Stocks in the spotlight

Driving investors' attention to a specific sector: An event study on the effect of fashion week on the fashion industry.

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Abstract

Investment decisions are not taken in a vacuum. Psychological and sociological aspects have been found to affect investors' decision making. Behavioural finance links findings from social sciences to stock market movements. Weather aspects, routine changes or important events have been found to significantly affect stock market returns. In this study, I investigate the effects of fashion week on stock market returns. Because I was able to identify the stocks "in the spotlight", I focused on uncovering significant effects in the relevant industry. Moreover, inspired by researches linking major sporting events to stock market returns, through their effect on individuals' mood, I investigate the effect of fashion week on the entire stock market. The main analysis is run on a pooled regression that includes data from London, Paris and Milan's stock exchanges. A city-by-city analysis is also performed. I use Generalized Least Squares to estimate the results. The variables used have been downloaded from DataStream. The dataset includes daily data, from 2003 to 2012 and comprise more than 15 million observations. No significant effect on fashion stocks' returns has been found, before, after or during fashion week events. Fashion week seems to have a statistically significant effect on the aggregated stock market, thirty days before and after the event. However these results can be misleading because of the effect of omitted variables and a large sample size. The inconclusiveness of the results, especially for the relevant industry, can be due to different factors, such as the limited reach and impact of the event.

Foreword

I would like to thank my supervisor, Steffen Andersen for the invaluable feedback and constant support while writing this thesis, Nicola for his patience and practical help, and my family, for being always close to me even if from far away.

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1. Introduction

1.1 Background

During the past decades we have seen an increasing number of researches that successfully linked the behaviour of the stock market to factors that affect the psychological aspects of human behaviour. From the alternation of the seasons (M. Kamstra et al. 2003), the amount of rainy days (D. Hirshleifer and T. Shumway, 2003) or available hours of sleep (M. Kamstra, L. Kramer and M. Levi, 2000), researchers have demonstrated that what affects our daily lives also affects the way we think and make financial decisions. Investors do not make investment decisions in a vacuum; what affects their daily lives also seems to affect trading behaviour. Trading is a social activity; investments attitude can change according to social interaction and noted events (R. Shiller, S. Fisher and B. Friedman, 1984). The use of behavioural factors in predicting market movements is strongly in contrast with the efficient market hypothesis (E. Fama, 1970). According to the efficient market hypothesis, available information is promptly reflected in market prices by the trading decisions of rational investors, which guarantee that prices reflect rational expectations (E. Fama, 1970). This theory has been the most widely accepted theory since recent years, when behavioural economics started questioning its main findings. When Kahneman and Tversky developed the prospect theory in 1979, they demonstrated that individuals systematically fail to correctly interpret probabilities and, as a consequence they make irrational decisions. Both lines of research, even if conflicting, have vastly contributed to the literature concerning asset pricing. Eugene Fama and Robert Shiller, two of the most influential researchers, one belonging to each line of thoughts, have been awarded the 2013 Nobel price in economics for their work in asset pricing. The recognition of both of their works underlines the importance of research investigating markets' behaviour. There is no final answer explaining how market reacts to information, instead it is a continuous discovery process where findings from different schools of thought contribute in uncovering how markets work.

It was also Kahneman (1973) who defined attention as "a scarce cognitive resource". His words have inspired a stream of studies aimed at understanding the consequences of investor's limited amount of attention. Grabbing the available span of investor's attention has also been the focus of marketing research. Marketing experts have been inventing new and more appealing ways to catch people's eyes. Today's mainstream role of advertising, as well as the large portions of budget allocated by firms to marketing purposes, are clear evidence that catching investor attention can be a winning and profitable strategy.

This study is an event study. I will investigate if hosting fashion week has a significant effect on the behaviour of the stock market and specifically on the stocks belonging to the relevant industry. The analysis is run on three different stock markets, specifically London, Paris and Milan. The study is run both between and within countries. Fama et al. (1969) was the first one to design an event study, analysing the effect of stocks split. The structural features of this analysis resemble the ones of Fama's paper; however, the event analysed in this paper does not convey any specific financial information about the companies participating in it. However, it is possible to argue that, for fashion companies, presenting their new collections is equivalent to launching new products; hence the event could convey future information about the company's financial results. Most important is the role of the media, and influencers, which take part in these events. The British Fashion Council, which organizes fashion week in London, estimated that the event brings together more than 5,000 journalists, photographers, radio, TV crews and buyers[1]. They affirm, in their website, that "the media coverage equals or exceeds most major news and international sport events". A good performance by a firm could lead to favourable reviews and positive endorsement by the media, which is key for obtaining good results and wide reach in this sector. Moreover, as mood is proven to be an important aspect influencing individuals' decisions (A. Edmans, D. Garcia and O. Norli, 2007; D. Hirshleifer and T. Shumway, 2003), the excitement created by fashion week events might affect the stock market behaviour, regardless of its advertising, attention-grabbing role.

1.2 Topic of issue

Two hypotheses will be tested in this study.

H1: Does the attention drawn by fashion week affect stocks belonging to the fashion industry?

[1] http://www.britishfashioncouncil.com/content/1143/London-Fashion-Week

H1 represents the main hypothesis to be tested and focus of my analysis. I argue that the attention drawn by fashion week affects the behaviour of the stock market, especially for the stocks belonging to the relevant sector, which in this study will be referred to as fashion stocks (FS). This could be the result of the media's attention and its advertising role during the events on the firms participating in fashion week. Attracting investors' attention has been proven to significantly affect investments' decisions (B. Barber and T. Odean, 2008; Z. Da, J. Engelberg and P. Gao, 2011). Individual's attention cannot be precisely estimated, but different measures have been used to proxy for it. The most common are excess return, abnormal trading volume and news coverage, which could be in the form of Google searches (Z. Da et al., 2011), number of mentions in a financial newspaper (B. Barber and T. Odean, 2008) or during the news on TV (J. Busse and T. Green, 2002). In this paper the main analysis will focus on the effects of fashion week on stock's returns. Trading volume will be considered in the robustness checks. The two chosen measures can be also considered to be measures for news reach and impact (B. Barber and T. Odean, 2008).

H2: Does the excitement and positive mood created by fashion week affect the entire stock market?

With the second hypothesis I argue that mood, in this case the excitement and positive sentiment created by fashion week events, could affect stock returns and trading volume. This hypothesis is inspired by the work of Edmans et al. (2007), which found investors' sentiment to significantly affect stock markets through World Cup games results. Regardless of the advertising role played by fashion week, the entire stock market could be affected by the positive mood and enthusiasm created by the event. Both hypotheses are strictly against the efficient market hypothesis.

1.3 Contribution

This paper represents a contribution to the behavioural finance literature, as an addition to the existing studies on investors' attention and its effect on the stock market. The most successful application of event studies has been on corporate finance events such as estimating the effect of financial decisions by firms (C. MacKinlay, 1997). This paper however considers a different point of view, by using an event that is not financial in its nature. Nevertheless, the event chosen carries information about the stock's financial assets, as fashion week can be considered as a way for fashion stocks to present their new product line. No study has ever investigated on the possible effect of fashion week on the relevant industry or on the aggregate stock market.

Most importantly, because it is possible to distinguish the stocks on which attention is drawn to, since fashion week is intentionally organized for fashion stocks only, I am able to investigate on the effect of attention on the specific industry in the spot light. Other papers, like Hirshleifer and Shumway (2003) or Edmans et al. (2007), consider nationwide effects and therefore, they have to measure the mean aggregate effect of the event on the entire stock market.

1.4 Outline

The paper is organized as follows. The next section will give an overview of the relevant sector and the event analysed. Section 3 will provide a comprehensive review of the literature supporting this study. Section 4 will explain the statistical methodology and the model applied. In section 5 I will present the main findings of the analysis and in section 6 I will run different robustness checks. Section 7 will include improvements suggestions and ideas for further research. Section 8 concludes.

2. Fashion week and the fashion industry

2.1 Overview of the event

Fashion Week (FW) takes place twice a year, once to promote the fall/winter collection and once to promote the spring/summer collection. Each of the two events occurs during the same period every year, for each of the cities considered. The cities host the event consecutively, starting from London, then moving to Milan and finally to Paris. Thanks to these events, which attract an incredible number of players of the sector, each country can promote its own designers and products. Each FW can be considered as a collection of single events, including on and off schedule catwalks, presentations and salon shows. For this year's FW in London, more than 130 events are on schedule. The British Fashion Council, which every year organizes London FW, estimated that over £100 million in orders are placed during each FW season and that the event attracts more media coverage than important international sport events[2]. The Fédération Française de la Couture du Prêt-à-Porter des Couturiers et des Créateurs de Mode, in charge of Paris FW, invites every year 800 buyers, 2,000 journalists and 400 photographers, to ensure global coverage of the event and a complete reach on every media platform[3]. In Milan, the organizing body, the Camera Nazionale della Moda Italiana, estimated the participation of 15,000 buyers and 2,500 journalists for each FW[4].

The organising bodies were founded to support the fashion industry in the respective countries. They organize different events and campaigns during the year, but fashion week is the biggest and highly recognized event. The pure aim of this event is to attract attention to the stocks of the industry, and ensure that the new collections are widely advertised and endorsed. The statistics discussed above are clear evidence of the important impact of this event on the fashion industry.

