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Course of Financial Statement Analysis

A study of the psychological effect of Covid-19 on stock prices

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Abstract

Does the market behave rationally in times of crisis? Does it value stocks using the same methods used in times of normal market conditions? What has happened in the stock market during the COVID-19 period?

These are the questions a rational investor should be thinking about in these times of crisis caused by the COVID-19 pandemic. Indeed, the market has not behaved rationally, with declines in the stock market being dictated more by fear than anything else.

Under normal circumstances, the market evaluates companies by giving the most attention to the future cash flows of a company, to prices paid in precedent transactions, to ratios of peer companies in the same industry, and so on. However, during the COVID-19 crisis, investors partially changed the way they valued companies. Indeed, the risk of bankruptcy and the consequent fear to lose most or the entirety of their investments has had a predominant effect on the stock prices of the various companies.

Then, why did investors behave irrationally? Because of a widespread sell-off, alimented by the chaos introduced in the market by the stringent measures adopted by the various countries (such as lockdowns) to contain the spreading of the virus, inducing investors to overestimate the probability of default inherent in some companies or to just adopt a panic-sell behavior. Such a phenomenon caused valuations of stocks to decrease drastically until the 23rd of March, when, in the United States, the FED started to directly purchase securities in the market, hence increasing the liquidity and decreasing the fear of investors.

By looking at the rating of the companies as for the S&P (External Credit Assessment Institution), I first segment stocks of the S&P500 in buckets, and then I create for each bucket a portfolio that maximizes the Sharpe Ratio. A comparative analysis is implemented to see how these portfolios have performed relative to each other. Indeed, those stocks which were not as risky as the market thought during the market crash in February and March will probably be among the top performers, in terms of stock price change, in the months following the decline.

Subsequently, the same portfolios are analyzed in different years to understand whether the cross-portfolio results are just due to the structure of the market, or if, oppositely, they have been the consequence of the panic-sell.

I expect the return of the portfolio with the highest Issuer Credit Rating to be the highest (in terms of Sharpe Ratio), considering that these stocks have been hugely penalized by investors without a fundamental reason.

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Chapter 1: The path towards the development of the Prospect Theory and the main heuristics for the behavioral analysis of the stock market amidst Covid-19

1. The various steps towards the development of the prospect theory

The steps into behavioral finance were made by the Expected Utility Theory, which was created by Daniel Bernoulli in 1738.[1] The theory is based on actions without certainty about the outcome, where the individual must decide without knowing the precise consequences. Indeed, people select the option which allows them to maximize their expected value, which is normally calculated by multiplying the various outcome of a prospect by their respective probabilities.

However, in the real-life, the Expected Utility Theory has been violated multiple times by individuals in different contexts. Such violations are due to the strong restrictions imposed by the axioms, which do not stick to the reality of human behavior in many cases. These violations normally stem from the independence axiom (if an individual prefers one lottery to another, adding one lottery to the precedent two will not affect the decision of the individual) of the Expected Utility Theory and the assumption that individuals tend to have well-defined preferences when they have to make a choice.

Considering the fallacy of the expected utility theory, a growing literature has become increasingly popular. Such studies started with the inclusion of decision weights. Indeed, it is common for an individual to overestimate the probability of an event happening.[2] Individuals tend to overestimate the probabilities of tail-events (that is, events characterized by low probability and high consequence). An example would be the mortality risk, which people normally tend to exasperate for very improbable events (while more probable causes of death are underestimated in terms of probability of happening).

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[1] D. Bernoulli, 1738, " *Specimen theoriae novae de mensura sortis* "

[2] W. J. W. Botzen, H. Kunreuther & E. Michel-Kerjan, 2015, "*Divergence between individual perceptions and objective indicators of tail risks: Evidence from floodplain residents in New York City*"

The integration of decision weights in the Expected Utility Theory was first proposed by Ward Edwards.[3] In his paper, he tries to explain the paradox of Daniel Bernoulli regarding why people buy insurance policies even though the payoff is negative. In his opinion, people try to maximize their utility function (as the Expected Utility Theory predicts) but using subjective probabilities, which can diverge quite substantially from the real ones.

In turn, he defines a subjective expected utility, which can be described as a function that weights the various outcomes of an event by their subjective probabilities (while, in the Expected Utility Theory, probabilities stick to the reality). Indeed, subjective probabilities are affected by the probability of obtaining the outcome, and by the payoff itself.

$$SEU = \psi_1\mu_1 + \psi_2\mu_2 + \cdots + \psi_n\mu_n$$

Where SEU is the subjective expected utility, ψ is the subjective probability of the event associated by the individual, while μ is the respective payoff of such event. The peculiarity of the probability weighting function is that it transforms probabilities without imposing monotonicity on the model.

Following this path, further advancements have been made, culminating in the Prospect Theory developed by Kahneman and Tversky in 1979.[4] Here, agents are considered boundedly rational, in the sense that their rationality is limited by the exercise of decision heuristics. Indeed, the environment in which individuals tend to take their decisions is most of the time complex in nature, hence forcing the agent to implement some strategies to ease their decision-making process.

In the Prospect Theory, Kahneman and Tversky argue that people's decision-making process can be divided into a two-step process: In the first phase, agents use choice heuristics to modify the prospects, while, in the second phase, they use a utility function to determine the decision of preference.

The implementation of a two-phase process is crucial. Indeed, individuals are influenced by a series of factors (that will be later discussed), such as myopic loss

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[3] W. Edwards, 1962, "*Utility, subjective probability, their interaction, and variance preferences*"
[4] D. Kahneman & A. Tversky, 1979, "*Prospect Theory: An Analysis of Decision under Risk*"

aversion, framing, herding behavior, etc. Thanks to the Prospect Theory, it is possible to connect theory and empirical data, considering that, as previously highlighted, the Expected Utility Theory is intrinsically flawed when compared to real-life data.

A major feature of the prospect theory is the fact that it interprets profits and losses only relative to a reference point. This reference point is defined as the current asset position of the agent. What the agent is interested in is the magnitude of change from the reference point. The utility function was previously described as a concave function, considering a risk-averse individual. Now, such function assumes another form: above the reference point, the function is concave, while below such point the function is convex (Figure 1).

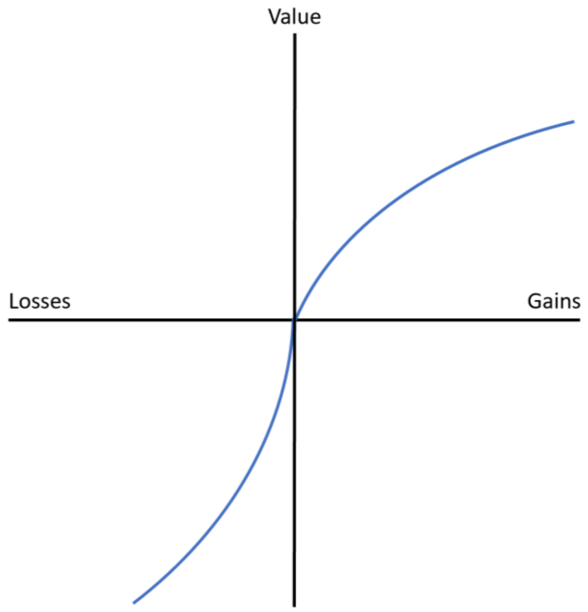

Figure 1: A hypothetical value function (D. Kahneman & A. Tversky, 1979)

This kink at the reference point conveys the idea that individuals are loss averse: the function is much steeper below the reference point, indicating that the absolute value of the utility derived from a loss is bigger than the absolute value of the utility generated by a gain of the same magnitude.

Considering the aforementioned reference point, the Prospect theory also implies that individuals, depending on where they stand concerning this point, can be risk-averse or risk-seeking. Such behavior is caused by the diminishing sensitivity of the utility function: after having received a loss, the marginal disutility coming from a further loss is lower than the marginal utility stemming from a gain. The same happens in the domain of gains: after receiving a gain, the utility coming from a further gain would always be lower than the disutility coming from a loss. Specifically, this effect is due to the decreasing marginal utility of the preference function, both in the domain of losses and in the one of gains.

This peculiarity of the utility function of the Prospect Theory is indeed highlighted in Figure 1. The inverted S-shaped curve represents such behavior because it gets steeper near the reference point, and then it flattens the further we go from that point.

In their paper, Kahneman and Tversky do not only establish the notion of the reference point (which is, as stated before, the current asset position) but also argue that this point could also be affected by the formulation of the prospects proposed to the agents. Indeed, depending on how the information is conveyed to the agent, he/she will "code" the probabilities and outcomes differently.

Other heuristics associated with the first phase of the dual-step decision-making process are discussed in the Prospect Theory (cancellation, combination, etc.). However, these are not considered in this paper, since they are not useful for the subsequent analysis regarding the crisis triggered by COVID-19.

The prospect theory has been a major advancement in the field of behavioral economics. This model has indeed partially reconciled investors' behavior with theory.

2. Alternative explanations of the stock market crisis during the COVID-19 period

To discuss the effect of the coronavirus crisis on people's behavior I will consider the United States as an example. Indeed, even though the COVID-19 pandemic and the consequent stringent measures adopted have left a mark on the various economies, each country has its peculiarities.

The United States has been selected also because the US stock market is by far the largest and most liquid one in the world. Such characteristics are of primary importance for the analysis. Indeed, the absence of strong liquidity in the market could cause the below analysis to be misled.

2.1 A shifting focus in companies valuation: the probability of default

Before the advent of the crisis, the US economy has been subject to a period of prolonged economic growth, the longest economic expansion in history (Figure 2).[5] During this period, the market experienced some moments of correction, where it declined by about 5%. However, such a decline is not enough to be considered a bear market.

People, and specifically investors, started to get used to ever-increasing stock market valuations. Moreover, thanks to the economic expansion and the increasing stock prices, many investors had accumulated some profits in their portfolios.

However, due to the advent of COVID-19, the real economy has been hit hard, with many companies forced to close their stores or to stop their production processes. As of March 23rd, the US stock market bottomed, with major indexes (S&P500, Dow Jones Industrial Average, etc.) plummeting more than 30%. Thanks to the monetary support of the FED (which infused in the market not only liquidity but also investor confidence) stock prices started to recover.

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[5] D. J. Marotta, 2020, *https://www.forbes.com/sites/davidmarotta/2020/01/21/longest-economic-expansion-in-united-states-history/#61a0716762a2*

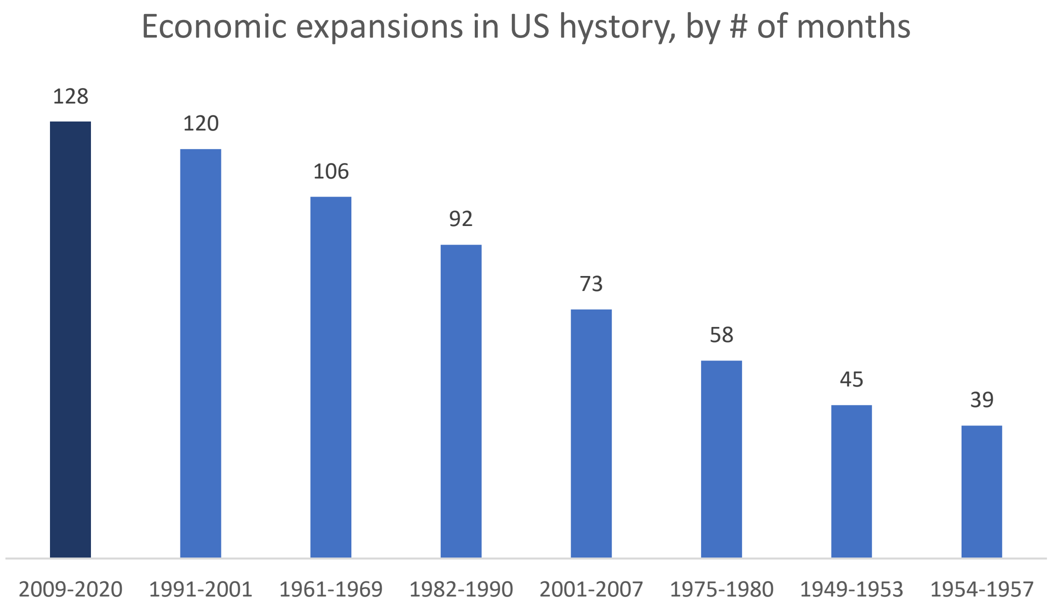

Figure 2: Ranking of US economic expansions in history, by number of months of expansion (National Bureau of Economic Research)

Both cross-country stock market correlation and cross-sector stock correlations increased during the period before the market bottom. A study from the Sichuan University[6], by conducting an event study, highlighted that the stock markets of the major affected countries fell quickly after the outbreak of the virus. This study has been conducted by taking into consideration the USA, Japan, Korea, Singapore, Germany, and the UK among others. This study has also highlighted the importance of investors' fear in the propagation of the effect of the coronavirus on the different stock markets. Such fear has been described as "*a complete mediator and transmission channel for the COVID-19 outbreak's effect on stock markets*" in the paper.

Regarding cross-sector correlation during the same timeframe (19th Feb – 23rd March 2020), another study from Monash University[7] examined sentiment across investors of different types. The results highlighted one sentiment shift during the coronavirus period: in a good economic state, sentiment across different industries moves independently from one another, while during the coronavirus recession period,

[6] H. Liu, A. Manzoor, C. Wang, L. Zhang, Z. Manzoor, 2020, "*The COVID-19 Outbreak and Affected Countries Stock Markets Response*"

[7] H. Fallahgoul, 2020, "*Inside the Mind of Investors During the COVID-19 Pandemic: Evidence from the StockTwist Data*"

healthcare tends to be negatively correlated with most of the other sectors. This shows that correlations across sectors, excluding healthcare, have increased substantially.

But how can we explain such coordinated movements in the stock markets? Investors have been subject to a widespread fear that made them change their traditional valuation methods, putting more emphasis on the probability of defaults then before. However, the chances are that such risk of default was not well considered by investors.

An example could be the stock prices of tech companies. Investors did not consider the potential benefit that the pandemic and the lockdowns could have brought to that industry. Indeed, in the beginning, also these stocks plummeted, even though they then experienced a strong V-shape recovery in price. Investors realized that those stocks were not exposed to a substantial risk of default and that they would even be favored by COVID-19 since digitalization trends have been massively accelerated by the pandemic.

Many sectors have been more hardly hit by the crisis than others. These are the industry linked to the economic reopening, such as aviation companies, cruise lines, travel agencies, oil companies, car manufacturers, restaurants, retail stores, etc. Indeed, these industries have been extensively damaged by lock-downs, travel restrictions, and social distancing, which have caused increases in balance sheet leverage, bankruptcies, lay-offs, and restructurings. Some examples of bankruptcy due to COVID-19 are Hertz (car rental company), J.C. Penny (retailer), 24 Hour Fitness (chain of gyms), and Brooks Brothers (retailer) among others.

