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Measuring and comparing the added value of analysts’ stock recommendations

Auteur : Guillaume Gomez
Promoteur : Pr. Mikael Petitjean
Année académique 2019-2020
Master 120 crédits en science de gestion, à finalité spécialisée

ABSTRACT

This master thesis reviews the recommendations made by the guests of the TV-Show “C’est votre argent” over the period May 8, 2015, to December 31, 2019, by employing various performance and risk-adjusted performance indicators: Annualized return, Sharpe ratio, Treynor ratio, Information ratio, Jensen’s Alpha and M-squared. But also, some risk indicators: standard deviation, Value at Risk and Expected Shortfall. Through the Peer Performance package developed by Ardia, Boudt and Bouamara (2018) in R, a luck corrected risk-adjusted performance analysis is also realized. The analysis of the size effect and the consequences of the home bias in the sample of recommendations is also developed. This thesis finds that four guests (Christian Bito, Sébastien Faijean, Louis de Montalembert and Virginie Robert) significantly outperformed the other guests. There is no evidence of the size effect in the sample of recommendations retrieved, but there is some evidence that the home bias has an impact on analysts’ performance.

Acknowledgements

I would like to express my sincere thanks to my master thesis promoter Professor Mikael Petitjean for his follow-up through the entire process of this master thesis. From the beginning, with the choice of the subject, until the end, he was always there to advise me, to guide me and to correct me when it was necessary.

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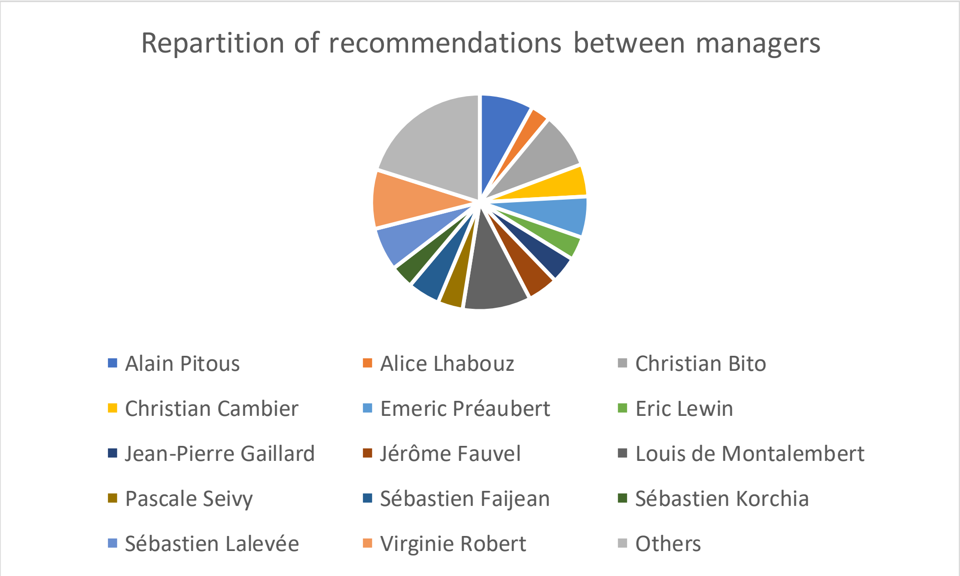
1. Introduction

"C'est votre argent" is a TV show broadcast on BFM Business on TV and on radio every Friday, excepted during the holidays, since 2013. It's presented by Marc Fiorentino who is always accompanied by many economists and financial experts. During those TV shows, Marc and his guests go through the economic and political news of the week, analyze how this affects the markets and the economic system and give advice to invest mostly in small and mid-capitalization. It's this last part and more precisely the recommendations given during this part that will be analyzed in this master thesis.

Marc Fiorentino is the presenter of "C'est votre argent." He studied at the well-known H.E.C. Paris and began his career in the trading room of the Bank of America at Paris. Then he worked successively for Drexel Burnham Lambert, PaineWebber and Salomon Smith Barney. Now, he works in Euroland Corporate that he founded in 1999.

Since the beginning, May 8, 2015, until the end, December 31, 2020, they were 38 professionals of the financial sector who came and gave advice on the TV show. But most of them gave fewer than 10 recommendations during this whole period and, as we can see in Figure 1, more than 75% of the recommendations are given by only 14 of them. These 14 managers are those on whom I will focus the most on.

Figure 1: Repartition of Recommendations Between Managers



As we can see in Table 1, all the guests who gave most of the recommendations, excepted Eric Lewin, are CEOs, partners or managers in the investment banking sector. We can so legitimately guess that they all have a strong academic background, a deep knowledge of the financial markets and so that their recommendations are pretty good advice to follow. This is what I will verify in this master thesis.

Table 1: List of guests and professions

Alain Pitous	Responsible finance director at OFI Asset Management
Alice Lhabouz	CEO of Trecento Asset Management
Christian Bito	CEO of C.B.T. Gestion
Christian Cambier	Director of the board of directors at Swisslife Gestion Privée
Emeric Préaubert	Founding partner at Sycomore Asset Management
Eric Lewin	Chief editor at Publications Agora
Jean-Pierre Gaillard	Erasmus Gestion
Jérôme Fauvel	Manager of small caps at La Française AM
Louis de Montalembert	Portfolio manager at Pléiade Investment
Pascale Seivy	Team manager at ODDO BHF
Sébastien Faijean	Managing director at IDMidCaps
Sébastien Korchia	CEO at UBS LA MAISON DE GESTION
Sébastien Lalevée	CEO at Financière ARBEVEL
Virginie Robert	CEO of Constance Associés (BFM Business, 2020)

The goal of this master thesis will be to analyze the recommendations of the managers and to determine if investors should follow their recommendations or not.

To achieve this, I will try to identify who are the more skilled managers and what returns investors could expect following their recommendations and different portfolio creation methodologies.

Because their recommendations are mainly focused on small and mid-capitalization and French companies, I will try to identify if this focus has an impact on the performances of the managers through the analyze of a potential size effect and the potential consequences of the home bias in this sample.

This master thesis will begin with a review of the literature about the stock picking and the difference between the active investment and the passive investment. This review of the literature will also cover the size effect with the evidence of it in the past, what the newest papers say about it and the possible causes of this size effect. Finally, in this review of the literature, I will cover the topic of the home bias looking at the evidence of it in the past and now and the possible causes and consequences of the home bias.

After this, I will explain which data I retrieved and how I retrieved them and manipulate them to create my database and I will explain the methodology that I followed to analyze those data.

Next, I will present the results of the analysis and I will interpret those results to see who the best managers are and if the hypothesis about the size effect and the home bias are verified in the sample that I analyzed.

Finally, I will conclude this master thesis by a summary of the results obtained and my advice to potential investors that follow the recommendations of the TV-show. And I will give the different limitations of this thesis and the potential amelioration and deepening that are possible by starting from the work already done.

2. Literature review

In this part, a review of the literature will be made about the main hypothesis that I will try to test in the analysis section. So, this will be divided in three parts. The first one is about the stock picking and the investment strategies, the second one is focused on the size premium and the last one will cover the home bias.

This literature review is based on many papers often published in well-known journals, mainly found through google scholar, the SSRN website and Libellule (UCL).

2.1. Stock picking and influence on performance

When we talk about investment and portfolio management, there are two different opposing strategies: the active investment and the passive investment. The stock picking is when an analyst or an investor conclude from an analysis that a stock would be a good investment and then should be added to a portfolio. This stock picking methodology is also known as active management.

In the financial world, active versus passive management is always a heated debate because investors and wealth managers tend to opt for one strategy over another and to favor this one. Even if passive investment is the most popular among investors, there are also benefits in the active investment.

2.1.1. Active Investment

Active investing has two goals: beat the stock market's average returns and take advantage of short-term price fluctuations. To achieve this, it requires a much deeper analysis than for passive management and the expertise to know when to buy or sell a stock, bond or any asset. This expertise is provided by a group of analysts, who look at qualitative and quantitative factors. They're coordinated by a portfolio manager. Successful active investment managers are the ones that are more often right than wrong.

Following an active management strategy presents some considerable advantages. The first one is the flexibility. Managers can buy what they want. So, if they believe that an asset will have abnormal growth in the future, they can buy it. The second one is the hedging. Because managers don't stick an index, they can freely hedge their bets by using different sorts of techniques such as short sales and put options. They can also exit positions if the risk seems to be too big. The last huge advantage of the active management is the opportunity to make some tax management. Managers can for example sell investment that are losing money to offset the taxes on the winners.

There are also some drawbacks to the active management strategy. Firstly, the active management of a portfolio leads to a lot more expenses. Analysts from Thomson Reuters Lipper have calculated that the average expense ratio is at 1.4 percent for an actively managed equity fund and around 0.6 for an average passive equity fund. Fees for an actively managed portfolio are higher due to the buying and selling transaction costs and because you must pay analysts that research the equity picks. All those fees over decades can kill returns.

Moreover, the fact that active managers are free to buy any asset that they think would bring high return is great when analysts are right, but it can lead to terrible outcomes when they're wrong.

2.1.2. Passive investment

A passive investment strategy is a long-term strategy based on the belief that markets are efficient. Managers limit the buying and selling operations within their portfolio, what reduce considerably the number of transactions cost and makes it a very cost-effective way to invest. This strategy requires a buy-and-hold mentality.

The best example of a passive investment strategy is to buy an index fund that follows one of the indices such as the CAC40, the Dow Jones or the S&P500.

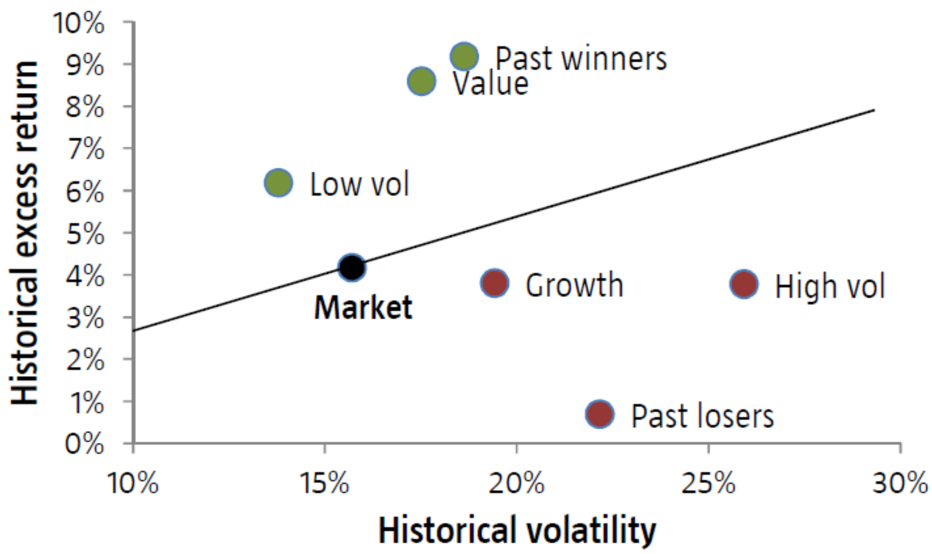
Passive management has a lot of advantages. We can identify three key benefits: the very low fees because nobody is picking stocks, the transparency because it's always clear which assets are in the index fund and the tax efficiency because it doesn't typically result in a massive capital gains tax for the year.

However, there are also some drawbacks to this strategy. The first one is the very limited possibility of actions by managers because they track an index or a predetermined basket of assets with little to no variance. So, investors are locked into those holdings, no matter what happens in the markets. Secondly, investors would usually have smaller returns because passive investors will try to have the same returns as a benchmark and so, will pretty much never beat the market. Also, the term of passive investment can be discussed because most of the passive funds follow just a part of the market portfolio. So, managers are making active asset allocation decisions.

Finally, there are some concerns about the passive investment. Firstly, some analysts consider that passive investors are free riders. Indeed, Lorie and Hamilton (1973) noted that the market can be efficient only if many investors truly believe that it's inefficient. Those investors are the active investors, and they're so necessary for efficiently functioning capital markets. They continuously trade on perceived mispricing, ensure that prices of securities are the closest of their true value and that the market is highly liquid. Moreover, without active investors, they wouldn't have an IPO anymore. In conclusion, the sustainability of the passive investment strategies is only possible thanks to the enough active investors.

The second concern is that passive investment goes against some proven factors. When passive investors begin to invest, they choose to ignore some evidence. They choose to invest in stocks with all sorts of characteristics. They invest as much in value stocks, in past winners and in low past volatility stocks as in growth stocks, in past losers and in high volatility stocks. However, as shown in the Figure 2 below, the value, past winner and low-volatility stocks have been much more attractive than the market portfolio in the US equity market over the July 1963-December 2010 period.

Figure 2: Historical performance characteristics of US equity factor portfolios, July 1963 – December 2010



Source: Kenneth French, Robeco

To conclude, even if over the last decades passive investment seems to be the most popular investment strategy, passive investors couldn't operate without the presence of active investors on the market and they aren't making the optimal decisions.

2.1.3. Performance of investors

Now that it's clearer what the active and passive investment are and the advantages and drawbacks of each strategy. It would be interesting to see the possible returns of both strategies and how well active and passive investors are doing.

Firstly, it's important to notice that passive investors will all have approximately the same kinds of results because, as explained earlier, their goal is to follow indices and so to be as close as possible to the results of those benchmarks. Here it's a buy-and-hold strategy, the investment horizons are usually long but can be different from one investor to another. Those differences of investment horizon can have a huge impact on the range of expected returns. As we can see on the Figure 3, looking at past data of the S&P 500, it seems to show that, after a critical minimum period of investment, long-term passive investors could always enjoy positive annualized total return. For the S&P 500 for a 20-year investment period between 1926 and 2011, in the worst case, passive investors had a 3.1% annualized total return and in the best case, they had a 17.9% annualized total return. However, if they have a shorter investment horizon, such as one year, the annualized total return can vary from -43.3% to 54%.

Figure 3: Range of S&P 500 returns, 1926 - 2011

Source: SchwabCenter for Financial Research

Secondly, in the literature, a significant amount of evidence that the average actively managed funds, net of fees and after risk adjustment, doesn’t outperform passive investment strategies. However, a small subset of funds consistently outperforms. This led us to believe that some managers have skills to make better investments than others. For the active investment, it’s important to distinguish and to decompose fund performance into stock picking and market timing to analyze the capacity of investment managers to add value for their clients. Those two skills aren’t talents one is born with, but the result of time spent working and analyzing data. In the literature, there is evidence of stock-picking ability among best managers. But only a little evidence for market timing.

Moreover, it has been proven that skilled managers successfully perform both tasks. The ones who are good stock pickers in booms are also good market timers in case of recessions. In this case of recession, successful managers, on average, hold more cash, their portfolios have lower market betas and they engage in a sector rotation by investing more money into defensive industries instead of cyclical industries in booms. This suggests that managers are actively adjusting their investment behavior over the business cycle.

Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) have analyzed many funds and managers and described the characteristic of skilled funds and managers. The best-case scenario for funds:

- They're younger (5 years below the average).
- They have less wealth under management ($400 million on average).
- They tend to charge higher expenses (by 0.26% per year).
- They have higher portfolio turnover rates (130% per year on average, and 80% for other funds).
- They receive higher inflows of new assets to manage.
- They tend to hold portfolios with fewer stocks and higher stock-level and industry-level portfolio dispersion.
- Their betas deviate more from their peers and so have different systematic risk exposure.
- They rely significantly more on aggregate information.

Now it's clear that only a few fund managers can beat the market and what the best conditions to beat it are. It's interesting to take a deeper look at the market abnormalities and their consequences.

2.2. Size effect

We know that active managers try to take advantage of the abnormalities in the market to create more value for their clients than a passive investor. One of those abnormalities is the size effect: it's the fact that, on average, smaller companies have higher returns than bigger companies. There is some evidence on the validity and the persistence of the size effect in the literature. So, it's interesting to analyze the impact of this size effect on the returns of assets, why there is this size effect and how investors can take advantage of this abnormality to increase the return of their portfolio.

2.2.1. Evidence of the size effect between 1980 and 2000

Banz (1981) was the first to write an empirical paper, when he was testing the Sharpe-Lintner Capital Asset Pricing Model, to present the evidence of a size effect in U.S. stock returns by analyzing all common stocks listed on the NYSE between 1936 and 1975. He proves in his report that stocks in the quintile portfolio with the smallest market capitalization earn a risk-adjusted return that is 0.4% per month higher than the other firms. However, he shows that the size effect isn't linear and is most pronounced for the smallest firms.

Based on a huge sample of firms over the period 1973-1985, Lamoureux and Sanger (1989) find a size premium of 2.0% for Nasdaq stocks and of 1.7% per month for NYSE stocks.

Finally, it’s only after the works of Fama and French (1992) that did research on the size effect and the integration of the SML (Small Minus Large) factor in their three-factor model that it’s only taken off. They make the case that the empirical shortcomings of the CAPM (Capital Asset Pricing Model) are too important to be ignored. For this they analyzed a sample of NYSE, Amex and Nasdaq stocks over the period 1963-1990 and find that the smallest decile outperforms the largest by 0.63% per month. They also analyzed the relation between beta and returns by subdividing each size decile into ten beta-sorted portfolio and they find no relation between the beta and returns.

2.2.2. Variation of the size effect

After Banz’s publication (1981) on the size effect, some studies tend to show that the size effect has diminished or disappeared since 1980 in the U.S. (Fama and French [1992], Eleswarapu and Reinganum [1993], Dichev [1998], Chan et al. [2000], Horowitz et al. [2000], Amihud [2002], Roll [2003]) and in the U.K. (Dimson and Marsh [1999], Michou et al. [2010]). Other studies document similar results in broad global markets.

Horowitz et al. (2000) analyzed it by dividing their data (U.S. markets) set in two sub-periods: from 1963 to 1981 and from 1982 to 1997. In the first sub-period, they find that the smallest size decile of firms had higher average returns than the largest decile, but they observe the opposite in the second sub-period. Other analysts obtained the same kinds of results between 1992 and 2010.

Fama and French (2011) find no more evidence of the size effect in any of four global regions based on the observation of stocks in 23 countries from November 1990 to September 2010.

2.2.3. Latest analysis of the size effect

Even if, between 1990 and 2010, the literature hasn't been kind to the size effect and that it's often dismissed as a "myth" or a "statistical fluke," latest analysts raised one important question: if small-cap stocks should indeed be riskier, where has the risk premium gone?

Asness et al. (2015) tried to answer this by analyzing a data set of U.S. equities from July 1926 to December 2012 and introduced a "quality minus junk" factor based on the profitability, growth, safety and payout of the stocks. They show that, by analyzing the size effect alone, it's relatively weak compared to other anomalies such as value and momentum and that it has experienced significant variation over time. However, they examine seven empirical challenges that have been hurled at the size effect: it's weak, not worked out of a sample, varies significantly through time, only works for extremes, only works in January, only works for market-price-based measures of size, it's subsumed by illiquidity, and it's only in the U.S.A. And, after controlling for the firm's quality, they show that every empirical challenge could be dismantled. So, they prove that size matter but only when controlling for junk.

