Why investors are not always rational

Prof André Heymans

Abstract

As humans we make roughly 10 000 decisions every day. Most of these decisions are not made with our energy intensive prefrontal cortex, with which we make calculated rational decisions, but rather our reactionary impulsive faculties that reacts to environmental stimulus. Investors, like all other humans, therefore falls prey to a host of cognitive biases, leading them to make systematic errors in thinking when it comes to investment decisions. So, although not all investment decisions are irrational, there are enough of them to cause significant losses to invertor portfolios, a theme prof Heymans highlights in his address.

Inaugural address

To understand why behavioural finance even exist, we must go back before the evolution of humans. Our brains evolved only moments ago when measured on the cosmic scale, and to appreciate just how recently, we must create some frame of reference on a time scale. To do this cosmologists make use of the cosmic calendar, fitting the expansion of the whole of the universe – over 13 billion years – into one year. On this scale every day represents 40 million years.

When broken up like this we see some important markers in the cosmic year. On the 1st of January all matter originates from a point of energy smaller than the size of an atom. After the point of creation it was dark for more than 200 million years after which stars started forming and clustered together in galaxies by the end of the first week of January. This star formation continues for billions of years with our milky way forming by March, and by the 31st of August our own sun is born. It is only by the 21st of September that the earth is finally cool enough to sustain life on earth. The next highlight is microbes that forms by November 9th, and animals on land only starts developing by the final week of December. At 6:24 AM on 30 December, an asteroid hits earth and destroys the dinosaurs which clears the way for mammals. Humans only start evolving in the last hour of December 31st. On this time scale the history of humans, all wars, the building of cities, all recorded history makes up the final 14 seconds of the year. So, humans are brand new.

Why is this relevant? Because our brains have developed in response to our environment in its quest to help us survive. This survival strategy is built on taking information and putting it into context. However, because life can also be dangerous, our brains evolved to skew the importance we attach to information. We are therefore more easily convinced of negative consequences than of positive consequences.

This is clear in all spheres of life, and we start off as children being cautioned by our parents about all the dangers out there. This continues when we watch the news as adults. The news is almost exclusively reporting what has gone wrong already, and how it can get worse.

The success of human civilization can therefore be attributed directly to our ability to learn from our environment, and more importantly to put what we have learned into language and then communicating this information to people around us, and also to record it for generations to come. Over time we have become better at accumulating information and finding ways to build on that information, changing it and adding to it to solve the issues of our day. We have in fact become so adept at information gathering and processing that we have built institutions around this activity in the form of universities, schools, and libraries.

Information, and the communication of information has become so engrained in our everyday lives that we do not even think about it anymore. It has become part of us and who we are as humans. It is therefore not surprising that a lot of research has been performed on the significance of information and the sharing of information, and as we arrive in what many call the information age, we as a species are governed by information.

This is however not a talk on biology, but economics, so the question is where my research fits in? My research largely centres around information itself, and how efficiently it is communicated. So, to be more specific, I investigate the informational efficiency of financial markets. A lot of my research therefore covers asset prices, trying to predict what they will do in the future – obviously trying to see whether it is possible for people to use this information to make money.[1]

The predictability of asset prices is only possible in markets where there is little or no informational efficiency. So, many of the papers on the topic starts with a reference to market efficiency and to what extent such a market is informationally efficient. Without delving too deep into the development of the efficient market hypothesis, I will give a short history of the development of the theory around asset prices and how they are determined.

We can trace the modern market theory back to the 16th century when the Italian mathematician, Girolamo Cardano published his book titled “The Book of Games of Chance” in 1564. The second part of the puzzle was discovered by the botanist Robert Brown that observed that grains of pollen suspended in water had a rapid random motion when viewed under a microscope. Although Robert Brown observed this phenomenon, he could not explain it. The mathematics that explains Brownian motion was developed by Louis Bachelier when completing his PhD in 1900, 5 years before Albert Einstein* discovered the same mathematics independent from Bachelier. In 1905 Karl Pearson introduced the term random walk based on the mathematics of Brownian motion and this is the term later used by Fama to explain his theory on market efficiency. Because of the two world wars, research in this area stood still for some time, and only continued after the second world war ended.

