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The Effect of Stock Return Sequences on Trading Volumes: Evidence from the London Stock Exchange

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Biographical Note

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Abstract

The present study analyzes the effect that stock return sequences have on trading volume. Kudryavtsev (2017) observed that when the price of a stock increases (or decreases) several days in a row, in the day this sequence is broken, an abnormal trading volume is noted. This would be consequence of some investors being affected by the gambler's fallacy which would create, in the day the stock's price decreases (increases), a higher level of disagreement between investors that would be translated in a higher trading volume. The objective of this study is to understand if the same applies for a European market, specifically London stock market, using daily prices and trading volumes of the FTSE components since the 1st of January 1990 or since the first day of the stock's trading history. The results are relevant as they work as a testing for market efficiency with the possibility of providing relevant information that enables investors to create strategies and consequently earn abnormal returns.

This dissertation documents a positive correlation between abnormal trading volume of days following negative sequences of stock returns while being inconclusive regarding the days after positive sequences and shows that within larger sequences, abnormal trading volume increases with the sequence length confirming the gambler's effect is also present in the London stock market even if only partially. Moreover, these results question market efficiency as they conclude prices do not always reflect all available and relevant information as they are, at least sometimes, affected by irrational investors whose actions are impacted by biases such as the gambler's fallacy. Consequently, investors may use these findings to create investment strategies that will result in abnormal returns by investing in stocks when they identify large negative sequences of returns as, according to results, these sequences are many times followed by a reversal.

Keywords: Trading Volume, Stock Prices, Stock Return Sequences, Gambler's Fallacy, Investment Decisions

JEL-Codes: G11, G14, G15, G41

Sumário

O presente estudo pretende analisar o efeito que as sequências de retorno das ações têm no volume de transações. Kudryavtsev (2017) concluiu que quando o preço de uma ação sobe (ou desce) vários dias seguidos, no dia em que essa sequência é quebrada, observa-se um volume de transações anormal. Isso seria consequência de alguns investidores serem afetados pela falácia do apostador que criaria, no dia em que o preço da ação cair (subir), um maior nível de desacordo entre os investidores que se traduziria num maior volume de transações. O principal objetivo deste estudo é perceber se as mesmas conclusões são alcançadas num mercado europeu, especificamente na bolsa de Londres. Os resultados são relevantes, pois funcionam como um teste de eficiência do mercado e, consequentemente, fornecem informações para que os investidores criem estratégias que lhes permitam obter retornos anormais.

Esta dissertação documenta uma correlação positiva entre o volume de negociação anormal de dias após sequências negativas de retornos de ações enquanto é inconclusiva em relação aos dias após sequências positivas e mostra que dentro de sequências maiores, o volume de transações anormal aumenta com o comprimento da sequência confirmando que a falácia do apostador também está presente no mercado de ações de Londres, mesmo que apenas parcialmente. Além disso, esses resultados questionam a eficiência do mercado, pois concluem que os preços nem sempre refletem todas as informações disponíveis e relevantes, pois são, pelo menos às vezes, afetados por investidores irracionais cujas ações são impactadas por vieses como a falácia do apostador. Consequentemente, os investidores podem usar essas descobertas para criar estratégias de investimento que resultarão em retornos anormais ao investir em ações quando identificarem grandes sequências negativas de retornos, pois, de acordo com os resultados, essas sequências são muitas vezes seguidas por uma reversão.

Palavras-chave: Volume de Transações, Preço de Ações, Sequências de Retornos de Ações, Falácia do Apostador, Decisões de Investimento

Classificação JEL: G11, G14, G15, G41

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1.Introduction

Investors and their decisions are a crucial aspect of financial markets and consequently of the stock exchange. Therefore, studying what might affect these decisions and which conclusions can be drawn from important indicators like trading volume is of extreme relevance.

The main objective of this research is to understand the effect of stock return sequences on trading volumes. While studying daily trading volumes and daily prices of the stocks that compose the S&P 500, Kudryavtsev (2017) found that after a sequence of positive or negative stock return sequence, when there is a reversal in the stock returns' sign (i.e. when the stock price decreases following several days of increase or increases following several days of decrease), abnormal trading volumes are observed. Further, Kudryavtsev (2017) also observed that the length of the sequence impacts the magnitude of the abnormal trading volume as it is higher for larger sequences of same sign stock returns. These results are found not to be explained by a merely correlation between stock returns and contemporaneous and lagged returns, as it is shown by a multifactor regression analysis and remain significant after controlling for other factors capable of influencing trading volume such as historical returns and volatilities as well as company-specific events.

The purpose of this study is to analyze if the same results are observed in another market, specifically London stock market as there are no studies that identify this effect in European markets. The choice of this market relied essentially in its dimension. The London Stock Exchange is the most important stock exchange in the United Kingdom with great importance in the whole Europe, its capitalization summed up to 3.2 trillion in 2020. This will allow to reach conclusions regarding whether this effect is exclusively of the US market or if it applies across several different (or even all) markets. Besides, this study (and its findings) will be of theoretical relevance as it will serve as test of the market efficiency and consequently also of empirical relevance by allowing investors to study the results and create strategies that will enable them to earn abnormal returns.

The explanation behind the reason why investors behave this way is given by the gambler's fallacy. Investors not always behave rationally, irrational behaviors are more common than what is thought as it is argued and analyzed in behavioral finance, a field that studies how biases and fallacies affect individual's behavior and impact the different financial contexts. The gambler's fallacy is an example of a bias that deviates investors from making

rational decisions, it consists in the inaccurate belief that a certain event is more or less likely because of a prior series of events. All this is imprecise as the outcome of the previous events does not influence the outcome of the future ones.

Actions incentivized by irrational beliefs, like the gambler's fallacy, influence financial realities such as the stock market in a variety of ways. Specifically, this fallacy has been found, on the one hand, to be significantly responsible for the optimal structure of a portfolio being considered in only 37.7% of all choices made by an investor (Filiz et al., 2018) and, on the other hand, to be positively correlated to investment performance (Khan, 2016). This means that even though it is not clear whether the effects of this fallacy's existence are always negative or positive, there is no doubt they occur, and so further studies are relevant to understand them.

In this research, the objective is to study this fallacy in the stock market hypothesizing that if the price of a stock rises or falls in several consecutive trading days then investors start to believe it must fall or rise, respectively. This is the same as hypothesizing that if the daily returns of a stock have been positive (negative) for several days, investors start to believe they will have to be negative (positive) sometime soon. Investors affected by this fallacy will then want to sell (buy) a stock after a sequence of days with positive (negative) returns which would create a higher disagreement between investors in that day. This would consequently be translated in an increase of the trading volume of the day the stock's returns actually change their sign.

Findings document the presence of the gambler's fallacy but only in negative sequences showing a positive correlation between abnormal trading volume of days following negative sequences of stock returns. Besides, results also suggest within larger sequences, abnormal trading volume increases with the sequence length meaning the gambler's fallacy effect is more prominent when sequences are larger.

The remaining of this paper is structured as follows. Chapter 2 contains a literature review on the main concepts related to this research, Chapter 3 explains the methodology that was used, Chapter 4 contains results of that methodology and Chapter 5 includes conclusions and limitations.

2. Literature review

The concept behind this research can be framed within behavioral finance's research. Behavioral finance studies how agents' decisions are influenced by psychologic aspects and suffer from several biases. It questions the assumptions traditional finance has made arguing that they are not realistic. Even though emotions impact the humans and therefore humans' behavior, traditional financial models assume that individuals use the rules of probability and statistics that are purely logic and mathematical when making decisions, completely ignoring the responsibility of emotions and biases that investors are subjected to that make their behavior deviate from what the traditional models predict. It is not wrong to assume calculations such as mathematical expectation are considered by individuals when deciding, but it is important not to ignore that they will be used imperfectly. It is important to remember the context will be of limited information, sometimes a will to maximize welfare might not exist as occasionally individuals are just aiming at satisfaction and will often behave unexpectedly because of a whim or sentiment (Keynes, 1936). How the decisions of individuals deviate from what is expected in traditional finance and the consequences of it are the focus of this area of studies. By applying psychology and sociology to finance, behavioral finance studies several cognitive biases that on an individual level affect financial agents (Ricciardi & Simon, 2000).