Ciliberti et al. (2017) show that when they measure the size effect in terms of dollar turnover instead of market capitalization and once β-neutralized and Low-Volatility neutralized, the size effect is still alive and not less significant than other well-known factors such as value or quality.

de Oliveira Souza (2020) analyzes how the size effect varies with the macro-economic fluctuations in the price of risk at the portfolio formation dates on data in the U.S. markets from 1926 to 2016. He highlights in his paper the fact that the size premium is a lot larger than previously estimated but appears infrequently (but more frequently in bad times) corresponding to less than 30% of the time and possibly less than 15% of the time. He also shows that the CAPM explains the size premium quantitatively at least 70% of the time when he tests portfolios double sorted by size and CAPM betas. And, finally he concludes that the size premium conclusions based on unconditional tests are unreliable because subsamples in which the premium exists are much smaller than subsamples in which the size premium is absent in typical unconditional tests.

So, most of the recent paper seems to show that the size premium still exists and is still significant. However, some conditions and controls must be added in tests to prove it on the long run.

2.2.4. Why this size effect exists

Even if there is some evidence of the size effect at the international scale, it's important to understand why there is this size effect in the markets, what are the possible explanations for smallest firms to outperform largest firms on average?

2.2.4.1. Risk-based effect

The first possible explanation of this size effect is the risk associated. Indeed, Keim shows that small firms have, on average, higher betas than large firms. This can be explained by the research of many economists:

- Fama and French (1995) suggested that one of the variables that produce variation in earnings and returns related to size is related to financial distress.
- Chan, Chen and Hsieh (1985) find evidence that the default spread among other variables that lead to changes in the environment capture the size effect in Fama-MacBeth regressions.
- Chan and Chen (1991) said that small firms are usually "fallen angels" that lost market value due to bad performance.
- Vassalou and Xing (2004) also did research on the relation between the size effect and the default risk and conclude that the size effect is only statistically significant within the highest default risk quintile.
- Campbell, Hilscher and Szilagyi (2008) show that U.S. firms with high probability of bankruptcies have a high loading on the size factor.

So, analysts, through their research, seems to tend to agree that the risk is an explanatory factor of the size effect. However, there is also evidence that the risk isn't the only explanatory factor.

2.2.4.2. Illiquidity and transaction costs associated

A second possible explanatory factor of the size effect is the illiquidity, and the higher transaction cost associated with the market microstructure. In the CAPM and other traditional asset pricing models, the influence of the liquidity and the other market microstructure issues are abstracted. However, transaction costs and liquidity risk can be two explanatory factors of the size premium. Through the years many analysts have done research about it:

- After analysis of firms listed on NYSE between 1960 and 1979, Stoll and Whaley (1983) find that it's impossible to earn abnormal risk-adjusted returns on small stocks after accounting for transaction costs. This has been extended to Amex by Schultz (1983).

- Amihud and Mendelson (1986) develop a model in which investors require a compensation for expected trading costs. The authors present empirical evidence that supports the fact that the larger is the bid-ask spread of a security, the higher is the premium required by investors. And smaller companies have on average securities with larger bid-ask spread than bigger companies.
- Brennan and Subrahmanyam (1996) show that fixed and variable transaction costs are positively and significantly related to returns.
- Amihud (2002) show that both size and illiquidity measure are significant in Fama-MacBeth regressions. It suggests that the size effect be not completely capture by the illiquidity variable.
- Pastor and Stambaugh (2003), and Acharya and Pedersen (2005) have through their analysis both show that the relation between firms' size and the illiquidity is significant but didn't examine if the liquidity risk absorbs the size effect.

It's clear through all those analyses that the size effect can be partially explained by the relation between the size of a firm and its liquidity risk. However, again, it's not proven that the liquidity risk and the higher transaction cost associated can absorb the size effect.

2.2.4.3. Investor behavior

A third possible explanation of the size effect is the investor behavior, and it's often used to explain the value effect. Many biases in the investor's behavior could be at the origin of the overperformance of small firms against bigger firms.

Lakonishok, Sheilfer and Vishny (1994) have brought the hypothesis of the overreaction of the investors. The idea is that value firms are usually the ones that have shown poor performance in the past. And, if investors over extrapolate the past performance, the stock price of small firms will be too low. This can result in higher returns when the overreaction is corrected. Chan and Chen (1991) have proven the fact that small firms tend to be firms that have done poorly in the past. However, it's harder to find any research that proves the evidence of the impact of the overextrapolation in the size effect.

A second possible bias that can explain the size effect is the preference of the investors for large stocks over small stocks. Gompers and Metrick (2001) suggest that the increase in demand for large and liquid stocks, and so, the relative bad performance of small stocks over the 1980-1996 period in the U.S. equity market is due to the growing share of the U.S. equity market held by institutional investors. Lakonishok, Sheilfer and Vishny (1992) explain this also by the fact that investments in small stocks are potentially harder to justify to sponsors for professional money managers.

The third possible element that can affect the investor behavior about investments in small firms is the lack of complete information about small firms. Banz (1981) thought that the size effect exists because many investors don't want to hold small stocks due to the lack of information and that led to higher returns on these stocks. This argument was supported by the investor recognition hypothesis developed by Merton (1987). In this hypothesis, Merton predicts that less well-known firms have higher expected return. It's supported by Hou and Moskowitz (2005) that offer an empirical analysis of the influence of investor recognition on the size effect.

Another interpretation of all those biases and investor behaviors is that we must relax the assumption that investors are fully rational in asset pricing models. Sometimes investors behave in a way that isn't fully rational.

2.2.5. Criticism of the size effect

Even if many analysts agreed on the fact that the size effect is real and significant in the markets, some detractors believe that the size effect in stock returns is a chance result, driven by data mining, missing or extreme observations and seasonal patterns.

2.2.5.1. Data mining and lack of robustness

So, the first criticism that can be made on research on the size effect is the data mining and the lack of robustness. Many analysts such as Black (1993), Lo and MacKinlay (1990) and MacKinlay (1995) argue that most of the research on the size effect has used the same data and that only the most successful, unusual and striking results are published.

Other analysts tested the robustness of the size effect over time. Banz (1981) and Keim (1983) proven that the size effect varies a lot over the period 1926-1975 in the U.S. Handa, Kothari and Wasley (1989) show that the size effect is negative for the period 1941-1954.

Moreover, some analysts believe that the size effect disappeared in the early 1980s. Eleswarapu and Reinganum (1993), Chan, Karceski and Lakonishok (2000), Horowitz, Lougharn and Savin (2000) and Amihud (2002) analyzed different periods of time and found no size premium. In short, even if there is a remarkable decline of the size effect in the U.S. after the early 1980s, it remains unclear what caused this decline.

2.2.5.2. *Delisting bias and extreme returns*

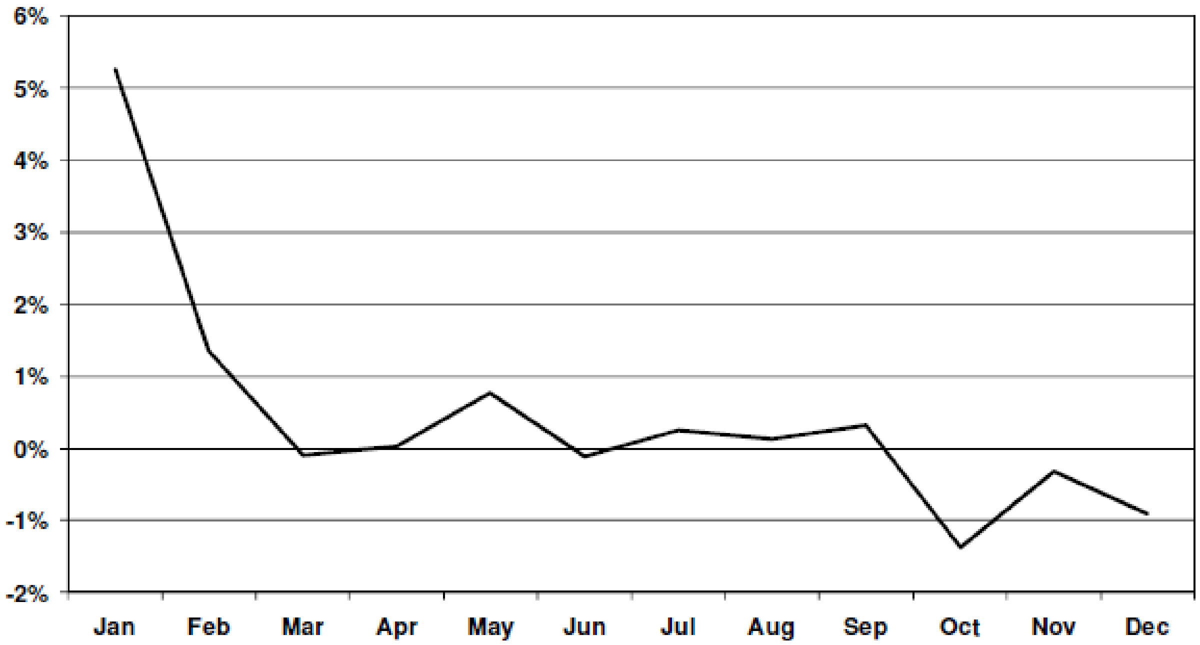
The second criticism made on the size premium is about the delisting bias and extreme returns. Shumway and Warther (1999) did research on the implication of the delisting bias in Nasdaq data. After the collection of data about the delisted stocks (they used a delisting return of -55% for the delisted stocks with missing data), they reanalyzed the Nasdaq data over the period 1972-1995. With this, they found no evidence of the size effect.

Knez and Ready (1997) did research on the impact of the extreme 1% of the observation on the Fama and French models. When they trim the extreme 1% observations, the Fama-MacBeth regressions don't have a significantly negative coefficient on firm size. However, they found a positive coefficient. This research suggests that most small firms underperform bigger firms and that the size effect is concentrated in the smallest firms.

2.2.5.3. *January effect*

The last criticism made on the possible explanation of the size effect is the fact that, following some analysts, it can be attributed to the extraordinary performance of small caps in January. Keim (1983) shows that the size effect is due to a difference in returns of about 15% between small and large stocks in January and that this difference originates from the first five trading days. Lamoureux and Sanger (1989) also observe that the smallest decile outperforms the largest by 10.4% in January and again, this happens much in the first five trading days. Moller and Zilca (2008) show that the January effect hasn't decreased in strength and that it has become more concentrated in the beginning of the month. As we can see on Figure 4, that highlights seasonal patterns in the market-weighted difference of returns (not adjusted for risk) between the smallest and the largest size quintile of the Amex, Nasdaq and NYSE firms over the period 1927-2010, the size effect in the U.S. is almost entirely due to higher returns of small stocks in January. The return differential is of more than 5% in January, not annualized, and, is close to 0% all other months.

Figure 4: Seasonal patterns in the size effect in U.S. equity returns 1927-2010



Source: van Dijk M., 2011, Is size dead? A review of the size effect in equity returns, Journal of Banking and Finance

However, this seasonality in the size effect may be only a U.S. phenomenon. Dimson et al. (2002) observe no evidence of the size-effect seasonality in any month in the U.K.

There are two possible hypotheses that can explain this January effect: the tax-loss selling and the window dressing.

Firstly, at the end of each year, investors have an incentive to sell the stocks that declined in price during the year to take advantage of tax benefits. However, at the beginning of each year, with the absence of selling pressures, prices recover. And this can be more important for portfolios of small stocks because they're biased against shares that have experienced large price declines.

The second hypothesis is that institutional investors have an incentive, at the end of the year, to buy winners and sell losers to present sound portfolio holdings. And then, at the beginning of the year, they rebalance their portfolios for more speculative assets.

As a brief conclusion, we can say that, since the first time that we talked about size effect in the literature and appears as a CAPM anomalies, many analysts have worked on it and, even if many of them conclude that it exists; today there is still ambiguity about the robustness and the causes of the size effect. However, most recent papers tend to prove that the size effect still exists and is still significant.

The conclusion of Banz (1981) after his studies on the size effect: “It’s not known whether size per se is responsible for the effect or whether size is just a proxy for one or more true unknown factors correlated with size,” seems to be an unanswered question today.

2.3. Home bias

The second focus of this report will be on the home bias in the investor behavior. The home bias can be described as the fact that investors tend to overinvest in domestic securities. It's still today one of the major puzzles of international finance.

Before going further, it's important to make the distinction between the home bias, that is the overweighting of domestic stocks, the foreign investment bias that is the relative underweighting for more “distant” countries and more different from home country and the local bias that refers to the fact that investors tend to tilt their domestic portfolios towards local stocks. Of course, they're linked and most of the models can be used to analyze both biases.

2.3.1. Evidence of the home bias

French and Poterba (1991), and Lewis (1999) were the first to show that investors tend to allocate too much of their portfolio to domestic securities and too little to international securities.

Coval and Moskowitz (1999) prove that U.S. fund managers exhibit a strong preference for firms with local headquarters.

Benartzi (2001) and Huberman and Sengmuller (2004) find that employees tend to invest most of the assets of their retirement plans in their company’s stock.

Chan et al. (2005) find robust evidence that mutual funds, in aggregate, allocate a huge fraction of investments to domestic stocks.

The home bias has also been documented among Finnish investors by Grinblatt and Keloharju (2001), Swedish investors by Massa and Simonov (2005), and Chinese investors by Feng and Seasholes (2004).

Aviat and Coeurdacier (2007) find that if the distance between two countries doubles, bilateral asset holdings are almost divided by two.

Campbell and Kraussl (2007) show that investors may think globally but act locally because of greater downside risk.

2.3.2. Current situation

Even if there was evidence of the home bias in the literature, we can accurately believe that the evolution of the situation regarding the financial integration and the regulatory quality in the last decades have a significant impact on the home bias.

2.3.2.1. Financial integration

Recent studies in the field have proved that increasing financial integration, which reduces the cost of financial transactions and information, can lead to a significant decrease in equity home bias.

Baele et al. (2007) and Sorensen et al. (2007) showed that as capital markets become more and more globally integrated, investors can trade assets freely and at lower costs. They also find that the decline in equity home bias is more pronounced for countries that are more financially linked with each other than those that aren't. So, the deepening economy and the financial integration have lower information asymmetry between domestic and foreign investors, what leads to a further decline in equity home bias.

Emery and Gulen (2019) analyzed the impact of the access to the internet on the information access and subsequently on the home bias. They document a negative relationship between information access and geographic bias. So, countries with higher internet penetration and better access to the internet invest a smaller percentage of their portfolio domestically.

On this aspect, there is a clear distinction between emerging markets and advanced economies: recent findings show that the home bias is greater in emerging markets than in advanced economies.

2.3.2.2. Regulatory quality

Another stream of recent studies is more focus on governance, regulatory and institutional quality and transparency. Coeurdacier and Rey (2013) and Bhamra et al. (2012) argued that regulatory policies and reforms that affect transaction costs, tax treatments between foreign and domestic portfolio incomes, capital controls, and differences in the legal and regulatory framework create frictions among investors. This led to an increase in home bias.

Park and Mercado (2014) analyze the emerging Asia markets and conclude that the increase in regulatory quality had significantly lower equity home bias.

2.3.3. Causes of the home bias

In the literature, we find many potential explanations for the home bias. From the behavioral to the more practical explanations, they all tend to explain partially why investors invest more in their home countries instead of foreign countries.

2.3.3.1. Cost of the information

The first explanation given in the literature is the cost of the information linked to a foreign investment. Indeed, investing in foreign equity markets may require understanding foreign accounting standards and legal environments that can lead to higher costs. Vissing-Jorgensen (2004) shows that high wealth households are more likely to invest in foreign assets than are low wealth households. What is consistent with the fact that high-wealth households can pay the information cost associated with an investment in foreign assets.

Ahearne et al. (2004) show that foreign countries whose firms don't alleviate information costs by opting in the U.S. regulatory environment are more underweighted in U.S. equity portfolios.

Moreover, Nieuwerburgh and Veldkamp (2009) state that local investors profit more from knowing information than other investors do. This learning amplifies information asymmetry and explains partially why investors invest in local stocks.

2.3.3.2. Competence effect

In their report, Graham, Harvey and Huang (2009) tried to analyze the link between the competence effect of an investor and the investor's portfolio allocation to foreign assets. They tested the hypothesis that when an investor feels that he fully understands the benefits and risks associated with investments in foreign assets, he's more likely to invest in foreign assets. And, at the opposite, when he feels incompetent, he will underinvest in foreign assets.

So, they investigate the relation between investor competence effect and home bias. They tested the competence perceived and attributed a quote through surveys among investors. After that, they analyzed the investments of investors and they show that only 33.1% of investors with low competences hold foreign assets compared to 51.6% for the ones with a high level of competence. This increase is significant both statistically and economically.

Graham et al. (2009) document that investors who perceive themselves as knowledgeable have more internationally diversified portfolios. And this has been also supported by Abreu et al. (2011).

So, if an investor feels more competent about investing in foreign assets, he's more likely to invest in foreign assets. However, if he feels less competent, he's more willing to avoid investing in foreign assets.

2.3.3.3. Optimism about home markets

Another possible explanation that we find in the behavioral finance literature is the fact that people tend to be more optimistic towards home markets than towards foreign markets. Here, the familiarity plays a crucial role in the investors' equity investment decision.

It has been demonstrated by Kilka and Weber (2000), and by Strong and Xu (2003).

2.3.3.4. Hedges for domestic risk

A fourth potential explanation is that domestic equities provide better hedges for domestic risks. Indeed, due to the uncertainty about future inflation rates and the fact that investors in different countries consume different bundles of goods, investors are inclined to hold portfolios that differ by a component designed to hedge portfolio risk. So, home bias may be explained if domestic equities provide a hedge against inflation risk.

This implicates that governments should promote cross borders trade in goods and services which indirectly improve cross border asset trade.

2.3.3.5. Financial openness

Another potential determinant of home bias is the existence of capital controls. Both target and holder country openness may matter because often capital controls are symmetric: both inflows and outflows are restricted. So, relatively closed countries may encounter significant home bias, even about open target countries. This link has been demonstrated by Bekaert and Wang (2009).

As state by Poshakwale and Thapa (2011) by improving the quality and efficiency of legal protections offered to foreign investors, policy makers may be able to attract more international equity portfolio investments. This can be considered as another financial openness. They considered five measures of institutions: control of corruption, rule of law, government effectiveness, investment profile and legal systems.

However, the globalization of the financial system leads to more openness. Thus, this link is more observed in emerging markets where capital controls are often binding.

2.3.3.6. Corporate governance issues

Dahlquist, Pinkowitz, Stulz and Williamson (2003) say that poor corporate governance is the main determinant of insufficient foreign investment. In their report, Bekaert and Wang (2009) confirm the hypothesis made by Dahlquist et al. (2003) that countries with poor corporate governance show more home bias by developing a "Quality of Institutions" subindexes based on Law and Order, Corruption and Bureaucratic Quality and analyzing the correlation between this subindex and the foreign investment.

2.3.4. Consequences of home bias

2.3.4.1. Lack of diversification benefits

It's well known in the financial field that international portfolio diversification allows investors to yield a risk-return trade-off that is superior to what a portfolio of domestic assets offers. However, home bias tends to induce investors to give up substantial diversification benefits even if transaction costs are considered.

Baele et al. (2007) state that investors that limit their investment to their home market bear not only systematic risk, but also country-specific risk what isn't compensated by higher returns.

Bailey et al. (2008) prove that investors who display behavioral biases are less likely to invest in foreign equities and tend to offset the benefits of international portfolio diversification due to their faulty investment decisions. This is supported by the research made by Baltzer, Stopler and Walter (2013) based on the German investors' behaviors. So, they don't only underuse but also misuse foreign equities.

2.3.4.2. Ignorance of portfolio theory

Moreover, due to the home bias, people tend to invest in the familiar equities while often ignoring the principles of portfolio theory.

