may function as independent or partially independent variables, particularly in IPPs. The study aligns with the finding that a reduction in absolute estimation bias correlates with an increase in skill level, indicating that higher precision in estimation is associated with enhanced performance, especially among EPPs. This relationship also suggests a learning effect within EPPs as they gain experience. One notable finding in the comparison between EPPs and IPPs is the tendency of EPPs to overestimate winning probabilities, particularly for accepted gambles within the 41% to 60% probability range. Several factors might contribute to this overestimation. First, EPPs may have limited experience with hands in this probability range, leading to a higher estimation bias. Second, past successes with these hands, even at lower odds due to opponents folding or other favourable circumstances, might reinforce a bias towards overvaluing these hands. Third, EPPs might assign a subjective value to certain low-probability hands, beyond their strict statistical likelihood of winning. This behaviour is often observed as experienced players alternate between weaker and stronger hands to maintain unpredictability. Consequently, some hands may hold a higher subjective value for EPPs despite having lower objective winning probabilities, especially in the 41% to 50% range where overestimation is most pronounced.

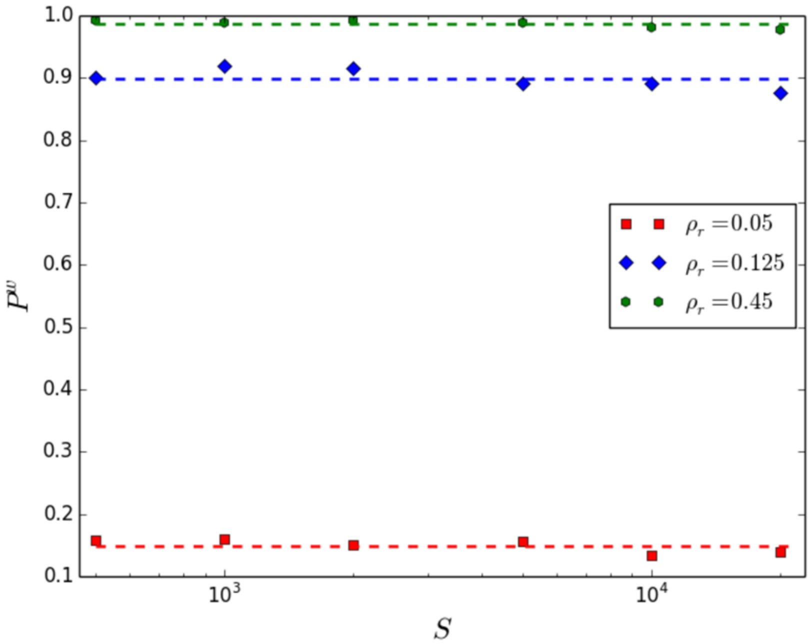
Interestingly, the study found no significant differences in estimation bias for rejected gambles between EPPs and IPPs. This may indicate that both groups have minimal experience with these hands, as unplayed hands provide little information for forming accurate estimates. Alternatively, it might suggest that EPPs place less emphasis on long-shot gambles, where the distinction between a hand with a 24% or 34% chance of winning is less crucial compared to discerning whether a hand has a 64% or 74% chance of winning.

Ultimately, the research demonstrates that there is no significant disparity in estimation bias for rejected gambles between EPPs and IPPs, possibly due to a lack of experience with unplayed hands or a diminished focus on low-probability gambles among EPPs. Despite their pronounced overestimation in specific contexts, EPPs exhibit superior decision-making capabilities compared to IPPs, driven by their lower overall estimation and decision biases. This reduced susceptibility to estimation biases and enhanced emotional control contribute to the stronger cognitive resilience observed in EPPs.