The stock price of these companies decreased substantially, mainly because the estimated probability of default increased substantially. However, investors have hit too hard on many stocks, and indeed the market experienced a strong rebound right after March 23rd. Even though such rebound was mainly caused by the intervention of the FED, we must also consider that the FED's intervention aimed at bringing back liquidity to the market and stop the chaotic sell-off which investors were fueling. Indeed, the support from the government has been used also to stop the herding behavior that investors put in place in the first three months of 2020.[8]

[8] R. Kizys, P. Tzouvanas, M. Donadelli, 2020, "*From COVID-19 herd immunity to investors herding in international stock markets: The role of government and regulatory restrictions*"

In the following sections, such decline will be analyzed with a behavioral finance lens, highlighting the possible explanations underneath the stock market crash between the 19th of February and the 23rd of March. Indeed, such decline has been exasperated because of a series of behavioral factors.

2.2 Risk Aversion, Loss Aversion & Myopic Loss Aversion

Normally, as explained in the Prospect Theory, loss aversion would be a counter-factor to describe why investors tend to disinvest when receiving losses. However, here the situation is different, considering that the reference point in investors' minds had been shifted by the prolonged period of economic expansion.

Empirical literature considers that investors' reference point stands at the initial purchase price of the financial instrument. Moreover, it has been proven that investors tend to adapt their reference point depending on, at least, two effects: prior outcome and future expectations of price movements.[9]

Considering that prior outcome is one of the main factors which influence investors when deciding about disposing of an investment or keeping it in their portfolio, it is clear that the prolonged increase in stock prices (related to the longest economic expansion ever) has made investors more risk-averse when dealing with losses.

If we use as a reference point the purchase price of an instrument X, those investors who have experienced large gains following the strong performance of X's stock price in the last years will receive almost no increase in utility when experiencing a new gain. Oppositely, they will tend to be more risk-averse, as a direct result of the decreasing marginal utility of the utility function.

[9] C. N. Chiyachantana & Z. Yang, 2013, "*Reference Point Adaptation and Disposition Effect*"

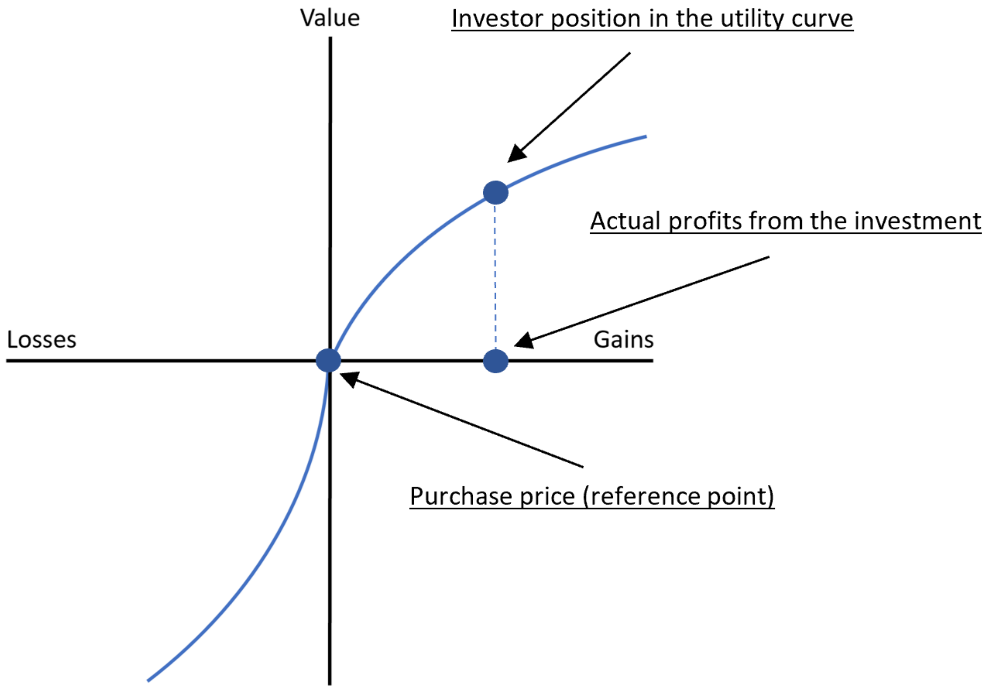

Figure 3: Example of an investor position in its utility curve after the long economic expansion

As depicted in Figure 3, at the advent of the crisis, the majority of investors found themselves in the position of having experienced relevant gains, therefore assuming a risk-averse position regarding future losses. Such risk-aversion has in turn pushed investors to liquidate their investments when the first losses arrived during the recession period, hence further alimenting the decline in stock prices.

Remaining on the topic of loss aversion and reference point, also future expectations of price movements affect the reference point and, in turn, investors' decision on whether to disinvest. Following the empirical test developed by the Lee Kong Chain School of Business[10], a downturn in market conditions could increase the possibility to sell an investment by about 60%. When information is not available, such an increase is even higher.

Therefore, when the market started to collapse, investors were negatively affected by a change in future expectations and by the uncertainty surrounding the virus and the possible repercussions over the economy (and, consequently, stock prices). This

[10] C. N. Chiyachantana & Z. Yang, 2013, "*Reference Point Adaptation and Disposition Effect*"

scenario pushed investors to sell their investments, hence worsening the stock market conditions and causing a further decrease in stock prices.

However, many could say that these types of loss aversion behaviors are common only among non-professional investors, given that professional investors should be more experienced, hence being capable of reducing the effect of mental biases.

This is not the case. Experimental analysis from the University of Maryland has highlighted the opposite regarding Myopic Loss Aversion[11]: such anomalies do not disappear but become even larger for professional traders.[12]

They created a subject pool composed of both professional traders from the Chicago Board of Trade, and non-professional traders (undergraduate students). The second group has been used as an experimental control group. The results of this study are very important considering that professional investors play a big role in stock price determination.

The result of this study highlighted that, not only professional traders do experience myopic risk aversion, but also they are subject to this anomaly even to a greater extent than what students are.

Positive results regarding loss aversion have also pushed other researchers to explore asset pricing[13], portfolio choices[14], and portfolio performance evaluation[15] taking into account loss aversion. These studies highlighted that loss aversion affects the price of assets and portfolio evaluation. For example, looking at asset pricing with portfolio aversion, results show that, by considering this mental fallacy in an asset pricing model, the results obtained are much better than the ones obtained by using conventional asset pricing models.

Therefore, considering the short-term view and the loss-aversion behavior to which investors are subject to, the market decline in the period between the 19th of

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[11] Myopic Loss Aversion is different from the well-known Loss Aversion effect. Indeed, this mental fallacy says that investors are not only loss-averse, but they also tend to evaluate their portfolios quite often. The latter implies that investors focus on more on the short-term.

[12] M.S. Haigh & J. A. List, 2002, "*Do Professional Traders Exhibit Myopic Loss Aversion? An Experimental Analysis*"

[13] L. Grune, W. Semmler, 2007, "*Asset Pricing with Loss Aversion*"

[14] A. Berkelaar, R. Kouwenberg, 2008, "*Optimal Portfolio Choices Under Loss Aversion*"

[15] V. Zakamouline, 2014, "*Portfolio Performance Evaluation with Loss Aversion*"

February and the 23rd of March most probably pushed investors to drastically change their short-term view on the economy and the stock market, having, as a result, an increased sale of stocks. Indeed, as highlighted above, a series of studies have not only proved the existence of these mental fallacies, but they also have successfully applied such effects in the price discovery mechanism and the portfolio evaluation process.

2.3 Herding Behavior

One behavioral fallacy cannot explain the entirety of the phenomenon that we experienced during the coronavirus crisis. Indeed, even though the average investor experiences loss aversion to some degree, it is not proven that every single investor does so. Therefore, to explain why the market collapse materialized itself, other effects should be taken under consideration, such as the herding behavior.

Herding behavior is a mental fallacy that pushes investors not to follow a logical analysis of their private information, but rather to trade according to what other investors are doing. Therefore, when the average investor starts to trade in a specific way, other investors will follow, even though the information they have is against such action. Indeed, even if there is no way for individuals to know the private information of other investors, they can observe their actions in the market. Therefore, to derive what other investors know, individuals tend to follow others' actions, hence causing a cascade effect.

Moreover, a study from the Poznan University of Economics[16] has highlighted that this effect increases in magnitude when the information available to the decision-maker is not precise. In this case, he/she will be more willing to ignore its private information and follow what other decision-makers are doing. On the other hand, if the agent has more precise information, he/she will tend to listen to his/her private signals, without copying other agents' behavior.

[16] A. Szyszka, 2014, "*Behavioral Anatomy of the Financial Crisis*"

Policymakers are increasingly concerned by the effect that herding behavior can have on the financial market.[17] Indeed, such mental fallacy can provoke an exacerbation of the market volatility[18], destabilization of the market, and augmented market fragility.

Depending on the type of investor, there are different explanations for the herding behavior:

1. Retail investors: a movement in the stock market could mean that other investors have some important information about the investment. Moreover, individuals prefer to make decisions in line with others;
2. Asset managers: conforming your investments to the market trend can be easily explained to investors in case of losses, while it is more difficult to protect yourself, as a manager, if you invest against the general market trend. Therefore, considering the risk of losing your job, imitation is rewarded for asset managers.

Even though this herding behavior could be reasonable for those investors who follow informed investors' decisions, it is not the case for the subsequent agents. The cascade effect creates indeed a negative effect considering that people start following those who are investing, in turn, by following others. These actions are called "uninformative imitative actions", and convey a negative effect to those who follow them.

This effect has been tested empirically by Josef Lakonishok, Andrei Shleifer, and Robert W. Vishny[19] and others, which found no significant evidence of herding behavior in the stock market by asset managers, even though they concluded that such effect is higher for smaller stocks, as less information is available for them. However, this study has been criticized[20] because it is incapable of capturing herding behavior for mainly two reasons: the use of the number of investors does not consider the amount bought/sold; the measure does not say if it is the same funds that continue to herd.

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[17] S. Bikhchandani, S. Sharma, 2000, "*Herd Behavior in Financial Markets: A Review*"

[18] Indeed, during the stock market collapse during the COVID-19 pandemic, the Volatility Index (VIX) surged to new historic highs, surpassing the previous peak level of 80.74 experienced during the Global Financial Crisis

[19] J. Lakonishok, A. Shleifer & R. W. Vishny, 1992, "*The impact of institutional trading on stock prices*"

[20] S. Bikhchandani, S. Sharma, 2000, "*Herd Behavior in Financial Markets: A Review*"

When connecting theory with reality, considering the circumstances surrounding the crisis triggered by the COVID-19 virus, herding behavior has played a role. This mental fallacy could have amplified the sell-off experienced in the market between February 19th and March 23rd, since many investors started selling their securities just because other investors were doing so. Indeed, even though the first investors could have somewhat better information regarding, for example, the probability of bankruptcy of many stocks, this is probably not the same for subsequent investors, which decided to divest because others were doing so.

Indeed, herding behavior tends to be amplified by the absence of precise information, and the Coronavirus spread uncertainty in the market. Even after it manifested itself, no one could have predicted the repercussions that it would have had on the economy. Also, professionals from the medical sector were not able to understand how to fight the virus, and misinformation started spreading. Politics itself started giving different messages to the population around the world, with different approaches to masks, travel restrictions, lockdowns, etc.

Therefore, not only information was not precise, but it was also chaotic and non-unique, pushing investors to rely less on their private signals. When the first sell-offs took place in the stock market, investors started to herd, hence creating a cascade effect.

A study of herding behavior of investors in the stock market during the COVID-19 pandemic[21] has highlighted that herding was present, and that government responses, together with short-selling restrictions, have been quite effective in reducing the magnitude of this effect. In this paper, herding behavior is measured using the cross-sectional standard deviation of the returns, while government response is described as the Oxford COVID-19 Government Response Tracker.

From this, we can conclude that herding, together with loss aversion (and myopic loss aversion), has been one of the mental fallacy guilty of having exasperated the widespread sell-off during the pandemic. Some investors were rationally divesting, following their private information about the high chance of default of companies, but this phenomenon was most probably inflated by other agents herding in the stock market.

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[21] R. Kinzys, P. Tzouvanas & M. Donadelli, 2020, "*From COVID-19 Herd Immunity to Investor Herding in International Stock Markets: The role of government and regulatory restrictions*"

2.4 Framing

Framing is a heuristic that suggests that the way the information is conveyed to the listener can affect the decision of the latter. Agents tend to decide differently depending on how the prospect is framed. Therefore, how the information is presented matters. Regarding investment decisions, framing an investment dilemma will affect the final investment decision of the agent.

To give a simple illustration of the effect of framing on people's decisions, the Müller-Lyer illusion[22] is considered below.

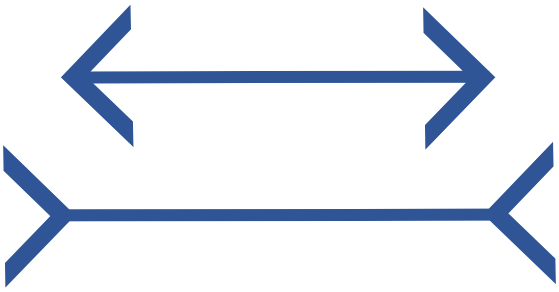

Figure 4: Reproduction of the Müller-Lyer illusion

In the Müller-Lyer illusion, people were asked to state which line is longer in their opinion. As a result, the majority of the sample indicated that the line at the bottom was longer, even though the two lines have the same length. This example is a famous example of framing considering that, by adding a certain configuration to the decision-making problem, the agent's decision can be biased.

Framing has a vast use in our society. For example, the government tends to emphasize the employment rate, instead of the unemployment rate, while addressing economic issues, or, again, companies tend to take peoples' attention by making them focus on the good chunk of a percentage instead of the one gathering the bad information.

[22] Müller & Lyer, 1889, "*Psychophysische Untersuchungen. Über die Abhängigkeit der relativen Unterschiedsempfindlichkeit von Intensität und Extension des Reizes*"

As previously demonstrated by different papers, framing is an important component of the decision making process regarding investment choices. A study from Alok Kumar and Sonya Seongyeon Lim[23] has proved the importance of framing in investment decisions, complementing the research of Barberis and Huang[24], who focused their work on the exploration of narrow framing[25].

Hersh Shefrin argues that frames are not "transparent" as traditional finance says (defining frames as "transparent" is to say that people do not consider them in their decision-making process). Indeed, frames are quite "opaque", that is, investors' decisions depend on the way the investment dilemma is presented to the former. Moreover, Shefrin also identifies some possible causes of frame dependence:

1. Loss Aversion, as previously identified;
2. Concurrent Decisions, hence cases in which people are required to take more than one decision concurrently;
3. Hedonic Editing, which consists of the cognitive strategy adopted by an agent to arrange multiple outcomes to maximize its perceived value.