Essentially two concepts will be addressed in this literature review as they are crucial notions to this study. The first concept is the gambler's fallacy which impacts individuals and their decisions and the second is trading volumes which is an important indicator of financial activity and whose importance was ignored for a while.

2.1 The gambler's fallacy

The gambler's fallacy is a bias that affects individuals' behavior and deviates them from making rational decisions therefore evidence about this fallacy can be found within behavioral finance's literature. Why this fallacy happens, what consequences it might have and situations where it is observed are all aspects previous literature comprises and so after an explanation of what this fallacy consists in these are the aspects that are covered in the literature review of this concept.

This fallacy can be understood as a wrong probability estimate in a context of random events and was first identified by Simon and Laplace (1951). This fallacy consists in the belief that a certain event is more or less likely because of a prior series of events creating the

illusion that a sequence of a particular outcome is more likely to be followed by the opposite outcome. Illustrations of this fallacy are, for example, when in a casino if the roulette wheel's ball has fallen on black several times in a row, individuals start believing that falling on red is now more likely or when tossing a (fair) coin if heads is observed several times in a row, individuals start believing tail is now "due" in order to balance. This belief is inaccurate and therefore constitutes a fallacy as these events are independent and so past events do not influence the outcome of the future ones.

This fallacy is commonly studied together with another fallacy that also affects decisions of individuals, is called the hot hand fallacy, and takes place in similar contexts even though it seems to be based in the exact opposite logic. Basically, it consists in the belief of a positive correlation between events with no correlation and so individuals who suffer from this fallacy have the perception that in a random context when an outcome has been drawn several times it is now more likely to be drawn again, as it is "hot". However, despite of its similarity to the gambler's fallacy, the hot hand is usually found in outcomes as wins and losses and not in head or tail kind of outcomes. For example, when tossing a (fair) coin, individuals who are affected by this fallacy and are able to guess several outcomes in a row will start believing they will guess the next one too (Croson & Sundali, 2005). Many studies incorporate both fallacies in their empirical tests, however, the fact that in a certain experience there is evidence that one of them is present does not mean the other cannot be as they are usually associated with different kinds of outcomes.

When it comes to why individuals are affected by the gambler's fallacy several explanations have been found. One of them is related to individuals mistaking situations where events are independent (as is the case of tossing a coin or the casino's roulette game) with very common situations of the daily context where events, in fact, are not independent. This is the case of events where the outcomes are part of a finite urn and there is no replacement and in that case expectations with negative recency are valid as witnessing an outcome makes it less likely for it to be witnessed again next (Ayton et al., 1991; Lopes, 1982; Treisman & Faulkner, 1987). This means the gambler's fallacy can rise as consequence of the experience of negative recency in daily life and therefore according to Pinker (1999) it makes sense for a careful observer to commit to gambler's fallacy. Another explanation suggested by Hahn and Warren (2009) is that the gambler's fallacy does not happen because individuals fail to understand and correctly estimate likelihoods but because individual's cognitive system

is closely adapted to the statistics of the environment they live in. As individual's experience is necessarily finite and their short-term memory is limited so a sequence of one outcome will appear to be less likely than a sequence with reversals by a direct reflection of statistical properties they find in the environment as during their lives they will never experience an infinite experience. This together with Sun and Wang (2010) demonstration that in finite data streams, same outcome sequences take more time to occur since the beginning of the monitoring than the sequences with reversals explains why the latter appears more probable to individuals. Another possible explanation is a cognitive one and is related to the representativeness heuristic also known as "The Law of Small Numbers" (Kahneman & Tversky, 1972). The representativeness heuristic basically consists in individuals determining the likelihood of an event by assessing how similar a sample is to the population or an occurrence is to a model. A famous example is when trying to judge if someone is a doctor assessing that probably by comparing that person with the characteristics that are usually seen in doctors. In other words, individuals asses the probability of an event by how easy it is to imagine (Kudryavtsev et al., 2012). This heuristic is presented in many situations and leads individuals to mistakenly assess the probability of an event due to overstating correlation between two events and ignoring the size of the sample when judging the likelihood. In this context, the representativeness heuristic leads individuals to expect that the characteristics of a random event (for example, if a coin was tossed infinite times, both outcomes should be drawn an equal amount of times) will not only observed globally (i.e. when done an infinite amount of times) but also locally which means they expect sequences of the same outcome to be less likely to occur and that is not accurate as these sequences lack local representativeness of the global statistically inevitability. Basically, a sequence of one outcome in a random context is harder to imagine than a sequence with reversals. Other possible explanation would be that individuals, when making repeated decisions, are not always aiming at maximizing their long-run outcomes but sometimes they want to make the game more interesting, or they might even value being able to predict a rare outcome more than having a high overall accuracy of predictions (Tversky & Edwards, 1966). Even though the intention to make the game more interesting might be a reason, boredom is not because as shown by Gal and Baron (1996), participants would use a logic similar to the gambler's fallacy when asked how they would maximize their earnings.

Additionally, Sundali and Croson (2005) also found that the gambler's fallacy and the hot hand fallacy have correlation in an individual level which means that individuals who are

affected by the gambler's fallacy are more prone to be affected by the hot hand fallacy which indicates that there might be a common factor in determining biased beliefs. In line with this and regarding financials markets, evidence shows that an investor who accepts an intuitive technique in decision making is more likely to accept other ones and that the most likely scenarios are that either stock market investors are skeptical when it comes to behavioral decision making techniques in general or use no less than some of them. (Kudryavtsev et al., 2012).

This fallacy is thought to be able to explain some behaviors individuals have and might sometimes lead to some unpleasant and suboptimal results in several different contexts. Gal and Baron (1996) found that several individuals do not understand that successive trials are independent and others that do have this understanding fail to use it to solve the problem they are presented with. Also, in financial markets, the disposition effect is a behavior that can be caused by the gambler's fallacy and it consists in the tendency of investors to hold stocks that have decreased in value and sell stocks that have increased in value, this could be explained by the tendency of investors to assume uncorrelated events are correlated and thus think that if a stock has risen in value it will have to decrease which means it is time to sell (Croson & Sundali, 2005). Goetzmann and Kumar (2008) found that investors in the US that have a trend-contrarian behavior are more likely to hold less diversified portfolio which implies a higher risk and possibility of a poorer performance.

The gambler's fallacy has been identified in several different circumstances, at first it was identified under controlled conditions in laboratory where individuals were asked to choose which of two lights with different colors would light up next and it was observed that after a sequence of one of the lights individuals were more likely to guess the other. (Simon & Laplace, 1951). Within the laboratory context, it was also found when asking individuals what color would appear next in a simulated roulette (Ayton & Fischer, 2004).

The conclusions that these studies bring to the reality outside of laboratory might be limited as literature suggests a discrepancy between what people say and what they actually do, proposing that there might be a difference in the performance individuals have in hypothetical tasks and in real ones (Reber, 1992). Besides, (Terrell, 1994) also suggests that behaviors related to this fallacy should decrease if the costs that are associated with the failure that behaving in accordance with this fallacy might bring, are higher. Specifically, in financial markets, proof of this behavior should not exist in final prices (Terrell & Farmer, 1996).

However, evidence outside of laboratory has also been found. Croson and Sundali (2005) found the gambler's fallacy existence in casino betting by observing individuals betting with their own money outside laboratory. There is also evidence of lottery players being affected by the gambler's fallacy, Clotfelter and Cook (1991) found observing bets done in Maryland's three digit number's game, that in the day after a hit of number there was a decrease of the amount bet on it by about 25 per cent and on the following day that decrease would go up to 50 per cent. In addition, Papachristou and Karamanis (1998) found that participants of the national Greek lottery are significantly more likely to bet on numbers that have not been drawn in a long period of time. The fallacy was also found in dog races in Kansas by Terrell (1998) as bettors underestimate the probability that the last winning dog will win again. Besides, regarding financial markets, Zielonka (2004) also found, by doing questionnaires on financial analysists and dealers of the banks and financial institutions of Warsaw about signals, that patterns discovered by believers of the technical analysis are consistent with several cognitive biases including the gambler's fallacy.

