# ANALYSIS OF THE CAUSES OF THE MOMENTUM EFFECT AND THEIR IMPLICATIONS FOR THE EFFICIENT MARKET HYPOTHESIS


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# ABSTRACT

The Efficient Market Hypothesis has largely been discussed in financial literature. Some authors are in favor and others disagree, but one anomaly is particularly in contradiction with the market efficiency: the momentum effect. The main goal of this thesis is to contribute to the momentum puzzle in trying to explain the causes of asset price continuation on medium term. Double sorted portfolios on past prices and investor attention of stocks from the composition of S&P 500 are formed to demonstrate the superior performance of strategy based both on price and investor attention. The results confirm the influence of investor biases on the formation of momentum. An "investor attention effect" is discovered in the S&P 500 and proven to be only present in momentum stocks. However, differences in investor attention do not seem to completely explain the momentum effect, and should probably cause momentum with another factor such as a risk-based one. This study contradicts the Efficient Market Hypothesis, but emphasizes that this conclusion should be taken cautiously into account and further analyzed.

# OVERVIEW

# 1. INTRODUCTION

The Efficient Market Hypothesis, first stated by Fama (1970), is one of the most important theories in finance. Investors base their decisions on the assumption that financial markets are informationally efficient. One particular supposition of the EMH is the random walk model. This model asserts that the price of an asset follows a random walk, which means that it can not be known in advance. Indeed, as the price of an asset always reflects the available information at this time, and investors do not know the information of the future, they can not predict its evolution.

However, the theory has been challenged by many authors. Among the arguments against the EMH, one empirical anomaly is often stated: the asset price reversal or continuation. First, De Bondt and Thaler (1985), and Jegadeesh (1990) have supplied proofs of price reversal in short and long term horizons, on what has developed into a well-known profitable strategy called contrarian. Then, Jegadeesh and Titman (1993), followed by many other authors cited in this essay, have observed a continuation in asset prices over the medium term horizon, what they called the momentum effect. The main problem between the momentum effect and the Efficient Market Hypothesis is that they are not compatible, even for the weakest form of the market efficiency. Indeed, momentum implies that prices are predictable based on their past records, which is totally excluded from the EMH, as only all the information on stocks (current and past) should reflect their prices.

To explicate the momentum anomaly, two kinds of explanations have been debated in the literature. To support the efficiency theory, some authors (e.g. Fama and French (1992, 1993 & 1996) and Conrad and Kaul (1998)) have argued that the superior profitability engendered by the momentum strategies resulted from an increase in risk. However, these risk-based explanations have been either rejected by other scientists, either proven to not fully explain the anomaly. Therefore, other authors have turned to a new type of explanation based on biases in the behavior of investors. According to behaviorists, stock price continuation comes from an initial underreaction of investors or a delayed overreaction. These arguments have been examined, and many papers have focused on the link between the momentum profitability and the characteristics of stocks that could have biased the behavior of investors. One particular promising path of the study is the impact of investor attention to a certain stock on the evolution of its price. For example, Chan (2003) shows that the attention of investors decreases the profitability of momentum strategies.

The latter has initiated the goal of this thesis. As the momentum effect remains unexplained, this study will attempt to find its causes, and more precisely, focus on the link between investor behavior and momentum. Therefore, two main questions are asked: “Is momentum driven by investor biases?” and “If so, does the profitability of momentum strategies comes from under- and/or overreaction of investors?”. Answering these questions would allow to contribute to the momentum puzzle, and the findings could help find the answer to the last research question: “Is momentum consistent with the EMH or does it reject market efficiency?”.

Following Da, Engelberg, and Gao (2011), a unique and direct measure of investor attention is collected for stocks of the S&P 500 composition. This measure, called Google Search Volume Index (SVI), gives an indexed value of the frequency of searches on a particular stock on the well-known search engine. Plus, it has some great characteristics, such as for example, the presence of searches from individual investors, who are the momentum creators, and the absence of institution attention from the index. Finally, all stocks prices are collected from Yahoo Finance.

To begin the analysis, four momentum strategies, which differ in terms of formation and holding periods, are formed with the available stocks. The presence of momentum in S&P 500 is first rejected in the period of analysis (i.e. between 2004 and 2016). Then, the study postpones the beginning of the period to 2010, because of data issues and bad market state (i.e. the financial crisis of 2007-2008), and validates the presence of momentum in this time frame. Results show significant and positive average returns of 0.20% to 0.41% per month for 3 out of the 4 momentum strategies between 2010 and 2016, the strategy with formation and holding periods of 3 months being the only non-profitable strategy. The same analysis is then executed with the selection of stocks of the best three and worst three deciles instead of only the extremes. The results are comparable: the momentum profitability decreases but remains significantly positive, except for the 3-month holding period strategy.

Then, the effect of investor attention on stock prices is checked. Portfolios based on investor attention are formed and 4 strategies with different lengths of holding period are built. As for momentum, these are zero cost strategies: stocks from the 3 deciles with the lowest attention are long, and the 30% highest attention stocks are short. Results shows that low attention stocks perform better than high attention stocks, but the profitability and significance decrease with the length of the holding period. Comparing to the momentum effect, the “investor attention” effect is less intensive but well present.

Finally, the effect of investor attention is analyzed in the last part of the study. Taking back the momentum portfolios formed in the first part of the analysis (i.e. that go long the top 30% stocks and short the worst 30% performers), sub-portfolios are formed inside the winners and losers. First, the presence of the previously called “investor attention” effect is proved to be present inside the losers and winners, but absent inside the medium past returns portfolios. This is particularly interesting, as it suggests that investor attention has a direct link with momentum. Then, five zero-cost strategies are developed. Each of them goes long one of the 3 winner portfolios based on investor attention and shorts at the same time one of the 3 loser portfolios. As expected, results show that the strategy that goes long low attention stocks, and shorts high attention stocks is not only profitable, but even more than the initial momentum strategy. This suggests that part of the momentum profitability come from an initial underreaction of investors regarding the winners, combined with an overreaction on the loser stocks.

The remaining of the paper is organized as follows. Chapter 2 reviews the current knowledge presented in the literature about the Efficient Market Hypothesis and the momentum effect. Chapter 3 describes the data used in the analysis. Chapter 4 develops the methodology for forming momentum, investor attention based and investor attention based momentum portfolios. Results are described in Chapter 5. Chapter 6 discusses the empirical results. Chapter 7 presents a conclusion in which the analysis is reviewed.

# 2. EFFICIENT MARKET HYPOTHESIS

The current chapter, as well as the next one, aims at reviewing the current knowledge about the topic studied in this essay. As the main purpose of this paper is to contribute to the momentum puzzle and its implication for the efficiency of financial markets, the Efficient Market Hypothesis stated by Fama (1970) and its critics will be presented first. Then, the current literature on momentum strategies will be reviewed, and more specifically, the evidence~~s~~ of the presence of momentum effects in financial markets and the possible explanation for these effects, as well as their implications for the EMH.

In this chapter, the Efficient Market Hypotheses will be defined, as well as its models, conditions, and different forms. Finally, different opinions about the efficiency of financial markets will be expressed.

## *2.1 Definition*

Fama (1970) is the first to express the efficient market hypothesis (EMH). He states that the primary role of capital markets is to allocate the ownership of the economy's capital stock. Therefore, an ideal market would be a market in which companies can take their investment decisions, and investors can choose to invest in a company based on all the information about the company's activities. According to Fama (1970), a market is efficient if the prices always fully reflect all available information.

## *2.2 Models*

To support the EMH, Fama (1970) uses 3 models: the "fair game" model, the submartingale model and the random walk model. First, the "fair game" model states that the expected returns of an asset depend on the level of risk of this asset. This means that it would be impossible to gain additional returns without taking additional risks. Second, the submartingale model used by Fama (1970) states that the expected value of the future price of an asset is always greater or equal to the current price of this asset, given the information of the current period. In this model, an investor in an expanding economy who has the choice to buy an asset, to short it, or to keep their cash, would always choose a buy-and-hold strategy. Third, the random walk model affirms that the evolution of the price of an asset follows a "random walk pattern": in other terms, it always reflects the information available at this time, thus the price of the asset of tomorrow will reflect the information of tomorrow, and therefore, the price of the asset will fluctuate without any possibility to predict its evolution in advance. Another conclusion of this model is that returns can only be explained by the arrival of new information.

## *2.3 Conditions*

Fama (1970) expresses three conditions for a market to be efficient. First, there should be no transaction costs in trading assets. Then, all market participants should have access to all available information without any cost. Finally, all agree on the implications of the current information for the current price and distributions of future prices of each security. However, these conditions are considered sufficient but not necessary. Indeed, Fama (1970) states that a market could be efficient even if all participants don't have access to the information, as long as a sufficient number of investors has access to it, and the absence of the two other conditions doesn't imply a market inefficiency.

## *2.4 Forms*

Fama (1970) divides efficient markets into three forms depending on the level of information available to the investors: the weak form, the semi-strong form, and the strong form. First, in a weak form of efficient market, it should be impossible for any participant to get abnormal returns based on historical prices because all historical information should already be taken into account in the current price. Then, Fama (1970) describes the semi-strong form of efficient market as a market in which nobody would be able to reach abnormal returns based on historical prices and public information. Indeed, as everyone has access to all public information and as the participants act rationally, a release of information would directly reflect into the price of the security. Therefore, nobody could gain a profit based on any public information because all the information would already be reflected in the current price. Finally, Fama (1970) expresses the case of the "theoretical" strong form of efficiency. In these markets, it would be impossible to achieve abnormal returns for an investor thanks to public and private information because they are already included in the price. Fama (1970) states that this form does probably not exist in practice.

## *2.5 Defense and critics*

The Efficient Market Hypothesis is highly discussed in the literature, and it is currently not clear if we should consider financial markets as efficient or not. Several studies and trading techniques have been presented as proofs of financial market inefficiency.

De Bondt and Thaler (1985) find a long-term profitable "*contrarian*" strategy which is based on past returns of the stocks. They attribute this abnormal profit to an overreaction of traders to unexpected news. The momentum strategy discovered by Jegadeesh and Titman (1993), which delivers medium-term high abnormal returns based on historical stock prices, is also an argument against the EMH, and remains the most important one nowadays. Other authors claim the impossibility of informationally efficient markets because of the cost of information (Grossman and Stiglitz,1980).

However, the EMH can also rest on many defenders. Fama (1998) explains that overreaction is as frequent as underreation, and post-event continuation appears also as much as post-event reversal. Consistent with the idea of Fama (1998), Malkiel (2003) reviews arguments against the efficiency to explain that we should not abandon the EMH because anomalies are only the results of pure chance.