Therefore, it is widespread that framing plays a relevant role in decision making, and specifically in investment decision making by individuals. The point of interest is now to understand how framing can be connected to the market collapse in February-March 2020.

At the beginning of the COVID-19 crisis, news started to be very negative, highlighting the potential damage and fatality rate of the virus. A vast amount of misinformation hit the financial market, which was not able to understand the reality of what was going on. No one knew how to combat the virus, neither the amount of economic damage it would have caused to the economy.

News created a frame that rendered the pandemic even worse in investor minds. A well-known example is the sentence "The hell is coming" pronounced by the hedge

[23] A. Kumar & S. S. Lim, 2008, "*How Do Decision Frames Influence the Stock Investment Choices of Individual Investors?*"
[24] N. Barberis & M. Huang, 2005, "*The Loss Aversion / Narrow Framing Approach to the Equity Premium Puzzle*"
[25] Investors tend to make investment decisions without taking into consideration the status quo of their portfolios, hence focusing on specific investment opportunities, and not on the entirety of investment options available to them.

fund manager Bill Ackman at a CNBC interview[26] on the 18th of March. Therefore, investors' look at the crisis got even worse, hence pushing some of them out of the market for the fear of losing money, and, in particular, to lose the profits accumulated in the period of economic expansion before COVID-19. Indeed, in this frame, people tended to overestimate the probability of default, reacting too much to bad news.

2.5 Mental accounting

Finally, the last heuristic that I retain guilty of having alimented the sell-off in the period before the 23rd of March is mental accounting. Mental accounting is a special case of narrow framing in that investors tend to create separate mental accounts for different purposes.

Is therefore important for this analysis to highlight that, normally, agents, when investing, tend to keep a low-risk account and a high-risk one. Indeed, as highlighted by Shefrin and Statman[27], investors usually operate with a two-layer portfolio:

1. Low-risk portfolio for downside protection;
2. High-risk portfolio for the desire to "become rich".

What if the low-risk portfolio suddenly shifted to a high-risk one? What would the average investor do in this case? These questions assume a high relevance during periods of crisis, and even more during the crisis caused by the advent of COVID-19 (and other relevant concurrent events). Indeed, the pandemic has transformed radically certain industries, bringing some very stable and profitable companies at the brink of bankruptcy. Investors were faced with a radical change of their low-risk portfolios.

What I presume happened in the market before the 23rd of March is a portfolio rebalancing process to exclude, from the low-risk portfolio, those previously low-risk investments that became much riskier. For example, aviation and cruise companies profoundly changed, and investors started to consider them more as "bets" than anything else.

[26] CNBC, 18/03/2020, *https://www.cnbc.com/2020/03/18/bill-ackman-pleads-to-trump-to-increase-closures-to-save-the-economy-shut-it-down-now.html*
[27] H. Shefrin & M. Statman, 2000, "*Behavioral Portfolio Theory*"

It is, therefore, possible that this mental fallacy contributed to the widespread sell-off experienced in the market, together with Loss Aversion (and Myopic Loss Aversion), Herding Behavior, and Framing. All these heuristics either somewhat influenced investors in their consideration of the risk of default of different stocks, or caused investors to act irrationally, following others' decisions and avoiding considering their own private information.

Chapter 2: The predominance of irrationality in stock prices during the COVID-19 recession period

In this section, I analyze the stock price performance of 373 stocks of the S&P500. To separate the stocks in 6 different groups I split them depending on the long-term issuer rating (as of the end of June 2020) as for the Standard & Poor ECAI.

The choice of the credit rating as the metric used for the split is dictated by the need of creating portfolios depending on the financial soundness of the stocks considered. The aim is to build different portfolios based on the financial quality of the companies.

During the Covid-19 crisis, the market has implemented a sell-off process which has impacted almost every stock in the market. Investors started to drastically increase their perception of the probability of default of these companies, with different behavioral factors contributing to the market decline (loss aversion, herding behavior, framing, and mental accounting).

This analysis aims at analyzing the risk-adjusted returns of the different portfolios to understand whether financially sound companies performed better than others. The underlying idea is that, considering the several behavioral factors involved in the market decline, investors did not base their decisions on a rational evaluation of the fundamentals and prospects of their stocks. Contrarily, they took their decisions based on fear, selling stocks that should have not been penalized to that extent.

The credit rating is a solid measure to perform an analysis of the soundness of the company. This measure is a forward-looking opinion on the obligor's overall creditworthiness, which can be summarized by the ability and willingness to meet its liabilities when they come due. The importance of such rating is also due to the material due diligence that the ECAI conduce, which involves the judgment of not only public but also private information, which is normally not available to investors.

Consequently, the 373 stocks selected from the S&P500 were divided into groups with a number of stocks which ranges between 48 and 76, depending on the availability of stocks for certain credit ratings. The 6 groups are defined as follow:

1. AAA to A: 70 stocks;
2. A- : 54 stocks;

3. BBB+ : 76 stocks;
4. BBB: 72 stocks;
5. BBB- : 48 stocks;
6. BB+ to B- : 53 stocks.

1. Portfolio composition and optimization in Python

The analysis described below is integrally performed using Python programming in Anaconda.

To perform the split I first download and save the tickers and the respective long-term issuer credit ratings for the stocks in the S&P500 from Bloomberg. The data is saved on an excel file, which is then uploaded on Python to understand the availability of stock price data of the single stocks. Daily stock prices are available for 373 stocks on the list.

The next step is to decide how to split the different stocks to create groups of similar dimensions. To do that the following piece of code is used:

```
# Import all the necessary packages and functions for the whole
code

% matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import cvxopt as opt
from cvxopt import blas, solvers
import pandas as pd
import plotly
import cufflinks
import pandas_datareader as web


# Import the file with the tickers and clean it

tickers = pd.read_excel('Tickers S&P500.xlsx')
tickers.set_index('Ticker', inplace = True)


# Convert credit ratings into categorical data and order them

available_stocks = list(returns.columns)
tickers_available = tickers[tickers.index.str.match(('|'.join(ava
     ilable_stocks)))].dropna()
```

```
tickers_available.astype(CategoricalDtype(categories = ['AAA',
      'AA +', 'AA', 'AA-', 'A +', 'A', 'A-', 'BBB +', 'BBB', 'BBB-
      ', 'BB +', 'BB', 'BB-', 'B +', 'B', 'B-'], ordered = True ))
tickers_available.to_excel("Available Stocks.xlsx")
to_plot  =  tickers_available['S&P LT Local Currency Issuer Credi
      t Rating'].value_counts().reset_index().'S&P LT Local Curren
      cy Issuer Credit Rating').astype(CategoricalDtype(categories
      = ['AAA', 'AA +', 'AA' , 'AA-', 'A +', 'A', 'A-', 'BBB +',
      'BBB', 'BBB-', 'BB +', 'BB', 'BB-', 'B +', 'B', 'B-'], order
      ed = True)).sort_values('index', axis = 0)

# Create bar graph

to_plot = to_plot.reset_index().set_index( 'index' )
ax = to_plot.plot.bar(figsize = ( 12 , 10 ))
plt.box(False)

# Insert bar labels

for i in ax.patches :
    ax.text(i.get_x() + 0.25, i.get_height() + 1.5, \
      str(round((i.get_height ()))), fontsize = 15, color = 'dimg
        rey', ha = 'center')
```

First, I import all the necessary functions, both for this part of the code and the next ones. Then I upload the tickers for the available stocks in Python, and I covert the ratings in categorical values, so as to be able toorder them properly. Finally, I create and format a graph to show the disposition of the stocks depending on the rating. The output distribution is the following:

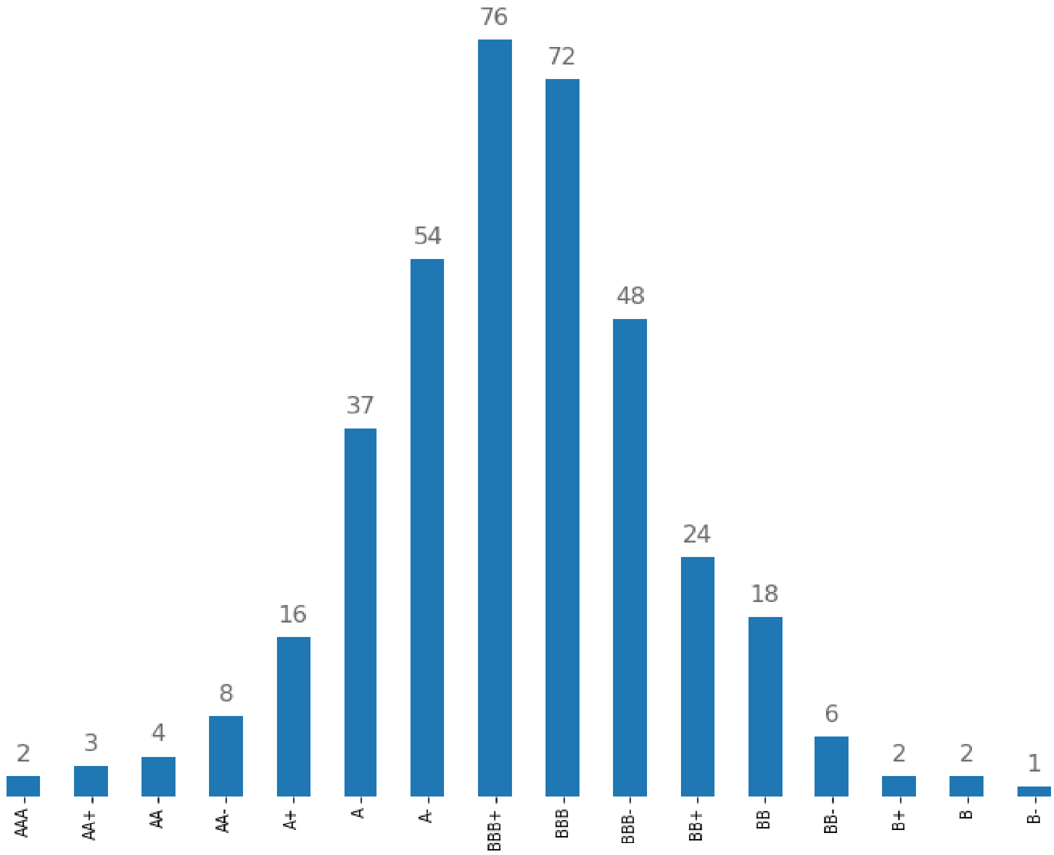

Figure 5: Distribution of stocks based on the issuer credit rating

From the graph, it is possible to see that the division of the stocks can be performed by grouping the tails, to obtain groups composed of about 50 to 70 stocks each. Therefore, I grouped stocks with a credit rating between AAA and A, as well as stocks with rating BB+ to B-.

To group the stocks I did not use python. Instead, I just did it manually, creating 6 different excel files with the respective tickers. However, such a process could be very easily automatized.

Once obtained the most suitable groups for the analysis, I proceed by analyzing each group separately. However, the code can be easily modified from group to group by changing the excel file to upload at the beginning, since the remaining part of the code is the same for each group.

The next step is to download data for the selected stocks (in the code below I take Group 1 (AAA to A) as an example.

```python
# Download daily stock price data for S&P500 stocks

group_1 = pd.read_excel("Group 1_AAA to A.xlsx")
tick =  list(group_1['Ticker'])
price_data = web.get_data_yahoo(tick,
                                start = '2020-03-23',
                                end = '2020-05-31')['Adj Close']
```

The output of this piece of code is a data frame indexed by date (daily, from 2020-03-23 to 2020-05-31), with each column representing a single stock price evolution. The period has been appositely chosen: I start gathering data as from March 23rd, when the Fed announced its commitment to purchase unlimited amounts of US Treasuries and agency MBS, hence halting investors' sell-offs, for a period of about 2 months. Indeed, I must consider a short period because otherwise, the market correction after the decline would have lost importance, and at the same time, I need to collect enough data to develop a decent stock price analysis.

The head of the data frame is represented below:

Symbols	AAPL	ACN	ADBE	ADM	ADP	AMP	AMZN	ANTM	APD	ATO	...
Date											
2020-03-23	223.361542	142.522415	307.269989	28.779951	108.433922	81.628555	1902.829956	174.127914	174.597290	79.574158	...
2020-03-24	245.770386	155.575485	310.000000	31.735519	120.254578	98.549156	1940.099976	196.217896	192.073822	87.571106	...
2020-03-25	244.416489	150.586349	305.910004	32.108646	121.875069	102.035706	1885.839966	215.686157	188.843292	89.261452	...
2020-03-26	257.278442	169.947723	322.670013	33.836815	136.260681	109.195938	1955.489990	234.925171	198.910324	95.162781	...
2020-03-27	246.626511	161.556488	305.829987	32.894180	130.613815	101.769783	1900.099976	222.255341	190.838913	96.289673	...

At this point I need to first drop the columns with N/A values (if present in the data frame) and then transforming the daily price matrix in the return matrix:

```python
# Drop na values from price matrix

price_data_no_na = price_data.dropna(axis=1)

# Transform the price matrix into a return matrix

returns = (price_data_no_na/price_data_no_na.shift(1)-1)[1:]
```

To obtain the return matrix, I apply the following formula to each column of the data frame:

$$Return_{i,T} = \frac{Stock\ Price_{i,T} - Stock\ Price_{i,T-1}}{Stock\ Price_{i,T-1}} = \frac{Stock\ Price_{i,T}}{Stock\ Price_{i,T-1}} - 1$$

The result of this step is the following return matrix (for reasons of space, only the head of the data frame is represented below):

Symbols	AAPL	ACN	ADBE	ADM	ADP	AMP	AMZN	ANTM	APD	ATO	...
Date											
2020-03-24	0.100325	0.091586	0.008885	0.102695	0.109013	0.207288	0.019587	0.126861	0.100096	0.100497	...
2020-03-25	-0.005509	-0.032069	-0.013194	0.011757	0.013476	0.035379	-0.027968	0.099218	-0.016819	0.019303	...
2020-03-26	0.052623	0.128573	0.054787	0.053823	0.118036	0.070174	0.036933	0.089199	0.053309	0.066113	...
2020-03-27	-0.041402	-0.049375	-0.052190	-0.027858	-0.041442	-0.068008	-0.028325	-0.053931	-0.040578	0.011842	...
2020-03-30	0.028538	0.042608	0.041069	0.069552	0.049018	0.056324	0.033603	0.034177	0.069162	0.055538	...