Javarone (2014) identified that the structure of a poker tournament is pivotal in shaping its dynamics. Specifically, in scenarios where blinds remain constant over time, rational players gain a significant advantage. This concept is well-understood among poker enthusiasts, as increasing blinds elevate the associated risks, potentially allowing the element of luck to overshadow players' skills. A critical strategic consideration is the interaction between payout discontinuities upon reaching the "money" phase and the convexity in payouts thereafter. As the number of remaining players nears the threshold for receiving prize money, those with fewer chips may adopt a highly conservative approach, prioritizing survival over maximizing expected value to secure a place in the money. This behaviour, in turn, enables players with larger chip stacks to exploit the situation by adopting a more aggressive strategy, leading to a wider dispersion of chip counts as the competition intensifies towards the payout threshold.

The study observed that the initial stack size (denoted as S) has minimal influence on these dynamics. This finding suggests that further analysis is warranted, as, in practical contexts, the initial stack size is typically considered a significant factor in tournament outcomes.

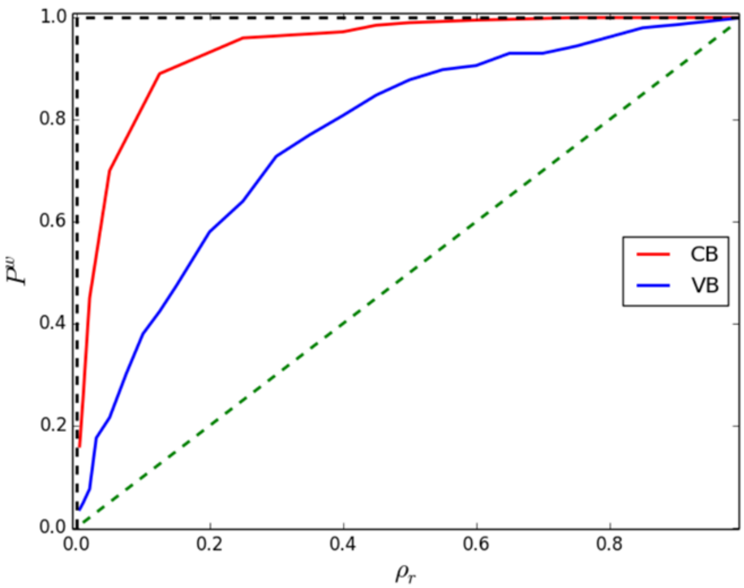
Figure 4: Likelihood of a rational agent achieving victory in a tournament while adjusting the initial stack size, denoted as S



Each symbol, as explained in the legend, corresponds to a distinct density of rational agents. Dotted lines are used to represent the associated average results, which have been computed by averaging the outcomes across 1000 simulation runs.

In his analysis, Javarone compared two distinct scenarios, or variants, of the poker model. The first scenario involves agents who exhibit consistent behaviour over time, reflecting a game primarily governed by skill. The second scenario involves agents whose behaviour can change, introducing a stronger element of chance akin to gambling. Javarone's model allows for rational agents to become irrational under specific conditions: if they lose half of their initial chip stack (denoted as $C(0)$) to an irrational player, they can become irrational with a probability of $1 - \frac{C(0)}{C(t)}$, where $C(t)$ is the current chip count, which must be below half of their initial amount.

Figure 5: Probability that a rational agent wins a tournament varying



The red curve denotes agents with constant behaviour (CB, in the legend). The blue curve denotes the variant of the proposed model where rational agents can vary their behaviour (VB in the legend) under opportune conditions. In both cases, the curves refer to the results obtained with.

The findings emphasize that even when only a minority of players consistently exhibit rational behaviour, rationality becomes a decisive factor for success in poker. Therefore, poker tends to be regarded as a skill-based game when players adhere to rational strategies. This insight highlights that, in such competitive contexts, the influence of human behaviour surpasses the significance of the game's rules in determining its nature.

