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MASTER’S THESIS

BEHAVIORAL ASPECTS OF THE GLOBAL EQUITY MARKETS IN 2020

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INTRODUCTION

Ever since the advent of Daniel Kahneman and Amos Tversky's prospect theory in 1979, economics and finance academia have become increasingly aware of the mistakes individuals commit when making many of their decisions. In light of the global 2019-nCoV pandemic and the shutdowns the viral outbreak brought about, many financial and other analysts expected the global equity markets to take a turn for the worse. Even though equity prices underwent a substantial correction in March and April of 2020, the world's largest stock market indices recovered much faster compared to the 2008 global financial crisis. Many claimed we witnessed a schism between the economy and stock markets. All-time highs in the U.S. equity markets only a few months after price corrections that triggered multiple circuit breakers implied that the broader economy could soon begin functioning normally.

An explanation for the apparent separation may be found in the field of behavioral finance, which uses a psychological approach to evaluating investment decisions, markets, and managers (Ackert & Deaves, 2010, p. xxvi). As investors and consumers, individuals have been often proven they do not necessarily act as completely rational agents, as they are commonly referred to in many microeconomics textbooks.

Efficient market hypothesis and rational agent hypothesis are two fundamental pillars in the field of finance. The two theories are commonly alluded to in explaining investor behavior and observing stock market returns, but have been undermined by more recent research conducted by psychologists and behavioral economists. No individual, including financial experts, always act rationally (Kahneman D. , 2011, p. 217), giving reason to believe this irrational behavior has explanatory power in observing past market trends. Prior work of Baltaci et al. (2020) indicates there is a statistically and economically significant relationship between cultural factors and the probability of a financial crisis. As the authors showed in their work, power distance and individualism were proven to have an impact in expediting the 2007-2009 financial crisis. The authors concluded that the probability of a financial crises is greater in countries scoring higher on the individualism and lower on the power distance index scale. Therefore, the objective of the master's thesis is to juxtapose rational behavior of investors within the realm of global equity markets that are assumed to be efficient alongside daily stock price movements and returns within the scope of the year 2020. This written work predominantly analyzes which cultural factors and their underlying behavioral biases are prevalent based on the origin of a hypothetical investor. This master's thesis builds upon the assumptions that, in practice, capital market participants are not rational, or not to the extent the efficient market hypothesis expects them to be and that Kahneman and Tversky's prospect theory combined with Hofstede's six-dimensional national culture model can provide an insight into the global equity market developments in 2020. More precisely, the thesis will analyse how stock market index returns of 55 countries have been (if at all) affected by their cultural characteristics during 2020.

The first part of the written work includes a detailed literature review of subjects most pertinent to the master's thesis. From a economics perspective, this includes: rational agent hypothesis, efficient market hypothesis and modern portfolio theory. The more psychological and social part of the thesis touches upon reviewing existing emotional and cognitive biases, and how societal differences quantified as cultural dimensions classify and help mold human behavior into six distinct categories. All reviews together formed the basis for the second, empirical part of the thesis, which begins with a Chi-squared test of the cultural traits in conjunction with the annual returns of stock market indices indigenous to their respective country. The Chi-squared analysis serves as a first test of how cultural factor are correlated and helped form the research questions which were later analyzed by means of an ordinary least squares (OLS) regression. Hofstede's cultural traits and two additional control variables of annual change in GDP and real interest rates serve as regressors in a regression where I analyzed their effect on the returns of major stock market indices indigenous to each of the countries under observation. Stock price data was collected from Eikon, while culture factor data was obtained from Hofstede's website. The data was managed and modeled with the use of Microsoft Excel and SPSS.

1 NEOCLASSICAL ECONOMICS, ASSET PRICING, AND MARKET EFFICIENCY

Neoclassical economics is a metatheory, or a set of paradigms upon which most economics research and teachings are based. The theory is grounded on the assumption that market prices of goods are governed by supply and demand, and that the two are controlled by economic agents. From the supply perspective, economic agents are companies which produce goods, seek out to produce them in a manner in which the cost of producing an additional unit of good is counter-balanced by the revenue the same unit generates. Conversely, in terms of demand, economic agents are represented by households. These essential agents of demand are seen as individual units with rational preferences, who assess all information accessible to them and subsequently seek out to purchase goods in goals of maximizing their satisfaction (Weintraub, 2020). The following two sections will discuss in-depth how various sources of literature define rational behavior and how theoretically rational behavior carries over into expected utility theory, or the axiom that all individuals set out to optimize their welfare.

1.1 Rational agent hypothesis

Originating from the Latin word "rationalis", the term rational describes an individual or action as one, which operates according to "facts or reason and not emotions or feelings" (Merriam-Webster, Inc., 2008). Within the confines of economic research, this rationality is projected onto the preferences of economic agents. For a preference to be rational, it needs to fulfill the following two conditions (Ackert & Deaves, 2010, p. 4):

a. Preferences must be complete. If the preferences of a rational agents are complete, then that particular agent has the power to compare all options and assess his or her preferences towards those choices. To illustrate with a simple example, an individual economic agent has the ability to decide whether they prefer apples over oranges ($x > y$), oranges over apples ($x < y$), or if they are simply indifferent towards the two options ($x = z$).
b. Preferences must also transitive. When an economic agent's preferences are transitive, the agent prefers x over y, y over z, and must therefore also prefer x over z. This may hold true in economic theory, but even the simplest real-life example taken from the previous point can expose a serious deficiency of this assumption. An economic agent may prefer apples over oranges ($x > y$), and oranges over bananas ($y > z$), but the very same agent may also prefer bananas over apples ($z > x$).

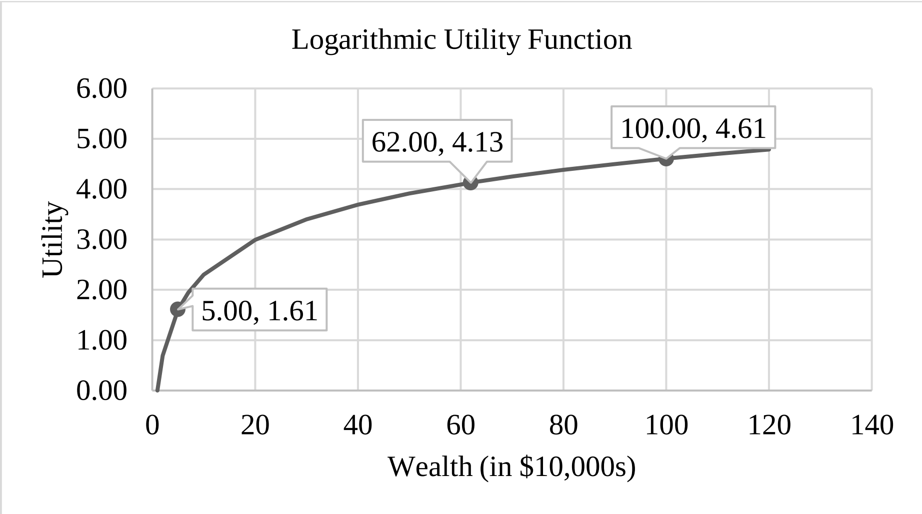
The abovementioned assumptions have withstood the test of time and research and to this day present two of the greatest assumptions one must make when partaking in economic research. Despite the simple, yet glaring limit of its second axiom, the rational agent hypothesis is robust enough to account for the few irrational agents that do not profoundly impact the equilibrium established by other rational agents (Mandler, 2014). As a result, economic theorists remain confident in the explanatory power of the rational agent hypothesis (Chen & Yeh, 2002).

1.2 Expected utility theory

After having established that the vast majority of economic agents are rational, let us now inspect how these agents actually make their choices. Neoclassical economics again makes the assumption these agents seek to maximize their utility. In this sense, utility is seen as the benefit a single or a bundle of assets brings to the decision-maker given their monetary constraints.

The foundations of expected utility theory were derived by John von Neumann and Oskar Morgenstern and described how people should act when facing risky prospects (Ackert & Deaves, 2010, pp. 5–11). In this sense, a risky prospect is one in which the participant is aware of the probabilities of a set of particular outcomes. On the other hand, uncertainty describes the characteristic of a situation where one cannot assign probabilities to a given set of outcomes. While we have discussed an overlying principle that people are expected to act rationally in face of risk, we can still observe different risk attitudes in a multitude of situations. Ackert and Deaves (2010, pp. 5–11) provide examples of utility functions with respect to a single good - wealth. The authors utilized a logarithmic function to present utilities for different levels of wealth. By taking levels of wealth in increments of $10,000, they created the following function.

Figure 1: Example of a logarithmic utility function



Source: Own work.

As we can observe from Figure 1, utility is greatly affected by an increase in the initial stages, but the slope of the utility curve slowly levels out after a certain level of wealth. This utility function is representative of the utility levels of risk averse individuals. People are mostly risk averse and wish to be compensated for exposing themselves to risk (Ackert & Deaves, 2010, p. 9). Different attitudes towards risk can be illustrated by Scenario 1:

An individual must choose between one of the given two options. Option A represents the prospects of receiving $50,000 with a probability of 40% and $1,000,000 with a probability of 60%. Option B, on the other hand, is representative of receiving $620,000 with certainty. The odds in Option A are clearly stacked in the individual's favor, considering the prospects of receiving $1,000,000 are higher than the prospects of receiving $50,000. If we were to calculate the expected value of this prospect and the utility this prospect brings about, the calculation would be as follows:

$$E(Option\ A) = 0.40\ (\$50{,}000) + 0.60(\$1{,}000{,}000) = \$620{,}000 \tag{1}$$

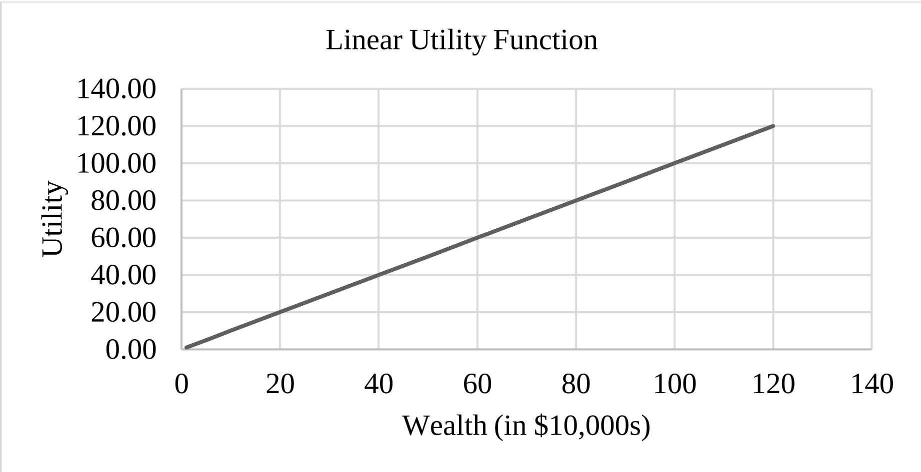
$$U(E(Option\ A)) = \ln(62) = 4.1271 \tag{2}$$

But, if we consider the utilities of the prospects in Option A separately, the total utility would be calculated as follows:

$$U(Option\ A) = 0.40(1.6094) + 0.60(4.6052) = 3.4069 \tag{3}$$

As we can observe, the utility of the expected value of a prospect outweighs the utility of the prospect itself. This implies that a rational, but risk averse individual would prefer to choose Option B over the riskier Option A. Risk averse individuals are willing to trade a fraction of their wealth for certainty. This adjustment can be expressed in monetary terms by means of a certainty equivalent. Certainty equivalent is the level of wealth which, if added to the certain prospect, would make and individual indifferent when choosing between the certain and the risky option. This premium makes the utility of the expected value of the prospect equal to the expected utility of the prospect itself. Whenever an individual is classified as indifferent towards the two options, they are considered risk neutral and their utility function is a simple linear function:

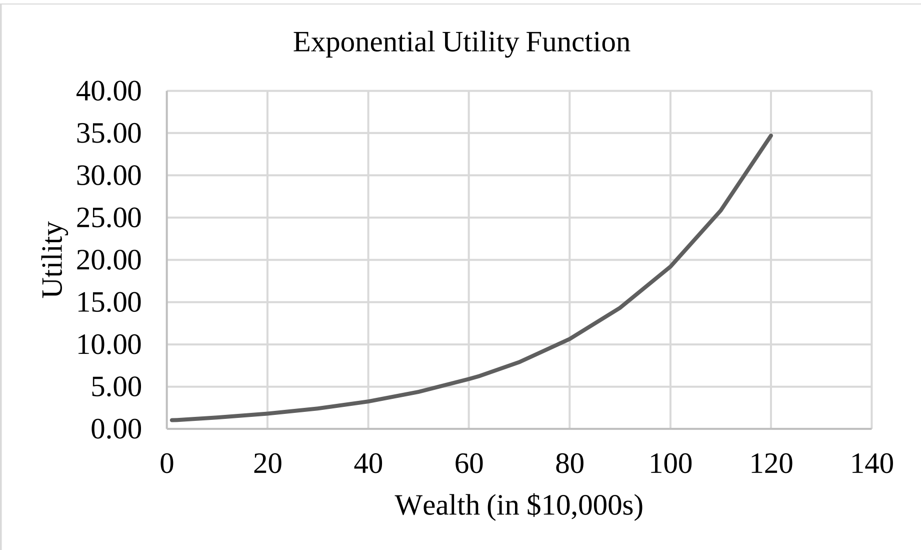
Figure 2: Example of a linear utility function



Source: Own work.

However, some people are inclined towards taking risks and forgoing certainty. In such instances, the risk seeking individuals favor the expected utility of the prospect over the utility of the expected value. In turn, their utility function is concave and representative of their inclination to gamble rather than to choose Option B.

Figure 3: Example of an exponential utility function



Source: Own work.

As we have previously observed, the rational agent hypothesis is based on the majority of individuals being risk averse. However, the mere presence of outliers, specifically risk neutral and risk seeking individuals, prompts a more thorough examination of the behavior of economic agents. Stating that neoclassical economic models are sufficiently robust to account for such anomalies is, broadly speaking, satisfactory, yet still gives reason to doubt even the rational agents are always rational; especially in times of economic uncertainty.

Now that we have discerned the fundamentals of how economic agents make their decisions in face of risk, let us now turn our attention the most prominent methods of pricing assets. Before making an informed decision that will help them maximize their utility, economic agents must first weigh the risk and return of a decision at hand.

1.3 Risk and return for individual assets

Built on the neoclassical assumptions that all individuals are rational and risk averse, modern portfolio theory as derived by Harry Markowitz employs the mean and variance of returns as the basis of people's preferences (Markowitz, 1952). Because future returns of securities are uncertain, individuals must be content with an expected value, or are predicted mean of past returns as an estimate of the future return of an individual investment.

$$\overline{R_\iota} = \frac{1}{n}\sum_{t=1}^{n} R_{i,t} \tag{4}$$

Variance, on the other hand, is a measure of risk and is calculated as the average squared deviation of an asset's price from its mean (Markowitz, 1952, p. 80). It is a measure of dispersion which can be mathematically expressed by:

$$s_i^2 = \frac{1}{n-1}\sum_{t=1}^{n}(R_{i,t} - \overline{R_\iota})^2 \tag{5}$$

The two most common methods of measuring risk are by means of variance, which I have already discussed, and standard deviation. Standard deviation is a risk proxy very similar to variance, since the former is simply the square root of the latter.

$$s_i = \sqrt{s_1^2} \tag{6}$$

The goal of a rational and risk averse individual is therefore to maximize their utility (return) and minimize variance which an individual asset inherently possesses. (Ackert & Deaves, 2010, pp. 20–21)

1.4 Risk and return for portfolios of assets

The very same reasoning with respect to maximizing return and seeking minimal variance can be extrapolated further onto a basket or a portfolio of assets. While individuals clearly have different preferences and risk tolerance, numerous pieces of literature support diversification as opposed to placing all one's "eggs in one basket". In the simplest of senses, if we assume all securities under observation are statistically independent (uncorrelated), the risk (variance) of a portfolio can be made infinitesimally small by increasing the number of securities that constitute a portfolio (Mao, 1970, p. 1109). However, it would be foolhardy to expect that securities are perfectly uncorrelated and the prospects of a riskless portfolio are miniscule. Unfortunately for investors, risk cannot be completely diversified away. Mao (1970) concluded that although a certain fraction of risk can be reduced by means of diversification, there is also an underlying (non-diversifiable) risk factor common to all securities that cannot be eliminated by means of adding more securities to a portfolio. This finding naturally prompts the following two questions: What is the number of securities which offer the greatest trade-off between risk and return, and, how can one optimize their portfolio to achieve maximal returns for minimal exposure to risk?