Once obtained the return matrix, I proceed by defining two functions, one to produce x random weight which adds up to one (where x is the number of stocks in the group), and one to calculate and return the standard deviations and return of the portfolio.

```
# Produce random weights for portfolio stocks, constraining them
to be additive to one

def weights(num_stocks):
    k  =  np.random.rand(num_stocks)
    return k / sum(k)

# Calculate mean daily return and daily stdev of portfolio i

def returns_and_stdevs(returns):
    mean_returns_vector = np.asmatrix(np.mean(returns, axis = 1))
    weights_vector = np.asmatrix(weights(returns.shape[0]))
    covariance_matrix = np.asmatrix(np.cov(returns))
    return_port = weights_vector * mean_returns_vector.T
    stdev_port = np.sqrt(weights_vector * covariance_matrix * wei
                 ghts_vector.T)
    return return_port, stdev_port
```

The function "returns_and_stdevs" performs the following tasks:

1. Calculate the mean return ("mean_return_vector") for each portfolios and then store the result in a matrix;
2. Create the weight matrix ("weights_vector") by recalling the precedent function ("weights"), whit as many weights as the number of stocks in the portfolio;
3. Create the covariance matrix ("covariance_matrix"), by taking the return matrix and applying the covariance function;
4. Calculates the return of the portfolio ("return_port") by doing the dot product between the weight vector and the transpose of the mean daily return vector;
5. Calculate the standard deviation of the portfolio ("stdev_port") by taking the square root of the dot product between the weight vector, the covariance matrix, and the transpose of the weight vector.

Now that the functions are defined and ready to use, the next step consists of creating 100,000 portfolios, store the results in two variables and then plot the portfolios in a graph.

```
# Create 100,000 portfolios, and record mean daily returns and
daily standard deviations for each of them

n  =  100000
means, stds = np.column_stack([returns_and_stdevs(returns) for x
                  in range(n)])

# Plot portfolios' mean daily returns and daily standard deviatio
ns previously created

import  matplotlib.ticker  as  mtick

fig, ax = plt.subplots(figsize = (13, 10))
plt.plot(stds, means, 'o', markersize = 4)
plt.xlabel('Standard Deviation', fontsize = 15, alpha = 0.8)
plt.ylabel('Mean return', fontsize = 15, alpha = 0.8)
plt.title('Return and volatility of {} portfolios'.format(str(n))
          , fontsize = 20, alpha = 0.8, fontweight = "bold")
plt.box(False)
plt.grid()
plt.tick_params(top = False, bottom = False, left = False, right
         = False, labelleft = True, labelbottom = 'on')
```

The output of this portion of the code is a formatted graph with the mean daily return of the portfolio in the y-axis and the standard deviation of the portfolios in the x-axis. To plot a better-defined example, the graph below comprises of only 10,000 portfolios (in the real simulation I create 100,000 portfolios instead).

Over the graph is represented (in red) an example of an efficient frontier, that is the line that connects those portfolios which offer the highest expected return for a specified level of risk. Portfolios below that line are considered to be sub-optimal, considering that there exists at least one portfolio with the same risk and higher return.

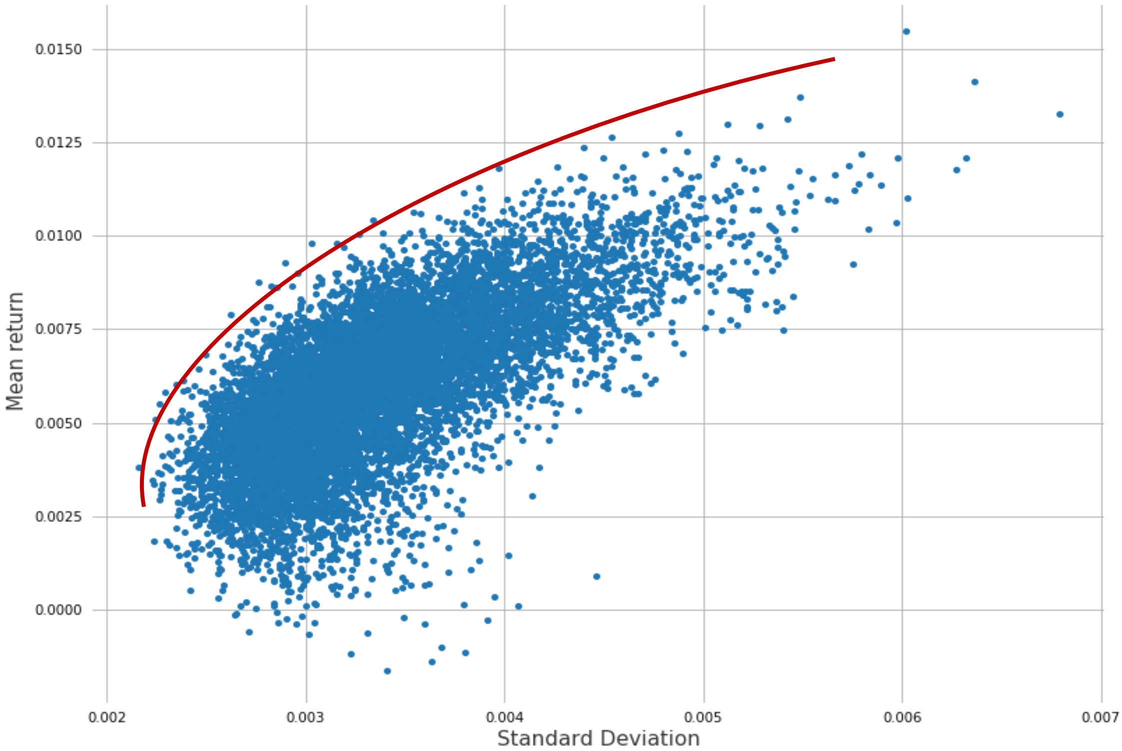

Figure 6: Portfolio returns vs standard deviations of returns (the red line represents the efficient frontier)

The scope of the analysis is to take the portfolio which maximizes the Sharpe ratio. Therefore, among the 100,000 simulated portfolios, the portfolio with the maximum Sharpe Ratio is going to be selected, and then considered in the comparative analysis, both against the other groups (to compare portfolios with different classes of issuer credit risk) and over time (to see if the effect is due to a structural component of the market, or if Covid-19 changed the physiognomy of the latter).

The Sharpe Ratio is calculated by dividing the portfolio return by its volatility (the standard deviation of the portfolio calculated for the same time frame as for the portfolio returns):

$$Sharp\ Ratio_T = \frac{Portfolio\ Return_T}{Portfolio\ Standard\ Deviation_T}$$

Where T is the period taken under consideration (23-03-2020 to 31-05-2020). Such a measure is particularly useful (even though simplistic when compared to others) to identify the risk-adjusted returns of the different portfolios.

To calculate and store the Sharpe Ratios of the 100,000 portfolios, the following piece of code is used:

```
# Function that implements the same calculation explained above,
with the exception that it returns Sharpe Ratio and weights
instead of return and standard deviation

def sharpe_ratios_and_weights(returns):

    mean_returns_vector = np.asmatrix(np.mean(returns, axis=1))
    weights_vector = np.asmatrix(weights(returns.shape[0]))
    covariance_matrix = np.asmatrix(np.cov(returns))

    return_port = weights_vector * mean_returns_vector.T
    stdev_port = np.sqrt(weights_vector * covariance_matrix * wei
                 ghts_vector.T)

    return (float(return_port/stdev_port), weights_vector)

# Simulate 100,000 portfolios and store the Sharpe Ratios and
weights for each of them

n = 100000
sharpe_ratios, wghts = np.column_stack([sharpe_ratios_and_weights
                      (returns) for x in range(n)])

# Find the maximum sharp ratio

max(sharp_ratios)
```

The interim output is a data frame composed by 100,000 Sharpe Ratios calculated using random weights for the stocks in the group, as well as another data frame containing all the portfolio weights for each portfolio, in the same order as for the Sharpe Ratios (therefore, for example, the Sharpe Ration number 15 would correspond to the portfolio weights number 15, in their respective data frames).

The final output is instead a number, hence the maximum Sharp Ratios in the data frame. Considering that 100,000 simulations have been performed, the result is very stable, with a minimal and insignificant difference in terms of Sharpe Ratio when re-performing the whole analysis.

2. Comparative analysis by group based on Issuer Credit Rating

The precedent analysis is performed for each group, where groups are defined by classes of issuer credit ratings as follows:

1. Group 1: AAA to A;
2. Group 2: A-;
3. Group 3: BBB+;
4. Group 4: BBB;
5. Group 5: BBB-;
6. Group 6: BB+ to B-.

The analysis is based on the period that goes from March 23rd to May 31st, 2020, taking and dividing the stock part of the S&P500 as previously stated. The results of the comparative analysis are shown below:

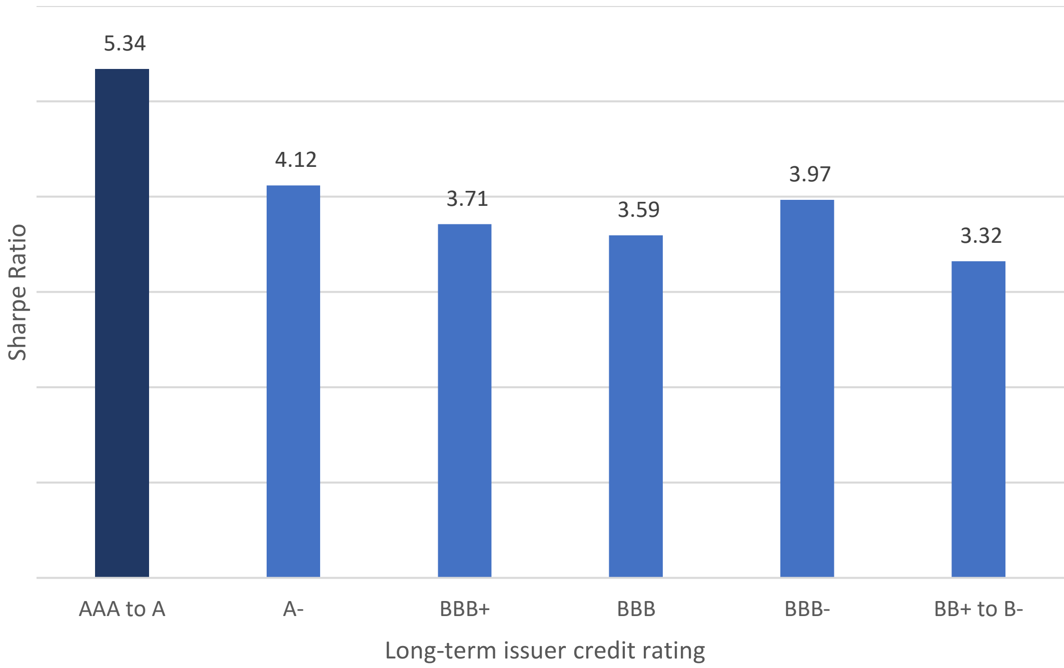

Figure 7: Cross-group comparison of the maximum Sharpe Ratio from the simulation

The result of the cross-group comparative analysis is clear: the maximum risk-adjusted return (Sharpe Ratio) is much higher for the group with the highest Issuer Credit Risk quality (AAA to A), even when compared with its closest group in terms of rating (A-). Moreover, the Sharpe Ratio tends to decline moving down from group 1 to group 6, with the only exception of group 5 (BBB-), which has a better risk-adjusted performance than the one of groups 3 and 4.

This result is totally in line with the behavioral analysis developed in the second section of this paper. Indeed, the idea underlying the analysis is that investors implemented a process of panic-sell, overestimating the risk of default for the majority of the quality stocks in the market. Since this sell-off was mainly dictated by irrational behaviors, after the intervention of the FED on March 23rd, the market calmed down and realized that actually, its reaction was too harsh on some quality stocks.

Below are summarized the main behavioral biases which pushed investors to sell-off stocks based on fear:

1. Loss aversion: considering the long economic expansion and the consequent strong equity returns in the past years, people were in the position of having accumulated a substantial return on their portfolios (with respect to a reference point which normally stands at the initial purchase price of the

investment). Therefore, the subjective marginal utility for a unit return was lower than the marginal disutility coming from a unit loss, hence pushing people to divest quickly at the beginning of the market fall, having overestimated the probability of default of their portfolio companies;

2. Myopic Loss Aversion: similar to the standard loss aversion, with the difference that investors are deemed to evaluate their portfolios quite often, hence causing a short-term view on their investments;
3. Herding behavior: especially in time of extreme uncertainty (such as the crisis triggered by the pandemic and the stringent government measures to contain the virus), private investors tend to trade according to what other investors are doing, not following their private information;
4. Framing: agents decide differently depending on how the information is presented to them. During the Covid-19 pandemic, many relevant investors and almost every news channel was very negative on the pandemic, hence influencing people thoughts;
5. Mental accounting: people normally tend to have at least two portfolios, one for low-risk investments (downside protection) and one for high-risk investments (desire to "become rich"). In the sell-off precedent to March 23rd, investments once considered low risk started to decrease substantially in price, with an average price decrease of about 30% (when considering the major indexes). Therefore, people ended up having high-risk stocks in their low-risk portfolios, which in turn incited investors to sell these stocks.

Such behavioral biases resulted in the Sharpe Ratio of the highest Issuer Credit Rating Portfolio to be the highest, considering a strong rebound from March lows, which were dictated more by fear than anything else. Moreover, this also explains the correlation between the Sharpe Ratios and the Issuer Credit Ratings of the stock in the portfolios: the higher the credit quality of the stock, the lower the risk of default, the more probable that investors sold-off the stock just based on fear, being influenced by behavioral biases.

Finally, it is important to highlight that the portfolios have been built randomly, hence not deciding the stocks to insert in each of them, but basing the split solely on the Issuer Credit Rating. Furthermore, the stocks with an Issuer Credit Rating between

AAA and A have been aggregated, to create a group with a decent number of stocks inside.

Following the logic coming from the results, it could be possible that this outperformance would be even more pronounced when considering stocks without aggregating different classes of rating.

3. Comparative analysis by group based on Issuer Credit Rating over time

We must consider that, even though multiple behavioral biases affected people's behavior during the Coronavirus pandemic, loss aversion and myopic loss aversion are the most measurable ones. Indeed, while other effects are more easily quantifiable through, for example, laboratory experiments and questionnaires, the presence of loss aversion can be here assessed by looking at two particular timeframes: last year returns (2019) and the subsequent stock market drop amidst Covid-19 (from 1st of January 2020 to 23rd of March 2020).

The median is in the case used to measure the performance of the 6 groups in the two aforementioned periods. Indeed, while the mean could lead to biased results by considering outliers, the median is not influenced by these characteristics of the dataset.