2.2 Stock trading volumes

Trading activity represents an important factor to examine when analyzing stocks and their returns. During many years, trading volumes were underestimated and researchers were only interested in explaining prices which, according to Ross (2005), represents something for economists to be ashamed of because they were only able to explain price but had no explanation whatsoever for the quantity. Since then, trading volume as only continued to increase, and more studies have been done regarding this matter. Trading activity was not only found to be able to indicate the level of disagreement between investors but also enables conclusions regarding several other aspects, especially stock's prices (and stock returns). These are the main topics discussed in the literature review of this concept.

Trading volume can be associated with investor disagreement as there is only a trade when an individual is willing to buy and other is willing to sell, this means at the same point in time and with the same level of (public) information two individuals make different valuations of the same stock. This disagreement can be expanded by the disclosure of new information which the investors will interpret in a different way. Trading volume was first linked with the level of disagreement between investors by Beaver (1968) that tried to understand if the earning's announcements provided information content by analyzing the trading volume of the week they were announced. By doing this, evidence that the trading

volume of this week was higher because it reflected a lack of consensus related to the price, due to different interpretations of the report (the new piece of information), was found. Besides, it was also noticed that eight weeks before the announcement, volume was lower than usual which might indicate that investors would be delaying their decisions waiting for the new information regarding the earnings announcements. Also, in line with this and according to Bamber et al. (2011), reactions of trading volume can bring understandings to the effects that financial disclosures have on disagreement that exists among investors, including the one that comes with asymmetric information. Bamber et al. (1999) also found that a significant part of the trading occurrence in a sample with higher trading volume than the firm's average in non-announcement period can be explained by differential interpretations and according to (Garfinkel, 2009) unexplained volume is the best proxy of disagreement. There is also evidence that volume might increase following a growth of the information asymmetry (caused by earnings announcements) in certain circumstances and argued that trading volume might rise due to informed trading and not liquidity reasons (Kim & Verrecchia, 1994). Finally, it was also discovered that volume based metrics provide a better measure of the investors reaction to public disclosure than do return based metrics (Cready & Hurtt, 2002).

Besides the conclusions one can extract regarding the disagreement degree, trading volume might also vary due to other aspects. Trading activity might decrease or increase seasonally, Hong and Yu (2009) found that trading activity falls during summer because investors "are gone fishing". Further, Lakonishok and Vermaelen (1986) noticed that trading volume is higher around ex-dividend days and that it is higher for stocks that are actively traded with a high yield. Trading volume might also be higher following analyst recommendations, Kliger and Kudryavtsev (2010) document the outcome availability effect, which consists in individuals making decisions based on immediate examples that come to one's mind faster, in stocks' trading volumes. This conclusion was reached as they found abnormal trading volumes following analyst recommendation upgrades (downgrades) to be significantly higher if these recommendations take place on the days of market rise (fall). Moreover, there is also the possibility that investors trade merely due to portfolio rebalancing reasons and not because information has arisen, this is called the liquidity or noise trading. Baker and Stein (2004) found that trading volume can represent an indicator that irrational investors are present when there are short sale restrictions and Chordia et al. (2007) found that noise trading is essentially based in the uncertainty about fundamental values, on needs

for rebalancing portfolio and on the stock's prominence. Additionally, more trading volume can also indicate that investors are simply more willing to trade maybe because they are more confident about their own skills. Statman et al. (2006) argue that high observed trading volume can be explained by the idea that investors are overconfident about their skills for trading and their valuations and finds that share turnover is positively related to lagged returns for many months. This is also confirmed by Weber (2008) that found past market and portfolio returns impact trading activity of individual investors.

Further, there is also an extent literature relating trading volumes with stock price and consequently stock returns. Evidence regarding volume increasing following positive returns and decreasing after negative returns contraries the liquidity explanation and also demonstrate that short-sale constraints are not sufficiently to explain trading volume's magnitude and variation (John M. Griffin, 2006). There is also statistical evidence that supports the idea that rising trading volumes have a positive impact in price variations and that when the price is rising but the trading volume is declining technical analysts consider the growth of the stock's price to be unstable (Caginalp & Desantis, 2011). Karpoff (1987) argues there is a positive correlation between volumes and the extent of the price change and to the price itself in the case of in equity markets. Westerfield (1977) also found there is a positive relation between the absolute value of daily price changes and daily trading volumes. In line with this, Chen et al. (2001) analyzing return indexes and trading volumes from U.S., Japan, U.K, France, Canada, Italy, Switzerland, the Netherlands, and Hong Kong found that there is a positive relation between the trading volume of a stock and its value of price change in absolute terms. The results of this study proved that returns cause volume and that volume causes returns although not as significantly. Strong evidence was also found by Gunasekarage (2007) regarding the existence of asymmetry in the relationship between the stock returns and trading volume as returns play an important role in forecasting trading volume's future dynamics, but trading volume, on the other hand impacts the future dynamics of stock returns not very significantly. Gervais et al. (2001) explored the idea that excessive trading activity comprises information regarding stock prices' evolution and found that stocks with abnormally high (low) trading volume on a day or a week tend to appreciate (depreciate) during the next month. Lee and Rui (2002) found a positive feedback relationship between trading volume and return volatility in the New York, Tokyo and London stock markets and that trading volume's importance, regarding the information it can provide, increased once options were introduced in the US and Japan. Llorente et al. (2002) found evidence

supporting the idea that stocks with an elevated level of informed trading show a higher return continuation on days the volume is high, and stocks that are associated with a small level of informed trading show a higher amount of return reversals on high-volume days which is in line with the idea that trading volumes contain information regarding future price changes. Further, Remorov (2014) discovered trading volume to be inversely proportional to the stock price's square when there are intense drops in price analyzing by the price and volume data of major recent market crashes such as the Lehman Brothers Inc. Safvenblad (2000) observed that there is a high autocorrelation between indexes returns when the trading volume is low, in the Swedish market. Lastly, Barber and Odean (2008) found that individual investors are net buyers of stocks that are present in the news, whose trading volumes are high, and which have extreme returns, basically, stocks with high attention.

Finally, trading volume might also be related to specific returns patterns such as the momentum and reversal. Price momentum consists in stocks that have performed well in the past (called "winners") continuing to perform well in the future and stocks that have performed badly (called "losers") will perform badly in the future. Jegadeesh and Titman (1993) show the existence of this pattern by observing that trading strategies consisting in buying "winner" stocks and selling "loser" stocks are able to produce considerable positive returns after 3 months or 12 months of holding. Price reversal consists in the exactly opposite logic. Fama and French (1996) document that their three-factor model is able to explain several asset pricing phenomena however fails to explain the short-term return momentum. Lee and Swaminathan (2000) showed that an important connection between "momentum" and "value" strategies is set by trading volume. This study also suggests that past trading volume predicts the persistence and scale of price momentum.

3. Methodology

This research follows essentially the same methodology used by Kudryavtsev (2017) in his article as the whole point is to understand if the same results will be reached. The hypothesis are the same, all the variables chosen are as close as possible and the formulas and equations were adapted with small adjustments that do not change its purpose.

3.1 Proposed hypothesis

This study and its hypothesis are included within the wide literature that relates stock returns and trading volumes as it analyzes another aspect of this concepts' mutual dependence. The two-research hypothesis of the present study intend to relate stock return sequences with trading volumes. The first hypothesis aims to represent the suggestion that if a stock's price falls (rises) several days in a row then some investors will be affected by the gambler's fallacy and believe the price of the stock must rise (fall) which increases their disposition to buy (sell) the stock. This results in a higher level of disagreement between the investors who are affected and those who are not and consequently an increase in the trading volume. Therefore, this hypothesis postulates that a stock experiencing a sequence of positive (negative) daily returns that is followed by a day with a negative (positive) return will show a higher trading volume in the day the return sign changed. The second hypothesis intends to translate the idea that this effect's strongness increases with the number of days that compose the sequence as it happens in other contexts such as the casino. Consequently, this hypothesis postulates that the higher the length of the sequence of same sign returns, the higher will be the trading volume in the day that sequence is broken. These hypothesis are the same Kudryavtsev (2017) used as the objective is to see if the same conclusions are reached in a different market.