2.3.4.3. Inefficiency of the markets

For a lot of analysts, the home bias can have a negative impact on the efficiency of the markets and more precisely on the liquidity of the markets.

Pirinsky and Wang (2006) show that the price formation in the markets has a significant geographic component that is linked to the trading patterns of local individuals. This result has been confirmed by Korniotis and Kumar (2012) and Liao et al. (2012).

Hong et al. (2008) show that the valuation of a company domiciled in a region is negatively related to the density of corporate headquarters in that region due to the presence of biased investors.

Shive (2012) finds that the investment decisions of local investors contribute disproportionally to stock liquidity and price discovery.

So, those findings tend to prove that local biased investors have an impact on the valuation of stocks.

3. Data and Methodology

In this section, I will explain where I found the data that I used in the analysis and how I retrieved them. I will also explain the methodology followed for the analysis: the steps followed, the ratios and other indicators.

3.1. Data

The data collection was a tough part of this master thesis and it's important to understand how the data have been collected and organized to understand the relevance of the following analysis.

3.1.1. Recommendations

The first step was to collect all the information about the recommendations given by the guests of the show. For this I searched on many websites, the first show available on the internet and it was the show on May 8, 2015, that was available on a podcast website calls "tunein." I followed the show through this audio podcast website from the first date until October 28, 2016, then I watched the videos of the show that were available on the website "Dailymotion," what was easier to follow than the audio podcast, until December 31, 2019. I listened or watched all the 180 "C'est votre argent" TV show of approximately 50 minutes from May 8, 2015, until December 31, 2019.

I ended up my recommendation collection with more than 500 recommendations including 373 buy recommendations. At this stage I collected the name of the company, the date of the recommendation, the name of the guest and the recommendation.

3.1.2. Financial information

The next step was to collect the financial information about every company. Because I would like to collect information to analyze the performance, the size effect and the home bias, I retrieved the ticker, the market capitalization and the country where companies are headquartered for every company from Yahoo!Finance manually.

For the market capitalization, I retrieved all the data at the same date of January 1, 2020, and I converted all the non-euro values in euro with the data given by Morningstar at the same date.

For the historical price data of each stock, I used the "quantmod" package of R that has useful tools to retrieve financial historical data from many data providers such as the function "getsymbols" and a short code that I created (Appendix 1). I decided to retrieve all those data from the same source: Yahoo!Finance. I kept only the last column of data that is the Adjusted Close because it's the closing price of every day after adjustments for all applicable splits and dividend distributions and it's considered to be the true price of a stock and the most relevant price when analyzing historical returns.

3.1.3. Reorganization of the database

The first problem with all those data retrieved from Yahoo!Finance was that they were about stocks from different markets and so markets with different open days. So, there was some blank in the database and due to the large number of recommendations and the period covered it was a tough work to do it manually. So, I decided to write a short code in VBA (Appendix 2) to fulfill automatically all those blank by the previous non-empty cell.

The second problem was that all those guests didn't make them buy and sell recommendations at the same time. So, I had to reorganize the database based on the information about the recommendation and the historical stock prices retrieved from Yahoo!Finance. The goal was to obtain a database with one row by buy recommendation and consider the potential sell recommendation for the same stock by the same guest and the fact that, for the continuity of the TV show, they all decided to sell all the assets of their portfolio January 1, 2016. Again, doing it manually would be a tough task so, I decided to automate it through a code in VBA (Appendix 3).

I ended up this process with the cleanest complete version of my database with an easy access to all the data and the possibility to sort the data by country, market capitalization or guests for the following analysis.

3.1.4. Benchmark and risk-free rate

For the benchmark and the risk-free rate, I retrieved the data from the website of the Dartmouth College in the section managed by Kenneth R. French. where he provides benchmarks for different markets and the risk-free rate as used for his 5-factor model developed with Fama.

I retrieved data for the European benchmark (Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, Great Britain, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Sweden), the North-America benchmark (Canada, the United States) and the developed country benchmark (European, North America, Australia, Hong Kong, Japan, New Zealand, Singapore). I retrieved those different benchmarks to make some robustness tests. The risk-free rate is the U.S. one-month T-Bill rate.

3.2. Methodology

In this section, the methodology followed to analyze the data retrieved will be explained. I will start with the explanation of the portfolio creation then I will explain the different performance indicators that I used.

3.2.1. Portfolio creation

Due to the different period of investment of every guest and for every stock, the most efficient way to analyze the data was to create different portfolios to can use tools such as the Performance Analytics package of R. For this, I created different groups of portfolios based on 4 aspects: the managers, the location, the size and the combination of the size and the location. The goal was to have the opportunity with those 4 groups of portfolios to analyze the 3 main topics of this master thesis: the performance of the guests, the size effect and the home bias.

3.2.1.1. By manager

Before everything, I decided to analyze in this section only the managers that made at least 10 “buy” recommendations during the sample period. So, I analyzed the 14 most active managers out of the 38 managers initially. I made this choice because, I considered that below 10 recommendations, performance could be more associated to luck than skills. To analyze the performance of the 14 guests, I decided to use different methodologies to create the portfolios to make robustness checks but, always, I created one portfolio by managers.

Firstly, I decided to create every portfolio starting on the date on which the manager gave the first recommendation and ending December 31, 2019. I decided to create these portfolios because it's the closest to what happened. However, there are some issues with this. Because all the managers were obliged to make recommendations when they came at the TV show, some of them made recommendations even if we were in a bearish market and it was a bad timing to invest. Otherwise, other managers came for the first time at the TV show at the perfect timing and so following this methodology, started to invest in a bullish market. So, with these portfolios, I will only use annualized metrics and it can be a bit biased by the different periods of investment.

The second methodology was to create portfolios considering that before the first recommendation was given by a manager, he was invested in the whole market. I considered the European Benchmark, as described earlier, as the whole market. I used this methodology because it was the easiest way to solve the problem of the different period of investment. With this, all the managers were invested from May 8, 2015, to December 31, 2019. This is less biased than the first methodology.

The last methodology that I followed was to create portfolios for every manager based on the core-satellite investing methodology. The core-satellite methodology is one of the most popular portfolio creation methodologies. This is used to minimize costs, tax liability and volatility while providing the opportunity to outperform the stock market. The principle of this methodology is that there is a core portion of the portfolio that is managed passively and that is dedicated to an index fund that tracks a benchmark such as the S&P500. And there is the satellite portion of the portfolio that is actively managed, where managers try to pick stocks that will outperform the core portion.

I used three asset allocations with the core-satellite methodology for every manager.

For the first one, I considered that the core portion is an index that tracks the European Benchmark as given by Kenneth R. French and accounted for 80% of the portfolio. I decided that the satellite portion was always 20% of the portfolio and equally weighted between all the recommendations given by the manager.

For the second one, I decided to keep the same core portion as for the first one and it's again 80% of the portfolio but, in this case, the satellite portion of the portfolio is more "progressive." The satellite portion is a maximum of 20% of the portfolio but every stock recommended by the manager is a maximum of 2% of the portfolio. So, if there are, at a time, fewer than 10 recommendations in the portfolio, each recommendation is 2% of the portfolio and the rest is invested as the core portion. However, if there are 10 or more recommendations, the satellite portion is 20% of the portfolio and the stocks recommended by the manager are equally weighted.

The last asset allocation is the same as the first one, but I considered that the core portion is 50% of the portfolio and the satellite portion is also 50% of the portfolio.

This core-satellite methodology is the closest to the reality of how an investor could invest with the recommendations given by every manager and what the expected returns for someone that follow their advice are. The fact that I use those three asset allocations allow me to evaluate the difference of expected returns between the investors that take less risk and the investors that take more risk.

3.2.1.2. By location

For the portfolio creation by region, I decided to divide the entire world in 3 regions and so 3 portfolios: France, Europe without France and the rest of the world. The period of investment begins the May 8, 2015, for all the portfolios and end the December 31, 2019. For the period when there is no recommendation for one region, I considered that 100% of the portfolio was in cash and that the managers considered that it wasn't the right time to invest in this region. I can do this hypothesis in this case because since the first day, managers could invest in every region.

3.2.1.3. By size

For the creation of the portfolios by size, I separated all the stocks by their market capitalization in 10 deciles. Then I created one portfolio by decile. Again, for the same reason, I considered the same period of investment and that when there was no recommendation for one decile, 100% of the portfolio was in cash.

3.2.1.4. By size and location

For this last category, I created the portfolios based on the size and on the region. The objective here is to can verify the consistency of the previous analysis across regions and across the different sizes. For this, I created 10 portfolios: 5 for the companies headquartered in France separated by their market capitalization in quintile and 5 for the companies headquartered outside France separated by their market capitalization in quintile.

3.2.2. Analysis of the portfolios

With all those data organized in portfolios (see Appendix 4 for example “by location”) as explained above, I could now use the Performance Analytics and the Peer Perfomance packages in R to analyze the data.

For the Performance Analytics package, I used a code that Pr. Mikael Petitjean gave me and that I slightly modified (Appendix 5). And for the Peer Performance package, I created the code (Appendix 6) to analyze the data and compare the managers.

Those two packages are powerful tools that allow me to retrieve the most important ratios and metrics that I need to analyze performances of portfolios. All those ratios and metrics will be explained below.

3.2.3. Ratios and other indicators

Thanks to the two packages, in one click, I could retrieve a lot of meaningful information about the different portfolios that I analyzed. A lot of metrics and ratios come up when we use those powerful tools and it's important to understand all them before going further and show the results of the analysis.

3.2.3.1. Daily returns

Because I already had the daily prices of every stock, I calculated the daily returns of every stock as follows:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

R_t is the return at time t.

P_t is the price at time t.

P_{t-1} is the price at time t-1.

To calculate the daily returns of the portfolios, because I considered that they were equally weighted, I calculated the returns of the portfolios (excepted the core-satellite that I explained above) as follows:

$$R_p = \frac{\sum_{i=1}^{n} R_i}{n}$$

R_p is the return of the portfolio at a given time.

R_i is the return of a stock i at a given time.

n is the number of stocks in the portfolio at a given time.

3.2.3.2. Annualized return

Thanks to R, the geometric average annualized return is automatically calculated for every portfolio. For this the daily annualized return is calculated on a 252 days per year basis as follows:

$$Annualized\ return = (1 + Daily\ return)^{252} - 1$$

In this case, it’s important to use the geometric mean because it considers the compounding effect that occurs period after period and gives a more accurate and closer to the reality measure of return than the arithmetic average. The geometric mean is calculated as follows:

$$Average\ return = \left(\prod_{t=1}^{n} 1 + R_t\right)^{\frac{1}{n}} - 1$$

R_t is the return at period t.

n is the number of periods.

3.2.3.3. Sharpe ratio

Created in 1964 by Sharpe, the annualized Sharpe ratio is a measure of the risk-adjusted performance of a stock or a portfolio. It measures the annualized excess return per unit of risk that is the volatility of the stock or portfolio. It's written as follows:

$$S_P = \frac{R_P - R_f}{\sigma_P}$$

The higher the Sharpe ratio, the better is the risk-adjusted performance of the portfolio. It means that the risk-reward balance is better for this portfolio. A negative Sharpe ratio means that invest in the portfolio was worse than invest in a risk-free asset and for example, if the Sharpe ratio is equal to 0.3, an increase of one unit of risk means an increase of excess return of 0.3%.

3.2.3.4. Modified Sharpe Ratio

The modified Sharpe Ratio is commonly used to evaluate the risk-adjusted performance of an investment with abnormal returns. It's the ratio between the excess return of a portfolio and its modified VaR. It's written as follows:

$$mS_p = \frac{R_p - R_b}{mVaR_p}$$

R_p is the mean return of the portfolio.

R_b is the mean return of a benchmark.

mVaR is the modified Value at Risk.

The modified Value at Risk approximates the Value at Risk under the true, unknown, distribution with the second order Cornish-Fisher expansion.

3.2.3.5. Treynor ratio

The Treynor ratio is an adaptation of the Sharpe ratio. It's also a measure of the risk-adjusted performance, but it replaces the standard deviation by the Beta of the stock or the portfolio. The main difference here is that the Beta is a measure of the systematic risk when the standard deviation is a measure of the global risk (systematic risk + non-systematic risk). So, the Treynor ratio considers that the portfolio is well diversified and therefore, ignore the non-systematic risk. It's calculated as follows:

$$T_p = \frac{R_P - R_f}{\beta_P}$$

Again, the higher the Treynor ratio, the better is the risk-adjusted performance of the portfolio.

3.2.3.6. Tracking error

The tracking Error is the standard deviation of the difference between the portfolio returns and the benchmark returns. It allows to identify the level of consistency in which a portfolio tracks the performance of a benchmark. If the tracking error is low, it means that the portfolio is beating the benchmark consistently over time. However, if it's high, it means that the portfolio returns are more volatile over time.

3.2.3.7. Information Ratio

The Information Ratio is another ratio that is like the Sharpe ratio. The difference in this case is at the numerator, because the Information Ratio is a measure of the portfolio annualized returns beyond a benchmark annualized returns (also called the active premium) divided by the Tracking Error. It's written as follows:

$$Information\ Ratio_p = \frac{R_p - R_B}{Tracking\ Error_p}$$

The Information Ratio is often used to measure a portfolio manager’s level of skill or ability to outperform a benchmark and include a notion of consistency with the tracking error. It's what we're looking for when we try to create a core-satellite portfolio. The higher the information ratio, the higher the level of consistency.

3.2.3.8. M-squared

The objective of the M-squared (or also called Modigliani risk-adjusted performance) is to enable the analyst to compare performances of different levels of risk’s assets. It's a useful measure to compare the theoretical performance of a portfolio if it had a similar risk as the market. The formula of the M-squared is:

$$M^2{}_p = \left(R_P - R_f\right) * \frac{\sigma_m}{\sigma_P} + R_f$$

The higher the M-squared, the better is the performance for a same level of risk. However, this ratio is more theoretical, because we can't flatten the level of risk of a portfolio as we want.

3.2.3.9. Jensen's Alpha

The alpha is considered as an estimation of the unexpected return of an investment. It's equal to the difference between the return of an asset and the estimated return based on the CAPM.

The CAPM (Capital Asset Pricing Model) is the well-known model used to predict future returns of an asset based on the risk-free rate, the return of the market and the systematic risk of the asset. The formula for assets i at a given point in time is the following:

$$R_i = R_f + \beta_i * (R_m - R_f)$$

Following this formula, we easily deduce the formula of the Jensen's Alpha that is the following formula:

$$\alpha_i = R_i - (R_f + \beta_i * \left(R_m - R_f\right))$$

There is a difference between the R_i in the CAPM which is the expected return of the asset and the R_i in the Jensen's Alpha which is the observed return.

If the alpha is >0, we consider that the asset has beaten the market and, if the alpha is <0, we consider that the asset has underperformed the market.

3.2.3.10. Downside Risk

The downside risk is an estimation of the potential decline in value of a portfolio if the market conditions change. It exposes the worst-case scenario of an investment and how much an investor can lose.

The lower the downside risk, the better for the investor, because it means that he's exposed to a lower potential loss.

3.2.3.11. VaR

The Value at Risk (or VaR) is a measure of the maximum loss that can happen when investing in a portfolio at different levels of confidence (usually 95% or 99%) for a defined periodicity. It's used to measure and control the level of risk exposure.

For a level of confidence of 95%, in our case with a daily basis, the potential daily loss encountered by an investor in one of the portfolios is expected to be lower than the VaR in 95% of the cases (95 days out of 100).

3.2.3.12. *Expected Shortfall*

The expected shortfall (or Conditional Value at Risk) is a measure that quantifies the tail risk in an investment at a certain level of confidence. The expected shortfall is calculated by taking the weighted average of the extreme losses in the tail of the distribution of possible returns beyond the VaR.

Such as the VaR, it's a measure that is more often used in the risk management. However, since the 2008 crisis, those two models are criticized because they underestimate the occurrence and the risk magnitude of the portfolios before the apparition of a crisis.

3.2.4. Peer Performance

The Peer Performance package in R has powerful tools and functions that allow to analyze and compare portfolios and eliminating the luck. The three “screening” functions analyze a complete database of portfolios and compare the portfolios on three metrics: The Alpha, the Sharpe ratio and the modified Sharpe ratio. The three functions correct for the luck by estimating the Peer Performance ratios through a pairwise approach and the False Discovery Rates approach developed by Storey (2002). The main goal of this package is really to evaluate how well does a portfolio perform compared to others.

False Discovery Rates (or FDR) are a tool to weed out bad data that looks good. This is all based on the p-value.

The p-value is the probability to observe results as extreme as the observed results of a statistical hypothesis test while assuming that the null hypothesis is correct. And the null hypothesis is the hypothesis that there is no difference between certain characteristics of a population. The p-value can be considered as the rejection point or the smallest level of significance at which the null hypothesis would be rejected.

The problem is that, when we compare two samples, we can have a small p-value that suggests that the two samples are from two different distributions when it’s not always the case. This means that we would reject the null hypothesis when we shouldn’t. This is what we call “false-positive” or the type I error. Normally false-positive are rare but in large samples they appear a lot. By exploiting the distribution of p-values under the null hypothesis, we obtain a reliable estimate of the peer performance ratios (equal-performance, outperformance and underperformance) that is robust to the presence of false discoveries. In other terms, with the

False Discovery Rates approach, we can considerably reduce the type I error, and this is what the functions of the Peer Performance package do.

To compute the equal-performance ratio, the function determines a sufficiently large lambda such that all p-values exceeding this lambda correspond to portfolios for which the null hypothesis is true. If n^0 is such a portfolio i that we expect $(1-\lambda) * n_i^0$ p-values exceeding λ, then we have:

$$Equal - performance\ ratio = \frac{n_i^0}{n}$$

With:

$$n_i^0 = \frac{1}{1-\lambda} * \sum_{j=1}^{n} (p - values_{\alpha_i = \alpha_j} > \lambda)$$

n is the number of peers.

α_i is the risk-adjusted performance indicator that we're analyzing (alpha or Sharpe ratio or modified Sharpe ratio) of the portfolio i.

To compute the two other ratios, it begins from the already calculated equal-performance ratio and it attributes the rest to the two other ratios based on the number of significant performance differences. Then:

$$Outperformance\ ratio = \frac{\#(\alpha_i > \alpha_j) - {n_i^0}/{2}}{n}$$

$$Underperformance\ ratio = \frac{\#(\alpha_i < \alpha_j) - {n_i^0}/{2}}{n}$$

If the outperformance ratio <0, he's equal to 0 and the underperformance ratio is equal to 1 minus the equal-performance ratio.

If the underperformance ratio <0, he's equal to 0 and the outperformance ratio is equal to 1 minus the equal-performance ratio.

The equal-performance ratio can be considered as the proportion of portfolios in the peer group that perform equally well as the portfolio that we're evaluating.

The outperformance ratio can be considered as the proportion of portfolios in the peer group that are outperformed by the portfolio that we're evaluating.

The underperformance ratio can be considered as the proportion of portfolios in the peer group that outperform the portfolio that we're evaluating.

As advised by the creators of the package (Ardia and Boudt), in the results I focus on the peer performance ratios for the three metrics (Alpha, Sharpe Ratio, Modified Sharpe Ratio) and the metrics themselves.

4. Analysis and results

After the data collection, organization and analyze through R, I will now present the results of the analysis in the following section. All the results come from the analysis of the database with the functions of the two packages in R: Performance Analytics and Peer Performance. It will always be explained in the results, but for most of the tests, I made robustness tests that can be found in the appendices.

