risks MDPI

Article

Does the Adaptive Market Hypothesis Reconcile the Behavioral Finance and the Efficient Market Hypothesis?

Umara Noreen [1], Attayah Shafique [2,3,*], Usman Ayub [2] and Syed Kashif Saeed [3]

[1] College of Business Administration, Prince Sultan University, Riyadh 11586, Saudi Arabia
[2] Department of Management Sciences, COMSATS University Islamabad, Islamabad 45550, Pakistan
[3] Department of Communication and Management Sciences, Pakistan Institute of Engineering and Applied Sciences, Nilore, Islamabad 44000, Pakistan
* Correspondence: attiya.shafique@comsats.edu.pk or attayah.shafique@pieas.edu.pk

Abstract: This study aims to test the adaptive market hypothesis by using the myopic behavior of investors as a new proxy. The data have been taken from New York Stock Exchange from December 1994 to December 2020. Following this collection of data, the companies' stock prices were distributed into six different portfolios based on size, investment, a book-to-market value, and operating profit. Ordinal logistic regression was used to calculate the probability of recovery of losses after experiencing a decline in the market. As part of the robustness analysis, this study replaces the Sharpe ratio with a Lower Partial Moment ratio. Most of the results for the Sharpe ratio and Lower Partial Moment ratio are similar. During 1995–1999, 2002–2006, and 2010–2020, the investors have not shown myopic behavior towards losses, but from 2000–2001 and 2007–2009 the investors exhibited myopic characteristics. Furthermore, as investors move between myopic and non-myopic loss aversion, the study reports that the US market is both efficient and inefficient at various points in time, following the adaptive market hypothesis. Thus, such a finding could act as a basis for future investment models by adapting traditional models or by building and contributing to the development of new ones.

Keywords: adaptive market hypothesis; myopic loss aversion; efficient market hypothesis; behavioral finance

check for updates

Citation: Noreen, Umara, Attayah Shafique, Usman Ayub, and Syed Kashif Saeed. 2022. Does the Adaptive Market Hypothesis Reconcile the Behavioral Finance and the Efficient Market Hypothesis? *Risks* 10: 168. https://doi.org/10.3390/risks10090168

Academic Editor: Mogens Steffensen

Received: 13 June 2022
Accepted: 10 August 2022
Published: 23 August 2022

1. Introduction

Traditional investment theories, commonly known as neoclassical finance theories, predominantly follow and place great emphasis on the behavioral rationality of investors. The portfolio theory serves as a benchmark for the creation of conventional finance models that explain the spectrum of risk, return, correlation, and diversification of portfolio construction. The theory argues that investors should prefer lower risk for a given level of return based on the presumption of rationality (Elton et al. 2009; Leibowitz et al. 2010; Markowitz 2010). One of the profound ways of advocating the rationality of behavior can be explained by the efficient market hypothesis (Ritter 2003).

Contrary to the previous statement, behavioral finance advocates that investors are not rational. What is more, it argues that the conventional theory of finance lacks the way ordinary people make decisions. Shefrin and Statman (2000) point out that behavioral psychology has shown how and in what ways information, inadequate processors and mistakes, prejudices, and other illusions of perception affect people. Behavioral differences arise as people make choices based on their views, desires, and elements of cognitive psychology. The leading proponents of behavioral finance are renowned authors Kahneman and Tversky: their works, namely Kahneman and Tversky (1979) and Tversky and Kahneman (1992), respectively, led to the development of prospect theory and cumulative prospect theory.

Lo (2004, 2005) questions the efficient market hypothesis (EMH) and the behavioral finance hypothesis and argues that investors are not entirely rational or irrational. Instead, the investor is at times rational and at times irrational. Lo (2005) also argues that investors are adaptive to different conditions by moving from irrationality to rationality and vice versa. He develops an adaptive market hypothesis by combining the conventional efficient market hypothesis with behavioral science theory. According to the theory of the adaptive market hypothesis, investors act rationally. However, if there are fluctuations in the market, investors suddenly respond to such market conditions and may act irrationally (Lim et al. 2013; Urquhart and McGroarty 2016).