Hypothesis 1. Stock trading volume should be higher on the days when the stock return's sign is reversed after a number of consecutive days with the same-sign returns.

Hypothesis 2. The increase in the stock trading volume following the reversal in the sign of the stock's return should be more pronounced the longer the sequence of the days with the same sign of the stock's returns.

3.2 Data Description

The primary data necessary to perform the present empirical analysis is the daily price and trading volume of the stocks that compose the main index of the London Stock

Exchange i.e. the components of the FTSE 100. This data was downloaded using Eikon DataStream according to the following specifications.

All components of the index as of 15th of March of 2022 were included according to London Stock Exchange official website.

The variables chosen were Eikon DataStream's variables that were similar to the ones Kudriavstev (2017) used in his study: Price Adjusted (unpadded) (P#S) and Turnover by Volume (VO). Price Adjusted (unpadded) represents the closing price already adjusted for any corporate actions such as stock splits, dividends, and rights offerings. Turnover by Volume variable shows the number of shares traded for a stock in a day, in thousands. Similar to Kudriavtsev (2017) study the period of time considered was also since 1 of January 1990 until the day all data was downloaded i.e. 16th of March of 2022 or since the first day of the stock's trading history according to Eikon DataStream's information.

Additionally, in a later phase with the objective of gathering the data necessary for the second part of the methodology, the dates of dividend payments and of the earnings announcements of the same components of the FTSE 100 were also downloaded to excel using Eikon DataStream. The variables chosen, being the ones that would provide the closest information to the one used by Kudriavtsev (2017), were Ex-dividend Date (XDDE) and EPS Actual Announcement Date (EPSANCDT). Ex-Dividend Date represents the ex-dividend date associated with a cash income dividend payment and so it allows all ex-dividend dates to be obtained. EPS actual announcement date enables the obtention of all dates an EPS announcement was made by all of these companies. Similarly, the time period considered was from the 1st of January of 1990 or the first day of the stock's trading history until the 9th of May of 2022.

3.3 Data Analysis

After downloading all data to excel it was necessary to identify the sequences of three days, four days, five days, six days and seven or more days as well as to arrange the data in order to be able to perform the methodology.

First, daily returns for all days for each stock were calculated using the formula:

$$r_j \equiv \frac{P_{jt+1} - P_{jt}}{P_{jt}}$$

Where r_j represents daily return for stock *j*, P_{t+1} represents the price of stock *j* at day $t+1$ and P_t represents the price of the stock *j* at day t.

Average trading volume including the 250 days preceding each day were also calculated as well as its standard deviation for all days.

Then, sequences of same sign returns composed by three, four, five, six and seven or more consecutive days followed by a reversal were identified. Days of no trading were deleted which means they were not counted as another day contributing to the sequences' length, besides, increases or decreases were considered and also when the price was kept the same i.e. the daily return was zero. This means, the sequences identified and used to perform this study are composed of consecutive days (ignoring non-trading days) where the stock's return was positive or zero and consecutive days where it was negative or zero.

As some stocks only had trading volume data starting later or did not have information regarding ex-dividend dates and EPS announcements for the first months or years, all data representing days that did not have some of the information regarding any variable were not considered during the methodology process as data regarding those days was eliminated in this phase of the data analysis.

After organizing the data, descriptive statistical analysis was also performed to obtain some information regarding the data in general.

Table 1 presents descriptive statistics for the sample. Returns on average are negative but very close to zero with a standard deviation that is close to 0.04 representing a sample where data is considerably dispersed around the mean. Trading volume in on average inferior but close to 9000 thousand shares with a standard deviation that is very high (2980477) suggesting that the data is very dispersed around that value.

Table 1– Sample statistics

#Days	Returns' mean	Trading volume's mean	Returns' Standard deviation	Trading volume's standard deviation
76456	-0.01373	8906.876	0.036638	29804.77

The table presents some descriptive statistics for the 76456 days that break a sequence of either three, four, five, six or seven or more days with same sign-returns. This data was obtained after organizing the data and identifying the sequences. Trading volume corresponds to the number of shares traded in a day in thousands.

3.4 Formulas and Regressions

In order to perform the analysis i.e. to be able to understand whether the trading volume is higher in days following sequences or not (hypothesis 1), the abnormal trading volume for all days follow these sequences was calculated, as referred above, using the same formula Kudriavtsev (2017) used:

$$ABVOL_{it} = \frac{Vol_{it} - AVol_i}{STDVol_i}$$

Where $ABVOL_{it}$ corresponds to the abnormal trading volume of the stock *i* in day *t*, Vol_{it} corresponds to the volume in thousands of shares traded of stock *i* on day *t*, $AVol_i$ corresponds to the average trading volume in thousands of shares traded of the stock *i* comprising 250 days before day *t* and $STDVol_i$ corresponds to the standard deviation of the average trading volume of stock *i* over the 250 days before day *t*.

After calculating all abnormal trading volumes for the days that the return sign is reversed after a sequence, the averages for each sequence using all days that followed that sequence were calculated.

As a next step, seeing if they were statistically significant was needed and so the T-Statistics was calculated, using the formula:

$$t = \frac{(x - \mu)}{\frac{s}{n}}$$

Where x is the sample mean, μ is the population mean, s is the standard deviation and n is the square of the number of observations.

Besides, differences between the averages were also calculated in order to compare the results for the different sequences and understand if the abnormal trading volume increased with the length of the sequence that preceded it (hypothesis 2).

Afterwards, proof that these differences were significant was also needed and so another T-test was performed this time using excel data analysis functions to perform the two-sample test assuming equal variances.

Then, the second part of the methodology was performed. Understanding that, as referred in the literature review, several other factors relate to trading volumes it was necessary to comprehend if the results were significant even when these other factors that

might affect trading volumes are controlled for. To do this, some regressions were run and coefficient differences were calculated using Wald Test in order to also obtain T-Statistics and p-values to check significance of those differences.

All regressions are similar to the ones Kudriavtsev (2017) used except they do not include the intercept because as the data used consists of days that follow sequences (days where the sequence is broken) and the explanatory variables representing the sequences are dummy variables, all data has the value one for at least one of the dummy variables. This means that if the intercept was not eliminated it would be impossible to run the regression because of the multicollinearity error. Only data representing days that follow sequences of three, four, five, six and seven or more days was used because those are the days that matter to this analysis as they are the days where it is relevant to understand that if the trading volume is really higher than usual that can be attributed to the sequences or not.

Besides, an additional regression was run (**3.4.1**) that considers only the abnormal trading volume as an independent variable and the dummy variables representing the sequences as the dependent one to confirm the correlation between the sequences and the abnormal trading volume that the first part of the methodology suggested.

Excel data was uploaded to Eviews and regression (**3.4.1**) was run using ordinary least squares method.

$$\textbf{3.4.1}\ ABVOL_{it} = \beta_{1i}POS3_{it} + \beta_{2i}POS4_{it} + \beta_{3i}POS5_{it} + \beta_{4i}POS6_{it} + \beta_{5i}POS7plus_{it} + \beta_{6i}NEG3_{it} + \beta_{7i}NEG4_{it} + \beta_{8i}NEG5_{it} + \beta_{9i}NEG6_{it} + \beta_{10i}NEG7plus_{it} + \varepsilon_{it}$$

The variables $POS3_{it}$ to $POS7plus_{it}$ represent the dummy variables that assume the value 1 if stock *i*'s return is negative on day *t* following, respectively, three to seven or more days of positive returns and 0 if not. $NEG3_{it}$ to $NEG7plus_{it}$ also represent dummy variables that assume the value 1 if, stock *i*'s return is positive on day *t* following, respectively, three to seven or more days of negative returns and 0 if not.

Stock returns (both in absolute and non-absolute terms) were found to be related with trading volumes so the first step in controlling variables was to analyze if the results remain significant after stock returns are controlled for. To do this it was necessary to upload the excel data to Eviews and run the following linear regressions (**3.4.2**) and (**3.4.3**), using Ordinary Least Squares method.

