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Can active management outperform Monkey portfolios?

A randomized procedure for the Belgian Financial Market

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Samenvatting

Bijna 50 jaar geleden heeft de Nobelprijswinnaar Eugène Fama de ‘Efficient Market Hypothesis’ ontwikkeld. Deze theorie stelt dat de prijzen van aandelen op elk moment correct zijn. Aandelen zijn bijgevolg nooit onder- of overgewaardeerd aangezien financiële markten efficiënt zijn en nieuwe financiële informatie onmiddellijk geïncorporeerd wordt in de prijs. Dit heeft tot gevolg dat financiële handel gebaseerd op fundamentele of technische analyse niet zal leiden tot hogere rendementen. De enige manier om een hoger rendement te behalen is door meer risico te nemen.

Op basis van dit onderzoek heeft Malkiel (2003) een zeer gedurfde uitspraak gedaan, hij stelde dat fondsbeheerders niet in staat zijn om een fonds samen te stellen dat beter presteert dan een portefeuille samengesteld door een geblinddoekte aap. Vele economen hebben dit onderzocht, maar tot op vandaag blijft er grote onenigheid binnen de financiële wereld over of het al dan niet mogelijk is om door actief beheer een hoger rendement te behalen.

Hoewel er een binnen de beschikbare literatuur een groeiende consensus blijkt te zijn over de onmogelijkheid om de markt te verslaan, zijn er nog steeds een aantal economen van mening dat een actieve portfoliostrategie wel degelijk resulteert in hogere returns. Het doel van ons onderzoek is om voor de Belgische markt te bepalen of actief beheer al dan niet loont. We testen of Belgische fondsbeheerder er de voorbije elf jaar in slaagden om beter te presteren dan aandelenportefeuilles die compleet willekeurig zijn samengesteld. Om ons onderzoek zo compleet mogelijk te maken verdelen we de onderzoeksperiode in drie sub periodes. Deze onderverdeling laat ons toe om een onderscheid te maken tussen de prestaties van actief beheerde fondsen voor, tijdens en na de financiële crisis.

Tijdens ons onderzoek maken wij gebruik van een Monte Carlo Simulatie om 500 willekeurige portefeuilles te genereren. Vervolgens vergelijken we het rendement van 12 Belgische fondsen met deze van de 500 ‘monkey portfolios’. We onderzoeken enerzijds hoeveel willekeurige portefeuilles een hogere cumulatief rendement behaalden gedurende de verschillende periodes, anderzijds vergelijken we hoeveel ‘random portfolios’ een hogere gemiddelde dagelijks rendement behaalden.

Onze resultaten zijn duidelijk in het voordeel van de aapjes, geen van de fondsen was in staat om een significant hoger rendement te behalen. Daarom besluiten wij dat het hoogste rendement behaald wordt door te investeren in een passief indexfonds.

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Abstract

Within literature there seems to be a growing consensus that the efficient market hypothesis holds true, the majority of the financial researchers starts to accept the impossibility for active managers to beat the market. Present literature indicates that portfolio managers are often not able to outperform the market. The purpose of this master thesis is to determine whether active portfolio management is able to outperform random portfolios, in the financial jargon known as monkey portfolios. We examine whether actively managed equity funds in the Belgian market are able to beat the monkeys. Our research covers a period from 2002 until 2012. This period is characterized by periods of economic growth, financial crisis and economic recovery. Based on the current literature we conclude that active managed portfolios are not able to outperform random portfolios. This research confirms previous conclusion. During none of the investigated time periods were active portfolios able to outperform the randomly generated portfolios.

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1. Introduction

In response to the financial crisis in 2007, people became very suspicious of investing in the financial markets. Because of the loss of confidence they no longer have the incentive to invest in stocks or other risk products. However, there are people who still believe in the possibility to beat the market but they rather transfer their money to a mutual fund manager in the belief that he is able to generate a higher return. Financial advisors enjoy the confidence of a lot of people. But are they worth the trust and the money that all their clients put in them? In other words: do they really add any value?

Within the literature there is a research of Eugene F. Fama (1965) about the efficient market hypothesis. According to this theory, an investor is not able to outperform the stock market when the market is efficient. In that state, prices of securities reflect all the available information, what makes it unnecessary for portfolio managers to examine information about future stock prices. Only by increasing the risk level is the manager able to achieve a higher return than the market. Malkiel (2003) goes one step further to state that a blindfolded monkey throwing darts at the financial page of the Wall Street Journal could select a stock portfolio that would perform just as well as one selected by professional financial advisors. The counterpart of this theory is located within the adaptive market hypothesis by Andrew Lo (2004). This research concludes that it is possible to beat the stock market under certain conditions.

The purpose of our thesis is to determine whether active management is able to outperform random portfolios, in the financial jargon also known as monkey portfolios. Active management has the intention to outperform the market. In order to do that they develop different strategies to benefit from different temporary market inefficiencies. In contrary to those active portfolios there exist also ‘passive investment strategies’ which do not have the incentive to predict and anticipate to the financial market evolutions. The approach of using random portfolios is motivated within the literature by i.a. Burns (2004), Lisi (2008) and Bartz and Kane (2010). Each of these economists have developed a similar but still slightly different method to evaluate the stock-selecting abilities of portfolio managers.

A lot of research has been conducted to the subject of active management, whether or not they are able to beat the market, on an international scale. Tudor (2012) carried out his research to the Romanian stock market. He concluded that there was no sign of possessing superior stock selecting skills. Despite the widely conducted examinations, more research on the Belgian market is recommended because of the absence of results that are applicable within this geographical location. The aim of this paper is to cope with this gap.

The question remains whether these active managers actually possess superior stock-selecting skills or is their performance only based on luck? Is it therefore justified to reward a managers' expertise if it was only based on luck?

The remainder of the paper is organized as follows. Section II discusses the related literature about the different market hypotheses in order to proceed to the different forms of evaluation methods and previous researches about the subject. Section III represents the gaps in the literature complemented with the added value of our paper. Section IV describes the data selection. Section V provides a clear view on the methodology we make use of.

2. Literature review

2.1 Theoretical framework

In order to determine whether or not managed portfolios can outperform random ones, we first examine the basic market theories. One of the founders of the idea that random portfolios perform just as well as actively managed portfolios is Eugene F. Fama. In his Efficient Market Hypothesis he substantiates why it is impossible to beat the market. Malkiel is another important economist who supports this idea, his Random Walk theory is built on the principles of Fama's Efficient Market Hypothesis. Opposite of this theory is formed by Andrew Lo (2004) in his Adaptive Market theory. He states that actively managed portfolios are able to systematically outperform random portfolios.

2.1.1 Efficient Market Hypothesis

The theory of efficient market is a theory literature puts a lot of emphasis on. The term of the 'efficient market' was first used by Eugene F. Fama (1965) in his article about the random walks in stock market prices. He states that in an efficient market, "*on the average,* competition will cause the full effects of new information on intrinsic values to be reflected 'instantaneously' in actual prices" (Fama, 1965).

In order to speak of an 'efficient market' the following requirements must be met. First, there has to be an existing amount of rational participants, who are competing with each other. Every single one of them is trying to predict future stock prices and gain advantage of it. Second, important current information has to be available to all participants free of charge or at low cost. If those requirements are met, this competition between the participants will be the cause of the incorporation of all information into the price, not only about past events, but also about events that the market expects to take place in the future. This implies that the actual price of a security is a good estimate of the true value of a share (Fama 1965).

Can we assume the stock market to be efficient? There are obviously many rational participants, who are looking for profit-maximization. On the other hand, important information seems to be available at a very low cost e.g. on the internet, where any investor can find large amount of information. In conclusion, stock markets have met the requirements, which would mean that all available information is already in the price, confirming the efficient market theory to be true.

According to how broad ‘all information’ is interpreted, Fama distinguishes three versions of his theory: a weak, a semi-strong and a strong version. In the weak version, all available information only covers all past stock prices and traded volumes. These historical figures about the stocks do not enable investors to gain abnormal returns. The semi-strong version adds something to the weak one and claims that the stock prices not only reflect all information about past prices and volumes, but also incorporate all publicly available information. Publicly available information includes i.a. annual reports, information about the accountancy methods that are used, patents, profit forecast and so on, in other words all fundamental information about the company. The strong version of his theory goes one step further and claims that a market is strongly efficient if the expectations of investors are based not only on public but also on private information. This is a very strong assumption, it would mean that insider trading is not profitable, considering, all private information is reflected into the price. Generally, the semi-strong version is the most accepted one.

All three forms of the efficient market hypothesis demonstrate the same basic idea: past price changes does not tell anything about the future, in other words “the stock market has no memory” (Malkiel 2003). Price changes in the past do not predict future ones. In his paper Fama stated that “the path of the price level of a security is no more predictable than the path of a series of cumulated random numbers” (Fama 1965). If markets are semi-efficient, new available information causes an immediate movement in price. It is such a quick movement that no one can buy or sell consistently fast enough to take an advantage from it. According to this theory, fundamental and technical analysis are useless, it is unnecessary to examine the annual results, changes in the management, acquisitions or also information about historical prices. None of those efforts will help achieve a higher return, the only thing that can be done in order to obtain higher returns is taking more risk. The theory implies that a portfolio manager is not able to outperform the market. In short, Fama states it is impossible to beat the market (Fama 1965).

2.1.2 The random walk theory

Another theory, which is similar with the efficient market hypothesis, is ‘the random walk theory’. The random walk theory states that stock prices follow a random path, this indicates that price changes are not at all related to previous ones and cannot be predicted. Anyone can achieve the same performance as an expert, after all a certain portfolio performance is nothing more than an outcome of a chance experiment. This theory was clarified and popularized by Malkiel (1973) in his bestseller ‘A random walk down Wall street’, but the underlying idea goes back to the 19th century.

According to Malkiel (1973) those random walks are a consequence of the efficient market hypothesis. As explained above, this theory assumes that all available information is reflected in the current price. Accordingly, Malkiel concluded that since the market is efficient -all information is incorporated into the price of stocks- future prices are unpredictable, after all real news develops randomly and so does the price of stocks.

That indicates that all stocks have an equal chance of gain. Malkiel took this to its extreme and stated that “today’s stock market is so efficient that a blindfolded chimpanzee aiming darts at the stock price pages of the Wall Street Journal could select a stock portfolio that would perform just as well as a fund actively managed by a professional broker” (Malkiel, 1973).