This study fills the gap by addressing the problem mentioned above. Consequently, the adaptiveness of the New York Stock Exchange was tested. We introduced myopic loss aversion as a proxy for the adaptive market hypothesis, instead of using calendar anomalies; the reasoning behind this refers to the fact that calendar anomalies only address the stock behavior at a particular time, such as the day-of-the-week, time-of-the-month, or time-of-the-year. To capture myopic loss aversion, the Sharpe ratio was used, and a lower partial moment (LPM) ratio was used for robustness. This study attempts to address the basis of EMH and behavioral finance. Behavioral anomalies and efficient markets are poles apart. The EMH reconciles efficient markets with behavioral finance by combining two theories in an internally consistent and intellectually satisfying way, thus creating a more holistic view of markets. The significance of the study refers to the fact that it provides researchers with a direction for building new finance theories in the field of portfolio management and asset pricing, by resting their views on the adaptive market hypothesis. In other words, the models will be flexible enough to incorporate classical models and adjustable enough to cater to the criticism of behavioral finance.

The present study makes a significant theoretical contribution to the theory of adaptive market hypothesis by using myopic behavior as a proxy for building and testing the model. The study provides an empirical contribution by introducing a new methodology for the analysis of robustness. Furthermore, the new methodology enables us to better examine periods of efficiency and inefficiency by identifying the factors that alter market conditions on the New York Stock Exchange. Overall, this will be the first comprehensive study that has applied the new methodology by using a model based on myopic behavior as a proxy.

Following this first introductory section, the paper is organized as follows: Section 2 presents aspects of the literature review, and Section 3 explains the methodology. Section 4 examines the results of the study, where discussions and deliberation are offered. Finally, Section 5 concludes the paper.

2. Literature Review

2.1. Neoclassical Finance and Its Evidence

The basic assumptions of Neoclassical finance are that the investors are rational, markets are perfectly competitive, and information is freely available. It includes major theories and models such as portfolio theory (Markowitz 1952, 2010), Modigliani's views, Miller's investment theory (Miller and Modigliani 1958), Capital Asset pricing model (Sharpe 1964; Lintner 1965), and the Black–Scholes option-pricing model (Black and Scholes 1973). The most popular and debatable models in Neoclassical finance are the Efficient Market Hypothesis and the Random Walk Theory. Malkiel (1973) clearly explains the latter theory, by arguing that the change and movement in price and price level cannot and will not follow any path; therefore, prices are randomly changed and are unpredictable over time. Random walk theory is linked with the Efficient Market Hypothesis, as the latter proposes that information determines stock prices. This information is characterized by its randomness. In financial literature, there are two schools of thought: one against the efficient market hypothesis, i.e., random walk theory (Borges 2010; Malkiel 2003; Mlambo and Biekpe 2007), and another school of thought that supports the random walk theory (Chitenderu et al. 2014; Levy 2017; Samuelson 1994).

The EMH framework is therefore simple and appealing, given that it attempts to capture investor behavior; this is especially the case when the assumption of the myopic behavior of investors is not held in it (Barberis and Thaler 2003). The rationality of investors forms the core of EMH and functions somewhat contrary to the myopic behavior of investors. As a result, difficulties arise when trying to explain financial phenomena by using the neoclassical paradigm, particularly when using EMH.

2.2. Behavioral Finance and Its Evidence

Behavioral finance explains market anomalies, especially when the markets face "bubbles" and periods of deep recession (Schwert 2003). It includes major theories, such as prospect theory (Kahneman and Tversky 1979), cumulative prospect theory (Tversky and Kahneman 1992), and the behavioral asset pricing model. Behavioral finance provides guidance and assistance when trying to understand the financial choices made by investors, by considering the influence of the psychological traits of those investors. It also argues that financial phenomena can be better understood when investors are not entirely rational.

Investors are generally criticized for their frequent irrational behaviors and beliefs. Such examples of irrationality take the form of "herd instinct" (do what other people do) and of emotionally driven responses to stressful circumstances (Haritha and Rishad 2020). Thus, such irrational practices and patterns ultimately affect stock prices and generate market inefficiencies (Hirshleifer 2001). Evidence is also available for high investor sentiment (Frazzini and Lamont 2008), financial bubbles (Feldman 2010), social network sentiment (Asur and Huberman 2010), and market effects (Abu Bakar et al. 2014). Several studies use behavioral aspects to investigate stock price volatility and report their existence in both developing and developed financial markets (Benartzi et al. 2004; Corredor et al. 2015; Kaplanski and Levy 2010).