1.5 Modern portfolio theory

The foundations of modern portfolio theory (MPT) were laid by Harry Markowitz in his article named 'Portfolio Selection' published in the Journal of Finance in 1952. His research was greatly contingent upon the uniformity of behavior displayed by individual market participants. Investors were assumed as homogenous, or to be in agreement that the fundamental parameters of portfolio analysis are the means, variances, and correlations of returns of various assets (West, 2006, p. 4).

Assuming a scenario where an individual faces the prospects of choosing between only two assets, negatively correlated by the factor of (-0.10), the power of diversification can already be quickly displayed by using a simple equation. Let us assume the two assets are named High Vol and Low Vol, and their expected (mean) returns and standard deviations are 12% and 25%, and 6% and 8%, respectively. Furthermore, let us attach arbitrary portfolio weights to the two assets: 30% to High Vol and 70% to Low Vol. Based on this data, the two equations below illustrate how this completely arbitrary process succeeds in reducing the variance of a portfolio without a critical sacrifice in returns.

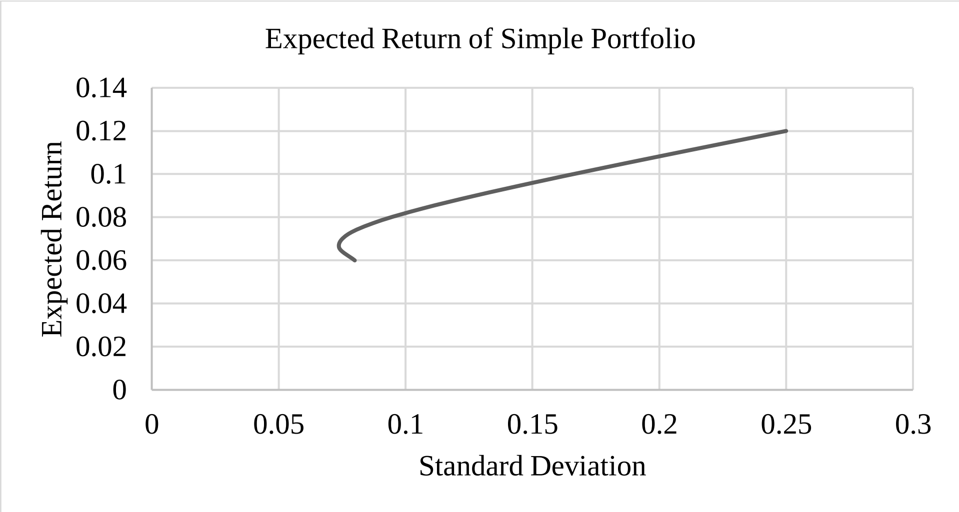
$$E\left(R_p\right) = 0.30(0.12) + 0.70(0.06) = 0.078 \tag{9}$$

$$s_i^2 = 0.30^2 0.25^2 + 0.70^2 0.08^2 + 2(0.30)(0.70)(-0.10)(0.25)(0.08) = 0.007921 \tag{10}$$

By taking the square root of the variance, we can observe this randomly-generated portfolio has an expected return of 7.8% and a variance (standard deviation) of 0.007921 (8.9%). However, this finding only provides the reasoning behind diversification given arbitrarily defined portfolio weights. Markowitz proceeded to define what is now known as the efficient frontier, which gives investors a clear understanding of how much money they should allocate to each of the assets within their portfolio.

Staying within the confines of stocks High Vol and Low Vol, Figure 4 shows all the possible combinations whereby the two stocks form a portfolio.

Figure 4: Expected return of a simple portfolio



Source: Own work.

We can observe from Figure 5 that despite the lower risk Low Vol stock inherently possesses, it is not the least risky investment in and of itself. The portfolio with the least amount of risk, or standard deviation, is the left-most point of the line represented in Figure 5. As more and more stocks are added to the equation, the degree of diversifiable, or nonsystematic risk increases. By introducing a risk-free asset to a stock-only portfolio, we also introduce the principle of two-fund separation and the possibility an investor borrows or lends money at the risk-free rate (Ackert & Deaves, 2010, pp. 24–26). We can further optimize the returns of a portfolio by combining the two separate funds into a tangent portfolio. The exact combination of funds is determined by a line tangent to the efficient frontier, the slope of which can be calculated by using the Sharpe ratio.

$$Sharpe\ Ratio = \frac{E(R_{p)-r_f}}{s_{(R_p)}} \tag{11}$$

The Sharpe ratio is a measurement of the ratio between the portfolio's excess returns and standard deviation. Investors should strive to find a portfolio with the highest Sharpe ratio, as it allows them to truly attain maximal earning per unit of risk. What is more, this method of asset allocation also eliminates the investor's risk profile out of the list of parameters that an investor should consider when creating a portfolio (Berk & DeMarzo, 2017, pp. 411–412). With the introduction of the tangency portfolio, the only decision now left to be made is to how much an individual invest in the risk-free rate and how much in the tangency portfolio, but exploring the tangency portfolio any further would deviate too significantly from the aim of this thesis.

1.6 Market efficiency and the efficient market hypothesis

In order for all of the aforementioned formulae and investment decision-making to function properly, the capital markets must also be deemed as efficient. In his work, Fama (1970, p. 383) surmised that: “The primary role of the capital market is allocation of ownership of the economy's capital stock. In general terms, the ideal is a market in which prices provide accurate signals for resource allocation: that is, a market in which firms can make production-investment decisions, and investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time “fully reflect” all available in- formation. A market in which prices always “fully reflect” available information is called “efficient.”

Fama’s research implies that all stock prices are completely transparent and that all new information is immediately accounted for in the prices (i.e. “priced in”). The critical factor in this statement is access to information, where the author assumed free flow of information to all market participants. In this instance, the powers of competition regulate the market so that there is little to no arbitrage opportunity, and, that the law of one price holds on aggregate. However, not all information can flow freely and some pieces of it may also remain private or simply be difficult to interpret. This is a minor caveat in the efficient market hypothesis, as the benefits of attaining private or difficult-to-interpret information may still outweigh their underlying costs for some market participants in the short-term. In the grand scheme, however, the competitive nature of the stock market negates such anomalies over time (Berk & DeMarzo, 2017, pp. 333–335).

2 BEHAVIORAL ECONOMICS AND FINANCE

As with many other academic fields, theorists of economy and finance too make many presuppositions when describing intricate market developments. Thus far, we have discerned that the preferences of all economic agents must be complete and transitive, or simply, rational. Everyone seeks to maximize their utility or when purchasing various goods. These goods may sometimes be financial assets, the prices of which are assumed to be perfectly representative of all publicly available information, and all investors strive to create portfolios that will maximize their returns (utilities) for accepting a certain level of risk. Despite all these assumptions that have robust explanatory power within the confines of theoretical models, probably each individual on this planet sees themself as unique at least in some fashion. This miniscule deviation from the collective uniformity which theoretical models assume create a gateway into exploring the areas these true and tested mathematical equations might have overlooked. We have already briefly discussed the different risk profiles portrayed by different individuals, but these shades of collective rationality may quickly create ripple effects capable of moving even the greatest of markets.

The analysis of decision-making in uncertain circumstances dates back to the late 17th century, when a group of mathematicians and other academia set out to construct the so-called decision theory. Decision theory or rational choice theory was among the first theories that used mathematical principles to illustrate optimal (rational) decision-making. A significant theoretical breakthrough was demonstrated with one of the first rational choice paradoxes in 1713. Nicholas Bernoulli demonstrated that he could construct scenarios where rational choice theory would yield results that differ from intuition (Heukelom, 2015). His most famous paradox is now known as the St. Petersburg paradox, and is constructed in the following manner. Suppose an individual is faced with a lottery game where they are first asked to pay a fixed sum of money to enter the lottery. From there, the individual flips a coin until it turns up heads. When the coin eventually turns up heads, the individual would receive a reward of 2^n monetary units, where n denotes the number of coin flips required for the coin to turn up heads. The expected value of the gain is then

$$\frac{1}{2}(2) + \frac{1}{4}(4) + \frac{1}{8}(8) \dots = 1 + 1 + 1 \dots \infty. \tag{14}$$

Equation (14) implies that the individual would be willing to spend an infinite amount of money to participate in this experiment since they would, on average, always reign victorious in this game. By considering expected value as the only decision-making criteria, a widely accepted axiom at the time, the scenario described would trap an individual into making an irrational decision, had they abandoned intuition and blindly followed exclusively mathematical principles.

What is now known as the Allais paradox was first presented by Maurice Allais to Jimmie Savage at a symposium in Paris in 1952 (Kahneman, 2011, p. 304). Allais proved that many participants of his study acted in ways which explicitly violate the expected utility axioms. Allais exposed these incongruities by conducting a study, where his subjects were asked to choose one scenario from each of the following pairs of hypothetical scenarios:

a. Common Consequence:
   Scenario A: 100% chance of receiving 100 million.
   Scenario B: 10% chance of receiving 500 million, 89% chance of 100 million and 1% chance of receiving nothing.
   Scenario A': 11% chance of 100 million, 89% chance of nothing.
   Scenario B': 10% chance of 500 million, 90% chance of nothing.
b. Common Ratio:
   Scenario C: 100% chance of receiving 100 million.
   Scenario D: 98% chance of 500 million, 2% chance of nothing.
   Situation C': 1% chance of 100 million, 99% chance of nothing.
   Situation D': 0.98% chance of 500 million, 99.02% chance of nothing.

Scenarios A and B both share the chance of receiving 100 million with probability of 89%. Scenarios A' and B', conversely, remove the shared probabilities of receiving 100 million.

According to expected utility theory, Scenario A should be preferred to Scenario B and Scenario A’ to Scenario B’, since the second set of scenarios only subtracts the common consequence of receiving 100 million with 89% probability. Scenarios C and D possess a probability ratio of 98%, while Scenarios C’ and D’ have a common ratio. Again, as per expected utility theory, if Scenario C is preferrable over Scenario D, then C’ should also be chosen over D’. In spite of these rational predictions, subjects of Allais’ study chose A over B, B’ over A’, C over D, and D’ over C’. These results implied that the independence axiom of expected utility theory is violated by choosing security in the presence of certainty (Andreoni & Sprenger, 2009).

The St Petersburg and Allais Paradoxes are only two of many examples which undermine the rationality of individuals, in turn also creating doubts in the minds of many proponents of uniform rationality of the human society. These revelations had a profound effect on the overall acceptance of the rational agent hypothesis, but it was only after the work of Kahneman and Tversky that the field of behavioral economics truly began gaining momentum.

2.1 Prospect theory

In 1738, Nicholas Bernoulli's brother, Daniel, provided a theoretical example of how most people act in a risk averse manner. Bernoulli created an example of a utility function, which depicted the relationship between wealth (in millions) and the utility each additional million brings to an individual. He claimed that an individual’s reaction to a change of wealth will be negatively correlated with their starting amount of wealth, thus creating a logarithmic function of utility (Kahneman, 2011, pp. 272-273). To illustrate with a simple example, a gift of 10 ducats to a person with 100 ducats will satisfy them equally as a gift of 20 ducats to an individual with 200 ducats. When Bernoulli extrapolated his theory to a larger scale, he created a utility function based on the parameters presented in Table 1.

Table 1: Bernoulli's utility function

Wealth (millions)	1	2	3	4	5	6	7	8	9	10
Utility units	0	30	48	60	70	78	84	90	96	100

Source: Kahneman (2011, p. 273).

As we can observe from Table 1, the initial changes in wealth psychologically greatly outweigh the utility brought about by each increase in wealth after the 5th million. Let us now consider the utilities of the following two choices:

a. 50% chance of receiving 1 million or 7 million. Utility: (0+84)/2 = 42
b. 100% chance of receiving 4 million . Utility: 60

If we consider the utility results, we see that an individual whose preferences match Bernoulli's function will prefer option 2 over 1. As we have observed in section 1.2, the psychological value of a gamble is thus not equivalent to the weighted average of the monetary prospects, but rather a weighted average of their utilities instead (Kahneman, 2011, p. 273). With his function, Bernoulli proved that most people are risk averse and his theory held for centuries. As Kahneman (2011, pp. 274–275) proceeds to explain, this theory has one glaring weakness. Bernoulli's theory presumes that an individuals' happiness is only dependent on their recent change of wealth and disregards their starting point altogether. Let us look at the following scenario:

Anthony's current wealth is 1 million, while Betty's current wealth is 4 million.

Both are offered a choice between a gamble (Option A) and a certain outcome (Option B):

> Option A: Equal chances of owning 1 million or 4 million.
>
> Option B: Own 2 million with certainty.

The expected monetary benefit of choosing Option A equals 2.5 million, whereas Option B only offers 2 million. According to Bernoulli's theory, both Anthony and Betty are faced with the same prospects and are expected to make identical decisions. However, the preceding information of their current wealth is what helped Kahneman identify the greatest shortcoming of Bernoulli's theory: the lack of a proper reference point. Kahneman (2011, p. 275) claims: "Bernoulli's theory assumes that the utility of their wealth is what makes people more or less happy. [However,] the happiness that [individuals] experience is determined by the recent change in their wealth, relative to the different states of wealth that define their reference points." This lack of a proper reference point is one of the focal reasons which prompted Kahneman and Tversky to develop their own theory which is now considered as the basis of behavioral economics.

Prospect theory, published in Econometrica in 1979, presented an alternative approach to evaluating individuals' decision making under risk as a choice between different prospect or gambles which usually prompt a monetary gain or loss. By means of multiple-choice problems, the two psychologists and economists presented instances in which rational individuals are highly likely to violate principles of expected utility theory (1979). For example, two scenarios of a simplified Allais paradox were presented as follows:

Scenario 1: Individual must choose between:

> Option A: 80% chance to receive 4,000 and 20% to receive nothing.
>
> Option B: Receive 3,000 with certainty.

Scenario 2: Individuals must choose between:

Option C: 20% chance to receive 4,000.

Option D: 25% chance to receive 3,000.

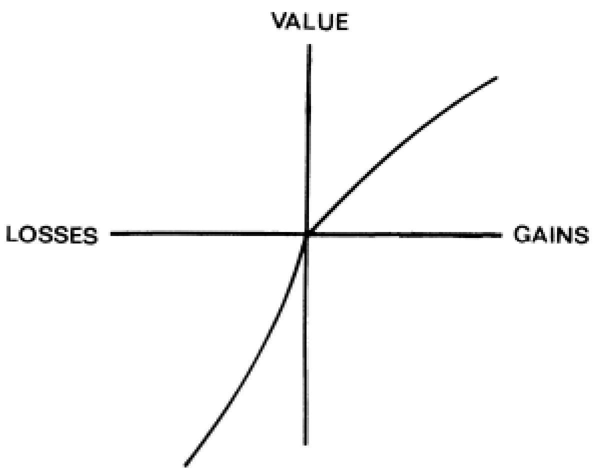
According to their research, Kahneman and Tversky claim that over half of the participants included in their study violated expected utility theory. Specifically, the authors illustrated how the participants violated the substitution axiom of the theory. Option C can be reframed as (A, 0.25) and Option D as (B, 0.25), or that the expected outcome of Option C is equal to 25% of the prospects presented in Option A and that the expected outcome of Option D is equal to 25% of the prospects of Option B. According to the substitution principle, therefore, if Option B is preferrable over Option A, then any variation of Option B must also be preferred over any variation of Option A. It seems that reducing the probabilities from a certain win to a gamble with only 20% chances of winning has had a greater psychological effect than a reduction of prospects from 80% to 20%. Kahneman and Tversky named this fallacy the certainty effect (1979, pp. 265–266).