2.1.3 Adaptive Market Hypothesis

In order to supplement the efficient market hypothesis, Andrew Lo (2004) developed a new insight into the financial market that is regarded as a groundbreaking theory. This theory was captured by the designation of the ‘adaptive market hypothesis’ in which the rational principles of the efficient market are reconciled with irrational behavioral principles. These principles are mainly based on evolutionary biology and psychology such as competition, reproduction and natural selection (Lo, 2004).The notion of ‘adaptive’ refers to the market participants who determine their investment strategies based on the continuously changing financial environment by relying on heuristics (Kim et al., 2011). In that way, the adaptive market hypothesis takes into account certain market dynamics such as crashes, bubbles and crises which are not presented within an efficient market.

Despite the qualitative approach of the hypothesis, the theory offers five practical implications of which the return predictability can be regarded as the most important one. The return predictability is able to arise occasionally due to changes in the market conditions (Charles, Darnéb &Kimc, 2012). Changes in the market conditions may lead to changes in the populations' behavior. This refers to the investment strategies that will undergo cycles due to changes in the market conditions, the amount of competitors and the availability of profit opportunities. Whenever these opportunities shift, the affected populations will also shift (Lo, 2004). This implication may serve as an incentive to motivate the portfolio manager to actively manage their funds in order to achieve a profitable management.

2.2 Performance Evaluation methods

If we reject Fama his theory of efficient markets and assume it is possible to outperform the market, another question arises: how are we going to measure the performance of those who outperform the market? During the past decades different economists tried to develop good evaluation methods. In general, we can divide these evaluation methods into two groups. First there are the 'traditional performance evaluation methods', which use either peer groups or benchmarks. Second there are what we call 'new performance evaluation methods'. These methods are based on the random walk theory and use the return of random portfolios to compare the achieved returns with. We examine the possibility that active managed portfolios of investment consultants can beat the stock market. Put differently, we investigate whether portfolio managers are capable of obtaining a higher return than someone who invest at random.

2.2.1 Traditional performance evaluation methods

The skills of a portfolio manager are evaluated based on the return of a portfolio derived from the variety of investment strategies that he manages. The rate of return gives an indication of how well he performs under certain market conditions. Amenc and Le Sourd (2003) state that the measurement of the performance in relation to a certain point of reference might be more relevant. After all, in good economic times portfolio managers could achieve a return of 12% on their portfolio. On first sight this might seem a good performance but when you put it in perspective by comparing with certain references, this might be an under average performance. Benchmarks or peer groups are able to serve as a reference which can be seen as the two most common traditional evaluation strategies for measuring a portfolio manager's performance. In the next paragraph, both methods will be discussed.

2.2.2 Benchmarks

A benchmark is a portfolio consisting of market instruments in which a portfolio manager may invest (Weber, 2007). It can be seen as an independent measure of the investment policy into a certain fund. Benchmarking is thus the comparison of the return of one portfolio manager with the return of all the portfolio managers together, seen as a whole market return. The benchmarking comparison results in two possible outcomes: the portfolio manager is underperforming the benchmark (when his return is below the market return), or he can outperform the market when his return is above the market return (Fong, 2005).

Benchmarking fits well to the phenomenon of passive management. The portfolio manager invests in market portfolios that follow the bench using index strategies. This type of management doesn't require specific predictions of the manager in which he does not have the intention to outperform the market (Hendriks, 2004). Outperformance of the market means an active management where the manager makes specific decisions regarding certain market developments to achieve a higher rate of return.

Benchmarks occur under various types of forms of which a normal benchmark is regarded as the most meaningful one. The designation of a 'normal portfolio' was first introduced by Barr Rosenberg (Fabozzi, 1998). In his book 'Active Equity Portfolio Management' Fabozzi (1998) defines a normal benchmark as "a set of securities that contains all of the securities from which a manager normally chooses, weighed as the manager would weigh them in a portfolio. As such, a normal portfolio is a specialized index". The notion of the word 'normal' served as a reference that for each portfolio manager a certain habitat of securities existed. The method allows managers to evaluate their performances and optimize their trading strategies. The portfolio manager performed poor when he achieved a return that is beneath the normal benchmark rate. This type of benchmark is accurate and equitable for improving and measuring a manager's performance.

A new tracking method of benchmark indices has been created by Liang-Chuan Wu and Liang-Hong Wu (2013). The tracking method uses a spreadsheet-based decision support system that serves as a driver throughout the tracking system. The aim of the renewed approach is to improve index investing. The method consists of two quantitative phases. The first phase is linked to the mean- variance theory which is based on the conceptual framework of Markowitz's (1952) mean-variance model. During that phase, they start by pre-filtering the efficient stocks and adding them into investing pools. Subsequently they select stocks with the highest return at every risk level or by selecting stocks with the smallest risk at every level of return (Wu & Wu,2013). The second phase consists of the use of a 'goal programming method'. The program weighs the proportion of the investment of each stock in order to construct the definite pool. Both phases result in a decision support system which assists the portfolio managers in their decision making of management problems. We conclude that the quantitative model of Wu & Wu (2013) provides a well-founded buy and hold strategy at a low cost for compiling enhanced index investment portfolios.

2.2.3 Peer Groups

Peer groups are defined within the literature through Amenc and Le Sourd (2003) as a collection of managers who invest in the same type of assets or use a similar investment style . These groups consist of managers who meet certain features that make it possible to compare their performances. The performance of one portfolio manager can be compared to the performance of other managers or peers who meet the chosen criteria. However, it is necessary that the peer groups are large enough in order to ensure that the comparisons are statistically significant (Amenc & Le Sourd, 2003). The peer group analysis is popular because of the simplicity and the comparability (Bailey, 1992). The method is easy to use and the management data is publicly available partly because consultants have marketed this data as a service towards their clients. Policy makers also prefer this analysis because it is possible to see how a manager performs against competitors (Weber, 2007).

2.2.4 Shortcomings of the traditional evaluation methods

Peer groups suffer from a collection of disadvantages called biases (Surz, 2005) , which have been identified by Ankrim (1998), Bailey (1992) and Bleiberg (1986). Through the extensive use of the peer group evaluation strategy, the investment industry never questioned the method and overlooked these shortcomings. One of these biases is the classification bias, where the portfolio managers are assigned to one specific investment grade. The portfolios are classified according to the different mandates and styles that the managers use within their portfolios. This leads to a wrong assumption that the portfolio managers have the exact same opportunity set (the opportunity set is a collection of the available shares for inclusion in a portfolio). In reality, the fund managers use a blend of styles which makes it difficult to make a fair comparison. Weber (2007) gives an example of how the bias could be misleading. When a certain share is adopted in the mandate of the peers but not in the mandate of the portfolio manager, the ranking of the manager could be very low when that share has a higher return than usual. This leads to a wrong classification and ranking of the portfolio manager.

A second bias is the composition bias as a result of a data problem. The problem occurs when the amount of available databases is not sufficient enough to make a significant statistical analysis. Eley (2004) cites the problem with the following quote: “Don’t like your ranking, pick another peer group provider” which clearly refers to the problem of composition bias. The differences in the data could result in different rankings and performances through whether a portfolio manager is able to rank good or poor against a group of a provider.

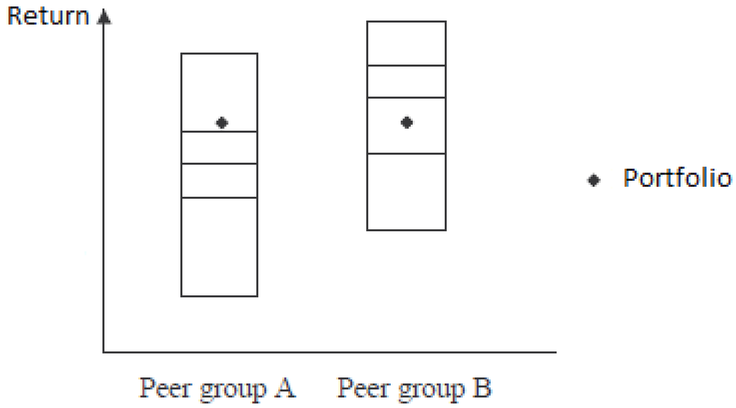


Figure 1: Success in A, Failure in B

(Weber, 2007)

Both biases, namely the classification bias and the composition bias ‘fight’ against each other. By widening the universe, the portfolios become less comparable, subsequently the classification bias increases. On the other hand, when we select databases that fit the managers better, the composition bias increases (Weber, 2007).

The last bias is the survivorship bias, which is the most documented and best understood source of the different biases (Wagner & Rieves, 2009). Surz (2005) gives a good illustration of the core of this bias by comparing the phenomenon with the ‘marathon analogy’. “If only 100 runners in a 1000 contestant marathon actually finish, is the 100th runner last, or in the top 10%?”. This example shows that it is possible that certain funds drop out of the peer group providers’ database due to an underperformance. The funds that were originally part of the database are then liquidated. The exclusion of these funds provokes a change in the ranking of the remaining funds (Van Heerden & Botha, 2012).

Burns (2004) is also critical towards the use of the peer group method by warning for imperfections. The use of the evaluation method makes it impossible to decide whether or not a manager has the potential to beat the market. The method is therefore not capable of indicating portfolio managers who performed on the basis of luck or skill.

In addition to the peer group method, benchmarks too are subjected to specific biases. Through the use of benchmarks, the look-ahead bias emerges. This bias is determined by Baquero et al. (2004) in their research about the performance of hedge funds. With benchmarking, it is possible that a poorly performing mutual fund leaves a certain index and is replaced by a mutual fund that performs better. Due to this switch, the composition of the index changes as well as the performance results, which could lead to faulty assumptions about performance.

Working with benchmarks also implies some disadvantages next to the biases. The major problem with benchmarks is situated within the statistical significance. In order to evaluate the performance of the portfolio manager, their rate of return is statistically determined by the use of a t-test which provides two potential hypotheses. The null hypotheses implies that the manager performed less or equal to the average market return. The alternative hypothesis involves an outperformance of the portfolio manager. The t-test only provides reliable results when the returns are independent and normally distributed. Within this field, the problem about normality assumptions rise. There is no certainty that the performance is normally distributed, especially because of the presence of derivatives within the investment strategies. A solution to this problem is given by the central limit theorem that states that the variance is normally distributed due to the presence of a sufficiently large number of independent variables. However, the performance of a manager does not satisfy to the normally distributed condition. To evaluate the performance, a large number of observations is needed to determine his skills in a reliable way (Weber, 2007).