[2] http://www.britishfashioncouncil.com/content/1143/London-Fashion-Week
[3] http://www.modeaparis.com/en/federation/Missions-actions-goals
[4] http://www.cameramoda.it/it/associazione/cosa-e-la-cnmi/

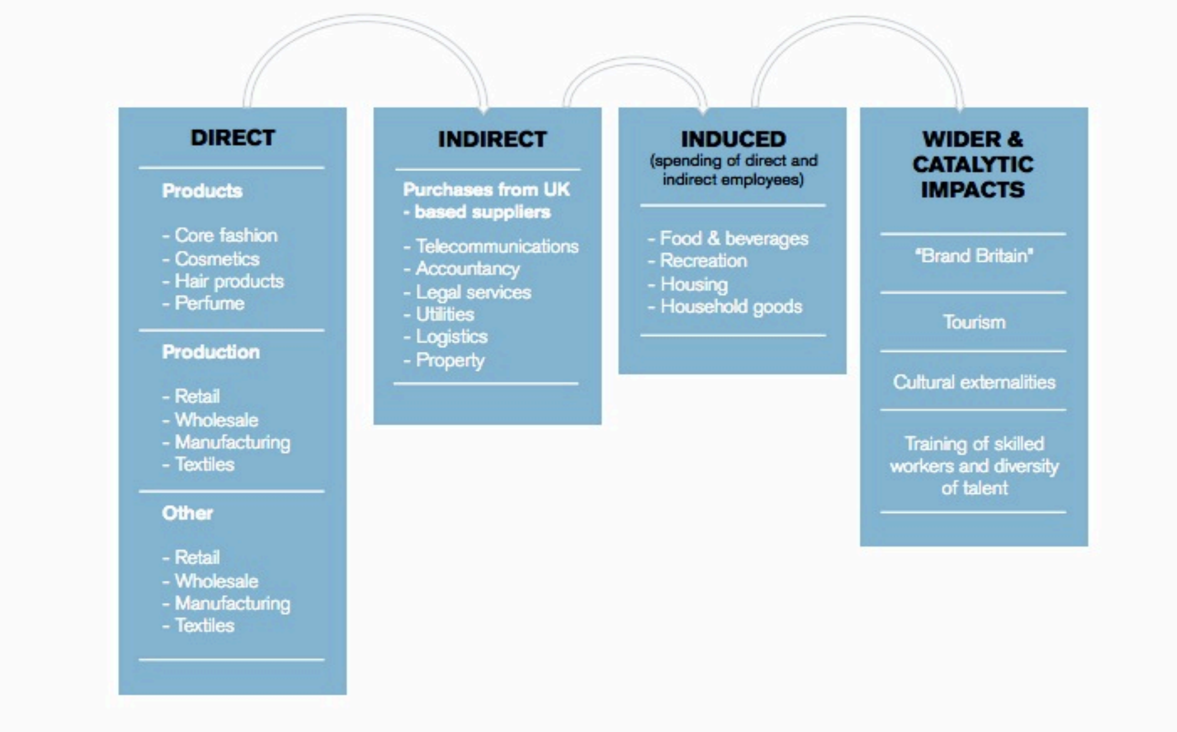
2.2 The fashion industry

Each of the cities considered, and the countries they represent, are known to be major players in the fashion industry, because of past tradition, prestige and popularity. The statistics presented below have been collected from the following reports: the "Value of Fashion Report" published by the British Fashion Council[5], the "Fashion Economic Trends" published by the Camera Nazionale della Moda Italiana[6] and the "Economic Importance of Creative French Fashion Companies" study published by the Fédération Française de la Couture du Prêt-à-Porter des Couturiers et des Créateurs de Mode[7].

The fashion industry has a wide economic impact, affecting different sectors and levels of the value chain. From farmers to plant growers and mineral companies, these are only some of the industry's needed suppliers. The value chain also includes manufacturing, wholesale, retailers, media and marketing experts. In Italy, in 2011, the fashion industry contributed to the creation of 654 thousand jobs. As stated in the Value of Fashion Report, in 2009, the fashion industry contributed £20.9 billion to the UK economy, equal to 1.7% of total GDP. In the same report, the contribution of the fashion industry to the country's economy is analysed in depth, considering direct, indirect, induced and catalytic effects, which are summarised in the picture below.

[5] http://www.britishfashioncouncil.com/content.aspx?CategoryID=1745
[6] http://www.cameramoda.it/it/associazione/documenti-istituzionali-pubblici/
[7] http://www.modeaparis.com/IMG/ecoFFC07-13VA.pdf

Figure 1: The economic impact of the UK fashion industry in the UK



Source: British Fashion Council. Value of Fashion Report

As documented above, the impact of the fashion industry in the countries analysed is wide and relatively strong. However, fashion stocks represent only a very small fraction of the overall stock market. Therefore, despite the important role played by the fashion industry in the countries considered, fashion stocks fluctuations should not have a strong impact on the aggregate stock market. Considering the cities included in the analysis, the Milan stock exchange is the one that has the largest percentage of firms belonging to the fashion industry, which is approximately equal to 6%. In London the percentage is considerately lower, equal to 1.4%.

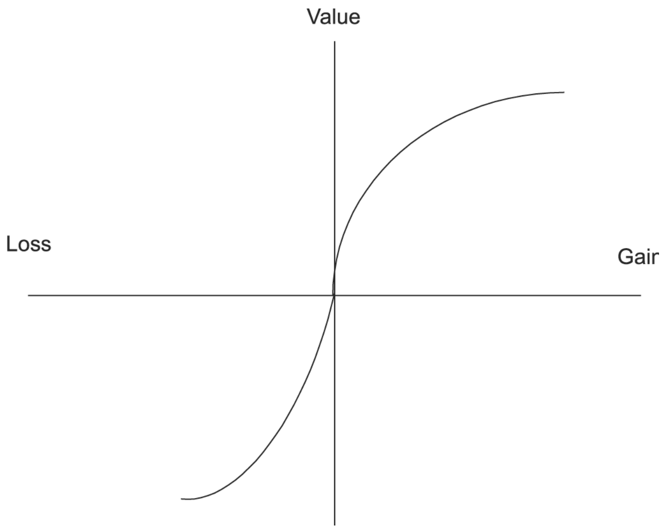
3. Theory

3.1 The Behavioural Finance Literature

Behavioural Finance originated from the collaboration between finance and other social sciences (R. Shiller, 2003). When scientist recognized that the efficient market theory failed to explain a number of anomalies in the stock market, the point of view of other social sciences, as psychology and sociology, began to be used to describe irrational market trends. Before the 90's, when behavioural finance theories became widely accepted, the Efficient Market Theory was the prominent theory. The efficient market theory is built on the belief that market participants are rational. Two are the main assumptions on which it stands, namely that: investors make decisions following the rules of Utility Theory and react to new information by updating their beliefs accordingly (N. Barberis and R. Thaler, 2003). The theory of No Arbitrage derives from these assumptions. Market efficiency tests can be divided in three different forms, each one concerned with the availability of different kinds of information. The *weak* form of efficiency considers historical prices, the *semi-strong* considers publicly available information and the *strong* form considers monopolistic information (E. Fama, 1970). Fama et al (1969), was the first one to run an event study investigating on the adjustment of prices to new information, by considering the effect of stock splits. This is an example of a test on semi-strong market efficiency. Researchers supporting the Efficiency Theory, in their tests, argue that new information becomes rapidly reflected in the price, as the rational investors immediately and correctly react to it. Even assuming that there are irrational investors operating in the market, the actions of rational investors would guarantee that the prices are always as close as possible to their fundamental values, correcting for every possible deviation.

Behavioural finance recognizes that investors do not always act rationally and that their behaviour can explain prices' deviations from fundamental values (N. Barberis and R. Thaler, 2003). In their paper, Kahneman and Tversky in 1979 developed an alternative theory to explain investors' decision making, known as Prospect Theory. They show that individuals do not always act rationally when making decisions. On the contrary, they systematically fail to interpret probabilities and as a consequence they misestimate risk and future outcomes. One of the most revolutionising ideas discussed in the paper is the shift of the reference point according to the individual's standpoint. The reference point becomes key in understanding how the investor will interpret market signals and react to it. The shape of Prospect Theory's value function also represented a drastic change from the traditional utility Theory's view. Prospect Theory value function is steeper for losses, to represent investors' loss aversion. For instance, bearing a loss will (negatively) affect the investor, more strongly than a gain of the same size. Moreover, a loss would reposition the investor's reference point to the negative side of the value function, creating a different prospective for future investment decisions.

Figure 2: Prospect Theory value function



Source: D. Kahneman and A. Tversky (1979)

Acknowledging that investors can act irrationally inspired researchers to investigate on the possible psychological and sociological aspects that affect investors' reference point and therefore decisions. An extensive literature refers directly to the Prospect Theory value function and uses it to explain investors' decision making. For example, recognized behavioural biases are the Sunk Cost Effect (H. Arkes and C. Blumer, 1985) and the Endowment Effect (J. Knetsch, 1989); both related to the loss aversion characteristic of the value function. As the field of research became more popular, researchers started to look for different sources of irrationality. What affects our daily actions and moods can in turn affect the way we make decisions. Sources of irrationality have been found on the most different grounds. Besides the personal aspects that affect our lives, irrationality can also be driven by external factors, like meteorological aspects, the political environment or fashionable trends. Those are aspects that affect a large number of individuals at the same time, and therefore can have a significant aggregate effect on the markets. I will focus on the literature concerning investors' lack of attention and investor's sentiment, to support my research and hypothesis.