3.4.2 $$ABVOL_{it} = \beta_{1i}POS3_{it} + \beta_{2i}POS4_{it} + \beta_{3i}POS5_{it} + \beta_{4i}POS6_{it} + \beta_{5i}POS7plus_{it} + \beta_{6i}NEG3_{it} + \beta_{7i}NEG4_{it} + \beta_{8i}NEG5_{it} + \beta_{9i}NEG6_{it} + \beta_{10i}NEG7plus_{it} + \beta_{11i}SRit_{it} + \varepsilon_{it}$$

This second regression was used to understand the impact of the sequences on the abnormal trading volume when stock returns are controlled for. This regression maintains all variables used in the previous one plus SR_{it} which corresponds to stock *i*'s log return on day *t*.

3.4.3 $$ABVOL_{it} = \beta_{1i}POS3_{it} + \beta_{2i}POS4_{it} + \beta_{3i}POS5_{it} + \beta_{4i}POS6_{it} + \beta_{5i}POS7plus_{it} + \beta_{6i}NEG3_{it} + \beta_{7i}NEG4_{it} + \beta_{8i}NEG5_{it} + \beta_{9i}NEG6_{it} + \beta_{10i}NEG7plus_{it} + \beta_{11i}|SR|_{it} + \varepsilon_{it}$$

The third regression was used to understand the impact of the sequences on trading volumes after absolute stock returns being controlled for. Regression (**3.4.3**) maintains all variables from regression (**3.4.2**) but instead of stock returns it includes the variable$|SR|_{it}$ that represents the absolute value of stock *i*'s log return on day *t*.

Besides the conclusions reached after running these regressions, two further regressions were used in order to understand if the correlation between stock return sequences and trading volumes still remains significant after controlling for additional factors such as lagged stock returns, historical stock returns and volatility, companies' earnings announcements and dividend payments because as referred above these factors have also been found to impact trading volume. To achieve this goal, regressions (**3.4.4**) and (**3.4.5**) were run using Ordinary Least Squares method in Eviews.

3.4.4 $$ABVOL_{it} = \beta_{1i}POS3_{it} + \beta_{2i}POS4_{it} + \beta_{3i}POS5_{it} + \beta_{4i}POS6_{it} + \beta_{5i}POS7plus_{it} + \beta_{6i}NEG3_{it} + \beta_{7i}NEG4_{it} + \beta_{8i}NEG5_{it} + \beta_{9i}NEG6_{it} + \beta_{10i}NEG7plus_{it} + \beta_{11i}SR_{it} + \beta_{12i}SR_{it-1} + \beta_{13i}CumSR_{it} + \beta_{14i}STDevSR_{it} + \beta_{15i}EarnAnn_{it} + \beta_{16i}Div_{it} + \varepsilon_{it}$$

All the variables used in regression (**3.4.2**) are maintained. Additionally, $CumSR_{it}$ represents stock *i*'s cumulative return over 250 trading days preceding day *t*. $STDevSR_{it}$ represents the standard deviation of stock *i*'s returns over 250 trading days preceding day *t*. $EarnAnn_{it}$ represents the dummy variable, taking the value 1 if on day *t* there was an earnings announcement published by firm *i*, and 0 otherwise. Div_{it} is the dummy variable, taking the value 1 if day *t* represents an ex-dividend day for firm *i*, and 0 otherwise.

$$\textbf{3.4.5}\ ABVOL_{it} = \beta_{1i}POS3_{it} + \beta_{2i}POS4_{it} + \beta_{3i}POS5_{it} + \beta_{4i}POS6_{it} + \beta_{5i}POS7plus_{it} + \beta_{6i}NEG3_{it} + \beta_{7i}NEG4_{IT} + \beta_{8i}NEG5_{it} + \beta_{9i}NEG6_{it} + \beta_{10i}NEG7plus_{it} + \beta_{11i}|SR|_{it} + \beta_{12i}|SR|_{it-1} + \beta_{13i}CumSR_{it} + \beta_{14i}STDevSR_{it} + \beta_{15i}EarnAnn_{it} + \beta_{16i}Div_{it} + \varepsilon_{it}$$

Regression (**3.4.5**) maintains the same variables used in regression (**3.4.4**) but using absolute value of stock *i*'s log return on day *t* and day *t*-1 ($|SR|_{it}$ and $|SR|_{it-1}$) instead of non-absolute.

After this, the differences between the coefficients were calculated to be able to compare the results for the different sequences and understand if the length of the sequences has a consequence on the impact on the abnormal trading volume.

4. Results and Discussion

4.1 Abnormal trading volume formula

Using the abnormal trading volume formula referred above, abnormal trading volumes for all days following positive and negative sequences of three, four, five, six and seven or more days were calculated as well as averages for each sequence length. Besides, using the explained above methods, T-Statistics and p-values were also calculated for all averages to understand the significance of the results.

The results for positive sequences in Table 2 suggest that sequences of three, four, five and six do not have the expected effect on trading volumes as the average abnormal trading volume for days following these sequences is negative meaning trading volume in smaller on these days than on average. On the other hand, sequences of seven or more days show a positive average of 0.255 which indicates the days that follow these sequences exhibit a higher trading volume than average. These results suggest that the expected effect of the gambler's fallacy might only affect investors when the sequences are significantly large (seven or more days).

Table 2 – Average abnormal trading volumes following positive sequences of same-sign stock returns and corresponding T-Statistics

Sequences	3 days	4 days	5 days	6 days	7 or more days
Average Abnormal Trading Volume	-0.107	-0.110	-0.029	-0.093	0.255
T-Statistics	-9.62***	-6.84***	-0.36	-3.64***	1.06

Asterisks denote 2-tailed p-values: *p<0.10;**p<0.05;***p<0.01.

However, T-statistics results for these averages suggest only averages of abnormal trading volume of the days following sequences of three, four and six are significant and so there is no indication that positive sequences affect the trading volume of the days following those sequences.

The results for negative sequences in Table 3 suggest that sequences of three, four, five, six and seven or more days do have an impact on trading volumes as the average abnormal trading volume for days following these sequences is positive meaning trading volume in higher on these days than on average. These results suggest that the expected

effect of the gambler's fallacy might be present in negative sequences even if the same does not happen for the positive ones.

Table 3 – Average abnormal trading volumes following negative sequences of same-sign stock returns and corresponding T-Statistics

Sequences	3 days	4 days	5 days	6 days	7 or more days
Average Abnormal Trading Volume	0.055	0.107	0.167	0.283	0.434
T-Statistics	6.70***	7.41***	10.14***	11.75***	16.37***

Asterisks denote 2-tailed p-values: *p<0.10;**p<0.05;***p<0.01.

T-Statistics results for these averages suggest all averages of abnormal trading volume of the days following sequences of either three, four, five, six or seven or more are significant and so there is an indication that negative sequences affect the trading volume of the day that follows those sequences making it higher.

Aiming to understand the differences between the impacts of the different length sequences, differences between the average abnormal trading volumes were calculated as well as the corresponding T-Statistics to understand if the results prove themselves to be significant.

Regarding positive sequences, findings on Table 4 indicate there is a positive difference between average abnormal trading volume of days following sequences of five days and days following sequences of four days (0.081) as well as between days following sequences of seven days or more and following sequences of six days (0.348). Furthermore, the largest difference is between days following sequences of seven days and days following sequences of three days (0.362). This suggests that, even though there is not a daily increase i.e. abnormal trading volume does not increase necessarily by a day increase in the sequence's length, abnormal trading volume does increase with the sequences' length suggesting the higher the number of days the stock return maintains its sign, the higher the number of investors suffering the effects of the gambler's fallacy.

Table 4 – Differences between average abnormal trading volumes of different lengths positive sequences and corresponding T-Statistics

Coefficient differences	Value of coefficient differences	T-Statistics
ABVOL(4 days) – ABVOL(3 days)	-0.003	1.96
ABVOL(5 days) – ABVOL(4 days)	0.081	1.96***
ABVOL(6 days) – ABVOL(5 days)	-0.064	1.96**
ABVOL(7+ days) – ABVOL(6 days)	0.348	1.96
ABVOL(7+ days) – ABVOL(3 days)	0.362	1.96***

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01.