The first step to find the median return for each portfolio is to download the stock price data for each group for the relevant period. The below piece of code has been used to extract this data for the period that goes from the beginning of 2020 to March 2020. The same code is then modified to retrieve 2019 stock price data.

```
# Download daily stock price data for the 6 portfolios

group_1 = pd.read_excel("Group 1_AAA to A.xlsx")
tick =  list(group_1['Ticker'])
price_data_1 = web.get_data_yahoo(tick,
                                 start = '2020-01-01',
                                 end = '2020-03-23')['Adj Close']

group_2 = pd.read_excel("Group 2_A-.xlsx")
tick =  list(group_2['Ticker'])
price_data_2 = web.get_data_yahoo(tick,
                                 start = '2020-01-01',
                                 end = '2020-03-23')['Adj Close']

group_3 = pd.read_excel("Group 3_BBB+.xlsx")
tick =  list(group_3['Ticker'])
```

```
price_data_3 = web.get_data_yahoo(tick,
                           start = '2020-01-01',
                           end = '2020-03-23')['Adj Close']

group_4 = pd.read_excel("Group 4_BBB.xlsx")
tick =  list(group_4['Ticker'])
price_data_4 = web.get_data_yahoo(tick,
                           start = '2020-01-01',
                           end = '2020-03-23')['Adj Close']

group_5 = pd.read_excel("Group 5_BBB-.xlsx")
tick =  list(group_5['Ticker'])
price_data_5 = web.get_data_yahoo(tick,
                           start = '2020-01-01',
                           end = '2020-03-23')['Adj Close']

group_6 = pd.read_excel("Group 6_BB+ to B-.xlsx")
tick =  list(group_6['Ticker'])
price_data_6 = web.get_data_yahoo(tick,
                           start = '2020-01-01',
                           end = '2020-03-23')['Adj Close']
```

Subsequently, for each group, I consider only the first and last price data, to then calculate the period return. Therefore, in the code showed, we keep only stock price data for the 1st of January 2020 and for the 23rd of March 2020. Then, for each group, I calculate the stock price change of every stock in the group. Finally, the median is calculated for each group.

```
# For each group, calculate the period return of every stock in
the group and then store the median in a variable

first_last_1 = price_data_1.iloc[[0,55]]
returns_1 = first_last_1.pct_change()
median_loss_1 = returns_1.iloc[1].dropna().median()

first_last_2 = price_data_2.iloc[[0,55]]
returns_2 = first_last_2.pct_change()
median_loss_2 = returns_2.iloc[1].dropna().median()

first_last_3 = price_data_3.iloc[[0,55]]
returns_3 = first_last_3.pct_change()
median_loss_3 = returns_3.iloc[1].dropna().median()

first_last_4 = price_data_4.iloc[[0,55]]
returns_4 = first_last_4.pct_change()
median_loss_4 = returns_4.iloc[1].dropna().median()

first_last_5 = price_data_5.iloc[[0,55]]
returns_5 = first_last_5.pct_change()
median_loss_5 = returns_5.iloc[1].dropna().median()
```

```
first_last_6 = price_data_6.iloc[[0,55]]
returns_6 = first_last_6.pct_change()
median_loss_6 = returns_6.iloc[1].dropna().median()
```

The same process is repeated by changing the period to 2019 (the entire year). The results are as follow:

Group	Median Return 01/01/2019 - 31/12/2019	Median return 01/01/2020 - 22/03/2020
AAA to A	27.0%	-30.8%
A-	30.3%	-35.3%
BBB+	32.4%	-39.3%
BBB	29.3%	-39.7%
BBB-	27.3%	-50.0%
BB+ to B-	25.5%	-45.7%

The table above highlights a strong year for stock returns of every credit-risk group in 2019, with a following disastrous first-quarter in 2020. If we consider an average investor who was invested in the market from, for example, the beginning of 2019, loss aversion would have caused this individual to divest during the market crash in the days before the 23rd of March, hence further alimenting the market sell-off. Indeed, after having accumulated strong returns, the agent was in the right-tale of the utility curve, hence implying a marginal disutility coming from a unit loss to be higher than the marginal utility coming from a unit gain.

After having shown the scenario and the probable reaction of the agent amidst the market sell-off, I now start analyzing the Sharpe Ratio results over time. To understand whether the results are structural of the market or if, contrarily, they are a direct consequence of a panic-sell dictated by behavioral biases, I repeat the precedent analysis over time, by keeping the same period (to adjust for seasonality) but changing the year of interest. Specifically, 4 periods are considered:

1. From 23/03/2020 to 31/05/2020;
2. From 23/03/2019 to 31/05/2019;
3. From 23/03/2018 to 31/05/2018;

4. From 23/03/2017 to 31/05/2017.

To perform the aforementioned analysis of the groups in various periods, I use the code previously run. Indeed, the only modification needed is to adapt the start and ending period of the code to the new start and ending period, for each one of the remaining 3 periods (from the 23rd of March to the 31st of May 2019, 2018 and 2017).

This part of the code aims to understand whether the maximum-sharp-ratio portfolio of the 6 groups displays the same trend over time. By doing this I want to rule out the possibility that the overperformance (adjusted for the risk) of group 1 (best issuer credit rating stocks) is just a structural component of the market: if group 1 strongly outperformed the other groups also in the same periods of the last years (2019, 2018 and 2017), it would mean that the outperformance in 2020 is not caused by the behavioral biases considered above (mostly by loss aversion), but it is just a recurring characteristic of the group.

The results of the intertemporal analysis are shown below:

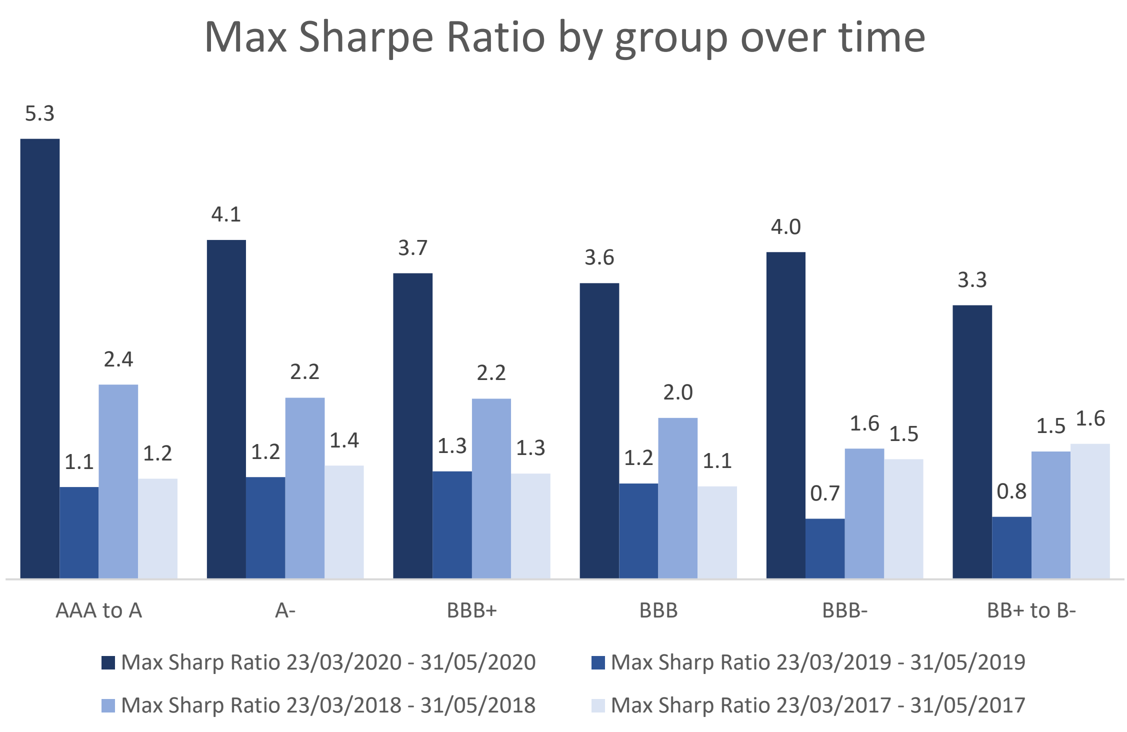

Figure 8: Cross-group analysis of max-Sharpe-Ratio portfolio over time

The maximum Sharpe Ratio by group has a different tendency over time:

1. In 2020, group 1 is the best one when compared to the other groups in the same year. Its Sharpe Ratio is extremely higher than the one for group 2 (closest comparable in terms of Sharpe Ratio), precisely 29.7% higher;
2. In 2019, the maximum result is scored by the third group, hence the one composed by stocks having a long-term issuer credit rating of BBB+. At the same time, group 1 ranks 4th in terms of Sharpe Ratio, after Group 2, 3, and 4;
3. In 2018, group 1 ranks 1st in terms of Sharpe Ratio, followed by the other groups in order of issuer credit rating, from the best one to the worst one. However, in this case, the maximum Sharpe Ratio of group 1 is only 7.2% higher than the Sharpe Ratio of its nearest comparable, group 2;
4. In 2017, the maximum result is scored by the last group, which has a Sharpe ratio of about 1.64. In this year, group 1 ranks 5th, almost at the end of the spectrum, with only the 4th group recording a lower Sharpe Ratio.

Therefore, it is reasonable to assess that the outperformance of group 1 is not a structural characteristic of the market, since, in the recent years, group 1 has never strongly outperformed the other groups in terms of Sharpe Ratio. Actually, the group normally underperforms the others, with only 2018 being an exception (also in this case, the outperformance is far smaller than the out registered in 2020).

This numerical analysis can be further reinforced by looking at the trend of the maximum Sharpe Ratio by group over time, showed in the graph below:

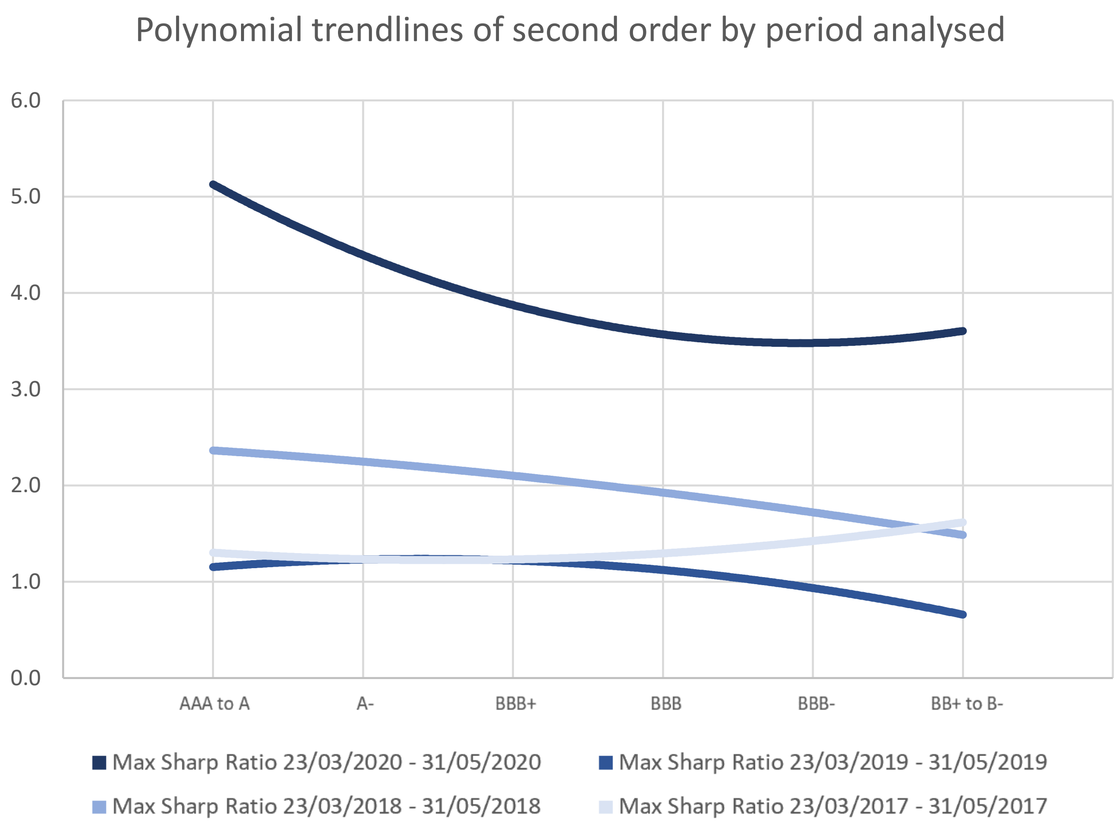

Figure 9: Intertemporal Second-order Polynomial analysis by group

In 2020, the second-order polynomial trendline is much steeper around group 1 then. Moreover, its shape is different from the one of the other periods' second-order polynomial. Such shape is dictated by the strong result obtained by Group 1, which renders the line convex and decreasing at the same time.

After having considered a numerical and second-order polynomial examination of the intertemporal results of the 6 groups, it is reasonable to conclude that the results obtained from the analysis of the period coinciding with the pandemic are not dictated by a structural overperformance of high-credit-rating stocks. Instead, they are far different from any other period analyzed, suggesting that something else (outside of …) has influenced the results.

Concerning this point, this paper aims precisely to provide an alternative behavioral explanation of the stock market collapse after the advent of the pandemic.

4. Sectorial analysis of the different groups to identify a possible source of disturbance to the analysis

After having ruled out the possibility of analysis to be biased by a structural component of the market (i.e. that stocks with higher long-term issuer credit rating normally outperform other groups of stocks with lower financial soundness), I now examine the sectorial composition of the various groups, to understand if the results have been influenced by the composition of the various groups.