3.2 Investor's attention

Acquiring information is costly. As much as we would like to be completely informed when taking decisions, gathering the needed information requires time and effort, which unfortunately are limited. H. Simon (1955) defines individuals as "a choosing organism of limited knowledge and ability". In his paper he argues that when individuals have to make a choice they simplify the real world, because of limited information, time and cognitive limitations. He defines this process as Bounded Rationality, which became an important line of research in behavioural finance. Because attention is limited, discovering what caches investors' attention is important in understanding investment decisions. Barber and Odean (2008) investigate on the effect of investors' lack of attention on stocks picking. They argue that, because investors cannot follow every stock in the stock market, they will trade the stocks that catch their attention. Because there is no direct measure of attention, they focus on three proxies, namely excess returns, abnormal trading volume and news coverage. They use excess returns and volume to measure the reach and impact of news. More precisely, they assume that abnormal trading volume is directly linked to more people paying attention to the stock, and also that the reason driving the prices higher must have also caught investors' attention. Their results show that investors are more likely to buy attention-grabbing stocks. Attention plays an important role in reducing the choice set. When the choice set is reduced, personal preferences are considered (B. Barber and T. Odean, 2008). In his previous paper, Odean (1999) recognized that investors are influenced by outside sources when making decisions, to overcome the difficulty of evaluating the large number of securities available. An extensive literature aimed at discovering important attention-grabbing factors followed his discovery. Media coverage has been proven to be an influential variable influencing attention and therefore choices. Different kind of available news and media sources of distribution have been analysed. Mitchell and Mulherin (1994), study the effect of Down Jones announcements. They significantly prove that public information, which in this case is represented by the number of news stories reported by the Down Jones, has an effect on market activity. Busse and Green (2001) show that being mentioned in the CNBC show Morning Call has a simultaneous effect on the stock' s returns. More recently, following the same line of research, Da, Engelberg and Gao (2011) analyse Google searches patterns. However, differently from the other papers mentioned, this paper considers a measure of revealed attention. It is defined as such because investors actively look for specific information, revealing which are the stocks that are attracting their attention. According to their results, higher search volume corresponds to higher stock prices in the following two weeks.

"Advertising is designed to attract attention" (D. Lou, 2011). Today, every firm is engaging in advertising activities. Marketing experts are asked to develop new and more appealing ways to sponsor the image of companies. As we live in a profit base economy, firms investing in advertising campaign believe that this is a profitable strategy to follow. Advertising is often non-informative and non-binding, but it can be used as a communication channel to both present and future investors (F. Fehle, S. Tsyplakov and V. Zdorovtsov, 2005). It has been proven that the effect of advertising on attention has an impact on the stocks' return and volume. Grullon, Kanatas and Weston (2004), show that advertising efforts are directly correlated with the number of investors investing in a company. They explain this result by assuming that advertising increases investors' familiarity with the stock and therefore, they are more likely to trade it. T. Chemmanur and A. Yan (2009) document the effect of advertising on firms stocks' prices. They find that advertising increases attention toward the stock; by increasing its visibility, and that consequently attention is associated with a larger stock return. However the positive effect on the price is limited to the short term. D. Lou (2011) documents the same results and shows that firms invest in advertising before insiders' sales take place, to profit from the short-term increase in price. This proves that firms clearly understand the effects of advertising. In contrast with the Efficiency Theory, advertising has an effect on price also when it is pre-announced (F. Fehle, S. Tsyplakov and V. Zdorovtsov, 2005). Fehle et al. (2005) document the effect of Super Bowl commercials and report a positive effect on prices for the companies that are clearly identified in the ad. Social interaction is also an important driver of investors' attention. Because of limited attention, investors pay more attention to topics reinforced by conversation (R. Shiller, 1999). Investors' opinions are not objective and therefore, the process by which they make decisions can be especially social (R. Shiller, S. Fisher and B. Friedman, 1984). Shiller and Pound (1989) findings show that investors buying decisions are affected by interpersonal communication; specifically, investors buy stocks that have been topic of conversation. Besides the attention effect, advertising is also used to create a positive mood about the product and the firm (F. Fehle, S. Tsyplakov and V. Zdorovtsov, 2005). Investors' sentiment is another important aspect that behavioural finance researches recognize as a driver of investors decision making. An overview of the literature focusing on investors' sentiment is presented below.

3.2 Investors' sentiment

Hirshleifer and Shumway (2003), when studying the effect of sunshine on investors' behaviour, suggested, "to view feelings as influencing preferences". They demonstrate that sunshine is highly significant correlated with daily stock returns, and they explain this evidence thanks to the psychological evidence that relates sunshine to good mood. The focus on environmental factors and their effects on individuals is an important slice of the literature concerning investor's sentiment. Environmental factor affect a large portion of investors at the same time and, if they all react unanimously, their aggregate reactions can visibly affect the stock market. M. Kamstra, L. Kramer and M. Levi (2003), relate the Seasonal Affective Disorder (SAD) to stock market movements. The SAD is a condition, linked to depression, which affects many people during winter months, when the hours of daylight are reduced. Their results show that the SAD condition does significantly affect stock markets around the world. Their argument is supported by the psychological literature that relates sunlight to mood and mood to risk taking. Always related to daylight is the finding by the same authors on the effect of the daylight saving clock shift on the stock market. Sleep desynchronosis caused by the change in available hours of sleep, which is compared to a jet lag, increases individual's anxiety and in turn investors prefer safer investments (M. Kamstra, L. Kramer and M. Levi, 2000). As this example demonstrates, factors that affect our physiological needs, like lack of sleep, also affect our behaviour. Loewenstein (1996) analyses different "visceral factors" that affect individuals' decision-making, between others: hunger, thirst and physical pain. He demonstrates that experiencing these "visceral factors" changes individuals' perception and preferences.

Important events can also alter the mood of market participants. Edmans, Garcia and Norli (2007) document a strong negative stock market reaction to losses by national football teams. In their analysis they focus on important games in the World Cup, namely the ones in the direct elimination stages. Their paper is an example of an event study that is not financial in its nature but, by affecting investors' moods, has an impact on the stock market. Edmans et al. (2007) define the required characteristics that an event, should have in order to create a significant reaction in the stock market. From their paper:

- The event must affect mood in an unambiguous way
- A large part of the population must be exposed to the event
- The effect should be correlated between individuals

Inspired by Edmans et al. paper, Kaplansky and Levy (2008) prove that it is possible to exploit the reaction of the stock market to games results. The aggregate effect of games results in fact, does not depend on the singular results, but is found to be always negative. Knowing the reaction of the stock market beforehand allows investors to profit from it.

Altering investors' mood in regard to a product or firm is often the focus of advertising efforts. Machleit et al. (1993) argue that advertising can change individuals' attitudes and build a more favourable view of the product and company. These positive feelings can lead to a more optimistic valuation of the company fundamentals, making it more attractive for investors (F. Fehle, S. Tsyplakov and V. Zdorovtsov, 2005).

4. Methodology and Data

4.1 Sample construction

The dataset used in this study was constructed by aggregating the data of three different stock markets: London, Paris and Milan. The data were downloaded from DataStream for every security, daily, from January 2003 to December 2012. The sample is a panel dataset. There are different advantages in using a panel. From Hirshleifer and Shumway paper (2003):

- It helps define if the hypothesized effect is widespread.
- Allows the comparison of different subsequent years. This information can be used to test if the effect of the event is persistent through time. This would be drastically against the efficient market hypothesis, which argues that rational investors, by learning how to react to an event, would ensure that any effect would disappear.
- Increases the power to detect an effect. Because of the high variability of returns, using a large number of markets increases the power of the analysis.

The stocks, which will be defined as fashion stocks (FS) throughout the analysis, are recognized as the ones belonging to the Personal Good category in DataStream. According to the Dow Jones Industry Classification Benchmark[8] (ICB), the Personal Goods sector includes the following subsectors: clothing and accessories, footwear and personal products. The fashion companies participating in fashion week all belong to this sector. Because of stocks being suspended or leaving the stock market, the total amount of observations per year might vary, making the panel unbalanced. In total, there are more than 15 million observations, which are divided between the stock markets and industry of interest as follows:

[8] http://www.icbenchmark.com/ICBDocs/Structure_Defs_English.pdf

Table 1: Sample composition

	Stock Exchange		Fashion Industry	
	Observations	Firms	Observations	Firms
London	9,966,380	3,821	140,886	55
Paris	4,059,604	1,557	117,405	46
Milan	1,380,161	530	91,315	36
Total	15,406,145	5,908	349,606	137

The table above gives an overview of the sample composition. Almost 6,000 companies are part of the sample. The observations belonging to the London stock exchange constitute 65% of the entire sample. The portion of the sample belonging to the fashion industry is also described, as it is the focus of the analysis. Fashion stocks represent only a small fraction of the respective stock exchanges. Only 2.3% of the firms in the dataset belong to the fashion industry. The Milan stock exchange has the largest proportion of stocks belonging to the fashion industry, equal to 6.7%. Whether in London the proportion is only 1.4%.

4.2 Variables of interest

From DataStream, I downloaded the price and volume for each individual security. The data are collected with a daily frequency, from Monday to Friday. The price represents the closing price, while volume is defined as the number of shares trader on that particular day. The price has been used to calculate each individual security return, which is equal to the daily percentage change in price. Because of the difference in currencies, two different risk free rates are included. The risk free rate applied to London is the 3-month UK Treasury bill rate. For Paris and Milan, the 3-month EURIBOR rate is used.

To investigate the effects of fashion week events in the stock market, I collected the dates on which fashion week took place, from 2003 to 2012, in each of the cities analysed. This information was found on the websites of the organizing bodies of the event and, for more distant years, in newspapers articles. Stocks belonging to the fashion industry are also recognized, in order to measure the effect of fashion week on the sector of interest.