Kahneman and Tversky proceeded to turn their attention to negative prospects, as deriving the certainty effect only considered scenarios in which individuals gain money. By changing the signs of the prospects described in the previous examples, the two turned potential gains into losses. Their research indicated individuals' preferences reverse in order when individuals face losses as opposed to gains. Assuming negative signs in front of all prospects described above, individuals more often opted for Options A and D. Kahneman and Tversky called this substitution pattern the reflection effect. These findings allude to the propensity of many individuals to be risk averse in the positive domain and risk seeking in the negative. Psychologically speaking, losses loom larger than gains of equal value, creating a phenomenon more commonly known as loss aversion.

When presenting their newly found theory, the two psychologists and economists distinguished two separate stages in the human choice process: the editing and the evaluating stage. In the former stage, the individual's mind first attaches the prospects to a reference point. This process, described by Kahneman and Tversky as coding, can be greatly affected by how the evidence or prospects of a particular scenarios are presented, or "framed". Next, the individual's mind often attempts to modify complex prospects into simpler ones with outcomes that are comparable to the original ones. For example, the prospect of receiving $200 with two probabilities of 25% are perceived as a 50% chance of receiving $200. Some choices also call for segregation; the process of discarding the riskless prospects. For instance, choosing between a 20% chance of receiving $600 and 80% of receiving $200. Such a scenario would be reduced to receiving $200 with certainty and a 20% of receiving an additional $400. The simplification process may also be performed via the isolation effect, where people disregard the common features of the alternatives, thus isolating only the differences between their prospects. In practice, this effect suggests that a prospect with contingent certainty of a fixed return is usually more appealing than a risky alternative with the same probabilities and returns. The editing stage thus provides a precursory analysis of mostly simplified versions of the provided options, while the evaluating stage yields a final selection of the option with the highest perceived value (Kahneman & Tversky, 1979, pp. 271–275).

Judgements of monetary gains and losses cannot be observed in a vacuum (i.e. without a reference point). Our perception usually functions by comparing sensory attributes such as brightness, volume, etc. to some other sensory input observed in the past and wealth is no different. The volume of a sound, for example a person yelling, may be seen as extremely high compared to someone whispering, but pales in comparison to the sound of a jet engine. Conversely, what alludes to poverty for one may be riches for another, depending on their current state of wealth. Kahneman and Tversky (1979, p. 277) stated the following when discussing the derivation of their value function: “Strictly speaking, value should be treated as a function in two arguments: the asset position that serves as reference point and the magnitude of the change (positive or negative” from that reference point.” Many sensory judgements have a concave function when plotting psychological response to the magnitude of a particular stimulus. It is easier for most to distinguish between 3°C and 6°C than it is to differentiate between 13°C and 16°C, and the authors proposed the same held true in terms of wealth. A change in wealth from $100 to $200 is much more prominent than a change from $1,100 and $1,200, and the same can be applied to losses. Losing $100 when the reference point is set at $200 will seem much graver than losing $100 when a person initially had $1,200 in their pocket. Based on their findings, the two created an S-shaped utility function, as presented in Figure 5.

Figure 5: S-shaped prospect theory function



Source: Kahneman & Tversky (1979, p. 279).

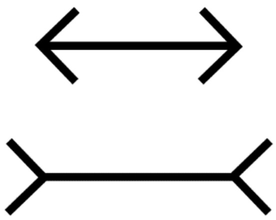
The S-shaped value function and the main postulates of prospect theory can be simplified by describing the function as steeper for convex losses, for concave gains, under the condition that these gains and losses are analyzed by comparing them a reference point.

Nevertheless, the two authors left room for exceptions to their theory by claiming "Any discussion of the utility function for money must leave room for the effect of special circumstances on preferences" (Kahneman & Tversky, 1979, p. 279).

2.2 Framing

Human observation and interpretation of events in their surroundings can be greatly affected by individuals' fast and intuitive, or System 1 mode of mental processing. Keith Stanovich and Richard West, two psychologists, divided the human mind into two operating systems: System 1 and System 2. System 1 operates automatically, quickly, and is cognitively undemanding, while System 2 is conscious, deliberate, and therefore slower in supplying answers or decisions. System 1 is usually the driving force behind: spatial awareness, facial gesticulation, simple arithmetic, detecting and analyzing other people's emotions, etc. It requires little to no effort to produce satisfactory results on average, which is why many of our daily decisions are driven by System 1 thinking. System 2, on the other hand, is time, attention and energy consuming, and is normally used for more complex tasks, such as filling out forms, focusing on a particular person's voice in a crowded room, or proof-reading one's master's thesis. Both Systems run simultaneously when we are awake and herein lies the reason for human susceptibility to irrational behavior. System 1 instinctively makes decisions on a continuous basis, but defers all complex tasks to System 2. However, in deferring data, System 1 can also form impressions and suggestions which affect how System 2 interprets data provided by System 1. This is often revealed through illusions, as simple as the Müller-Lyer visual illusion depicted in Figure 6.

Figure 6: Müller-Lyer visual illusion



Source: Barrett (2021).

This illusion convinces many that the bottom horizontal line is longer, but if we were to measure the two, we would see that both horizontal lines are equal in length (Kahneman, 2011, pp. 20–28). In similar fashion, System 1 can easily be influenced when relaying complex issues to System 2, leading to suboptimal results.

Framing, is a concrete example of System 1 affecting the cognitive perception of a more complex problem. It is a concept that assumes decisions are affected by an individual's perception (frame) of a particular decision-making problem. This concept can be illustrated with the following hypothetical situation:

The United States is preparing for an outbreak of an unknown disease, which is expected to kill 600 people. Two programs have been proposed to combat the disease:

> Program A: Certain rescue of 200 people.
>
> Program B: 33.3% probability of rescuing 600 people, and 66.6% probability of saving none.

Nearly 72% of the Kahneman and Tversky's study subjects chose Program A over Program B. These two options were written in a 'survival frame'. The next two options were written in a 'mortality frame'.

> Program C: Certain death of 400 people.
>
> Program D: 33.3% probability of rescuing everyone and 66.6% probability of everyone dying.

In this instance, 78% participants chose Program D over Program C. While the problems and their outcomes are identical in both frames, the majority of study subjects now seem to be risk seeking. This indicates that the frame in which problems are presented has a significant effect on our choices (Kahneman & Tversky, 1981). These conclusions had a profound impact on the illusion of people's rational behavior.

2.3 Mental accounting

As we can observe, the human mind is highly susceptible to taking shortcuts when making decisions. The strenuous nature of our analytical, or System 2 thinking, makes it much more alluring to depend on the automatic System 1 reasoning for most of our decisions. Because such decision-making usually yields satisfactory results, this creates a feedback loop which further condones such kind of behavior. Such over-reliance on one's experience or "instincts" is what gives more credibility to the theory that economic subjects are not in fact completely rational. Ackert and Deaves (2010, p. 50), presented the term mental accounting by presenting the following two situations:

You decide to see a play, where the admission ticket costs $10. As you reach the theatre, you realize you have lost $10 somewhere on your way to the theatre. Would you still pay $10 to see the play?

You decide to see a play and buy a ticket that cost $10 in advance. As you reach the theatre, you realize you have lost your ticket. Would you pay another $10 to purchase a new ticket?

In monetary terms, two scenarios are completely identical – $10 have been lost, but many participants of the experiment would disagree. Had they lost $10 as described in the first scenario, 88% would still buy the ticket, but only 46% would purchase another ticket had they lost their pre-purchased one. This phenomenon occurs as a result of mental accounting, which is a set of cognitive processes individuals commonly use when considering their individual or houesehold-related financial activities (Thaler, 1999, p. 186). Richard Thaler described that mental accounting is based on three components. Firstly, mental accounting includes an evaluation of inputs and outcomes both ex ante and ex post. A second component is account assignment. Individuals often perceive different sources of income of different value and categorize their expenditures. Therefore, one will act differently when making a purchase using money from their monthly salary compared to money they have received arbitrarily. The last component of mental accounting is how the accounts are segregated and the frequency with which one evaluates them. Kahneman and Tversky (1984, p. 347) distinguished between a minimal, topical, and comprehensive account by presenting the next scenario:

You are about to purchase a jacket for $125 and a calculator for $15. The calculator salesman informs you the calculator you wish to buy is on sale at another store branch located 20 minutes away. Would you drive 20 minutes to buy the same calculator for $10?

This scenario introduces a prospect where the potential savings are offset by the nuisance of a 20-minute drive. The minimal account only accounts for the differences between the two options and perceives this prospect as an absolute $5 gain, thus entirely disregarding any potential opportunity costs of driving to another store. A topical account does include the reference point and context of the scenario, and sees this scenario framed as a reduction of the calculator price; for the purposes of this account, the jacket is still irrelevant. A comprehensive account, therefore, considers the benefits (saving $5 when purchasing the calculator) as well as the opportunity cost of driving 20 minutes to purchase the discounted calculator. Kahneman and Tversky discerned that people most often use the topical account, leading them to most often evaluating gains and losses in relative rather than absolute terms. This finding is in direct opposition of the rational agent hypothesis, which presupposes indifference and therefore does not allow for mental accounting.

Opening and closing these accounts is greatly affected by the individual's psyche. Let us consider an individual who bought 10 shares of stock at a price of $100. This investor's investment is initially worth $1,000, and the value of the investment will rise and fall in accordance with the stock's price movement. Before the investor closes his position or account, they will only measure paper gains or losses – i.e. gains or losses that could potentially have been realized had the investor closed their position. Mental accounting of paper gains or losses can be much different from accounting for realized gains and losses. Intuitively, observing the stock price plumet from $100 to $90 will be much more painful for our investor if they were urged to close their position. This facet of mental accounting, known as the disposition effect, is why many investors are reluctant to sell losing stocks and revert to selling their 'winners' too quickly instead (Thaler, 1999, p. 189). Instead of realizing paper losses and closing them immediately, investors often integrate the cause for this paper loss into their present behavior and investment decisions. Integration often occurs because of the convexity of the loss function, which materializes as offsetting losses with larger gains to avoid the feelings of loss aversion. A theoretically rational investor would avoid the disposition effect and the integration processes by segregating the past performance of a losing stock and resetting their reference point to the current stock price (Thaler, 1999, p. 187).

2.4 Heuristics and biases

Continuing the premise made at the beginning of the previous section, the simplification of most cognitive processes is not only expedient, but also necessary. Human mental processing capacity is a large limitation when the mind undergoes episodes of cognitive strain. Majority of theoretical models assume individuals have unlimited processing power and neglect the effects of individuals' psychosomatic states on their mental performance and thought patterns. Humans do not have unlimited processing power that would enable them to use System 2 thinking to drive all of their daily decisions, and because System 2 processes are cognitively strenuous using it constantly would likely lead into information overload and 'paralysis by analysis'. As we previously observed, framing serves as the lens System 1 creates for System 2 when delegating complex tasks to the latter. The frame can be affected in a multitude of ways, including by means of perception, memory, experience, impressions, and affects. As we observed with the Müller-Lyer visual illusion, perception can be misled. Memories, on the other hand, can be misleading. Memory is retrospective and memories are often altered based on how an individual wishes to remember them. Therefore, memories are fundamentally a deficient foundation for creating mental shortcuts. Alongside framing, System 1 promotes cognitive ease by creating individual mental shortcuts called heuristics, but their availability can also lead to the formation of biases.

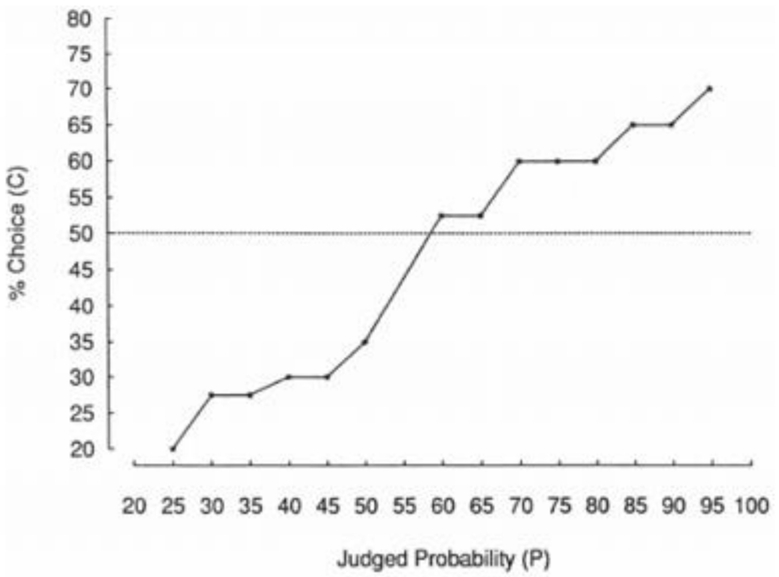
2.4.1 Familiarity and ambiguity aversion

Heath and Tversky's (1991) research showed that individuals gravitate towards the familiar when accepting gambles. Their work, as shown in Figure 7, indicated that a basic level of competence or understanding of a field made people more likely to accept gambles relevant to that field. Even more, their level of comfort relating to a given field was directly related to their perceived likelihood of the gamble turning out in their favor. Participants in their experiment were asked to answer a set of general knowledge multiple choice questions. Heath and Tversky also asked the participants to specify (on a scale from 25% to 100%) how confident they are in the accuracy of their answers to each particular question. Upon completing the test, each participant was offered two gambles.

- Gamble 1: Betting their answer to a random question is correct,
- Gamble 2: Betting on lottery which corresponded to the confidence level for their answer to a random question.

For example, if a participant exhibited 60% certainty in the accuracy of their answer, they could choose to either bet their answer was correct or choose to bet on a lottery with a 60% success rate.

Figure 7: Preference and judged probability



Source: Ackert & Deaves (2010, p. 88).

Figure 7 presents the results by plotting the percentage of choices over the percentage of participants chose Gamble 1. Results above the horizontal line indicate that participants of this experiment were much more likely to accept Gamble 1 when they were familiar with the field/subject a particular question referred to, thus confirming the familiarity bias. Data below the horizontal line alludes to a heuristic called ambiguity aversion. When perceived probability and familiarity decreased, individuals were more likely to take on gambles with a random payoff (Heath & Tversky, 1991, pp. 6–13). The reason for this behavior is the (un)familiarity of a field prevents the individual from correctly assessing the level of comfort with their answers which coincides with their perceived success rate. For example, even if there was a 35% probability of answering the questions correctly, individuals did not connect this probability to the probability of their gamble's outcome (Ackert & Deaves, 2010, pp. 87–89).

Familiarity does not end with gambles either, as research performed by French and Poterba (1991) indicated that investors have an affinity for domestic securities and therefore overweight their portfolios in favor of domestic securities. Their research revealed that British investors invested 82.0% of their funds in U.K. stocks, American investors' portfolios consisted of 93.8% U.S. securities, and Japanese investors allocated held 98.1% in Japanese stocks. It appears the familiarity with local market developments makes the majority of investors more comfortable with choosing their domestic or local securities and more apprehensive towards choosing foreign ones for their investment portfolios. Investors are motivated to purchase local securities due to relative optimism with respect to their market's price trends and improved access to pertinent investment information. What is more, a number of mutual funds have actually been proven to benefit from investing locally (in companies that are situated within a 160km radius). Fund managers who invested locally annually outperformed managers who did not invest locally by 2.67%, and even retail investors with local investments outperformed individuals with remote investments by 3.2% (Ackert & Deaves, 2010, pp. 140–141). Retail investors also seem to be more at ease with investing into companies with more recognizable brands and companies by which they are employed, often neglect potential diversification options and ending up with portfolios that are overweighted beyond what any informational advantage might explain (Ackert & Deaves, 2010, p. 141).

