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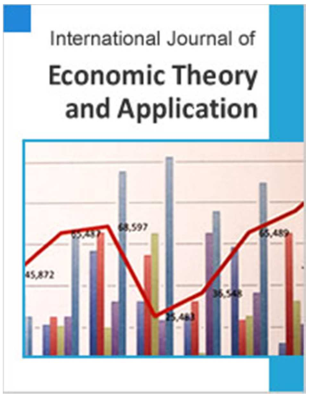

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The Gambler's Fallacy in the Stock Markets: Investors' Beliefs in Stock Price Reversals

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Abstract
The present study analyzes stock returns in order to shed light on the effect of the gambler's fallacy on investors' beliefs. I expect that if during several trading days in a row a stock's price rises (falls), then investors whose trading decisions are biased by the gambler's fallacy may believe that the respective stock's price is going to change its direction. This belief in stock price reversals may result in a selling (buying) pressure on the stock's price, and respectively, in negative (positive) abnormal stock returns. I analyze a large historical sample of stocks currently making up the S&P 500 Index, and find that following relatively long sequences of trading days characterized by the same-sign returns for given stocks, the respective stocks' abnormal returns tend to obtain the opposite sign. The effect becomes even more pronounced following longer preceding return sequences. It is stronger for small and volatile stocks and remains significant after accounting for a number of relevant company- and market-specific factors.

1. Introduction

Stock prices and returns have traditionally attracted enormous attention of both stock market researchers and practitioners. Numerous attempts to explain and predict stock performance have been made, by employing a wide range of techniques, methods and explanatory factors. In the recent decades, an increasing number of stock market studies explicitly account for the fact that investors are human beings, and detect various psychological factors that appear to exert significant influence on investors' ways of making decisions, and consequently, on the stock prices. In the present study, I make an attempt to contribute to this strand of literature by shedding light on the effect of the gambler's fallacy on stock returns.

The gambler's fallacy [1] is one of the oldest documented psychological biases and refers to an (incorrect) belief in negative autocorrelation of random sequences that are in fact non-autocorrelated. For example, a person whose expectations are based on the gambler's fallacy believes that after three red numbers appearing on the roulette wheel, a black number is "due," that is, becomes more likely to appear than a red one. In this respect, I suggest that if a stock's price rises (falls) during a number of consecutive trading days, then the gambler's fallacy may cause at least some of the intuitively acting investors to expect that the stock's price "has" to subsequently fall (rise), and thus, to increase their willingness to sell (buy) the stock, creating a selling (buying) pressure, which is beyond the one rationally motivated by the stock's fundamentals and future profit potential. In other words, I expect that excess market-adjusted stock returns should be, on average, lower (higher) following relatively long sequences of positive (negative) stock returns. In addition, I hypothesize that, just like in the case of a casino where people are more prone to bet on a black number the longer the consecutive series of red numbers appearing on the wheel, in the case of the stock market, the longer the sequence of trading days with the same-sign return for the respective stock, the stronger may be the investors' inclination to expect the reversal in the sign of the stock's return, leading to the price pressure in the direction of the reversal.

Employing the daily stock price data for all the constituents of S&P 500 Index during the years 1990 to 2016, I find supportive evidence for both research hypotheses of the study. First, I document that following the sequences of different length of positive (negative) stock returns, abnormal stock returns are on average significantly negative (positive), indicating the existence of the price pressure towards the return sign reversal, which on average indeed leads to the reversal. This effect appears to be slightly more pronounced following the sequences of positive, compared to the respective sequences of negative, stock returns, possibly indicating that the fear of the stock price decrease following a sequence of positive-return days is stronger than the hope for the stock price increase following a sequence of negative-return days. Second, the absolute values of average and median ARs, as well as the percentage of days ended up with return reversals, gradually and significantly increase with the length of the preceding sequence, suggesting that the tendency for return sign reversal is enhanced by longer sequences of the same-sign returns. Furthermore, in line with the previous literature dealing with psychological effects on investors' behavior, I detect that the effect of preceding sequences on stock returns is significantly more pronounced for smaller and more volatile stocks, suggesting that in the cases when investors possess a relatively smaller amount of relevant information about the stocks they trade, they are more inclined to apply simplifying decision-making techniques. Finally, by running a multifactor regression, I document that the effect of preceding sequences on stock returns persists and remains significant after controlling for other potentially influential factors, including contemporaneous market returns, firms' market capitalization, Market-Model beta, and historical stock returns and volatilities.