When analysing the return of a security, the observed return has to be compared to a measure of expected return. The main concern of event studies is to measure the abnormal return of a security around the event date (S. Brown and J. Warner, 1980). Three are the most utilized benchmarks for returns in event studies, namely the Mean Adjusted Returns, the Market Adjusted Returns and the Market and Risk Adjusted Returns (derived from the latter). From their paper, the three different return measures are defined as follows:

- The Mean Adjusted Return model:

$$E(R_i) = K_i$$

Ex-ante security returns are equal to a constant (K_i), which can vary for each individual security. Using this model the abnormal return is equal to the difference between the observed returns and the constant. This model assumes constant returns.

- The Market Adjusted Return Model:

$$E(R_{it}) = E(R_{mt})$$

This model relates individual security returns (R_{it}) to the market return (R_{mt}). Because the market portfolio is a linear combination of all the securities in the market, the expected return of the security should equal the expected return of the market. The abnormal return is therefore the difference between the security return and the market return.

- The Market and Risk Adjusted Return Model:

$$E(R_{it}) = E(K_{it}) + \varepsilon_{it}$$

The model considers both the market return and the systematic risk for each security. Different variation of the Capital Asset Pricing Model can be used to measure the expected market return. (K_{it}) represents the expected return calculated by the chosen model. ε_{it} is the unknown, abnormal component.

After an in depth analysis Brown and Warner (1980) conclude that, especially for event studies, the market model and the market and risk adjusted return model both lead to superior results compared to the mean return model. Analysing their results, the market and risk adjusted return model is the method that reduces the most the occurrence of type 1 and 2 errors in hypothesis testing. However the reported difference in efficiency between the two market models is small. E. Mackinlay (1997) studies the different methodologies used for event studies and also compares the two adjusted returns model. He also supports the use of the market model, as it reduces the variability of the abnormal returns. Following their results, I choose to use the market adjusted return model as a benchmark when testing for abnormal security return. The measure of market return chosen is the S&P500 composite index. The value of the index was downloaded from DataStream, with daily frequency. The daily rate of return was calculated by estimating its daily change in value. I decided to use a US index for consistency reasons. There are different indices that specifically represent the different stock markets analysed, respectively the FTSE (London) the CAC (Paris) and the FTSE MIB (Milan). However I considered it important to use the same index for each stock market in order to get consistent results and make more reliable country-by-country comparisons. I also considered using an index based on different European countries. However, each European country's economy is strongly affected by nation specific circumstances and the inclusion of companies from different countries can comprise specific countries' disturbances. In addition, because countries are represented in the index in different proportions, the effects of these disturbances might be unbalanced. Using the S&P500, the three stock exchanges considered are affected by the same economic shocks. Moreover, European and American indexes are highly correlated. I believe that the S&P 500 index is a satisfying measure for the general market condition and can be reliably used on each of the three stock markets.

4.3 The event study methodology

The event study methodology is the standard method used to measure securities reaction to new information or events (J. Binder, 1998). Following Binder (1998), events studies are a joint test of two hypotheses:

- A test of the Efficient Market Hypothesis
- A test to measure the impact of new publicly available information

Fama, Fisher, Jensen and Roll (FFJR)(1969) paper introduced the event study methodology. The methodology they developed is still widely used and is summarized below. The prime concern of their research was to analyse the response of the stock market to new information. The event examined is the announcement of stock splits. They define the month on which the split takes place as month zero. They then consider the effect on the day of the announcement and on the month previous and after the split. Differently from the study conducted in this paper, they used monthly returns. To test for the existence of a significant mean abnormal return around the split date, they estimate the following market model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \mu_{it}$$

(Equation 1)

Where R_{it} is the return for security *i*, R_{mt} is the market return and μ_{it} is the residual for security *i.* The residual calculated from the market model above is the measure used to estimate individual securities' abnormal returns. As in FFJR paper, I will also identify the time when the event takes place as time *t=o* and consider 30 days before and after the event to investigate the effects of fashion week on the stock market. To do so, I created two different variables, which are defined as Pre_Event and Post_Event, for each event. Because fashion week events take place consecutively, Pre and Post event dates overlap between the cities. When event dates overlap, the covariance of abnormal returns is different from zero and this can create inference issues, since the returns are assumed to be identically and independently distributed (i.i.d.) by the above model (C. MacKinlay, 1997).

Another model used to estimate abnormal returns in event studies is the Multivariate Regression Model (MVRM), which was first developed by Gibbons (1980) and subsequently elaborated and applied to event studies by Binder (1985, 1998). In his paper, J. Binder (1985) discusses three limitations of the FFJR methodology:

- The abnormal returns, measured by the residuals, are likely to differ across securities. Contrary to the assumption made by FFJR (1969) of independent and identically distributed returns.
- The residual variance differs across firms.
- The assumption of independence for the residuals will not hold if the event occurs during the same calendar time period for more firms in the same industry.

The model is built on the following specification, from Binder (1998):

$$R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i D_t + \mu_{it}$$

(Equation 2)

Where R_{it} is equal to the security *i* return at time *t*, R_{mt} is equal to the market return and D_t is a dummy variable that is equal to one when the event takes place. γ_i is the measure of abnormal return for security *i* during the event. In this model, the abnormal return in the market model is parameterized (J. Binder, 1998). I will use this model specification as it allows me to include an event-dummy variable, which will be equal to one for each day on which fashion week takes place. Moreover, as explained by Mackinlay (1997), the multivariate approach is a suitable solution to handle event clustering. This method allows individual abnormal returns to differ across securities, and it can be estimated with different methods that control for heteroskedasticity and between and within panel autocorrelation, which are common issues when analysing panel data (Binder, 1985). Relaxing the assumption that residuals are independent and identically distributed increases the power of hypothesis testing (J. Binder, 1998).

The following regression will be estimated:

$$R_{it} = \alpha_i + \beta_m R_{mt} + \gamma_i FW_t + \gamma_i Pre\_FW_t + \gamma_i Post\_FW_t + \beta_i (FW * FS_{it}) + \beta_i (Pre\_FW_t * FS_{it}) + \beta_i (Post\_FW_t * FS_{it}) + \mu_{it}$$

(Equation 3)

The model represents a market model as it relates the return of an individual security to the market return. R_{it} represents the return of individual security *i* at time *t.* R_{mt} is the measure of market return, which is equal to the rate of return of the S&P500 composite index. The market return is considered to be the expected return for each security. FW is a dummy variable that takes the value of one for each day on which fashion week takes place. Pre and Post FW dummy variables are also included to investigate if the event significantly affects the stock market before and after it occurs. Because fashion week is strongly publicized, market expectations could be reflected in the security price before the event. Similarly, the stock market could be affected after the event, when investors have had access to the companies' new products. $(FW * FS_{it})$ it's an interaction term used to separate the effect of fashion week on the stocks belonging to the fashion industry. It will be equal to one when fashion week takes place and the stocks belong to the fashion industry. Thanks to the inclusion of this variable I can estimate the impact of attention precisely on the recipient, namely fashion stocks. Following the same reasoning, I will create two additional interaction terms, $(Pre\_FW_t * FS_{it})\ and\ (Post\_FW_t * FS_{it})$ to account for possible pre and post event effects on fashion stocks. I will do this by interacting the Pre and Post event dummies with the dummy accounting for the fashion industry category. Because volume, as explained above, is also a variable widely recognized to be a proxy for attention, the same regression will be run using trading volume as the independent variable in the robustness checks.

Different variables will be included when running robustness checks, in order to control for other omitted variables affecting stocks returns. I will include dummies of the different days of the week to account for a possible weekend effect, which was first documented by Lakonishok and Maberly (1990). Seasonal effects will also be controlled for, by adding individual dummies for each month, supported by the work of Kamstra, Kramer and Levi (2003).

The analysis structure resembles the one implemented by Hirshleifer and Shumway (2003), but with important differences. I decided to follow the structure of their study because of the similarities between their dataset and the one used in this paper. They also utilize a panel dataset, which was constructed by pooling together the data from different cities. Moreover, as in their analysis, I want to analyse both the effect of the event on the pooled dataset and on the singular cities. I will approach the analysis as follows: I will estimate the above regression using Ordinary Leas Squares (OLS) estimates. By doing so, I assume that the residuals are independent and identically distributed (i.i.d.). Hirshleifer and Shumway (2003), do the same, but consider this assumption "naive" and subsequently run a different regression to relax it. I will run the same regression using generalized least squares (GLS). As suggested by J. Binder (1985), GLS estimates the individual return equations jointly allowing the individual returns to differ across firms, therefore is a better fit for panel data regression.

Hirshleifer and Shumway (2003) investigated on the effect of sunshine on the aggregate stock market. Because I can clearly identify the stocks belonging to the fashion industry, I can separate the effect of the event and only consider the direct subject of attention. This allows me to estimate a more direct measure of the effect of attention. Therefore, the main aim of this study will be to analyse the effect of fashion week on the relevant industry, by focusing on the effect on fashion stocks.

4.4 Econometrical considerations

As explained above, I will use a multivariate equation model, estimated using GLS. The MVRM allows individual abnormal returns to differ across securities (J. Binder, 1998). Abnormal returns in panel dataset have been found to be cross-sectionally correlated and to have different variances across firms (J. Binder 1998). By assuming that the variance and covariances between the regressions are non-zero, this method includes possible contemporaneous correlation of the disturbances in the estimation results (J. Binder, 1985). This corrects for the cross-correlation problem of the abnormal returns.