As the main purpose of this essay is to find the implication of the presence of a momentum effect in financial markets to their efficiency, other critics of the EMH will not be reviewed. In a few words, opinions are divergent among authors about the presence of inefficiency and it is currently not sure if markets are informationally efficient or not. However, the hypothesis has not been completely banned yet and though many evidence of inefficiency has been reported, a lot of scientists still stay in favor of the EMH. Finally, as the momentum effect is the most challenging argument against the hypothesis, it is important to study its causes and origins in order to know its implication for the efficiency of financial markets.

# 3. MOMENTUM EFFECT

A strategy that consists in going long stocks whose past returns are high and going short stocks whose past returns are low and that delivers significant abnormal returns, would directly contradict the EMH. Indeed, the only information needed to build this strategy is the historical prices of the stocks. Therefore, this strategy, called a momentum strategy, even contradicts the weak form of efficient markets.

In this section, I will first present evidence of momentum strategies on different markets and among different asset classes. Then, possible explanations of this momentum effect will be reviewed, as well as their implications for the EMH. Finally, the explanation of momentum that argues that the anomaly is caused by investor attention to stock will be further examined, as well as the role of individual and institutional investors in creating this effect.

## *3.1 Evidence*

De Bondt and Thaler (1985) are the first to discuss a strategy based on stocks past returns. They implement a strategy (e.g. the contrarian strategy) that consists in buying past losers (e.g. stocks with low past returns) and selling past winners (e.g. stocks with high past returns) on New York Stock Exchange (NYSE) between January 1926 and December 1982. Their study reveals that the portfolio of losers outperforms the market on average by 19.6% after a period of 36 months, and that the portfolio of winners underperforms the market on average by 5% for the same holding period. The difference of approximately 25% between the loser stocks and the winner stocks indicates that investors usually overreact to unexpected events. Moreover, the profits of this long-term contrarian strategy come mainly from the stocks with low past returns while they have less systematic risk.

The first to test a mid-term momentum strategy are Jagadeesh and Titman (1993). They study all stocks listed on New York Stock Exchange (NYSE) and American Stock Exchange between 1965 and 1989. They rank those stocks into deciles based on their past returns during the past 3 to 12 months. Then, they derive strategies that buy winners, which are stocks in the top decile, and sell losers, which are stocks in the bottom decile, and hold them for a period of 3 to 12 months. They also analyze the same strategies with one month between the ranking and the holding period to increase the power of their test. They denote these strategies K/S/J where K represents the number of months of the ranking period, J is the number of months of the holding period, and S the number of months between ranking and holding. Jagadeesh and Titman (1993) find that the strategy, that consists in buying past winners and selling past losers based on their past 6-month returns, and holding them for 6 months, delivered an excess return of 12,01% per year on average. Moreover, they report that all studied strategies delivered an excess return, except for the 3/0/3 strategy. Finally, they express that the profits of such strategies come mostly from the buying part of the portfolio, rather than the losers.

This first study on a momentum effect in the U.S. has motivated the community to search if it was present on all geographic markets and for all asset classes, in order to ensure that this was not a pure fortuity.

The study in the U.S. market has encouraged other scientists to search if the momentum effect was existing internationally. To examine if momentum was actually present in other markets, Rouwenhorst (1998) conduct a study using a sample of 2,190 stocks from 12 different European countries between 1978 and 1995, while following the methodology of Jagadeesh and Titman (1993). The findings indicate that the international portfolio, that holds past medium-term winners and short medium-term losers, reaches a return of approximately 1 percent. More importantly, the momentum effect does not seem to be due to a particular country as it is present in each of the 12 European states. However, the correlation between the U.S. and European markets indicates that the momentum effects could be driven by a common factor.

The momentum has also been examined into the Asian markets (Chui et al., 2000). Indeed, the authors analyze the stocks on eight different Asian markets (Hong Kong, Indonesia, Japan, Korea, Malaysia, Singapore, Taiwan and Thailand) because of their cultural and institutional differences with western countries. They follow the methodology of Jagadeesh and Titman (1993) and Rouwenhorst (1998) to conduct their study to be able to compare their results (e.g. 6/0/6 momentum strategy) but are forced to change the weight in the portfolio (e.g. 30% instead of 10%) because of a smaller sample in some countries. Their findings indicate that the momentum strategy provides only 0.376% and thus, that the momentum effect is negligible in the Asian markets. However, when the authors exclude Japan from the sample, the strategy becomes profitable and is comparable to the profits reported by Jagadeesh and Titman (1993). This suggests that the momentum effect is also real in Asian markets, except in Japan. Another finding of the study (Chui et al., 2000) is that even if the momentum is quite strong before the crisis (1.45% per month), it decreases to only 0.54 percent after the crisis, which indicates that the momentum can be driven by the market states.

The exception that Japan represents for the momentum puzzle is worth noticing because it could help for the comprehension of the momentum effect, as it is one of the few countries where momentum is not present.

Griffin et al. (2003) study the momentum in 40 countries from different continents where the markets are composed of at least 50 stocks. Their strategies are a 6/0/6 momentum strategies with loser and winner portfolios of 20% of all stocks. They calculate average monthly returns per continent of 1.63, 0.78, 0.77, and 0.32 in Africa, America (excluding the U.S.), Europe and Asia, respectively. The authors highlight the weaker momentum in Asia, which remains weak even if Japan is excluded from the sample. They also note that emerging markets provide weaker momentum profits (0.27%) than developed countries, excluding the U.S. (0.73%).

The different studies present in the literature indicate that the momentum effect is real in stock markets around the world, with some exceptions. However, it could be interesting to check if momentum strategies are also profitable for other asset classes.

Van Luu and Yu (2012) partly answer this question. They form portfolios with government bonds (Australia, Canada, Germany, Japan, the U.S. and the U.K.) between 1987 and 2011. The strategy is different from the general momentum strategy on stock markets. They go long a bond bucket, if the excess returns of the bonds are positive, and short if not, and remove US$1M Libor cash return from the performance of the portfolio, rebalancing portfolios every month. As a result, all portfolios deliver momentum excess returns of 0.7% to 2.6% per year over the Libor. Moreover, they state that highly liquid markets (i.e. the U.S, Japan, and Germany) earn better momentum profits.

Menkhoff et al. (2012) study the momentum effect on foreign exchange market. They study the currencies of 48 countries for the sample period from 1976 to 2010. They form six portfolios based on the returns of the past 1 to 12 months and hold them for the same period. The momentum strategy that consists in holding the winner portfolio and selling the losers provides an excess return between 6% and 10% for the strategy that holds the position for 1 month. It is also interesting to observe that these returns decline when the holding period becomes longer.

To observe if momentum was present everywhere (e.g. in all geographical markets and among all asset classes), Asness et al. (2013) examine the momentum strategy in four different stock markets (the U.S, the U.K., Japan, and continental Europe) and four other asset classes (country equity index futures, government bonds, currencies, and commodity futures).

In short, the literature has provided a lot of evidence of profitability of momentum strategies in most of the stock markets and among other asset classes. The reason for this profitability is still uncertain even though many scientists have tried to explain it. I will now look over the current possible explanations available in the literature, and more precisely over the two common types: risk-based and behavioral explanations.

### *3.2 Risk-based explanations*

As the momentum strategies have been demonstrated to be profitable in a wide range of financial markets, scientists have searched possible explanations for the abnormal returns provided by these strategies. Assuming that the markets were informationally efficient, researchers have first tried to build a model that can explain the excess returns with an additional risk implied by the strategy.

In their paper that indicates the presence of momentum in the U.S. stocks markets, Jegadeesh and Titman (1993) study the implication of this effect on the EMH. According to the EMH, in an efficient market, profits should only be due to systematic risks since unsystematic risks could be diversified away. Based on a one-factor model (i.e. CAPM), they examine the superior profits and decompose them into three components. The first two components are sources of systematic risks and could be present in efficient markets. However, the third component relates to unsystematic risks and would contradict the market efficiency if it explained the portfolio profitability.

$$E\{(r_{it} - r_t)(r_{it-1} - r_{t-1})\} = \sigma_\mu^2 + \sigma_b^2 \, Cov(f_t, f_{t-1}) + Cov_i(e_{it}, e_{it-1})$$

where

$\mu_i$ is the unconditional expected return on stock i,

$r_{it}$ is the return on security i,

$f_t$ is the unconditional unexpected return on a factor-mimicking portfolio,

$e_{it}$ is the firm-specific component of returns at time t,

$b_i$ is the factor sensitivity of security i, and $\sigma_\mu^2$ and $\sigma_b^2$ are the cross-sectional variances of expected returns and factor sensitivities respectively.

They find that the beta of stocks that deliver extreme results is higher than the beta of their entire sample, and moreover, that the beta of past losers is higher than the beta of past winners, resulting in a negative beta for the zero-cost winner minus loser portfolio. This negative beta indicates that the profits of the strategy are not due to the first term of the equation. Furthermore, the second term of the equation, which is the serial covariance of the factor portfolio returns, does not either seem to explain the profitability of the strategy. Indeed, this serial covariance is negative for the 6-month returns of the index which should even decrease the profitability of the strategy. Finally, they find that the estimates of the serial covariance of market model residuals for individual stocks are on average positive, which suggests that relative strength profits could be due to an underreaction of stock prices to firm-specific information. Although the relative strength profits can come from a lead-lag effect in stock prices, Jegadeesh and Titman (1993) demonstrate that this effect is not a significant source of profits, and therefore that the market underreaction explanation should be considered. This last finding supports directly behavioral explanations.

As the traditional CAPM does not seem to completely explain stocks returns, other authors have started to build a new model that could explain market anomalies. In 1992, Fama and French noticed that two particular measures (i.e. the size and book to market equity) capture the cross sectional variation in average stock returns associated with size (i.e. the number of shares multiplied by their price), E/P (i.e. earnings-price ratio), book to market equity, and leverage. Following that, Fama and French (1993) built a common three factor model that encompasses these two measures, as well as the excess market return. In 1996, Fama and French tested their model to determine if it explained market anomalies. As a result, they found that Fama and French's three factor model was able to explain most of the market anomalies (for example, the long-term return reversal of DeBondt and Thaler (1985)), but could not explain the excess returns generated by momentum strategies.

Conrad and Kaul (1998) analyze the strategies based on past returns – that are momentum and contrarian strategies – at different horizons and periods, and question their profitability. They decompose the profits into two components and find that the estimated cross-sectional dispersion in the mean returns of individual securities in the portfolio is responsible for the momentum abnormal profits rather than the component coming from the time-series patterns in returns. In other words, momentum profits are due to the difference in mean returns (e.g. the strategy buy winner stocks that have high-mean returns and go short loser stocks that have low-mean returns), and not the price predictability that forms the portfolio of the strategy. However, Jegadeesh and Titman (2001) disprove the theory of Conrad and Kaul (1998). Indeed, they show that the positive returns provided by the medium-term momentum strategies are followed by a negative performance of the momentum portfolio in the 13 to 60 months following the portfolio formation. They conclude that the behavioral model should be better to give an explanation, at least partial, for the momentum anomaly.