2.4.2 Availability and representativeness

Kahneman (2011, pp. 129–131) described availability as a heuristic whereby individuals connect the frequency of a category to the ease with which they are able to recall an instance of this category. For example, an individual's perception of the number of single mothers per 100 households is directly correlated to the ability to recall single mothers they might be acquainted with. This also holds true when analyzing the frequency of events. The more salient, distinct, or personal a particular event might have been for an individual, the more likely they are to bring it to mind when creating mental samples of the frequency with which this event occurs. Availability is closely related to representativeness, which is descriptive of evaluating probabilities by the degree to which one category is representative of another. As Ackert and Deaves (2010, p. 91) describe, representativeness heuristic is particularly evident when individuals attempt to distinguish between simple and joint probabilities. Let us assume that A describes winning the lottery and B describes happiness. A simple Venn diagram can show that A and B have commonalities, but the probability of winning the lottery and being happy at the same time is lower than the individual probabilities of A and B. This facet of representativeness is known as conjunction fallacy and individuals that have fallen victim to it will argue that it is only natural to expect lottery winners to be happy. However, what if the same individual had simultaneously received news of winning the lottery and their parent passed away?

Availability of information also affects how individuals process information when presented with multiple sources. What Kahneman (2011, p. 85) calls as "What you see is all there is" or WYSIATI, is a characteristic of System 1 which often leads to base rate neglect. System 1 is highly efficient in creating quick solutions but it does not account for the quality of information it processes and is unable to account for any information it had not been able to recall momentarily. As a result, many decisions individuals make are made based on data last available to them, in effect neglecting the base rate, or the inferred probability of an outcome. For example, imagine opting to buy a new car and narrowing down your choices to a Fiat and a Subaru which cost approximately the same. When watching the most recent episode of your favorite automotive TV show, you are informed that Subarus are known for being resilient cars and do not break down easily. A few days later, your uncle, who used to own a Subaru, gives you his perspective and tells you his old car required many costly repairs. Pennycook and Thompson (2016, p. 44) report that people often respond they would prefer to buy the Fiat – "the car that is probabilistically more likely to have mechanical issues, but that has intuitive appeal".

Brand recognition, quality of management teams and other facets that make a company "good" in the eyes of the public also make many managers and investors think that investing in such companies is a good investment. As Shefrin and Statman's research indicates, even senior executives believe that management quality dictates the investment value of their company, but no company's investment value can be measured by means of quantifying their management's performance (Ackert & Deaves, 2010, p. 142). Any past performance and the accompanying company's positive image are "priced in" by the market and do therefore a company's good image cannot be representative of the company's investment value. Nevertheless, many institutional and retail investors mistake good companies for good investments or end up chasing the ones that have been performing well in more recent past. While there are some indications that such investment strategies work well in 3- to 12-month periods, more evidence suggests trends reverse to the mean over the long run, making momentum a poor proxy for future returns. Retail investors, particularly, are more likely to chase momentum and winning stocks in the fear of missing out. This fear is compounded when there is increased media attention around a particular company's stock price development and the volume of transactions surrounding this stock. Barber and Odean's findings revealed retail investors often end up purchasing a stock based on the availability of information surrounding that stock, regardless if the news is good or bad (Ackert & Deaves, 2010, p. 145).

2.4.3 Anchoring

Promoting cognitive ease can also yield results that stem from completely irrelevant sources, as Kahneman and Tversky proved in their research on anchoring. The experimenters once used a wheel of fortune marked from 0 to 100 rigged to stop only at 10 and 65. University of Oregon students would observe the wheel of fortune and after one spin, asked them to answer following two questions:

- Is the percentage of African nations among the UN members larger or smaller than the number you just wrote?
- What is your best guess of the percentage of African nations in the UN?

Something as arbitrary as a wheel of fortune (regardless if it is rigged or not) could certainly have not predicted or helped the students with their answers. Regardless, it appears they did not completely ignore the wheel of fortune, as the students who witnessed the wheel stop at 10 and 65 reported average answers of 25% and 45%, respectively. This means that an arbitrary number seen moments before answering to the two questions affected their reasoning in spite of the number being completely irrelevant to the two questions (Kahneman, 2011, p. 118). Because a quick reference point is readily available, the participants were able to create answers based on a few spins of a rigged wheel. As long as the arbitrary piece of information is not immediately rejected by System 1, both Systems are likely to use it in their subsequent work. Tversky proposed anchoring was a System 2 fallacy and argued System 2 used an anchor, assessed whether it is too high or too low, and then deviated from the anchor until people are no longer certain they should move away from the anchor. An example where anchoring is a System 2 process would be answering to the question: “When did George Washington become president?” When answering, people must immediately think of an anchor, usually 1776, and then move away from this year to arrive to their conclusion. Kahneman, on the contrary, claimed that similarly to framing, anchoring is a System 1 process where the System by means of systematic errors attempts to formulate a scenario where the anchor seems true.

Ultimately, subsequent research proved that both schools of thought were correct and that anchoring is one of the rare psychological phenomena that can be quantifiable. The two created an anchoring index, a measure of how much a person falls prey to the anchoring fallacy. Visitors at the San Francisco Exploratorium were asked to provide their estimates of the highest redwood. Half were given an anchor of 180 feet and half an anchor of 1,200 feet, and their mean estimates reflected the anchor they had been given. The former provided a mean estimate of 282 feet whereas the latter a mean estimate of 844. The anchoring index was then calculated as the difference of the two mean estimates divided by the difference of the two anchors. An anchoring index of 100% would indicate people have blindly accepted the given anchor as their estimate, while an index of 0% would imply the anchor had been ignored altogether. The anchoring index in the experiment described above yielded a 55% anchoring index which was considered as typical compared to similar research (Kahneman, 2011, pp. 119–124).

Anchoring has been proven to affect real-estate appraisers and is likely to affect individuals in financial situations as well (Ackert & Deaves, 2010, p. 146). Financial markets are seen as efficient, and the market price is continuously updated by market developments to be indicative of a stock’s value. Financial analysts create their quarterly revenue and target price forecasts, which together form consensus estimates. Consensus estimates, then help shape the market prices, because when a company reveals their quarterly results, any deviations from the consensus targets are seen as a signal to the market that a company has been under/overperforming. No two financial analysts are alike in their forecasts and therefore some boundary forecasts will likely affect the consensus target estimates. This then creates a circularity – if everyone is anchored on the market price, any market price or its prediction will affect the eventual market price. Anchoring is most evident in times of market bubbles, where good performance fuels market estimates, which, once beaten, fuel price rallies further upward (Ackert & Deaves, 2010, p. 146).

As we can observe, all heuristics allow individuals to make fast decisions with little to no effort. While it is expedient, the results such behavior produces can be described as satisfactory for daily life at best. This casts a light on the axiom that all individuals are rational at all times. One cannot expect rationality and sound decision-making when most of our decisions are governed by our System 1 thinking. Herbert Simon named this issue “bounded rationality” and claimed that people only strive for the best available decisions considering their given situation (Ackert & Deaves, 2010, p. 100). In doing so, it is difficult to believe individuals therefore make rational decisions in the financial and other markets.

2.5 The force of emotion and overconfidence

So far, I have only discussed the human mind as a computer which formulates series of processes which are executed based on how the data is delivered to this computer. A simple but profound memory can trigger a short circuit in one's mind that will make them react to a stimulus or information completely different from another. The last two faculties of the human mind I will address in this thesis are human emotions and confidence. I will assess how the two affect our decision making since sentiment is often used by the financial press as a potent driving force behind market developments.

Scientific research has shown that emotion and reasoning are intertwined to the extent where reasoning and decision making suffers in absence of emotion. Damasio's evidence (Ackert & Deaves, 2010, p. 128) suggests that physical trauma to the brain's frontal lobe, which is responsible for forming emotions, pacifies the individual's character and negatively impacts or even completely cripples their ability to make plans. Referring back to prospect theory aversion, individuals with injured frontal lobes would thus have difficulties opting to buy car insurance and probably would not see the upside of purchasing a lottery ticket.

Confidence or self-confidence is a belief in oneself that their abilities will drive them towards achieving their goals (American Psychological Association, 2021). Being confident requires a critical assessment of one's capabilities and how these translate to the field in which one aims to succeed. Overconfidence, however, is a miscalibration of one's abilities and their belief in them. The feelings of superiority, though sometimes stemming from one's profession or education, is mostly reinforced through three mutually supporting biases. Attribution theory of social psychology analyzes how individuals prefer to make judgements of others and attribute their behavior to their disposition rather than situation (Ackert & Deaves, 2010, p. 114). This means that we mostly believe people make the decisions they make because they are inherently so, and not because of the situation they are in. Many do the same when evaluating their own behavior, often lead to self-attribution bias. Self-attribution bias makes individuals feel responsible for their successes, but also blame their failures on unfortunate circumstances (Ackert & Deaves, 2010, p. 114). In such instances, especially with clearly defined alternatives, people often then convince themselves that despite their failure, they knew what the final outcome would be all along. This is known as hindsight bias and is closely related to confirmation bias, which is the tendency to for individuals to seek out information that is only consistent with their beliefs and neglect any conflicting data (Ackert & Deaves, 2010, p. 114). We can observe how these biases are interconnected and create a strong coping mechanism that nurture us times of success and protect our egos in face of failure.

2.6 Biases, emotion, and financial decision-making

One need not injuries to their frontal lobe to observe how emotions affect financial and other decision making. Fairly simple elements, such as sunshine and inadequate sleep have been suggested as two factors that can swing the markets up or down. Though these factors cannot be directly responsible for stock price movement, people's willingness to buy or sell stocks and their risk profiles can be temporarily altered by their mood. Some people become more risk seeking when happy, while others have been proven to become even more risk averse. As a result, there is no compelling evidence which would clearly specify how mood affects stock prices. The uncertainty of how many people belong to the former and how many to the latter group only answers the “if” and not the “how” investor' mood affects the stock market. (Ackert & Deaves, 2010, p. 169). Researchers have, however, been able to specify two emotions that can impact our decision making and alter it in a way that will make us act against what neoclassical expected utility theory predicts.

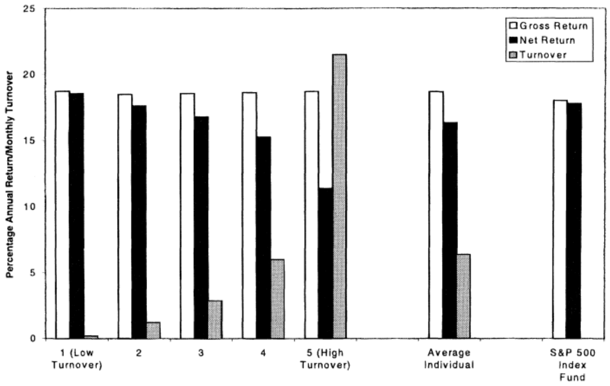
As discussed in section 3.1, prospect theory describes the asymmetric nature of people's risk profiles. Prospect theory suggests that most are risk seeking in the negative and risk averse in the positive domain and the two emotions that support such behavior are pride and regret. Individuals do not integrate their previous performance and often wish to forgo the pain and regret of a loss by becoming even more risk seeking – often by 'doubling down' on a bet or stock. The wish to avoid a loss overpowers the natural, more risk-averse tendencies of an individual, causing them to increase their stock positions in hopes of an even larger payoff in the future (Ackert & Deaves, 2010, pp. 170–171). This is often described as the break-even effect, where people will choose increasingly riskier prospect in order to cover their previous losses. Thaler and Johnson (1990) have concluded that more than 60% of their research participants chose a risky gamble in hopes of off-setting a prior financial loss.

Increased risk tolerance has also been shown to be connected with pride. On the one hand, it can also play a part in the break-even effect, where one refuses to lose a bet or close a stock pick in the red to save and keep their pride untouched. On the other, pride has also been shown to foster risk-seeking in completely speculative environments, explaining why people are so keen on buying lottery tickets and picking unknown stocks which they hope will produce a substantial payoff for the “visionary investor”. One's prior performance can also make them more risk seeking, as observed in the house money effect. In this instance, prior gains are mentally integrated and any loss that is smaller than the original gain will not cause the individual to become risk averse, as they are 'playing while ahead' or 'playing with house money'. This means that as long as the individual only loses the money they have previously won and not their own, they will continue to seek risk (Thaler & Johnson, 1990, p. 657).

Tightly intertwined with prospect theory is also a theory I have already briefly alluded to. Disposition effect causes people to often hold on to losing stocks for too long while selling well-performing stocks too early. Odean's research (1998) analyzed the proportion of realized gains versus the proportion of realized losses. Even though realizing losses creates tax benefits, individuals have been proven to sell their losers in only 9.8% of the time, compared to winners, which have been sold in 14.8% of the time between 1987 and 1993. Closing a position with a loss triggers regret while realizing gains causes pride, as both outcomes cause the investor to reconsider their poor (or sound) investment decision. Recent studies by Barberis and Xiong show that one must also consider the reason for purchasing a stock should when analyzing the disposition effect within the sphere of prospect theory. They claim that prospect theory always predicts the opposite of what the theory actually necessitates and describes behavior that is in direct contrast with the disposition effect. Their theoretical model predicts an investor with prospect theory preferences will buy after a gain and sell after a loss (Ackert & Deaves, 2010, pp. 172–175).

Pride in one's performance fuels confidence, but even a simple theoretical model has the explanatory power of demonstrating how overconfidence can lead to poor investment decision-making. Excessive trading is one of the fallacies that overconfident investors have been proven to demonstrate. Barber and Odean's research (Barber & Odean, 2000) performed between 1991 and 1996 sought to examine the implications of overtrading on overall portfolio performance. The researchers divided their sample of investors into five equal groups based on their portfolio turnover rate. On average, investors turn over 75% of their portfolio annually, which means they trade 75% of their total portfolio value within a given year. The groups were formed to segregate the most passive traders in quintile 1 and most aggressive traders in quintile 5. Their gross and net returns were observed and the results were illustrated by means of the chart in Figure 8.

Figure 8: Gross and net performance of portfolios with different turnovers



Source: Barber & Odean (2000, p. 775).

As we can observe, increased trading frequency marginally increased gross returns, but it drastically decreased net returns; i.e. after accounting for all transaction fees. Figure 8 implies that higher risk increased absolute returns, but costs related to each individual purchase or sale of a stock greatly affected the investors' net results. Excessive trading led by overconfidence in one's capabilities or superiority of their information thus decreased their net returns and caused them to perform almost 10% below the market returns on a net risk-adjusted basis (Ackert & Deaves, 2010, p. 158). Overconfidence seems to also bear demographic implications. Barber and Odean further analysed the dataset used in their aforementioned research and concluded that gender impacts the number of trades an investor is willing to undertake, with men being proven to undertake more trades. On average, men traded 45% more than women, and by incurring greater transaction costs, reduced their net returns by 0.94%. Single men have appeared to be even more aggressive in their trading, as they traded 67% more than single women and effectively reduced their net returns by 1.44% (Ackert & Deaves, 2010, p. 161).

While Barber and Odean's research was conducted on retail investors, financial professionals are not immune to overconfidence either and their decisions have the potential to move the markets even more dramatically. Investors' past failures are often played down, while successful trading decisions promoted self-attribution, hindsight, and confirmation bias.