Also in this case, a piece of code has been developed to automatize the task. The first step is to import the packages and functions needed. Then, I use Financial Modelling Prep to download data for the industry of the various stocks. The data coming from Financial Modelling Prep is encoded in Json, which is a JavaScript's subset used for the structured transmission of data from the server. An example of the Json data used is provided below for the stock "Apple":


```
[ {
  "symbol" : "AAPL",
  "price" : 499.23,
  "beta" : 1.22156,
  "volAvg" : 39483057,
  "mktCap" : 2134522860000,
  "lastDiv" : 3.0,
  "range" : "204.22-515.14",
  "changes" : -0.81,
  "companyName" : "Apple Inc",
  "exchange" : "Nasdaq Global Select",
  "exchangeShortName" : "NASDAQ",
  "industry" : "Consumer Electronics",
  "website" : "https://www.apple.com/",
  "description" : "Apple, Inc. engages in the design,
manufacture, and sale of smartphones, personal
computers, tablets, wearables and accessories, and other
variety of related services. The company is
headquartered in Cupertino, California and currently
employs 137,000 full-time employees. The company is
considered one of the Big Four technology companies,
alongside Amazon, Google, and Microsoft. The firm's
hardware products include the iPhone smartphone, the
iPad tablet computer, the Mac personal computer, the
iPod portable media player, the Apple Watch smartwatch,
the Apple TV digital media player, the AirPods wireless
earbuds and the HomePod smart speaker. Apple's software
includes the macOS, iOS, iPadOS, watchOS, and tvOS
operating systems, the iTunes media player, the Safari
web browser, the Shazam acoustic fingerprint utility,
and the iLife and iWork creativity and productivity
```

```
suites, as well as professional applications like Final
Cut Pro, Logic Pro, and Xcode. Its online services
include the iTunes Store, the iOS App Store, Mac App
Store, Apple Music, Apple TV+, iMessage, and iCloud.
Other services include Apple Store, Genius Bar,
AppleCare, Apple Pay, Apple Pay Cash, and Apple Card.",
  "ceo" : "Mr. Timothy Cook",
  "sector" : "Technology",
  "country" : "US",
  "fullTimeEmployees" : "137000",
  "phone" : "14089961010",
  "address" : "1 Apple Park Way",
  "city" : "1 Apple Park Way",
  "state" : "CALIFORNIA",
  "zip" : "95014",
  "dcfDiff" : 89.92,
  "dcf" : 297.11,
  "image" : "https://financialmodelingprep.com/image-
stock/AAPL.jpg"
} ]
```


Considering that Json is built-in Python, we can use the Json library to parse Json data and receive a well-formatted Pandas data frame as shown below:

	AAPL
symbol	AAPL
price	499.23
beta	1.22156
volAvg	39483057
mktCap	2134522860000
lastDiv	3
range	204.22-515.14
changes	-0.81
companyName	Apple Inc
exchange	Nasdaq Global Select
exchangeShortName	NASDAQ
industry	Consumer Electronics

```
#import packages necessary for the code

import requests
import json
from bs4 import BeautifulSoup as bs
import pandas as pd
import matplotlib.pyplot as plt


try:
    # For Python 3.0 and later
    from urllib.request import urlopen
```

```python
except ImportError:
    # Fall back to Python 2's urllib2
    from urllib2 import urlopen

# Set up function to parse Json data

def get_jsonparsed_data(url):

    response = urlopen(url)
    data = response.read().decode("utf-8")
    return json.loads(data)
```

After having set up the function to use to parse Json data, I create an empty data frame to store the data, I take the list of stock for each group (one by one), and I call the previous function to download the industry data of each stock:

```python
# Create an empty list and a list of the stocks included in the
group

df1 = pd.DataFrame()
stocks = pd.read_excel('Group 1_AAA to A.xlsx')
stock_list = list(stocks['Ticker'])

# For each ticker in the previous list, create a loop to query
the data and store it in the previously created data frame

for ticker in stock_list:
    url = ("https://financialmodelingprep.com/api/v3/profile/" +
           ticker + "?apikey=7f3999ed50273c3b6f9b889a4b1e28dc")
    ratios = get_jsonparsed_data(url)
    data = pd.Series(ratios[0])
    df1[ticker] = data

df1 = df1.loc['sector']
```

Following the download of the data and the following data cleaning, the data is visualized with the use of a bar graph. The piece of code below creates the graph and formats it:

```python
# Create a data frame with the number of stock by industry for
the group

to_plot = df1.value_counts(sort=False)

# Create the graph and apply some formatting
```

```python
ax = to_plot.plot.bar(figsize=(12,10))
plt.yticks([])
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.spines['left'].set_visible(False)

# Set individual bar labels using the above list

for i in ax.patches:
    # get_width pulls left or right; get_y pushes up or down
    ax.text(i.get_x()+0.25,i.get_height()+0.25, \
            str(round((i.get_height()))), fontsize=15, color='dim
            grey',ha='center')
```

The output of this part of the code is the following graph, which highlights the number of stocks by industry in the group analyzed:

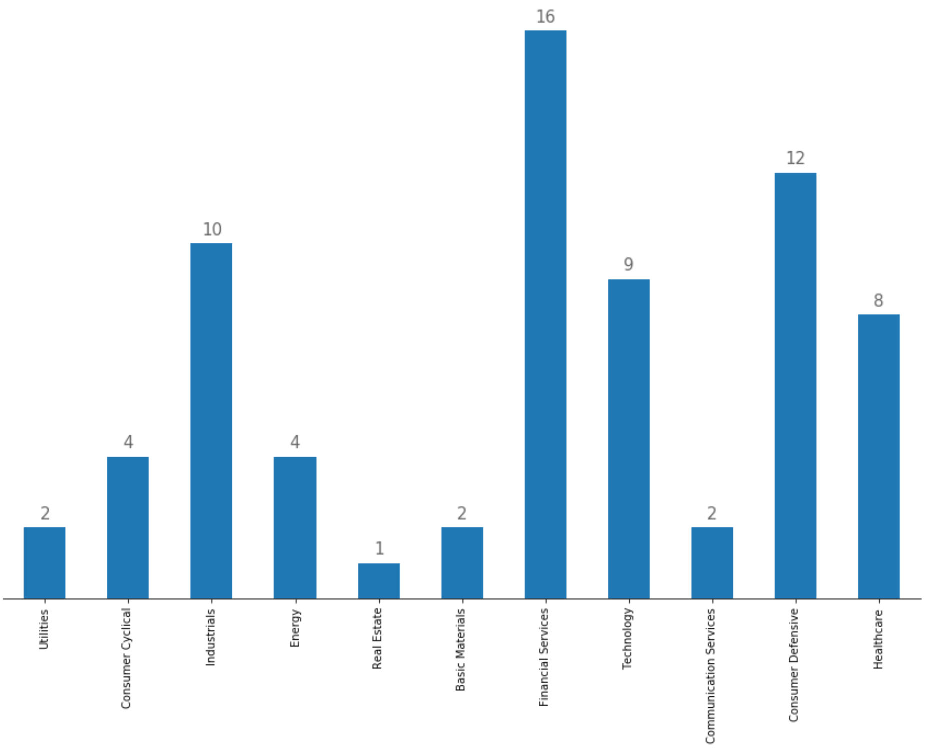

Figure 10: Number of stock by industry, for group 1

The same process is applied to the other groups. Then, for each of these databases, I standardize the stocks in each industry bucket by dividing each number by the total number of stocks in the respective group. In fact, considering that each group has a different number of stocks inside, it is better to compare the industrial concentrations by turning the numbers into percentages. To do this, the following code snippet has been used:

```
# Create an empty data frame

dataframe = pd.DataFrame()

# Standardize industry data by turning it into percent form,
while also storing them into a single dataset

dataframe['Group 1'] = to_plot/sum(to_plot)
dataframe['Group 2'] = data2/sum(to_plot)
dataframe['Group 3'] = data3/sum(to_plot)
dataframe['Group 4'] = data4/sum(to_plot)
dataframe['Group 5'] = data5/sum(to_plot)
dataframe['Group 6'] = data6/sum(to_plot)

# Export the dataset in excel format

dataframe.to_excel('Sectorial allocation by group.xlsx')
```

At this point, the dataset "Sectorial allocation by group" contains the percentage concentration of each industry for every group. Using excel, a graph is created to show the different sectorial concentrations of each group:

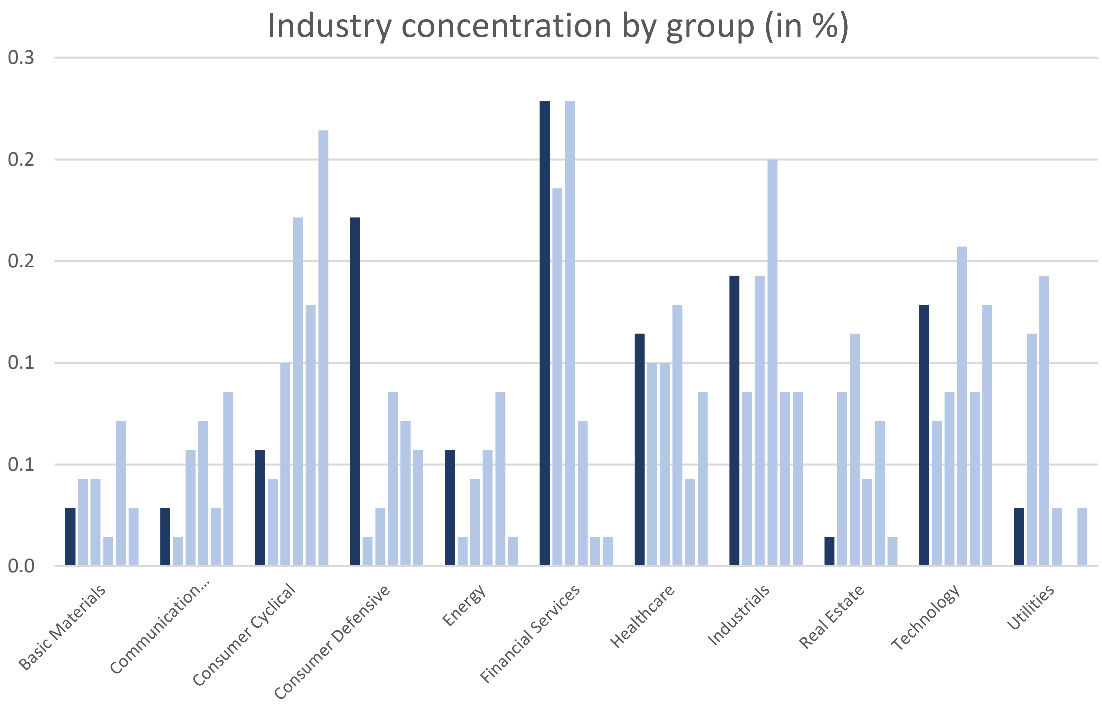

Figure 11: Industry concentration by group, sorted by group number (group 1 in dark blue)

Furthermore, another code snipped is written to create a box plot with an overlapping scatter plot for Group 1:

```
# Read excel file and store data in a data frame

df = pd.read_excel('For box plot.xlsx')
df.set_index('Unnamed: 0', inplace=True)

# Create a box plot and then insert the values for group 1

plt.figure(figsize=(28,10))
ax = df[1:].plot.box(figsize=(28,10), color = 'midnightblue')
group_1 = df.iloc[0]
count = 0
lista = list(df.columns)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.spines['left'].set_visible(False)
for row in group_1:
    x = count +1
    count += 1
    y = row
    plt.scatter(x, y, color = 'royalblue', s=200)
plt.show()
```

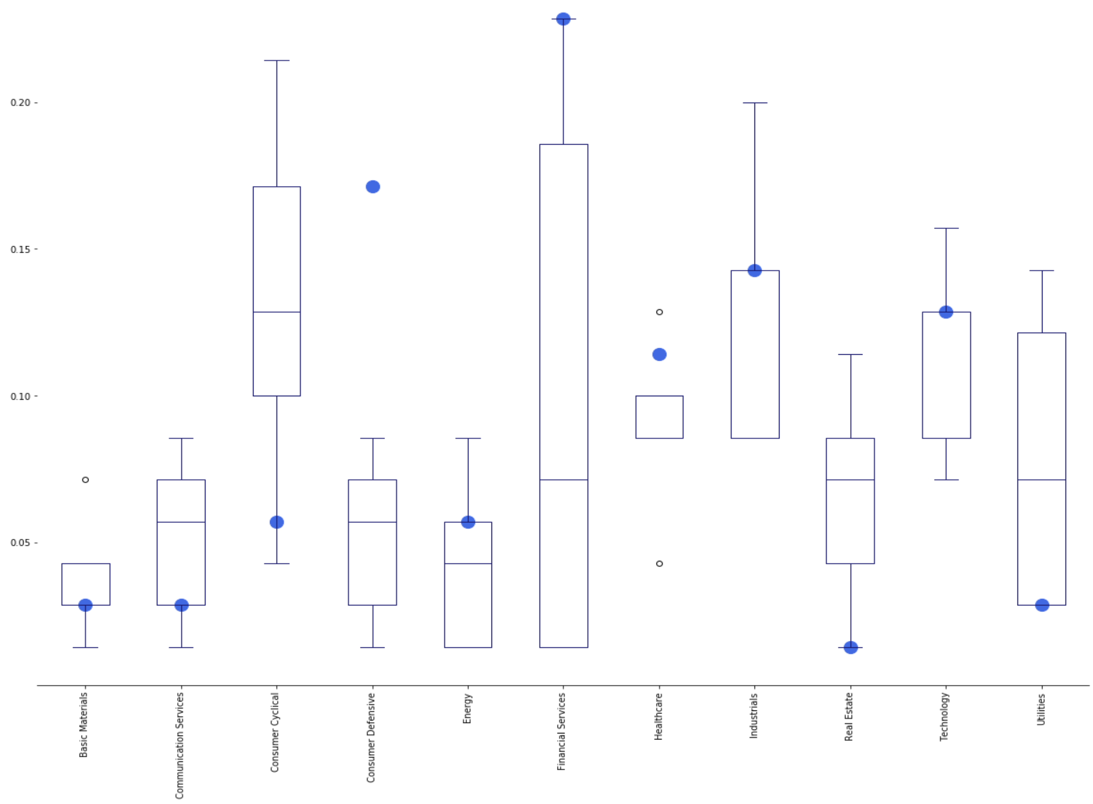

Figure 12: Box plot of industry allocation of group 2 to 6, with an overlapping scatter plot for group 1

From the two graphs (the previous bar chart and the box plot) it is reasonable to assess that, even though the concentration in the different sectors varies between the groups, group 1 does not significantly differ from the others, except for few cases.

Moreover, it is useful to take into account the following table, which ranks the sectors of the S&P500 from the best performer to the worst one, in the period between the 10th of March and the 7th of August:

S&P 500 SECTOR	PRICE CHANGE - MARCH 10 THROUGH AUG. 7 [28]
Information Technology	30.20%
Consumer Cyclical	30.00%
Basic Materials	22.80%
Communication Services	19.20%
Health Care	11.90%
Industrials	9.20%
Energy	4.90%
Consumer Defensive	4.70%
Financial Services	3.20%
Real Estate	-2.70%
Utilities	-3.30%

From this table and the graphs we can draw the following conclusions on the sectorial allocation of the various groups:

1. Group 1 has the highest number of stocks operating in the consumer discretionary industry and the financial services industry. However, such concentrations could not have caused such an outperformance, in terms of Sharpe Ratio, of the best performing portfolio, considering that both sectors have been poorly performed in the period;
2. Group 1 has the lowest number of stocks operating in the real estate industry (together with group 6) and a low amount of utility stocks. However, considering that the code implemented aimed to find the

[28] FactSet & MarketWatch, https://www.marketwatch.com/story/after-150-days-of-the-covid-19-pandemic-here-are-the-best--and-worst-performing-stocks-2020-08-10

portfolio, inside each group, with the highest Sharpe Ratio, it is reasonable to think that, even if the concentration in real estate was higher, real estate stocks would have not been selected by the algorithm.