To complement the problem described above, the benchmark method is affected by some additional disadvantages. Benchmarks are compared to theoretical portfolios in contrary to the peer group method, which uses real portfolios. The comparison to real portfolios involves transaction costs, management fees and taxes which do not apply to benchmarks. This rejection can lead to wrong assumptions. In addition to the fact that benchmarks do not take into account the different costs, they also ignore the different sources of incomes such as dividends and coupon rates. This problem though can be avoided by working with 'total return indices'.

2.3 New performance evaluation methods

2.3.1 Overview of new performance evaluation methods

To overcome the above mentioned shortcomings and weaknesses of the classical evaluation methods, economists developed new approaches to measure the performance of actively managed portfolios. A lot of these new methods are related to each other, in fact they are founded upon the same basic idea, the idea of the random walk theory, which we explained in detail in the previous chapter.

It is clear that the question if random portfolios perform as well as professionally composite ones is a much-discussed issue. The idea of random portfolios form the basis of a new approach to measure the performance of actively managed portfolios. They all more or less do the same thing, which is trying to make a comparison between the return of a professionally composite portfolio and the returns of all possible portfolios. In all new evaluation methods, a random portfolio is generated to compare with a real one. Once the random portfolio is composed, there is supposed to be a buy-and-hold strategy, this means that there will be no transactions anymore. The real portfolios on the other hand does not necessarily follow a buy-and-hold strategy. In the following paragraph we discuss in detail a few specific methods to evaluate the portfolio performance of actively managed portfolios.

Although the idea of comparing randomly composed portfolios with professionally managed ones has gained increasing importance the last two decades, it is certainly not new. Already in 1966, before the random walk theory was popularized by Malkiel, Cohen and Fitch developed the Average Investment Performance Index (AIPI). The AIPI calculates the average of the returns of all the possible portfolios in a certain market and over a certain time period. In other words the AIPI represents the average return an investor could obtain by investing in any portfolio in a particular market. This average return serves as benchmark against which the performance of a managed portfolio can be measured. According to Cohen and Fitch (1966), one of the shortcomings of commonly used classical approaches to measure the performance of a portfolio is that they do not clarify whether managed portfolios really obtain larger returns than could be expected by non-managed, randomly chosen portfolios. That is why they introduced the AIPI as an objective standard of comparison against which achieved portfolio returns can be measured (Cohen and Fitch, 1966).

As mentioned before, it is mainly in the last decades that the idea of those random portfolios has gained popularity. One of the many economists, who is in favour of using the return of random portfolios to compare real ones with, is Burns. He describes this as the perfect measurement (Burns, 2007). A comparison between the return of a given portfolio and the returns of all the portfolios –under the same constraints- that could have been chosen, would give you all possible information about the skill of the fund manager. However, it is impractical to work out every possible portfolio, taken into account the constraints of the real portfolio. The solution is to look at a random sample of portfolios (Burns, 2007).

The new methods to measure the managers' performance may be based on the same theory, there are, however, major differences. In the following paragraphs we discuss more in detail a few of these new approaches. Burns (2004) is convinced that random portfolios are better than benchmarks when it comes to the measurement of fund managers' skill. Based on these random portfolios, he evolved a new method to measure portfolio performance. The mean idea of this method is to use the p-value; this is "the probability of seeing a result as extreme or more extreme than what is observed given the null hypothesis is true." (Burns, 2004). In other words: what is the chance that a random portfolio performs better than the observed one? In his paper Burns also concluded that random portfolios are useful in another respect, namely forming portfolio mandates. But in this paper we are not going to pursue this question in greater dept.

A similar method to the one put forward by Burns is the one proposed by Bartz and Kane (2010). They developed the idea of using 'random matching portfolios' to compare the target portfolio with. The difference between the two is that these random matching portfolios not only obey the same constraints but also have the same characteristics as the target portfolio. They do not just compose portfolios at random, but they analyze the target portfolio and search a match for every security in the portfolio. A –in our eyes- negative aspect of this method is the fact that you probably need more information about the target portfolio. It is not possible to just compare the return of the portfolio with the average of all possible portfolios in that market (as with the method proposed by Burns (2004)). At every moment you need to know the exact composition of the target portfolio. On the other hand, there would not occur any bias in the result caused by specific characteristics of the target portfolio. Which is, of course, an advantage (Bartz and Kane, 2010).

A third new method to evaluate the stock picking skills -and thus the usefulness- of fund managers is the idea to not only make use of random portfolios, but also of semi-random portfolios. This idea was introduced by Lisi (2008) and also this method resembles the one developed by Burns (2004). These semi-random portfolios exclude a certain percentage of the worst stocks. For instance, instead of selecting a fully random portfolio, you can compose a portfolio by choosing at random stocks among the top 50% of the stocks. Another example is to select at random for instance 20 stocks among the best 50% and 10 among the worst 50% of the stocks (Lisi, 2008).

Ron Surz (1996) developed the Portfolio Opportunity Distributions, or PODs, in which he makes use of the Monte Carlo simulation to create a number of hypothetical portfolios. These hypothetical, randomly chosen portfolios are composite from the same set of stocks from which the fund manager can choose in order to put together his portfolio. An important aspect is the fact that the management style is taken into account. By doing this, the hypothetical portfolios will provide a fairly good reflection of all the portfolios in which the manager could have invested following his particular management style. In other words, it would represent every possible opportunity the fund manager had, if he wants to remain true to his style. The distribution of these random portfolios form a benchmark against which the real portfolio can be evaluated. This method allows us to determine if the fund manager used the available opportunities well, given a certain management universe (Adam Lundqvist, 2010).

2.3.2 Advantages and disadvantages of the new evaluation method

Let us take another look at the different biases from which some traditional evaluation methods, namely peer groups, suffer. Does the new method, based on random portfolios, also suffer from those biases? The most imported bias we described was the classification bias. The reason for this bias is the fact that different portfolio managers also implies different styles and mandates. For this reason their returns are not completely comparable and it causes a wrong ranking of portfolio managers. In some of the new method, for example PODs, random portfolios are drawn from the same opportunity set. The style and mandates are taken into account, that is why this evaluation method does not suffer from the classification bias.

Also the second bias we described, the composition bias, is not applicable to the new evaluation method. The composition bias is caused by the possibility to pick another peer group provider when you do not like your ranking. This bias does not exist when we use the random portfolio method. After all the idea is to compare the examined portfolio return to all possible portfolio returns. You could try to make your result look better by taking another sample. But the change this will influence the result is very small. Since the sample contains very much (at least 1000) possible portfolios, the average return of the sample is supposed to be a very good estimate of the average of all possible portfolio returns.

The third bias is called the survivorship bias, which is the consequence of the possibility that some underperforming funds drop out of the peer group providers' database. This causes a change in the ranking of the remaining ones. Methods using random portfolios will not suffer from this bias, as mentioned before, the idea is to compare with all possible portfolios, underperforming or not. That is why underperforming portfolios will not be removed from the database.

By the use of benchmarks we discovered one bias, the look-ahead bias. This one will not emerge when using random portfolios to evaluate portfolio performance. The underlying reason is the same as we explained above, there will be no elimination of funds that performed bad. Next to this bias, we also mentioned a few disadvantages of benchmarks. The first one was the fact that the assumption of a normal distribution seemed to be not fully correct. In our research we also assume a normal distribution, but this is will be more correct because of the following reasons. First, the random portfolios are drawn from a database consisting of 90 % shares, moreover, the remaining 10% exists mainly of bonds. Derivatives will be very rare. On the other hand we will take a sample consisting of more than thousand portfolios, since this size of the sample, it is reasonable to assume a normal distribution of the returns. Whether this assumption is fully correct or not will become apparent after further analysis.

Although, the use of random portfolios in the evaluation of management skills has a lot of advantages, above all the fact that it does not suffer from the biases, we also find criticism in the literature. Surz mentioned another negative point of the use of random portfolios, namely the fact that it is not real. Investors want to know how other managers did, they want to know if they would have earned a higher return when they had entrusted their money to another fund manager (Surz, 2005). But still, we can conclude that the use of random portfolios to evaluate actively managed portfolio performance offers more advantages than drawbacks.

2.4 Empirical research

One of the first researches on the performance of mutual funds was done by Jensen (1968). He investigated a time period of 20 years, starting in 1945. For that time period, he compared the returns of 115 mutual funds with the returns of randomly selected portfolios. Unlike the real funds, the random portfolios were supposed to follow a buy and hold policy. He concluded that “these 115 mutual funds were on average not able to predict security prices well enough to outperform a buy-the-market-and-hold policy” (Jensen, 1968).

A few years later, Malkiel’s book ‘A random walk down Wall street’ was released, it was in this work that Malkiel stated that a blindfolded monkey throwing darts at the financial page of the Wall Street Journal could select a stock portfolio that would perform just as well as one selected by professional financial advisors (Malkiel, 1973).

This release caused a surge of similar research on the performance of actively managed portfolios. Researchers have put Malkiel’s bold statement to the test, these ‘monkey portfolios’ were compared with those of real investment advisors. Also the Wall Street Journal was inspired by Malkiel’s statement. In the year 1988 they started a contest, called ‘The Dartboard Game’. This game was another experiment to test whether professional investors, with their outstanding knowledge of financial markets and their sophisticated analyses, really can perform better than a naïve investor, without any experience at all (Jasen, 2002).

This ‘Dartboard Game’ encouraged a lot of economists to do similar research. Liang, Ramchander & Sharma (2005) used this dartboard game to, in their turn, investigate whether portfolios put together on professional advice could outperform random portfolios. This is how they approached the matter, they examined the ‘Investment Dartboard Column’ of the *Wall street Journal* on a monthly basis from October 1988 through June 1991, formed a portfolio based on the recommendations of professional fund managers in that column and compared it with a portfolio selected at random. Liang, Ramchander and Sharma (1995) concluded that only over a one-week period portfolios composite on managers’ advice could outperform random portfolios. In all the other observed time periods dartboard portfolios performed better (Liang, Ramchander and Sharma, 1995).