### *3.3Behavioral explanations*

The difficulties in finding a risk-based explanation for market anomalies have led scientists to search for other potential theories. As the opinions of researchers diverged from one to another, the behavioral theory appeared. For behaviorists, market anomalies (and more precisely the abnormal return generated by momentum strategies) come from biases in the behavior of investors and not directly from the components of the assets, which is in direct contradiction with risk-based explanations.

One of the first study on investor behavior was conducted by Barberis, Shleifer, and Vichny (1998). They built a model of investor sentiment to explain the evidences of underreaction of stock prices to news in the short term (i.e. over a period of one month to one year), and the evidence of overreaction of stock prices in the long-term (i.e. over 3 to 5 years). In their model, the authors analyzed the behavior of one investor with regards to one stock. Although the earnings of the stock follow a random walk, the investor will think that earnings are in one "state". In his mind, either the earnings follow a specific trend, meaning that if the earnings are rising, they will keep on rising, either the earnings are mean reverting. The model of Barberis et al. (1998) show that underreaction happens when the investor is in a state of mean reverting. Indeed, if the earnings announcement is positive, the investor will think that the next earnings announcement will be negative. However, as the earnings follow a random walk, there are the same probabilities that the next earnings will be positive or negative. If they are negative such as the investor has anticipated, it will provide low returns, but if they are positive, returns will be highly positive because the investor has not expected that at all. Thus, on average, the realized returns will be positive, as it is the case in underreaction evidence. On the opposite, overreaction happens when the investor thinks that earnings follow a trend. Indeed, in the case where earnings are rising, he will think that they will keep rising, but there isn't more chance that they rise instead of decrease (again, because they follow a random walk). With the same reasoning as if he was in the mean reverting state, the investor will get low returns if the earnings keep rising because he expected that, but he will have highly negative returns if the earnings decrease. On average, he will realize negative returns, consistent with the overreaction evidence.

Altough the study of Barberis et al. (1998) is important for behavioral finance, it doesn't encompass the time variable. Therefore, it does not explain when an investor will be in one state or another, or in other terms, when there will be underreaction or overreaction. In 1998, Daniel, Hirshleifer, and Subrahmanyam also searched investor biases that could explain this phenomenon on security markets. They investigated two psychological biases, that are overconfidence and biased self-attribution, to explain market under- and overreactions. They state that investors are overconfident, meaning that they overreact when they are able to reach private information. However, when the information is leaked publicly, they suffer from a self-attribution bias, meaning that if the information confirms their sentiment, they will be even more confident, but if the information contradicts their beliefs, they will not lose confidence as much as what they would gain if they were right. People are so confident in their asset valuation skills that they overprice the best stocks compared with their fundamental value. In the long-run, the asset prices should converge to their fundamental prices. Therefore, this overconfidence explains the short-term momentum effect, and the reversal effect in the long-term.

In 1999, Hong and Stein built a model that considers two groups, those groups are the “newswatchers” and the “momentum traders”. The first bases their investment decisions on the expected future values thanks to private information they have access to, but they neglect the current and past prices. On the opposite, momentum traders base their decision on past values, but they don't consider any other kind of information. Two final important assumptions were also made: private information doesn't reach all the newswatchers at the same time, but diffuses gradually among them, and the momentum traders use simple strategies. The authors demonstrate that in the first instance, there is underreaction caused by the information diffusion process among the newswatchers. Then, momentum traders will enter the model. As they based their investment decisions on past prices, they will go in the same direction as newswatchers, and so, they will accelerate the convergence between the actual and fundamental prices. However, when the asset price will reach its fundamental, momentum traders will keep on buying or selling the asset because the trend has not changed.

Therefore, there is overreaction in the long run. Thus, this model explains the primary underreaction, followed by an overreaction in asset prices.

To test this theory, Hong, Lim, and Stein (2000) sort stocks into different classes according to the firm size and its residual analyst overage. They state that investors should reach information about small firms and firms with low analyst coverage more slowly. However, as firm size and analyst coverage are highly correlated, they consider the residual analyst coverage, which is a regression of analyst coverage on firm size. The authors find that momentum strategies generate much more important profits for small firms and firms with low analyst coverage. This is consistent with the underreaction model of Hong and Stein (1999) because firms with slow information diffusion get higher momentum profits. Another important result of their study is that momentum strategies work particularly well for loser stocks with low information diffusion. They explain this phenomenon by the fact that managers of firms with bad news will try to retain the information, which will even slow down the information diffusion process, and thus, will increase the momentum profits.

In 2001, Jegadeesh and Titman attempted to determine which of the risk-based or behavioral theories was more plausible to explain the momentum anomalies. They analyzed all stocks traded on the New York Stock Exchange (NYSE), American Stock Exchange, and Nasdaq with the exception of the smallest stocks (i.e. stocks for which prices are less than five dollars or which take place in the smallest NYSE decile), and formed a 6/0/6 momentum strategy between 1965 and 1998. First, they confirmed the profitability of the strategy. Then, they investigated the profitability of the momentum portfolios in the 13 to 60 months following the formation period, and found that it is negative. Even if the results should be tempered because there are some concerns about reasons behind the negative post-holding period returns, their findings reject the risk-based model of Conrad and Kaul (1998), and are, at least partly, consistent with the behavioral models.

In 2010, Chui, Titman and Wei analyzed the effect of the difference of culture of a society on the performance of a momentum strategy. They used the individualism index of Hofstede (2001) to examine if the momentum profits were driven by investor biases and they linked this individualism measure to the overconfidence and attribution bias similar as Daniel et al. (1998), by showing that trading volume and volatility are correlated to the degree of individualism. To conduct their research, they used a sample of more than 20.000 stocks present in 41 countries. The authors explain the differences in momentum profits across countries by the differences in degree of individualism of the countries. Indeed, zero-cost momentum portfolio of more individualistic countries (i.e. top 30%) exhibits 0,6% more returns that the same portfolio for countries with low individualism (i.e. bottom 30%). Therefore, this study shows evidence that momentum could be driven by behavioral biases.

Since the beginning of the behavioral studies, there have been a lot of researches on the correlations between firm characteristics and momentum. Among them, Lee and Swaminathan show that high trading volume delivers higher momentum profits, Jegadeesh and Titman (1993) and Hong, et al. (2000) argue that momentum profits come mainly from small firms, and that analyst coverage decreases the profitability of momentum strategies (Hong, et al. (2000)), and Zhang (2006) analyze the role of information uncertainty through proxies such as volatility of cash flows and of returns, the dispersion in analyst forecasts, firm size and age, and analyst coverage to show that momentum strategies work particularly well when there is more information uncertainty, which indicates an underreaction to news.

Although all these studies aim to explain the momentum anomaly, none of them achieves to deliver a full explanation of the phenomenon. However, one path, which is the study of the reactions of investors to new information, seems to be really promising. These studies focus on the investor behavior and their attention to new information to discuss if momentum profits are driven by under- or overreactions or none of them. For example, the mentioned above study of Zhang (2006) concludes that investors underreact to news.

## *3.4 Investor attention*

To analyze investor attention to news, researchers have chosen several proxies. The most obvious proxies for attention, and therefore the first that have been studied, are the firm size and the analyst coverage. As presented before in this thesis, Hong, et al. (2000) have chosen these proxies because it seems plausible that investors will pay more attention to firms that are bigger and have more analyst coverage. They find that momentum is greater for small and low covered firms, which indicates that investor attention lowers the momentum profitability. The role of analysts has been studied by Jegadeesh, Kim, Krische, and Lee (2004). More specifically, they examined the analyst stock recommendations and changes in recommendations to determine the usefulness of these and their limitations. Therefore, they profiled the firms that are recommended by analysts and noticed that they tend to have high trading volume and to present positive past returns. They concluded that after controlling for momentum, the recommendations of analysts become less predictive and no longer significant.

In 2003, Chan used headlines in newspapers to study stock price reactions to public news. The author examined 4200 randomly selected stocks between 1980 and 2000 and their appearances in newspapers. Chan (2003) sorted stocks into three portfolios based on their returns over the last 6 months and then divided each portfolio into two separate portfolios depending if the stock appeared or not in the news in the previous month. He found that no-news stocks reduce highly the momentum profitability (i.e. the momentum strategy that has only news stocks generates 40 to 50% higher returns than the momentum strategy with all stocks). His study supports the Hong and Stein model (1999) in which two classes of investors are present (i.e. one class underreacts to public signals but the other overreacts to perceived private signals).

Barber and Odean (2007) also use trading volumes, extreme returns and news to study the effect of attention on investors. They argue that investors have limited attention while there is a huge amount of stocks available, and therefore, they have to choose on which stock they should pay attention to reduce their choice set and make their decision easier. Moreover, they state that individuals have little possibilities to sell stocks because they could not short stocks, so they should first own the stocks to sell them back. Therefore, they predict that individual investors are net buyers of high attention-grabbing stocks (i.e. stocks that appears in the news and that have extreme returns and high trading volume). After sorting stocks by these three proxies, they note that the buying behavior of individual investors is driven by the attention they pay on stocks and they confirm their predictions. A final important note is that they separate the individuals from the institutions which seem to behave differently. These differences will be reviewed in the next section.

In 2009, Kewei, Lin, and Wei used trading volume to analyze the role played by investor attention in momentum profits. By sorting all stocks listed on the NYSE and AMEX by their turnover, and then, by their past returns, they found that high turnover stocks deliver significant higher momentum profits.

Another study demonstrates that media can alleviate the pricing of securities (Fang and Peress, 2009). The authors examine stocks on the NYSE and NASDAQ, and their coverage in four major U.S. newspapers. They sort stocks into three groups depending on their media coverage and analyze the profitability of a zero-investment portfolio, which consists in buying stocks with no media coverage and shorting the ones with high media coverage. Their findings indicate that there is a no-media return premium even if a significant part of the premium could be due to a decrease of the alphas in factor models. On average, this premium account for 0.20% per month, even after accounting for risk factors. The no media premium even increases for small stocks and stocks with low analyst coverage.

In 2013, Chen, Pantzalis and Park examined the impact of press coverage on stock prices deviation from fundamental value to know whether information intermediary improves the pricing process or not. As Fang and Peress (2009), they collected news of their sample firms from the four major U.S. newspapers to determine the stock press coverage, and then, they adjusted the measure to the size and industry of the firm to get the "abnormal" press coverage. Finally, they compared this measure with the excess price, which is the difference of the price of a stock and its fundamental value. They found that abnormal press coverage increases significantly the mispricing, which indicates that media biases the pricing evaluation of investors by creating sentiments among them. After, they examined separately firms that have experienced good and bad news, which indicates that abnormal press coverage leads to mispricing mostly when there is good news, and therefore, it leads to an overvaluation.