3. Group 1 outperformance does not depend on having a large number of stocks in the best performing industries, considering that, for information technology, consumer cyclical, and basic materials (the best-performing markets), the group has an average concentration (even lower than the average for consumer cyclical).

Therefore, the results of the sectorial analysis do not discredit the Sharpe Ratio analysis performed at the beginning. In fact, the outperformance of group 1 in terms of risk-adjusted return does not seem to depend on the group being severely skewed towards those industries which outperformed the market in the period. This result further supports the hypothesis made above regarding the behavioral reasons (primarily loss aversion) that caused the market drop and the subsequent returns.

5. Final remarks

Considering the results from the intertemporal analysis and the sectorial analysis, the strong outperformance of group 1 in terms of Sharpe Ratio suggests that it is reasonable to believe that the stock market crash was severely influenced by some behavioral factors (with the main one being loss aversion), which caused investors to arbitrarily and materially increase their expectation of probability of default even for financially solid companies with bright prospects. Furthermore, the long-term issuer credit rating seems a solid measure to identify the financial and operating quality of the stocks.

In this case, when investors' fear started to increasingly fade away (as from the 23rd of March), the market started to realize that it had been too harsh on some companies which should not have been so penalized. Hence, such a dynamic would explain the strong difference in Sharpe Ratio between group 1 and the other groups.

Finally, even if the intervention of the FED had a massive influence on the returns of the stock market in the period after the 23rd of March, this intervention could have not been the cause of the strong outperformance of Group 1. Indeed, my analysis does not focus on a general outperformance of the whole market, but it aims to investigate the outperformance of a specific group (best-in-class issuer credit rating stocks of the S&P500) regarding the other ones (based on other levels of issuer credit rating).

Conclusion

The research developed in this paper aimed to find a possible explanation of the stock market collapse of Q1 2020. The analysis starts on the theoretical side, by taking under consideration the development of the Prospect Theory, as well as its utility on the practical side.

Following this introduction, a series of heuristics (or behavioral biases) are taken under consideration. In fact, loss aversion, herding behavior, framing, and mental accounting could have been the possible behavioral fallacies that have caused the stock market crash during the coronavirus pandemic. Of these heuristics, loss aversion is also discussed on the quantitative side, showing to the reader that the situation during Q1 2020 was the perfect set up for the average investor to develop loss aversion, at least to some extent.

The precedent behavioral biases most probably caused the investor to overestimate the probability of default inherent in some companies or to just adopt a panic-sell behavior, hence alimenting the market decline already in place. If this was the case, the market would have rapidly corrected this irrationality, by re-stabilizing the price of those stocks whose stock price had previously been erroneously hammered (the most financially solid ones).

To test this hypothesis, an analysis based on long-term issuer credit rating has been performed by dividing 373 stocks of the S&P500 into 6 groups based on this rating. Then, for each group, 100,000 portfolios are created, and the maximum Sharpe Ratio is taken. The result from the benchmarking across the maximum Sharpe Ratio of the 6 groups support the previously stated hypothesis: the best risk-adjusted return of Group 1 (stocks with the highest long-term issuer credit rating) for the, approximately, two months after the market bottom outperforms by far the ones of the other groups, which is what should be expected as a market correction.

Besides, to tackle some possible issues which could have undermined the results of the study, an intertemporal analysis, as well as a sectorial one, are developed. The outcome of the former is the confirmation that the results obtained are not due to an intrinsic characteristic of the market (i.e. stocks with the highest ratings outperform the other ones). Finally, the latter analysis has the objective to demonstrate that sectorial concentrations have not been the cause of the outperformance of group 1. In fact, the best-credit-rating group does not present a strong concentration in the best performing industries for the relevant period.

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List of figures

Summary

Does the market behave rationally in times of crisis? Does it value stocks using the same methods used in times of normal market conditions? What has happened in the stock market during the COVID-19 period?

These are the questions a rational investor should be thinking about in these times of crisis caused by the COVID-19 pandemic. Indeed, the market has not behaved rationally, with declines in the stock market being dictated more by fear than anything else.

Under normal circumstances, the market evaluates companies by giving the most attention to the future cash flows of a company, to prices paid in precedent transactions, to ratios of peer companies in the same industry, and so on. However, during the COVID-19 crisis, investors partially changed the way they valued companies. Indeed, the risk of bankruptcy and the consequent fear to lose most or the entirety of their investments has had a predominant effect on the stock prices of the various companies.

Then, why did investors behave irrationally? Because of a widespread sell-off, alimented by the chaos introduced in the market by the stringent measures adopted by the various countries (such as lockdowns) to contain the spreading of the virus, inducing investors to overestimate the probability of default inherent in some companies or to just adopt a panic-sell behavior. Such a phenomenon caused valuations of stocks to decrease drastically until the 23rd of March, when, in the United States, the FED started to directly purchase securities in the market, hence increasing the liquidity and decreasing the fear of investors.

The final goal of this paper is to test whether high-quality companies' stock prices were impacted more than what they should have been, considered the market sell-off and the behavioral biases which guided investors in their decision making process amidst Covid-19.

One way to understand whether the aforementioned scenario manifested itself in the market would be to look at returns: a stock which has been strongly and erroneously impacted by the investors' sell-off would be better off in the subsequent

period, after that the FED injected in the market the liquidity needed to calm down investors' spirits. Indeed, if in the period between the 23rd of March and the 31st of May 2020 a certain group of stocks strongly outperformed the others, it would be a reason in favor of those stocks being hit too hard in the market sell-off.

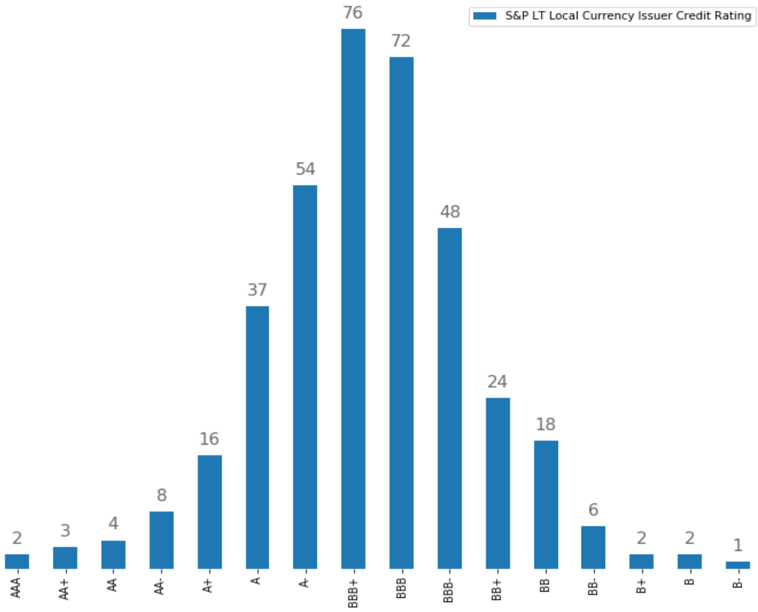
When dividing stocks into different groups, the scope has been to find a measure that could have helped in understanding the financial quality of a specific stock. This measure has been identified as the Long Term Issuer Credit Rating as for the S&P500. The credit rating is a solid measure to perform an analysis of the financial soundness of a company. This measure is a forward-looking opinion on the obligor's overall creditworthiness, which can be summarized by the ability and willingness to meet its liabilities when they come due. The importance of such rating is also due to the material due diligence that the ECAI conduce, which involves the judgment of not only public but also private information, which is normally not available to investors.

Consequently, 373 stocks selected from the S&P500 were divided into groups with a number of stocks which ranges between 48 and 76, depending on the availability of stocks for certain credit ratings. The 6 groups are defined as follow:

1. AAA to A: 70 stocks;
2. A- : 54 stocks;
3. BBB+ : 76 stocks;
4. BBB: 72 stocks;
5. BBB- : 48 stocks;
6. BB+ to B- : 53 stocks.

The analysis developed in this paper is integrally performed using Python programming in Anaconda. Section two contains a step-by-step guide, where the code is commented and the results are analyzed.

To perform the split I first download and save the tickers and the respective long-term issuer credit ratings for the stocks in the S&P500 from Bloomberg. The data is saved on an excel file, which is then uploaded on Python to understand the availability of stock price data of the single stocks. Daily stock prices are available for 373 stocks on the list, which are divided into the following credit rating buckets:



From the graph, it is possible to see that the division of the stocks can be performed by grouping the tails, to obtain groups composed of about 50 to 70 stocks each. Therefore, I grouped stocks with a credit rating between AAA and A, as well as stocks with rating BB+ to B-.

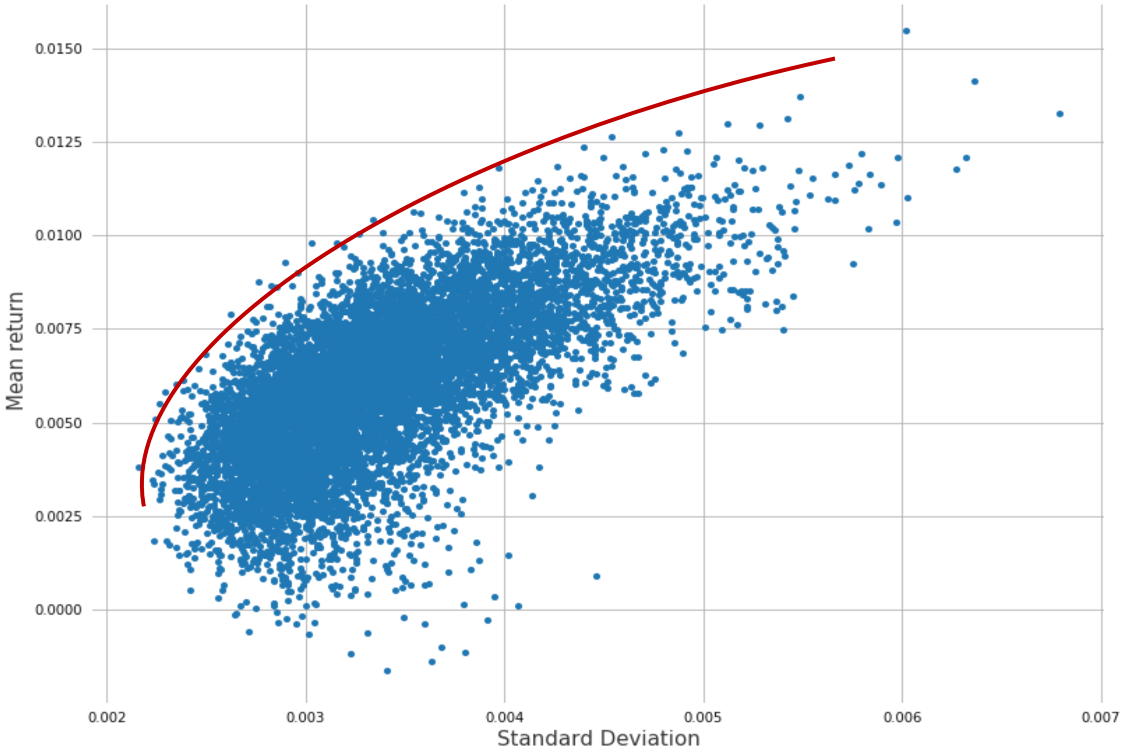
Once obtained the most suitable groups for the analysis, I proceed by analyzing each group separately. However, the code can be easily modified from group to group by changing the excel file to upload at the beginning, since the remaining part of the code is the same for each group.

To begin, I download the stock price data for each stock to be analyzed. The period has been appositely chosen, starting from March 23rd, when the Fed announced its commitment to purchase unlimited amounts of US Treasuries and agency MBS, hence halting investors' sell-offs, for a period of about 2 months. Indeed, I must consider a short period because otherwise, the market correction after the decline would have lost importance, and at the same time, I need to collect enough data to develop a decent stock price analysis.

Then I transform the price matrix downloaded in Python into a return matrix, adopting the following calculation:

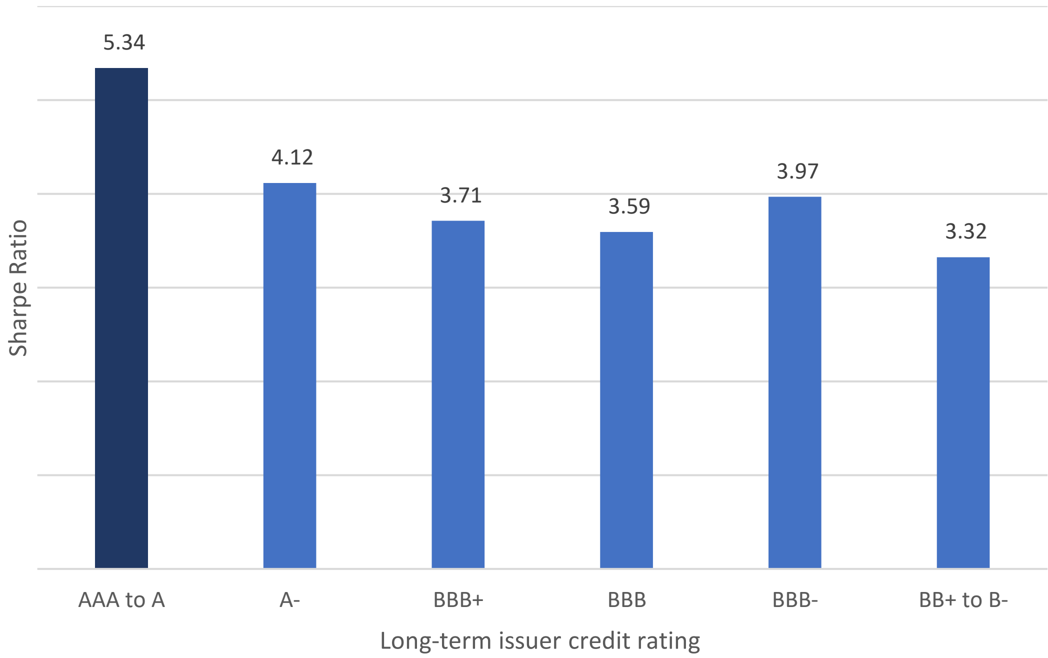
$$Return_{i,T} = \frac{Stock\ Price_{i,T} - Stock\ Price_{i,T-1}}{Stock\ Price_{i,T-1}} = \frac{Stock\ Price_{i,T}}{Stock\ Price_{i,T-1}} - 1$$

Once obtained the return matrix, I proceed by defining two functions, one to produce x random weight which adds up to one (where x is the number of stocks in the group), and one to calculate and return the standard deviations and return of the portfolio. The next step consists of creating 100,000 portfolios, store the results in two variables, and then plot the portfolios in a graph.