The rest of the paper is structured as follows. Section 2 reviews the literature dealing with the gambler's fallacy and its economic and financial implications. In Section 3, I formulate and explain the study's research hypotheses. Section 4 describes the database employed in this study. Section 5 introduces the empirical tests and presents the results. Section 6 concludes and provides a brief discussion.

2. Literature Review: Gambler's Fallacy, Its Causes and Implications

Previous literature formally defines the gambler’s fallacy as an (incorrect) belief in negative autocorrelation of non-autocorrelated random sequences. For example, individuals whose expectations are based on the gambler’s fallacy may believe that after three red numbers appearing on the roulette wheel, a black number is “due,” that is, becomes more likely to appear than a red number.

Gambler’s fallacy is first described by Laplace [1]. The respective biased beliefs are first observed in the laboratory (under controlled conditions) in the literature on probability matching. In these experiments, subjects are asked to guess which of two colored lights would next illuminate, and after seeing a string of one outcome, they are significantly more likely to guess the other. This effect is referred to in the literature as negative recency (see [2] and [3] for reviews). [4] show the existence of similar beliefs in the laboratory when subjects choose which of two colors will appear next on a simulated roulette wheel. [5] demonstrate that gambler’s fallacy behavior is not simply caused by boredom. The authors ask participants in their experiments how they would best maximize their earnings, and get responses based on gambler’s fallacy type logic.

The gambler’s fallacy is commonly thought to be caused by the representativeness heuristic ([6], [7]). Here, chance is perceived as “a self-correcting process in which a deviation in one direction induces a deviation in the opposite direction to restore the equilibrium” [7]. Thus after a sequence of three red numbers appearing on the roulette wheel, black seems more likely to occur than red because a sequence "red-red-red-black" looks more representative of the underlying distribution than a sequence "red-red-red-red".

A number of researchers empirically demonstrate the existence of the gambler’s fallacy in gambling. For example, [8], [9] and [10] document that soon after a lottery number wins, people are significantly less likely to place their bets on it. This effect diminishes over time; so that months later, the winning number is again as popular as any other 'usual' number. [11], [12] and [13] show the effects of this fallacy in horse and dog racing. [14] and [15] use videotapes of play of a roulette table in casino and detect a significant gambler's fallacy in betting. That is, following a sequence of one color outcomes, people are more likely to bet on the other color.

[16] asks a group of stock market professionals a number of questions aimed at detecting their way of making decisions, and finds that market "signals" considered by technical analysts are consistent with a number of behavioral biases, including the gambler's fallacy. [17] document that U.S. investors who exhibit trend-contrarian behavior (gambler's fallacy) hold less diversified portfolios, implying

negative risk and performance consequences. [18] conduct a survey among stock market investors and quantify the extent to which each of them is affected by a number of behavioral biases, including the gambler's fallacy. They conclude that the degrees of the biases are positively correlated in the cross-section, that is, if an investor accepts certain intuitive decision-making technique, she will probably not reject other ones, as well.

Overall, the gambler's fallacy is well-documented both in the laboratory and in the real-world, including money-related behavior. Yet, on the other hand, there seems to be relatively little evidence of this behavioral pattern in financial, including stock market decision-making.

3. Research Hypotheses

As discussed in the previous Section, the gambler's fallacy may cause people to expect that after a sequence of instances in which a certain outcome has been realized, the probability of the opposite outcome's realization increases. Stock market investors, as human beings, might also share this belief. Assuming that this may be true, one may expect that if a stock's price rises (falls) during a number of consecutive trading days, then at least some of the investors may expect that the stock's price "has" to fall (rise), so that their willingness to sell (buy) the stock increases, creating a selling (buying) pressure, which is beyond the one rationally motivated by the stock's fundamentals and future profit potential. Furthermore, just like in the case of a casino where the feverish striving for betting on a black number grows with the length of the consecutive series of red numbers appearing on the wheel, the longer the sequence of trading days with the same-sign return for the respective stock, the stronger may be the investors' inclination to expect the reversal in the sign of the stock's return, leading to the price pressure in the direction of the reversal.

Therefore, I hypothesize that, all other things being equal:

Hypothesis 1: A stock's excess market-adjusted return should be lower (higher) following a number of consecutive trading days when the stock's return was positive (negative).

Hypothesis 2: The decrease (increase) in the stock's excess market-adjusted return should be more pronounced the longer the preceding sequence of the positive (negative)-return days.

In other words, I suggest that relatively long sequences of the same-sign stock returns may create expectations for the return reversals that finally end up with the reversals, or at least, push the stock returns towards the reversals. I furthermore test for the existence of this "preceding sequence" effect on stock returns.