The effect of media on investor behavior has been more deeply studied and linked with the momentum effect by Hillert, Jacobs and Müller (2014). As Fang and Peress (2009) and Chen et al. (2013), they used the number of articles in the four major newspapers in the U.S. to determine the media coverage. Following Jegadeesh and Titman (1993), they formed 6/1/6 momentum portfolios, and then, formed five portfolios based on the media coverage during the formation period inside the momentum portfolios. They noted that momentum strategies based on the highest coverage portfolio are over 3 times more profitable than the momentum strategies based on lowest coverage (i.e. 1.02% per month against 0.33%). This profitable "media" momentum strategies tend to confirm the investor overconfidence bias presented by Daniel et al. (1998): public information that confirms initial "private" information leads investors to overreact to this information.

Da, Engelberg, and Gao (2011) decided to use a different proxy to measure investor attention: The Google Search Volume Index (SVI). Indeed, they noticed that traditional proxies for attention (i.e. extreme returns, trading volume, news and headlines, advertising expenditure, analyst coverage, and price limits) are in fact indirect proxies based on the assumption that investors pay more attention to high trading volume stocks, stocks that are more covered by analysts, and so on… Therefore, they decided to use a new direct measure, the Google SVI, which corresponds to an aggregate search frequency index in Google. Not only search engines are extremely popular to search information, but also Google is the most used in the United States. Moreover, contrarily to the indirect proxies for attention, researches on search engine are undoubtedly a direct attention measure. Indeed, if an investor launches a research on Google on a particular stock, this means that they pay attention to this stock. So, the authors analyzed the stocks in the composition of the Russell 3000 between January 2004 and June 2008. They began their analysis by comparing the SVI with other common proxies for attention, which demonstrates that the new direct proxy has a low correlation with other variables such as extreme returns, trading volume, and analyst coverage, even if the latter has a positive relation with SVI. Then, they analyzed the relation between SVI and the price of stocks, and found that an increase in SVI foresee increases in returns in the following 2 weeks.

### *3.5 Institutional versus individual investors*

In the previous section, the attention of investor to certain stocks has been introduced as a source of the momentum anomalies. However, the type of investors who are responsible for creating the previously presented biases has not been defined yet, while it is important to note that there is a group of investor that is more responsible for the presence of momentum on financial markets than another. In this view, the role of institutions will be compared to the behavior of individual investors in this section.

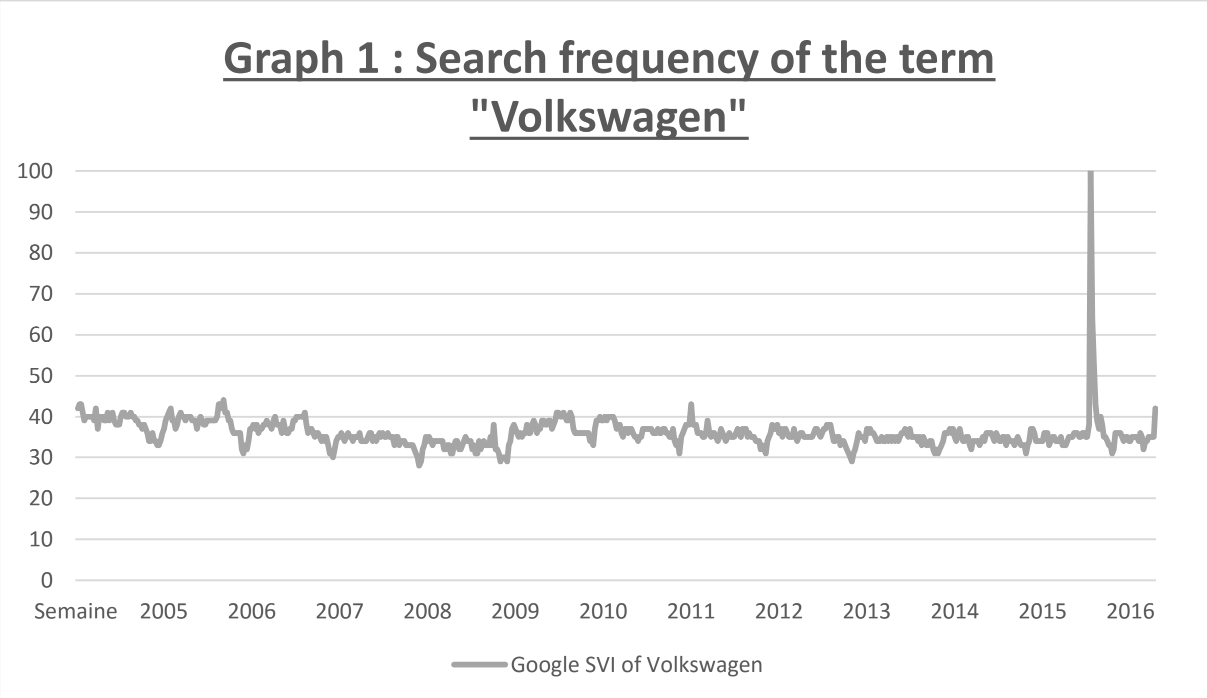
Barber and Odean (2008) differentiate individual and institutional investors in their paper. According to the authors, several differences can be observed in their behaviors. Individuals do not sell short; they usually sell stocks that they hold, while institutions are used to short. In the same time, individual investors own a limited number of stocks at the same time, while institutions can hold a larger stock portfolio. Moreover, institutions can pay more attention than individuals to their research on stocks, because of their resources that are far less limited. Therefore, Barber and Odean (2008) show that individuals are more likely to buy stocks that exhibit strong past returns because these stocks are attention grabbing and individuals have limited attention, while institutions have a more diversified approach and do better analyses.

In 2006, Hvidkjaer studied the behavior of small and large traders separately to see if momentum is driven by cognitive biases. The author classified trades into two categories, small and large trades, depending on the amount traded. Small trades are considered to be the results of individual investors, while large trades reflect the trading activities of institutions. The findings of this paper indicate that individual and institutional investors show distinct trading behaviors. Momentum is reported to be caused by individual investors. Indeed, institutions demonstrate informed trading by buying or selling almost only during the formation period of the momentum portfolios, while almost no trades are made after this period. On the contrary, individuals reveal a “momentum” behavior: Small trades show a buying behavior of loser stocks during the formation period, followed by a gradually increasing selling behavior of the losers over the next years. The phenomenon is also observable for winner stocks among small trades: if there is already a trend of buying these stocks during the formation period, this behavior accelerates after. This corresponds to an initial underreaction followed by a delayed reaction. This is consistent with the models of Barberis et al. (1998) and Hong and Stein (1999). Finally, the author noticed that these trading behaviors are reflected into prices. Indeed, losers that suffer from underreaction underperform other losers in the following year. That indicates that individuals could be responsible for the momentum anomaly, while institutions should not.

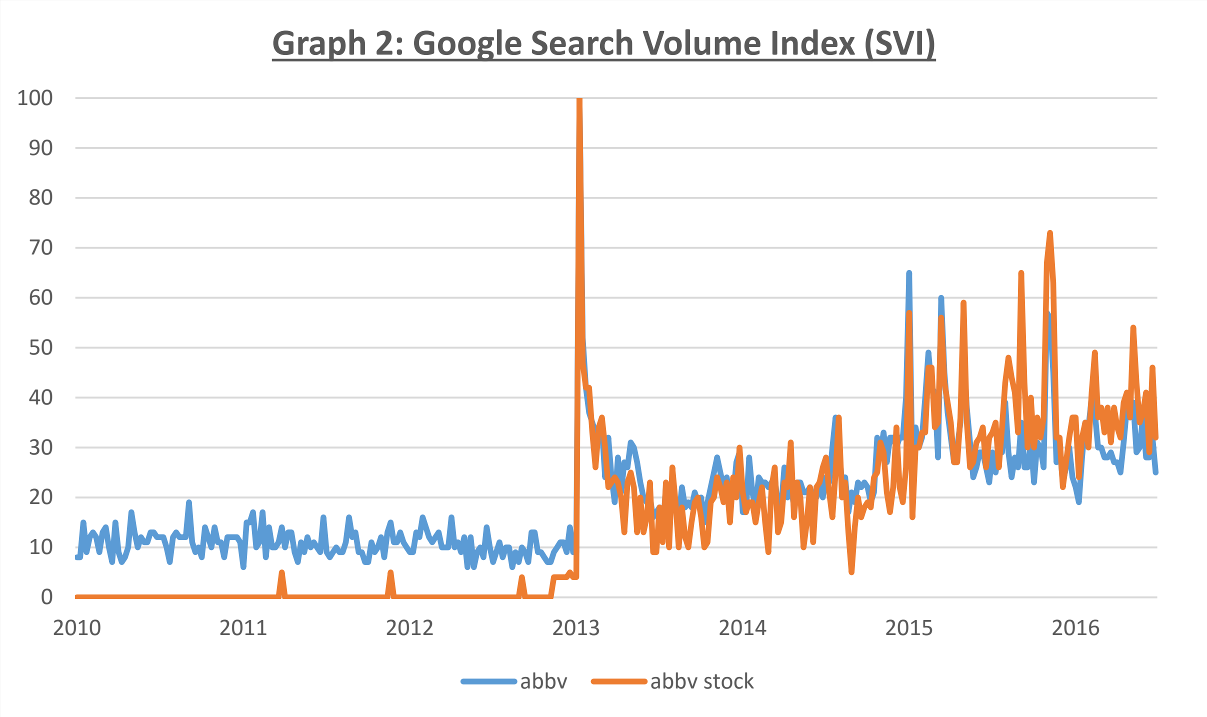
# 4. DATA

The data are of two kinds: the prices of stocks, which are needed to determine the momentum strategy, and the Google Search Volume Index, that will help to determine the attention of investors. Two sources are used to obtain these data. First, Google Trends provides the Google Search Volume Index (SVI) on a weekly basis for the period between January 2004 and Mai 2016, representing more than 12 years of data. Then, prices of stocks are obtained from Yahoo Finance within the same period and time interval to have a sample comparable with the attention measure (i.e. the SVI). The data are collected for all stocks that have been in the composition of S&P500 since 2008.