I applied the modified Wald test for groupwise heteroskedasticity to test for the presence of heteroskedasticity. The table below shows the result.

Table 2: Modified Wald for groupwise heteroskedasticity test

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model
H0: sigma(i)^2 = sigma^2 for all i
chi2 (5902) = 1.8e+31 Prob>chi2 = 0.0000

Because P=0 I can strongly reject the null hypothesis of homoscedasticity. To correct for heteroskedasticity, namely the fact that residuals could have different variances, I will estimate the GLS regression using robust standard errors.

Another possible issue is serial correlation. Serial correlation of the error term can cause standard errors to be biased and results less efficient (D. Drukker, 2003). I used the Wooldridge test to investigate if the samples residuals are serially correlated. The test is run on the variables included in the regression presented above (Equation 3). The results of the test are presented below:

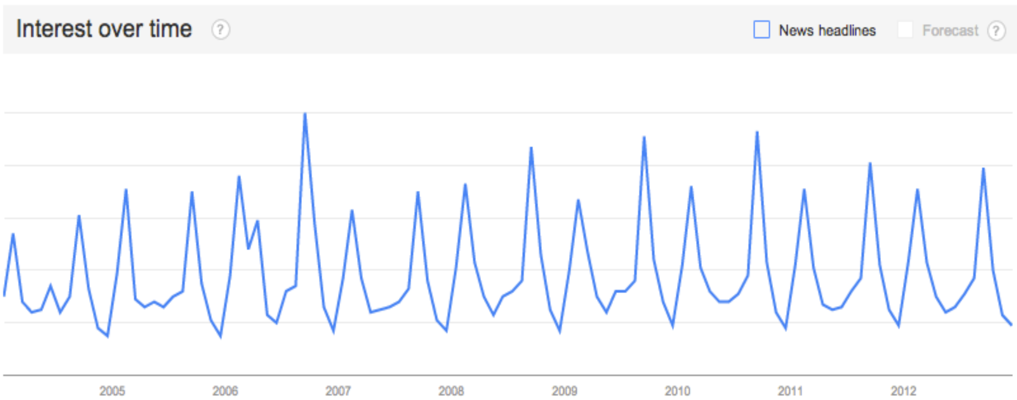
Table 3: *Wooldridge test for autocorrelation*

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
F(1, 5891) = 0.315 Prob > F = 0.5744

Because P = 0.57 I fail to reject the null hypothesis that there is no first order autocorrelation. Therefore, I will not need to correct for autocorrelation when estimating the regression.

Fashion Week is organized with the purpose of attracting attention to the fashion industry. As mentioned above, the organizing bodies ensure massive coverage of the event, by inviting journalist belonging to different media, buyers, endorsers and celebrities. The British fashion Council, which organizes London fashion week, estimated that during last year fashion week more than £100 million in orders were placed[9]. The statistics released by the organizing bodies, which have been previously discussed, are evidence of the considerable amount of attention that is directed to the fashion industry during fashion week. The extent of the reach of the event is also evident by looking at the distribution of Google searches volume over time. Da, Engelberg and Gao (2011), consider Google searches as a direct measure of attention since investors actively look for the wanted information. The table below shows the distribution of Google searches volume for the term "fashion week", during the years 2004 to 2012. The peek in interest occurs every year in September and February, exactly when fashion week takes place. The distribution presented below is further evidence that during fashion week there is an active search for information regarding the events. Individuals seem to be actively interested in fashion week events.

Figure 3: *Google search volume for the word "fashion week"*



Source: http://www.google.com/trends/

[9] http://www.britishfashioncouncil.com/content/1143/London-Fashion-Week

5.1.1 Pooled Regression

In this section I will analyse the results obtained by running Equation 3 on the pooled sample. The pooled sample includes daily data from the three different stock exchanges, for 10 years and contains a total of 15 million observations. The regression is estimated both using OLS and GLS with robust standard errors.

The table below compares the estimated results for the two model specifications.

Table 4: *Pooled regression estimation results*

	OLS	GLS
returnSP	0.122***	0.122***
	(8.38)	(26.79)
FW	-0.000491	-0.000486
	(-0.71)	(-1.36)
PreEvent	0.000485	0.000472*
	(1.02)	(2.00)
PostEvent	0.000469	0.000454*
	(0.99)	(2.20)
FW_FS	-0.0226***	-0.0226
	(-4.90)	(-1.01)
Pre_FS	0.0298***	0.0332
	(11.51)	(0.99)
Post_FS	0.00121	0.00611
	(0.47)	(0.98)
_cons	0.000307	0.00188
	(1.06)	(1.24)
* p<0.05, ** p<0.01, *** p<0.001		

The sizes of the estimated coefficients are similar across the two regressions. However, the standard error estimates differ strongly, as expected. Accounting for heteroskedasticity and cross-correlation of the residuals, using GLS, results in a more accurate estimate of the standard errors and therefore more reliable hypothesis testing (J. Binder, 1998). Therefore, in the following analysis I will rely on the GLS estimates. The interpretation of the coefficient is equivalent to OLS, since GLS represents a linear transformation of the data. Respectively, reported in parenthesis are the t-values for the coefficients estimated using OLS and the z-value for the GLS estimates.

In both regressions we can see that the variable accounting for fashion week (FW), has a negative coefficient. FW seems to have a negative effect on the aggregated stock market. However, in both regressions the variable is not statistically significant, although its significance increases using GLS. Pre and Post event dummies on the contrary have a positive coefficient, suggesting that there is an effect in place that positively affect stocks' returns during the thirty days before and after the event takes place. Both variables are not statistically significant in the OLS regression and significant at the 95% confidence level in the GLS estimation. The interaction terms, included to separate the effect of FW on the relevant industry, are the ones that vary the most between the two methods. In the OLS regression, FW_FS and Pre_FW are significant at the 95% level, while Post_FW is not significant. The direction of the effect is, as indicated above, negative during fashion week and positive for the Pre and Post event variables. In the GLS regression, all three variables are not statistically significant.

The size of the coefficient relates to its economical significance. A large percentage change in the returns is translated into higher monetary returns. A positive change in returns is not profitable unless it is large enough to cover the costs of exploiting it, e.g.: transaction costs. Regardless of its statistical significance, the size of the coefficient is therefore important to define the exploitability of the event. From the GLS estimation results, the coefficient of the interaction term, FW_FS, is equal to -0.0226. This means that, on average during each FW day, for a 1-percentage point increase in the aggregate stock market returns, the stocks belonging to the fashion industry earn -0.02 percentage points less, ceteris paribus. The same interpretation can be applied to all the coefficients.

The coefficient of determination (R^2) is a measure used to define how well the included explanatory variables explain the variation in the depended variable. The R^2 of the pooled regression, estimated with both methods, is virtually equal to zero. This can be explained by the use of daily data. Hirshleifer and Shumway (2003), considering sunshine, explain that is unreasonable to expect a high explanatory power since daily returns are affected by a multitude of shocks and, therefore do not consider R^2 a relevant measure in their study. Moreover, the presence of omitted variables could further reduce the R^2.

5.1.2 Pooled regression – Discussion

Below I will relate the results presented above to the two hypotheses investigated in this study.

Hypothesis 1 – Fashion week and attention

$H1_1$*: Fashion week events have a significant effect on the returns of the stocks belonging to the fashion industry.*

$$\left.\begin{aligned} \beta_i(FW * FS_{it}) \\ \beta_i(Pre_{FW_t} * FS_{it}) \\ \beta_i(Post\_FW_t * FS_{it}) \end{aligned}\right\} \neq 0$$

$H1_0$*: Fashion week events have no significant effect on the returns of the stocks belonging to the fashion industry – the variables are not statistically significant from zero.*

When defining my hypothesis, I expected that the attention driven by fashion week events to the fashion industry would have an effect on the stocks belonging to the fashion industry. This assumption is supported by relevant literature presented in the dedicated section (B. Barber and T. Odean, 2008; J. Busse and T. Green, 2002; Z. Da, J. Engelberg and P. Gao, 2011). As already mentioned, FW is not a financial event per se, but it carries important information about the financial assets of the firms participating in it. The event's effect on the relevant industry is represented by the coefficients and level of significance of the three interaction terms. Two of the variables are significant in the OLS regression. However, these results are not reliable, because the standard errors in the OLS regression are not corrected for cross-correlation and heteroskedasticity. In the GLS regression none of the coefficient are statistically significant. Because each of the three interaction terms is not statistically different from zero, $H_1$is rejected.

Despite the statistics documented by the organizing bodies, as the amount of advertising and order's placed during the event, the attention drawn by FW to the relevant sector does not impact the returns of the stock belonging to the fashion industry. The reason for this lack of effect could be the reached audience. Potential investors and market participants might not be reached by the event because there are only a limited amount of stocks in the stock market belonging to the fashion industry. Therefore, the limited number of investment opportunities in the sector could explain investors' lack of attention. Moreover, the events are more likely to interest a female audience and, because female investors represent only a portion of the total investors in the stock market, the effect could be limited.

However it is interesting to investigate on the direction of the effect. Stock returns seems to be negatively affected during the days when fashion week takes place, but positively affected on the thirty days before and after the event. FW is designed to attract attention and therefore is highly advertised. The positive effect before FW could be caused by expectations about the presentation of the collections and the events around it. The anticipation and excitement stops building up when FW takes place and this could explain the reverse trend that we see in the $(FW * FS_{it})$ coefficient. The positive effect after the event can be the result of the presentation of the new collections. The new collections represent the new product offering of the firms, for the upcoming semester, and therefore include important information about the future prospects of the firms. Moreover the media response and reviews could drive post-event effects. Positive reviews and product endorsement by influential bloggers or celebrities can further catch attention and influence post event returns.