More recent research was done by Lisi (2008). He compared the performance of 23 actively managed Italian mutual funds with the performance of thousand randomly created portfolios, for a time period from 2002 to 2007. He generated these random portfolios from the set of stock that he believed to represent the investor's true environment. In contrast to Jensen (1968) he concluded a few active managers possessed superior skills and could outperform random portfolios.

The same research has been done for the Swedish market by Lundqvist (2010). His research was more extensive, both in terms of time period as in terms of number of investigated funds. In his research he did not found any evidence of the existence of superior stock selecting skills. He assumes the semi-strong version of Fama's Efficient Market Hypothesis to hold true in the Swedish financial market. His advice for investors: do not put your money in the hands of expensive fund managers. "If gambling is what the investors are looking for, I would advise them to go to a casino. If they are saving for the future, I would tell them to buy and hold, diversify or invest in an index fund" (Lundqvist, 2010). Tudor (2012) investigated the Romanian stock market. Although he used another measurement method, his results confirmed conclusion of Jensen (1968) and Lundqvist (2010) that actively managed portfolios are not able to outperform the market.

A completely different result was found by Nicolai Wüsten (2012). After examining the German mutual market he rejected the Efficient Market Theory of Fama and concluded that "an investor can generate higher returns on the German stock market if he is using an active portfolio management strategy rather than its passive counterpart" (Wüsten, 2012).

Within literature we find evidence both in favour and against the Efficient Market Hypothesis. This led us to the following consideration; could it be that the degree of market efficiency not only differs over time but also over regions? Since the market efficiency is believed to be caused by the extensive analysis of new available information, it seems rational to assume that less intensively analyzed markets such as the emerging markets are not -or less- efficient. By consequence, in these markets profits could be made by actively looking for investment opportunities.

Within this framework, it is worth mentioning the recent research carried out by Mishra, Mishra and Smyth (2014). By making use of unit root tests, Mishra, Mishra and Smyth (2014) tested the Random Walk Hypothesis for the Indian stock market. Despite the fact that they used a fundamentally different approach compared to our research, their result may provide new relevant insights. In their research they argue that the emerging markets –in contrast to their developed counterparties- do not have highly developed information distribution mechanisms. By consequence, new information is not available for all relevant parties at the same moment in time. This creates a situation in which certain investors may temporarily benefit from having information that is not available to their competitors. The results of their research indicate that Indian stock prices are mean reverting, which means that they tend to move to an average. Therefore, the prices of Indian stocks can be predicted and the Efficient Market Hypothesis seems not to hold for the Indian stock market. Hence, active portfolio management performs better than passive management in this markets (Mishra, Mishra, & Smyth, 2014). This result is in line with previous research results by Hamid, Suleman, Shah & Akash (2010). They tested the weak-form market efficiency of the stock returns of fourteen Asian-Pacific countries and concluded that these do not follow a random walk.

Although emerging countries will not be the focus of our research, it seems valuable to point to the differences over regions. In developed countries there is a growing consensus amongst economists that the stock prices follow a random path, hence, random portfolios are supposed to perform just as well as actively managed portfolios. Although this does not mean that random portfolios are superior all over the world. In emerging countries it seems possible for active managers to gain superior returns by taking advantages of the information disequilibria.

We conclude that economists do not agree upon the question whether or not an actively managed portfolio can outperform random ones. While most of the researchers (Jensen (1968), Lundqvist (2010) and Tudor (2012)) conclude there exists no possibility to outperform the market, others belief it is possible, but rarely, that actively managed portfolios perform better (Liang, Ramchander and Sharma, 1995 and Lisi, 2008). Besides, there are some researchers i.a. Wüsten (2012) who came to the conclusion that actively managed portfolios do systematically outperform the market. Note that not all economists used the same measurement method, for example Lisi (2008) and Lundqvist (2010) made use of random portfolios, Tudor (2012) and Wüsten (2012) on the other hand used benchmarks in order to measure the performance of the active portfolios. Even though these different opinions may be the consequence of a difference in method, it seems acceptable to assume that, while it is generally not possible for active managers to beat the stock market, it might be so in certain countries, for example in emerging countries with a less developed information distribution system.

3. Gap & Added value

3.1 Gaps in literature

After analyzing the current literature on the performance of actively managed portfolios we determine the presence of gaps in the existing literature. We distinguish two types of gaps. The first gap is considered as a geographical gap, consisting in the absence of research on our research question in the Belgian financial markets. The second gap is related to the performance of random portfolios during different economic circumstances. The examined literature provides results which do not take into account the effects of the financial crisis and its after-effects. Such extreme conditions as we have known during the last six years could drastically influence the results of past research. In our opinion it is important to make a distinction between the performance of actively managed portfolios during a booming economy and during a situation of economic hardship.

3.1.1 Geographical Gap

The geographical gap indicates the lack of relevant and useable results on the use of random portfolios as a decent performance evaluation method applied to the Belgian financial market. Current literature often only deals with the traditional methods, namely the peer group and benchmark method. Although these methods are subjected to shortcomings, as mentioned above, they still are widely accepted as decent methods to evaluate the performance of portfolio managers. During our research we found practicable results on the use of random portfolios which were only applicable to specific national markets, such as the German stock market, the Romanian stock market and the Swedish mutual fund market. The aim of our research is to cope with this geographical gap by executing the random portfolio method within the Belgian market in order to achieve decisive results for our research question.

3.1.2 Gap concerning different market climates

An- in our eyes- shortcoming of most of the current literature, is the fact that they do not take into consideration that the financial climate might have an influence on the obtained results. It might be possible for active managers who do not outperform the market during periods with a positive economy, to do so during periods of economic and financial crisis, or maybe the other way around. For that reason it seems wrong of economists to generalize the conclusion of their investigation, if they only examined one single economic climate.

Lisi (2008) investigated the Italian market for a time period from 2002 – 2007. He concluded that a few managers possess superior skills. During that period of time, there was no question of the financial crisis yet, when repeating the exact same investigation today, the result may be completely different, because the economic climate has changed drastically. Tudor (2012) drew his conclusion based on stock data from 2007 to 2011. This period of time only contains a period of global crisis. Here again, it seems wrong to generalize the conclusion. Wüsten (2012) on the other hand investigated a time period of 20 years, which included both periods of economic growth and hardship. However, he did not make a distinction between different market climates and came to only one general conclusion.

We conclude that there is a gap concerning the influence of different financial climates. It is necessary to investigate the question separately for periods of booming economy, periods of crisis and periods of recovery. We are coping with this gap by dividing our investigated time period into two different sub periods. The first sub period starts on January 1, 2002 and ends on December 31, 2006. This time period represents a period of economic welfare. The second sub period covers the period from January 1, 2007 to December 31, 2012. This represents a period of financial and economic crisis.

3.2. Added Value

The added value of our paper consists in the fact that we make use of portfolio opportunity distributions, also known as random portfolios or monkey portfolios. This approach provides a better evaluation of the portfolio manager's performance because the evaluation method copes with the shortcomings of the traditional evaluation methods as described in paragraph 2.2.4. The POD method is not only a decent method to evaluate the performance, but also offers the possibility to measure the skills of the portfolio manager to determine whether or not his performance was based on his expertise rather than on luck.

<u>Why is the POD method better than the Benchmark method?:</u>

- ✓ A longer time period is not necessary to obtain statistical significance;
- ✓ Random Portfolios are fully representative for their mandate;
- ✓ Random Portfolios take into account different sources of incomes;
- ✓ Random Portfolios take into account corrections for transaction costs;
- ✓ The survivorship bias disappears;

Why is the POD method better than the Peer Group method?:

- ✓ The classification bias disappears;
- ✓ The composition bias disappears;
- ✓ The survivorship bias disappears;

In line with the added value that states that the POD method is a much more decent method than the traditional methods, she also offers the possibility to individuals, bankers, investors and fund managers themselves to determine their performance. The method does not require complex models or large amounts of data to determine their performance in order to respond to changes in their fund compositions.

4. Data Selection

4.1 Data

4.1.1 Time period

The period related to our research starts on January 1, 2002 and ends on December 31, 2012. The reason for this time horizon consists of two underlying thoughts. We want to cover a current period in which there is both a positive economic climate as well as a period of the financial crisis situated between 2007 and 2009 with his legacy. On the one hand we tried to limit the time period with the intention of minimizing the survivorship bias, but on the other hand we need a time period which is large enough to generalize our conclusions. A research period of eleven years satisfies these two criteria.

In order to be able to study differences on the performance of active management and random portfolios during different market climates, we divide the time period in three sub periods. The time frame is divided into the following sub periods:

1. Pre-crisis : January 1, 2002 – August 8, 2007
2. Financial crisis : August 9, 2007 – April 2, 2009
3. Post-crisis : April 3, 2009 – December 31, 2012

As start date for the financial crisis we opted for August 9, 2007, the day on which the European Central Bank injected €95bn of liquidity into the European banking system (ECB, 2014). By this action the European Central Bank tried to respond on the changing conditions in the European money market. This major liquidity injection was the first one since the terrorist attacks of 9/11, which underlined the seriousness of the situation.

We believe April 3th 2009 to be an appropriate estimate for the end of the financial crisis. Even though the financial crisis was not over yet, the European stock markets started to recover after having reached their lowest level in March. April 3, 2009 was the date on which the ECB cuts interest rates again in order to boost the economy, on the same day the G20 established the Financial Stability Board, which will work together with the IMF to recommend actions to accelerate economic recovery (ECB, 2014).