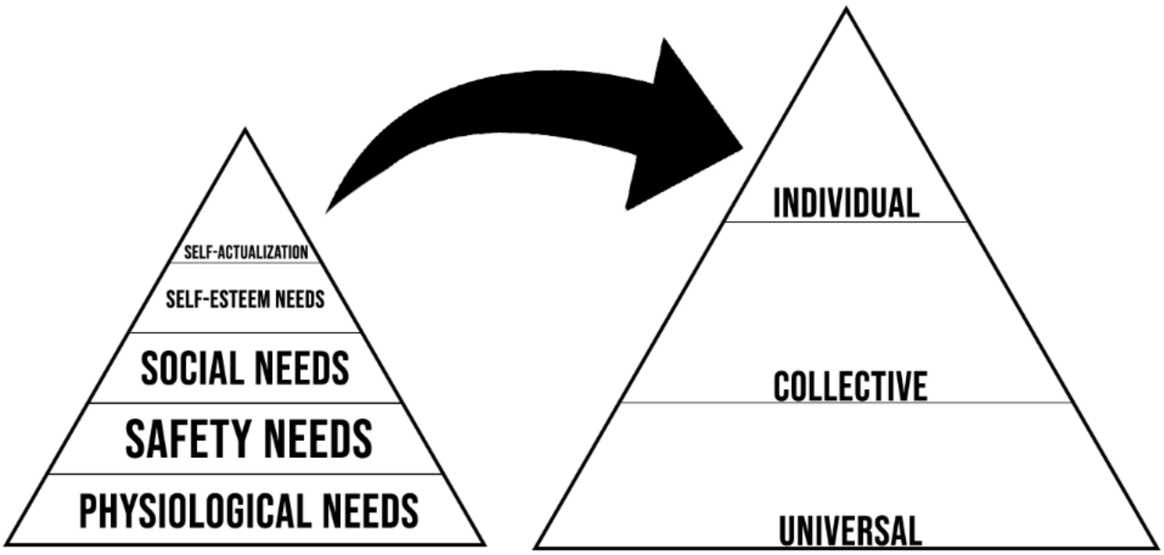
Self-attribution and hindsight biases allow people to envision their past successes in great detail, often idealizing them, while confirmation bias makes our System 2 thinking quickly retrieve these memories when a particular decision needs to be justified by the investor. Ackert and Deaves (2010, p. 162) report of recent research of the German stock market indicating there is a positive correlation between past returns and changes in confidence, thus supporting claims that overconfidence can affect entire markets. Such behavioral tendencies of market professionals can have a profound effect on the capital markets, despite being assumed as efficient. Even though half of the U.S. stock trading volume is being performed by high-frequency-trading algorithms (NASDAQ, 2018), there are still some human institutional traders whose overconfidence can potentially cause them to make market shifting trades. As algorithm trading gains momentum and its market share, such trades may also become increasingly magnified by the automatized nature of the algorithms, where one human error can trigger a sell-off which can only be contained by market circuit-breakers.

Conversely, the number of retail investors has grown since the beginning of the 2019-nCoV pandemic (Moses, 2020). Inexperienced investors looking to bring thrill to the boredom of quarantined life can quickly be swayed to overweight/underweight a security when receiving a positive/negative signal, causing them to underdiversify their portfolios and expose themselves to unnecessary risk. A study performed by Kelly (1995) revealed that only 5% of a sample of 3,000 U.S. individuals held at least 10 stocks in their investment portfolio, where owning 10 different stocks (preferably situated in different sectors) is perceived as sufficient diversification. Furthermore, Goetzmann and Kumar (2005) discerned that portfolio sophistication greatly increased with the investor’s income, wealth, and age. In an age where stocks are readily available for purchase via aggressively advertised online brokers, boredom and pent-up demand of relatively underdiversified retail investors, combined with automatized algorithmic trading that has difficulties accounting for human errors and follies, the potential for volatile price action is truly high.

3 DIMENSIONS OF CULTURE

Despite globalization, cultural differences can still be observed around the world. While all investors wish to maximize their returns with as little risk as possible, cultural differences have been proven to affect how people set out to achieve their desired returns. All individuals carry their own "mental program" which has been developed through their childhood and is continuously reinforced in educational and other institutions (Hofstede, 2001, p. xix). Mental programming is inherited as well as taught, making it predictable partly on an individual, partly collective, and partly on a universal scale. Universal mental programming comes from "preprogramming", a term coined by Irenäus Eibl-Eibesfeldst and describes behavior which has been inherited from our ancestors, dating back to the ages of hunters and gatherers (Hofstede, 2001, pp. 2–3). For decades, people's most basic needs have been depicted by Maslow's (1943) hierarchy of needs, but the intensity and distribution of an individual's needs may not necessarily resemble a perfect pyramid. Upbringing shapes an individual's values, which then help dictate their wants and needs. As depicted in Figure 9, individual's needs on the left-hand side help shape only the top part of the pyramid on the right-hand side, whereas preprogramming covers the bottom layer of the right-hand side pyramid.

Figure 9: Maslow's hierarchy of needs and the three levels of human mental programming



Adapted from Maslow (1943, p. 3).

According to Hofstede (2001, p. 3), the middle (collective) layer is the layer which is mostly learned through integration into a society of people that have a different genetic constitution but have gone through similar learning processes. Social integration instills values into individuals, who through their natural and provoked behaviors form different cultures. Values presuppose collectivity and as such, describe people's broader tendencies to desire certain states of affairs over others that are individually, collectively, or universally seen as undesirable. Values are programmed early in our childhood and are often very subjective and nonrational. Many people may hold conflicting values of varying direction and intensity and these internal conflicts are one of the sources of uncertainty when observing individual and collective human behavior. (Hofstede, 2001, pp. 5–6).

Nevertheless, a great degree of homogeneity and behavioral norms can be observed, making human behavior not completely arbitrary. Behavioral norms which originate from values are reinforced through an indvidual's social integration and help develop and strengthen the institutions through which they are being taught. These institutions include the immediate and more distant family, education, political, and legislative systems that are present in a particular geographical, historical or demographical area (Hofstede, 2001, pp. 11–12). Such self-reinforcing learning processes helped formed collective identities commonly known as cultures. Culture is defined as a set of patterned modes of thinking, feeling and reacting that are based on values, acquired and transmitted via social integration through historical artifacts such as symbols and heroes. Where personality shapes the identity of an individual, culture shapes the shared identities of individuals forming larger groups (Hofstede, 2001, pp. 9–10).

In an extensive study of IBM personnel across 50 different countries, the Dutch sociologist Geert Hofstede developed six factors that describe our social behavior: Power Distance Index, Individualism, Masculinity, Uncertainty avoidance, Long-term orientation, and, most recently, Indulgence. The gathered data allowed Hofstede to place each country on a scale represented by each dimension, and the number of analyzed countries grew with time. By utilizing these metrics, subsequent research of other authors revealed that cultural differences influence investors' confidence, judgement, and even interpretation of information. What is more, when researching time discounting, Wang, Rieger and Hens (2016) claimed these cultural factors had been superior in explanatory power to some more commonly used economic variables.

3.1 Power distance index (PDI)

One of the most natural and basic behaviors that greatly affects the formation of societies is dominance and the outward depiction thereof. 'Pecking orders' are easily observed in human and especially animal societies, which makes dominance a universal facet of social existence. However, how this dominance is expressed belongs to the second, collective layer. Different societies approach dominance differently, with some formalizing dominance and others going to great extents to de-emphasize dominance (Hofstede, 2001, p. 80). Dominant behavior where one party assumes the higher ground and the other subordinates itself ultimately leads to inequality of different forms. Dominance (or submission) immediately creates a schism in the power structure, where the dominant party overpowers the submissive, thereby establishing ranks within a particular area. Inequality can form through different physical and mental capabilities, social status, wealth, and even laws. Inequalities from these different areas are not necessarily intertwined (Hofstede, 2001, p. 80). Physically dominant individuals, such as athletes, rely on their physical prowess and sporting success to gain status and wealth, but they do not necessarily gain power. Conversely, the work of politicians that may not be physically imposing allows them to gain power and wealth, but often also to the detriment of their social status. Throughout history and with time, consistent differences among humans helped form a myriad of social power structures. (Hofstede, 2001, p. 81).

Narrowing down our focus to the present time and to the hierarchical structures found in most companies, the superior-subordinate relationship can be described as a basic human relationship which bears grounds on unequal distribution of power. Such superiority (subordination) is carried over from more fundamental interaction between children and parents and later pupils and teachers (Hofstede, 2001, p. 82). In Hofstede's research, power distance is described as a concept, which measures interpersonal power structures from the perspective of a subordinated individual. Power is defined as one individual's potential to affect another person's behavior more than the latter can affect the former's. Power distance, therefore, is the measure of inequality in power between a more and a less powerful individual who both belong to the same social system. In a corporate setting, power distance is the difference between how a superior affects the behavior of a subordinate and how the subordinate affects the behavior of their superior (Hofstede, 2001, p. 83). In mathematical terms, the Power Distance Index was calculated as:

$$PDI = 135 - 25(a) + b - c. \tag{15}$$

Equation (15) uses three variables, all of which are mean results of the following three items:

a) Subordinate employees' opinion on other employees being afraid to disagree with their superiors.
b) Subordinates' stance that their superiors make decisions in an autocratic or persuasive/paternalistic manner.
c) Subordinate employees' preference for their superior's decision-making process, ranging from autocratic, persuasive/paternalistic to democratic.

Results would theoretically range from -90, where no employee would feel afraid of their superiors, whose decision-making style would be completely consultatory, to +210, where every employee would be mortified of their autocratic and dictator-like superiors.

3.2 Uncertainty avoidance (UAI)

In chapter 1.2 we described uncertainty as the characteristic of a situation where one cannot assign probabilities to a given set of outcomes. Regardless if a situation is uncertain or simply risky, we discerned that people dislike uncertainty as it breeds anxiety. Coping with uncertainty is part of our collective programming, manifesting itself via laws, technology, and religion in various degrees of ambivalence towards parents, moralism, dichotomization, externalization, institutionalism (Hofstede, 2001, p. 146). General boundaries and partitions are created by societies to help themselves make life more predictable. Corporate settings similarly rely on technology, rules and rituals presented as standard operating procedures and industry traditions to minimize short- to medium-term uncertainty. Technology enables individuals within a society to explain the laws of nature, but can lead to morally questionable decisions in corporate settings. It allows human labor to be replaced with computers and machinery, creating greater short-term predictability of events. While rituals connect people, rules try to control the future. Industry practices and firm standards create a sense of belonging for individuals working in a particular field and company, but combined with rules also help anticipate future events and successive courses of action, creating a more controlled environment. Similarly (Hofstede, 2001, pp. 146–147).

Conceptually, uncertainty avoidance is to the authority of rules as what power distance is to the authority of individuals. Hofstede used the following equation to determine people's uncertainty avoidance index:

$$UAI = 300 - 30(a) - \frac{b}{100} - 40(c). \tag{16}$$

The variables again represent mean scores for three distinct metrics:

a) Agreement with an individual breaking company rules, regardless if breaking the rules is in the company's best interest.
b) Employees' prediction of their remaining tenure with the company; where b represented a percentage of employees intending to stay with the company for less than 5 years.
c) Stress and how often employees felt nervous or tense at work.

Theoretically, Results on the lowest end of the spectrum (-150) would indicate that everyone would be inclined to break the rules, quickly quit their job, and never feel stressed. Conversely, a score of +230 would describe an organization whose entire staff would never like to quit their job where they always feel stressed and perfectly abide all rules which they believe should never be broken.

3.3 Individualism and collectivism (IDV)

Societies can also be dissected by analysing the degree to which individuals within a society show gregarious or solitary behaviour. The first division is observed at the family level, where children's autonomy can be seen as either a sign of maturity or as a sign of alienation. Some societies form nuclear families, others seem to prefer forming larger groups in the form of extended family, while some rare societies create even larger tribes where kinship may run even past the extended family. Social inclusion infers a certain degree of collectivism, and historical roots of a nation or society bear important implications. In areas historically occupied by hunter-gatherers, people still prefer to form nuclear families. Conversely, people in areas with more agricultural foundations tend to live with their extended families, but modernization appears to break down such families into more nuclear units (Hofstede, 2001, p. 210).

Individualism and collectivism carry moral undertones and are best observed when observing citizens of the United States and the Chinese. Americans see individualism as the foundation of their country, while the Chinese have a distinctly different moral view of the matter. Individualism and liberalism were frowned upon Mao Zedung, a view which is deeply rooted in the Chinese tradition; maintaining the group's well-being is in the best interest of the individual (Hofstede, 2001, p. 211). Similarly, individualistic societies distance themselves when a member of the group wishes to convert their religious beliefs. Adopting religious beliefs is nowadays an act made at the individual's discretion, especially in Western societies. Historically, the adoption of religious beliefs was a collectivistic matter as it allowed groups to strengthen the cohesion through the adoption of mutual beliefs (Hofstede, 2001, p. 210). However, modernization and globalization promote individualism to the extent where: "[M]odern man […] is open to new experiences; relatively independent of parental authority; concerned with time, planning, willing to defer gratification" (Hofstede, 2001, p. 211).

Hofstede (2001, p. 212) claims that the collectivistic or individualistic nature of a society in which an organization is set directly coincides with the work culture in that given company and will determine the employees' willingness to comply with organizational requirements. Additionally, Hofstede also reports on research of others which support the idea that employees foster more collectivistic groups within smaller companies and that the individualism grows with the size of the company. This also appears to be the strongest evidence which supports the aforementioned claim that modernization favours individualists.

Using factor analysis, Hofstede based his Individualism index on questionnaire scores that pertained to employees' assessments of their work goals. The scores were analysed by comparing the factor score with the country mean scores for each work goal. Based on the results of the factor analysis, Hofstede concluded that the following six work goals have the greatest power in describing individuality and ranked them in order of their correlation factor:

- Personal time (0.86),
- Freedom (0.49),

- Challenge (0.46),
- Use of skills (-0.63),
- Physical conditions (-0.69),
- Training (-0.82).

The results indicate individualism is highly correlated to the mean importance in a country attached to the amount of personal time their employer offers. The opportunity to learn new and improve old skills, on the contrary, appears to have distinctly collectivistic implications (Hofstede, 2001, p. 214).

Countries with individualistic social programming, such as the United States, raise children to think of themselves as above average in skill and in possession of unique abilities. Individualistic programming has been reported to produce individuals prone to overconfidence and self-attribution bias. Because people raised in individualistic societies think of their skills as superior to those of their peers, they are much more likely to overestimate the accuracy of their information, which can result in miscalibration. Ferris, Jayaraman, and Sabherwal (2013) who have used Hofstede's dimensions to assess mergers and acquisitions discerned that CEOs who scored high on the individualism index overestimate potential synergies attained via an acquisition. Chui, Titman and Wei (2010) report a strong positive correlation between individualism and share price momentum, challenging the efficient market hypothesis. Individualism and stock market volatility have also been proven to be strongly correlated (Graham & Pirouz, 2010). In case of a failed investment, their self-attribution bias would cause them to save their own face by denying responsibility for their own failure as their programming teaches them to preserve their self-esteem. Collectivistic societies, conversely, tend to be more introspective and self-monitoring which helps reduce cognitive bias in the financial markets (Chui, Titman & Wei, 2010, pp. 364–365).

3.4 Masculinity and femininity (MAS)

Innately, the only absolute difference between the two genders is that women bear children and men beget them. Different sources imply that this natural distinction and subsequent social programming makes women, on average, more nurturing, responsible, and more inclined to use conversation to build emotional rapport. Conversely, the inability to bear children causes many men to seek success and accomplishment elsewhere. At the most primal level, men were required to succeed in providing food and shelter. The means to fulfil the two elementary needs might have change over centuries, but the motivation remains the same. Goal oriented thinking and behaviour causes men to act assertively and use conversation to relay information as instead of emotion (Hofstede, 2001, pp. 279–280). Hofstede's research focused on the divergence between men and women's values, and the higher the masculinity index, the higher the disparity between the two genders' most important values. Hofstede discerned the most significant trends indicate that professionally, men hold advancement, earnings, training, and contemporaneity in higher regard while women find more value in relationships, position security, physical conditions and cooperation (Hofstede, 2001, p. 281).

Similar to individuality index, the masculinity index was also based on factor analysis which produced two factors: intrinsic/extrinsic and social/ego factor. The latter accounted for 22% of the mean work goal scores and proved to be a proxy for female/male preferences. Hofstede reported the following work goals and loadings as the constituents of the social/ego factor:

- Manager (0.69),
- Cooperation (0.69),
- Desirable area (0.59),
- Employment security (0.48),
- Challenge (-0.54),
- Recognition (-0.59),
- Earnings (-0.70).

By taking the inverse values of the abovementioned loadings, Hofstede created a masculinity and femininity index, which relates back to the dominant behavioral traits associated with each gender – assertiveness and nurturance (Hofstede, 2001, pp. 282–284).

Gender differences in masculinity are decreasing, and recent research shows masculinity is more associated with upbringing rather than gender. Women from matriarchal societies have been proven to be just as competitive as men from patriarchal societies. Masculinity must not be mistaken for high testosterone levels, as studies suggest that higher testosterone levels can explain lower risk aversion and preferences for riskier careers. This is particularly prominent in single individuals, where joint risk assessment and financial planning is not required as is with married or couples living together (Iliyanova, 2016).