Levit and Miles (2011) conducted a detailed analysis of Return on Investment (ROI) figures for individual poker players, providing a robust metric for assessing poker skill. Their methodology involved categorizing players who, based on data from the World Series of Poker (WSOP) prior to 2010, could be reasonably classified as exceptionally skilled. This elite group included top money earners from the 2009 WSOP and players recognized in prestigious rankings of top poker professionals. The study then compared the ROIs (Return on Investment) of these identified skilled players with those of the broader player population. Specifically, among the 720 players pre-identified as highly skilled, the 2010 WSOP results demonstrated an average ROI of 30.5%, translating to an average profit exceeding $1,200 per player per event. In stark contrast, all other players recorded an average ROI of -15.6%, indicating an average loss exceeding $400 per event. These stark differences in ROI between the skilled players and the general pool of participants are statistically significant, underscoring the substantial impact of skill in poker performance.

4. Practical application of the intersection of Poker and Asset Management

After exploring the theoretical aspects, we take a closer look at the practical side. Specifically, we examine empirical evidence through a particular interesting study "Hedge Fund Hold'em," we analyse how poker players leverage their expertise to be good asset managers and how the financial market responds to the demonstrated correlation between poker skills and effective asset management.

4.1. Empirical evidence on the correlation of Poker and Fund Management

Lu, Mortal, and Ray (2022) present compelling evidence that hedge fund managers who have secured at least one cash prize in a poker tournament achieve higher monthly returns and alpha, ranging between 10 to 40 basis points, compared to their peers who do not participate in poker. To ensure the accurate assessment of a manager's skill in poker tournaments, the study meticulously considers factors such as the amount of the cash prize, the number of tournament entries, the total buy-ins, and the instances of tournament victories within the sample period. The key results are shown in Annex 2.

The researchers identify a consistent pattern indicating that superior cash winnings and success in more competitive tournaments are closely linked to improved fund performance. Specifically, funds associated with managers who secure prizes above the median demonstrate a mean return of 0.86%, in contrast to a 0.48% return for those with prizes below the median—a difference statistically significant at the 5% level. Similarly, the fund alpha for above-median prize-winning funds is 0.53%, compared to 0.29% for below-median funds, with this difference also being statistically significant at the 5% level. Moreover, funds with above-median cash prizes experience fund flows of 3.43%, markedly higher than the 0.81% for below-median prize funds, with this distinction significant at the 1% level.

The study further reveals that fund managers experience substantial increases in net inflows following success in poker tournaments. Managers who achieve tournament success see a significant rise in monthly average net inflows, ranging from 1.6% to 1.9%, compared to their counterparts who do not succeed in poker competitions. Additionally, funds managed by poker-playing managers exhibit higher net fund flows, with a significant differential of 0.23% at the 10% level.

The analysis highlights that specific groups of managers witness notable increases in net inflows. Managers receiving media coverage for their poker achievements report significant monthly net inflow increases between 3.3% and 3.8%. Similarly, managers who perform better in tournaments, win in events with more participants, or secure cashes in higher buy-in tournaments, observe significant monthly net inflow increments ranging from 2.0% to 2.1%.

In the comprehensive dataset, the researchers analysed 3,017 funds managed by individuals without any poker tournament wins and 220 funds managed by those with at least one tournament win. The comparative analysis of these groups shows that most fund characteristics are similar, suggesting that funds managed by poker players are representative of typical hedge funds. Notably, the study finds no significant difference in risk levels between poker-managed and non-poker-managed funds. Both categories exhibit comparable levels of total and idiosyncratic risk, indicating that poker players are not inherently more prone to risk-taking than their non-playing peers. Moreover, poker-managed funds tend to have greater longevity, with an average age of 3.72 years compared to 3.02 years for non-poker funds.

Furthermore, the study notes that poker-managed funds yield average monthly raw returns of 0.67%, compared to 0.58% for non-poker-managed funds. This 0.09% difference is statistically significant at the 1% level, underscoring the superior performance of poker-managed funds. When evaluating fund alpha using the Fung & Hsieh seven-factor model and out-of-sample estimates via a 14-month rolling regression, funds managed by poker professionals exhibit a higher alpha by 0.11%, with this increase being statistically significant at the 1% level.