2.3. Reconciling EMH and Behavioral Finance via the Adaptive Market Hypothesis

In 2004, Andrew Lo attempted to reconcile EMH and behavioral finance by claiming that investors are adaptive to changes. The arrival of new players, changes in the levels of market competition, various economic and political circumstances, and the ability of investors to adopt the latest market conditions are all elements that cause changes in the level of market efficiency. In other words, markets can be efficient at times and inefficient at other times; however, there is a distinct pattern of efficiency and inefficiency. This distinct nature of financial markets connects traditional finance and behavioral finance theories into a unique hypothesis, namely, the adaptive market hypothesis (AMH) (Lo 2004, 2005).

Several empirical studies have been conducted on the application of AMH in different stock markets around the world. Urquhart and Hudson (2013) find that AMH offers a better explanation of the stock-return behavior of the US, UK, and Japanese markets. Another study conducted by Urquhart et al. (2015) in the US, UK, and Japan confirms that all three markets are aligned with the adaptive market hypothesis. The Indonesian stock market was also investigated by Almudhaf (2018) to determine whether or not the market is aligned with the adaptive market hypothesis. According to the observations in that study, market efficiencies fluctuate over time but are consistent with the adaptive market hypothesis. Haritha and Rishad (2020) also indicate the deviations from the random walk model and the invalidity of the efficient market hypothesis in the Indian Stock Exchange.

Several other studies have been conducted on theoretical and empirical testing of the adaptive market hypothesis, and some drawbacks have been found while testing AMH. Researchers have empirically tested the adaptive market hypothesis by taking the country indices, e.g., the French market index, and the US, UK, and Japanese market indexes. These data on indices have been used for different periods by using volatility models. Furthermore, GARCH, Auto-correlations test, Runs test, and VAR test were all used to test the hypothesis (Boya 2019; Ndubuisi and Okere 2018; Urquhart and McGroarty 2016). These tests are based on the simple assumption that the lag(s) term(s) correlate(s) with present values irrespective of different financial periods and types of stocks used.

This relationship is self-negating as it rests on the presumption that current markets are independent of historical data. Robustness analysis is therefore required to observe that almost the same proxies and models are used both for the theoretical and empirical testing of the adaptive market hypothesis and for testing the efficient market hypothesis.

2.4. Myopic Loss Aversion as a Proxy of the Adaptive Market Hypothesis

Generally, emotions determine the personality traits or behavior of an individual. These emotions tend to become unstable when an investor's fear arises due to perceived losses. Chen et al. (2004) find that; Chinese investors behave irrationally while investing because of emotional and behavioral biases. Myopic loss aversion is an important psychological factor that investors tend to exhibit. According to Thaler et al. (1997), "Myopic Loss Aversion is defined as the combination of a greater sensitivity to losses than to gains and a tendency to evaluate outcomes frequently". Benartzi suggests that myopic loss aversion is an explanation for the so-called premium equity puzzle, and also reports that individuals depicting myopic loss aversion are more willing to take risks if they evaluate the results of their investments less frequently.

Thaler et al. (1997) report that risk-taking behavior towards myopic loss tends to increase when information is given less frequently. He and Zhou (2014) have checked the Benartzi and Thaler (1995) hypothesis by taking the data of NYSE equity and US treasury bond returns for the period from 1926–1990 and suggest that manager's loss aversion, evaluation period, and reference point for evaluation impact the decision for asset allocation. Alrabadi et al. (2018) investigate different behavioral biases that impact the investment decisions of investors in the Amman Stock Exchange. This means that Myopic behavior is a behavior based on the pursuance of short-term results and represents an action regarding what one wants now, without considering any future consequences. Myopic behavior is linked with behavioral finance including myopic loss aversion, self-deception, heuristic simplification, emotions, and social influence factors. Lee and Veld-Merkoulova (2016) have studied the connection between myopic loss aversion and investment decisions by investors using a survey. The study results show that investors who evaluate their portfolios more frequently observe fewer losses. As a result, they also did not wish to invest further in stocks. Investors observe myopic loss aversion and as such, more investigations of their portfolio performance are being done on a more regular basis; what is more, given this, investors also trade stocks regularly.