This research was taken up again by Harry Markowitz*, the first of the pioneers of what we know today as Modern Portfolio Theory (MPT). He published his paper on minimum variance portfolio optimisation in 1952. Following on Markowitz (1952), Jack Treynor, William Sharpe* (1964), John Lintner (1965), and Jan Mossin (1966) developed the Capital Asset Pricing Model (CAPM). The CAPM endeavours to describe the relationship between risk and return for assets, particularly stocks. Armed with the CAPM and Markowitz’s minimum variance portfolio, several researchers – including Eugene Fama – set out to test whether markets do act as effective clearing places for the buyers and sellers of stocks and other financial instruments. The prominent studies that tested for market efficiency was the study by Paul Samuelson and Eugene Fama* in 1965, and Benoit Mandelbrot* in 1966.

It was however Eugene Fama that finally formalised the efficient market hypothesis (EMH) in 1970. According to the EMH “A market in which prices always *fully reflect* available

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[1] To show that some bright minds have been thinking about this topic, I have highlighted the Nobel prize winners with an asterisk next to their names.

information is called *efficient*" or more accurately described that "*an efficient market is defined as a market where there are large numbers of rational, profit-maximisers actively competing with each other trying to predict future market values of individual securities, and where important current information is almost freely available to all participants.*"

Such a market will be deemed informationally efficient when all information that affects prices enter the market in a random, independent, and unpredictable manner. But what does this mean? It simply means that everyone will attempt to adjust the market price to reflect the fair market price as soon as any new information arrives. The easy way to describe the impact of market efficiency is with an example. If all of us went out now to buy 500ml of bottled water in different parts of town, all of us might pay different prices for it. The fact that these identical products are sold at different prices on different markets (Shoprite, the grocer around the corner, Pick 'n Pay or Woolworths) means that the market is not informationally efficient.

The reason for this inefficiency comes from several sources. There are different labels on the bottles (brands). The different suppliers have different buying prices when they buy the product. They also have different overheads and the like. The reasons for the different input costs are also a function of market inefficiency in the rental and labour markets for example.

In a more efficient market, like the stock market, you find shares that trade at the same price for anyone that is willing to buy at the same time. If you and I would like to buy the same shares at the same time, then we will pay the exact same price for those shares. Now off course these share prices for large companies changes several times a second, as buyers and sellers use the information to their disposal to gauge what the value of these shares should be. If the market is efficient, then the price of a specific share will change randomly without the possibility for any buyer or seller to guess correctly what the next price will be. If this market is inefficient however, it might be possible for superior traders to form a fairly accurate educated guess where prices will go in the future.

However, the more superior traders are out there, the more the guessing is about the average guesses of what the average guesses are. In fact, John Maynard Keynes compared the picking of stocks by the money managers on the stock exchange to a common competition that ran in the male dominated London financial scene in the 1930s during which these men would pick the prettiest faces from a set of 100 photographs. The winner of this competition would not be the one that picked the 6 prettiest faces, but the one that got closest to the average of the top 6 pictures that everyone else picked. The competitors would therefore not pick those pictures they thought were the prettiest, but the ones that they thought others would pick.

Keynes state that "*It is not a case of choosing those which, to the best of one's own judgement, are really the prettiest, nor even those which average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligences to anticipating what the average opinion expects the average opinion to be. And there are some, I believe, who practice the fourth, fifth, and higher degrees*."

By the late 1970s, the EMH was challenged by exactly this idea. A new body of research began to form as many researchers began to point out that certain anomalies cannot be explained by the EMH. In fact, the literature between the 1970s and late 1990s is littered with proof of market anomalies. The most prominent of these are: the seasonality in stock returns; the existence of dividend yields and earnings yields in stock returns; size related anomalies; the impact of macroeconomic factors on stock returns; and the presence of autocorrelation in stock returns.

These are just different ways to say that sometimes stock prices are predictable, and that really smart investors can beat the market if they do their analysis. This new school of thought was later called behavioural finance, and described how asset prices could be explained, not by randomness, but based on human reactions to external shocks. This new finance field was born out of the work done by cognitive psychologists such as Herbert A Simon* (1990), Amos Tversky* and Daniel Kahneman* (1984) and economists Robert Shiller* and Richard Thaler* (1987).