3.5 Long vs. short term orientation (LTOWVS)

All of the factors described so far have been created based on a global IBM survey created by researchers of British, Dutch, French, Norwegian, and U.S. descent. Hofstede admits this assembly of Western researchers and their inputs ought to have caused a cause for concern as their survey questions surely could not have been truly representative of all global values. By creating a questionnaire which had drawn upon values of traditional Chinese philosophy, Michael Harris Bond of the Chinese University of Hong Kong conducted a Chinese Value Survey (CVS) which analysed the value structures of 100 men and women of different ethnicities in relation to 10 values perceived as fundamental to Chinese people. The initial results indicated some of Bond’s dimensions correlate to Hofstede’s findings. A CVS dimension called moral discipline carried a 0.55 correlation with Hofstede’s power distance and -0,54 correlation with individuals. Another CVS dimension, integration, correlated with individualism and power distance with correlation coefficients of 0.65 and -0.54, respectively. Lastly, a factor named human-heartedness showed a positive correlation of 0.67 with Hofstede's masculinity index (Hofstede, 2001, p. 352). This explanatory power prompted Hofstede to analyse national differences in long-term orientation.

Again, by utilizing factor analysis, the following factors and their loadings have been identified as indicators of people's long or short-term orientation:

- Persistence (0.76),
- Ordering relationships by status and observing the order (0.64),
- Thrift (0.63),
- Possessing a sense of shame (0.61),
- Personal steadiness and stability (-0.76),
- Protecting one's "face" (-0.72),
- Respect for tradition (-0.62),
- Reciprocation of gifts, greetings, and favours (-0-58).

As such, the factors with positive loadings are indicative of a person's long term, and the factors with negative loadings short-term orientation.

3.6 Indulgence vs. restraint (IVR)

Indulgence is the most recent factor included in Hofstede's research, having been added to the model in 2010. Indulgence has been characterized as a factor, which stands for an individual's belief to freely pursue their personal happiness by way of quickly fulfilling their basic and natural human desires, often facilitated by increased spending. The factor was created by observing people's responses to survey questions pertaining to happiness, life control, and the importance of leisure. This factor is thus highly connected to the extent individuals like to have fun on their own terms, either alone or with their friends. Individuals described as indulgent believe they are very happy, have a great deal of freedom of choice and in steering their life events, and, therefore give great weight to (spending on) leisure activities. On the other side of the spectrum lies restraint, which describes people who are convinced their cravings for amusement and gratification need to be restrained by thrift and self-discipline as governed by various social norms (Hofstede, Hofstede & Minkov, 2010, p. 284). In countries with higher indulgence ratings, corporate settings appear to be more relaxed and open to individuals expressing their emotions, as Hofstede, Hofstede and Minkov (2010, p. 295) discuss how Russian McDonald's employees experienced difficulties in adopting a more cheerful, 'American' style of greeting their customers.

Though still fairly unexplored in terms of stock market implications, Hammerich (2020) observed that in countries with lower indulgence ratings, portfolios consisting of the bottom 20% (i.e. high-risk, lower priced) stocks perform better than portfolios made up of the top 20% stocks with higher prices and lower volatility. Unfortunately, the results also included highly significant t-test statistics which dispute the validity of the author's observations. The very notion that more conservative and restrained societies prefer to invest in low-priced high-risk assets as opposed to less volatile instruments is disputable and only highlights we are currently in the early stages of exploring indulgence as statistically significant factor which could impact stock market returns.

4 RESEARCH METHODOLOGY, HYPOTHESES AND ANALYSIS

The empirical part of this thesis analyses how individual stock market indices performed in the year 2020 and how their performance linked to the cultural dimensions described in chapter 3. Since Hofstede's research data is incomplete for particular countries, my research used a sample of the 55 different countries with complete cultural dimension data (there were no missing cultural factors). Next, I selected the countries' most prominent stock market indices and collected daily closing prices for the period January 1 to December 31, 2020. From there, the return data was segregated into four different time periods: annual, February-March, April-August, and February-August. The segregation was made to gather return data which spans across the entire year while also giving us more insight within the year across the periods of greatest stock price movement (to potentially identify additional inferences how cultural dimensions affect stock market prices in times of increased volume and volatility). Daily stock index prices were gathered from Eikon's Dataservice, GDP data from World Bank, and real interest rates from World Bank and Statista. The tests performed in my analyses were the Pearson's Chi-square, Fisher's test and the OLS regression using statistical software SPSS. Table 2 presents cultural data per country and the stock market indices, the returns of which helped form the final four datasets.

Table 2: Country-specific Cultural and Stock Market Index Data

Country	Stock Market Index Ticker	PDI	IDV	MAS	UAI	LTOWVS	IVR
Argentina	MERV	49.00	46.00	56.00	86.00	20.40	61.83
Australia	ASX100	38.00	90.00	61.00	51.00	21.16	71.43
Austria	ATX20	11.00	55.00	79.00	70.00	60.45	62.72
Belgium	BEL20	65.00	75.00	54.00	94.00	81.86	56.70
Brazil	BOVESPA	69.00	38.00	49.00	76.00	43.83	59.15
Bulgaria	SOFIX	70.00	30.00	40.00	85.00	69.02	15.85
Canada	TSX60	39.00	80.00	52.00	48.00	36.02	68.30
Chile	SPIPSA	63.00	23.00	28.00	86.00	30.98	68.00
China	SSEC	80.00	20.00	66.00	30.00	87.41	23.66
Colombia	COLCAP	67.00	13.00	64.00	80.00	13.10	83.04
Croatia	CROBEX	73.00	33.00	40.00	80.00	58.44	33.26
Czech Rep	PX	57.00	58.00	57.00	74.00	70.03	29.46
Denmark	OMX20	18.00	74.00	16.00	23.00	34.76	69.64
Estonia	OMXTGI	40.00	60.00	30.00	60.00	82.12	16.29

table continues

Table 2: Country-specific Cultural and Stock Market Index Data (con.)

Country	Stock Market Index Ticker	PDI	IDV	MAS	UAI	LTOWVS	IVR
Finland	OMXH25	33.00	63.00	26.00	59.00	38.29	57.37
France	CAC40	68.00	71.00	43.00	86.00	63.48	47.77
Germany	DAX	35.00	67.00	66.00	65.00	82.87	40.40
Great Britain	FTSE100	35.00	89.00	66.00	35.00	51.13	69.42
Greece	ATF	60.00	35.00	57.00	112.00	45.34	49.55
Hong Kong	HSI	68.00	25.00	57.00	29.00	60.96	16.96
Hungary	BUX	46.00	80.00	88.00	82.00	58.19	31.47
India	NIFTY50 (NSEI)	77.00	48.00	56.00	40.00	50.88	26.12
Indonesia	JKSE	78.00	14.00	46.00	48.00	61.96	37.72
Ireland	ISEQ	28.00	70.00	68.00	35.00	24.43	64.96
Italy	FTSEMIB	50.00	76.00	70.00	75.00	61.46	29.69
Japan	JPXNK400	54.00	46.00	95.00	92.00	87.91	41.74
Korea South	KOSPI50	60.00	18.00	39.00	85.00	100.00	29.46
Latvia	OMXRGI	44.00	70.00	9.00	63.00	68.77	12.95
Lithuania	OMXVGI	42.00	60.00	19.00	65.00	81.86	15.63
Malaysia	KLSE	104.00	26.00	50.00	36.00	40.81	57.14
Malta	MSE	56.00	59.00	47.00	96.00	47.10	65.63
Mexico	MXX	81.00	30.00	69.00	82.00	24.18	97.32
Morocco	FTFCSE	70.00	46.00	53.00	68.00	14.11	25.45
Netherlands	AEX	38.00	80.00	14.00	53.00	67.00	68.30
Norway	OBX25	31.00	69.00	8.00	50.00	34.51	55.13
Pakistan	KSE100	55.00	14.00	50.00	70.00	49.87	0.00
Peru	SPBL25PT	64.00	16.00	42.00	87.00	25.19	46.21
Philippines	PSEi	94.00	32.00	64.00	44.00	27.46	41.96
Poland	WIG20	68.00	60.00	64.00	93.00	37.78	29.24
Portugal	PSI20	63.00	27.00	31.00	104.00	28.21	33.26
Romania	BETI	90.00	30.00	42.00	90.00	51.89	19.87
Russia	IRTS	93.00	39.00	36.00	95.00	81.36	19.87
Serbia	BELEX15	86.00	25.00	43.00	92.00	52.14	28.13
Singapore	STI	74.00	20.00	48.00	8.00	71.54	45.54
Slovak Rep	SAX	104.00	52.00	110.00	51.00	76.57	28.35
Slovenia	SBITOP	71.00	27.00	19.00	88.00	48.61	47.54
Spain	IBEX35	57.00	51.00	42.00	86.00	47.61	43.53
Sweden	OMXS	31.00	71.00	5.00	29.00	52.90	77.68
Switzerland	SSMI	34.00	68.00	70.00	58.00	73.55	66.07
Taiwan	FTSETW50	58.00	17.00	45.00	69.00	92.95	49.11
Thailand	SET50	64.00	20.00	34.00	64.00	31.74	45.09
Turkey	BIST100	66.00	37.00	45.00	85.00	45.59	49.11
U.S.A.	S&P500	40.00	91.00	62.00	46.00	25.69	68.08
Venezuela	IBC	81.00	12.00	73.00	76.00	15.62	100.00
Vietnam	VNI	70.00	20.00	40.00	30.00	57.18	35.49

Source: Hofstede (2022).

Before performing any regressions, Fisher's exact test was performed to initially assess connections between the cultural factors and annual stock returns. Fisher's test was performed after the initial Chi-squared goodness of fit test indicated that the sample size of 55 countries failed to meet one of Chi-squared model's basic assumption. The Chi-squared test of independence analyses how likely it is that random chance can explain any observed difference between expected and actual frequencies. If two variables were completely independent, the expected frequencies and distribution of data should be approximately equal (Hayes, 2022). The model assumes a minimal number of expected values per cell to be equal to, or greater than five.

My dataset was too small to meet the assumption and since there were only 55 countries with complete cultural data, I decided to forgo expanding the dataset and used the Fisher's test instead. Fisher's test is commonly used as an alternative to the Chi-squared test when when rows or columns are random or the dataset proves itself to be too small. The numerical data for the Chi-squared and Fisher's tests was modified into categorical variables and segregated into quartiles and terciles, so the cultural factors were ultimately divided into groups named 'High', 'Moderate' and '(Very) Low', based on where each country's individual cultural factor placed on a scale of 0 to 112. The return data, conversely, was split into groups of 'Excellent', "Moderate", and "(Very) Poor", where the latter encompassed the tercile (quartile) of countries with the lowest annual returns. Cultural factors held constant, the index returns were calculated according to the following timeframes, in turn creating four distinct datasets:

- January 1 – December 31, 2020 (Dataset 1),
- February 1 – March 31, 2020 (Dataset 2),
- April 1 – August 31, 2020 (Dataset 3),
- February 1 – August 31 (Dataset 4).

While Dataset 1 observed the returns across the entire year, the other three datasets were created to analyse returns in times of greatest market volatility. Dataset 2 takes a closer look at cultural factors in relation to the greatest downturn of 2020, followed by a period of greatest recovery observed in Dataset 3. Finally, Dataset 4 combines datasets 2 and 3.

Pearson's Chi-squared and Fisher's crosstabulation was performed six times (one for each cultural factor in relation to the return) across all four time periods and with data segregated into quartiles and terciles. Table 3 shows only outputs that have been identified as statistically significant.

Table 3: Fisher's test results

Dataset	Data Segregation	Cultural Factor	Fisher's Test P-Value
Dataset 1	Quartiles	PDI	0.043
Dataset 1	Quartiles	UAI	0.002
Dataset 1	Terciles	UAI	0.028
Dataset 2	Quartiles	IVR	0.032
Dataset 2	Quartiles	UAI	0.013
Dataset 3	Quartiles	PDI	0.042
Dataset 3	Quartiles	MAS	0.025
Dataset 3	Terciles	PDI	0.030
Dataset 4	Quartiles	PDI	0.029
Dataset 4	Quartiles	UAI	0.024
Dataset 4	Terciles	UAI	0.023
Dataset 4	Terciles	LTOWVS	0.007

Source: Own work.

As we can infer from Table 3, UAI and PDI are the two cultural factors that occurred the most often as statistically significant in the Fisher's test analyses, with 9 out of 12 statistically significant results being the very two cultural factors. This implies that there is a possibility of the uncertainty avoidance and power distance index as quite likely of having a statistically significant impact on how the stock market behaved in the four observed time periods. The remaining three factors that were statistically significant in the initial analyses were IVR, MAS, and LTOWVS, which is why they will also receive additional consideration in the subsequent OLS regressions. Given what we have already discerned about the cultural factors and how they describe human behaviour, the results from Table 2 prompted the following 9 research questions:

- 1: The UAI factor is independent of stock returns and therefore did not affect price movement on an annual level in the year 2020.
- 2: The PDI factor is independent of stock returns and therefore did not affect price movement on an annual level in the year 2020.
- 3: The UAI factor is independent of stock returns and therefore did not affect price movement in the period between February 1 and March 31, 2020.
- 4: The IVR factor is independent of stock returns and therefore did not affect price movement in the period between February 1 and March 31, 2020.
- 5: The PDI factor is independent of stock returns and therefore did not affect price movement in the period between April 1 and August 31, 2020.
- 6: The MAS factor is independent of stock returns and therefore did not affect price movement in the period between April 1 and August 31, 2020.
- 7: The UAI factor is independent of stock returns and therefore did not affect price movement in the period between February 1 and August 31, 2020.

- 8: The PDI factor is independent of stock returns and therefore did not affect price movement in the period between February 1 and August 31, 2020.
- 9: The LTOWVS factor is independent of stock returns and therefore did not affect price movement in the period between February 1 and August 31, 2020.

There is little data in terms of quantifying behavioral biases, hence why we are initially only interested in the potential statistical significance of individual cultural factors. Consequently, the nine hypotheses are all very similar, varying only in the observed factor and time period.

Fisher's tests were followed by an OLS regression across the four time periods. Returns were selected as the dependent variable and the cultural factors were selected as the explanatory variables during the first stage of testing. To observe how the cultural models behave after introducing control variables, second-stage analyses included annual changes in GDP from 2019 to 2020 (marked as 'gdpdelta') and the latest real interest rates available in the period leading up to and including 2020 (marked as 'rir'). There were two countries whose real interest rates were unavailable (Turkey and Taiwan), so the mean of all other countries' real interest rates was used as a substitute for the second-stage regressions.

To test for statistical significance of the observed results, I have used ANOVA F-test results. The F-test, in conjunction with the critical p-value, look for statistical significance of a group of regressed variables by testing the hypothesis whether the variances of two samples are equal. The sample is expected to follow an F-distribution and the samples must be independent (Glen, 2022a). For my data to be statistically significant. the F-test value should exceed 2.295 for first-stage regressions (with $\nu_1 = 6$ and $\nu_2 = 48$ degrees of freedom) and 2.147 for second-stage regressions (with $\nu_1 = 8$ and $\nu_2 = 46$ degrees of freedom) following an F-test distribution at the 5% significance level.

For OLS model diagnostics and to make valid statistical inferences from an OLS regression model, the following further four key assumptions must be verified: normality of the disturbances, absence of (perfect) multicollinearity, homoscedasticity, and absence of autocorrelation.