4.1.2 Fund data

In order to investigate the Belgian market, we collected 12 equity funds (see appendix) derived from six major commercial banks active in Belgium.[1] The data of these funds are derived from the Morningstar site (Morningstar, 2014). Since, it is essential that our research is useable, the data need to meet certain criteria:

- ✓ Only funds derived from six major commercial banks active in Belgium are included;
- ✓ Only the Belgian funds that exist over the whole research period are included;
- ✓ Only funds that invest for at least ca. 90% in Belgian equities are included;
- ✓ Only open-ended funds are included;
- ✓ Only funds with a sufficiently large amount of stocks (25-35) are included;

[1]Argenta, AXA, BNP Paribas Fortis, Dexia Belgium, ING & KBC

5. Methodology

5.1. Mutual fund performance analysis

In his work ‘Dicing with the market: randomized procedures for evaluation of mutual funds’, Francesco Lisi (2008) developed a procedure for evaluating the skills of the mutual fund manager. This procedure has a statistical approach and is completely data driven, based on random portfolios. The framework makes use of statistical significance, working with a null- and alternative hypothesis.

$$H_0 = The\ mutual\ fund\ manager\ shows\ no\ stock\ selection\ skills$$
$$H_a = The\ mutual\ fund\ manager\ shows\ \ stock\ selection\ skills$$

The notion of ‘skill’ refers to the competence of a mutual fund manager to yield returns, net of mutual fund costs, which are significantly higher than the returns realized by fund managers without any stock selecting skills. These ‘unskilled’ managers are represented by random portfolios (monkeys).

5.2 Procedure random portfolio technique

In order to test the null hypothesis, we follow Lisi’s (2008) stepwise approach for working with random portfolios. We use the Statistical Analysis Software (SAS) to encode the algorithm that generates random portfolios.[2]

Step 1: Determine the investment universe

Let S = $\{S_i\}$, i = 1, …, N_s be the manager’s investment universe. The investment universe can be considered as a collection of all the stocks of which a random portfolio can be composed. Within our research, the investment universe consists of all the stocks that were listed on the NYSE Euronext Brussels during the observed period.

[2] Appendix: Random portfolio algorithm

Step 2: Generating *m* portfolios by a random selection of *k* assets from *S*

We generate fund m = 500 random portfolios composed of k = 30 stocks. These random portfolios follow a buy and hold strategy. This is a passive investment strategy that holds the selected stocks in the portfolio during the entire period, regardless the short term market evolutions.

Step 3: Calculate the holding period return

We calculate the holding period return $r_t(F_i)$ for each of the m portfolios F_i, (i = 1,..,500). The series of m measures $r_t(F_i)$ that is used for estimating the distribution under the null hypothesis.

Step 4: Compare the observed return

We use the three different indicators to compare the observed return $r_t(F)$ with the cumulative return and the average daily return of the set of random portfolios. We examine whether the observed portfolios are able to achieve a higher cumulative return than the average random portfolio. Besides, we compare the observed returns with the distribution of the returns achieved by the generated random portfolios. In other words, we look how many random portfolios perform better than the examined mutual fund, both in terms of cumulative return and in terms of average daily return. All of these tests are done for the full period and sub periods separately.

Step 5: Testing the two hypotheses

Let α represents the fraction which discriminates between the two hypotheses. If the 'Daily p-value' $< \alpha$, the null hypothesis is rejected at the 1-α confidence level. For this research, the confidence level is set at 90 percentage. By consequence, if the 'Daily p-Value' is smaller than 10% we reject the null hypotheses and conclude that active managers do possess stock selecting skills.

5.3 Correction for the degree of risk

The procedure described above is considered as a basic method to evaluate mutual fund performance. Within a real concept some aspects have to be generalized, especially the degree of risk that is inherent within portfolios. A higher performance of random portfolios could have been achieved due to a higher level of risk. There are two approaches for taking into account the level of risk. The first one consists of verifying the ex post riskiness of both the random portfolios and the mutual fund. The ex post riskiness of a portfolio is the volatility of the returns, measured by the standard deviation. The second approach was proposed by Modigliani and Modigliani (1997). They introduced an alternative risk adjustment on the performance of the random portfolios. They state that, when the risk level of the random portfolios is higher than the risk level of the mutual fund, a risk correction needs to be implemented on the level of the random portfolio. The correction for risk is computed by the following equation:

$$AR = \frac{V_F}{VF_{i\,R_t(F_i)}}$$

Equation 1: Risk adjustment

Where 'AR' is the adjusted return , V_F is the risk level of the fund represented by the standard deviation. $VF_{i\,R_t(F_i)}$ is the risk level of the random portfolio multiplied by the randomly generated return.

As result, a certain performance level , due to a higher risk will be corrected by the penalty factor $\frac{V_F}{VF_{i\,R_t(F_i)}}$.

Another assumption that we take into account is the amount of *k* stocks in the portfolio. The number of stocks needs to be sufficient in order to speak of a differentiated portfolio. Meir Statman (1987) concludes in his research on 'how many stocks make a diversified portfolio?' that approximately 30 till 40 stocks are enough. To meet the realistic sphere, we generate portfolios that are initially equally weighted.

5.4 Informative performance statistics

Within this evaluation procedure three statistics serve as a performance indicator: the 'Mean Alpha', the 'P-value' and the 'Daily p-Value'.

The 'Mean Alpha' represents the difference in the cumulative return between the observed funds and the random portfolios at the end of the invested time period and is given by the following formula:

$$Mean\ Alpha \ = \frac{\sum_{i=1}^{m} Alpha}{m}$$

Equation 2: Mean Alpha

In which 'Alpha' represents the return of the fund $r_t(F)$ minus the random return $r_t(F_i)$ or the adjusted return for risk 'AR'. Both results, with and without risk correction, are reported in the review of the results.

The second statistic the 'P-Value' represents the fraction of monkey portfolios that perform better than the observed fund. The statistical significance is set on a confidence interval of 90%. If 'P-Value' $\leq$ 0,10 we reject the null hypothesis and conclude that the portfolio manager shows stock selecting skills. The 'P-value' is given by the following equation:

$$P - Value = 1 - \frac{Count}{m}$$

Equation 3: P- Value

In which 'count' represents each occurrence where the fund was able to achieve a higher return than the monkey portfolios (Fund-return > Adjusted risk return) and *m* the amount of random portfolios.[3] The 'P-value' is an evaluation of the fund performance on the end of the researched period. It is a measure of the cumulative return, which may lead to skewed results. If one day the fund manager is able to achieve a very high return, this will be reflected in the cumulative return and you would conclude that active managers are able to outperform the random funds over the whole period, based on a one day event. Vice versa, if the monkey portfolio performs extremely well on one day and only moderate during the rest of the period, this one day event will have a significant influence on the cumulative return on the end of the period.

[3] For a more detailed view : source code in appendix.

In order to obtain more correct results and to be in line with the methodology applied by Lisi (2008) we provide the 'Daily p-value' which represents the fraction of monkey portfolios that is able to outperform the fund under examination at time *t*. This measure determines the percentage of random portfolios with a higher performance than the actual mutual fund. Linked back to the hypothesis, suppose that α is the probability that discriminates whether or not to accept the null hypothesis. For a certain period *t*, the null hypothesis will be rejected if the 'Daily p- value' < α. This measure is calculated as follows:

$$Daily\ PV_t = \frac{\sum_{i=1}^{m} I\ (\ r_t\ (F_i\ ) >\ r_t\ (F))}{m}$$

Equation 4 : Daily p-value

Where *I* is the indicator function, r_t represents the return of the random portfolio on day *t* and $r_t(F)$ the return of the fund. *M* stands for the number of randomly generated portfolios.

6. Results

In this paragraph we discuss the results of our research. This includes answering the question whether or not active portfolio managers are able to beat monkey portfolios. In the first part we determine the cumulative returns and the standard deviations of the selected funds. In the second part we discuss the performance of the examined Belgian funds regarding to the different periods. In the third part we compare the evaluation results with the findings of previous studies. The last paragraph provides a possible rationale behind the results.

6.1 Cumulative return

The cumulative return 'R' is the percentage of capital gained or lost on an investment and this compared to the initial amount of invested capital. The ratio is given by the following formula:

$$R = \frac{R_1 - R_0}{R_0}$$

Equation 4 : Cumulative return

In which R_0 represents the market value of the fund at the beginning of the period and R_1 the market value at the end of the period. The cumulative return can be considered as the relative growth of the value of the investment.

6.2 Standard deviation / risk of the portfolio

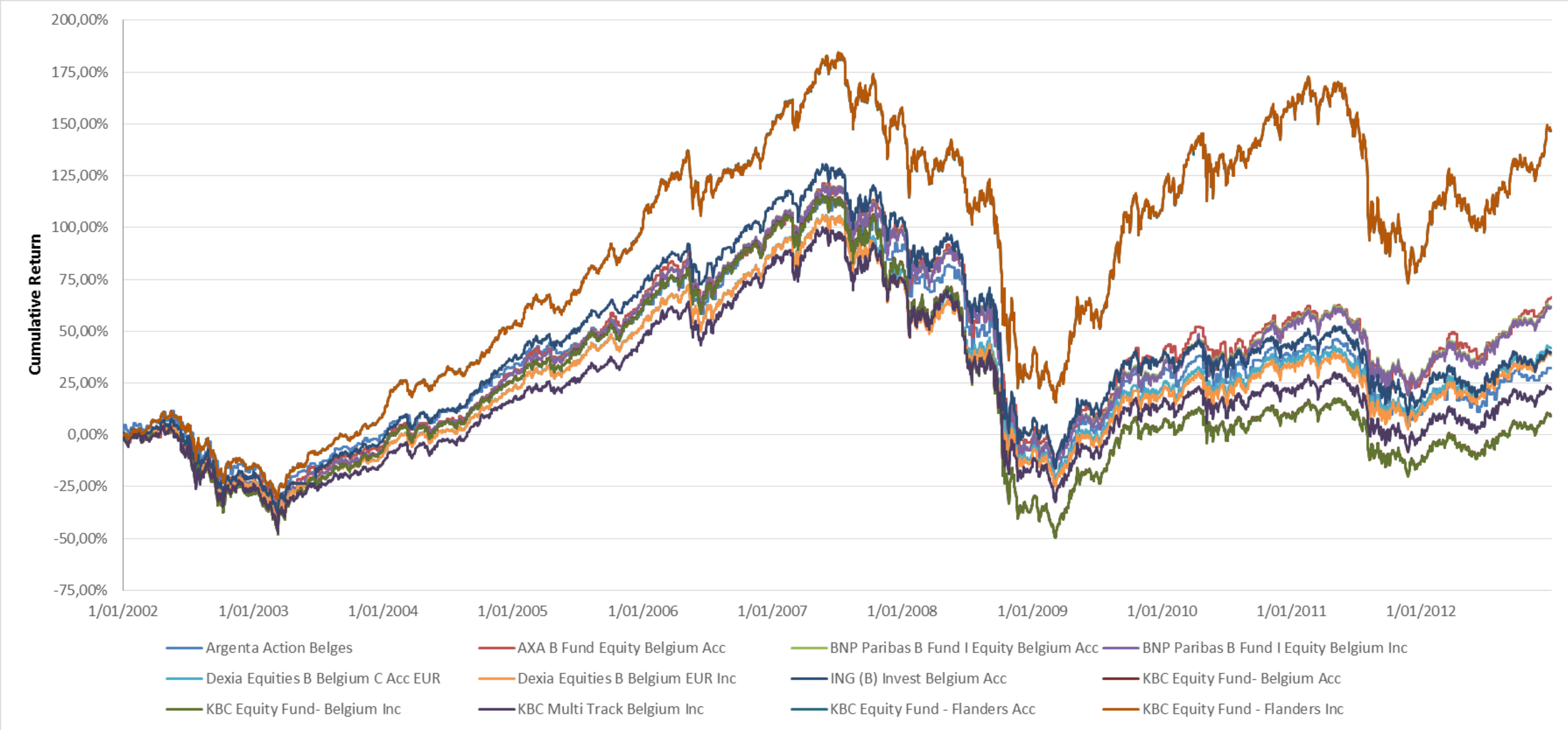
The standard deviation measures the volatility of the portfolio return, this measure is commonly used as an indication of risk factor of the portfolio. A low standard deviation indicates that the observed returns tend to be close to the average return. This implies a lower risk inherent to the portfolio. The ratio is given by the following equation:

$$Risk = \sqrt{\frac{\Sigma(R_1 - \bar{R})^2}{N}}$$

Equation 5 : Standard deviation of returns

In which R1 represents the daily return, $\bar{R}$ the average daily return and N the number of daily returns. This measure is used to adjust the fund return for the risk inherent to the portfolio. In annex, an overview of the previous statistics is given for each fund and time period. [4]

[4] Appendix: overview of cumulative return and risk per fund and time period.



Graph 1 : Cumulative return of the 12 selected funds

Graph 1 illustrates the cumulative returns of the selected funds during the research period of January 2002 – December 2012. This cumulative return represents the total return of the fund during the investigated time period. Throughout the whole observed period, the mutual funds show a similar trend, but since the financial crisis the spread between the trend lines enlarges. All open funds achieved returns between 9% and 66%, with the exception of the two funds 'KBC Equity Flanders Inc' and 'KBC Equity Flanders Acc' which clearly predominate the others. Those two funds obtained a return of 149% over the entire period, which is a large difference with all other funds. Both funds have nearly the exact same evolution, in fact it concerns the same portfolio, the difference between the funds is that the 'KBC Equity Flanders Acc' is a capitalization fund and 'KBC Equity Flanders Inc' is an income funds, meaning that dividends are paid out in the latest one and automatically reinvested in the first. But, since we do not take into account the dividends that are paid out by the fund, there is almost no difference in evolution. We assume that this significantly higher return is either the consequence of a higher risk profile, the result of better stock selecting skills of the fund managers or based on luck. In the following part we will sort out the true cause of this outstanding performance. The graphs regarding the sub periods are included in annex.

6.3 Performance of the mutual funds

Graph 2 gives an overview of the main results of the research. The first column provides the cumulative returns for each period, the second gives the standard deviation, which is an indication for the risk level of the portfolio. Column 3 to 7 represent the three different performance indicators.

			Mean-Alpha		Level outperformance					Mean-Alpha		Level outperformance		
	Return	**Risk**	**w/o RC**	**With RC**	**w/o RC**	**With RC**	**Daily PV**	**Return**	**Risk**	**w/o RC**	**With RC**	**w/o RC**	**With RC**	**Daily PV**
Name fund	Period: full period							Period: pre-crisis						
Argenta Action Belges	0,3225	0,0128	-1,1550	-1,7640	0,9980	1,0000	0,5273	0,9621	0,0111	-0,5667	-0,8890	0,8380	1,0000	0,5392
AXA B Fund Equity Belgium Acc	0,6620	0,0122	-0,8155	-1,3282	0,9760	1,0000	0,5223	1,0588	0,0122	-0,4700	-0,9740	0,7820	1,0000	0,5340
BNP Paribas B Fund I Equity Belgium Acc	0,6255	0,0114	-0,8520	-1,2328	0,9820	1,0000	0,5032	1,0579	0,0114	-0,4710	-0,8403	0,7820	1,0000	0,5116
BNP Paribas B Fund I Equity Belgium Inc	0,6161	0,0117	-0,8614	-1,2821	0,9820	1,0000	0,5036	1,0558	0,0116	-0,4730	-0,8831	0,7820	1,0000	0,5119
Dexia Equities B Belgium C Acc EUR	0,4166	0,0119	-1,0609	-1,5152	0,9960	1,0000	0,5160	0,9169	0,0119	-0,6120	-1,0566	0,8620	1,0000	0,5120
Dexia Equities B Belgium EUR Inc	0,3842	0,0119	-1,0932	-1,5569	0,9980	1,0000	0,5206	0,9154	0,0119	-0,6134	-1,0675	0,8620	1,0000	0,5117
ING Invest Belgium Acc	0,3992	0,0120	-1,0783	-1,5496	0,9980	1,0000	0,5161	1,1310	0,0120	-0,3978	-0,8599	0,7440	1,0000	0,5214
KBC Equity Fund- Belgium Acc	0,0926	0,0143	-1,3848	-2,2376	1,0000	1,0000	0,5180	0,9904	0,0143	-0,5384	-1,3901	0,8200	1,0000	0,5126
KBC Equity Fund- Belgium Inc	0,0898	0,0143	-1,3877	-2,2404	1,0000	1,0000	0,5104	0,9874	0,0143	-0,5414	-1,3933	0,8220	1,0000	0,5126
KBC Multi Track Belgium Inc	0,2198	0,0137	-1,2577	-2,0091	0,9980	1,0000	0,5211	0,8316	0,0137	-0,6973	-1,4455	0,9060	1,0000	0,5159
KBC Equity Flanders - Acc	1,4663	0,0116	-0,0112	-0,4219	0,4740	0,7500	0,4949	1,6515	0,0116	0,1226	-0,2757	0,3240	0,6640	0,4930
KBC Equity Flanders - Inc	1,4682	0,0116	-0,0093	-0,4196	0,4740	0,7440	0,4950	1,6544	0,0116	0,1255	-0,2725	0,3240	0,6580	0,4931
Name fund	Period: crisis							Period: post-crisis						
Argenta Action Belges	-0,4093	0,0262	-1,7216	-4,0038	1,0000	1,0000	0,4903	0,4874	0,0120	-0,6770	-1,0508	0,9300	0,9760	0,5240
AXA B Fund Equity Belgium Acc	-0,4061	0,0252	-1,6958	-3,8626	1,0000	1,0000	0,4906	0,7728	0,0115	-0,3915	-0,6993	0,7760	0,9060	0,5152
BNP Paribas B Fund I Equity Belgium Acc	-0,4090	0,0237	-1,6674	-3,6579	1,0000	1,0000	0,5019	0,7118	0,0106	-0,4459	-0,6541	0,8080	0,9080	0,4906
BNP Paribas B Fund I Equity Belgium Inc	-0,4090	0,0237	-1,6649	-3,6582	1,0000	1,0000	0,5028	0,7054	0,0111	-0,4589	-0,7515	0,8180	0,9240	0,4907
Dexia Equities B Belgium C Acc EUR	-0,3906	0,0232	-1,6393	-3,5766	1,0000	1,0000	0,5089	0,6324	0,0114	-0,5132	-0,8269	0,8240	0,9520	0,4960
Dexia Equities B Belgium EUR Inc	-0,3896	0,0234	-1,6513	-3,5989	1,0000	1,0000	0,5085	0,6288	0,0115	-0,5355	-1,0962	0,8620	0,9820	0,4939
ING Invest Belgium Acc	-0,4016	0,0248	-1,7812	-5,0243	1,0000	1,0000	0,5083	0,4104	0,0117	-0,7540	-1,0037	0,9700	0,9980	0,5115
KBC Equity Fund- Belgium Acc	-0,5316	0,0327	-1,7813	-5,0446	1,0000	1,0000	0,5245	0,7079	0,0133	-0,4466	-1,0050	0,8160	0,9580	0,5021
KBC Equity Fund- Belgium Inc	-0,5316	0,0327	-1,0000	-4,1632	1,0000	1,0000	0,5245	0,7066	0,0135	-0,4578	-1,0310	0,8180	0,9600	0,5021
KBC Multi Track Belgium Inc	-0,4026	0,0274	-1,7157	-3,9856	1,0000	1,0000	0,5040	0,5227	0,0130	-0,6415	-1,1479	0,9240	0,9760	0,5090
KBC Equity Flanders - Acc	-0,3850	0,0238	-1,6347	-3,6555	1,0000	1,0000	0,5116	0,8404	0,0129	-0,3240	-0,8128	0,7340	0,9180	0,4902
KBC Equity Flanders - Inc	-0,3851	0,0238	-1,6348	-3,6756	1,0000	1,0000	0,5116	0,8402	0,0129	-0,3241	-0,8216	0,7340	0,9180	0,4864

	Min.	**Max.**	**St. Dev.**	**Mean**	**Median**	**10th percentile**	**25th percentile**	**75th percentile**	**90th percentile**	**Mean Risk**
random portfolio	0,3365	3,1040	0,4918	1,5074	1,4766	0,9095	1,1341	1,8428	2,1570	0,0097

Table 1: main research results

The cumulative returns for the full period range between 8,98% and 146,82%. Interesting to note is that the funds with the lowest returns, namely ‘KBC Equity fund Belgium Acc’ and ‘KBC Equity Fund Belgium Inc’, seem to be the funds with the highest risk. Which contradicts the generally accepted risk-return relationship. During the pre-crisis period these funds had an average performance compared to the other funds, but during the financial crisis they were hit particularly hard, however, since they already had the highest risk pre-crisis, this result could be expected.