If there are no contraindications, all the results are given based on the European benchmark and the risk-free rate is the U.S. one-month T-bill rate.

4.1. Managers performance analysis

This first section is focused on the analysis of the performance of the 14 most active managers: Alain Pitous, Alice Lhabouz, Christian Bito, Christian Cambier, Emeric Préaubert, Eric Lewin, Jean-Pierre Gaillard, Jérome Fauvel, Louis de Montalembert, Pascale Seivy, Sébastien Faijean, Sébastien Korchia, Sébastien Lalevée et Virginie Robert.

In this section, there will be the analyze of the managers following the 5 different portfolios creation. "Reality" stands for the portfolios that take only into account the period of investment. "Benchmark" stands for the portfolios when the non-investment periods have been replaced by an investment like the benchmark. "Core-sat. (20%)" stands for the portfolios following the core-satellite methodology with a core of 80% and satellite of 20%. "Core-sat. (progr. 20%)" stands for the portfolios following the same strategy as the previous one but with a cap of 2% per stock. "Core-sat. (50%)" is the same as the core-sat. (20%) but with a core of 50% and satellite of 50%.

4.1.1. Annualized return and standard deviation

Table 2: Annualized return of managers

Portfolio	Reality	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Eric Lewin	-12.61%	-0.76%	3.61%	4.06%	2.00%
Alice Lhabouz	-0.78%	-2.76%	3.36%	4.20%	1.24%
Sébastien Lalevée	1.54%	-2.25%	3.52%	3.92%	1.57%
Benchmark	4.66%	4.66%	4.66%	4.66%	4.66%
Sébastien Korchia	4.97%	1.91%	4.16%	4.20%	3.36%
Christian Cambier	5.13%	0.78%	4.04%	3.77%	2.96%
Pascale Seivy	5.62%	1.12%	4.04%	4.55%	3.02%
Emeric Préaubert	6.89%	4.98%	5.12%	4.46%	5.44%
Jérôme Fauvel	7.53%	2.12%	4.51%	3.70%	3.94%
Alain Pitous	7.61%	6.02%	5.12%	4.74%	5.64%
Jean-Pierre Gaillard	9.47%	6.30%	5.14%	4.66%	5.71%
Christian Bito	10.70%	7.51%	5.33%	4.89%	6.24%
Louis de Montalembert	18.01%	14.28%	6.81%	6.08%	9.83%
Sébastien Faijean	19.79%	12.90%	6.54%	4.65%	9.14%
Virginie Robert	19.94%	17.91%	7.49%	6.26%	11.58%

Looking at the Table 2, we see clearly that most of the managers (11 out of 14) outperformed the benchmark in the reality but the problem of this portfolio is that they all have different periods of investment. This is corrected by the other type of portfolios that have a common period of investment. We see with the other type of portfolios that only half of the managers (7 out of 14) outperformed the benchmark on a common period of investment. This difference is because some managers started to invest (to come at the TV Show) after a bearish market period during the year 2015 for the European markets (Appendix7).

We can also see that following a safer strategy such as the core-satellite, whatever the portion attributed to the core or to the satellite, eliminate the negative annualized returns but, of course, also decrease the performance of the best managers.

At this stage we can see that 3 managers clearly standout: Louis de Montalembert, Sébastien Faijean et Virginie Robert.

Table 3: standard deviation of managers

Portfolio	Reality	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Pascale Seivy	13.20%	13.99%	13.35%	13.68%	12.97%
Benchmark	14.00%	14.00%	14.00%	14.00%	14.00%
Christian Bito	16.14%	16.56%	13.85%	13.88%	14.29%
Eric Lewin	16.44%	15.11%	13.87%	13.90%	14.02%
Christian Cambier	16.64%	17.44%	13.62%	13.63%	14.13%
Jean-Pierre Gaillard	18.58%	18.61%	14.06%	13.96%	15.06%
Alice Lhabouz	18.64%	19.04%	13.59%	13.91%	14.48%
Virginie Robert	19.14%	19.19%	13.19%	13.58%	13.92%
Alain Pitous	19.51%	19.69%	14.07%	14.00%	15.33%
Sébastien Faijean	19.55%	19.63%	13.47%	13.67%	14.44%
Louis de Montalembert	20.77%	20.88%	13.79%	13.66%	15.22%
Sébastien Korchia	21.56%	16.64%	14.18%	14.00%	14.80%
Sébastien Lalevée	21.90%	21.32%	13.92%	14.12%	15.52%
Jérôme Fauvel	24.49%	24.31%	14.27%	14.04%	16.79%
Emeric Préaubert	25.97%	26.24%	14.69%	14.17%	17.87%

The volatility (or standard deviation) is the most common measure of risk in finance. Looking at the Table 3, we can see that most of the portfolios (13 out of 14) were riskier than the benchmark when we look at the real period of investment of every portfolio. Only the portfolio held by Pascale Seivy has a lower annualized standard deviation than the benchmark in those conditions.

However, if we place ourselves as a real investor that followed one of the core-satellite strategies, we see that it considerably reduces the standard deviation of the portfolios. The volatility of those portfolios becomes close to the volatility of the benchmark and so, investors that would have invested in those portfolios would have borne the same risk as an investor that had invested in an index that replicates the benchmark. This is largely explained by the fact that 50% or at least 80% of the portfolio is invested in the benchmark and so that there is a strong correlation between the portfolios and the benchmark (Appendix 8).

4.1.2. Annualized Sharpe Ratio

Table 4: Annualized Sharpe ratio of managers

Portfolio	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Alice Lhabouz	-0.1978	0.1690	0.2245	0.0132
Sébastien Lalevée	-0.1532	0.1759	0.2016	0.0337
Eric Lewin	-0.1182	0.1827	0.2148	0.0671
Christian Cambier	-0.0151	0.2176	0.1976	0.1340
Pascale Seivy	0.0055	0.2218	0.2537	0.1508
Jérôme Fauvel	0.0436	0.2402	0.1869	0.1705
Sébastien Korchia	0.0512	0.2175	0.2233	0.1551
Emeric Préaubert	0.1485	0.2747	0.2385	0.2433
Alain Pitous	0.2500	0.2869	0.2615	0.2967
Benchmark	0.2556	0.2556	0.2556	0.2556
Jean-Pierre Gaillard	0.2795	0.2879	0.2567	0.3067
Christian Bito	0.3862	0.3061	0.2744	0.3599
Sébastien Faijean	0.5980	0.4035	0.2611	0.5551
Louis de Montalembert	0.6273	0.4136	0.3644	0.5711
Virginie Robert	0.8700	0.4836	0.3802	0.7491

The Annualized Sharpe ratio delivers information on the excess return per unit of global risk. The higher the Sharpe ratio, the better.

We can observe that the best managers have a better Annualized Sharpe ratio when we analyze their recommendations without creating a core-satellite portfolio. While, the managers that performed less well have a better risk-adjusted performance when we consider their recommendations in a core-satellite approach.

We usually consider that a Sharpe ratio of 1 or better is good and a Sharpe ratio lower than 1 is considered as suboptimal. No one of the portfolios have a Sharpe ratio higher than 1 so following this indicator, the portfolios of the managers have a bad risk-adjusted performance. Some managers even have a Sharpe ratio lower than 0 for the Benchmark approach, which means that invest in their portfolios would earn a lower return than the risk-free asset. It's the worst result possible.

As we can see again here, the three managers that have the best annualized Sharpe ratio are: Sébastien Faijean, Louis de Montalembert and Virginie Robert. However, when we consider the progressive core-satellite approach, many managers have a risk-adjusted performance close to the Sharpe ratio obtained following the recommendations of the three best performing managers.

4.1.3. Treynor Ratio

Table 5: Treynor ratio of managers

Portfolio	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Alice Lhabouz	-0.3768	0.1740	0.2256	0.0160
Sébastien Lalevée	-0.2917	0.1822	0.2063	0.0415
Eric Lewin	-0.1383	0.1839	0.2153	0.0699
Christian Cambier	-0.0247	0.2222	0.1989	0.1535
Pascale Seivy	0.0077	0.2242	0.2544	0.1628
Sébastien Korchia	0.0592	0.2190	0.2236	0.1615
Jérôme Fauvel	0.0870	0.2513	0.1901	0.2187
Emeric Préaubert	0.2779	0.2881	0.2429	0.3102
Alain Pitous	0.3873	0.2937	0.2638	0.3405
Jean-Pierre Gaillard	0.3989	0.2932	0.2578	0.3416
Christian Bito	0.5178	0.3100	0.2757	0.3901
Louis de Montalembert	1.2465	0.4285	0.3685	0.7091
Sébastien Faijean	1.2976	0.4177	0.2632	0.6956
Virginie Robert	2.2144	0.5019	0.3868	0.9682

The Treynor ratio delivers information on the excess return per unit of systematic risk of the portfolio. The higher the Treynor ratio, the better is the risk-adjusted performance of a portfolio. The Treynor ratio is mainly used to analyze well-diversified portfolios.

As we can observe when we compare Table 4 and Table 5, the ranking of the managers is quite the same and we also observe a decrease of the risk-adjusted performance for the core-satellite portfolios. This tends to show that on a risk-adjusted basis, the Benchmark portfolio is more efficient than the Core-satellite portfolios. That means that the increase of risk in the benchmark portfolio is largely compensated by a higher return.

Moreover, we observe a considerable difference between the Treynor ratio and the Sharpe ratio mainly for the Benchmark portfolios. It highlights the lack of diversification of the portfolios held by the managers, because if they were fully diversified, the Treynor and the Sharpe ratio would be equal.

Here again, there are three managers that standout: Sébastien Faijean, Louis de Montalembert and Virginie Robert.

4.1.4. Information ratio

Table 6: Information ratio of managers

Portfolio	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Eric Lewin	-0.6828	-0.6642	-0.6725	-0.6715
Alice Lhabouz	-0.4444	-0.3880	-0.3279	-0.4100
Sébastien Lalevée	-0.3767	-0.3109	-0.2448	-0.3364
Pascale Seivy	-0.3359	-0.2963	-0.1043	-0.3114
Sébastien Korchia	-0.3307	-0.2997	-0.5640	-0.3115
Christian Cambier	-0.2736	-0.2191	-0.5502	-0.2400
Jérôme Fauvel	-0.1205	-0.0361	-0.3742	-0.0684
Emeric Préaubert	0.0144	0.1039	-0.0745	0.0699
Alain Pitous	0.0900	0.1533	0.0442	0.1298
Jean-Pierre Gaillard	0.1231	0.1785	0.0026	0.1579
Christian Bito	0.2551	0.2993	0.1664	0.2830
Sébastien Faijean	0.4550	0.5176	-0.0057	0.4951
Louis de Montalembert	0.5233	0.5834	0.6755	0.5620
Virginie Robert	0.7050	0.7530	0.6159	0.7366

The information ratio is usually the most recommended risk-adjusted performance indicator. It's used to measure the performance of an active manager. The higher the information ratio, the better.

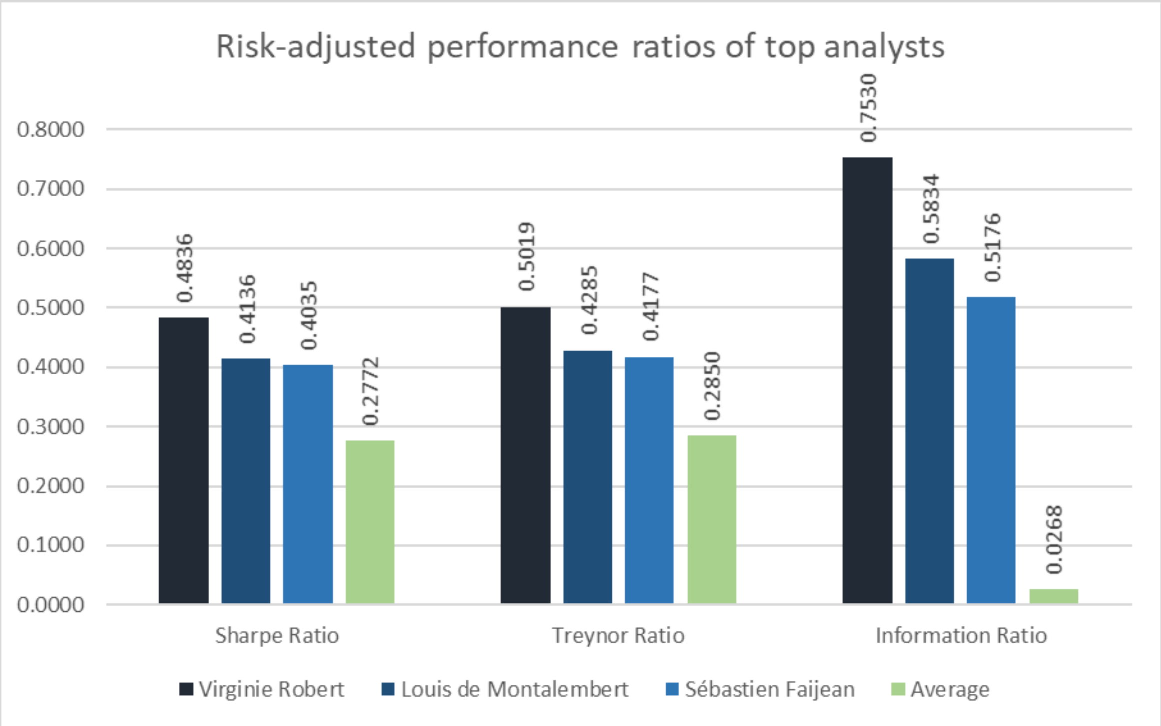
As we can see in Table 6, approximately half of the portfolios (7 out of 14 for "Benchmark," "Core-Sat. (20%)", and "Core-Sat. (50%)" and 9 out of 14 for "Core-Sat. (Progr. 20%)") created following the recommendations of the managers have a negative information ratio. This means that these portfolios have a lower return than the European Benchmark and that the other half has a higher return than the Benchmark.

The information ratio finds out the incremental return generated by the portfolio manager for the incremental risk undertaken by the manager. A higher information ratio reflects a higher skill of the portfolio manager to beat the benchmark.

Usually we consider an information ratio superior at 0.4 as good. Again, here the three managers that seems to be the most skilled are Sébastien Faijean, Louis de Montalembert and Virginie Robert. This is highlighted by Figure 5 that shows the risk-adjusted performance of the 3 best managers against the average considering the "Core-Sat. (20%)" portfolio construction. Moreover, this is consistent whatever the portfolio construction methodology selected excepted for the progressive core-satellite approach following the recommendations of Sébastien Faijean.

This is mostly explained by the fact that the bearish market of 2015 had a huge impact on his performance due to the low number of recommendations given in 2015.

Figure 5: Risk-adjusted performance ratios of top analysts



4.1.5. M-squared

Table 7: M-squared of managers

Portfolio	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Alice Lhabouz	-2.03%	3.47%	4.23%	1.20%
Sébastien Lalevée	-1.48%	3.54%	3.89%	1.42%
Eric Lewin	-0.70%	3.64%	4.09%	1.99%
Christian Cambier	0.63%	4.15%	3.87%	2.93%
Pascale Seivy	1.12%	4.23%	4.66%	3.26%
Jérôme Fauvel	1.22%	4.42%	3.69%	3.28%
Sébastien Korchia	1.60%	4.11%	4.20%	3.18%
Emeric Préaubert	2.66%	4.88%	4.41%	4.26%
Alain Pitous	4.28%	5.10%	4.74%	5.15%
Jean-Pierre Gaillard	4.74%	5.11%	4.68%	5.31%
Christian Bito	6.35%	5.39%	4.94%	6.12%
Sébastien Faijean	9.21%	6.80%	4.76%	8.87%
Louis de Montalembert	9.58%	6.91%	6.23%	9.04%
Virginie Robert	13.07%	7.95%	6.46%	11.65%

The objective of the M-squared is to compare the return of a theoretical portfolio that mimics the risk of the market together. It's used to compare portfolios with different levels of risk. The higher the M², the better.

Looking at Table 7, we can conclude that most of the portfolios (11 out of 14 for the "Benchmark" and all the portfolios for the other's methodology) have positive returns on the same risk basis as the Benchmark.

If we compare the managers, we see again that the three best managers are the same. If we compare the results of the "Benchmark" portfolios with the "Core-Sat." portfolios, we can observe that most of the "Core-Sat. (50%)" portfolios (10 out of 14) have a higher M-squared than the "Benchmark" portfolios for the same manager and are close to the "Benchmark" portfolios for the others. This show that, on a same risk basis, most of the "Core-Sat. (50%)" portfolios outperform the "Benchmark" portfolios.

4.1.6. Annualized Jensen's Alpha

Table 8: Annualized Jensen's Alpha of managers

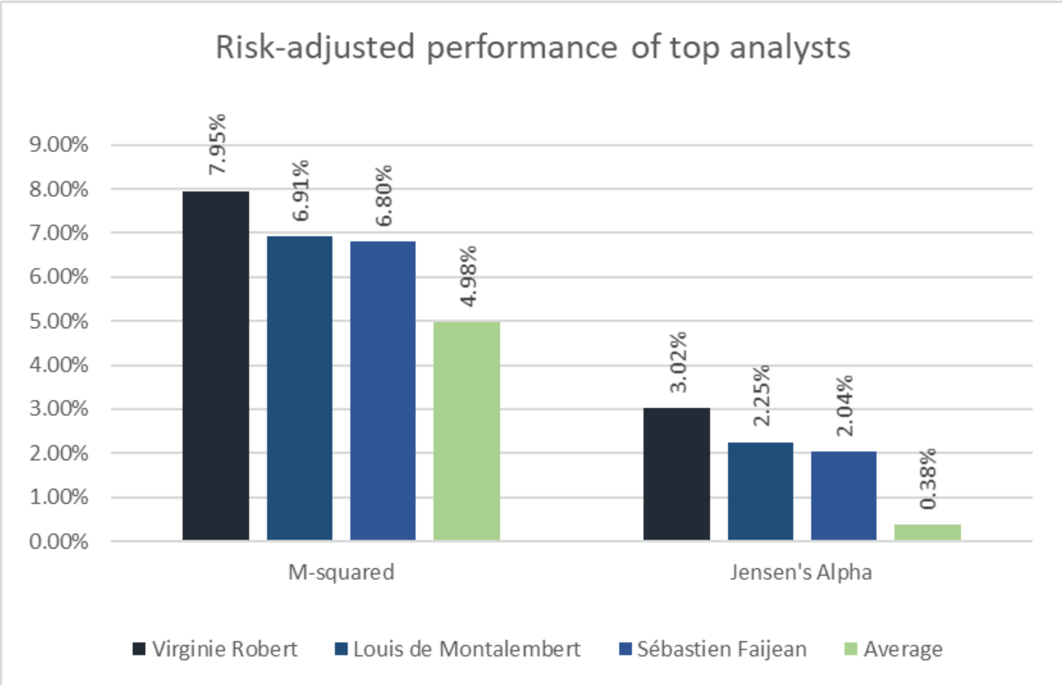
Portfolio	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Alice Lhabouz	-5.10%	-1.04%	-0.40%	-2.58%
Eric Lewin	-4.69%	-0.96%	-0.54%	-2.37%
Sébastien Lalevée	-4.54%	-0.92%	-0.62%	-2.30%
Sébastien Korchia	-2.37%	-0.48%	-0.43%	-1.19%
Christian Cambier	-2.16%	-0.44%	-0.76%	-1.09%
Pascale Seivy	-2.14%	-0.43%	-0.03%	-1.08%
Jérôme Fauvel	0.04%	0.01%	-0.85%	0.02%
Jean-Pierre Gaillard	2.65%	0.52%	0.03%	1.32%
Alain Pitous	2.70%	0.53%	0.12%	1.34%
Emeric Préaubert	2.73%	0.54%	-0.14%	1.35%
Christian Bito	3.67%	0.72%	0.27%	1.82%
Sébastien Faijean	10.63%	2.04%	0.09%	5.18%
Louis de Montalembert	11.75%	2.25%	1.46%	5.71%
Virginie Robert	16.02%	3.02%	1.68%	7.71%

The Jensen's Alpha is the difference between the return of a portfolio, and the modeled risk-adjusted performance based on the CAPM. It's a measure of the performance relative to the market. The higher the Jensen's Alpha, the better and a positive alpha means that the portfolio has outperformed the benchmark whereas a negative alpha means that the portfolio has underperformed the benchmark.