The Google SVI is an index on a certain research term scaled to 100 (i.e. the number of searches for this term scaled by its time-series average). This index is available from 2004, and it gives the evolution of the frequency of research of a given term. For example, Graph 1 shows the evolution of the frequency of research of the word "Volkswagen". It is interesting to note that this seems to be researched more or less at the same frequency (with a seasonal decrease at the end of each year), but when the cheating pollution emissions test scandal happened in 2015, the frequency of research has jumped.




This proxy is directly related to the attention of investors, while other proxies used to be indirect. Indeed, as Goddard, Kita and Wang (2015) state, media coverage, extreme price movements, or even advertising expenditure are indirect measures of attention, based on the assumption that if a stock is more covered in media, investors should give more attention to this stock. Barber and Odean (2008, p.787) write: “A direct measure would be to go back in time and, each day, question the hundreds of thousands of investors in our datasets as to which stocks they thought about that day”. This is exactly what can be done thanks to the Google SVI. Indeed, the SVI reports a direct action of investors, which is to enter the name of a company in the Google search engine to collect information on this firm by themselves. This measure of attention obviously does not represent all investors on the market but it presents some important characteristics. As Da, et al. (2011) note, search engines are extremely used nowadays, and Google is the most favorite one in the United States. Plus, the Google SVI is surely more related to trading by individual investors than by institutions because institutions are more likely to use more sophisticated tools such as Bloomberg. In this vein, Da et al. (2011) prove that this index is directly related to the attention of individuals. Following the literature (e.g. Da, et al., 2011), the ticker symbol (e.g. “AAPL”) is used instead of the company name (e.g. “Apple Inc.”). Indeed, company names could be researched for multiple purposes, while ticker symbols are more likely to be used for financial information (e.g. the word “Microsoft” could be used to get information about a product of the company to buy it, while the word “MSFT” should be used to access financial information about the firm by potential investors). When we enter a research term in the Google Trends application, Google gives us which researches are usually associated with our term. For example, the term “GOOG” has “goog stock” as most associated research, which seems to prove that ticker names are more related to financial information, while the term “Google” has as most associated researches “maps”, “google maps”, and “google translate”. However, some terms do not send a valid SVI. This is because the terms could have a generic meaning, or another meaning in a different language. For example, if we look at the term “ABT” (i.e. for Abbott Laboratories), the associated researches are “audi abt”, “abt tuning”, “abt electronics”, and so on… While if look at the combined terms “ABT stocks”, the associated researches are “abt stock price” and “Abbott stock”. Moreover, the addition of the term “stock” is useful to eliminate abnormal variability of the researched term. For example, consider the case of AbbVie for which the ticker name is “ABBV”. This company was launched in 2013 (Abbvie, 2016) but if we look at Graph 2, the SVI is fixed at 0 before the creation of the company for the term “abbv stock”, while it is abnormally fluctuating for the term “abbv”, which indicates that the SVI for this term could be biased by irrelevant researches. After that, both terms jumps to the maximum SVI (i.e. 100) and follow the same trends.




Therefore, the term “stock” is added to the ticker name to collect more relevant data. However, even if it gives more relevance, some terms are still not related to the stocks, so, these stocks have to be excluded from the sample (e.g. “ALL stock” for Allstate Corp.).

This collection of data is done manually for all stocks present in S&P500 because rather large stocks are needed to have enough data on the Google Trends application. Stocks that have been excluded from the index since 2008 are also included to have a broader sample. Only valid data are kept in the sample selection. To be valid, the data must fit all the following conditions:

- ✓ Have available prices at the beginning and the end of the formation and holding periods;
- ✓ Have a valid SVI[1] for the 8 weeks that precede the holding period and the first week of the holding period;

This gives a total of 601 stocks, for which the data are collected for 648 weeks (between January 2004 and Mei 2016). However, the average number of observations per week is increasing with time because a lot of SVI were not valid at the beginning of the sample period.

[1] To be valid, the SVI must first be different from zero. Then, stocks that gives irrelevant SVI are manually excluded from the sample; this is the case when the ticker name has a generic meaning for example.

# 5. METHODOLOGY

In this chapter, the methodology of the study will be presented.

## *5.1 Momentum portfolios*

Before analyzing the impact of investor attention on momentum profits, the presence of momentum will be verified in the sample. Therefore, momentum portfolios are formed following the methodology of Jegadeesh and Titman (1993). Portfolios have the same formation and holding period lengths, which are 3 months (13 weeks), 6 months (26 weeks), 9 months (39 weeks), and 12 months (52 weeks), with a week between the two periods to avoid bid-ask spread, price pressure, and lagged reaction effects. As Jegadeesh and Titman (1993), overlapping holding periods are used to increase the number of observations. Finally, momentum portfolios are the zero costs portfolios that go long the top 10% performers and short the worst 10% performing stocks.

First, returns are computed according to the following formula:

$$R_{i,t+j} = \frac{P_{i,t+j} - P_{i,t}}{P_{i,t}}$$

where

$R_{i,t}$ is the return of stock i at time t,

$P_{i,t}$ is the price of stock i at time t,

and j is the length of the formation and holding periods.

Then, stocks are ranked by returns in the previous week to avoid lead-lag effects. The performers below the $10^{th}$ percentile form the losers (P1), the stocks that rank between the $10^{th}$ and $90^{th}$ percentiles are part of the medium group (P2 to P9), and the winner group (P10) includes all stocks that perform above the $90^{th}$ percentile. The zero cost momentum portfolio is therefore P10-P1.

The returns of the momentum portfolios are therefore:

$$R_t^{Mom} = R_t^W - R_t^L$$

where

$R_t^{Mom}$ is the return of the momentum portfolio at time t,

$R_t^W$ is the average return of the winner stocks at time t,

and $R_t^L$ is the average return of the loser stocks at time t.

### *5.2 Sorting by investor attention*

Once the presence of momentum in the composition of S&P500 is checked, the profitability of a zero cost strategy based on investor attention will be discussed. The methodology is comparable to the methodology of momentum portfolios, but the investor attention is used to form the portfolios, instead of the past returns of stocks. To determine the attention of investor, the Abnormal Search Volume Index (ASVI) is computed as Da et al. (2011):

$$ASVI_{i,t} = \log(SVI_{i,t}) - \log(MED_{(SVI_{i,t-8}\,;\,\dots\,;\,SVI_{i,t-1})})$$

where

$ASVI_{i,t}$ is the abnormal search volume index of stock i at time t,

$\log(SVI_{i,t})$ is the logarithm of the SVI of stock i at time t,

and $\log(MED_{(SVI_{i,t-8}\,;\,\dots\,;\,SVI_{i,t-1})})$ is the logarithm of the median of the SVIs of stock I during the previous 8 weeks.

As Da et al. (2011) argue, taking the median of the SVI of the previous 8 weeks should give the normal level of attention, avoiding to take into account recent jumps or decreases.

Following the same methodology as for the momentum strategy, stocks are ranked each weeks according to their ASVIs. Stocks that ranks below the 30$^{th}$ percentile form the low attention portfolio (A1), and stocks that ranks above the 70$^{th}$ percentile form the high attention stocks portfolio (A3). The strategy that consists in buying stocks from A1 and shorting stocks from A3 is expected to be profitable. The returns of this strategy are computed considering a holding period of 3, 6, 9, and 12 months.

As for momentum, returns can be expressed as:

$$R_t^{IA} = R_t^l - R_t^h$$

where

$R_t^{IA}$ is the return of the zero cost portfolio based on investor attention at time t,

$R_t^l$ is the average return of the low attention stocks at time t, and $R_t^h$ is the return of the high attention stocks at time t.

### *5.3 Double sorting by momentum and investor attention*

Finally, the influence of investor attention will be determined using portfolios based both on past returns and investor attention. To do that, stocks will first be ranked into 3 portfolios based on their past returns instead of 10 portfolios such as in *a)* to ensure that final portfolios still include a significant amount of stocks. Stocks below the 30$^{th}$ percentile are the losers (P1), stocks above the 70$^{th}$ percentile form the winners (P3), and stocks between these two percentiles form P2. The formation period is again 3, 6, 9 and 12 months. Then, portfolios based on attention are formed inside the momentum portfolios to ensure that all portfolios are equally weighted. Therefore, 9 final portfolios are obtained for each formation period. For example, A1P1 is the portfolio of stocks that rank in the bottom 30% on their ASVIs compared to other stocks of P1, A3P2 includes all high attention stocks inside P2, A1P3 is formed by all low attention winner stocks, and so on… As for the momentum portfolios, the holding period lengths correspond to the formation period lengths.

To study the impact of investor attention, 5 strategies will be examined for each holding period. First, the zero cost momentum strategies that go long high attention winners (A3P3), and short simultaneously high attention losers (A3P1) called HH, that buys medium attention winners (A2P3) and shorts medium attention losers (A2P1) called MM, and that buys low attention winners (A1P3) and sells low attention losers (A1P1) called LL. Then, two other strategies are considered. One consists in buying high attention winners (A3P3) and selling low attention losers (A1P1), renamed HL, and one which buys low attention winners (A1P3) and shorts high attention losers (A3P1), renamed LH. For example, the return of HH is computed as follow:

$$R_t^{HH} = R_t^{A3P3} - R_t^{A3P1}$$

where

$R_t^{HH}$ is the return of the strategy HH at time t,

$R_t^{A3P3}$ is the return of the portfolio A3P3 (high attention winners) at time t,

and $R_t^{A3P1}$ is the return of the portfolio A3P1 (high attention losers) at time t.

The same formula is used for MM, LL, HL, and LH with their own composing portfolios.

# 6. EMPIRICAL RESULTS

Now that the methodology has been discussed, the results will be presented in this section.

## *6.1 Presence of momentum*

As previously stated, the first step of this study is to verify the presence of momentum. The average profits of momentum strategies on the whole sample period are presented in table 1.

**Table 1: profitability of momentum strategies**

| Strategy | Average monthly profit | \|T-test\| |
|---|---|---|
| ***3/1/3*** | -0.28% | 1.80* |
| ***6/1/6*** | -0.44% | 3.25** |
| ***9/1/9*** | -0.38% | 3.33** |
| ***12/1/12*** | -0.29% | 3.47** |

* Statistically significant at the 5% level.

** Statistically significant at the 0.5% level.

The negative momentum profits seem rather surprising, given the abundance of proofs of presence of momentum effects on financial markets presented in section 2.2. Therefore, it is interesting to look at the causes of this negativity. The table 2 gives the average profits of momentum strategies for each year of the study (i.e. the year of the strategy is given by the beginning date of the holding period). Large variations can be observed through the years (see Appendix 1), and more interestingly, the years 2008 and 2009 demonstrate high negative values, which could indicate an effect of the financial crisis. When years are grouped by periods, such as in graph 3, positive momentum profits are observed for the post-crisis period, while high negative profitability is recorded during the financial crisis of 2007-2008 and the following year of 2009.