Following poker tournament cashes, the study indicates no significant difference in overall returns, but a noticeable decline in alpha, with these funds underperforming their matched peers by an average of 40-60 basis points per month. Further analysis suggests that this decline in alpha is predominantly observed in funds that experience above-median increases in net inflows post-poker victories, supporting the hypothesis of decreasing returns to scale as fund sizes grow. Although a fund manager's skill may remain consistent, the expansion necessitates adjustments to previously successful investment strategies that may have been more effective on a smaller scale. Additionally, the manager might adopt a more conservative stance, aligning the portfolio more closely with the benchmark. This shift is often driven by a desire to manage and mitigate potential risks associated with the larger fund size.

4.2. People involved in both worlds

The investment industry has come to appreciate and leverage the unique abilities developed through playing poker. Many professionals have successfully transitioned from poker to finance, demonstrating how expertise in one field can enhance performance in the other. Here are some notable examples of individuals who excel in both worlds:

Vanessa Selbst, a 39-year-old three-time World Series of Poker champion with $11.9 million in tournament winnings, embarked on a new career path in 2018 as an investment associate at Bridgewater Associates, the world’s largest hedge fund founded by Ray Dalio. At Bridgewater, she was surprised to find that the firm's investment strategy focuses on predicting broad shifts in international macroeconomic data, rather than trading individual stocks. This was a significant shift from her poker career, where she thrived by cultivating a persona of intimidation and aggression. At Bridgewater, she had to adapt to a culture that values approachability and collaboration. However, her ability for independent thinking, a fundamental aspect of the company’s culture, has proven to be an essential asset in her new role.

David Einhorn, president of Greenlight Capital, showcased his poker talent by achieving an impressive third-place finish in a prestigious three-day tournament at the World Series of Poker in Las Vegas. The event, which featured 48 players and required a hefty $1 million buy-in, awarded Einhorn a substantial $4.35 million prize. Although Einhorn has competed in the World Series of Poker before, this recent victory marks his most notable accomplishment at the event. Back in 2006, he finished in 18th place, earning $600,000, and in the previous year, he walked away without winnings. However, this latest success underscores Einhorn's exceptional prowess in the realm of high-stakes poker.

Steve A. Cohen, a billionaire, and the driving force behind the highly secretive hedge fund SAC Capital Advisors, has earned a reputation as one of Wall Street's most successful traders. A 2003 profile in Bloomberg Businessweek spotlighted Cohen's deep-rooted passion for stocks, noting that he even traded between his college classes. Beyond his impressive stock trading skills, Cohen has a long-standing interest in poker, dating back to his high school days where he consistently outplayed his friends. He credits poker with sharpening his risk-taking abilities, a critical skill for successful trading. In a 2010 interview with Vanity Fair, Cohen revealed that poker taught him crucial lessons in assessing risks and making trades without becoming overly concerned about monetary gains. This mindset has been instrumental in his remarkable trading career.

Talal Shakerchi, a UK-based hedge fund manager, has made a significant mark in the world of high-stakes poker. He won the esteemed European Poker Tour (EPT) London High Roller title, amassing over $13 million in prize money. Shakerchi has a formidable record in major poker tournaments, including competing in the groundbreaking $1 million buy-in event at the World Series of Poker in Las Vegas. His success against some of the world's top poker players highlights his exceptional skills and strategic acumen in the game.

Finally, Vanessa Selbst, David Einhorn, Steve A. Cohen, and Talal Shakerchi are all remarkable success stories that highlight the powerful synergy between poker and asset management. Their achievements underscore the valuable crossover of skills between these two fields.

4.3. How do Asset Managers respond to the clear evidence of the skill correlation between successful Asset Management and Poker playing?