Some of the studies show contradictory results regarding myopic loss aversion theory. Kaustia et al. (2008) and Alevy et al. (2007) find that financial managers are less prone to behavioral biases than students who have been involved in investment decisions. Blavatskyy and Pogrebna (2009) confirm that from a behavioral standpoint, the majority of investors act in a somewhat contradictory manner to myopic loss aversion. Aggarwal and Damodaran (2020) report that their sample displays an escalation of commitment while playing the game in the domains of losses.

The financial literature also shows different methods for the measurement of myopic loss aversion; for example, one of the studies used large-scale field experiments to measure the phenomenon of myopic loss aversion (Larson et al. 2016). Another study used survey data for the measurement of private investors' myopic behavior (Lee and Veld-Merkoulova 2016). Costa (2018) used a systematic test to assess the theory of myopic loss aversion by considering the relationship between inflation and equity premium. It is also observed that several studies used the experimental method to determine the phenomenon of myopic loss aversion (Schwaiger and Hueber 2021; Wesslen et al. 2021).

The evidence of myopic loss aversion is not a conclusion, and mixed results are reported. The presence of myopic loss behavior can be considered as a proxy for irrationality; whereas, its absence leads to the rationality of investors. Furthermore, the adaptive market hypothesis is non-restrictive only to rationality or irrationality. It advocates that the market is adaptive given that investors react to information of all sorts, and thus, at times, they are rational, and at other times they are irrational. To test this hypothesis, we employ the proxy of rationality and irrationality in terms of the myopic loss behavior of an investor. In this study, myopic behavior is measured by determining the probability of recovering losses in a particular period through the evaluation of the performance of portfolios. If the recovery is not possible, the investors show irrational behavior and become panicked and start selling stocks and making the market adaptive. Based on the discussion above, the following hypothesis is proposed:

Hypothesis $\mathbf{H_1}$. *The investors show myopic loss aversion behavior and thus market follows the adaptive market hypothesis.*

3. Data and Methodology

3.1. Data

The data has been taken from the companies listed on the New York Stock Exchange (NYSE), starting from December 1994 and running to December 2020. The prices of the companies have been converted into returns by using the simple formula of the log returns. As a benchmark, the S&P 500 has been used. For six months T-bills have been used as the risk-free rate of return. The returns of different companies have also been converted into portfolios; the double-sorted portfolios have been formed by using the methodology of Fama and French (1995). The factors that have been used for the formation of portfolios are size, the book-to-market value, investment, and operating profits.

Afterwards, these portfolios have been divided into sub-portfolios, also known as decile portfolios (Shafique et al. 2019). In this way, six categories of portfolios have been used, namely: Big–High Book-to-Market Stocks; Small–Low Book-to-Market Stocks; Big–High Investment Stocks; Small–Low Investment Stocks; Big–High Operating Profit Stocks; and Small–Low Operating Profit Stocks.

The used methodology is divided into two parts: the first part is related to the calculation of the performance of the portfolio (by using performance measures); and the second part refers to the determination of the myopic loss aversion behavior of investors.

3.2. Part 1: Calculating a Portfolio's Performance by Using Performance Measures

In this study, the Sharpe ratio and LPM ratio have been used as performance measures. The Sharpe ratio is the traditional and most widely used performance measure (Liu and Chen 2020) and is based on modern portfolio theory. Sharpe ratio is defined as "the ratio of the excess returns to the risk (standard deviation) of that return" (Sharpe 1966). It is widely used by investors and managers for the evaluation of portfolio performance. The return in Sharpe ratio is calculated via arithmetic returns. The reason for choosing the arithmetic mean is that theories like portfolio theory and capital asset pricing theory, which are the basic portfolio management theories use the same return. The risk is calculated by using the standard deviation, as the standard deviation is the proxy of total risk.