4. Data Description

In my empirical analysis, I employ the adjusted daily stock price data for all the constituents of S&P 500 Index as of December 31, 2016, as recorded at www.finance.yahoo.com. The sampling period for each given stock starts on January 1, 1990 or at the first day of the stock's trading history reported by the website, and ends on December 31, 2016, yielding an overall sample of 2,425,650 stock-days. Daily values of the S&P 500 Index, which I use as a proxy for the general stock market index, are downloaded from the same website.

For each trading day t, I calculate abnormal, or excess, stock returns (ARs) for each stock i, according to the Market Model, that is:

$$AR_{it} = SR_{it} - \alpha_{it} - \beta_{it} MR_t \quad (1)$$

where: AR_{it} is stock i's abnormal return on day t; SR_{it} is stock i's log return on day t; MR_t is the market index (S&P 500) log return on day t; and α_{it}, β_{it} are the Market-Model parameters for stock i corresponding to day t, estimated by regressing the stock's returns on the contemporaneous market returns over 250 trading days (approximately one year) preceding day t[1].

Finally, for each day t, I match the underlying firm's market capitalization, as recorded on a quarterly basis at http://ycharts.com/, for the closest preceding date.

5. Research Methodology and Results

5.1. The Effect of Preceding Sequences on Stock Returns: Comparative Analysis

First of all, I perform a simple calculation of abnormal stock returns following sequences of days characterized by the same-sign stock returns. In order to be able to simultaneously test both research hypotheses, I define a number of alternative return sequence lengths, namely: (i) three days; (ii) four days; (iii) five days; (iv) six days; (v) seven days or more. Since the return sequence effect may be expected to emerge on the trading day when the return sign is reversed, I append the days with exactly zero stock returns to the sequences. That is, for example, if a stock's returns were positive during three consecutive days, zero on the fourth day and positive again on the fifth day, I assume that the sequence of positive returns was not interrupted, and consider the stock's abnormal returns following the sequences of three, four and five positive-return trading days.

Table 1 presents basic descriptive AR statistics for the days following the sequences of different length of positive and negative stock returns, and their statistical significance.

1 Alternatively, I calculate ARs using Market Adjusted Returns (MAR) – return differences from the market index, and the Fama-French three-factor plus momentum model. The results (available upon request from the author) remain qualitatively similar to those reported in Section 5.

Table 1. *Descriptive statistics of abnormal stock returns (ARs) following sequences of the same-sign stock returns.*

Panel A: AR statistics following the sequences of positive stock returns					
Statistic measures	**Preceding sequence length**				
	3 days	**4 days**	**5 days**	**6 days**	**7 days or more**
Mean, %	*-0.274	**-0.342	***-0.389	***-0.461	***-0.543
Median, %	*-0.264	**-0.331	**-0.374	***-0.447	***-0.521
Standard deviation, %	1.105	1.114	1.118	1.132	1.157
Percent of positive	42.35	41.64	40.05	38.76	36.29
Panel B: AR statistics following the sequences of negative stock returns					
Statistic measures	Preceding sequence length				
	3 days	4 days	5 days	6 days	7 days or more
Mean, %	*0.234	*0.285	**0.343	***0.409	***0.485
Median, %	*0.219	*0.268	**0.331	**0.387	***0.459
Standard deviation, %	1.075	1.086	1.093	1.108	1.120
Percent of positive	56.47	57.43	58.09	59.87	61.08

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

The results corroborate both research hypotheses. First, consistently with Hypothesis 1, following the sequences of all lengths of positive (negative) stock returns, stock ARs are on average significantly negative (positive), indicating the existence of the price pressure towards the return sign reversal, which on average indeed leads to the reversal. Second, in line with Hypothesis 2, the absolute values of average and median ARs, as well as the percentage of days ended up with return reversals, gradually and significantly increase with the length of the preceding sequence, suggesting that the tendency for return sign reversal is enhanced by longer sequences of the same-sign returns. For example, average ARs following the three-day sequences of positive (negative) stock returns equal -0.274% (0.234%), compared to -0.543% (0.485%) following the sequences of seven or more days. An additional observation is that the effect of the preceding sequences on stock returns is slightly more pronounced following the sequences of positive returns, possibly suggesting that the fear of the stock price decrease following a sequence of positive-return days is stronger than the hope for the stock price increase following a sequence of negative-return days.