The size of the coefficients is relevant to evaluate the economical significance of the results. There is an important difference between the magnitudes of the coefficients of the three interaction terms. The size of the interaction term accounting for post event effects is considerably smaller. It can be interpreted as follows: ceteris paribus, on the thirty days after FW, for 1 percentage point increase in the stock markets' aggregated returns the returns of the stocks belonging to the fashion industry are 0.00611 percentage points higher, on average. The coefficients of $(FW * FS_{it})$ and $(Pre_{FW_t} * FS_{it})$ are respectively equal to -0.0226 and 0.0332. The size of each of the three interaction terms is rather small, suggesting a trivial economic impact of the event on the fashion industry.

Hypothesis 2 – Fashion week and costumer's sentiment

$H2_1$*: Fashion week events affect stock markets' returns*

$$\left.\begin{array}{r} \gamma_i FW_t \\ \gamma_i Pre\_FW_t \\ \gamma_i Post\_FW_t \end{array}\right\} \neq 0$$

$H2_0$*: Fashion week events do not affect stock market's returns – the variables are not statistically significant from zero.*

With the second hypothesis I wanted to examine if FW has an effect on the aggregate stock market. The dummy variables for FW, Pre and Post event days measure the effect of the event on the aggregate stock market on the days during the events and on the thirty days before and after the event. Mood has been found to be an important driver of individuals' decision making. There is a growing literature which aims at uncovering factors that affect moods and in turn investment decisions. Weather conditions (D. Hirshleifer and T. Shumway, 2003), lack of sleep (M. Kamstra, L. Kramer and M. Levi, 2000) as well as advertising (K. Machleit, C. Allen and T. Madden, 1993), have been proven to significantly affect stock markets. Important events, which simultaneously affect the mood of a multitude of people, can also impact stock markets. For an event to have a significant effect on the aggregated stock market, a large amount of people has to be exposed to it (A. Edmans et al., 2007). The organizing bodies of FW in each city guarantee a massive coverage of the event, which they affirm to be equal to major sporting events. However, FW is solely targeted to the stocks belonging to the fashion industry, and the percentage of those firms in the sample is very small. Yet, if a sufficient number of investors are exposed to the event, the excitement and positive mood generated by the event could affect the aggregated stock market, as in the case of World Cup results documented by Edmans et al. (2007). In the OLS regression, all of the three dummy variables are not statistically significant. Two of the variables, specifically Pre_FW_t and $Post\_FW_t$ become statistically significant, at the 95% level, in the GLS regression. Therefore, according to the GLS results, I cannot reject the null hypothesis (H_0) that FW_t is not statistically different from zero. There seems to be no significant effect during FW on the stock market. However, i can reject the null hypothesis with a 95% confidence level, for the variables accounting for pre and post event days. On average, returns during the thirty days before and after FW are respectively 0.000472 and 0.000454 percentage points higher, ceteris paribus. The size of the coefficients is remarkably small, thus despite their statistical significance, their economical significance is negligible. Moreover, the proportion of fashion stocks in the stock market is very low, therefore an event aimed at targeting these stocks is unlikely to have an effect on the aggregate stock market. The captured effects could be driven by the presence of omitted variables, which affect the stock market during these days and are not accounted for in the regression. The large sample size could also drive the significance of the coefficients. These results can therefore be misleading.

The direction of the effect of the three variables is identical to the one in place on the fashion industry. The positive effect that is in place before the event could be caused by the excitement in the anticipation of the events and of the new collections. During fashion week the effect reverts, becoming negative. As in the case of attention, this could be the result of the reshaping of expectation once FW begins. The effect of mood can also persist after the event as individuals evaluate the new collections and internalize this new information.

5.2 City-by-City Regressions

In the following section I will investigate on the effects of FW by analysing each city separately. For comparison reasons, I will first present the results of the OLS regressions and then the ones estimated by GLS. As explained above, I will rely on the GLS results for hypothesis testing and coefficients interpretations.

Table 5: *City-by-City – OLS estimation results*

	London	Paris	Milan
returnSP	0.0976***	0.120***	0.391***
	(4.43)	(49.77)	(103.38)
FW	-0.00123	-0.0000921	0.000592*
	(-0.72)	(-0.59)	(2.26)
PreEvent	-0.000340	0.000292***	0.000892***
	(-0.46)	(3.59)	(6.99)
PostEvent	-0.000282	0.000157	0.000552***
	(-0.38)	(1.94)	(4.31)
FW_FS	0.000133	-0.000233	-0.0000424
	(0.01)	(-0.27)	(-0.04)
Pre_FS	-0.000974	-0.0000528	0.0000163
	(-0.20)	(-0.14)	(0.04)
Post_FS	-0.000287	0.000202	0.000348
	(-0.06)	(0.52)	(0.78)
_cons	0.000976*	0.000563***	-0.000395***
	(2.37)	(12.42)	(-5.54)
* p<0.05, ** p<0.01, *** p<0.001			

The number in parenthesis represent the t-values. There are important differences both between the countries and with the pooled regression's results. Most interesting is the difference in the sign of the coefficients, which represents the direction of the event's effect. The effect of the event seems to be different between the cities.

Considering the three dummy variables, FW_t, Pre_FW_t and $Post\_FW_t$, in London the event seems to have a negative effect on the stock market, whether in Milan the effect is positive. Paris's results are consistent with ones of the pooled regression. These variables measure the extent to which FW affects the entire stock market. According to Edmans et al. (2003), an event has to have an unambiguous effect on mood to have a significant effect. It is possible that the excitement created by FW events differs across cities, explaining the difference in signs between the coefficients.

The effect of the three interaction terms also differs across cities. The effect of fashion week on the fashion industry is positive in London but negative in Paris and Milan. The sign of the coefficients: $(Pre_{FW_t} * FS_{it})$ and$(Post_{FW_t} * FS_{it})$ are also different across cities. Both variables are negative for London and positive for Milan. Whether in Paris the effect is positive during the thirty days after the event and negative during the month before the event. Different reasons could cause these differences. First of all, the events occur consecutively, therefore the events in one city could affect the impact of the event in another city. For example, the excitement for Milan's FW could increase in the presence of positive reviews for London FW, which takes place during the week before. Moreover, the extent to which attention affects the stock market depends on the amount of people reached (A. Edmans et al., 2007). This can also explain the noted differences between countries, as the proportion of people reached could differ between cities.

The table below shows the estimation results using the GLS method. As in the analysis of the pooled regression, I will rely on these results for interpretations and hypothesis testing, because correcting for cross-correlation and heteroskedasticity allows for a more reliable estimation of the coefficients' standard deviations (J. Binder, 1985). In parenthesis are the z-values.

Table 6: *City-by-City – GLS estimation results*

	London	**Paris**	**Milan**
returnSP	0.0978***	0.120***	0.390***
	(16.44)	(20.78)	(35.82)
FW	-0.000813**	-0.0000921	0.000617***
	(-3.55)	(-0.67)	(4.32)
PreEvent	0.0000730	0.000292**	0.000920***
	(0.32)	(3.16)	(9.06)
PostEvent	0.000134	0.000157*	0.000583***
	(0.30)	(2.37)	(5.42)
FW_FS	-0.0148	-0.000233	-0.000218
	(-0.96)	(-0.66)	(-0.40)
Pre_FS	-0.0186	-0.0000528	-0.000119
	(-1.02)	(-0.17)	(-0.39)
Post_FS	-0.0179	0.000202	0.000214
	(-0.99)	(1.10)	(0.62)
_cons	0.00310	0.000563***	0.00890
	(1.18)	(12.83)	(0.97)
* p<0.05, ** p<0.01, *** p<0.001			

In all of the three regressions, the interaction terms are not statistically significant. I can therefore reject the hypothesis that FW has a significant effect on the stocks belonging to the fashion industry. These variables were also not significant in the pooled regression. The discussion of the pooled regression results also applies to the individual cities results.

The level of significance for the three dummy variables, FW_t, Pre_FW_t and $Post\_FW_t$ is higher than in the pooled regression. Considering Milan's results, the three coefficients are significant with a 99.9% confidence level. The effect of FW days is also highly significant in London, whether in Paris there is a significant effect on the 30 days before the event. Because the portion of the market represented by the fashion industry is very small, it is unlikely that an event aimed at targeting these stocks has an effect on the entire stock market. As for the pooled regression, these results could be misleading and could be driven by the effect of omitted variables and large sample size.