T-Statics for these differences suggest the difference between abnormal trading volume of the days following sequences of five days and following sequences of four as well as the difference between the abnormal trading volume of the days following sequences of seven days or more and sequences of three days are significant. Because of this, even though the difference between days following sequences of seven or more and sequences of six is not significant, the conclusion reached above still maintains.

When it comes to negative sequences, results in Table 5 indicate there is always a positive difference between average abnormal trading volume of days following sequences of more days and days following sequences of less. The best example is the difference between days following sequences of seven or more days and days following sequences of three (0.379). This means that when sequences are composed of negative returns then abnormal trading volume does always increase with the sequences' length suggesting the higher the number of days the stock return is negative, the higher the number of investors suffering the effects of the gambler's fallacy.

Table 5 – Differences between average abnormal trading volumes of different lengths negative sequences and corresponding T-Statistics

Coefficient differences	Value of coefficient differences	T-Statistics
ABVOL(4 days) – ABVOL(3 days)	0,052	1.96**
ABVOL(5 days) – ABVOL(4 days)	0,060	1.96**
ABVOL(6 days) – ABVOL(5 days)	0,116	1.96***
ABVOL(7+ days) – ABVOL(6 days)	0,150	1.96***
ABVOL(7+ days) – ABVOL(3 days)	0,379	1.96***

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01.

T-Statistics for these differences suggesting all differences are significant which means the reasoning described above regarding negative sequences holds.

4.2 Multifactor Linear Regression

Different regressions were run aiming to understand if the results presented above remained the same at the same time as other variables that could possibly influence were being controlled. Coefficient differences were also calculated for each regression in order to understand if the length of the sequence's impact also holds. T-Statistics and p-values were calculated for all coefficient and all coefficient differences with the goal of confirming the significance of the estimates.

Results for the first regression are presented in Table 6 and show that coefficient estimates are positive for days following positive sequences of five or more days and for days following negative sequences of four or more days. These results are in line with the ones presented on the chapter above (4.1) even though they are not exactly the same. Almost all negative sequences show a positive correlation and only larger positive sequences have that outcome.

However, looking at the significance of these estimates, only the coefficient of the days following sequences of seven or more days proves its significance therefore the conclusion regarding the negative ones cannot be confirmed.

Table 6 – Regression analysis (Regression 3.4.1): Return sequences effect on stock trading volumes and corresponding T-Statistics

Explanatory Variables	Coefficient Estimates	T-Statistic
POS3t	-0.028	-0.91
POS4t	-0.005	-0.13
POS5t	0.054	0.95
POS6t	0.004	0.05
POS7plust	0.368	5.30***
NEG3t	-0.032	-1.08
NEG4t	0.004	0.09
NEG5t	0.050	0.90
NEG6t	0.017	0.22
NEG7plust	0.099	1.45
Adjusted R-Squared	0.0003	

Dependent variable is ABVOL. Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01.

Differences between the coefficients presented in Table 7 also present similar results to those discussed in the previous chapter (4.1) as the difference is positive in almost all cases for both positive and negative sequences and it is larger when subtracting the coefficient of the days following seven days or more sequences to the coefficient of the days following three days sequences. For positive sequences that difference is 0.396 and for negative ones it is 0.131.

Once again, not all coefficients are significant, however, the ones concerning differences between days following seven and three days sequences are allowing that conclusion to hold.

Table 7 – Coefficient differences (Regression 3.4.1): Return sequences effect on stock trading volumes and corresponding T-Statistics

Positive Sequences	Coefficient Differences	T- Statistics
$\beta_{2-}\beta_1$	0.022	0.43
$\beta_{3-}\beta_2$	0.060	0.84
$\beta_{4-}\beta_3$	-0.050	-0.52
$\beta_{5-}\beta_4$	0.364	3.47***
$\beta_{5-}\beta_1$	0.396	5.22***
Negative Sequences	Coefficient Diferences	T-Statistics
$\beta_{7-}\beta_6$	0.036	0.71
$\beta_{8-}\beta_7$	0.047	0.67
$\beta_{9-}\beta_8$	-0.034	-0.35
$\beta_{10-}\beta_9$	0.082	0.79
$\beta_{10-}\beta_6$	0.131	1.76*

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01.

Table 8 presents results concerning the second regression which included stocks log returns. These results indicate there is no positive correlation between the sequences of days with same-sign returns and the abnormal trading volume as all coefficients became negative (except for days following sequences of seven or more days but that was the only coefficient did not prove itself to be significant and so cannot be considered). This implies that the effect suggested above that same-sign sequences have on trading volume might be actually an effect of log returns as the results change significantly when that variable is being controlled for. As demonstrated in the literature review, returns relate to trading volumes and in this case, they seem to be correlated negatively justifying the abnormal trading volume for these days instead of the sequences that preceded those days.

Table 8 – Regression analysis (Regression 3.4.2): Return sequences effect on stock trading volumes and corresponding T-Statistics

Explanatory Variables	Coefficient Estimates	T-statistic
POS3t	-0.325	-9.89***
POS4t	-0.286	-6.58***
POS5t	-0.240	-4.09***
POS6t	-0.266	-3.35***
POS7plust	0.098	1.40
NEG3t	-0.309	-9.71***
NEG4t	-0.264	-6.20***
NEG5t	-0.229	-4.00***
NEG6t	-0.245	-3.12***
NEG7plust	-0.156	-2.25**
SRt	-22.093	-23.39***
Adjusted R-Squared	0.007	

Dependent variable is ABVOL. Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01.

Despite, results in Table 9 show differences between coefficients and, even though all significant coefficients are negative, we can still see coefficients representing days following larger sequences are less negative than days following shorter sequences which indicates some part of the length effect still applies even if not the way described above. Coefficient differences that are significant are the ones between the largest and the smallest sequences which allow this conclusion to hold.

Table 9 – Coefficient differences (Regression 3.4.2): Return sequences effect on stock trading volumes and corresponding T-Statistics

Positive Sequences	Coefficient Differences	T- Statistics
$\beta_{2-}\beta_1$	0.039	0.75
$\beta_{3-}\beta_2$	0.046	0.65
$\beta_{4-}\beta_3$	-0.026	-0.27
$\beta_{5-}\beta_4$	0.365	3.48***
$\beta_{5-}\beta_1$	0.423	5.59***
Negative Sequences	Coefficient Diferences	T-Statistics
$\beta_{7-}\beta_6$	0.044	0.87
$\beta_{8-}\beta_7$	0.035	0.56
$\beta_{9-}\beta_8$	-0.015	-0.16
$\beta_{10-}\beta_9$	0.089	0.86
$\beta_{10-}\beta_6$	0.153	2.05**

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01.

Table 10 presents results for the regression including absolute stock log returns instead of stock log returns and deductions are exactly the same except absolute stock log returns seem to be positively correlated to abnormal trading volume instead of negative.

Table 10 – Regression analysis (Regression 3.4.3): Return sequences effect on stock trading volumes and corresponding T-Statistics

Explanatory Variables	Coefficient Estimates	T-Statistics
POS3t	-0.351	-10.66***
POS4t	-0.311	-7.15***
POS5t	-0.266	-4.53***
POS6t	-0.290	-3.65***
POS7plust	0.074	1.05
NEG3t	-0.354	-10.99***
NEG4t	-0.306	-7.12***
NEG5t	-0.273	-4.74***
NEG6t	-0.287	-3.66***
NEG7plust	-0.202	-2.91***
|SRt|	24.035	24.86***
Adjusted R-Squared	0.008	

Dependent variabe is ABVOL. Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01.

Moreover, Table 11 shows differences between coefficients that also suggest the exact same conclusions.

Table 11 – Coefficient differences (Regression 3.4.3): Return sequences effect on stock trading volumes and corresponding T-Statistics

Positive Sequences	Coefficient Differences	T-Statistics
$\beta_{2-}\beta_1$	0.040	0.77
$\beta_{3-}\beta_2$	0.045	0.64
$\beta_{4-}\beta_3$	-0.024	-0.25
$\beta_{5-}\beta_4$	0.364	3.48***
$\beta_{5-}\beta_1$	0.425	5.62***
Negative Sequences	Coefficient Differences	T-Statistics
$\beta_{7-}\beta_6$	0.048	0.95
$\beta_{8-}\beta_7$	0.033	0.48
$\beta_{9-}\beta_8$	0.876	-0.16
$\beta_{10-}\beta_9$	0.086	0.83
$\beta_{10-}\beta_6$	0.152	2.05

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01.