Behavioural finance is based on the idea of bounded rationality that states that humans take mental shortcuts. This is different to the idea that investors find it easy to make financial decisions because they are well-informed, careful, consistent and always rational. The traditional theory holds that investors are not confused by how information is presented to them and not influenced by their emotions.

But clearly reality does not match these assumptions, and I hope to demonstrate some of that tonight. Established financial theory focuses on the trade-off between risk and return. However, behavioural finance suggests investors are overconfident with respect to making gains and oversensitive to losses. Research in psychology has documented a range of decision-making behaviours called biases. These biases can affect all types of decision making but have particular implications in relation to money and investing.

These biases are the result of thousands of years' evolution, and the purpose is to use mental short cuts to keep us alive. Because they are a fundamental part of human nature, these biases affect all types of investors, both professional and private. However, if we understand them and their effects, we may be able to reduce their influence and learn to work around them.

These biases can be categorised in four large categories. The first category includes cases where we have too much information, the second includes cases where we do not have enough information, the third category cases where there is some time pressure and we need to act fast, and the final category includes cases where we act on memory – which is very unreliable. Not all cognitive biases are relevant when it comes to investing, but there are enough of them to cause people to make irrational investment decisions.

The list of biases that lead to faulty decisions and eventually losses on our investment portfolios are ever growing. Psychologists and behavioural scientists find new ways in which our brains make systematic errors when it comes to our decisions about money every year, so the following is by no means an exhaustive list.

Too much information

Although there are more than three biases under each category, I will only discuss some of the most prominent of them tonight.

The first of the biases that we observe when we are presented with too much information is the availability heuristic. This phenomenon takes place when people tend to make judgments about the likelihood of an event based on how easily a case comes to mind. For example, investors may judge the quality of an investment based on information that was recently in the news, ignoring other relevant facts. To see how this plays out in everyday life, you only have to look at the stocks retail investors hold in their portfolios. The majority of these stocks are well known brand names and are covered regularly by analysts.

The second bias in this category is anchoring. Anchoring refers to the attachment of a spending level to a certain reference. Examples may include spending consistently based on a budget level or rationalizing spending based on different satisfaction utilities. In the investment space this plays out when investors invest in stocks that fell a lot in value. The reasoning is that a stock that traded at a $100 before, and that now trades at $50 is selling at a discount, and that there is $50 to be made it this price.
The third bias we observe when we have too much information is the confirmation bias. The confirmation bias is when investors have a bias toward accepting information that confirms their already-held belief in an investment. If information surfaces, investors accept it readily to confirm that they're correct about their investment decision—even if the information is flawed.

The second category of biases occur when we do not have enough information to make our decisions.

Not enough information
The first of the biases that we observe when we are presented with too little information is the gambler’s fallacy. This bias occurs when an individual erroneously believes that a certain random event is less likely or more likely to happen based on the outcome of a previous event or series of events. This line of thinking is incorrect, since past events do not change the probability that certain events will occur in the future. When observing this in the investment arena investors are often fooled into thinking that the price of a particular stock must go up or down, based on the previous up or down movement of the stock price. Since previous moves in price have nothing to do with future price movements betting on future price movements on this basis is folly.

The second bias, the *hot hand*, is the notion that because one has had a string of successes, an individual or entity is more likely to have continued success. For example, if one flipped a (fair) coin and guessed correctly that it would land on heads three times in a row, it might be said that they have a *hot hand*. Under such circumstances, a person believes that their odds of guessing which side the coin will land on next are greater than the 50% they are. When there is a series of failures, the same concept works as the *cold hand*. This effect is visible in the investment arena where investors gain unwarranted confidence in their stock picking ability – especially in a strong bull market. When the market turns around these investors believe that they are *lucky* and that they need not perform the rigorous analysis necessary to spot good investment opportunities. This then ultimately leads to a string of losses that could have been avoided if more prudence was taken.