5.2. The Effect of Preceding Sequences on Stock Returns: Subsample Analysis

Having documented the effect of preceding sequences on stock returns for the total sample, I now verify if the magnitude of the effect may differ for different groups of stocks. The motivation for this analysis arises from the previous literature dealing with the effects of various behavioral biases on investors' decisions. A number of studies in this field (e.g., [19], [20]) conclude that stocks that are attractive to optimists and speculators and at the same time unattractive to arbitrageurs - younger stocks, small stocks, unprofitable stocks, non-dividend paying stocks, high volatility stocks, extreme growth stocks, and distressed stocks - are especially likely to be disproportionately sensitive to psychological biases.

Following these findings, I first divide my working sample in subsamples according to the firm size. For each trading day during the sampling period, I split the total sample into three roughly equal parts by the firms' market capitalization (low, medium and high) reported for the end of the preceding quarter, and then calculate average stock ARs following the sequences of the same-sign returns separately for the different size groups. Table 2 contains the respective average AR measures and their statistical significance. The results are clearly consistent with the previous literature, indicating that the effect of preceding sequences on stock returns is significantly more pronounced for smaller stocks. For example, average ARs following the sequences of seven or more days of positive (negative) stock returns equal -0.466% (0.420%) for high capitalization stocks, compared to -0.632% (0.557%) for low capitalization stocks.

Table 2. *Average abnormal stock returns (ARs) following sequences of the same-sign stock returns: By the firms' market capitalization.*

Panel A: Average ARs, % for the days following the sequences of positive stock returns					
Stock categories	**Preceding sequence length**				
	3 days	**4 days**	**5 days**	**6 days**	**7 days or more**
Low capitalization	**-0.385	***-0.412	***-0.476	***-0.534	***-0.632
Medium capitalization	*-0.258	**-0.334	**-0.375	***-0.448	***-0.531
High capitalization	-0.179	*-0.280	*-0.316	**-0.401	**-0.466
Panel B: Average ARs, % for the days following the sequences of negative stock returns					
Stock categories	Preceding sequence length				
	3 days	4 days	5 days	6 days	7 days or more
Low capitalization	**0.289	**0.359	***0.397	***0.468	***0.557
Medium capitalization	*0.221	*0.276	**0.344	**0.407	***0.478
High capitalization	0.192	*0.220	*0.288	**0.352	**0.420

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

Furthermore, I classify my sample according to the stocks' historical volatility. For each trading day during the sampling period, I split the total sample into three roughly equal parts by the standard deviation of stock returns over 250 preceding trading days (low, medium and high volatility stocks). Table 3 reports average ARs and their significance separately for the three subsamples. Once again, in line with the previous literature, the effect of preceding sequences on stock returns appears to be significantly more pronounced for more volatile stocks. For example, average ARs following the sequences of seven or more days of positive (negative) stock returns equal -0.599% (0.543%) for high volatility stocks, compared to -0.487% (0.426%) for low volatility stocks.

Table 3. *Average abnormal stock returns (ARs) following sequences of the same-sign stock returns: By the stocks' historical volatility.*

Panel A: Average ARs, % for the days following the sequences of positive stock returns					
Stock categories	**Preceding sequence length**				
	3 days	**4 days**	**5 days**	**6 days**	**7 days or more**
Low volatility	-0.196	*-0.293	*-0.325	**-0.408	***-0.487
Medium volatility	*-0.264	**-0.342	**-0.379	***-0.457	***-0.543
High volatility	**-0.362	**-0.391	***-0.463	***-0.518	***-0.599
Panel B: Average ARs, % for the days following the sequences of negative stock returns					
Stock categories	Preceding sequence length				
	3 days	4 days	5 days	6 days	7 days or more
Low volatility	0.194	*0.228	*0.295	**0.362	**0.426
Medium volatility	*0.233	*0.281	**0.353	**0.414	***0.486
High volatility	**0.275	**0.346	***0.381	***0.451	***0.543

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

Overall, the results in this subsection look well expected and quite intuitive. They suggest that in the cases when investors possess a relatively smaller amount of relevant information about the stocks they trade (small and volatile stocks), they are more inclined to apply simplifying decision-making techniques, which, among other psychological biases, may lead to the effect of preceding sequences on stock returns.