Results for coefficients of the regression including all variables pretended to be controlled are presented in Table 12 and, contrary to what was shown in the regression involving only the log stock returns or absolute log stock return, these results suggest days following sequences of same-sign returns are positively correlated to abnormal trading volumes. Log stock returns maintain its negative correlation however, now that more explanatory variables were added, this correlation does not result in a negative correlation regarding days following sequences anymore. This means, after all, sequences of same-sign returns do seem to affect abnormal trading volumes even when other variables are being controlled for.

Besides, considering only standard deviation of returns is considered to be significant among the other explanatory variables, we can also see that abnormal trading volumes and standard deviation of returns correlate negatively (-8.081).

Table 12 – Regression analysis (Regression 3.4.4): Return sequences effect on stock trading volumes and corresponding T-Statistics

Explanatory Variable	Coefficient Estimate	T-Statistics
POS3t	0.903	5.67***
POS4t	0.940	5.71***
POS5t	0.987	5.82***
POS6t	0.961	5.38***
POS7plust	1.318	7.62***
NEG3t	0.905	5.65***
NEG4t	0.947	5.83***
NEG5t	0.982	5.87***
NEG6t	0.963	5.49***
NEG7plust	1.044	6.13***
SRt	-22.350	-22.04***
SRt-1	0.951	1.03
CumSRt	0.046	1.11
STDevSRt	-8.081	-7.87***
EarnAnnt	0.233	1.00
Divt	0.053	0.42
Adjusted R-Squared	0.008	

Dependent variable is ABVOL. Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01.

Table 13 shows coefficient differences and allows the conclusion that the higher the sequence that precedes the day the higher the trading volume on that day. Almost all coefficient differences are positive however, only coefficient the difference between days following sequences of four days and three days as well as the difference between days following five days and four days are significant. This means that this conclusion can be proved essentially regarding larger sequences of positive returns.

Table 13 – Coefficient differences (Regression 3.4.4): Return sequences effect on stock trading volumes and corresponding T-Statistics

Positive Sequences	Coefficient Differences	T- Statistics
$\beta_{2-}\beta_1$	0.037	0.70
$\beta_{3-}\beta_2$	0.047	0.65
$\beta_{4-}\beta_3$	-0.026	5.36***
$\beta_{5-}\beta_4$	0.357	3.34***
$\beta_{5-}\beta_1$	0.415	-0.27
Negative Sequences	Coefficient Differences	T-Statistics
$\beta_{7-}\beta_6$	0.042	0.81
$\beta_{8-}\beta_7$	0.035	0.49
$\beta_{9-}\beta_8$	-0.018	-0.19
$\beta_{10-}\beta_9$	0.081	0.77
$\beta_{10-}\beta_6$	0.139	1.84*

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01.

Finally, Table 14 shows returns for the regression where the explanatory variables are essentially the same, except for the log returns that are absolute. The results suggest the same as the last regression, all coefficients of dummy variables representing the sequences are positive and significant meaning they suggest a positive correlation between days following sequences of same-sign returns and abnormal trading volume. Absolute log return continues to correlate positively with a high significant coefficient (24.079), standard deviation of returns also continues to relate negatively (-8.183) showing a significant coefficient and, this time, cumulative returns also indicate a significant coefficient that is positive even though very small.

Table 14 – Regression analysis (Regression 3.4.5): Return sequences effect on stock trading volumes and corresponding T-Statistics

Explanatary Variables	Cofficient Estimates	T-Statistics
POS3t	0.874	5.39***
POS4t	0.917	5.55***
POS5t	0.959	5.65***
POS6t	0.934	5.23***
POS7plust	1.292	7.47***
NEG3t	0.856	5.35***
NEG4t	0.902	5.55***
NEG5t	0.934	5.59***
NEG6t	0.916	5.22***
NEG7plust	0.996	5.85***
|SRt|	24.079	23.39***
|SRt-1|	2.286	2.43**
CumSRt	0.069	1.68*
STDevSRt	-8.183	-7.97***
EarnAnnt	0.237	1.02
Divt	0.050	0.40
Adjusted R-Squared	0.009	

Dependent variable is ABVOL. Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01.

On Table 15 results for coefficient differences are presented and are in general positive, however only the differences between larger sequences of days are significant for both positive and negative sequences therefore, as above, we can conclude that within larger sequences, the abnormal trading volume is more correlated the higher the sequence's length.

Table 15 – Coefficient differences (Regression 3.4.5): Return sequences effect on stock trading volumes and corresponding T-Statistics

Positive Sequences	Coefficient Diferences	T-Statistics
$\beta_{2-}\beta_1$	0.038	0.73
$\beta_{3-}\beta_2$	0.046	0.64
$\beta_{4-}\beta_3$	-0.024	-0.25
$\beta_{5-}\beta_4$	0.358	3.35***
$\beta_{5-}\beta_1$	0.418	5.40***
Negative Sequences	Coefficient Diferences	T-Statistics
$\beta_{7-}\beta_6$	0.046	0.90
$\beta_{8-}\beta_7$	0.032	0.46
$\beta_{9-}\beta_8$	-0.018	-0.18
$\beta_{10-}\beta_9$	0.079	0.76
$\beta_{10-}\beta_6$	0.140	1.86*

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01.

5. Conclusions, Limitations and Suggestions for Future Research

5.1 Conclusions

This dissertation examines if the gambler's fallacy effect is present in the London stock market i.e. if investors are more willing to sell (buy) a stock after a sequence of positive (negative) returns in this market. The goal is to check if stock returns sequences of same-sign returns are followed by a day with a higher trading volume than usual traducing a higher disagreement between investors. This study is based on Kudriavtsev (2017) article and is applied to a different market to understand if the results reached are the same i.e. identify if they are dependent on the market or if we can suppose they are a general conclusion.

Findings are in general aligned with the ones of Kudriavtsev (2017), however, they also present some surprising twists.

Results indicate that in the London Stock Market investors suffer from the gambler's fallacy essentially after negative sequences of stock returns occur. Positive sequences, however, do not show that effect because even though some results suggest that it happens when positive sequences are large, there are not enough significative variables to prove that conclusion. This confirms hypothesis one but only partially and can be related to individuals being more affected by losses differently than they are affected by gains (Kahneman & Tversky, 1979) which would lead them pay more attention to sequences of losses and make more irrational choices, such as the ones based on the gambler's fallacy, disregarding, on other hand, the stocks that are earning positive returns. In this market the increase of the gambler's impact presence increases with the sequence's length but only within higher lengths suggesting that investors only start to make more irrational choices and are more willing to suffer from cognitive biases when they recognize a more defined pattern. This confirms hypothesis two but only partially as well. Besides, log stock returns and absolute log stock returns are correlated to abnormal trading volumes, the first in a negative way and the second, in a positive one in line with previous literature (Ying, 1966). Standard deviation of returns also presented its negative correlation.

Comparing these results with the ones Kudriavtsev (2017) reached in his article, it can be concluded that the presence of the gambler's effect is not subject to only one market as evidence of a part of it were also found in the London Stock Market. However, as conclusions were not exactly the same, it can also be presumed that the way it affects and how much it affects investors will depend on the market.

Besides, when it comes to the Efficient Market Hypothesis (EMH), these results are not consistent with the definition of Brealey et al. (2011) that an efficient market is when it is not possible to earn a return higher than the market return and with the definition of Eakins and Mishkin (2012) that an efficient market is where prices reflect all information available. These findings conclude prices are, at least sometimes, affected by irrational investors whose actions are impacted by biases such as the gambler's fallacy and so are not a perfect reflection of all available information. This means that abnormal returns may become a possible reality. When it comes to investors and their decisions, these findings might be used to create investment strategies that will result in abnormal returns by investing in stocks when they identify large negative sequences of returns as, according to evidence provided by this study, these sequences are many times followed by a reversal.