Following the results in Table 8, we can see that, whatever the methodology followed (excepted for the progressive core-satellite), half of the manager has outperformed the benchmark. We see that following the "Benchmark" portfolio strategy and the recommendation of the managers, Sébastien Faijean, Louis de Montalembert and Virginie Robert have outperformed the market by more than 10% annually what is significant.

Of course, if the investor had followed a safer portfolio methodology the results are closer to 0 because they have returns closer to the returns of the benchmark. However, we can see that even if the investors followed a safe strategy such as the Core-Satellite (20%), they could outperform the benchmark by 2.04% to 3.02% following the recommendations of the three best managers. The fact that those three analysts outperformed the others is again highlighted in Figure 6 that shows the comparison between the M-squared and the Jensen’s Alpha of the “Core-Sat. (20%)” portfolios of those analysts and the average of all the portfolios following the same methodology.

Figure 6: Risk-adjusted performance of top analysts



4.1.7. Value at Risk and Expected Shortfall

Table 9: Value at Risk of managers

Portfolio	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Emeric Préaubert	-3.99%	-2.53%	-2.45%	-3.02%
Jérôme Fauvel	-3.89%	-2.46%	-2.46%	-2.90%
Alice Lhabouz	-3.88%	-2.48%	-2.43%	-2.89%
Sébastien Lalevée	-3.75%	-2.46%	-2.46%	-2.93%
Louis de Montalembert	-3.68%	-2.41%	-2.44%	-2.58%
Alain Pitous	-3.60%	-2.52%	-2.43%	-2.67%
Virginie Robert	-3.46%	-2.27%	-2.36%	-2.54%
Jean-Pierre Gaillard	-3.34%	-2.47%	-2.44%	-2.54%
Sébastien Faijean	-3.12%	-2.42%	-2.46%	-2.44%
Sébastien Korchia	-2.95%	-2.46%	-2.46%	-2.65%
Christian Cambier	-2.95%	-2.40%	-2.38%	-2.53%
Pascale Seivy	-2.79%	-2.44%	-2.44%	-2.46%
Christian Bito	-2.68%	-2.35%	-2.39%	-2.41%
Eric Lewin	-2.54%	-2.46%	-2.44%	-2.46%
Benchmark	-2.46%	-2.46%	-2.46%	-2.46%

The Value at Risk (or VaR) is a downside risk measure that is an estimation of the potential decline in value of the portfolio, it's the worst-case scenario. Here the confidence level for the calculation is 99%. The lower the VaR, the better.

The results presented in Table 9 are the VaR values following the historical methodology, which is the most common methodology. However, some robustness checks have been made following the Gaussian and the modified methodology (Appendix 9) to verify the consistency of the results obtained and the results are consistent following the different methodologies.

As we can see in Table 9, all the managers have a higher VaR than the European benchmark in the case of a "Benchmark" portfolio construction but for the other portfolio construction methodologies, they have a VaR close to the European benchmark's VaR and, sometimes even lower.

The three best managers aren't the three that have the highest VaR but they're in the upper middle. For example, in the case of "Benchmark" portfolio methodology constructed following the recommendations of Virginie Robert, the VaR says that 1 day out of 100, investors of this portfolio will suffer from a loss equal or superior to 3.46%.

Table 10: Expected Shortfall of Managers

Portfolio	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Emeric Préaubert	-5.99%	-3.59%	-3.44%	-4.25%
Sébastien Lalevée	-5.16%	-3.26%	-3.34%	-3.71%
Alain Pitous	-5.12%	-3.44%	-3.39%	-3.80%
Jérôme Fauvel	-4.89%	-3.45%	-3.41%	-3.72%
Louis de Montalembert	-4.84%	-3.44%	-3.33%	-3.75%
Alice Lhabouz	-4.55%	-3.29%	-3.38%	-3.46%
Virginie Robert	-4.50%	-3.15%	-3.30%	-3.35%
Sébastien Korchia	-4.26%	-3.42%	-3.40%	-3.61%
Jean-Pierre Gaillard	-4.24%	-3.39%	-3.40%	-3.51%
Eric Lewin	-3.93%	-3.43%	-3.39%	-3.53%
Christian Cambier	-3.88%	-3.30%	-3.36%	-3.36%
Sébastien Faijean	-3.75%	-3.27%	-3.38%	-3.11%
Christian Bito	-3.63%	-3.35%	-3.38%	-3.33%
Benchmark	-3.40%	-3.40%	-3.40%	-3.40%
Pascale Seivy	-3.23%	-3.30%	-3.37%	-3.17%

The expected shortfall is a more complete measure of the downside risk. It's the measure of the average of the potential loss below a certain confidence level (here 99%). The lower the expected shortfall, the better.

Here again, the results in Table 10 are the values of the expected shortfall following the historical methodology, but some robustness tests have been done following the Gaussian and the modified methodology (Appendix 10).

Obviously, the ranking of the managers by the expected shortfall is approximately the same as the ones by the VaR, and here again, we observe a substantial decrease between the portfolio created following the “Benchmark” and the ones following the other methodologies.

For example, in the case of “Benchmark” portfolio methodology constructed following the recommendations of Virginie Robert, the expected shortfall says that 1 day out of 100 investors of this portfolio will suffer from a loss of 4.5% on average.

4.1.8. Peer performance

In this section, I will only analyze the peer performance ratios obtained following the methodology explained in the methodology section of this thesis for the Alpha, Sharpe ratio and modified Sharpe ratio.

For the readability, I present in this section only the outperformance ratio that helps me to determine which manager has outperformed the peers on a risk and luck-adjusted basis. However, the complete tables with the three peer performance ratios can be found in the appendices (Alpha screening: Appendix 11, Sharpe screening: Appendix 12 and modified Sharpe screening: Appendix 13).

4.1.8.1. Alpha

Table 11: Alpha screening

Portfolio	Benchmark outperformance ratio	Core-Sat. (20%) outperformance ratio	Core-Sat. (Progr. 20%) outperformance ratio	Core-Sat. (50%) outperformance ratio
Alain Pitous	0.13	0.13	0.00	0.13
Alice Lhabouz	0.00	0.00	0.00	0.00
Christian Bito	0.34	0.30	0.09	0.34
Christian Cambier	0.00	0.00	0.00	0.00
Emeric Préaubert	0.00	0.00	0.00	0.00
Eric Lewin	0.00	0.00	0.00	0.00
Jean-Pierre Gaillard	0.23	0.23	0.00	0.23
Jérôme Fauvel	0.00	0.00	0.00	0.00
Louis de Montalembert	0.66	0.68	0.89	0.66
Pascale Seivy	0.00	0.00	0.00	0.00
Sébastien Faijean	0.76	0.76	0.00	0.76
Sébastien Korchia	0.00	0.00	0.00	0.00
Sébastien Lalevée	0.00	0.00	0.00	0.00
Virginie Robert	0.76	0.76	0.89	0.76
Benchmark	0.02	0.02	0.02	0.02

The results in the Table 11 are the values of the outperformance ratio based on the alpha with a correction for the luck. They can be interpreted as the probability to outperform peers or to have a higher alpha than a peer.

The outperformance ratio confirms what I have previously seen in my analysis: there are three managers that outperformed the other managers. In any case (excepted for the progressive core-satellite for Sébastien Faijean), Virginie Robert, Louis de Montalembert and Sébastien Faijean outperformed the other managers clearly.

4.1.8.2. Sharpe ratio

Table 12: Sharpe ratio screening

Portfolio	Benchmark outperformance ratio	Core-Sat. (20%) outperformance ratio	Core-Sat. (Progr. 20%) outperformance ratio	Core-Sat. (50%) outperformance ratio
Alain Pitous	0.00	0.00	0.00	0.00
Alice Lhabouz	0.00	0.00	0.00	0.00
Christian Bito	0.23	0.40	0.23	0.50
Christian Cambier	0.00	0.00	0.00	0.00
Emeric Préaubert	0.00	0.00	0.00	0.00
Eric Lewin	0.00	0.00	0.00	0.00
Jean-Pierre Gaillard	0.13	0.06	0.00	0.00
Jérôme Fauvel	0.00	0.00	0.00	0.00
Louis de Montalembert	0.60	0.76	0.90	0.78
Pascale Seivy	0.00	0.00	0.00	0.00
Sébastien Faijean	0.76	0.79	0.00	0.79
Sébastien Korchia	0.00	0.00	0.00	0.00
Sébastien Lalevée	0.00	0.00	0.00	0.00
Virginie Robert	0.78	1.00	0.89	1.00
Benchmark	0.23	0.00	0.02	0.20

The results in the Table 12 are the values of the outperformance ratio based on the Sharpe ratio with a correction for the luck. They can be interpreted as the probability to outperform peers or to have a higher Sharpe ratio than a peer.

Again, the outperformance ratio based on the Sharpe ratio confirms what I have previously seen in my analysis: the same three managers outperformed other managers even when we correct the risk-adjusted performance indicators for luck. In any case (excepted for the progressive core-satellite for Sébastien Faijean), Virginie Robert, Louis de Montalembert and Sébastien Faijean outperformed the other managers clearly.

4.1.8.3. Modified Sharpe ratio

Table 13: modified Sharpe ratio screening

Portfolio	Benchmark outperformance ratio	Core-Sat. (20%) outperformance ratio	Core-Sat. (Progr. 20%) outperformance ratio	Core-Sat. (50%) outperformance ratio
Alain Pitous	0.00	0.00	0.00	0.00
Alice Lhabouz	0.00	0.00	0.00	0.00
Christian Bito	0.45	0.45	0.76	0.05
Christian Cambier	0.00	0.00	0.00	0.00
Emeric Préaubert		0.00	0.00	0.00
Eric Lewin	0.00	0.00	0.00	0.00
Jean-Pierre Gaillard	0.00	0.00	0.00	0.05
Jérôme Fauvel		0.00	0.00	0.00
Louis de Montalembert	0.83	0.33	0.60	0.25
Pascale Seivy	0.00	0.00	0.00	0.00
Sébastien Faijean	0.77	0.38	0.00	0.33
Sébastien Korchia	0.00	0.00	0.00	0.00
Sébastien Lalevée	0.00	0.00	0.00	0.00
Virginie Robert	0.82	0.42	0.76	0.39
Benchmark	0.03	0.35	0.06	0.22

The results in the Table 13 are the values of the outperformance ratio based on the modified Sharpe ratio with a correction for the luck. They can be interpreted as the probability to outperform peers or to have a higher modified Sharpe ratio than a peer.

In this analyze, the outperformance ratio based on the modified Sharpe ratio confirms that there are three managers that outperformed, and they're always the same. However, this analyze show that there is also a fourth manager (Christian Bito) that also outperform most of the other managers and it's even clearer when we look the outperformance ratio of the progressive core-satellite portfolio. It's consistent with what we saw in the previous analysis, because Christian Bito was often ranked fourth. We can so consider that there are four managers that outperform the others: Christian Bito, Sébastien Faijean, Louis de Montalembert and Virginie Robert.

4.2. By size analysis

In this section, I will analyze all the recommendations given by the managers divided in 10 deciles by market capitalization. The objective is to discover if there is some evidence of a size effect in the recommendations given by the managers.

I performed those analyses on 3 different benchmarks, the results given in this section are based on the European benchmark. However, the results based on the Developed countries and USA benchmark used to make some robustness tests can be found in the appendices.

4.2.1. Annualized return, standard deviation and correlation

Table 14: Annualized return, volatility and correlation of portfolios by size

Portfolio	Annualized return	Annualized volatility	Correlation
1st Decile	-16.67%	21.94%	0.388
2nd Decile	7.58%	19.29%	0.547
3rd Decile	16.13%	19.93%	0.474
4th Decile	11.82%	17.81%	0.516
5th Decile	19.58%	17.13%	0.460
6th Decile	5.03%	16.47%	0.634
7th Decile	3.42%	16.16%	0.604
8th Decile	14.17%	18.17%	0.700
9th Decile	7.33%	17.43%	0.650
10th Decile	12.87%	13.89%	0.554
Benchmark	4.66%	14.00%	1.000

The Table 14 gives the annualized return, annualized volatility and the correlation with the benchmark of the ten portfolios created by decile based on the market capitalization. Some robustness tests have been made to verify the robustness of the analysis concerning the correlation (Appendix 14) and a graph to visualize the cumulative returns of the different portfolios through the entire investment period (Appendix 15).

Looking at the annualized return, we don’t observe a clear size effect in the sample of recommendations given by the managers. Indeed, the mean of the annualized return of the first five deciles is 6.84% while that of the last five deciles is 8.48%. This is inconsistent with the size effect hypothesis.

The first decile has an annualized return of -16.67% what a bad result is looking at the other decile and the benchmark performances. This is mainly due to a short proportion of stocks that had bad performances and that decrease the performance of this decile and so the performance of the small stocks. If we calculate the mean of the small stocks without the first decile, we obtain an annualized return of 13.69% what is a lot more consistent with the size effect hypothesis.

In Table 14, we also see that the standard deviation decreases progressively with the decile what means that higher companies in the sample are safer than the smaller companies. Moreover, the correlation of the small stocks with the benchmark is lower than the correlation of the bigger stocks with the benchmark. What means that large companies recommended by the managers were more correlated to the benchmark than the smaller companies.

4.2.2. Risk-adjusted performances

Table 15: Risk-adjusted performances of portfolios by size

Portfolio	Ann. Sharpe ratio	Treynor ratio	Information ratio	Jensen's Alpha	M-squared
1st Decile	-0.799	-2.057	-1.018	-17.81%	-10.64%
2nd Decile	0.335	0.613	0.177	4.86%	5.50%
3rd Decile	0.749	1.580	0.632	13.73%	11.33%
4th Decile	0.599	1.161	0.448	9.16%	9.30%
5th Decile	1.071	2.331	0.910	17.09%	16.01%
6th Decile	0.240	0.378	0.028	1.89%	4.28%
7th Decile	0.145	0.241	-0.092	0.50%	2.96%
8th Decile	0.715	1.021	0.730	10.29%	10.93%
9th Decile	0.357	0.550	0.198	4.00%	5.89%
10th Decile	0.843	1.522	0.623	10.03%	12.98%

In the Table 15, we find the different measure of risk-adjusted performance used previously for the managers risk-adjusted performance analysis. Some robustness tests have been made with two benchmarks (Appendix 16) to verify the consistency of the results.

Through this table we see that, even on a risk-adjusted basis, we find no evidence of the size effect in this sample. However, we see that some decile has outperformed the benchmark such as the 3rd, 4th, 5th, 8th, 10th decile that outperformed the benchmark by more than 9%.

4.3. By location analysis

In this section, I will analyze the recommendations given by all the managers divided in three portfolios by region: France, Europe without France and rest of the world. The objective is to see if the home bias has an impact on the performances of the managers.

I performed those analyses on 3 different benchmarks, the results given in this section are based on the European benchmark. However, the results based on the Developed countries and USA benchmark used to make some robustness tests can be found in the appendices.

4.3.1. Annualized return, standard deviation and correlation

Table 16: Annualized return, volatility and correlation of portfolios by location

Portfolio	Annualized return	Annualized volatility	Correlation
France	7.91%	15.69%	0.751
Foreign EU	9.87%	15.79%	0.628
Foreign Outside EU	6.81%	14.80%	0.512
Benchmark	4.66%	14.00%	1.000

The Table 16 gives the annualized return, annualized volatility and the correlation with the benchmark of the three portfolios created by region. Some robustness tests have been made to verify the robustness of the analysis concerning the correlation (Appendix 17) and a graph to visualize the cumulative returns of the different portfolios through the entire investment period (Appendix 18).

We can observe that the investments in countries close to the managers brought higher returns than investments in countries far from the France. However, the investments abroad but in the European Union leads to higher returns than the investments in French companies.

The standard deviations are approximately the same for the three regions, but the standard deviation of the investments outside the EU is a bit lower than the others.

Obviously, the investments in the EU are more correlated to the European benchmark than the investments outside the EU.

4.3.2. Risk-adjusted performance

Table 17: Risk-adjusted performances of portfolios by location

Portfolio	Ann. Sharpe ratio	Treynor ratio	Information ratio	Jensen's Alpha	M-squared
France	0.4329	0.5763	0.3063	4.10%	7.06%
Foreign EU	0.5533	0.8815	0.4022	6.65%	8.76%
Foreign Outside EU	0.3859	0.7531	0.1513	4.30%	6.45%

In the Table 17, we find the different measure of risk-adjusted performance. Some robustness tests have been made with two benchmarks (Appendix 19) to verify the consistency of the results.

As we can see in this table the portfolio "Foreign EU" have significantly better risk-adjusted performances than the two other portfolios. What means that the investments made by the managers outside the France but in the EU brought better risk-adjusted performance. And this is consistent with the other benchmarks. However, the portfolio "France" and "Foreign outside EU" have approximately the same risk-adjusted performance when looking at the European

Benchmark, but looking at the other benchmarks, investments in France tend to outperform the investments outside the EU.

Looking at the information ratio through the analysis with the three benchmarks, managers tend to be more skilled when investing in closer countries than when they invest abroad.

4.4. By location and size

In this section, I will analyze the recommendations given by all the managers divided in ten portfolios by region (France vs. Abroad) and for each region by quintile based on the market capitalization. The objective is to see if the potential effects of the home bias observed in the last section are consistent across the different size and if a potential size effect appears for isolated French companies and for isolated other companies.

I performed those analyses on 3 different benchmarks, the results given in this section are based on the European benchmark. However, the results based on the Developed countries and USA benchmark used to make some robustness tests can be found in the appendices.

4.4.1. Annualized return, standard deviation and correlation

Table 18: Annualized return, volatility and correlation of portfolios by size and location

Portfolio	Annualized return	Annualized volatility	Correlation
France 1st Quintile	-7.97%	20.38%	0.420
France 2nd Quintile	11.13%	17.47%	0.583
France 3rd Quintile	13.61%	16.17%	0.554
France 4th Quintile	9.23%	17.71%	0.702
France 5th Quintile	11.51%	17.72%	0.753
Foreign 1st Quintile	-7.13%	27.68%	0.405
Foreign 2nd Quintile	15.70%	18.47%	0.343
Foreign 3rd Quintile	4.41%	13.59%	0.434
Foreign 4th Quintile	9.52%	15.44%	0.476
Foreign 5th Quintile	14.56%	14.81%	0.535
Benchmark	4.66%	14.00%	1.000

The Table 18 gives the annualized return, annualized volatility and the correlation with the benchmark of the ten portfolios created by region and by market capitalization. Some robustness tests have been made to verify the robustness of the analysis concerning the correlation (Appendix 20) and a graph to visualize the cumulative returns of the different portfolios through the entire investment period (Appendix 21).