Recognizing the value of poker-related skills, prestigious academic institutions have started incorporating poker theory into their curricula. For instance, the Ivy League - MIT Sloan School of Management offers a graduate-level course titled "Poker Theory and Analytics." This course aims to develop students' understanding of fundamental poker strategies, game theory, and high-pressure decision-making. The ultimate goal of the course is to cultivate skills necessary for future management and leadership roles in finance, trade, and global markets. Kevin Desmond, the course instructor, emphasizes that many are surprised by the depth of poker analysis, which prepares students for future roles in finance and global markets. The class he conducted offered students the chance to become risk-takers in a global market, an experience challenging to replicate elsewhere. Poker serves as a game with minimal barriers to entry, allowing players to compete with others from around the world, mirroring the essence of traders making decisions amidst a vast market. Both activities involve risking personal funds and effectively playing against the global market, fostering a connection between the two endeavours.

Ed Thorp, a distinguished quantitative analyst and blackjack expert, posits that poker provides a significant and practical application of game theory. He further conjectures that financial institutions might actively seek to employ individuals who possess a profound understanding of game theory, coupled with expertise in risk assessment and adept decision-making skills, to enhance their business operations.

Indeed, in the corporate world, companies like Susquehanna International Group have integrated poker into their training programs. Susquehanna, a prominent trading firm with 1,500 employees (3 of which have won a World Series of Poker bracelets), recognizes the parallels between poker and trading. Susquehanna's training programs combined instructional sessions on options pricing theories with poker-playing tournaments, aimed at evaluating and sharpening employees' decision-making abilities. Additionally, new hires receive essential poker literature, such as "The Theory of Poker" and "Hold‘em Poker” and dedicate one full day each week to studying and practicing the game. Similarly, Toro Trading, a firm specializing in high-speed trading, values the qualities often found in successful online poker players. When recruiting, they prioritize candidates who demonstrate quick-thinking, composure under pressure, and strong numerical skills — attributes that align with those often found in successful online poker players.

In conclusion, the strategic thinking, risk management, and analytical abilities developed through playing poker are becoming increasingly valuable in asset management. This recognition has led to a growing trend in the financial sector, where both educational institutions and financial firms are embracing this intersection, training, and recruiting professionals who can bring these critical skills to the investing sector.

5. Conclusion

A frequent error in competitive contexts where skill influences outcomes is the failure to recognize that it is the relative level of skill among competitors that ultimately determines success. This is particularly evident in various forms of competition, including poker and investment strategies. It is not the absolute skill level that is paramount, but rather the relative skill compared to others. This concept, known as the "paradox of skill," suggests that as the general skill level increases, the role of luck in determining outcomes becomes more pronounced if the level of competition rises concurrently.

An important lesson can be gleaned from poker. Nolan Dallo has observed that the majority of profit at the poker table derives not from one's own brilliance but from capitalizing on the mistakes of others. In other words, in a zero-sum game such as poker—or in the context of investing, which is effectively a negative-sum game after expenses—success often depends on the presence of less skilled participants to exploit.

Robert Stambaugh, in his study “Investment Noise and Trends,” (2014) highlights a significant trend in the ownership of U.S. equity. Following World War II, households directly owned more than 90% of U.S. corporate equity. However, by 2008, this figure had declined to approximately 20%. This reduction in individual ownership suggests that the pool of less sophisticated investors—those more likely to be exploited—is diminishing. Many of these investors are increasingly moving towards passive investment strategies, thereby reducing the opportunities for more skilled players to exploit less experienced market participants.

Aaron Brown, after a distinguished 30-year career on Wall Street, including roles as a trader, portfolio manager, and risk manager at Morgan Stanley and other firms, has retired from both his financial career and his lifelong pursuit as a professional poker player, reflecting on his experiences in these two domains.

Firstly, both poker players and traders must evaluate their decision-making processes impartially, distinctly separating the quality of the decision from the outcome. Understanding the underlying reasons for the success or failure of a decision is vital. Without this discernment, individuals risk merely replicating past trades or bets that have worked, eventually leading to failure. Brown advocates for a "zero memory" attitude, emphasizing the importance of a resilient mindset. By adopting such an approach, one can effectively navigate setbacks and prevent defeats from undermining progress and determination. He notes that individuals often exhibit heightened stubbornness following significant losses, a behaviour that can be particularly challenging to overcome. In both poker and trading, pattern recognition is crucial. However, the methodologies differ significantly. Poker players rely on keen observation of cues, such as changes in body language, to predict opponents' actions. In contrast, traders engage in the meticulous analysis of extensive historical data to forecast market trends. It is essential in both fields to distinguish between normal fluctuations and significant pattern changes. Brown points out that people often overreact to random events while underestimating the importance of non-random signals.