Compared to the pooled regression, the size of the coefficients is considerably smaller. The economical significance of the coefficients is therefore reduced even further. Only the coefficients of the interaction terms in the London regression resemble the size of the pooled regression coefficients. The effect in place in London on the fashion industry is the largest in magnitude. During each day of fashion week, on average, returns of the stocks belonging to the fashion industry are -0.0148 percentage points lower, ceteris paribus. However, it is interesting to define a trading strategy that could be implemented to collect the event's effects. It is more straightforward to do so by analysing the results of a singular country. Because of the high significance of the coefficients, I will use Milan's results as an example to discuss the economical implications of these results. There seems to be a positive effect in place on the thirty days before the event, during FW and on the thirty days after. Because FW takes place for a week, the daily effect shown in the results can be aggregated over five days, whether the pre a post daily effect should be aggregated over thirty days for each variable. To collect the total effect, an investor would have to invest in the market portfolio thirty days before the event and sell the portfolio thirty days after the event took place. The portfolio would have to be held for a total of 35 days. For the strategy to be profitable the profits must be higher than the cost of putting it into place, which include transaction costs and commission costs. I would have to define a number of different assumptions on the costs of this strategy to measure its monetary value. As I cannot obtain a truthful measure of these costs, these assumptions would lead to misleading results. Moreover, it is problematical to draw important conclusions, since the estimated effect on the stock market could be driven by omitted variables, making these results unreliable. It is unlikely that an event aimed at attracting attention on a small portion of stocks would affect the whole stock market. The considerably small size of the coefficients is also not promising. Because of the above, I will not investigate further on the exploitability of this trading strategy.

6. Robustness Checks

In this section I will include other relevant variables in the pooled regression, to control for their effect on the dependent variable. The variables used have been chosen because they have been proven to significantly affect stocks' returns. Moreover I will run the same analysis using trading volume as the dependent variable, as it is another measure widely recognized to measure the effect of attention in the stock market.

6.1 The effect of Fashion Week on Trading Volume

Barber and Odean (2008) use abnormal returns and trading volume to measure the effect of attention in the stock market. They consider these two variables to be proxies for the reach and impact of the news analysed. In their paper, they consider straightforward that if investors are trading a stock they are also paying attention to it. To measure the effects of FW events on trading volume, I will run the following regression:

$$Volume_{it} = \alpha_i + \gamma_i FW_t + \gamma_i Pre\_FW_t + \gamma_i Post\_FW_t + \beta_i (FW * FS_{it}) + \beta_i (Pre\_FW_t * FS_{it}) + \beta_i (Post\_FW_t * FS_{it}) + \mu_{it}$$

(Equation 4)

From DataStream I collected the daily trading volume for each stock, and then calculated its daily change. The variable $Volume_{it}$ included in the regression measures the percentage change in trading volume on day t from the previous day, for security *i*. The table below shows the estimation results. The t-values and z-values are in parenthesis, respectively for OLS and GLS coefficients.

Table 7: *FW effects on trading volume*

	OLS	GLS
FW	0.377	0.377
	(1.04)	(1.28)
PreEvent	-0.462	-0.462*
	(-1.84)	(-2.00)
PostEvent	0.110	0.110
	(0.44)	(0.43)
FW_FS	0.731	0.731
	(0.30)	(0.32)
Pre_FS	-1.388	-1.388
	(-1.01)	(-1.42)
Post_FS	-1.434	-1.434
	(-1.05)	(-1.82)
_cons	5.041***	5.041***
	(32.79)	(24.63)
* p<0.05, ** p<0.01, *** p<0.001		

As for the previous regressions, the interaction terms used to separate the effect of FW on the relevant industry are not statistically significant. Therefore, there is no statistically significant effect on the returns and volume of the fashion stocks. The only statistically significant coefficient is Pre_FW_t. However, as for the analysis of the returns, these results are misleading and therefore will not be pondered. It is difficult to draw inferences from the percentage change in trading volume for the whole stock market, as there are a multitude of factors non included in the regression that affect this measure.

6.2 The weekend effect

Systematic trade imbalances have been observed in the stock market during different days of the week. Osborne (1962) in his paper predicts that investors are more likely to invest more actively on Monday because they use their free time in the weekends to define trading strategies. On the contrary, he expects institutional investors to invest less intensively on Monday, as it is most likely a day used for strategic planning. Lakonishok and Maberly (1990) tested Osborne's predictions, and found significant results. During Mondays, investors trade more and have a higher propensity to sell. Lakonishok and Maberly (1990) refer to this effect as to "the weekend effect". To control for this effect I will include dummy variables accounting for the different days of the week in the pooled regression. The reference category used will be Friday. The regression is structured as follows:

$$R_{it} = \alpha_i + \beta_m R_{mt} + \gamma_i FW_t + \gamma_i Pre\_FW_t + \gamma_i Post\_FW_t + \beta_i (FW * FS_{it}) + \beta_i (Pre\_FW_t * FS_{it}) + \beta_i (Post\_FW_t * FS_{it}) + \delta Week\_Day_t + \mu_{it}$$

(Equation 5)

$\delta Week\_Day_t$ is the dummy variable representing the day of the week. Four dummy variables will be included in the regression, one for each day of the week, except Friday.

The table below shows the results. OLS t-values and GLS z-values are shown in parenthesis.

Table 8: Pooled regression and the weekend effect

	OLS	GLS
returnSP	0.123***	0.123***
	(8.43)	(26.63)
FW	-0.000441	-0.000436
	(-0.64)	(-1.22)
PreEvent	0.000473	0.000459
	(0.99)	(1.94)
PostEvent	0.000461	0.000446*
	(0.98)	(2.18)
FW_FS	-0.0226***	-0.0226
	(-4.90)	(-1.01)
Pre_FS	0.0298***	0.0332
	(11.51)	(0.99)
Post_FS	0.00121	0.00614
	(0.47)	(0.98)
monday	-0.000353	-0.000355
	(-0.58)	(-1.38)
tuesday	-0.00117	-0.00117***
	(-1.91)	(-15.69)
wednesday	-0.000524	-0.000518***
	(-0.86)	(-4.89)
thursday	0.000859	0.000861
	(1.40)	(0.92)
_cons	0.000545	0.00211
	(1.12)	(1.58)
* p<0.05, ** p<0.01, *** p<0.001		

When including dummy variables accounting for the days of the week, only one variable from the original pooled regression remains significant. The variable accounting for post fashion week effects in the aggregated stock market is statistically significant with a 95% confidence level. The variable Pre_FW_t loses its significance. The size of the estimated coefficient does not differ notably from the pooled regression's results. As expected from the relevant literature, compared with Fridays, on Mondays returns seems to be lower, however the effect is not statistically significant. Statistically significant, with a 99% confidence level, are the dummies variables for Tuesday and Wednesday. On both days, the aggregated stock market's returns are lower compared with Friday. It is important to stress the presence of omitted variables in the model, which could lead to a wrongful estimation of the coefficients' significance. As for the pooled regression, the R^2 is virtually equal to zero. The use of daily data could explain the low R^2 level. As stated by Hirshleifer and Shumway (2003), it is unreasonable to expect a high explanatory power since daily returns are affected by a multitude of shocks.

6.3 Seasonal effects

Seasonal differences in weather conditions were also found to affect stock markets behavior. As in Hirshleifer and Shumway (2003), the amount of sunlight was found to affect investors' behaviour and markets' returns by Kamstra et al. (2003). In their paper, they associated the reduction in daily sunlight during winter months to stock market returns. According to psychological research, people are more likely to be affected by depression during winter months and this condition affects individuals' mood and decision-making. Investors' preferences seem to be distorted, becoming more averse to risk. Besides seasonal effects, researchers documented a significant effect occurring during the first month of the year, known as the January effect. R. Thaler (1987), in his paper, reviews the literature addressing this anomaly. In January the return of a broad market index was found to be higher than during the other months of the year (M. Rozeff and W. Kinney, 1976). This effects is driven by the higher returns collected by small firms, which can be explained by tax motives (M. Reinganum, 1983). In the following regression I will include dummies for each month to analyse monthly differences. The dummy variable separating December effects is not included in the regression and will represent the reference category.

$$R_{it} = \alpha_i + \beta_m R_{mt} + \gamma_i FW_t + \gamma_i Pre\_FW_t + \gamma_i Post\_FW_t + \beta_i (FW * FS_{it}) + \beta_i (Pre\_FW_t * FS_{it}) + \beta_i (Post\_FW_t * FS_{it}) + \delta Month_t + \mu_{it}$$

(Equation 6)

Table 9: Pooled regression and seasonal effects

	OLS	GLS
returnSP	0.121***	0.121***
	(8.30)	(25.42)
FW	-0.000224	-0.000228
	(-0.29)	(-0.58)
PreEvent	0.000830	0.000774
	(1.07)	(0.91)
PostEvent	0.000213	0.000135
	(0.20)	(0.37)
FW_FS	-0.0226***	-0.0226
	(-4.90)	(-1.01)
Pre_FS	0.0299***	0.0333
	(11.51)	(0.99)
Post_FS	0.00121	0.00622
	(0.47)	(0.98)
january	0.000194	0.000367
	(0.15)	(1.12)
february	-0.0000275	0.000142
	(-0.02)	(0.25)
march	-0.00156	-0.00137
	(-1.30)	(-1.20)
april	0.00284**	0.00285
	(2.69)	(1.49)
may	-0.000409	-0.000421***
	(-0.44)	(-3.91)
june	-0.000270	-0.000264*
	(-0.29)	(-2.11)
july	-0.000437	-0.000436***
	(-0.47)	(-3.92)
august	0.0000412	0.00000667
	(0.03)	(0.02)
september	-0.0000550	-0.0000709
	(-0.04)	(-0.14)
october	-0.00119	-0.00122
	(-1.00)	(-0.91)
november	-0.00132	-0.00133
	(-1.26)	(-1.63)
_cons	0.000441	0.00199
	(0.67)	(1.34)

* p<0.05, ** p<0.01, *** p<0.001

The table above reports the regression's estimation results. When accounting for monthly differences in returns, none of the variables of the original regression remains significant. There is no statistical proof supporting the hypothesis that FW has an effect on the relevant industry. The size of the coefficients of the variables $(FW * FS_{it})$ and $(Pre\_FW_t * FS_{it})$ remain the largest. On the thirty days before FW, each day on average stocks in the fashion industry earn 0.0333 percentage points more, ceteris paribus. I find no significant effect occurring in January. Returns are slightly higher but their economical significance is trivial.