As we can observe in the table, there is no evidence of the size effect in the sample of recommendations in France or abroad. However, the fact that larger companies are safer than smaller companies seems to be confirmed by this analysis.

4.4.2. Risk-adjusted performance

Table 19: Risk-adjusted performances of portfolios by size and location

Portfolio	Ann. Sharpe ratio	Treynor ratio	Information ratio	Jensen's Alpha	M-squared
France 1st Quintile	-0.438	-1.044	-0.655	-9.54%	-5.48%
France 2nd Quintile	0.571	0.980	0.440	8.08%	8.92%
France 3rd Quintile	0.769	1.387	0.622	10.68%	11.78%
France 4th Quintile	0.457	0.651	0.360	5.51%	7.30%
France 5th Quintile	0.584	0.776	0.586	7.40%	9.10%
Foreign 1st Quintile	-0.292	-0.722	-0.463	-7.86%	-3.61%
Foreign 2nd Quintile	0.785	2.286	0.582	14.06%	11.90%
Foreign 3rd Quintile	0.245	0.565	-0.017	2.33%	4.55%
Foreign 4th Quintile	0.543	1.142	0.321	7.13%	8.63%
Foreign 5th Quintile	0.903	1.687	0.712	11.74%	13.76%

In the Table 19, we find the different measures of risk-adjusted performance. Some robustness tests have been made with two benchmarks (Appendix 22) to verify the consistency of the results.

One interesting information in this table is the fact that the information ratio is more stable among quintile for the investments in France than for the foreign investments. This tends to show that managers are more consistent when they invest in their home countries than abroad. However, the other risk-adjusted performance ratios are on average higher for the foreign investments than for the investments in France, but this isn't significant for the Sharpe ratio and this isn't robust for the Treynor ratio.

We also see that managers outperformed the benchmark in most of the quintile in the two regions. This is consistent among the different benchmark analysis.

5. Conclusion

In this last section of my master thesis on the TV-Show “C’est votre argent,” I will summarize the results obtained and interpret them. The objective is to answer the initial questions about managers, the size effect and the home bias.

I will also present the limits that I noticed during the master thesis and give potential amelioration and deepening about the subjects tackle in this work.

All the managers (the guests of the TV-show) are experienced financial analysts and they're all well implemented in the financial field in France by their key positions in reputed financial institutions. However, even if most of them had a higher annualized return than the benchmark in the reality, when we analyze the risk-adjusted performance with the Jensen’s alpha or the information ratio of the more realistic portfolios based on their recommendations, only half of them outperformed the European Benchmark.

However, when we look at all the managers, there are four managers who stand out of the crowd. Whatever the risk-adjusted performance indicator that we look, or the portfolio methodology followed based on their recommendations, Christian Bito, Sébastien Faijean, Louis de Montalembert and Virginie Robert outperformed the other managers.

This has been confirmed by the utilization of the Peer Performance package to analyze the luck corrected risk-adjusted performance that validates the fact that those four managers were more successful than the others. This is even more impressing knowing the fact that Christian Bito, Sébastien Faijean, Louis de Montalembert and Virginie Robert gave respectively 31, 18, 38 and 33 buy recommendations. This is for three of them high above the average of 21 recommendations given by the managers that I analyzed and place them respectively third, seventh, first and second most present guests out of the 38 guests. This proves the consistency of those four managers and tends to confirm the fact that those results are more linked to skills than luck.

Then, I took a look at the analysis of a potential size effect in the sample of recommendations given by the managers. I can only conclude that there is no evidence of the size effect in this sample. This is mainly due to the bad performances of the first decile that are linked to the global underperformance of the small stocks in Europe in 2018. This is also due to some managers that gave some buy recommendations on small capitalization stocks and never came back to the TV-Show to recommend selling those stocks whose prices sometimes collapsed and considerably affected the performance of this first decile.

After that, by analyzing the portfolios based on the location of the headquarters of the companies, I observed some interesting results. Firstly, there is clearly the dominance of the French companies in the recommendations given by the managers (237 buy recommendations of French companies out of 373 buy recommendations). However, this can be biased by the fact that it's a French TV-Show and the managers are encouraged to give recommendations about French companies.

The analysis tends to prove that managers are more competent to invest in France but even more in countries close to France. This can be explained by a better knowledge of the markets due to the proximity and, moreover, the lack of knowledge of the foreign markets too far from their home countries. The fact that they seem to be more competent in foreign countries close to the France than in France can be explained by a too strong emotional effect of the managers that lead to overreaction to information about French companies.

Furthermore, I observe a significantly higher volatility of the manager portfolios than of the benchmark that leads to an increased risk for the investors in these portfolios. This is probably due to the lack of diversification linked to the overinvestment in French companies.

If I had to advise someone looking to invest following the recommendations given in the TV-Show "C'est votre argent," I would advise him to follow mostly the recommendations given by Christian Bito, Sébastien Faijean, Louis de Montalembert and Virginie Robert. And, depending on his degree of aversion to the risk and his horizon of investment, I would recommend three possible strategies.

If he likes risk and with quite a long horizon of investment, I would advise him to invest his money following the recommendations given by those four managers following an equally weighted portfolio creation methodology. And when there is no recommendation, to be invested in an ETF that tracks the developed country benchmark.

If he's indifferent to the risk, I would advise him to follow the core-satellite portfolio methodology with 50% invested in the core and 50% invested in the satellite. The core would be the developed country benchmark and the satellite an equally weighted portfolio composed of the recommendations given by the four best managers.

If it's someone who is averse to the risk and has a relatively small investment horizon, I would advise him to follow the core-satellite portfolio methodology with 80% invested in the core and 20% in the satellite. The core and the satellite would be the same as for the previous one.

Those last two portfolios recommendation, besides the fact that they're more suitable for more averse to the risk investors, decrease considerably the transaction costs that I neglected in this work.

Of course, there are some limits to this master thesis that mainly comes from the choices that I made and the scope of this work.

Firstly, the database is biased by the buy recommendations given by some managers that never came back to the TV-show to advise selling. To create my database, I placed myself as a naïve investor that strictly followed the recommendations of the managers, and so, I kept those stocks in my database until the end of the investment horizon.

However, some managers never explicitly made a sell recommendation about some previous buy recommendation but stopped enumerating some stocks when they talked about their portfolios. I considered that, after the first show during which they decided not to talk about a stock of their portfolio and that they never talked about it later, they made a sell recommendation.

Secondly, I decided not to consider in the performance calculation any transaction cost.

Moreover, I decided to retrieve the market capitalization of the companies at the date of January 1, 2020, to avoid any inflation or market condition consideration. However, this led to a huge decrease of the performance of the first decile by market capitalization, because all the companies that experienced a huge price decrease during the investment period are more likely to be in this first decile.

Finally, of course, I made some choices about benchmarks, portfolios creation methodologies and other methodologies that are debatable. There is a possible deepening that can be made especially about the size effect because another methodology can possibly highlight a more significant size effect in the sample or about other portfolios methodologies or optimization.

If someone who read this master thesis want to continue this work over the years or test other methodologies on this sample, I left a link here to an online folder that contains all my databases, codes and analysis: https://1drv.ms/u/s!AlKV-nDLm_haadZ29K2tSW55hBc?e=WodAIX

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7. Appendices

Appendix1 – R code for stock prices

```
library(quantmod)
library(openxlsx)

#Initiate the startdate
startdate <- "2015-05-08"
#Collect the tickers for all the stocks
tickers <- c("ALMIL.PA","ABEO.PA","AC.PA","ATI.PA","ALAGR.PA","AF.PA","AI.PA","AKA.PA","ALD.PA","ALO.PA","ATE.PA","ALT.PA","
stockPrices <- NULL
#For each ticker, get the daily stock price from Yahoo!Finance
for(ticker in tickers)
  stockPrices <- cbind(stockPrices, getSymbols(ticker, startdate, auto.assign = F)[,4])
colnames(stockPrices) <- tickers
#Write all the daily prices in an excel file
write.xlsx(stockPrices, file = "stockPrices.xlsx", sheetName = "StockPrice", append = FALSE)
```

Appendix2 – VBA code to fill blank

```
Sub AutoFill()
Dim FL1 As Worksheet, Cell As Range, NoCol As Integer
Dim NoLig As Long, DerLig As Long, Var As Variant

    'Instance de la feuille qui permet d'utiliser FL1 partout dans
    'le code à la place du nom de la feuille
    Set FL1 = Worksheets("StockPrice")

    'Détermine la dernière ligne renseignée de la feuille de calculs
    '(Voir explication sur l'utilisation de Split en bas de cette discussion)
    DerLig = 1213

    'Fixe le N° de la colonne à lire
    NoCol = 2

    'Utilisation du N° de ligne dans une boucle For ... Next
    For NoCol = 2 To Columns(Split(FL1.UsedRange.Address, "$")(3)).Column
    For NoLig = 3 To DerLig
           If IsEmpty(FL1.Cells(NoLig, NoCol).Value) = True Then
           FL1.Cells(NoLig, NoCol).Value = FL1.Cells(NoLig - 1, NoCol).Value
   End If
    Next
    Next
    End Sub
```

Appendix3 – VBA code to organize data

```
Sub DataOk()
    Dim source As Worksheet, output As Worksheet, info As Worksheet
    Dim NoLig As Long, DerLig As Long
    Dim CurrentCol As Long, Temp As Long
    Dim CurrentLigInfo As Long, EndDate As Date, StartDate As Date
    Dim Colsource As Long, Ligsource As Long, CurrentLig As Long
    Dim Cell As Range, NoCol As Integer


    'Instance de les feuille qui permet de les utiliser partout dans
    'le code à la place du nom de la feuille
    Set source = Worksheets("StockData")
    Set output = Worksheets("DataBase")
    Set info = Worksheets("TempSheet")

    'Fixe la ligne à 1
    NoLig = 1
    'Recherche et fixe la dernière ligne des infos
    DerLig = Split(info.UsedRange.Address, "$")(4)
    CurrentCol = Columns(Split(output.UsedRange.Address, "$")(3)).Column + 1

    'Boucle qui parcourt les lignes des infos
    For NoLig = 1 To DerLig
        'Agit seulement en cas de Buy
        If info.Cells(NoLig, 6).Value = "Buy" Then
            'Recherche la colonne à remplir et attribue déjà les données importantes
            output.Cells(1, CurrentCol).Value = info.Cells(NoLig, 1).Value
            output.Cells(2, CurrentCol).Value = info.Cells(NoLig, 2).Value
            output.Cells(3, CurrentCol).Value = info.Cells(NoLig, 3).Value
            output.Cells(4, CurrentCol).Value = info.Cells(NoLig, 4).Value
```

```
            output.Cells(5, CurrentCol).Value = info.Cells(NoLig, 7).Value
            StartDate = info.Cells(NoLig, 5).Value
            'Va rechercher la EndDate de la recommendation
            'Cas où l'on est avant 2016
            If info.Cells(NoLig, 5).Value < DateValue("Janvier 1, 2016") Then
                EndDate = DateValue("Janvier 1, 2016")
                For CurrentLigInfo = NoLig To DerLig
                    If info.Cells(CurrentLigInfo, 2).Value = output.Cells(2, CurrentCol).Value Then
                    If info.Cells(CurrentLigInfo, 6).Value = "Sell (Close)" Then
                        EndDate = info.Cells(CurrentLigInfo, 5).Value
                        If EndDate > DateValue("Janvier 1, 2016") Then
                            EndDate = DateValue("Janvier 1, 2016")
                        End If
                        Exit For
                    End If
                    End If
                Next
            'Cas où l'on est après 2016
            Else
                EndDate = DateValue("Décembre 31, 2019")
                For CurrentLigInfo = NoLig To DerLig
                    If info.Cells(CurrentLigInfo, 2).Value = output.Cells(2, CurrentCol).Value Then
                    If info.Cells(CurrentLigInfo, 6).Value = "Sell (Close)" Then
                        EndDate = info.Cells(CurrentLigInfo, 5).Value
                        Exit For
                    End If
                    End If
                Next
            End If
```

```
            'Va rechercher la colonne des sources qui contient les informations du stock en cours d'analyse
            For Colsource = 1 To Columns(Split(source.UsedRange.Address, "$")(3)).Column
                If source.Cells(1, Colsource).Value = info.Cells(NoLig, 2).Value Then
                    Exit For
                End If
            Next

            'Recherche la première ligne de donnée et attribue les données dans la Data Base jusqu'à la EndDate
            For Ligsource = 2 To Split(source.UsedRange.Address, "$")(4)
                If source.Cells(Ligsource, 1).Value >= StartDate Then
                    For CurrentLig = Ligsource To Split(source.UsedRange.Address, "$")(4)
                        If source.Cells(CurrentLig, 1).Value > EndDate Then
                            Exit For
                        End If
                        output.Cells(CurrentLig + 4, CurrentCol).Value = source.Cells(CurrentLig, Colsource).Value
                    Next
                    Exit For
                End If
            Next
            Temp = CurrentCol + 1
            CurrentCol = Temp
        End If
    Next

End Sub
```

Appendix4 – Example of data

Number	1	2	3	4	5
2015-05-11	0.04288939	0	0	-0.0037	0
2015-05-12	-0.03246753	0	0	-0.0026	0
2015-05-13	-0.00894855	0	0	0.0002	0
2015-05-14	-0.01128668	0	0	0.0095	0
2015-05-15	0	0	0	0.0008	0
2015-05-18	-0.01826484	0	0	0.0032	0
2015-05-19	0.00697674	0	0	-0.0012	0
2015-05-20	0.01847575	0	0	-0.0004	0
2015-05-21	0.00680272	0	0	0.0029	0
2015-05-22	-0.00225225	0	0	-0.0025	0
2015-05-25	-0.00436147	0	0	-0.0002	0
2015-05-26	-0.01296237	0	-0.0080429	-0.0107	0
2015-05-27	0.00187075	0	0	0.0087	0
2015-05-28	-0.01568466	0	0.03063063	-0.0008	0
2015-05-29	-0.02190405	0	-0.01573427	-0.0058	0
2015-06-01	-0.01626607	0	-0.00315312	0.0014	0
2015-06-02	0.0108017	0	0.00459212	0.0007	0
2015-06-03	0.02583018	0	-0.00603267	0.0036	0
2015-06-04	-0.01436289	0	0.00711553	-0.0092	0
2015-06-05	-0.02340029	0	-0.01110668	0.0005	0
2015-06-08	-0.01817866	0.00920343	-0.00946758	-0.007	0
2015-06-09	-0.00391301	-0.00943396	0.00147971	0.0009	0
2015-06-10	0.02848867	0.00603175	0.00543709	0.0119	0
2015-06-11	0.0022733	0	-0.00373228	0.0016	0
2015-06-12	-0.01790304	-0.05017356	-0.0030998	-0.0064	0
2015-06-15	-0.01771534	0.03289037	-0.0063664	-0.0042	0
2015-06-16	-0.00010667	-0.00289482	0.00942002	0.0053	0
2015-06-17	0.00367788	-0.00032258	-0.00776931	0.0017	0
2015-06-18	2.9936E-05	-0.03226847	0.00451759	0.0093	0
2015-06-19	-0.00023846	0.00566856	-0.00430284	-0.0049	0
2015-06-22	0.03502625	0.02718833	0.00258024	0.0062	0
2015-06-23	0.00148252	-0.00258231	0.01125527	0.0016	0
2015-06-24	-0.00356577	0	-0.00335135	-0.0075	0
2015-06-25	0.0039148	0	-0.00502286	-0.0022	0
2015-06-26	0.01981895	0.03203883	0.00027731	-0.0009	0
2015-06-29	-0.04284914	-0.02790844	-0.02178608	-0.0218	0
2015-06-30	-0.00791643	0.01612903	-0.00390474	0.0029	0

Appendix5 – R code for Performance Analytics

```
R.version
if (!require("PerformanceAnalytics")) {
  install.packages("PerformanceAnalytics", dependencies = TRUE)
  library(dplyr)
}
if (!require("readr")) {
  install.packages("readr", dependencies = TRUE)
  library(dplyr)
}
if (!require("zoo")) {
  install.packages("zoo", dependencies = TRUE)
  library(dplyr)
}
if (!require("zoo")) {
  install.packages("zoo", dependencies = TRUE)
  library(dplyr)
}
if (!require("openxlsx")) {
  install.packages("openxlsx", dependencies = TRUE)
  library(dplyr)
}
if (!require("zoo")) {
  install.packages("zoo", dependencies = TRUE)
  library(dplyr)
}

options("scipen"=50, "digits"=10)

library("openxlsx")  # To read xlsx
db <- read.xlsx("By Manager.xlsx", sheet = 6)
library("readr")   # Fast csv write
write_csv(db, path="FR.csv")
db <- read.table("FR.csv", header=T,sep=",")
library(zoo)
mydata <-read.zoo(db)


View(mydata)


library(PerformanceAnalytics)

start(as.zoo(mydata))
end(as.zoo(mydata))
colnames(mydata)

# graphical analysis of manager data

pdf("CumulativeReturns.pdf",width=16,height=5)
chart.CumReturns(mydata[,c(1:16)], main="Cumulative Returns", wealth.index=TRUE, legend.loc="topleft", cex.legend = 0.4)
dev.off()
chart.CumReturns(mydata[,c(1:7,2)], main="Cumulative Returns", wealth.index=TRUE, legend.loc="topleft", cex.legend = 0.4)
chart.CumReturns(mydata[,c(8:16)], main="Cumulative Returns", wealth.index=TRUE, legend.loc="topleft", cex.legend = 0.4)
dev.off()


# panel function to put horizontal lines at zero in each panel
my.panel <- function(...) {
  lines(...)
  abline(h=0)
}
# use plot.zoo() to create a multiple panel time series plot
# plot returns over time to illustrate monotone missing data
plot.zoo(mydata[,1:16], main="Returns",plot.type="multiple", type="h", lwd=2, col="blue", panel=my.panel)
#plot.zoo(mydata[,1:18], main="Returns",plot.type="multiple", type="h", lwd=2, col="blue",          panel=my.panel)
dev.copy(png,'ReturnsPlot.png',width=16,height=6,units="in",res=1000)
dev.off()

#mydata = mydata["2001-09-30::2006"] # remove data prior to 2001-09-30 b/c some data are not observed
#head(mydata) # give a quick of the data
```