The third bias that draws from this category is the *bandwagon effect* or herd behaviour. This bias plays out as people tend to mimic the financial behaviours of most of the herd. Herding is notorious in the stock market as the cause behind dramatic rallies and sell-offs.

Time limitation
When it comes to the decisions, we make under time limitations the following biases are relevant: Loss aversion, the disposition bias and the over confidence effect.

Loss aversion occurs when investors place a greater weighting on the concern for losses than the pleasure from market gains. People are far more likely to try to assign a higher priority on avoiding losses than making investment gains. As a result, some investors might want a higher pay out to compensate for losses. If the high pay out isn't likely, they might try to avoid losses altogether even if the investment's risk is acceptable from a rational standpoint.

The *disposition bias* refers to the phenomenon of investors selling their winners and hanging onto their losers. Investors’ thinking is that they want to realise gains quickly. However, when an investment is losing money, they'll hold onto it because they want to get back to even or their initial price. Investors tend to admit their correct about an investment quickly (when there’s a gain). However, investors are reluctant to admit when they made an investment mistake (when there's a loss). The flaw in disposition bias is that the performance of the investment is often tied to the entry price for the investor. In other words, investors gauge the performance of their investment based on their individual entry price disregarding fundamentals or attributes of the investment that may have changed.

The final bias observed under this category is the *over confidence effect*. This bias is a tendency to hold a false and misleading assessment of our skills, intellect, or talent. In short, it’s an egotistical belief that we’re better than we are. It can be a dangerous bias and is very prolific in behavioural finance and capital markets.

Memory effects

The final category of systematic mistakes we make in our thinking is based on our memories. It is often the case that we must make decisions based on information we received in the past, thereby exposing us to the risk of making decisions on information that we may have forgotten, or worse, remembered incorrectly or incompletely.

The three biases through which these errors in thinking occurs are the recency effect, the misinformation effect, and the negativity bias.

The recency effect occurs when recent market news or events can lead investors to irrationally believe that a similar event is more likely to occur again than its objective probability. As a result, investors may make decisions to sell into bear markets, or buy into bubbles, since crashes and bubbles can be salient in the minds of individuals as they are occurring.

The misinformation effect plays out when investors react to fake news. Investors act swiftly on news whether it is good or bad. Once the news is confirmed to be fake, these investors have to reverse their positions, often leading to large losses.

The negativity bias plays out when investors put more weight on bad news than on good news. In some sense this is the original cognitive bias that often prevents investors from investing, missing out on returns.

These biases, although defined and discussed in isolation here, are all active in the standard investor’s brain. Since we are all human, and investors are no less human, we are all subject to these mental shortcuts that often lead to the wrong decision being made. To demonstrate how these mental shortcuts work, I have devised a number of questions for every member of the audience to answer. The results of these *tests* will demonstrate the effect of these mental shortcuts and illustrate the frequency with which they occur in our regular thinking patterns.

The first set of questions will illustrate cases where we must make decisions based on too much information. The questions put to the audience were paired such that some personal detail was asked from every member of the audience that would be unique to every person, followed by a question where everyone is asked to make a decision. The effect that I tested for here was the anchoring effect. The questions were paired as follows:

Write down the last three digits of your phone number, followed by *What is the maximum amount you would you be willing to pay for a good quality wine?*

Write down the day of the month you were born – for example 2nd of September = 2 followed by *What is the maximum amount you would you be willing to pay for this wedge of cheese?*

Please write down your length in centimetres for example 175 cm (without the cm) followed by *What is the maximum amount you would you be willing to pay for this box of chocolate?*

Please write down the first three digits of your ID number followed by *What is the maximum amount you would you be willing to pay for this ice cream?*

The results of these test questions were as expected. The variance in the answers to the first and fourth questions were statistically significantly higher than the answers to the second and third questions. Because the decision questions in questions one and four were linked to answers that had three digits, the range in the answers were a lot higher than the ranges of the answers to questions two and three which were linked to data that had low values and tight ranges.

The next exercise was devised to show how we anchor answers to random information without realising what our brains are doing. To illustrate this, I divided the audience into two groups. I asked each group the same question, only changing the order of the information. Since each group responded to a unique QR code, neither of the groups knew what the other group was asked. Group A was asked to guess the answer to (8 × 7 × 6 × 5 × 4 × 3 × 2 × 1) while group B was asked to guess the answer to (1 × 2 × 3 × 4 × 5 × 6 × 7 × 8).