Since I only used cross-sectional and no time-series data in my regressions, there was no need to test for the absence of autocorrelation. Autocorrelation is a measure of inertia underlying to a particular time-series dataset that may create cyclical developments. To test the other three assumptions, I have reviewed graphical outputs for normality of disturbances and homoscedasticity, and checked for the absence of (perfect) multicollinearity by using the VIF index for each individual explanatory variable per dataset and regression. For OLS regressions to be valid, their stochastic variables (disturbances) must first be normally distributed and to review the distribution disturbances, a histogram of disturbances was plotted along with each of the eight regressions. The assumption of normally distributed error terms is essential, as it serves as the foundation for t-, F- and χ^2 distributions. Secondly, there must be an absence of (perfect) multicollinearity or (perfect) linear dependence among the explanatory variables. Multicollinearity can be tested by observing the signs of one or more regression coefficients or the regression's R^2 results. If the sign of any coefficient is in contradiction to the theoretical presuppositions or the R^2 value is higher compared to relatively insignificant regressions coefficients, one can suspect the model might be subjected to issues of (perfect) multicollinearity. The Variance Inflation Factor (VIF) measure the extent of multicollinearity within a set of multiple regression variables. VIF values are calculated by taking an explanatory variable and regressing it against all other dependent variables within the model. The R^2 value is then inserted into the equation presented below.

$$\text{VIF} = \frac{1}{1-R_i^2} \quad (16)$$

VIF scores range from 1 upwards, where an index of between 1 and 5 indicate moderate correlation and values over 5 severe correlation. Some authors even suggest more a conservative level of 2.50 (Glen, 2022b). For the purposes of my research, I will use 2.50 as the critical level for (perfect) multicollinearity. Lastly, the assumption of homoscedasticity presupposes that the dispersion of deviations around the regression line is the same for each explanatory variable of the model. While heteroscedasticity does not bias the explanatory coefficients, it does negatively affect their explanatory power in terms of precision.

4.1 Dataset 1

Beginning with the analysis of annual returns, the first OLS regression yielded results found in Table 4.

Table 4: OLS Output - Dataset 1/Regression1

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0.188	0.138		1.357	0.181		
	pdi	-0.002	0.001	-0.225	-1.454	0.152	0.503	1.987
	idv	0.000	0.001	0.048	0.325	0.747	0.553	1.809
	mas	-0.002	0.001	-0.242	-2.078	0.043	0.892	1.121
	uai	-0.002	0.001	-0.252	-2.242	0.030	0.953	1.049
	ltowvs	0.003	0.001	0.393	3.036	0.004	0.723	1.384
	ivr	-0.001	0.001	-0.079	-0.583	0.563	0.656	1.523

a. Dependent Variable: ret

Source: Own work.

As we can observe, there are three cultural factors with statistically significant results: MAS (p-value: 0.043), UAI (p-value: 0.03), and LTOWVS (p-value: 0.04). Observing the F-test statistic, histogram of standardized residuals, scatterplot of disturbances, and VIF results all below the critical 2.50 mark, it is safe to assume the model results are statistically significant. The first OLS model assumes there is a negative statistical relationship between MAS and UAI in relation to the annual stock returns. With beta coefficients of -0.002 and standardized beta coefficients of -0.242 and -0.252, respectively, we can summarize that as the two factor scores increase, the annual returns are projected to decrease in the time period between January 1 and December 31, 2020 by a factor of the expressed beta coefficient had the cultural factor in question have increased by 1.

LTOWVS, conversely, appears to have a positive impact on annual stock market returns, with a corresponding beta coefficient 0.003 and a standardized beta coefficient of 0.393. Theoretically speaking, a single point increase in the LTOWVS rating would increase the return of that particular country's market index by a factor of 0.003, or 0.393 in standardized terms.

Accounting for the control variables, Table 5 summarizes the output of our second OLS regression.

Table 5: OLS Output - Dataset 1/Regression 2

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0.176	0.113		1.563	0.125		
	pdi	-0.001	0.001	-0.099	-0.776	0.441	0.482	2.073
	idv	0.000	0.001	-0.048	-0.398	0.693	0.540	1.851
	mas	-0.002	0.001	-0.212	-2.237	0.030	0.872	1.147
	uai	-0.001	0.001	-0.127	-1.358	0.181	0.891	1.122
	ltowvs	0.001	0.001	0.191	1.725	0.091	0.637	1.570
	ivr	0.001	0.001	0.094	0.810	0.422	0.588	1.700
	rir	-0.017	0.236	-0.006	-0.070	0.945	0.921	1.086
	gdpdelta	1.423	0.269	0.611	5.291	0.000	0.587	1.702

a. Dependent Variable: ret

Source: Own work.

We can observe that by introducing the two control variables, annual change in GDP expectedly has the greatest impact on the annual stock returns. With a p-value of 0.000, gdpdelta has a beta coefficient of 1.423 and 0.611 in standardized terms. Of the cultural factors that were statistically significant in the first analysis, only MAS remains statistically significant with a p-value of 0.03 and beta coefficient (standardized) of -0.002 (-0.212). As with the initial regression, the model diagnostic tools do not show any model deficiencies.

On the basis of the gathered results, we can reject the null hypothesis of research question 1, but only when observed in a vacuum where there are no control variables that would 'dilute' the impact of UAI on the stock market prices. PDI, conversely, shows no statistical significance and therefore we fail to reject the null of research question 2.

4.2 Dataset 2

Moving on to reduced time horizons, our first time period encompassed February and March, two months of greatest price decreases of the year 2020, where the price drops were severe enough to trigger market circuit breakers (Menton, 2020). First-stage OLS regressions, using only the cultural factors reveal statistical significance of two factors, as can be seen in Table 6.

Table 6: OLS Output - Dataset 2/Regression 1

Coefficients[a]								
		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	-0.323	0.082		-3.951	0.000		
	pdi	0.000	0.001	0.102	0.599	0.552	0.503	1.987
	idv	0.001	0.001	0.225	1.386	0.172	0.553	1.809
	mas	0.000	0.000	-0.065	-0.504	0.616	0.892	1.121
	uai	-0.001	0.000	-0.335	-2.704	0.009	0.953	1.049
	ltowvs	0.001	0.001	0.355	2.494	0.016	0.723	1.384
	ivr	-3.990E-5	0.001	-0.011	-0.072	0.943	0.656	1.523

a. Dependent Variable: ret

Source: Own work.

UAI and LTOWVS are shown to have a statistical significance at p-values of 0.009 and 0.016, with beta coeffiecients (standardized) of -0.001 (-0.335) and 0.001 (0.355), respectively. Model diagnostics confirm the validity of the model, with a F-test value above 2.295, histogram of standardized residuals showing normal distribution and no remarkable patterns in the scatterplot of standardized predicted values. VIF results all fall below the 2.50. After introducing our control variables, the regression outputs were as presented in Table 7.

Table 7: OLS Output - Dataset 2/Regression 2

Coefficients[a]									
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-0.304	0.073		-4.170	0.000		
	pdi	0.001	0.001	0.225	1.466	0.150	0.482	2.073
	idv	0.001	0.000	0.150	1.033	0.307	0.540	1.851
	mas	0.000	0.000	-0.076	-0.665	0.509	0.872	1.147
	uai	-0.001	0.000	-0.247	-2.188	0.034	0.891	1.122
	ltowvs	0.001	0.000	0.193	1.448	0.154	0.637	1.570
	ivr	0.000	0.001	0.074	0.535	0.595	0.588	1.700
	rir	-0.336	0.153	-0.244	-2.198	0.033	0.921	1.086
	gdpdelta	0.590	0.174	0.472	3.395	0.001	0.587	1.702

a. Dependent Variable: ret

Source: Own work.

Again, the model appears to produce valid data with no suspicions of disturbance abnormalities, (perfect) multicollinearity or heteroscedasticity. Both control variables greatly increase the explanatory power of the OLS model, but, more importantly, do not eliminate UAI as a statistically significant explanatory variable, as was the case with Dataset 1. The beta coefficient of the cultural factor is negative, at values of -0.001 and -0.247 at a standardized level. Based on the observations, we can reject the null hypothesis of research question 3 and assume a statistically significant impact of uncertainty avoidance on stock returns in times of severely negative price performance of global stock indices. The data indicates that a single point increase in the UAI factor would reduce the returns of a particular country's stock market index by a factor (standardized) of 0.001 (0.257). However, there is no statistical significance of the IVR factor at the 0.05 p-value level in either of the two regressions, so we fail to reject the null hypothesis of question 4.

4.3 Dataset 3

Next observed time period covered the months immediately after the "flash-crash" of February and March, where the observed stock market indices increased from their lows at the end of March by an average of 27.08% by the end of August. Our initial Fisher's test identified PDI and MAS as two cultural factors that could have potentially contributed to the price resurgence. Table 8 presents findings of the first regression.

Table 8: OLS Output - Dataset 3/Regression 1

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0.580	0.127		4.570	0.000		
	pdi	-0.002	0.001	-0.404	-2.281	0.027	0.503	1.987
	idv	0.000	0.001	-0.021	-0.121	0.904	0.553	1.809
	mas	-0.001	0.001	-0.185	-1.392	0.170	0.892	1.121
	uai	-0.001	0.001	-0.111	-0.860	0.394	0.953	1.049
	ltowvs	-0.001	0.001	-0.135	-0.915	0.365	0.723	1.384
	ivr	-0.001	0.001	-0.139	-0.892	0.377	0.656	1.523

a. Dependent Variable: ret

Source: Own work.

While MAS fails to fulfil the standard requirements of OLS regression, PDI proves itself to be statistically significant at a p-value of 0.027 and beta coefficient (standardized) of -0.002 (-0.404). with the model passing all diagnostic tests.

Table 9: OLS Output - Dataset 3/Regression 2

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0.606	0.128		4.746	0.000		
	pdi	-0.002	0.001	-0.362	-2.011	0.050	0.482	2.073
	idv	0.000	0.001	-0.039	-0.227	0.821	0.540	1.851
	mas	-0.001	0.001	-0.207	-1.545	0.129	0.872	1.147
	uai	0.000	0.001	-0.095	-0.721	0.475	0.891	1.122
	ltowvs	-0.001	0.001	-0.176	-1.121	0.268	0.637	1.570
	ivr	-0.001	0.001	-0.146	-0.896	0.375	0.588	1.700
	rir	-0.389	0.268	-0.190	-1.454	0.153	0.921	1.086
	gdpdelta	0.201	0.305	0.108	0.660	0.513	0.587	1.702

a. Dependent Variable: ret

Source: Own work.

After introducing our standard control variables, the explanatory power of the model expressed by the R^2 metric increased from 0.241 to 0.280. This would be surprising were it not for the fact the two control variables that fail to be statistically significant within the confines of Dataset 3.

PDI proves itself to be the only variable with explanatory power in the entire model with a beta coefficient (standardized) of -0.002 (-0.362). Based on the findings, we can reject the null hypothesis of research question 5 and assume statistically significant impact of PDI on market returns within the bounds of Dataset 3. On the other hand, we fail to reject the null hypothesis of question 6. Interestingly, neither of the control variables managed to have a statistically significant effect on the dependent variable.

4.4 Dataset 4

Our final dataset is a combination of Dataset 2 and 3, encompassing both the crash and recovery spanning from February 1 to August 31, 2020. Initial regression produced the output provided in Table 10.

Table 10: OLS Output - Dataset 4/Regression 1

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0.025	0.118		0.209	0.835		
	pdi	-0.001	0.001	-0.119	-0.750	0.457	0.503	1.987
	idv	0.001	0.001	0.201	1.330	0.190	0.553	1.809
	mas	-0.001	0.001	-0.224	-1.888	0.065	0.892	1.121
	uai	-0.002	0.001	-0.342	-2.976	0.005	0.953	1.049
	ltowvs	0.002	0.001	0.275	2.087	0.042	0.723	1.384
	ivr	0.000	0.001	-0.056	-0.403	0.688	0.656	1.523

a. Dependent Variable: ret

Source: Own work.

We can observe both UAI as well LTOWVS factors are statistically significant at the critical p-value with coefficients (standardized) of -0.002 (-0.342) and 0.002 (0.275), respectively. F-test is above the critical 2.295 value, with all other model diagnostic tools supporting the model adheres to the fundamental assumption of OLS regressions. Table 11 shows the outputs of our final second-stage regression.

After passing all the regression diagnostics, my final regression results allow me to only reject the null hypothesis of question 7, signifying a statistically significant effect of uncertainty avoidance on stock market index returns spanning between February 1 and August 31, 2020. Based on the results, I cannot reject the null hypothesis of research questions 8 and 9. However, MAS emerges as a statistically significant cultural factor alongside the two control variables.

Table 11: OLS Output - Dataset 4/Regression 2

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0.054	.103		.520	.606		
	pdi	1.133E-5	.001	0.002	0.013	0.989	0.482	2.073
	idv	0.001	0.001	0.126	0.958	0.343	0.540	1.851
	mas	-0.001	0.001	-0.235	-2.267	0.028	0.872	1.147
	uai	-0.001	0.001	-0.255	-2.489	0.016	0.891	1.122
	ltowvs	0.001	0.001	0.117	0.961	0.342	0.637	1.570
	ivr	0.000	0.001	0.028	0.225	0.823	0.588	1.700
	rir	-0.507	0.216	-0.237	-2.347	0.023	0.921	1.086
	gdpdelta	0.903	0.246	0.464	3.677	0.001	0.587	1.702

a. Dependent Variable: ret

Source: Own work.

4.5 Discussion

Our final observations suggest that UAI and PDI have a statistically significant relationship with the stock market index returns within bounds of the given datasets. The two factors have passed the first, Fisher's test of independence, as well as proven themselves to be (albeit minimally) conducive to affecting stock market returns in the year 2020. When accounting for both the cultural factors as well as our control variables, we can reject the null hypotheses of research questions 3, 5, and 7.

Rejecting the null for research questions 3 and 7 implies that we can observe uncertainty avoidance having an inverse effect on stock market returns in Dataset 2 and Dataset 4, covering the periods February-March and February-August, 2020. People inherently dislike uncertainty and, as a result, form different boundaries to make their lives more predictable. People taking part in stock market investing, particularly retail investors, often decrease their perceived uncertainty by investing in stocks they are most familiar with – stocks of their local companies. As we observed, familiarity is a potent barrier which can make many investors greatly overweight their portfolios with their local stocks, falling prey to home bias. Erdogan's (2014) findings suggest that unfamiliarity of the foreign markets discourages investors from investing in those markets.

The higher a country's uncertainty avoidance index, the less likely are the investors of that particular nationality to invest in foreign assets. Higher uncertainty avoidance scores therefore relate to higher risk-aversion in relation to foreign stocks, creating home bias. Low uncertainty avoidance results have also been linked to higher gambling turnovers (Ozorio, Lam & Fong, 2010); a fact which can indicate a potential for highly speculative investments to take place regardless of one's risk tolerance. Uncertainty avoidance seems to also affect the selection and behavior within different investment time horizons. Wang, Rieger and Hens (2016, p. 115) report of countries with higher uncertainty avoidance scores exhibiting stronger hyperbolic discounting tendencies. Hyperbolic discounting can be defined as immediate future being discounted more than the far future, implying that people, on average, are more patient with their investments in the long rather than short-term.

Situationally, this indicates that investors could be prone to overtrading, which leads to sub-par returns. This assumption holds true in our four datasets, where the difference in average returns between the top and bottom half in terms uncertainty avoidance scores equaled 993 basis points. Investors with higher uncertainty avoidance scores, generally speaking, emphasize shorter terms (up to a year) more than longer-term investments, causing them to overtrade and perform sub-optimally within the very timeframe they wish to generate returns on their investments. Hofstede (2001) explains that people from countries with high uncertainty avoidance may paradoxically take bigger risks to avoid uncertainty and Wang, Rieger and Hens (2021, p. 113) report of higher degrees of uncertainty avoidance associated with greater propensity to to risk seeking in negative as well as positive domain, showing how different risk attitudes can also differ within a framework such as prospect theory.

We cannot reject the null hypothesis of research question 1, but rejecting the null for question 5 is possible. The data suggests that power distance, like uncertainty avoidance, had an inverse effect on stock market returns, this time in the period between April and August, 2020. It is well documented that how people express and regulate emotions is country specific and cross-country variation quite significant. Recent studies also indicate that emotions play a crucial role in loss aversion in spite of varying degrees of expression and regulation. (Wang, Rieger & Hens, 2021, pp. 130–132). Wang, Rieger and Hens (2021, p. 145) conclude that individuals from countries exhibiting higher levels of power distance (and individualism) are more prone to loss-averse behavior. Surprisingly, no statistically significant association could be found between loss aversion and uncertainty avoidance.