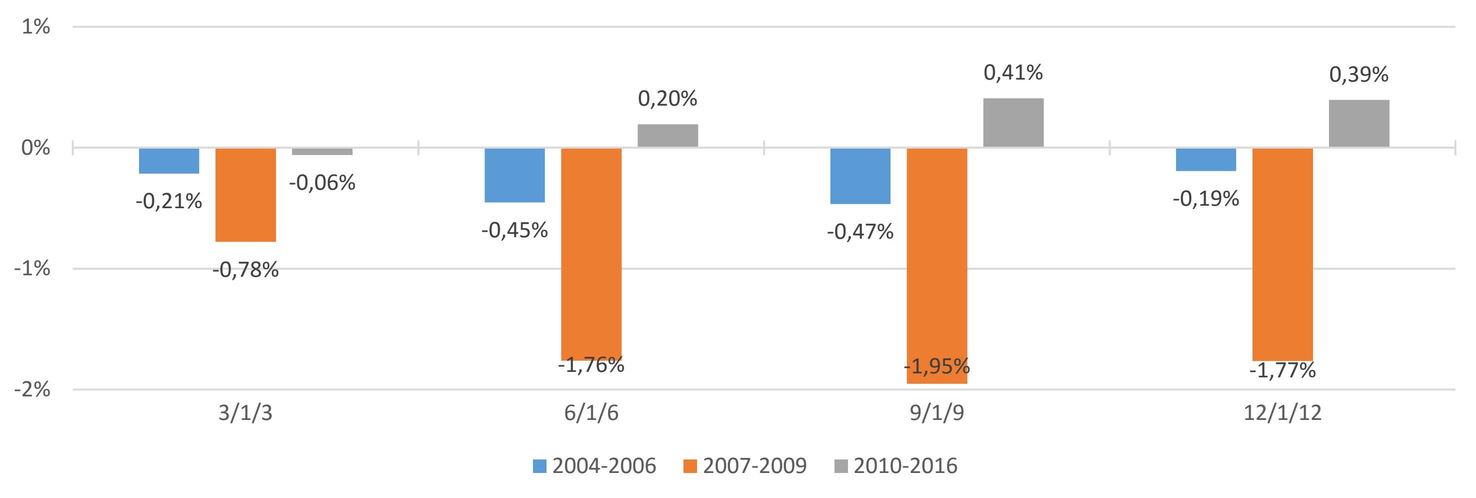
In 2004, Cooper, Gutierrez and Hameed studied the impact of market states on momentum on the U.S. markets between 1926 and 1995. They defined two states on financial markets and noticed that momentum profits are only significant in up markets, while down markets do not show momentum in the short-run. Moreover, they demonstrated that momentum profits increase when market performs better until a certain level. Hammami (2013) also examined the effect of good and bad times on momentum. They argue that momentum is inexistent in period of high risk premium, which is considered as bad times, while the strategy works well in period of good times. In 2014, Tai studied the behavior of investor during the financial crisis of 2008 to evaluate the presence or not of momentum between 2003 and 2012. The author showed that short-term momentum strategies, as well as long-term contrarian strategies were significant in time of crisis on Asians markets (i.e. in Hong Kong, Singapore, and Taiwan).

As the purpose of the study is not to discuss the impact of the financial crisis on momentum, the period from 2007 to 2009 will not be covered. Moreover, the period between 2004 and 2007 will also be dropped. Indeed, the Google SVI is available from 2004, but many data are yet missing in the beginning of the period, which causes the number of stocks available each week to be rather low. Therefore, the remaining of the study will analyze the sub-sample between 2010 and 2016, when the number of observations per week is large enough (i.e. more than 500), and the profitability of momentum is not affected by the economic crisis.

Table 3 presents the profitability of the momentum strategies between 2010 and 2016. All momentum strategies deliver statistically significant profitability, with the exception of the shortest term strategy, 3/1/3 momentum, which yields no significant returns. In appendix 2, the returns of each sub-group are presented. This shows that the momentum profits come mainly from the winners instead of the losers (which also deliver positive returns, which decreases the profitability of the momentum strategy). These results are consistent with the findings of Jegadeesh and Titman (1993) who demonstrate that all their momentum strategies were significantly positive, except for the 3/0/3 strategy. They also show that most of the profits come from the winner side of the strategies.

| **Table 2 : profitability of momentum strategies by years** | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Strategy** | **Average monthly returns** | | | | | | | | | | | | | |
| | ***04/16*** | ***2004*** | ***2005*** | ***2006*** | ***2007*** | ***2008*** | ***2009*** | ***2010*** | ***2011*** | ***2012*** | ***2013*** | ***2014*** | ***2015*** | ***2016*** |
| ***3/1/3*** | *-0.28%* | *0.63%* | *-0.59%* | *-0.48%* | *1.61%* | *-0.86%* | *-3.26%* | *-0.31%* | *-0.09%* | *-0.29%* | *0.44%* | *0.82%* | *0.40%* | *-8.58%* |
| ***6/1/6*** | *-0.44%* | *-0.59%* | *0.11%* | *-0.97%* | *1.21%* | *-2.51%* | *-4.47%* | *-0.08%* | *-1.28%* | *-0.04%* | *0.95%* | *0.17%* | *1.43%* | |
| ***9/1/9*** | *-0.38%* | *-3.56%* | *0.46%* | *-0.74%* | *0.78%* | *-2.01%* | *-5.48%* | *0.39%* | *0.00%* | *-0.24%* | *0.75%* | *0.47%* | *1.33%* | |
| ***12/1/12*** | *-0.29%* | | *0.33%* | *-0.75%* | *-0.25%* | *-1.94%* | *-3.42%* | *0.75%* | *0.34%* | *-0.60%* | *0.54%* | *0.60%* | *1.03%* | |

**Graph 3: Monthly profitability of momentum strategies by sub-periods**



| Table 3: Profitability of momentum strategies between 2010 and 2016 | | |
|---|---|---|
| **Strategy** | **Average monthly returns** | **\|T-test\|** |
| ***3/1/3*** | *-0.06%* | *0.45** |
| ***6/1/6*** | *0.20%* | *2.13*** |
| ***9/1/9*** | *0.41%* | *6.50**** |
| ***12/1/12*** | *0.39%* | *8.05**** |

* not statistically significant.

** statistically significant at the 2.5% level.

*** statistically significant at the 0.05% level.

## *6.2 Investor attention*

The presence of momentum being now demonstrated, the impact of investor attention will be analyzed between 2010 and 2016. The profitability of the zero cost portfolios formed on the basis of the attention given to the stocks is given in Table 4.

| Table 4: Profitability of low attention minus high attention portfolios | | |
|---|---|---|
| **Strategy (holding period)** | **Average annual returns** | **T-test** |
| *3 months* | *0.92%* | *2.39**** |
| *6 months* | *0.49%* | *1.85*** |
| *9 months* | *0.26%* | *1.19** |
| *12 months* | *0.17%* | *0.81** |

* Not statistically significant.

** Statistically significant at the 5% level.

*** Statistically significant at the 1% level.

As indicated by the table, the profitability of the strategy decreases with the length of the holding period. The profitability is only significant for the shortest holding periods (3 and 6 months), while the holding periods of 9 months and 1 year do not provide significant returns. This is the opposite from the momentum strategies, from which the profitability was more significant with the holding period length.

## *6.3 Portfolios double-sorted by momentum and investor attention*

As seen in section *5.1* and *5.2,* the profitability of strategies based on past returns, as well as investor attention, is positive and significant for the period between 2010 and 2016, except for the 3/1/3 momentum strategy (which is negative and non-significant), and for the low attention minus high attention portfolios with holding period of 9 and 12 months (which are not significant either). This part of the study will now focus on the link between the two phenomena. As many studies argue that momentum is caused by a delayed reaction of investor or overreaction, the profitability of momentum strategies should be amplified when focusing on low attention stocks. However, as the sample is not large enough, a second type of momentum strategy will be built following the methodology of Chan (2003): instead of using the top and bottom decile, stocks that perform below the 30$^{th}$ centile will form the losers and stocks that perform above the 70$^{th}$ percentile will form the winners. The profitability of this second type of strategy is presented in Table 5.

**Table 5: Profitability of momentum strategies (top 30$^{th}$ – bottom 30$^{th}$ percentile)**

| Strategy | Average monthly returns | Average annual returns | \|T-test\| |
|---|---|---|---|
| ***3/1/3*** | -0.07% | -0.89% | 0.87* |
| ***6/1/6*** | 0.08% | 0.94% | 1.41** |
| ***9/1/9*** | 0.24% | 2.94% | 6.05*** |
| ***12/1/12*** | 0.22% | 2.66% | 6.67*** |

* Not statistically significant.

** Statistically significant at the 10% level.

*** Statistically significant at the 0.05% level.

By comparison with the other type of momentum strategy (i.e. momentum strategy that buys the top 10% performers and sells the bottom 10%), the average returns are lower and less significant. However, this is not so important, as momentum is still present and significant. Moreover, the initial purpose of the study is to examine if investor attention lowers or increases the profitability, which can still be done.

The returns of each 9 sub-portfolios are showed in Table 6 for each holding period length. P1 are the loser, P2 the medium, and P3 the winner portfolios. Each A1 (A3) is the sub portfolio formed by low (high) attention stocks. For example, the column A1 under P3 presents the

## Table 6: Average returns of sub-portfolios

(Returns are annually expressed in %)

| | P1 | | | P2 | | | P3 | | |
|---|---|---|---|---|---|---|---|---|---|
| **Holding period length** | **A1** | **A2** | **A3** | **A1** | **A2** | **A3** | **A1** | **A2** | **A3** |
| **3 months** | *12.33* | *11.04* | *10.45* | *10.62* | *11.42* | *10.66* | *11.08* | *10.36* | *9.32* |
| A1-A3 | *1.88****** *\|t-value\| = 2.36* | | | *-0.03** *\|t-value\| = 0.06* | | | *1.76****** *\|t-value\| = 2.35* | | |
| **6 months** | *10.32* | *8.74* | *9.58* | *11.10* | *11.00* | *11.00* | *10.87* | *10.63* | *9.74* |
| A1-A3 | *0.74*** *\|t-value\| = 1.30* | | | *0.11** *\|t-value\| = 0.29* | | | *1.13***** *\|t-value\| = 2.25* | | |
| **9 months** | *10.01* | *8.68* | *9.07* | *11.89* | *11.36* | *12.03* | *12.43* | *12.57* | *11.55* |
| A1-A3 | *0.94***** *\|t-value\| = 2.06* | | | *-0.13** *\|t-value\| = 0.49* | | | *0.88***** *\|t-value\| = 2.09* | | |
| **12 months** | *10.20* | *9.14* | *8.96* | *11.91* | *11.30* | *11.85* | *12.20* | *12.02* | *12.00* |
| A1-A3 | *1.24****** *\|t-value\| = 3.09* | | | *0.06** *\|t-value\| = 0.24* | | | *0.20** *\|t-value\| = 0.56* | | |
| **Average** | ***10.71*** | ***9.40*** | ***9.51*** | ***11.38*** | ***11.27*** | ***11.38*** | ***11.64*** | ***11.40*** | ***10.65*** |
| **Av.(A1-A3)** | ***1.20*** | | | ***0.00*** | | | ***0.99*** | | |

* Not statistically significant
** Statistically significant at the 10% level.
*** Statistically significant at the 5% level.
**** Statistically significant at the 2.5% level.
***** Statistically significant at the 1% level.

returns of the low attention and high past returns stocks portfolio. The lines "A1-A3" indicate the returns of the zero cost portfolios based on investor attention inside each momentum portfolio. The line "Av.(A1-A3)" is the average annual return delivered by the zero cost investor attention-based strategy inside each momentum group.