Although the answer in both instances is 40 320, the answers of the two groups were far removed from one another. The average of the answers provided by group A was 507 135,89 while the average of the answers provided by group B was 221 532,95. The reason for this phenomenon is that our brains are overwhelmed when it must engage a slow and methodological process. When pressed for time you tend to perform the first three to four calculations after which a guess is ventured. Because 8 × 7 × 6 × 5 = 1680, people tend to guess a higher answer than a group who does the same starting 1 × 2 × 3 × 4 which is 24. The average guess in the first instance is therefore invariably higher than the second case.

The second bias that I illustrated was the gambler’s fallacy which occurs when we do not have enough meaning. To illustrate this, I allowed the members of the audience to guess on which colour (red or black) the roulette wheel will land with the next spin. Although the results of this exercise were never going to render statistically useful results, the audience were admittedly fooled by the idea that a string of results on one or the other colour warranted a different outcome on the nest spin.

The third bias I illustrated was the over confidence effect that occurs when we are making decisions under time pressure. To this end I asked the audience members to guess the range of the correct answer for the following questions:

How long is the longest river in the world – Range min? Range max?
How many books are there in the Bible?
How many countries are there in Asia?
The fourth most widely practiced religion is Buddhism, how many followers are there worldwide – Range min? Range max?

Even though the average participant could have easily guessed the correct answer by giving a range between zero and infinity, all the answers to these questions had minimum values above zero and maximum values far below infinity. Instead, very few people were able to give an accurate range for each of the questions. When giving a range for the longest river in the world, only 21.28% of the audience members were able to provide a minimum value below the real length as well as a maximum value above the real length. This implies that people are so confident that they can guess the correct length that they narrow down their chances of success to eventually end up outside the bounds of the answer.

The range for the books of the Bible were even narrower and only 8.51% of the audience members managed to guess a range wide enough to include the answer. The successful ranges for the number of Asian countries were 21.28% and for the ranges of the number of craters on the moon 6.38%. This is conclusive proof that we often think that our abilities are better than they really are.

To illustrate how my own research fits into the existing literature I have categorised my research under the following headings: Data handling to ensure trustworthy results, Patterns in the data, and Profiting from inefficiency. Although these three broader categories do not incorporate all my research, I will discuss the critical topics in each category.

Data handling to ensure trustworthy results

Diligence in determining the appropriate form of stationarity
This article challenged the assumption that most financial time series are first differenced stationary. The common difference first, ask questions later approach was revisited by taking a more systematic approach when analysing the statistical properties of financial time series data. We found that many economic data series are in fact not first difference stationary but takes on various other forms of stationarity.

The prominence of stationarity in time series forecasting
Because the stationarity of a time series can have a significant influence on its properties and forecasting behaviour, most researchers render a time series stationarity using the first differencing method. In this paper we designed a process to determine whether using the correct form of stationary data would enhance forecasting accuracy. The results from this paper proved our hypothesis that the correct form of stationarity will outperform any other form of stationarity.

Other papers under this category includes:

A risk-adjusted performance evaluation of US and EU hedge funds and associated equity markets over the 2007–2009 financial crisis

Hedge fund performance evaluation using the Sharpe and Omega ratios

Hedge fund performance using scaled Sharpe and Treynor measures

The bias ratio as a hedge fund fraud indicator: An empirical performance study under different economic conditions

Evaluating novel hedge fund performance measures under different economic conditions

The impact of different forms of stationarity on forecasting with financial time series

Patterns in the data

Seasonality as an unobservable component in South African agricultural market data

Because most of the tests for seasonal patterns are designed to let you know when there are no patterns in the data, they miss underlying patterns that can be used to profit from them. The aim of this paper was to test for unobserved seasonal patterns in South African agricultural market data, showing that these patterns can be exploited by pairs traders to turn a profit from their trades. These patterns seem to describe the actual series more accurately than the deterministic approach.

How efficient is the JSE really?