Now, the Sharpe ratio is calculated by using the following formula:

$$\textbf{Sharpe Ratio} = \frac{\overline{\mathbf{R}}_{\mathbf{p}} - \mathbf{R_F}}{\boldsymbol{\sigma}_{\mathbf{p}}} \tag{1}$$

where: $\overline{R_p}$ is the portfolio's expected return, R_f is the risk-free rate and σ_p = portfolio's risk standard deviation

The lower partial moment (LPM) ratio is proposed by using the concept of downside risk, which was first used in the Postmodern Portfolio theory. Bawa (1975) introduced partial moments as upper partial moments and lower partial moments, where the Lower Partial Moment (LPM) will handle all below-target observations. Bawa (1975) and Fishburn (1977) define downside risk as the lower partial moments by incorporating the risk tolerance of investors in terms of "a". Bawa (1975) also mathematically proves that LPM as a risk measure is related to stochastic dominance. Nawrocki (1991) also concludes that traditional portfolio theory has gone under major improvement over the years concerning downside risk measures. According to that study, the semi-variance and LPM are the most widely used measure for downside risk.

Now, the lower partial moment (LPM) ratio is calculated by using the same concept and replacing the risk with LPM (downside risk) as follows:

$$\textbf{LPM Ratio} = \frac{\overline{\mathbf{R}}_\mathbf{p} - \mathbf{R_F}}{\sigma_{lpm}} \tag{2}$$

where: $\overline{R_p}$ is the expected return of portfolio "p", R_f is the risk-free rate and LPM is the portfolio's risk using lower partial moments.

3.3. Part 2: Determination of the Myopic Loss Aversion Behavior of an Investor

In the second part of the methodology, we checked whether investors present myopic loss aversion or not. For the in-depth analysis, different steps have been introduced in this part:

In Step 1, the investment horizon is selected, which is one month in this study. After one month, the investors evaluate the performance of their portfolios. After facing the market downward trends, what would be the probability of recovering the loss in one month? There are several alternatives: either the recovery is up to benchmark, which means that the investors earn a full recovery, or the recovery benchmarks follow the next values: 75%, 50%, and 25%, respectively.

In Step 2, data is arranged into panels. Setting the data into panels will result in a more precise and accurate analysis as compared to separate cross-sectional or time-series data. According to the literature, there are several advantages of panel data. The main benefit of using panel data is its ability to deal with heterogeneity, which makes it superior (Baltagi 2008). The second advantage of panel data is that it enables researchers to deal with a large number of observations, and what is more, it also grants them the opportunity to make better predictions (Dougherty 2011).

The third advantage of using panel data is to control the effect of omitted variables (Wooldridge 1995). Most of the relationships are dynamic and it is not possible to reveal dynamic relationships easily, so panel data allows us to adjust these dynamic behaviors in a better way (Pakes and Griliches 1984). It also gives a greater degree of freedom and more variability, which enables us to get a larger inference of parameters as defined in the model (Hsiao 2022).

After the arrangement of data into panels, the data was again divided into several periods, normally taking five years except for 2000–2001 and 2007–2009. These two periods have different lengths because of the important events documented in them: in 2000, the regime in United State was changed; in 2001, there was a terrorist attack in September. In 2007–2009, there was a financial global crisis that affected the financial markets adversely. Consequently, these two periods are separately observed by using different period lengths.

In Step 3, ordinal logistic regression is used for the calculation of the probability by using Sharpe and LPM ratios. Firstly, accumulative probability can be computed for each category. In this study, four categories are used 25%, 50%, 75%, and 100% or full.

$$\mathbf{P_{it}} = \frac{\mathbf{e^{Zit}}}{1 + \mathbf{e^{zit}}} \tag{3}$$

where: P_{it} is the probability of ith case experiences the event of interest, Z_{it} is the value of the explanatory variable for the ith case.

Generally, the value Zi is an odd ratio which is calculated as follows:

$$\mathbf{Z_{it}} = \boldsymbol{\beta}_{\mathbf{it}} + \boldsymbol{\beta}_\mathbf{1}\ \mathbf{X1_{it}} + \boldsymbol{\beta}_\mathbf{2}\ \mathbf{X2_{it}} + \ldots\ldots\ldots\ldots\ldots + \boldsymbol{\beta}_\mathbf{p}\ \mathbf{XP_{it}} \tag{4}$$

where: $x1_{it}$ is the ith predictor for the ith the case for time t, β_{it} is the ith beta coefficient (slope parameters) for time t and P is the number of predictors.