The average annual returns of sub-portfolios tend to confirm that an investor bias is present in the momentum strategy. Indeed, there is almost no profit to make inside the portfolio of stocks that have no extreme returns. On average, this return is null and insignificant. On the other side, returns of investor attention based portfolios are significant inside both the loser and winner portfolios, except for the winner portfolio with a holding period of 12 months, however this effect is even greater inside the loser portfolio.

The profitability of the five momentum strategies based on investor attention is presented in Table 7. The column "Momentum" shows the returns of the initial momentum strategy presented in Table 5, and the columns LL, MM, HH, LH and HL present the returns of the strategies explained in section *4.3*. Important results can be observed. First, the strategy 3/1/3 does not achieve to become positive and significant while taking into account the attention of investors. Then, for the other strategies (i.e. strategies with holding periods of 6, 9 and 12 months), only the MM and LH strategies achieve to beat the initial momentum strategy for each holding period length. This is particularly surprising. Indeed, as momentum strategies based on investor attention were expected to deliver superior performance, indicating that (part of) the momentum profitability came from investor behavior, the opposite is actually observed with the MM strategy. However, the strategy LH (which follow the ideas in *5.1* to buy winners and sell losers and in *5.2* to buy low attention stocks and sell high attention stocks) also reaches a superior performance compared to the initial momentum strategy. It is the only strategy that has positive returns for the 3-month holding period, but it is not statistically significant. LH beats MM when holding stocks for 12 months, but it is the opposite for the 6 and 9-month holding periods, yet LH still beats the "normal" momentum strategy.

A look at both Table 6 and Table 7 allow to understand better the origins of the returns of momentum. Among them, momentum profits still come from the winner side of the portfolios, yet the investor attention has a bigger influence on the loser side.

## **Table 7: Profitability of momentum strategies based on investor attention**

(returns are expressed annually)

| **Holding period of portfolios** | **Momentum** | **LL** | **MM** | **HH** | **LH** | **HL** |
|---|---|---|---|---|---|---|
| *3 months* | -0.89%* <br> \|T-stat\| = 0.87 | -1.15%* <br> \|T-stat\| = 1.07 | -0.63%* <br> \|T-stat\| = 0.54 | -1.05%* <br> \|T-stat\| = 0.86 | 0.58%* <br> \|T-stat\| = 0.48 | -2.76%**** <br> \|T-stat\| = 2.47 |
| *6 months* | 0.94%** <br> \|T-stat\| = 1.41 | 0.52%* <br> \|T-stat\| = 0.69 | **1.82%******** <br> \|T-stat\| = 2.47 | 0.16%* <br> \|T-stat\| = 0.20 | **1.23%**** <br> \|T-stat\| = 1.57 | -0.55%* <br> \|T-stat\| = 0.73 |
| *9 months* | 2.94%**** <br> \|T-stat\| = 6.05 | 2.36%**** <br> \|T-stat\| = 3.81 | **3.81%******** <br> \|T-stat\| = 7.25 | 2.43%**** <br> \|T-stat\| = 4.30 | **3.29%******** <br> \|T-stat\| = 5.53 | 1.51%**** <br> \|T-stat\| = 2.48 |
| *12 months* | 2.66%**** <br> \|T-stat\| = 6.67 | 2.00%**** <br> \|T-stat\| = 3.85 | **2.88%******** <br> \|T-stat\| = 6.93 | **3.04%******** <br> \|T-stat\| = 6.03 | **3.24%******** <br> \|T-stat\| = 6.42 | 1.80%**** <br> \|T-stat\| = 3.42 |

* Not statistically significant.
** Statistically significant at the 10% level.
*** Statistically significant at the 5% level.
**** Statistically significant at the 1% level.

# 7. DISCUSSION

In this chapter, the results on momentum strategies and attention based strategies that have been presented in chapter 5 will be discussed. First, the presence of momentum in the sample will be argued, and then, the influence of investor attention on the creation of a momentum effect will be debated.

As presented in Chapter 5, returns provided by all momentum strategies between 2004 and 2016 were negative. However, this does not mean that momentum does not exist during this time lapse. First, to be able to pursue the analysis with the same data, only stocks that satisfy conditions for a given week were taken into account. Among these conditions, the presence of a valid SVI was required for the week of the beginning of the holding period, as well as for the 8 prior weeks. Therefore, the number of valid stocks in the sample is rather low at the beginning of the analysis period. For example, roughly 100 firms formed the sample for the year 2004, which means that the momentum strategy consisted in 2 portfolios of around 10 stocks. Therefore, the average returns could be greatly influenced by variations of one single stock price. To conclude, results in the beginning period (i.e. from 2004 to 2006) should be taken into account very cautiously.

Then, many authors have argued that momentum is dependent on the market states (see Chui et al. (2000), Cooper et al. (2004), Hammami (2013) and Tai (2014)). In this vein, Table 2 and Appendix 1 demonstrate that the average momentum returns are mostly negative because of the years 2008 and 2009. As the date of the strategy is the beginning of the holding period, the holding period is therefore 3 months to one year before the date, and so, returns of 2008 and 2009 have formation periods between 2007 and mid-2009 (for the strategies that are significant). In other terms, returns that drive down returns are from strategies based on returns in the period of the financial crisis. Therefore, the absence of momentum from 2007 to 2009 is considered to be due to the financial crisis and a separation is made between this period and the years 2010 to 2016. Indeed, as the purpose of the study is not to discuss the influence of market states on momentum, it is more interesting to study the momentum where it is present.

Regarding the period between 2010 and 2016, all strategies are profitable and significant, except the 3/1/3 strategy. These results are comparable to the first study of Jegadeesh and Titman (1993) on momentum, which found momentum on the U.S. markets for all momentum strategies, except for the 3/0/3 strategy (which is almost the same as the 3/1/3 strategy here, as only one week is skipped instead of one month). Another similarity with their findings is that momentum returns come from the winner side of the portfolios.

The presence of momentum being proven in the composition of S&P500 index between 2010 and 2016, a second momentum strategy has been conducted with larger groups of losers and winners following the methodology of Chan (2003). This has been done in order to have more practical portfolios for the remaining of the study. As for the other momentum strategies, they all yield significant positive returns, except for the 3/1/3 strategy. Returns are obviously less important in term of amplitude, which is surely due to the less extreme returns during the formation periods, but this is not important for the study here.

The second part of the study examines the impact of investor attention on stock returns, and more importantly, on momentum. First, strategies based on investor attention, without taking into account the past returns, are demonstrated to be profitable. Indeed, stocks that receive less attention from investors perform consistently better than stocks that are actively searched on the Internet. This result differs from the results of Da et al. (2011), who found that stocks with high attention performed better than others. However, that does not especially contradict their results. Indeed, Da et al. (2011) showed that the overreaction phenomenon delivers superior returns for a very short term period (i.e. 2 weeks), while the present study focusses on medium term horizon. In this vein, researchers (e.g. Jegadeesh (1990)) have shown that medium term momentum was preceded by short term contrarian. Therefore, the overreaction phenomenon demonstrated by Da et al. (2011) could bring both superior returns in short term and poorer returns in medium term horizon. Another indication of the present study is that shorter holding period increases the returns of the investor attention based strategies and their significance. This is the opposite trend compared to the momentum strategy (for the given period lengths).

Then, the same analysis has been conducted inside the momentum portfolios of stocks. In other words, portfolios of low and high attention stocks have been formed inside the portfolios of losers, medium past returns and winners. Results show that there is not any profitable or significant attention-based strategy inside the medium returns portfolios. On the other side, the strategy yields a significant positive return of 0.99% per year on average inside the winner portfolios, and the average annual return reaches 1.20% inside the loser portfolios. This has several implications. First, the presence of differences in returns based on investor attention in the momentum portfolios but not in the medium returns portfolios indicates that momentum and investor attention are most probably linked together. Then, the larger profits in the loser portfolios reveal that the effect of attention could be greater for stocks with low past returns than for stocks with high past returns. The latter is also consistent with the results of Hong et al. (2000) who found that the effect of analyst coverage was stronger among losers than winners.

Finally, 5 momentum strategies have been constructed for each (formation and) holding period. These strategies always buy low or high attention stocks from the winner side and short low or high attention stocks from the losers, except for the MM strategy which buys medium attention winners and sells medium attention losers. Some important results can be observed from their average returns. As expected, the strategy LH (i.e. strategy that buys low attention winners and sells high attention losers) provides larger average returns than the initial momentum strategy for all strategies where momentum was positive and significant (i.e. 6, 9 and 12 months). This has important implications, as it suggests that the difference in investor attention causes (at least partly) momentum. Results are also consistent with Hong et al. (2000), who argue that the investor attention lowers the momentum profitability, and therefore, with the underreaction model of Hong and Stein (1999). However, there are some differences with the findings of Hong et al. (2000). While the investor attention decreases the profitability of momentum strategies among winner stocks, this is the opposite among losers. This finding is even more important considering that the effect of investor attention on the momentum profitability is greater for losers than for winners. In other words, high attention loser stocks contribute more to the momentum profitability than low attention winners. This is particularly the case for the holding period of 12 months, where even the HH strategy outperforms the normal momentum strategy, while the LL strategy still fails to beat the latter.