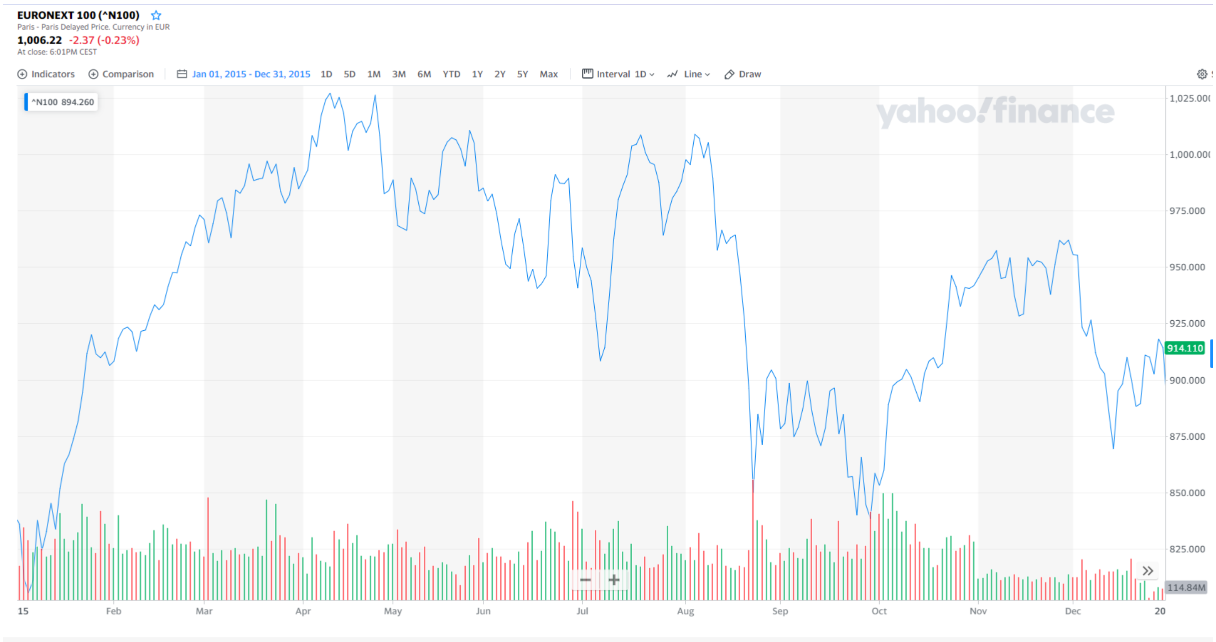
```
#table.CalendarReturns works only for monthly returns
#table.CalendarReturns(mydata[,1:18], digits = 1, as.perc = TRUE,geometric = TRUE) # display calendar (monthly and annual
wb <- createWorkbook()

addWorksheet(wb, "Stats")
stats <- table.Stats(mydata[,1:16]) # give stats for all the time series ? including monthly arith and geom mean returns
writeData(wb, "Stats", stats, startCol = 2, startRow = 2, rowNames = TRUE)

chart.Correlation(mydata[,1:16], histogram=TRUE, pch="+")
#chart.Correlation(mydata[,1:18], histogram=TRUE, pch="+")
dev.copy(png,'CorrelationPlot.png',width=16,height=6,units="in",res=1000)
dev.off()
#pdf("C:/Users/mipetitjean/OneDrive/UCL SRI/Graph1.pdf",width=7,height=5)
#chart.Correlation(mydata[,1:18], histogram=TRUE, pch="+")

addWorksheet(wb, "Tail")
tai <- tail(cumprod(1+mydata[,1:16])-1,1) #Global Return
writeData(wb, "Tail", tai, startCol = 2, startRow = 2, rowNames = TRUE)

addWorksheet(wb, "Return Ann")
ret <- Return.annualized(mydata[,1:16]) #Annualised Return: Geometric average (%), identical to annualised log returns
writeData(wb, "Return Ann", ret, startCol = 2, startRow = 2, rowNames = TRUE)

addWorksheet(wb, "Variability")
varia <- table.Variability(mydata[,1:16]) #Give volatility among others (i.e. annual std dev)
writeData(wb, "Variability", varia, startCol = 2, startRow = 2, rowNames = TRUE)

#CAPM useful when portfolios or individual stocks must be compared to a benchmark
addWorksheet(wb, "CAPM")
capm <- table.CAPM(mydata[,1:14], mydata[,15,drop=FALSE], Rf = mydata[,16,drop=FALSE]) # Report a lot of information on tl
writeData(wb, "CAPM", capm, startCol = 2, startRow = 2, rowNames = TRUE)


#SharpeRatio(mydata[,1:13], Rf = mydata[,19,drop=FALSE], FUN="StdDev") #Report the traditional monthly Sharpe ratio
addWorksheet(wb, "RiskAdjusted")
sharpe <- SharpeRatio(mydata[,1:15], Rf = mydata[,16,drop=FALSE], FUN="StdDev") #Report the traditional daily Sharpe
writeData(wb, "RiskAdjusted", sharpe, startCol = 2, startRow = 2, rowNames = TRUE)

#SharpeRatio.annualized(mydata[,1:18], Rf = mydata[,19,drop=FALSE])
annsharpe <- SharpeRatio.annualized(mydata[,1:15], Rf = mydata[,16,drop=FALSE])
writeData(wb, "RiskAdjusted", annsharpe, startCol = 2, startRow = 5, rowNames = TRUE)

#CAPM useful when portfolios or individual stocks must be compared to a benchmark
treynor <- TreynorRatio(mydata[,1:14], mydata[,15], Rf = mydata[,16,drop=FALSE],modified = TRUE) #Report the modifiec
msq <- MSquared(mydata[,1:14], mydata[,15],Rf = 0) #Report the M2 with annualized geom. mean risk-free rate
writeData(wb, "RiskAdjusted", treynor, startCol = 2, startRow = 8, rowNames = TRUE)
writeData(wb, "RiskAdjusted", msq, startCol = 2, startRow = 11, rowNames = TRUE)

addWorksheet(wb, "DownsideRiskRatio")
downrisk <- table.DownsideRiskRatio(mydata[,1:16],MAR=0) #Report various Downside Risk Ratios (Sortino, UDR, Omega, €
writeData(wb, "DownsideRiskRatio", downrisk, startCol = 2, startRow = 2, rowNames = TRUE)

table.Drawdowns(mydata[,2,drop=FALSE], 5, 4) #Identify the 5 most severe drawdowns for the asset (in column 2) under

addWorksheet(wb, "DrawdownsRatio")
draw <- table.DrawdownsRatio(mydata[,1:15], Rf= 0) #Report various Drawdowns Ratios (Sterling, Burke, Calmar, etc.)
#Average of Daily risk-free rate = 4.21985E-05
writeData(wb, "DrawdownsRatio", draw, startCol = 2, startRow = 2, rowNames = TRUE)

addWorksheet(wb, "VaR")
avar <- VaR(mydata[,1:15], p=.99,method="gaussian")
bvar <- VaR(mydata[,1:15], p=.99,method="historical")
cvar <- VaR(mydata[,1:15], p=.99,method="modified")
writeData(wb, "VaR", avar, startCol = 2, startRow = 2, rowNames = TRUE)
writeData(wb, "VaR", bvar, startCol = 2, startRow = 5, rowNames = TRUE)
writeData(wb, "VaR", cvar, startCol = 2, startRow = 8, rowNames = TRUE)


addWorksheet(wb, "ExpectedShortfall")
aes <- ES(mydata[,1:15], p=.99,method="gaussian")
bes <- ES(mydata[,1:15], p=.99,method="historical")
ces <- ES(mydata[,1:15], p=.99,method="modified")
writeData(wb, "ExpectedShortfall", aes, startCol = 2, startRow = 2, rowNames = TRUE)
writeData(wb, "ExpectedShortfall", bes, startCol = 2, startRow = 5, rowNames = TRUE)
writeData(wb, "ExpectedShortfall", ces, startCol = 2, startRow = 8, rowNames = TRUE)

addWorksheet(wb, "SharpeRatio")
asharp <- SharpeRatio(mydata[,1:15], Rf = mydata[,16,drop=FALSE],p=0.99, method="gaussian")
bsharp <- SharpeRatio(mydata[,1:15], Rf = mydata[,16,drop=FALSE],p=0.99, method="historical")
csharp <- SharpeRatio(mydata[,1:15], Rf = mydata[,16,drop=FALSE],p=0.99, method="modified")
writeData(wb, "SharpeRatio", asharp, startCol = 2, startRow = 2, rowNames = TRUE)
writeData(wb, "SharpeRatio", bsharp, startCol = 2, startRow = 7, rowNames = TRUE)
writeData(wb, "SharpeRatio", csharp, startCol = 2, startRow = 12, rowNames = TRUE)

saveWorkbook(wb, "Performance Analysis.xlsx", overwrite = TRUE)
```

Appendix6 – R code for Peer Performance

```
R.version
#Initiate all the packages requided
if (!require("PeerPerformance")) {
  install.packages("PeerPerformance", dependencies = TRUE)
  library(dplyr)
}
if (!require("readr")) {
  install.packages("readr", dependencies = TRUE)
  library(dplyr)
}
if (!require("zoo")) {
  install.packages("zoo", dependencies = TRUE)
  library(dplyr)
}
if (!require("openxlsx")) {
  install.packages("openxlsx", dependencies = TRUE)
  library(dplyr)
}

#Choose the number of digits
options("scipen"=50, "digits"=10)

#Read the sheet of the excel file and write it in a CSV file and read it with zoo
library("openxlsx")  # To read xlsx
db <- read.xlsx("By Manager.xlsx", sheet = 6)
library("readr")   # Fast csv write
write_csv(db, path="FR.csv")
db <- read.table("FR.csv", header=T,sep=",")
library(zoo)
mydata <-read.zoo(db)

View(mydata)
#Select the range of datas that matters
data = mydata[,1:15]
```

```
#Create a workbook to insert the output of each functions
wb <- createWorkbook()

#Use the function alphaScreening and write the output in the workbook
addWorksheet(wb, "Screenalpha")
screenalpha = alphaScreening(data)
print(screenalpha)
writeData(wb, "Screenalpha", screenalpha, startCol = 2, startRow = 2, rowNames = TRUE)

#Use the function mSharpeScreening and write the output in the workbook
addWorksheet(wb, "Screenmsharpe")
screenmodsharpe = msharpeScreening(data)
print(screenmodsharpe)
writeData(wb, "Screenmsharpe", screenmodsharpe, startCol = 2, startRow = 2, rowNames = TRUE)

#Use the function SharpeScreening and write the output in the workbook
addWorksheet(wb, "Screensharpe")
screensharpe = sharpeScreening(data)
print(screensharpe)
writeData(wb, "Screensharpe", screensharpe, startCol = 2, startRow = 2, rowNames = TRUE)

#Use the function mSharpeScreening with the bootstrap approach and write the output in the workbook
addWorksheet(wb, "Screenmsharpeboot")
screenmsharpeboot = msharpeScreening(data, control = list(nCore = 1, type = 2, nboot=500,hac = TRUE))
print(screenmsharpeboot)
writeData(wb, "Screenmsharpeboot", screenmsharpeboot, startCol = 2, startRow = 2, rowNames = TRUE)

#Use the function SharpeScreening with the bootstrap approach and write the output in the workbook
addWorksheet(wb, "Screensharpeboot")
screensharpeboot = sharpeScreening(data, control = list(nCore = 1, type = 2, nboot=500,hac = TRUE))
print(screensharpeboot)
writeData(wb, "Screensharpeboot", screensharpeboot, startCol = 2, startRow = 2, rowNames = TRUE)

#Save the workbook in the excel file
saveWorkbook(wb, "Peer Performance.xlsx", overwrite = TRUE)
```

Appendix7 – Euronext 100 stock prices (year 2015)



Source: Yahoo! Finance

Appendix 8 – Correlation of managers with EU benchmark

Portfolio	Reality	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Alain Pitous	0.62	0.65	0.98	0.99	0.87
Alice Lhabouz	0.46	0.52	0.97	1.00	0.83
Christian Bito	0.69	0.75	0.99	1.00	0.92
Christian Cambier	0.48	0.61	0.98	0.99	0.87
Emeric Préaubert	0.50	0.53	0.95	0.98	0.78
Eric Lewin	0.47	0.85	0.99	1.00	0.96
Jean-Pierre Gaillard	0.68	0.70	0.98	1.00	0.90
Jérôme Fauvel	0.43	0.50	0.96	0.98	0.78
Louis de Montalembert	0.47	0.50	0.97	0.99	0.81
Pascale Seivy	0.62	0.72	0.99	1.00	0.93
Sébastien Faijean	0.38	0.46	0.97	0.99	0.80
Sébastien Korchia	0.65	0.87	0.99	1.00	0.96
Sébastien Lalevée	0.44	0.53	0.97	0.98	0.81
Virginie Robert	0.38	0.39	0.96	0.98	0.77
Benchmark	1.00	1.00	1.00	1.00	1.00

Appendix 9 – Managers Value at Risk

9.1. Gaussian methodology

Portfolio	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Alain Pitous	-2.85%	-2.04%	-2.03%	-2.22%
Alice Lhabouz	-2.79%	-1.97%	-2.02%	-2.11%
Christian Bito	-2.39%	-2.00%	-2.01%	-2.06%
Christian Cambier	-2.55%	-1.98%	-1.98%	-2.05%
Emeric Préaubert	-3.81%	-2.13%	-2.05%	-2.59%
Eric Lewin	-2.21%	-2.01%	-2.02%	-2.04%
Jean-Pierre Gaillard	-2.70%	-2.04%	-2.02%	-2.18%
Jérôme Fauvel	-3.54%	-2.07%	-2.04%	-2.44%
Louis de Montalembert	-3.00%	-1.99%	-1.97%	-2.19%
Pascale Seivy	-2.04%	-1.94%	-1.98%	-1.88%
Sébastien Faijean	-2.82%	-1.94%	-1.98%	-2.08%
Sébastien Korchia	-2.42%	-2.06%	-2.03%	-2.15%
Sébastien Lalevée	-3.12%	-2.02%	-2.05%	-2.26%
Virginie Robert	-2.74%	-1.90%	-1.96%	-1.99%
Benchmark	-2.03%	-2.03%	-2.03%	-2.03%

9.2. Modified methodology

Portfolio	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Alain Pitous	-4.43%	-3.95%	-4.17%	-3.65%
Alice Lhabouz	-3.89%	-3.72%	-4.22%	-3.15%
Christian Bito	-4.08%	-4.36%	-4.38%	-4.28%
Christian Cambier	-4.61%	-3.72%	-4.20%	-3.23%
Emeric Préaubert	-10.08%	-4.56%	-4.42%	-5.74%
Eric Lewin	-4.48%	-4.39%	-4.38%	-4.41%
Jean-Pierre Gaillard	-3.60%	-3.92%	-4.22%	-3.45%
Jérôme Fauvel	-8.07%	-3.83%	-4.17%	-4.40%
Louis de Montalembert	-4.75%	-3.84%	-3.94%	-3.63%
Pascale Seivy	-2.80%	-3.72%	-4.27%	-2.98%
Sébastien Faijean	-4.19%	-3.77%	-4.22%	-3.26%
Sébastien Korchia	-4.66%	-4.32%	-4.36%	-4.30%
Sébastien Lalevée	-6.81%	-3.75%	-4.02%	-3.74%
Virginie Robert	-5.54%	-3.57%	-3.96%	-3.11%
Benchmark	-4.35%	-4.35%	-4.35%	-4.35%

Appendix10 – Managers Expected Shortfall

10.1. Gaussian methodology

Portfolio	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Alain Pitous	-3.27%	-2.34%	-2.33%	-2.55%
Alice Lhabouz	-3.20%	-2.26%	-2.32%	-2.42%
Christian Bito	-2.74%	-2.30%	-2.31%	-2.37%
Christian Cambier	-2.92%	-2.27%	-2.27%	-2.36%
Emeric Préaubert	-4.37%	-2.44%	-2.36%	-2.97%
Eric Lewin	-2.54%	-2.31%	-2.31%	-2.34%
Jean-Pierre Gaillard	-3.09%	-2.34%	-2.32%	-2.50%
Jérôme Fauvel	-4.06%	-2.37%	-2.34%	-2.80%
Louis de Montalembert	-3.44%	-2.28%	-2.27%	-2.51%
Pascale Seivy	-2.34%	-2.22%	-2.27%	-2.16%
Sébastien Faijean	-3.24%	-2.23%	-2.27%	-2.39%
Sébastien Korchia	-2.78%	-2.36%	-2.33%	-2.47%
Sébastien Lalevée	-3.58%	-2.32%	-2.35%	-2.59%
Virginie Robert	-3.15%	-2.18%	-2.25%	-2.29%
Benchmark	-2.33%	-2.33%	-2.33%	-2.33%

10.2. Modified methodology

Portfolio	Benchmark	Core-Sat. (20%)	Core-Sat. (Progr. 20%)	Core-Sat. (50%)
Alain Pitous	-4.43%	-3.95%	-4.17%	-3.65%
Alice Lhabouz	-3.89%	-3.72%	-4.22%	-3.15%
Christian Bito	-4.08%	-4.36%	-4.38%	-4.28%
Christian Cambier	-4.61%	-3.72%	-4.20%	-3.23%
Emeric Préaubert	-10.08%	-4.56%	-4.42%	-5.74%
Eric Lewin	-4.48%	-4.39%	-4.38%	-4.41%
Jean-Pierre Gaillard	-3.92%	-3.92%	-4.22%	-3.45%
Jérôme Fauvel	-8.07%	-3.83%	-4.17%	-4.40%
Louis de Montalembert	-4.75%	-3.84%	-3.94%	-3.63%
Pascale Seivy	-2.83%	-3.72%	-4.27%	-2.98%
Sébastien Faijean	-6.55%	-3.77%	-4.22%	-3.26%
Sébastien Korchia	-4.66%	-4.32%	-4.36%	-4.30%
Sébastien Lalevée	-6.81%	-3.75%	-4.02%	-3.74%
Virginie Robert	-5.54%	-3.57%	-3.96%	-3.11%
Benchmark	-4.35%	-4.35%	-4.35%	-4.35%

Appendix11 – Complete Alpha Screening

Portfolio	Benchmark			Core-Sat. (20%)			Core-Sat. (Progr. 20%)			Core-Sat. (50%)		
	equal	out	under	equal	out	under	equal	out	under	equal	out	under
Alain Pitous	0.87	0.13	0.00	0.87	0.13	0.00	1.00	0.00	0.00	0.87	0.13	0.00
Alice Lhabouz	0.77	0.00	0.23	0.77	0.00	0.23	1.00	0.00	0.00	0.77	0.00	0.23
Christian Bito	0.66	0.34	0.00	0.70	0.30	0.00	0.91	0.09	0.00	0.66	0.34	0.00
Christian Cambier	1.00	0.00	0.00	1.00	0.00	0.00	0.48	0.00	0.52	1.00	0.00	0.00
Emeric Préaubert	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Eric Lewin	0.77	0.00	0.23	0.77	0.00	0.23	1.00	0.00	0.00	0.77	0.00	0.23
Jean-Pierre Gaillard	0.77	0.23	0.00	0.77	0.23	0.00	1.00	0.00	0.00	0.77	0.23	0.00
Jérôme Fauvel	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Louis de Montalembert	0.34	0.66	0.00	0.32	0.68	0.00	0.11	0.89	0.00	0.34	0.66	0.00
Pascale Seivy	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Sébastien Faijean	0.24	0.76	0.00	0.24	0.76	0.00	1.00	0.00	0.00	0.24	0.76	0.00
Sébastien Korchia	0.87	0.00	0.13	0.87	0.00	0.13	1.00	0.00	0.00	0.97	0.00	0.03
Sébastien Lalevée	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Virginie Robert	0.24	0.76	0.00	0.24	0.76	0.00	0.11	0.89	0.00	0.24	0.76	0.00
Benchmark	0.80	0.02	0.18	0.80	0.02	0.18	0.98	0.02	0.00	0.80	0.02	0.18