Specifically, the ordinal logistic model for the recovery in terms of Sharpe and LPM ratio is as follows:

$$\mathbf{REC_{it}} = \boldsymbol{\beta}_{\mathbf{it}} + \boldsymbol{\beta}_{\mathbf{1}}\ \mathbf{SR_{it}} + \mathbf{U_{it}} \tag{5}$$

$$\mathbf{REC_{it}} = \boldsymbol{\beta}_{\mathbf{it}} + \boldsymbol{\beta}_{\mathbf{1}}\ \mathbf{LPM_{it}} + \mathbf{U_{it}} \tag{6}$$

where: REC_{it} is recovery represented for the *i*th the case for time *t*, β_{it} is the *i*th beta coefficient (slope parameters) for time *t* and SR_{it} and LPM_{it} are the predictors.

The individual probability of each response category is calculated by using the difference between the cumulative probabilities.

In Step 4, the data is divided into different time frames from the following periods: 1995–1999, 2000–2004, 2005–2009, 2010–2014, and 2015–2020. For every time window, the above procedure is followed to determine the recovery of loss during a particular time horizon. There are four benchmarks introduced to assess the level of recovery of loss, which are: full recovery; 75% recovery of the benchmark; 50% recovery of the benchmark; and 25% recovery of the benchmark. If there is a high probability of recovery of the ratio to its respective benchmark by taking the portfolio evaluation frequency for one month, then it is confirmed that the investors of the United States are not experiencing a myopic loss aversion; however, if there is no recovery of loss to its full level, then that means that investors are experiencing a myopic loss behavior. According to the prospect theory, the investors feel more pain of loss as compared to the gains in a particular period. Therefore, in this period, the recovery of loss was important. If the recovery is high respective to its benchmark it means that the investors did not show any panic and waited for the recovery, thus they did not experience myopic behavior. On the other side, if the recovery is low, the investor becomes panicked and starts selling and shows myopic behavior during that period. Moreover, most investors' myopic behavior makes the market adaptive.

4. Results and Discussion

Results for Recovery Probabilities Using Sharpe and LPM Ratio

The results are discussed in terms of the likelihood of recovery of ratios during a specific time, which is one month in this study. Table 1 consists of panels A–F, which gives the results related to the Sharpe ratio of six different stock types: Big–High Book-to-Market Stocks, Small–Low Book-to-Market Stocks, Big–High Investment Stocks, Small–Low Investment Stocks, Big–High Operating Profit Stocks, and Small–Low Operating Profit Stocks. The data sample is divided into different sets of years, i.e., 1995–1999, 2000–2001, 2002–2006, 2007–2009, 2010–2014, and 2015–2020. Four benchmarks have been introduced to determine the level of recovery: 25% recovery of benchmark; 50% recovery of benchmark; 75% recovery of benchmark; and 100% recovery of the benchmark. The levels are set to find out if investors display myopic behavior or not. The cutoff point used in this study is 50%. In other words, investors will feel better off and less threatened at levels above 50% of the recovery of wealth. This is an optimistic view with at least a 50% chance of recovery in all periods. If the probability of recovery to any benchmark level is more than or equal to 50%, it means that the investors did not show any panic and do not experience myopic behavior. However, if the probability of recovery to any benchmark level is less than 50%, this means that investors show myopic behavior and are ready to sell the stocks in a panic. In this situation, most of the time, the market follows the adaptive market hypothesis.

By using the Sharpe ratio, the results for the average predicted probability to fully recover investments to their benchmark levels for S&P-500 stocks during 1995–1999, 2002–2006, 2010–2014, and 2015–2020 time periods are 97.23%, 95.70%, 99%, and 98.34%, respectively. During 2000–2001 and 2007–2009, the entire stock portfolio shows an average predicted probability of recovery of 25% of the benchmark, which revolves around the following levels: 95.6%, and 82.50%, respectively. The investors who are using the Sharpe ratio for the evaluation of portfolios have less than a 10% chance of recovering 50% and 75% of the benchmark during the time.

Panels A–F of Table 2 give the results of an average predicted probability to fully recover the investment, by using the LPM ratio for all-stock portfolios during the 1995–1999, 2010–2014, and 2015–2020 timeframes. These average predicted probabilities are: 62.70%, 63.70%, and 98.06%, respectively. During 2000–2001, 2002–2006, and 2007–2009, for the entire stock portfolio, Table 2 shows that the average predicted probability of recovery of 25% of the benchmark is 94.50%, 61.05%, and 96.04%, respectively. By using the LPM ratio, investors are unable to achieve 25%, 50%, and 75% of the benchmark, but they do manage to achieve full recovery after one month.