Even if the results are robust, some limitations have to be taken into account. First, stocks of S&P500 index composition have been chosen to analyze the causes of momentum. However, these stocks are mostly large stocks, which is a necessary condition to have enough valid data on the Google Trends application, but as Hong et al. (2000) have demonstrated, momentum is mostly present among small stocks. Therefore, results could be biased as the sample does not fully represent the markets. Then, data were collected from 2004 to 2016, and this period had to be shortened as the data availability issues confronted the study, and the financial crisis led to negative momentum. In this vein, it would be interesting to look further at the causes of the absence of momentum during bad times, and to conduct the same study when more data is available. Finally, the momentum strategy that buys and sells medium past returns stocks was not discussed. However, this strategy has consistently beaten the normal momentum strategy. In other words, if stocks with “unusual” investor attention are excluded from the momentum strategy, the returns increase. This has the opposite consequences as the previous findings. Indeed, this could indicate that the investor bias reduces the momentum profitability, and therefore that momentum should find an explanation elsewhere. However, if both findings are combined, the momentum profitability should be at least partly explained by the investor attention, while other explanations have to be looked for.

In next chapter, a conclusion will be drawn. The whole present study will therefore be summarized.

# 8. CONCLUSION

The final part of this thesis is dedicated to a conclusion that will summarize the present analysis. First, the research questions will be restated. Then, a brief description of the analysis will be presented. Finally, the findings and limits of the analysis will be exposed, and some suggestions for future researches will be suggested.

The goal of this thesis is to contribute to the momentum puzzle. More explicitly, the study focusses on the causes of momentum and their implication for the Efficient Market Hypothesis first stated by Fama (1970). To do so, an attempt was made in order to answer the following specific questions: "Is momentum driven by investor biases?" and "If so, does the profitability of momentum strategies come from the under- and/or overreaction of investors?". The final question is related to the implications for the EMH: "Is momentum consistent with the EMH or does it reject market efficiency?".

The first part of the empirical analysis consisted in selecting the right data. Two types of data were needed: the price of stocks, which was available thanks to Yahoo Finance, in order to form and compute returns of momentum strategies, and a measure for investor attention. The latter was already studied in the literature with a lot of different proxies, such as trading volume and press or analyst coverage. However, one single proxy was chosen because of its interesting characteristics: the Google Search Volume Index (SVI). Not only the SVI was freely available thanks to the Google Trends application, but also it was the unique direct measure of attention of individual investor already used by scientists. However, it has also disadvantages. The Google SVI is only available from 2004, which restricts the number of year of the analysis. Moreover, to obtain a valid SVI, big stocks had to be chosen to ensure that a sufficient number of searches on these stocks were made on the search engine each week. Therefore, the final sample consisted in all stocks of the S&P 500 index composition, and the time frame was from January 2004 to May 2016.

When the sample selection was made, the presence of momentum had to be checked before further examination. The profitability of four momentum strategies (i.e. 3/1/3, 6/1/6, 9/1/9, and 12/1/12) was analyzed and turned out to be negative for the period of the analysis. However, after excluding the period between 2004 and 2009 because of the lack of data at the beginning of the period and the influence of a bad market state later on (i.e. the financial crisis of 2007-2008), the profitability of all momentum strategies was shown to be positive and significant, except for the 3/1/3 strategy. A second type of more practical momentum strategies with broader amount of stocks was also proven to be positive and significant between 2010 and 2016, except for the 3/1/3 strategy. A last statement was made regarding the origin of the momentum profitability which comes from the winner side of the strategy.

Then, the presence of profitable zero cost strategies based on investor attention was displayed. This existence was considered as a sign of investor underreaction and overreaction on the S&P500. The significant outperformance of stocks that receive low attention from investors compared to stocks that receive high attention, was called the "investor attention effect". It was shown to be more effective in shorter holding periods. Lastly, this investor attention effect was compared to the momentum effect, and shown to be less intensive.

Finally, taking back the momentum strategies of the first part of the analysis, loser and winner portfolios were each divided into 3 sub portfolios based on investor attention. The last mentioned investor attention effect was observed inside the momentum portfolios (i.e. inside the loser and winner portfolios) but not inside the portfolios with stocks that have medium past returns. As for the investor attention portfolios, the portfolios double sorted on momentum and investor attention reach to deliver positive and significant returns, except when the holding period was the shortest (i.e. 3 months). More importantly, the strategy that consists in going long winner stocks with low investor attention and going short loser stock with high attention, outperformed the initial momentum strategy, which should indicate that momentum takes its sources from the investor initial underreaction regarding well-performing stocks, and the investor overreaction regarding the stocks with low past returns. Last of all, for the "normal" momentum strategy, the profitability came from the winner side.

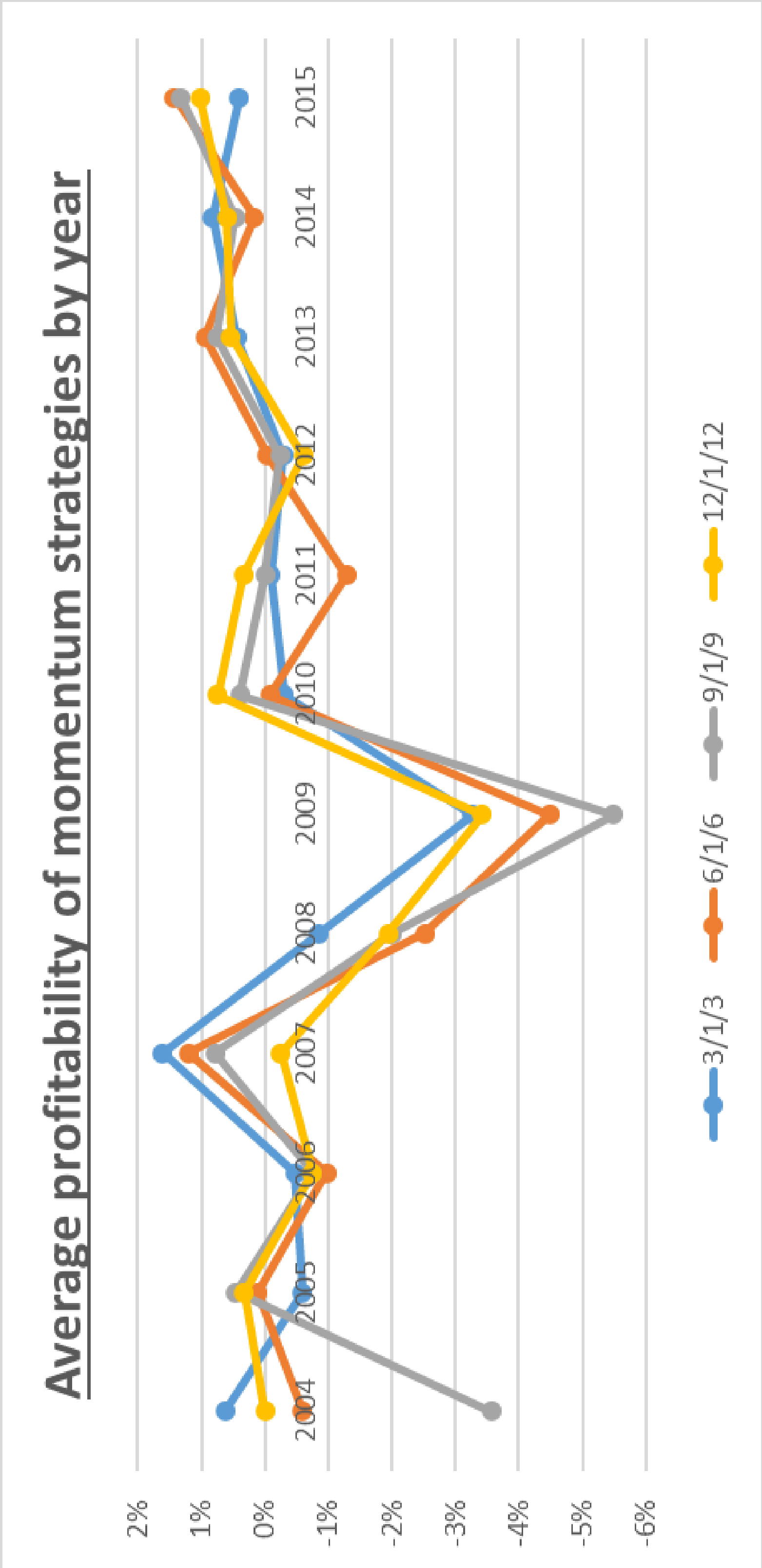
Although the findings are important and strong, some limitations need to be stated. First, the choice of a proxy for investor attention has restricted the sample of analysis to the stocks present in the S&P 500 index and limited the period of analysis to begin in 2004 and then 2010. Therefore, the final analysis takes into account only 5 years and 5 months of data, and therefore, the results could be biased by the market state at this time. Furthermore, the large stocks of S&P 500 are not the best possible choice for an analysis on momentum, as it has been shown that momentum is more present in small stocks. Finally, the last part of the study has revealed a second strategy that always performs better than the initial momentum strategy in addition to the low attention winners minus high attention loser strategy. Indeed, the strategy that only buys (sells) stocks with medium investor attention from the winner (loser) portfolios outperformed the normal momentum, which could indicate that abnormal investor attention actually decreases the profitability of momentum.

To summarize all these findings, the research questions will be answered. First, momentum has been shown to be driven by investor biases, as the investor attention effect increases the momentum and has been shown to be present only in extreme returns stocks. Then, the initial underreaction could explain momentum as low attention stocks increase the profitability of winners and high attention stocks decrease the profitability of losers (and so, of the momentum strategy). Finally, if momentum is caused by investor biases, it should reject the Efficient Market Hypothesis. However, it should be taken very cautiously, as investor biases could not explain the whole momentum phenomenon if medium attention stocks also increase the momentum profitability.

Further researches on the momentum puzzle should consider analyzing its causes thanks to the Google SVI with a broader sample, or with a new proxy for investor attention that provides more years of data. The combination of behavioral and risk-based explanations also appears to be a promising path of research.

# APPENDICES

## *Appendix 1 : Evolution of momentum profitability*




The graph gives the average returns per month of momentum strategies by year of the beginning of the holding period.

## *Appendix 2 : Decomposition of momentum returns*

**<u>Decomposition of average returns of momentum strategies from 2010 to 2016</u>**

(Returns are monthly expressed in %)

| Strategy | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P10-P1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **3/1/3** | *0.95* | *0.86* | *0.85* | *0.92* | *0.90* | *0.84* | *0.82* | *0.83* | *0.72* | *0.89* | *-0.06* |
| **6/1/6** | *0.75* | *0.73* | *0.78* | *0.91* | *0.88* | *0.88* | *0.83* | *0.80* | *0.75* | *0.94* | *0.20* |
| **9/1/9** | *0.64* | *0.69* | *0.88* | *0.93* | *0.94* | *0.92* | *0.92* | *0.90* | *0.95* | *1.03* | *0.41* |
| **12/1/12** | *0.65* | *0.74* | *0.86* | *0.91* | *0.92* | *0.93* | *0.93* | *0.90* | *0.94* | *1.02* | *0.39* |

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