Appendix12 – Complete Sharpe Screening

Portfolio	Benchmark			Core-Sat. (20%)			Core-Sat. (Progr. 20%)			Core-Sat. (50%)		
	equal	out	under	equal	out	under	equal	out	under	equal	out	under
Alain Pitous	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Alice Lhabouz	0.71	0.00	0.29	0.77	0.00	0.23	1.00	0.00	0.00	0.71	0.00	0.29
Christian Bito	0.77	0.23	0.00	0.60	0.40	0.00	0.77	0.23	0.00	0.48	0.50	0.02
Christian Cambier	1.00	0.00	0.00	1.00	0.00	0.00	0.75	0.00	0.25	1.00	0.00	0.00
Emeric Préaubert	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Eric Lewin	0.87	0.00	0.13	0.77	0.00	0.23	0.93	0.00	0.07	0.87	0.00	0.13
Jean-Pierre Gaillard	0.87	0.13	0.00	0.94	0.06	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Jérôme Fauvel	1.00	0.00	0.00	1.00	0.00	0.00	0.77	0.00	0.23	1.00	0.00	0.00
Louis de Montalembert	0.40	0.60	0.00	0.24	0.76	0.00	0.10	0.90	0.00	0.22	0.78	0.00
Pascale Seivy	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Sébastien Faijean	0.24	0.76	0.00	0.21	0.79	0.00	1.00	0.00	0.00	0.21	0.79	0.00
Sébastien Korchia	0.99	0.00	0.01	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Sébastien Lalevée	0.87	0.00	0.13	1.00	0.00	0.00	1.00	0.00	0.00	0.97	0.00	0.03
Virginie Robert	0.22	0.78	0.00	0.00	1.00	0.00	0.11	0.89	0.00	0.00	1.00	0.00
Benchmark	0.77	0.23	0.00	1.00	0.00	0.00	0.98	0.02	0.00	0.80	0.20	0.00

Appendix13 – Complete modified Sharpe Screening

Portfolio	Benchmark			Core-Sat. (20%)			Core-Sat. (Progr. 20%)			Core-Sat. (50%)		
	equal	out	under	equal	out	under	equal	out	under	equal	out	under
Alain Pitous	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Alice Lhabouz	0.63	0.00	0.37	0.45	0.00	0.55	1.00	0.00	0.00	0.42	0.00	0.58
Christian Bito	0.49	0.45	0.05	0.55	0.45	0.00	0.24	0.76	0.00	0.95	0.05	0.00
Christian Cambier	1.00	0.00	0.00	1.00	0.00	0.00	0.57	0.00	0.43	1.00	0.00	0.00
Emeric Préaubert				1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Eric Lewin	0.80	0.00	0.20	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Jean-Pierre Gaillard	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.87	0.05	0.08
Jérôme Fauvel				1.00	0.00	0.00	0.42	0.00	0.58	1.00	0.00	0.00
Louis de Montalembert	0.00	0.83	0.17	0.67	0.33	0.00	0.40	0.60	0.00	0.75	0.25	0.00
Pascale Seivy	0.93	0.00	0.07	0.77	0.00	0.23	1.00	0.00	0.00	0.99	0.00	0.01
Sébastien Faijean	0.23	0.77	0.00	0.62	0.38	0.00	1.00	0.00	0.00	0.67	0.33	0.00
Sébastien Korchia	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Sébastien Lalevée	1.00	0.00	0.00	0.45	0.00	0.55	0.42	0.00	0.58	0.87	0.00	0.13
Virginie Robert	0.18	0.82	0.00	0.58	0.42	0.00	0.24	0.76	0.00	0.61	0.39	0.00
Benchmark	0.97	0.03	0.00	0.61	0.35	0.04	0.94	0.06	0.00	0.71	0.22	0.08

Appendix14 – Annualized return, volatility and correlation by size

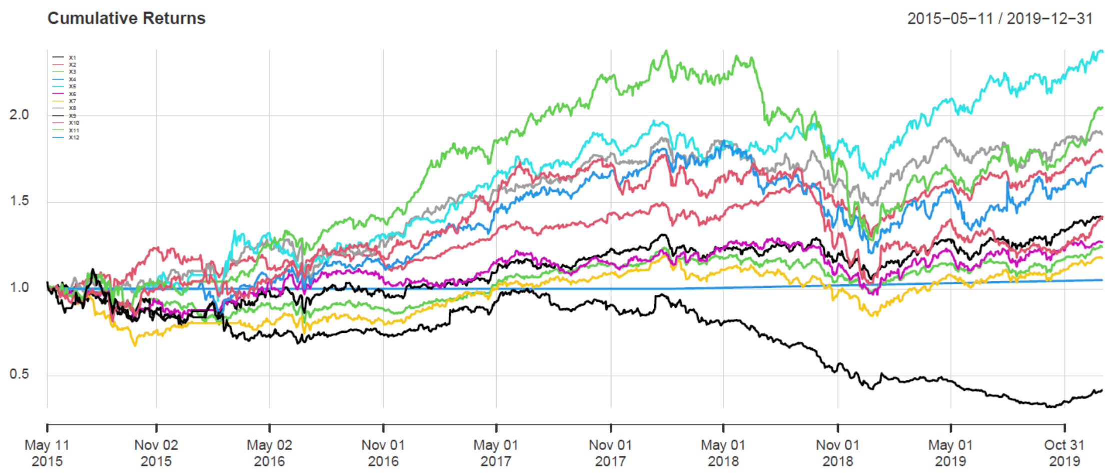
14.1. Developed countries benchmark

Portfolio	Annualized return	Annualized volatility	Correlation
1st Decile	-16.67%	21.94%	0.336
2nd Decile	7.58%	19.29%	0.496
3rd Decile	16.13%	19.93%	0.436
4th Decile	11.82%	17.81%	0.475
5th Decile	19.58%	17.13%	0.415
6th Decile	5.03%	16.47%	0.626
7th Decile	3.42%	16.16%	0.590
8th Decile	14.17%	18.17%	0.658
9th Decile	7.33%	17.43%	0.671
10th Decile	12.87%	13.89%	0.740
Benchmark	7.83%	10.92%	1.000

14.2. USA benchmark

Portfolio	Annualized return	Annualized volatility	Correlation
1st Decile	-16.67%	21.94%	0.237
2nd Decile	7.58%	19.29%	0.365
3rd Decile	16.13%	19.93%	0.334
4th Decile	11.82%	17.81%	0.376
5th Decile	19.58%	17.13%	0.314
6th Decile	5.03%	16.47%	0.534
7th Decile	3.42%	16.16%	0.493
8th Decile	14.17%	18.17%	0.533
9th Decile	7.33%	17.43%	0.588
10th Decile	12.87%	13.89%	0.753
Benchmark	10.21%	13.35%	1.000

Appendix15 – Cumulative returns portfolios by size



1	2	3	4	5	6	7	8	9	10	11	12
1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile	Benchmark	Risk-Free Asset

Appendix16 – Risk-adjusted performances by size

16.1. Developed countries benchmark

Portfolio	Ann. Sharpe ratio	Treynor ratio	Information ratio	Jensen's Alpha	M-squared
1st Decile	-0.799	-2.376	-1.168	-19.48%	-8.29%
2nd Decile	0.335	0.677	-0.015	1.93%	4.29%
3rd Decile	0.749	1.715	0.459	10.79%	8.83%
4th Decile	0.599	1.260	0.251	6.41%	7.25%
5th Decile	1.071	2.580	0.732	14.67%	12.48%
6th Decile	0.240	0.383	-0.218	-1.46%	3.34%
7th Decile	0.145	0.246	-0.337	-2.54%	2.31%
8th Decile	0.715	1.087	0.462	6.30%	8.52%
9th Decile	0.357	0.532	-0.039	-0.05%	4.59%
10th Decile	0.843	1.139	0.538	5.49%	10.12%

16.2. USA benchmark

Portfolio	Ann. Sharpe ratio	Treynor ratio	Information ratio	Jensen's Alpha	M-squared
1st Decile	-0.799	-3.378	-1.177	-18.61%	-10.14%
2nd Decile	0.335	0.919	-0.138	3.13%	5.25%
3rd Decile	0.749	2.241	0.297	11.77%	10.80%
4th Decile	0.599	1.595	0.091	7.17%	8.86%
5th Decile	1.071	3.412	0.517	15.55%	15.27%
6th Decile	0.240	0.449	-0.353	-1.07%	4.08%
7th Decile	0.145	0.295	-0.451	-2.06%	2.82%
8th Decile	0.715	1.341	0.251	7.19%	10.42%
9th Decile	0.357	0.608	-0.199	0.22%	5.62%
10th Decile	0.843	1.119	0.278	4.63%	12.38%

Appendix17 - Annualized return, volatility and correlation by location

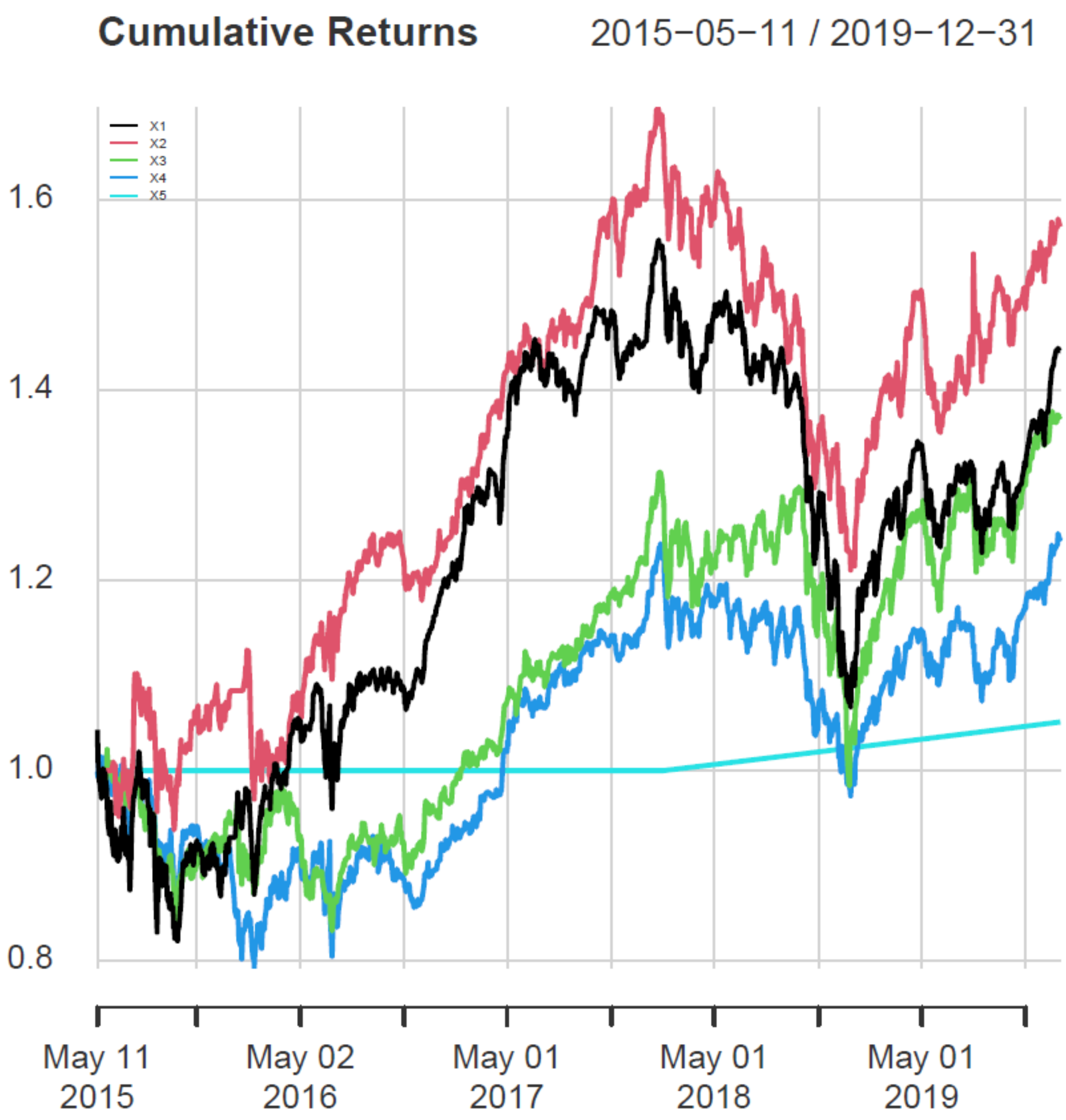
17.1. Developed countries benchmark

Portfolio	Annualized return	Annualized volatility	Correlation
France	7.91%	15.69%	0.648
Foreign EU	9.87%	15.79%	0.560
Foreign Outside EU	6.81%	14.80%	0.790
Benchmark	7.83%	10.92%	1.000

17.2. USA benchmark

Portfolio	Annualized return	Annualized volatility	Correlation
France	7.91%	15.69%	0.473
Foreign EU	9.87%	15.79%	0.438
Foreign Outside EU	6.81%	14.80%	0.845
Benchmark	10.21%	13.35%	1.000

Appendix18 – Cumulative returns for portfolios by location



1	2	3	4	5
France	Foreign EU	Foreign Outside EU	Benchmark	Risk-Free

Appendix19 – Risk-adjusted performances by location

19.1. Developed countries benchmark

Portfolio	Ann. Sharpe ratio	Treynor ratio	Information ratio	Jensen's Alpha	M-squared
France	0.4329	0.6682	0.0061	1.20%	5.50%
Foreign EU	0.5533	0.9883	0.1538	3.95%	6.83%
Foreign Outside EU	0.3859	0.4886	-0.1118	-0.95%	5.03%

19.2. USA benchmark

Portfolio	Ann. Sharpe ratio	Treynor ratio	Information ratio	Jensen's Alpha	M-squared
France	0.4329	0.9142	-0.1532	2.51%	6.73%
Foreign EU	0.5533	1.2630	-0.0217	4.77%	8.35%
Foreign Outside EU	0.3859	0.4567	-0.4264	-2.29%	6.15%

Appendix20 – Annualized return, volatility and correlation by location and size

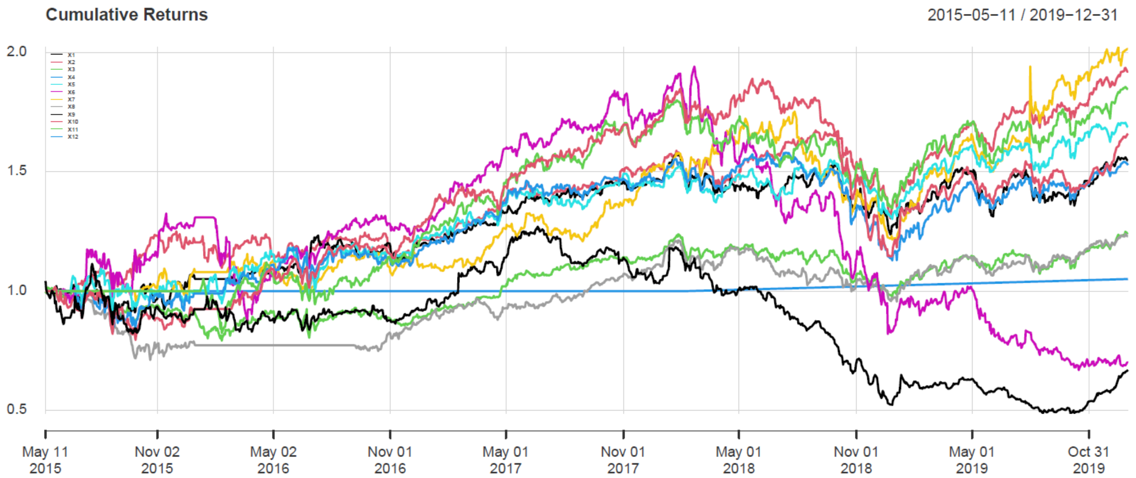
20.1. Developed countries benchmark

Portfolio	Annualized return	Annualized volatility	Correlation
France 1st Quintile	-7.97%	20.38%	0.362
France 2nd Quintile	11.13%	17.47%	0.543
France 3rd Quintile	13.61%	16.17%	0.490
France 4th Quintile	9.23%	17.71%	0.609
France 5th Quintile	11.51%	17.72%	0.634
Foreign 1st Quintile	-7.13%	27.68%	0.374
Foreign 2nd Quintile	15.70%	18.47%	0.375
Foreign 3rd Quintile	4.41%	13.59%	0.566
Foreign 4th Quintile	9.52%	15.44%	0.645
Foreign 5th Quintile	14.56%	14.81%	0.750
Benchmark	7.83%	10.92%	1.000

20.2. USA benchmark

Portfolio	Annualized return	Annualized volatility	Correlation
France 1st Quintile	-7.97%	20.38%	0.253
France 2nd Quintile	11.13%	17.47%	0.411
France 3rd Quintile	13.61%	16.17%	0.365
France 4th Quintile	9.23%	17.71%	0.464
France 5th Quintile	11.51%	17.72%	0.469
Foreign 1st Quintile	-7.13%	27.68%	0.291
Foreign 2nd Quintile	15.70%	18.47%	0.343
Foreign 3rd Quintile	4.41%	13.59%	0.549
Foreign 4th Quintile	9.52%	15.44%	0.662
Foreign 5th Quintile	14.56%	14.81%	0.778
Benchmark	10.21%	13.35%	1.000

Appendix21 – Cumulative returns for portfolios by location and size



1	2	3	4	5	6
France 1st Quintile	France 2nd Quintile	France 3rd Quintile	France 4th Quintile	France 5th Quintile	Foreign 1st Quintile
7	8	9	10	11	12
Foreign 2nd Quintile	Foreign 3rd Quintile	Foreign 4th Quintile	Foreign 5th Quintile	Benchmark	Risk-Free

Appendix22 – Risk-adjusted performances by location and size

22.1. Developed countries benchmark

Portfolio	Ann. Sharpe ratio	Treynor ratio	Information ratio	Jensen's Alpha	M-squared
France 1st Quintile	-0.438	-1.208	-0.818	-11.38%	-4.27%
France 2nd Quintile	0.571	1.051	0.223	4.99%	6.95%
France 3rd Quintile	0.769	1.568	0.401	8.19%	9.19%
France 4th Quintile	0.457	0.751	0.099	2.37%	5.69%
France 5th Quintile	0.584	0.922	0.268	4.21%	7.09%
Foreign 1st Quintile	-0.292	-0.782	-0.583	-10.70%	-2.81%
Foreign 2nd Quintile	0.785	2.094	0.447	11.28%	9.28%
Foreign 3rd Quintile	0.245	0.433	-0.294	-0.79%	3.54%
Foreign 4th Quintile	0.543	0.841	0.142	2.80%	6.73%
Foreign 5th Quintile	0.903	1.204	0.686	6.64%	10.73%

22.2. USA benchmark

Portfolio	Ann. Sharpe ratio	Treynor ratio	Information ratio	Jensen's Alpha	M-squared
France 1st Quintile	-0.438	-1.729	-0.851	-10.40%	-5.22%
France 2nd Quintile	0.571	1.388	0.054	6.06%	8.50%
France 3rd Quintile	0.769	2.107	0.202	9.20%	11.24%
France 4th Quintile	0.457	0.985	-0.059	3.52%	6.96%
France 5th Quintile	0.584	1.246	0.079	5.62%	8.67%
Foreign 1st Quintile	-0.292	-1.004	-0.642	-9.85%	-3.44%
Foreign 2nd Quintile	0.785	2.288	0.293	11.23%	11.35%
Foreign 3rd Quintile	0.245	0.447	-0.453	-1.14%	4.33%
Foreign 4th Quintile	0.543	0.821	-0.058	1.94%	8.23%
Foreign 5th Quintile	0.903	1.161	0.458	5.54%	13.13%

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Louvain School of Management
Chaussée de Binche 151, 7000 Mons, Belgique | **www.uclouvain.be/lsm**