5.3. The Effect of Preceding Sequences on Stock Returns: Multifactor Regression Analysis

At this stage, I proceed to testing if the effect of preceding sequences on stock returns remains significant if other potentially influential factors are controlled for. In order to do that, I run the following regression based on the panel data of stock returns over the sampling period:

$$\begin{aligned} AR_{it} &= \alpha_i + \beta_{1i} POS3_{it} + \beta_{2i} POS4_{it} + \beta_{3i} POS5_{it} + \beta_{4i} POS6_{it} + \\ &+ \beta_{5i} POS7plus_{it} + \beta_{6i} NEG3_{it} + \beta_{7i} NEG4_{it} + \beta_{8i} NEG5_{it} + \beta_{9i} NEG6_{it} + \\ &+ \beta_{10i} NEG7plus_{it} + \beta_{11i} SR_{it-1} + \beta_{12i} MR_{it} + \beta_{13i} MCap_{it} + \beta_{14i} Beta_{it} + \\ &+ \beta_{15i} CumSR_{it} + \beta_{16i} STDevSR_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

where: $POS3_{it}$ to $POS7plus_{it}$ are the dummy variables, taking the value 1 if for stock *i*, day *t* was preceded by three to seven or more days of positive returns, respectively, and 0 otherwise; $NEG3_{it}$ to $NEG7plus_{it}$ are the dummy variables, taking the value 1 if for stock *i*, day *t* was preceded by three to seven or more days of negative returns, respectively, and 0 otherwise; $MCap_{it}$ is the natural logarithm of firm *i*'s market capitalization for the end of the quarter preceding day *t*; $Beta_{it}$ is stock *i*'s Market-Model beta estimated over 250 trading days preceding day *t*; $CumSR_{it}$ is stock *i*'s cumulative return over 250 trading days preceding day *t*; and $STDevSR_{it}$ is the standard deviation of stock *i*'s returns over 250 trading days preceding day *t*.

Table 4 comprises the results of regression (2), including the coefficient estimates and their statistical significance.

Table 4. *Regression analysis: Preceding sequence effect on stock returns (Dependent variable – AR, %).*

Explanatory variables	**Coefficient estimates (t-statistics)**
Intercept	***0.012 (2.98)
POS3t	**-0.196 (-2.12)
POS4t	***-0.245 (-2.56)
POS5t	***-0.296 (-3.21)
POS6t	***-0.357 (-4.09)
POS7 plust	***-0.432 (-4.89)
NEG3t	**0.175 (1.98)
NEG4t	**0.221 (2.30)
NEG5t	***0.277 (2.84)
NEG6t	***0.320 (3.42)
NEG7 plust	***0.384 (4.13)
SRt-1	-0.037 (-0.76)
MRt	*0.117 (1.74)
MCapt	*0.034 (1.85)
Betat	0.231 (0.97)
CumSRt	0.061 (1.25)
STDevSRt	0.033 (0.47)
Adjusted R-squared	0.235

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

The results indicate that:

The coefficient estimates of all the dummy variables related to the preceding sequences of positive (negative) returns are negative (positive) and highly statistically significant. This represents a strong support for Hypothesis 1, demonstrating that preceding sequences of positive (negative)-return days tend to decrease (increase) the subsequent stock returns, and this effect is not driven by other relevant company-specific factors.

For both positive and negative return sequences, the absolute values of the sequence dummies' coefficient estimates significantly increase with the sequence length, supporting Hypothesis 2.

Consistently with subsection 5.1, the absolute values of the coefficient estimates of *POS* dummies are slightly higher than those of the respective *NEG* ones, indicating that the preceding sequence effect on stock returns is slightly more pronounced following positive return sequences.

6. Conclusion and Discussion

In the present study, I make an effort to contribute to the rapidly developing strand of literature which deals with behavioral factors affecting stock prices. Namely, I hypothesize that investors' decisions to buy or sell stocks may be affected by the gambler's fallacy, and if so, following a number of consecutive trading days characterized by positive (negative) returns for a given stock, its abnormal market-adjusted returns should be, on average, negative (positive), and even more so, the longer the preceding return sequence.

Employing a large sample of daily stock price data, I find corroborative evidence for the study's research hypotheses. First, I document that following the sequences of different length of positive (negative) stock returns, abnormal stock returns tend to be negative (positive), indicating the existence of the price pressure towards the return sign reversal. Second, the magnitude of the effect of preceding sequences on stock returns gradually and significantly increases with the return sequence length, and is higher for low capitalization and highly volatile stocks. Finally, the effect remains significant after controlling for additional company-specific and market-wide factors.

The study's empirical findings may have a number of important practical implications. They imply that the multi-level and complicated mechanism of investors' trading activity may be affected by the gambler's fallacy, calling for further research that would test if the documented effect persists for shorter (intraday) and longer (weekly, monthly) time intervals, different sectors and categories of stocks, different countries, and different macroeconomic backgrounds, including the periods of financial crises.

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