The aim of the research was to prove that the sub-indices on the JSE go through cycles of efficiency and inefficiency even though the JSE as a whole might be considered informationally efficient. The results confirm that some of the smaller, and in some instances younger, indices are not always as efficient as the All-share index, meaning that portfolio managers with an active management approach can profit from these inefficiencies. The fact that active management is practiced by portfolio managers in the South African market is anecdotal proof that there are inefficient pockets on the JSE.

Other papers under this category includes:

Seasonality as an unobservable component in South African agricultural market data

The relationship between the forward and realised spot exchange rate in South Africa

Measuring the systematic risk transfer from the United States to the South African financial sector

Measuring the systemic risk in the South African banking sector

The effect of Chicago Board of Trade prices and fundamental factors on South African yellow maize prices

Profiting from inefficiency

A comparison of the efficient and fractal market hypotheses in developing markets

A causal relationship is found between these quantities: the larger the change in the fractal dimension before breaching, the larger the rally in the price index after the breach. In addition, breaches are found to occur principally during times when the market is trending.

Forecasting the price of Bitcoin using neural networks

This research compared eight classical linear statistical methodologies with machine learning to forecast the price of Bitcoin. The appropriate machine learning forecasting technique outperformed the classical linear statistical models.

Measuring spill-over effects of foreign markets on the JSE before, during and after international financial crises
During this research we found the JSE All share index is directly affected through contagion by the returns of the economic area where the crises originates. Because negative returns on foreign markets spills over to the JSE during crisis periods, local portfolio managers have the opportunity to react in time to adjust their portfolios before the market movement is complete, thereby profiting from the observed prices on foreign stock exchanges.

The influence of volatility spill overs and market beta on portfolio construction
In this paper we proved that portfolio managers should not only focus on the established mean variance portfolio optimization practice, but that they should also consider that stocks in a portfolio transmit information between one another. Taking this into account, portfolio managers can construct stock portfolios with less risk for the same level of return.

Analysing white maize hedging strategies in South Africa
In this study we designed a decision-making tool for maize producers to combine a number of factors that allow them to model all the influential market factors necessary to make an informed hedging strategy decision based on the expected price progression of the following production year. This allows them in effect to realize a higher selling price than would otherwise be possible over the longer run.

Measuring the volatility spill-over effects between Chicago Board of Trade and the South African maize market
In this study we found that the volatility in the South African market is locally driven and does not spill over from Chicago which is the largest and most influential commodities market in the world. We also found that the returns of the South African maize market are more sensitive to bad news than good news.

Other papers under this category includes:
A fundamental evaluation of the top five South African banks after the financial crisis
Managing capital procyclicality in African banks using contingent convertible bonds
The price and volatility transmission of international financial crises to the South African equity market
Measuring the volatility spill-over effects between Chicago Board of Trade and the South African maize market
Measuring the relationship between intraday returns, volatility spill overs and market beta during financial distress
Hedging against exporting risks in the South African extractive industry
Optimising hedging costs within a South African agricultural derivatives portfolio
Decision making under uncertainty: Markowitz optimisation as a passive strategy on the JSE

Current research

My current research endeavours to dig deeper into the inefficiencies of the equity markets as well as the nascent blockchain markets. The most promising topics I'm covering over the next few years are:

Why shares don’t always trade at their intrinsic value: an experimental research approach
In this study we aim to explain the irrationality of human behaviour on stock prices and the impact thereof on the profitability of stock portfolios.

Developing an optimal weighting model for Fund of Funds portfolio construction
In this study we aim to show that the risk weighted profitability of stock portfolios within Funds of Funds can be improved by moving away from the current practise of simply running an equally weighted portfolio of fund managers.

Utilising market efficiency to improve portfolio asset allocation
In this study we aim to show that even if the JSE All-share index is weak form efficient, that individual stocks are not necessarily, making the changes in their prices more predictable. This allows portfolio managers to outperform the market with an active management style.

Evaluating the effect of the market efficiency of cryptocurrencies on portfolio performance
In this study we aim to show that the current inefficiency of the crypto markets allows portfolio managers to include these assets into their portfolios to improve the overall risk-weighted returns on these portfolios.