The two mutual funds that had a remarkable return based on graph 1, are by far the best performing funds when we look at table 1. When looking at the sub periods we conclude that indeed ‘KBC Equity Flanders – Acc’ and ‘KBC Equity Flanders- Inc’ systematically outperform the other portfolios in the sample; they achieve the highest returns during the pre-crisis period, they suffer the lowest losses during the financial crisis and they know the strongest recovery. Although these two funds outperformed the other funds in this research, they were not able to outperform the monkey portfolios, which had an average cumulative end return of 149,18%.

As mentioned above, there are three possible causes for these systematically higher returns. Either the fund is more risky than other funds within the research, what makes the return more volatile, or the fund manager does possess a little more stock selecting skills than other fund managers, or their performance is solely based on luck. Since the standard deviation of these funds belongs to the lowest ones within sample (column 2), their return seems not to be caused by a higher risk profile. This leaves the question whether their performance is based on luck or true talent. As mentioned previously we provide three parameters to answer this question, the Mean-Alpha, the ‘Level of Outperformance’ and the ‘Daily p-value’. In the following paragraphs we discuss each of these performance statistics.

The ‘Mean Alpha’ is calculated as the difference between the cumulative return of the fund and the average cumulative return of the random portfolios. For the full period and all the sub periods separately, all the ‘Mean Alphas’ are negative, which means that random portfolios were –on average- able to achieve a higher cumulative return than each of the funds under scope of this research. There is only one exception, namely the two best performing funds, they have a positive ‘Mean Alpha’ during the pre-crisis time period. Once corrected for risk, even for the two best performing funds there is clearly no question of outperformance.

The second statistic that measures the performance of actively managed funds is the ‘Level of Outperformance’. This is the fraction of random portfolios that were able to obtain a higher cumulative return at the end of the research period. If the level of outperformance is lower than 10%, in other words, only 10% or less of the random portfolios perform better than the real fund, we assume that the portfolio manager possess some stock selecting skills. For most of the funds the level of outperformance is extremely high during all the researched time periods. During the financial crisis, each of the observed funds is outperformed by all of the monkey portfolios. Throughout the pre-crisis period, the two funds of ‘KBC Equity Flanders’ were only beaten by 32% of the monkey portfolios. Compared to the other funds under scope of this research, this is a remarkably good result, but still far from the 10% border in order to conclude the presence of stock selecting skills. After risk correction the level of outperformance increased.

The ‘Daily p-value’ measures the proportion of random portfolios that outperform the observed fund. This indicator results in less distinctive figures. Even though there are differences between the different funds, we state that all of the observed portfolios are outperformed by approximately 50% of the random funds, this figure does not vary much over the different sub periods. The ‘Daily p-value’ is used to draw conclusions concerning the null hypothesis. We decided α to be 0,10. For both the full period and the individual sub periods, we find ‘Daily p-values’ that are greater than 0,10. Hence, we accept the null hypothesis for each individual fund, during every researched time period. This means that, based on this research, fund managers possess no skills. Also the other indicators already reveals no evidence for the existence of stock selecting skills.

According to the ‘Daily p-value’, the actively managed funds perform on average, while based on the ‘Level of Outperformance’ we would conclude that actively managed funds systematically underperform random portfolios.

This result confirms earlier findings of Jensen (1968), ‘The Dartboard Game’ of the Wall Street Journal (1988), Lunqvist (2010) and Tudor (2012), they all conclude that actively managed portfolios are not able to outperform the market. Lunqvist (2010) used a similar research method as used within this research, this makes a more detailed comparison possible. He concludes that none of the observed funds had a significant positive p-value, some funds had a significant negative P-Value, indicating that some fund managers have negative stock selecting skills. When we draw conclusions based on the ‘Level of Outperformance’ we agree upon this idea.

Our results clearly contradict the conclusion of Wüsten (2012) who states that it is possible for active managers to systematically outperform random portfolios, however this difference in result can be the consequence of a different measurement method, which makes a more detailed comparison not possible.

Liang, Ramchander and Sharma (1995) and Lisi (2008) became mixed results, they believe that it sometimes is possible for active managers to beat the market. Even though we used an approach similar to Lisi (2008), the results of both researches are not in line. Lisi (2008) concludes that some active managers are able to outperform a passive buy-and-hold strategy. While our results suggest that even the best performing funds are not at all outperforming the random portfolios. Lisi’s research results in average ‘Daily p-values’ ranging between 1,57% and 33,33%. While our research results in ‘Daily p-values’ close to 50%. Besides, Lisi (2008) concludes that in a bearish market it becomes harder for active portfolio managers to outperform the monkeys. Our results on the other hand show no general influence of the financial crisis, for some funds the ‘Daily p-value’ will increase, while for others it will decrease.

Our conclusion is intuitively supported when taking a closer look at the funds under scope of this research. Both the best performing funds and the worst performing funds are KBC Equity funds. What's more, both funds have the same fund manager. At first sight we might believe that the fund manager of 'KBC Equity Flanders inc' and 'KBC Equity Flanders acc' does possess some stock selecting skills, compared to the other funds in the sample. But, this fund manager is also the manager of the two funds that perform by far the worst. So it seems that the performance is based on either the asset allocation strategy or luck.

This means that, no matter how promising their prospectus might look, actively managed funds will not achieve capital returns higher than an index funds. They are not able to outperform a random portfolio. Note that within our research we do not take into account the charges and fees of active portfolios. Once these costs are deduced from their achieved return, the end result will be even worse. Based on this research we conclude that the best investment strategy is to invest in a well-diversified passive portfolio, we advise not to waste your money in the illusion that active management does pay off.

6.4 Possible explanations

Based on the efficient market hypothesis we would expect fund managers to achieve an average return. However, when looking at the cumulative returns during the different time periods we conclude that active managers systematically underperform random portfolios. Even though the aim of our thesis is limited to answering the research question, we also try to provide some rationale about why they seem to systematically underperform the monkey portfolios.

One possible reason would be the fact that fund managers do not invest the entire amount of funds assets. Since all the funds under scope of this research are open-ended funds, they need to keep a aside a small proportion of the available money in order to meet the fund redemptions and to be able to buy stocks when market opportunities arise. The second reason is the typical behavior of the people that invested in the fund. They have the tendency to sell their shares of the funds when the stock markets perform very bad. This forces fund managers to sell certain assets at their lowest level, in order to be able to meet the increased redemptions. The random portfolios on the other hand invest the total amount of available capital. Besides they follow a buy-and-hold strategy, which means they do not sell any assets during the research period. After a crash, the stocks will stay in the portfolio and have the chance to increase in value again.

7. Conclusion

Whether active managers are able to outperform random portfolios is still a widely discussed questions. The opponents of random portfolios are in favour of the Efficient Market Hypothesis and the Random Walk theory. They believe that since the market is efficient and all available information is reflected in the current price, it is impossible to predict future prices. The underlying reason is that stock prices only change as a consequence of the appearance of new information and this happens randomly. The proponents of the random portfolios do believe it is possible to beat the market, they will typically be in favour of the Adaptive Market Hypothesis, which can be considered as a supplement to the Efficient Market Hypothesis. But in contrast to the Efficient Market Hypothesis in which rational behavior is supposed, the Adaptive Market Hypotheses highlights the existence of irrational behavior principles. These irrational behavior principles make it possible to beat the market.

Empirical research shows there is a growing consensus about the impossibility for actively managed portfolios to outperform random ones. However, some economists do conclude that outperformance is possible. For instance, since the Random Walk theory results from the efficient information distribution, it seems rational to believe that –even though the Western stock markets are efficient- the stock markets in the emerging countries are not. As a consequence, we assume that it might be possible to beat the market in emerging countries, while current literature shows that it is not possible in Western stock markets.

We analyzed whether Belgian mutual funds are able to outperform random portfolios that are drawn from the same investment universe. The research covers a period from January 1, 2002 until December 31, 2012. This research period is divided into three sub periods in order to make a distinction between the performance before, during and after the financial crisis. Three different indicators are used to answer our research question, the 'Mean-Alpha', the 'Level of Outperformance' and the 'Daily P-Value'. All of these indicators suggest that random portfolios outperform the Belgian mutual funds, not only during the full period , but also during each of the sub periods.

This result confirms our expectations that were based on the current literature. The many empirical researches on this question caused a global tendency towards the acceptation of the Random Walk theory and the impossibility for active managers to outperform random portfolios. This research provides additional prove for this growing consensus, after all the results of this research are clear: the Belgian fund managers are beaten by the monkeys.

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9. Appendix

[Table 2] presents the selection of 12 mutual funds which solely invest on stocks that are listed on the NYSE Euronext Brussels. Only funds which consists out of more than 90% of shares are selected.

Name Fund	ISIN	Fouding Date	% Investment in shares	Open fund
Argenta Action Belges	LU0056758476	26/04/1994	98,74%	Yes
AXA B Fund Equity Belgium Acc	BE0152676954	13/01/1995	96,87%	Yes
BNP Paribas B Fund I Equity Belgium Acc	BE0127752039	15/05/1991	97,68%	Yes
BNP Paribas B Fund I Equity Belgium Inc	BE0127750017	16/05/1991	98,15%	Yes
Dexia Equities B Belgium C Acc EUR	BE0942851115	30/04/1998	93,45%	Yes
Dexia Equities B Belgium EUR Inc	BE0948876223	30/04/1998	92,40%	Yes
ING (B) Invest Belgium Acc	BE0124921827	3/01/1991	93,32%	Yes
KBC Equity Fund- Belgium Acc	BE0129009966	1/10/1991	99,57%	Yes
KBC Equity Fund- Belgium Inc	BE0129141348	1/10/1991	99,43%	Yes
KBC Multi Track Belgium Inc	BE0152248556	7/07/1987	100,00%	Yes
KBC Equity Flanders- Acc	BE0164243223	28/05/1997	100,00%	yes
KBC Equity Flanders - Inc	BE0164244239	29/05/1997	100,00%	Yes

Table 2: Overview Mutual funds

[Figure 2] provides the distribution of the randomly generated portfolios.