The scope of the analysis is to take the portfolio which maximizes the Sharpe ratio. Therefore, among the 100,000 simulated portfolios, the portfolio with the maximum Sharpe Ratio is going to be selected, and then considered in the comparative analysis, both against the other groups (to compare portfolios with different classes of issuer credit risk) and over time (to see if the effect is due to a structural component of the market, or if Covid-19 changed the physiognomy of the latter).

The final output is a number, the maximum Sharp Ratios in the data frame. Considering that 100,000 simulations have been performed, the result is very stable, with a minimal and insignificant difference in terms of Sharpe Ratio when re-performing the whole analysis. The results of the comparative analysis are shown below:



The result of the cross-group comparative analysis is clear: the maximum risk-adjusted return (Sharpe Ratio) is much higher for the group with the highest Issuer Credit Risk quality (AAA to A), even when compared with its closest group in terms of rating (A-). Moreover, the Sharpe Ratio tends to decline moving down from group 1 to group 6, with the only exception of group 5 (BBB-), which has a better risk-adjusted performance than the one of groups 3 and 4.

This result is totally in line with the behavioral analysis developed in the second section of this paper. Indeed, the idea underlying the analysis is that investors implemented a process of panic-sell, overestimating the risk of default for the majority of the quality stocks in the market. Since this sell-off was mainly dictated by irrational behaviors, after the intervention of the FED on March 23rd, the market calmed down and realized that actually, its reaction was too harsh on some quality stocks.

Below are summarized the main behavioral biases which pushed investors to sell-off stocks based on fear:

1. Loss aversion: considering the long economic expansion and the consequent strong equity returns in the past years, people were in the position of having

accumulated a substantial return on their portfolios (with respect to a reference point which normally stands at the initial purchase price of the investment). Therefore, the subjective marginal utility for a unit return was lower than the marginal disutility coming from a unit loss, hence pushing people to divest quickly at the beginning of the market fall, having overestimated the probability of default of their portfolio companies;

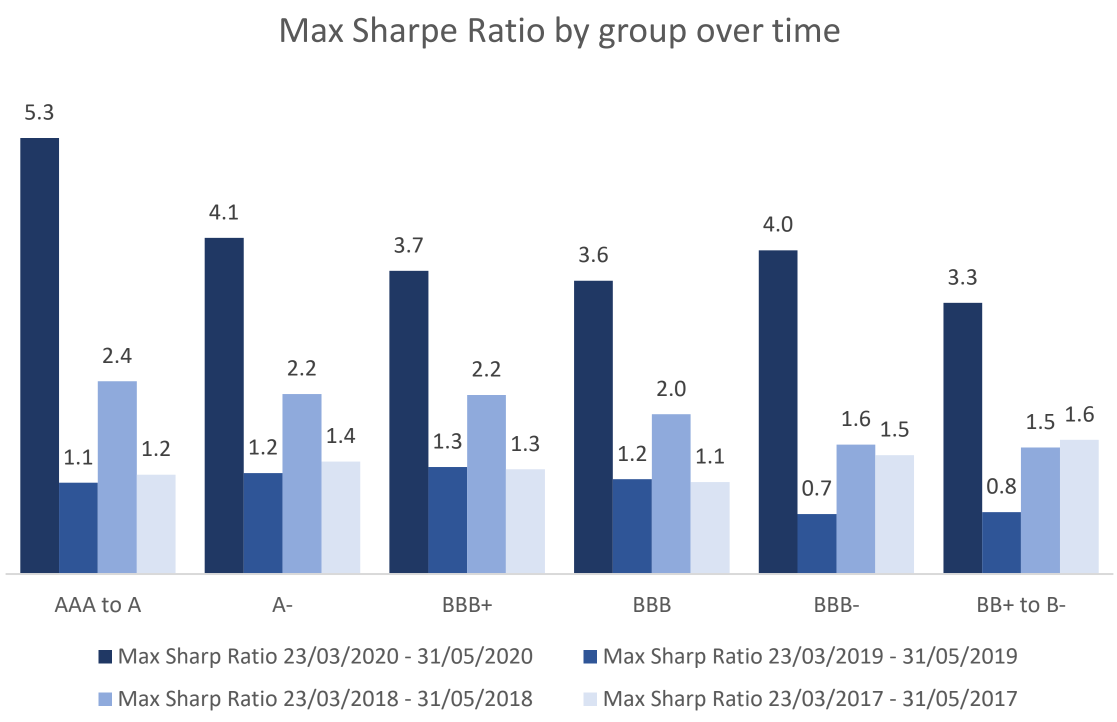
2. Myopic Loss Aversion: similar to the standard loss aversion, with the difference that investors are deemed to evaluate their portfolios quite often, hence causing a short-term view on their investments;
3. Herding behavior: especially in time of extreme uncertainty (such as the crisis triggered by the pandemic and the stringent government measures to contain the virus), private investors tend to trade according to what other investors are doing, not following their private information;
4. Framing: agents decide differently depending on how the information is presented to them. During the Covid-19 pandemic, many relevant investors and almost every news channel was very negative on the pandemic, hence influencing people thoughts;
5. Mental accounting: people normally tend to have at least two portfolios, one for low-risk investments (downside protection) and one for high-risk investments (desire to "become rich"). In the sell-off precedent to March 23rd, investments once considered low risk started to decrease substantially in price, with an average price decrease of about 30% (when considering the major indexes). Therefore, people ended up having high-risk stocks in their low-risk portfolios, which in turn incited investors to sell these stocks.

Now, it is important to assess whether the results are driven by the behavioral biases described above, or contrarily by two other causes: 1) constant overperformance of high-quality stocks (by Long Term Issuer Credit Rating) over time; or 2) sectorial differences among groups.

To understand whether the results are structural of the market or if, contrarily, they are a direct consequence of a panic-sell dictated by behavioral biases, I repeat the precedent analysis over time, by keeping the same period (to adjust for seasonality) but changing the year of interest. Specifically, 4 periods are considered:

1. From 23/03/2020 to 31/05/2020;
2. From 23/03/2019 to 31/05/2019;
3. From 23/03/2018 to 31/05/2018;
4. From 23/03/2017 to 31/05/2017.

The results of the intertemporal analysis are shown below:



The maximum Sharpe Ratio by group has a different tendency over time:

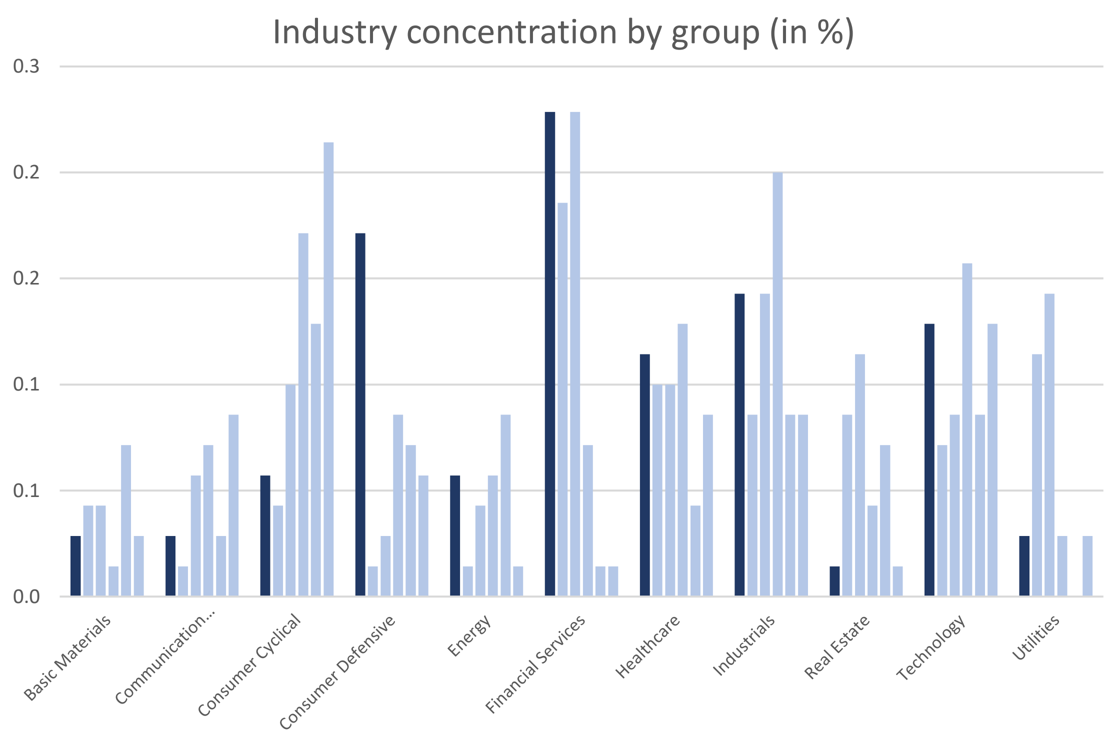
1. In 2020, group 1 is the best one when compared to the other groups in the same year. Its Sharpe Ratio is extremely higher than the one for group 2 (closest comparable in terms of Sharpe Ratio), precisely 29.7% higher;
2. In 2019, the maximum result is scored by the third group, hence the one composed by stocks having a long-term issuer credit rating of BBB+. At the same time, group 1 ranks 4th in terms of Sharpe Ratio, after Group 2, 3, and 4;
3. In 2018, group 1 ranks 1st in terms of Sharpe Ratio, followed by the other groups in order of issuer credit rating, from the best one to the worst one.

However, in this case, the maximum Sharpe Ratio of group 1 is only 7.2% higher than the Sharpe Ratio of its nearest comparable, group 2;

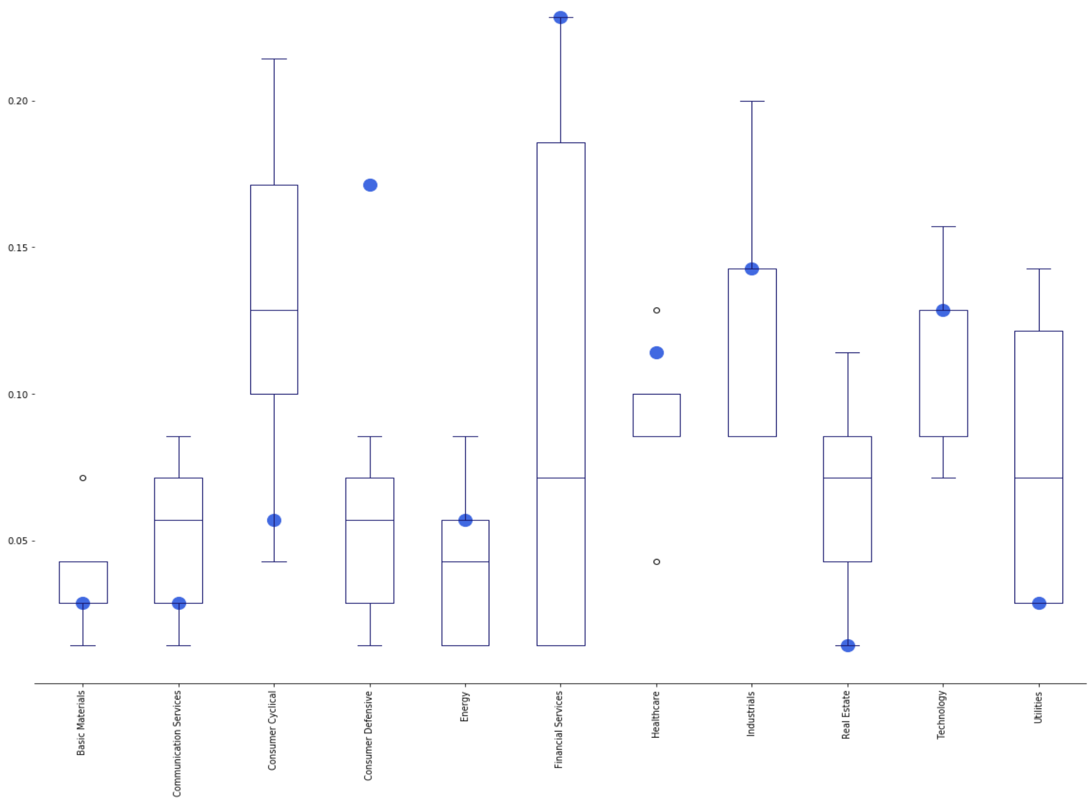
4. In 2017, the maximum result is scored by the last group, which has a Sharpe ratio of about 1.64. In this year, group 1 ranks 5th, almost at the end of the spectrum, with only the 4th group recording a lower Sharpe Ratio.

Therefore, it is reasonable to assess that the outperformance of group 1 is not a structural characteristic of the market, since, in the recent years, group 1 has never strongly outperformed the other groups in terms of Sharpe Ratio. Actually, the group normally underperform the others, with only 2018 being an exception (also in this case, the outperformance is far smaller than the out registered in 2020).

After having ruled out the possibility of analysis to be biased by a structural component of the market, I then examine the sectorial composition of the various groups, to understand if the results have been influenced by the composition of the various groups. Therefore, by using Python, I identify the composition of the various groups, with the following results:



Furthermore, I create a box plot in Python using the sector weights for each group (excluding group 1), to which then I overlap a scatter plot with the sector weights of the group 1 (blue points over the box plots):



From the resulting graph, group 1 seems in line with other groups in terms of sectorial concentration of the stocks inside the group, with some few exceptions which, however, do not affect the results:

1. Group 1 has the highest number of stocks operating in the consumer discretionary industry and the financial services industry. However, such concentrations could not have caused such an outperformance, in terms of Sharpe Ratio, of the best performing portfolio, considering that both sectors have been poorly performed in the period;
2. Group 1 has the lowest number of stocks operating in the real estate industry (together with group 6) and a low amount of utility stocks, the

worst performers in the period. However, considering that the code implemented aimed to find the portfolio, inside each group, with the highest Sharpe Ratio, it is reasonable to think that, even if the concentration in real estate was higher, real estate stocks would have not been selected by the algorithm.

3. Group 1 outperformance does not depend on having a large number of stocks in the best performing industries, considering that, for information technology, consumer cyclical, and basic materials (the best-performing markets), the group has an average concentration (even lower than the average for consumer cyclical).

Considering the results from the intertemporal analysis and the sectorial analysis, the strong outperformance of group 1 in terms of Sharpe Ratio suggests that the stock market crash was severely influenced by some behavioral factors, which caused investors to arbitrarily and materially increase their expectation of the probability of default even for financially solid companies with bright prospects. Furthermore, the long-term issuer credit rating seems a solid measure to identify the financial and operating quality of the stocks.

In this case, when investors' fear started to increasingly fade away (as from the 23rd of March), the market started to realize that it had been too harsh on some companies which should not have been so penalized.