Countries with higher power distance index results are proven to be less prone to herding behavior (Lobão & Maio, 2019, p. 54). Herding behavior produces momentum swings in the financial markets, therefore a low degree of herding implies lower stock price volatility. Graham and Pirouz (2010) as well as Tokar Asaad (2013) confirm this notion, reporting of a strong inverse correlation between PDI and stock market volatility. Higher power distance index results have also been connected with more conservative risk profiles and asset allocation. Amirhosseini's work (2012) indicates that Iran's high power distance index and investor's age, income, and status influence affect their strategic behavior, causing them to be more conservative investors. High PDI has also been connected to negative sentiment towards cross-border investments (Tokar Asaad, 2013), making conservative portfolios even more restricted and conservative.

While only UAI and PDI have proven themselves to be statistically significant in the regressions that included control variables, LTOWVS and MAS have shown to have an impact when observed in a vacuum of cultural factors vis-à-vis stock returns. The former was proven to have a p-value below the critical 5% threshold in Dataset 1, 2, and 4, and the latter in Dataset 1 and 4. This could imply statistical inference of the cultural factors on stock returns, but those would be even smaller compared to the effects of UAI and PDI.

According to Breitmayer, Hasso and Pelster (2019), higher scores on the long-term orientation scale are related to decreased levels of disposition effect, with investors from countries of Asia-Pacific region showing a greater propensity to the disposition effect compared to Europeans and investors in the Sub-Saharan regions in years 2014 to 2017. What is more, a one standard-deviation in long-term orientation was shown to relate to a 15.7% decrease in the disposition effect. Comparing Breitmayer's data to the returns observed in my dataset, his findings hold true for Datasets 2 and 4, where European stocks outperformed those found in the Asia-Pacific indices. This indicates that investors from Asia-Pacific countries used in my analysis have shown inclinations to selling off winning and holding on to losing stocks within their respective indices for too long. Additionally, Hammerich (2020) concluded his research on LTOWVS and IDV provides data with robust predictive power for global firm-level returns, as well as summarizing that the two factors along with UAI and MAS all contribute to country-specific home bias.

Masculinity was proven as statistically significant across longer time horizons, as supported by statistical significance at the 5% threshold for data spanning between February and August as well as the entire year of 2020 (Dataset 1 and 4). Lobão and Maio (2019) have reported that similarly to high power distance results, high masculinity levels negatively affect herd behavior. Herding is often seen as a culprit for large market swings, which, as we have observed, may be more prominent in countries with lower masculinity index results. The authors also report of findings of the factor being associated with overconfidence, which often results in overtrading and greater portfolio diversification, since more masculine investors believe they possess information superior to others. Amirhosseini's reports (2012, p. 687) further support the notion masculinity levels correlate with higher risk tolerance, characterized by more aggressive investment portfolios and higher trading volume. Observing market returns across our four datasets, it appears countries with lower masculinity scores did, in fact, outperform those with higher scores, providing further support to the mentioned observations.

To test the models' robustness, I performed an additional OLS regression on Dataset 1. Using excess returns over the required returns calculated according to the capital asset pricing model as the dependent variable, I regressed the regressand over all eight explanatory factors (six cultural and the two control variables). The results proved the factors have greater explanatory power when observed in relation to absolute rather than excess returns. As can be observed in Table 12 and Appendix J, the only statistically significant variable is gdpdelta, which has a positive effect on our excess returns.

Table 12: OLS Output - Dataset 1/Robustness Test

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	9.071	11.989		0.757	0.453		
	pdi	-0.052	0.099	-0.072	-0.522	0.604	0.482	2.073
	idv	-0.033	0.082	-0.053	-0.407	0.686	0.540	1.851
	mas	-0.123	0.072	-0.176	-1.716	0.093	0.872	1.147
	uai	-0.087	0.064	-0.138	-1.360	0.180	0.891	1.122
	ltowvs	0.121	0.080	0.181	1.504	0.139	0.637	1.570
	ivr	0.064	0.085	0.094	0.752	0.456	0.588	1.700
	rir	-0.073	0.251	-0.029	-0.292	0.772	0.921	1.086
	gdpdelta	1.364	0.286	0.597	4.773	0.000	0.587	1.702

a. Dependent Variable: Excess Returns

Source: Own work.

The robustness test implies that annual change in GDP explains the variability of our excess returns, but the model as such has a weaker explanatory value compared to the R^2 observed in Regression 2 of Dataset 1, where the same explanatory values are analysed against the indices' absolute returns. The R^2 value decreased from 0.640 in Dataset 1 Regression 2 to 0.577 in the robustness test of Dataset 1

CONCLUSION

Behavioural and cultural factors continue to gain traction in explaining economic and financial phenomena. Kahneman and Tversky helped form the foundations of modern behavioural finance and economics with their prospect theory. Geert Hofstede, on the other hand, built the basis of quantifiable cultural analysis by creating six cultural dimensions, allowing us to observe cultural differences on a numerical spectrum. The purpose of this master's thesis was to analyse the interplay between tried and tested assumptions of neoclassical economics, behavioural finance, variations in culture and stock market returns in the year 2020, a year of great uncertainty brought about by the 2019-nCoV pandemic. I have begun my thesis by reviewing existing literature on neoclassical economics, prospect theory, behavioral biases connected with investment decisions and cultural factors as presented by Geert Hofstede. My empirical analysis consisted of Fisher's test and OLS regressions, by means of which I attempted to draw statistically significant inferences between cultural factors and stock market returns on a sample of 55 different countries across four different time periods – the entire year 2020, February – March 2020, April – August 2020, and February – August 2020.

My findings suggest that cultural factors of uncertainty avoidance and power distance index had a statistically significant, inverse effect on returns of individual stock market indices for each of the 55 countries in my sample. Investors with higher uncertainty avoidance have been shown to prefer shorter investing time horizons, which can lead to overtrading and subpar performance in the very time domain they wish to excel. Avoiding or decreasing uncertainty also leads to investors falling prey to home bias, where they overweigh their portfolios in favour of domestic stocks as opposed to diversifying their portfolios with stock of foreign origin. When paired with high power distance scores, individuals avoid cross-border investments even further, making their portfolios even more restricted and biased. Higher power distance results have also been shown to predict herding behaviour, which can produce momentum swings in the financial markets, a facet that was on full display in 2020.

While the field of cultural finance is still in its early stages, this thesis helps expand on the existing assumption of the effects cultural factors have on stock market returns by observing their effects within a shorter timespan with highly volatile price movement, a stage ripe with opportunity for behavioural biases to shine through the inadequacies that neoclassical economics assumptions tend to disregard.

REFERENCE LIST

1. Ackert, F. L. & Deaves, R. (2010). *Behavioral Finance: Psychology, Decsion-Making and Markets.* Mason, OH: South-Western Cengage Learning.
2. American Psychological Association. (2021, April 5). *APA Dictionary of Psychology.* Retrieved 21 September 2022, from https://dictionary.apa.org/self-confidence
3. Amirhosseini, Z. (2012). Effect Of Cultural Dimensions On Stock Exchange Investment Decisions in Iran. *Journal of Business & Economics Research*, 10(2), 681–688.
4. Andreoni, J. & Sprenger, C. (2009). *Certain and Uncertain Utility: The Allais Paradox and Five Decision Theory Phenomena*. La Jolla, CA: University of California, San Diego.
5. Baltaci, A., Cergibozan, R., & Ali, A. (2020). Cultural values and the global fnancial crisis: a missing link? *Eurasian Economic Review*.
6. Barber, B. M. & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The journal of Finance*, *55*(2), 773–806.
7. Barrett, L. (2021, February 19). *Müller-Lyer illusion*. Retrieved 4 September 2022, from https://how-emotions-are-made.com/notes/File:M%C3%BCller-Lyer_illusion.png
8. Berk, J. & DeMarzo, P. (2017*). Corporate Finance* (4th ed.). Harlow: Pearson Education Limited.
9. Breitmayer, B., Hasso, T. & Pelster, M. (2019). Culture and the disposition effect. *Economics Letters*, *184*, 108653.
10. Chen, S. H. & Yeh, C. H. (2002). On the emergent properties of artificial stock markets: the efficient market hypothesis and the rational expectations hypothesis. *Journal of Economic Behavior & Organization*, *49*(2), 217–239.
11. Chui, A. C., Titman, S. & Wei, K. J. (2010). Individualism and momentum around the world. *The Journal of Finance*, *65*(1), 361–392.
12. Erdogan, B. (2014). *The role of uncertainty avoidance in foreign investment bias*. Trier: University of Trier, Department of Economics.
13. Fama, E. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383–417.
14. Ferris, S. P., Jayaraman, N. & Sabherwal, S. (2013). CEO overconfidence and international merger and acquisition activity. *Journal of Financial and Quantitative Analysis*, *48*(1), 137–164.
15. French, K. R. & Poterba, J. M. (1991). Investor diversification and and invernational equity markets. *American Economic Review*, *81*(2), 222–226.
16. Glen, S. (2022a, August 28). *F Test.* Retrieved 4 September 2022, from https://www.statisticshowto.com/probability-and-statistics/hypothesis-testing/f-test/
17. Glen, S. (2022b, August 28). *Variance Inflation Factor*. Retrieved 4 September 2022, from https://www.statisticshowto.com/variance-inflation-factor
18. Goetzmann, W. N. & Kumar, A. (2008). Equity portfolio diversification. *Review of Finance*, *12*(3), 433–463.

19. Graham, J. & Pirouz, D. (2010). Culture, Globalization, and Stock Price Volatility. *SSRN Electronic Journal*, 1–48.
20. Hammerich, U. J. (2020). *Price, Cultural Dimensions, and the Cross-Section of Expected Stock Returns*. Bremen: University of Bremen.
21. Hayes, A. (2022, August 21). *Chi-Square (χ2) Statistic*. Retrieved 4 September 2022, from https://www.investopedia.com/terms/c/chi-square-statistic.asp
22. Heath, C. & Tversky, A. (1991). Preference and belief: Ambiguity and competence in choice under uncertainty. *Journal of risk and uncertainty*, *4*(1), 5–28.
23. Heukelom, F. (2015). A history of the Allais paradox. *The British journal for the history of science*, *48*(1), 147–169.
24. Hofstede, G. (2001). *Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations*. Thousand Oaks, CA: Sage Publications, Inc.
25. Hofstede, G. (2022, June 10). *Dimension data matrix*. Retrieved 12 September 2022, from https://geerthofstede.com/research-and-vsm/dimension-data-matrix and Eikon Datastream
26. Hofstede, G., Hofstede, J. & Minkov, M. (2010). *Cultures and Organizations: Software of the Mind.* New York: McGraw-Hill.
27. Iliyanova, E. (2016). *Does Masculinity Affect Financial Risk Taking and Behavior?* Tilburg: Tilburg University.
28. Kahneman, D. & Tversky, A. (1979, March). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263–291.
29. Kahneman, D. & Tversky, A. (1981). The Framing of Decisions and the Psychology of Choice. *Science*, *3*, 453–458.
30. Kahneman, D. & Tversky, A. (1984). Choices, Values, and Frames. *American Psychologist*, *39*, 341–350.
31. Kahneman, D. (2011). *Thinking, Fast and Slow*. London: Penguin Random House UK.
32. Kelly, M. (1995). All their eggs in one basket: Portfolio diversification of US households. *Journal of Economic Behavior & Organization*, *27*(1), 87–96.
33. Lobão, J. & Maio, J. (2019). Herding around the World: Do Cultural Differences Influence Investors' Behavior? *Portuguese Journal of Finance, Management and Accounting*, *2021*, 48–68.
34. Mandler, M. (2014). Irrationality-Proofness: Markets Versus Games. *International Economic Review*, *55*(2), 443–458.
35. Mao, J. C. (1970). Essentials of Portfolio Diversification Strategy. *The Journal of Finance*, 1109–1121.
36. Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, *7*(1), 77–91.
37. Maslow, A. (1943). A theory of Human Motivation. *Psychological Review*, *50*(4), 370–396.
38. Menton, J. (2020, March 16). *What zero rates, sub-1% bond yields mean for your mortgages, student loans and credit cards*. Retrieved 4 September 2022, from

https://eu.usatoday.com/story/money/2020/03/16/coronavirus-what-zero-rates-sub-1-bond-yields-mean-your-loans/5046861002/

39. Merriam-Webster, Inc. (2008). *Merriam-Webster's Advanced Learner's English Dictionary.* Springfield, MA: Merriam-Webster, Incorporated.
40. Moses, J. (2020, August 27). *App-Based Brokerages and the Rise of the Retail Investor.* Retrieved 4 September 2022, from https://www.ibisworld.com/industry-insider/analyst-insights/app-based-brokerages-and-the-rise-of-the-retail-investor
41. NASDAQ. (2018). *High Frequency Trading (HFT).* Retrieved 4 September 2022, from https://www.nasdaq.com/ glossary/h/high-frequency-trading
42. Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of finance, 53*(5), 1775–1798.
43. Ozorio, B., Lam, D. & Fong, H. N. (2010). The influence of individualism and uncertainty avoidance on per capita gambling turnover. *International Gambling Studies, 10*(3), 221–238.
44. Pennycook, G. & Thompson, V. (2016). Base-Rate Neglect. In R. Pohl (ed.), *Cognitive Illusions: Intriguing Phenomena in Thinking, Judgment, and Memory* (p. 44). Hove: Psychology Press.
45. Thaler, R. H. & Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management science, 36*(6), 643–660.
46. Thaler, R. H. (1999). Mental accounting matters. *Journal of Behavioral decision making, 12*(3), 183–206.
47. Tokar Asaad, C. (2013). *Two essays in finance: Cultural finance and behavioral financial literacy.* Kent, OH: Kent State University Graduate School of Management.
48. Wang, M., Rieger, M. & Hens, T. (2021). Cultural Finance: A World Map of Risk, Time and Money. Singapore: World Scientific Publishing Co. Pte. Ltd.
49. Wang, M., Rieger, M. O. & Hens, T. (2016). How time preferences differ: Evidence from 53 countries. *Journal of Economic Psychology, 52,* 115–135.
50. Weintraub, E. R. (2020, December 26). *Neoclassical Economics*. Retrieved 4 September 2022, from https://www.econlib.org/library/Enc1/NeoclassicalEconomics.html
51. West, G. (2006). *An introduction to Modern Portfolio Theory: Markowitz, CAP-M, APT and Black Litterman*. Cape Town: Financial Modelling Agency.

APPENDICES

Appendix 1: Povzetek (Summary in Slovene language)

V luči novodbnih pristopov k analizi delniških trgov, kjer slednji niso več striktno videni kot popolnoma racionalni, je namen te magistrske naloge obravnavati vpliv kulturoloških faktorjev in z njim povezanimi vedenjskimi pristranskostmi na gibanje delniških trgov v letu 2020. Prvotnemu pregledu in analizi ustrezne literature sledi empirična analiza 55 držav in z njimi povezanimi kulturološkimi faktorji in donosi njihovih delniških trgov. Prvotno je bila opravljena Chi-square analiza, kjer sta izstopala dva kulturološka faktorja, natančneje faktor povezan z izogibanjem negotovosti ter faktor povezan z ohranjanjem razdalje z družbeno nadrejenimi posamezniki. Na podlagi the ugotovitev so se formulirala raziskovalna vprašanja, ki so proučevala posamezne kulturološke faktorje in njihov vpliv na donose delniških indeksov v različnih časovnih intervalih. Analiza je bila izvedena s pomočjo običajne regresijske analize najmanjših kvadratov, kjer so bili uporabljeni kulturološki faktorji, realne obrestne mere ter bruto domači proizvod kot neodvisne spremenljivke, donos pa kot odvisna spremenljivka. Rezultati analiz so prikazali statistično relevanten odnos med prej omenjenima faktorjema na donose delniških trgov znotraj leta 2020. Oba kulturološka faktorja sta imela negativna beta koeficienta, kar pomeni da so delniški indeksi držav z višjimi rezultati meritev faktorjev, povezanih z izogibanjem negotovosti in ohranjanjem razdalje z nadrejenimi, trgovali slabše, kot tisti z nižjimi rezultati meritev.

Ključne besede: vedenjske finance, finančni trgi, vedenjske pristranskosti, hevristike, delniški indeks, donos