7. Improvements and further research

In contrast with the supporting literature, I did not find attention and consumer's sentiment to significantly affect either the stock market or the relevant industry. Differences in the event characteristics can explain the differences in results. Edmans et al. (2007) report a significant effect of World Cup Games results on markets through the effect on investors' moods. The perceived importance and reach of the event could explain the conflict in our findings. In Edmans et al. (2007) the reach of the event is world wide and, most importantly; psychological research findings demonstrated that World Cup Results have an effect on people's moods. Despite the statements of the organizing bodies, which define the coverage of fashion week as equal to major sporting events, the event might not attract a sufficient number of investors to have a significant effect on the stock market. Moreover, differently from the literature linking news coverage to individual stocks' returns, I study the effect of attention on the entire fashion industry. The strong results reported by Busse and Green (2001), which analyse the effect of being mentioned in the news, can stand from their ability to identify the specific stock that is the subject of attention. Besides, because the event is recurrent, market participants might have learned to internalize it and therefore the information is already reflected in the markets, supporting the efficiency market theory.

This analysis can be used as a starting point for future researches wanting to investigate further on the effects of FW on the relevant industry. Different modifications of the above analysis can be applied to test the truthfulness of the results. I will discuss some ideas for further research below.

The main focus of this paper was to analyse if FW events have a significant effect on the returns of the stocks belonging to the fashion industry. To test this hypothesis, fashion stocks' returns had to be compared to a benchmark measure of expected returns. The measure used was the daily return of a market index, namely the S&P 500. According to Brown and Warner (1980) using the market return as a measure of expected returns leads to consistent results. However, there are different relevant variables that could be included in the estimation of the expected return, which would narrow down the portion that can be attributed to FW events. The most widely recognized method measuring expected returns is the Fama and French "Three factors model" (1993), which considers the market return, a size factor and a book to market equity factor. Using this specification for the sample analysed in this study is problematic. J. Griffin (2002) tests the model developed by Fama and French and shows that the factors used are country specific and, therefore calculating these factors for multiple countries leads to misleading results. Despite the fact that the Fama and French specification is not appropriate for this study, the measure of expected return used in the above analysis could be improved, for example accounting for securities' systematic risk. Different benchmark measures of returns could be tested in subsequent studies, to examine the truthfulness of the results.

Different econometrical models can be used to estimate the pooled regression. In the above analysis I compared the results obtained through OLS against the GLS estimates. The decision of using OLS to compare estimation results resembles the work of Hirshleifer and Shumway (2003). In their paper, they define the results obtained with this method "naive", however they use the results for comparison reasons. Binder (1985) suggests the use of the GLS methodology to estimate panel regressions because it provides more exact estimates of the coefficients' standard deviations and therefore more reliable hypothesis testing. There are various different econometrical specifications that can be used to estimate the pooled regression. For example, Hirshleifer and Shumway (2003) use Panel Corrected Standard Errors (PCSE), which represent an alternative to GLS. Comparing different econometrical models is beyond the scope of this thesis. However, the effect of FW can be investigated further using different econometrical specifications.

In the analysis I focused on the effect of FW on stocks' returns. More precisely, I wanted to investigate if the amount of attention driven to the relevant industry during FW days would have an effect on fashion stock's returns. However, there is no direct measure of consumer attention. Barber and Odean (2008), in their paper use stocks returns and trading volume as proxies for attention. They believe that these two measures also represent the extent of news coverage and reach. When using a proxy, hypothesis testing represents a joint test of both the hypothesis and the relevance of the proxy. In further researches it would be interesting to include different measures of attention. For example measures of news coverage could be included, as headlines or relevant articles, as in Mitchell and Mulherin (1994) and Busse and Green (2001). Even if a measure of news coverage would still represent a proxy for attention, it would provide more specific information. Unfortunately, I had no access to this type of information when writing this research.

8. Conclusion

Nowadays it is widely recognized that psychological and sociological factors affect individuals' investment decisions. Behavioural finance research originated from this acknowledgment (R. Shiller, 2003) and focuses on linking finance research with findings from social sciences. Behavioural economics findings are now widely recognized, and pioneers of this field have been awarded the Nobel price in economics, as Kahneman (2002) and Shiller (2013). External events, such as weather conditions, have been found to affect investors' decision making through their effects on moods. Limited amount of sunshine, which is linked to depression, seems to lead to greater risk aversion (M. Kamstra, L. Kramer and M. Levi, 2003). Hirshleifer and Shumway (2003) show that the market is positively affected by sunny days, because sunlight positively affects people's moods. Important events can also significantly affect individuals' actions. Edmans et al. (2007), analyse the effect of World Cup games' results and finds that when a national team loses an important game, stock markets' returns in the respective country are lower. Edmans et al. (2007) define different features that an event should have to significantly affect the stock markets, namely it should affect a large part of the population in an unambiguous way.

Despite the effect on moods, attracting investors' attention can affect their decision-making. Attention is "a scarce cognitive resource"(D. Kahneman, 1973). Investors fail to gather and process all available information and therefore update their beliefs using the knowledge they have. Barber and Odean (2008), investigate on the effect of attracting investors' attention. They find that, because investors have to choose between a vast universe of securities when purchasing a stock, attracting their attention reduces their spectrum of possibilities and when paying attention to a specific stock, investors are more likely to consider it and invest in it. Measuring the extent of attention is problematic, because there is no direct measure for investors' attention. Different proxies have been used, such as excess returns, abnormal trading volume and news coverage.

I investigated on the effects of fashion week on stock returns. Fashion week occurs twice a year and can be considered as a collection of events, including catwalks, presentation and salon shows. Three cities are included in the analysis: London, Paris and Milan. Because the event is organized to target only the firms belonging to the fashion industry, I was able to separate the effect of the events on the relevant stocks. Previous studies, such as Hirshleifer and Shumway (2003) and Edmans et al. (2007), analysed countrywide effects and therefore could only measure the average effect of the event on the entire stock market. Fama et al. (1969) was the first one to realize an event study to analyse the effect of new information, specifically stock splits. The event investigated in this study is not financial in its nature, however it conveys important information about the assets of the firms participating in it. In fact, the presentation of the new collection can be considered as the presentation of the new product offering of the firm. The organizing bodies of the event, in each of the three cities considered, guarantee a massive coverage of the event, which they affirm is equal to major sporting events. Journalist from every media channel are invited, together with buyers, endorses and celebrities.

Two hypotheses were investigated in this study. The first hypothesis considers only the effect of FW on the relevant industry. The attention driven by FW to the fashion industry could affect stocks' returns, as supported by the relevant literature. Because I can separate the effects of the event on the stocks "in the spotlight" I expected the event to have a significant effect on returns. With the second hypothesis I investigated on the effect of FW on the entire stock market. If the event's reach and impact is large enough, it could affect individuals' decision making through its effect on mood (Edmans et al., 2007). However, the percentage of stocks belonging to the fashion industry is very small in each of the three stock markets analysed, therefore an event targeted only to these stocks is unlikely to affect the entire stock market.

The main analysis was run on a pooled sample, which includes observations from London, Paris and Milan. Country-by-Country effects are also investigated. The sample is composed by daily observations, from 2003 to 2012. Because the sample represents a panel dataset and important econometrical considerations have to be considered, I have used Generalized Least Squares to estimate my results.

I find that fashion week has no significant effect on the returns of the stocks belonging to the relevant industry. This result is consistent for both the pooled regression and for each individual city. The first hypothesis is therefore rejected. There seems to be a statistically significant effect affecting stock market returns on the thirty days before and after the event takes place. However, despite their statistical significance, their economic significance is trivial as indicated by the small size of the coefficients. These results do not hold true for each of the cities analysed. It is difficult to draw a meaningful conclusion. The captured significance could be caused by omitted variables or a large sample size. The results concerning the second hypothesis are inconclusive. Running different robustness checks, as including dummies for weekdays or months, did not notably change the above-mentioned results.

Different assumptions can be defined to explain the insignificance of the results. Only a small number of fashion stocks are available in each stock market, and so investors might not be paying enough attention to them as they represent only a limited number of investment opportunities. Moreover the event might attract more intensively a female crowd, which only represent a portion of the total investors in the stock market, limiting the effect. The size and reach of the event might also be too limited to have a significant impact on markets. Lastly because the event is recurrent and investors might have learned to internalize its effects, there is no significant effect in the markets, supporting the market efficiency theory described in Fama (1970).

Despite the fact that the results of this study are not significant, it is important to report and consider them. A recent article from The Economist[10] discusses the contemporary problems with scientific research. Negative results are hardly published, as Journals prefer to reveal what seem to be astonishing findings, yet often these results are prone to mistakes and cannot be easily replicated. However, as stated in the article, "knowing what is false is as important to science as knowing what is true". This analysis can be used as a starting point for future researches wanting to investigate further on the effects of FW on the relevant industry. The results reported could be improved by the comparison of different econometrical models or variable specifications. Moreover, a more specific measure of attention could be included, as news coverage or number of headlines, to include a more direct measure of attention reach and impact.

[10] http://www.economist.com/news/leaders/21588069-scientific-research-has-changed-world-now-it-needs-change-itself-how-science-goes-wrong?spc=scode&spv=xm&ah=9d7f7ab945510a56fa6d37c30b6f1709

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