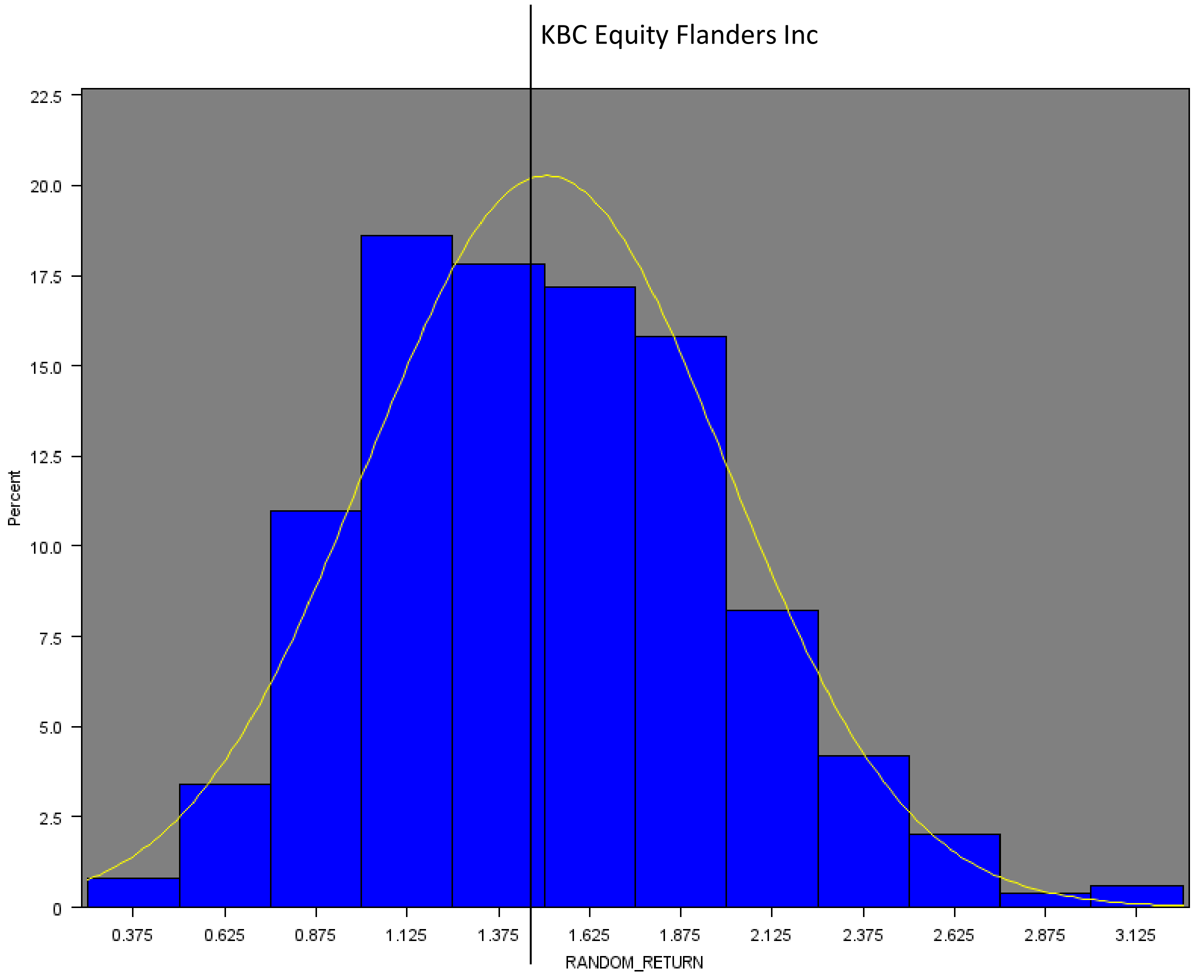

Figure 2: Random portfolio distribution

[Table 3] gives an overview of the statistics of the random portfolios

Distribution analysis of: RANDOM_RETURN

The UNIVARIATE Procedure
Variable: RANDOM_RETURN

Basic Statistical Measures			
Location		Variability	
Mean	1.507366	Std Deviation	0.49189
Median	1.476608	Variance	0.24196
Mode	.	Range	2.76752
		Interquartile Range	0.70874

Basic Confidence Limits Assuming Normality			
Parameter	Estimate	95% Confidence Limits	
Mean	1.50737	1.46415	1.55059
Std Deviation	0.49189	0.46318	0.52443
Variance	0.24196	0.21454	0.27503

Tests for Location: Mu0=0				
Test		Statistic	p Value	
Student's t	t	68.52226	Pr > |t|	<.0001
Sign	M	250	Pr >= |M|	<.0001
Signed Rank	S	62625	Pr >= |S|	<.0001

Quantiles (Definition 5)	
Level	Quantile
100% Max	3.104094
99%	2.747252
95%	2.333925
90%	2.157046
75% Q3	1.842838
50% Median	1.476608
25% Q1	1.134094
10%	0.909586
5%	0.785629
1%	0.555013
0% Min	0.336572

Table 3: Summary statistics random portfolios

Random portfolio algorithm

The next code represents the algorithm of random portfolios.

Program 1 : Period Selection

```
Importing a dataset with the following variables
-     Date
-     Stock (=index)
-     Price

This is the raw dataset ( the investment universe of the mutual
fund manager ( in our case the Euronext Brussels)


data STEP_PRE;
set WORK.DAILY_RETURNS;
if '1JAN2002'D =<DATE =< '31DEC2012'd; /*Adjust manually based on
the observed time period */

flag=1;
if RET NE .;
run;

proc sort data=STEP_PRE;
by STOCK;
run;


proc summary data=step_pre noprint;
var flag;
by STOCK;
output out=STEP_PRE_1  sum(FLAG)=NUM_DAYS;
run;

data STEP_PRE_2;
set STEP_PRE_1;
IF NUM_DAYS = 2869; /*Choose the amount of observed days */
run;

proc sort data=STEP_PRE_2;
by stock;
run;

data GOOD_DATA;
merge
      DAILY_RETURNS (in=A)
      STEP_PRE_2 (in=B);
      by STOCK;
      if B;
      run;
```

Program 2 : Data selection

```
proc sort data=WORK.XXX out=WORK.YYY;
by STOCK DATE;
run;

data DAILY_RETURNS;
do until(last.STOCK);
set WORK.YYY;
by STOCK DATE;
if prev = . then RET = .;
else RET = (PRICE - prev) / prev;
output;
prev = PRICE;
end;
drop prev;
run;
```

Program 3 : Randomizer

```
proc sort data=GOOD_DATA;
by STOCK DATE;
run;

data GOOD_DATA_1;
set GOOD_DATA;
by stock;
if first.STOCK then count+1; /* assigning a number to each unique
stock*/
run;

/*2. We create a random dataset from scratch, we hereby use
random number to generate a random sequence*/

data randomizer;
do port=1 to 500; /*30 stocks in the portfolio gives 500
portfolios*/

      do stock_number=1 to 30;
count=int(91*ranuni(0)+1); /* We create a random number between 1
and 500, i.e. count , a number for each stock*/
      output;
end;
end;
run;

proc sort data=randomizer;
by count;
run;
PROC SQL;
      create table FINAL_STEP AS
      Select     t1.port,
                 t1.stock_number,
                 t1.count,
                 t2.DATE,
```

```
                t2.PRICE,
                t2.RET,
                t2.count AS count1
           From Work.randomizer t1 LEFT JOIN Work.GOOD_DATA_1 t2
ON (t1.count = t2.count);
Quit;

Proc sort data=FINAL_STEP;
by port stock_number date;
run;

/*dataset to calculate standard deviation*/

data FINAL_STEP_CUM_RETURNS;
set work.final_step;
by port stock_number DATE;
if first.stock_number then do;
if missing(RET)=0 then cumret0=(1+RET);
else cumret0=1;
end;
else do;
if missing (RET)=0 then cumret0=cumret0*(1+RET);
else cumret0=cumret0;
end;
retain cumret0;
run;

/* Calculating the standard deviation*/

proc sort data=final_step_cum_returns;
by port date;
run;
proc means data=final_step_cum_returns noprint;
var cumret0;
by port date;
output out=STDEV_1 (drop= _TYPE_) sum=AVE;

/* End_Step*/

data STDEV_2;
set Work.STDEV_1;
by port;
if last.port; /*the last cumulative return of the portfolio*/
run;

data STDEV_3;
do until(last.PORT);
set Work.STDEV_1;
by port date;
if prev= . then RET= .;
else RET=(AVE - prev)/prev;
output;
prev = AVE;
end;
drop prev;
run;
```

```
proc means data=STDEV_3 noprint;
var RET;
by port;
output out=VOLAT_1 std=RISK; /* We calculate the standard
deviation of each portfolio*/
Run;

Proc SQL;
     create table Work.FINAL_DATASET AS
     select    t1.port,
               t1.DATE,
               t1._FREQ_,
               t1.AVE LABEL="end_cum" AS end_cum,
               t2.RISK
          FROM Work.STDEV_2 t1 LEFT JOIN Work.volat_1 t2 on
(t1.port = t2.port);
Quit;
```

Program 4 : Risk correction

```
/* Risk correction*/


data FINAL_DATASET_1 /*(keep=P_VAL MEAN_ALFA)*/;
set work.final_dataset /* end=eof1*/;
RANDOM_RETURN = (END_CUM -30)/30;

FUND_RETURN = 0.322515016; /*Enter manually*/

AR_1 = /*Standard deviation of the observed funds */ 0.014151948
/*Enter manually*/ / RISK *RANDOM_RETURN;


if FUND_RETURN > AR_1 /*RANDOM_RETURN*/  then GG =1;

/* Calculate ALFA*/

ALFA = FUND_RETURN - /*RANDOM_RETURN*/ AR_1;
SUM_ALFA + ALFA;
MEAN_ALFA = SUM_ALFA /500;
if GG = 1 then count+1;
P_VAL = 1 - (count/500);
/*if eof1*/;
run;

proc datasets library=work;
save FINAL_DATASET FINAL_DATASET_1 ;
run;
```

Program 5 : Daily p-value

```
data DAILY_P;
set WORK.QUERY_FOR_STDEV_33;
if RET_FUND >= RET THEN FLAG = 1;
if RET_FUND < RET THEN FLAG =0;
run;

proc sort data=daily_p;
by DATE;
run;

proc means data=DAILY_P noprint;
var flag;
by DATE;
output out=RESS mean(flag)=P_VALUE;
run;

proc means data=RESS noprint;
var P_VALUE;
output out=FINAL_TABEL mean(P_VALUE)=FINAL ;
```