5.2 Limitations and Suggestions for Future Research

This research has some limitations that should be considered when reflecting about its results. In the first place, the variable suggested to confirm if stock return sequences have led investors to make irrational, cognitive based decisions of whether to buy or sell the stock is abnormal trading volume due to being a representative of the investor's disagreement. However, disagreement between investors can happen due to a variety of factors and not only because of irrational investors that are being affected by the gambler's fallacy. Some other potential factors that are known to influence trading volumes are controlled for in order to surpass this limitation however several other factors exist, some that already known and other that are not even known yet.

Secondly, FTSE 100 index is considered as a London stock market proxy which means conclusions for the whole market are inducted based on the results of data comprising only the index.

Thirdly, results of this study are compared with the ones of Kudriavtsev (2017) article, however, the two markets are of considerable different dimension.

Besides, trading volume variable used is expressed as the number of shares traded in one day (in thousands) and not in total amount as this was the variable available, however, results could have differed if the second way of measuring was used.

Finally, not all days of the time period considered were used as only days with all information available in DataStream regarding all variables were considered.

Regarding future research, concerning the same market as the results were more impactful regarding higher sequences it would be interesting to perform this study but with sequences starting at seven days and going further to understand if the gambler's effect is more present. Besides, it would always be interesting to perform this study in shorter time intervals (intra-day) and longer time intervals (weeks or even months). Also, it would be relevant to perform the study with more data (more stocks) and to compare other different markets with, for example, similar sizes. Moreover, it could also be worth to perform a similar study considering a trading volume variable expressed in value to see if the results are related or if further conclusions can be obtained.

Finally, comparisons between different sectors, different categories of stocks, different periods of time with relevant different macroeconomic specifications would provide further conclusions regarding this matter.

6.References

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7.Appendices

7.1 Appendix A: Multifactor Linear Regressions Results

Dependent Variable: ABVOL				
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
POS3	-0.027649	0.030273	-0.913319	0.3611
POS4	-0.005337	0.041713	-0.127943	0.8982
POS5	0.054243	0.057394	0.945096	0.3446
POS6	0.003975	0.078719	0.050498	0.9597
POS7PLUS	0.368108	0.069455	5.299934	0.0000
NEG3	-0.031787	0.029488	-1.077971	0.2811
NEG4	0.003838	0.041116	0.093347	0.9256
NEG5	0.050427	0.056143	0.898180	0.3691
NEG6	0.016923	0.077776	0.217588	0.8278
NEG7PLUS	0.098823	0.068292	1.447067	0.1479
R-squared: 0.000432				
Adjusted R-squared: 0.000314				
S.E. of regression: 4.000762				
Sum squared resid: 1223602.				
Log likelihood: -214486.5				
Durbin-Watson stat: 1.993366				
Mean dependent var: 0.013792				
S.D. dependent var: 4.001391				
Akaike info criterion: 5.610978				
Schwarz criterion: 5.612187				
Hannan-Quinn criter.: 5.611349				

Dependent Variable: ABVOL				
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
POS3	-0.350924	0.032924	-10.65874	0.0000
POS4	-0.311296	0.043547	-7.148486	0.0000
POS5	-0.265975	0.058704	-4.530779	0.0000
POS6	-0.290254	0.079439	-3.653787	0.0003
POS7PLUS	0.073886	0.070374	1.049897	0.2938
NEG3	-0.354031	0.032215	-10.98966	0.0000
NEG4	-0.305863	0.042928	-7.124985	0.0000
NEG5	-0.272526	0.057522	-4.737739	0.0000
NEG6	-0.287439	0.078605	-3.656740	0.0003
NEG7PLUS	-0.201580	0.069332	-2.907462	0.0036
_SR_	24.03466	0.966735	24.86167	0.0000
R-squared: 0.008472				
Adjusted R-squared: 0.008342				
S.E. of regression: 3.989623				
Sum squared resid: 1213455.				
Log likelihood: -213687.0				
Durbin-Watson stat: 1.996570				
Mean dependent var: 0.016112				
S.D. dependent var: 4.006368				
Akaike info criterion: 5.605415				
Schwarz criterion: 5.606748				
Hannan-Quinn criter.: 5.605824				

Dependent Variable: ABVOL				
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
POS3	-0.324651	0.032818	-9.892576	0.0000
POS4	-0.286057	0.043483	-6.578643	0.0000
POS5	-0.239969	0.058665	-4.090527	0.0000
POS6	-0.266391	0.079434	-3.353599	0.0008
POS7PLUS	0.098289	0.070357	1.397013	0.1624
NEG3	-0.308591	0.031789	-9.707400	0.0000
NEG4	-0.264361	0.042669	-6.195675	0.0000
NEG5	-0.229249	0.057323	-3.999266	0.0001
NEG6	-0.244530	0.078482	-3.115753	0.0018
NEG7PLUS	-0.155727	0.069163	-2.251580	0.0244
SR	-22.09307	0.944418	-23.39332	0.0000
R-squared: 0.007557				
Adjusted R-squared: 0.007427				
S.E. of regression: 3.991463				
Sum squared resid: 1214575.				
Log likelihood: -213722.2				
Durbin-Watson stat: 1.995871				
Mean dependent var: 0.016112				
S.D. dependent var: 4.006368				
Akaike info criterion: 5.606337				
Schwarz criterion: 5.607670				
Hannan-Quinn criter.: 5.606747				

Dependent Variable: ABVOL				
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
POS3	0.874428	0.162089	5.394742	0.0000
POS4	0.912620	0.164445	5.549686	0.0000
POS5	0.958506	0.169692	5.648518	0.0000
POS6	0.934065	0.178517	5.232368	0.0000
POS7PLUS	1.292087	0.172965	7.470202	0.0000
NEG3	0.855799	0.160028	5.347823	0.0000
NEG4	0.901846	0.162380	5.553929	0.0000
NEG5	0.934328	0.167127	5.590520	0.0000
NEG6	0.916147	0.175540	5.219021	0.0000
NEG7PLUS	0.995608	0.170304	5.846065	0.0000
_SR_	24.07923	1.029411	23.39126	0.0000
_SR__T_1	2.285691	0.938748	2.434830	0.0149
DIV	0.049656	0.124250	0.399641	0.6894
EARNANN	0.237410	0.233885	1.015072	0.3101
CUMSR	0.069353	0.041386	1.675750	0.0938
STDEVSR	-8.182772	1.026155	-7.974203	0.0000
R-squared: 0.009375				
Adjusted R-squared: 0.009177				
S.E. of regression: 4.019706				
Sum squared resid: 1211125.				
Log likelihood: -210671.5				
Durbin-Watson stat: 1.996140				
Mean dependent var: 0.017041				
S.D. dependent var: 4.038278				
Akaike info criterion: 5.620508				
Schwarz criterion: 5.622476				
Hannan-Quinn criter.: 5.621113				

Dependent Variable: ABVOL				
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
POS3	0.903217	0.162176	5.569355	0.0000
POS4	0.939997	0.164534	5.713081	0.0000
POS5	0.987279	0.169778	5.815113	0.0000
POS6	0.960870	0.178613	5.379609	0.0000
POS7PLUS	1.317869	0.173052	7.615445	0.0000
NEG3	0.905146	0.160062	5.654986	0.0000
NEG4	0.946774	0.162430	5.828812	0.0000
NEG5	0.981557	0.167170	5.871603	0.0000
NEG6	0.963433	0.175592	5.486757	0.0000
NEG7PLUS	2.043999	0.170349	6.128583	0.0000
SR	-22.34992	1.013904	-22.04343	0.0000
SR_T_1	0.951449	0.926698	1.026708	0.3046
DIV	0.052574	0.124327	0.422866	0.6724
EARNANN	0.233109	0.234003	0.996178	0.3192
CUMSR	0.046041	0.041319	1.114277	0.2652
STDEVSR	-8.081022	1.026568	-7.871883	0.0000
R-squared: 0.008361				
Adjusted R-squared: 0.008163				
S.E. of regression: 4.021762				
Sum squared resid: 1212365.				
Log likelihood: -210709.9				
Durbin-Watson stat: 1.995531				
Mean dependent var: 0.017041				
S.D. dependent var: 4.038278				
Akaike info criterion: 5.621531				
Schwarz criterion: 5.623499				
Hannan-Quinn criter.: 5.622136				