However, a significant difference between these two activities is the nature of their solitary work. In poker, the lack of shared experiences means that the highs are less fulfilling, as they are not celebrated collectively. Conversely, the lows can be more pronounced due to the solitary nature of the game, though this can ease the burden of disappointing others. This solitary aspect can be problematic in trading, where teamwork and partnership are vital for sustained success.

Lastly, Kevin Zollman, a game strategist and professor at Carnegie Mellon University, elucidates that in both game theory and financial markets, decisions that appear rational and well-founded can still lead to adverse outcomes due to unforeseen events. For example, unexpected occurrences such as the COVID-19 pandemic or the Russian-Ukrainian conflict have had profound and disruptive impacts on the global stock market. These instances highlight how even the most carefully considered decisions can be undermined by external, unpredictable factors, underscoring the inherent uncertainty and risk in both strategic games and financial investing.

Throughout this thesis, we presented what are the main decisions poker players and asset managers face in their respective fields, and dove into their approaches to such decisions, with all the biases that their reasonings entail. After looking at these aspects from a theoretical standpoint, we provided empirical evidence and real-life examples of how these two words are connected, concluding by highlighting key aspects in common.

Annexes

Annex 1: Summary Table of the Study "Poker Player Behaviour after Big Wins and Big Losses"

Table 1 Predicted Play After a Big Win or Loss

	Big win	Big loss
Revised assessment	Less cautious	More cautious
Break even		Less cautious
Moods	Less cautious	More cautious
House money	Less cautious	More cautious
Gambler's fallacy	More cautious	Less cautious
Hot and cold streaks	Less cautious	More cautious
Doyle Branson strategy	Less cautious	

Annex 2: Summary Statistics of the Study "Hedge Fund Hold'em"

Table 1: Summary statistics

This table reports the summary statistics of 220 hedge funds with poker-playing managers and 3017 hedge funds without poker-playing managers. Panel A reports the means of fund-level variables. *High-water mark* is an indicator variable for the hedge fund using a high-water mark and zero otherwise. *Lockup period* is in days, conditional on non-zero records. This table also reports the fraction of funds with lockups. Time-varying fund-level variables include monthly fund raw returns, seven factor alphas, net flows, total risk, idiosyncratic risk and assets under management. Panel B displays the frequency of poker tournaments by hedge fund managers. Panel C reports summary statistics for poker tournaments. *Prize* is the dollar prize won by the hedge fund manager. *Media* is a dummy variable which takes a value of one if the tournament has media coverage, and zero otherwise. *Jobs Act* is a dummy variable which takes a value of one if the tournament takes place after the passage of the Jobs Act, and zero otherwise.

Panel A: Summary Statistics of Fund-level Variables

	Not poker	Poker	Difference
Fund Characteristics			
N	3017	220	
Management Fee (%)	1.43	1.44	0.01
Incentive Fee (%)	14.70	14.33	-0.37
High Water Mark	0.65	0.63	-0.02
Proportion with Lockups	0.30	0.14	-0.16
Mean Lockups (days)	262.96	301.31	38.35
Redemption Period (days)	50.36	44.75	-5.61
Fund Age(years)	3.02	3.72	0.70^{***}
Time series data			
Raw return (%)	0.58	0.67	0.09^{***}
Alpha (%)	0.23	0.34	0.11^{***}
Flow (%)	1.34	1.57	0.23^{*}
Total Risk (%)	3.20	3.06	-0.14
Idiosyncratic Risk (%)	2.21	2.06	-0.15
Mean Assets (MM$)	228.13	234.83	6.70

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