Table 1. Recovery Probabilities for Sharpe ratio of Six Types of Stocks for Different Time Periods.

Panel A: Recovery Probabilities for Sharpe Ratio of Big–High Book-to-Market Stocks					**Panel B: Recovery Probabilities for Sharpe Ratio of Small–Low Book-to-Market Stocks**				
	Benchmark Recovery (%)					**Benchmark Recovery (%)**			
Year	**25**	**50**	**75**	**Full**	**Year**	**25**	**50**	**75**	**Full**
1995–1999	0.43	0.04	0.00	99.52	**1995–1999**	0.45	0.27	0.05	99.23
2000–2001	94.30	2.61	2.60	0.49	**2000–2001**	93.22	0.68	1.86	4.25
2002–2006	1.54	1.07	2.18	95.21	**2002–2006**	4.00	2.86	0.65	92.49
2007–2009	95.08	3.36	1.25	0.30	**2007–2009**	99.43	0.48	0.08	0.01
2010–2014	0.39	0.03	0.00	99.58	**2010–2014**	1.01	0.33	1.44	97.22
2015–2020	0.28	0.00	0.04	99.68	**2015–2020**	0.70	0.60	1.91	96.79
Panel C: Recovery Probabilities for Sharpe Ratio of Big–High Investment Stocks					**Panel D: Recovery Probabilities for Sharpe Ratio of Small–Low Investment Stocks**				
	Benchmark Recovery (%)					**Benchmark Recovery (%)**			
Year	**25**	**50**	**75**	**Full**	**Year**	**25**	**50**	**75**	**Full**
1995–1999	0.75	0.00	0.40	98.85	**1995–1999**	0.74	0.35	0.59	98.32
2000–2001	96.44	2.38	0.78	0.39	**2000–2001**	96.31	1.64	0.82	1.23
2002–2006	2.04	0.75	1.48	95.74	**2002–2006**	1.08	0.34	0.43	98.15
2007–2009	96.96	1.65	0.93	0.45	**2007–2009**	99.92	0.0	0.01	0.00
2010–2014	0.17	0.04	0.04	99.76	**2010–2014**	0.28	0.06	0.15	99.51
2015–2020	1.00	0.33	0.45	98.23	**2015–2020**	2.00	1.80	1.20	95.00
Panel E: Recovery Probabilities for Sharpe Ratio of Big–High Operating Profit Stocks					**Panel F: Recovery Probabilities for Sharpe Ratio of Small–Low Operating Profit Stocks**				
	Benchmark Recovery (%)					**Benchmark Recovery (%)**			
Year	**25**	**50**	**75**	**Full**	**Year**	**25**	**50**	**75**	**Full**
1995–1999	0.48	0.18	0.19	99.15	**1995–1999**	1.04	0.35	0.53	98.08
2000–2001	96.55	1.93	1.52	0.00	**2000–2001**	96.86	1.58	1.56	0.00
2002–2006	1.42	1.14	2.89	94.54	**2002–2006**	0.99	0.44	0.35	98.23
2007–2009	98.99	0.73	0.16	0.13	**2007–2009**	99.52	0.41	0.07	0.01
2010–2014	0.09	0.02	0.02	99.88	**2010–2014**	0.79	0.26	0.40	98.55
2015–2020	1.00	0.34	0.66	98.00	**2015–2020**	0.67	0.10	0.42	98.81

Thus, it is observed that by using the Sharpe ratio, the investors in the United States do not display myopic loss aversion as they fully recovered losses between 1995 and 1999, 2002–2006, 2010–2014, and 2015–2020. During these periods, the investors remain calm, composed, and are likely to continue with their previous strategy, and do not want to sell stocks. From 2000 to 2001 and from 2007 to 2009, the investors display myopic loss aversion, and they show panic in their behavior during this period. Thus, they start selling their stocks because there is no recovery of their losses during these periods. The results for the LPM ratio are the same as in the Sharpe ratio during 2010–2020, a period in which the markets are efficient, and investors are no more representing myopic behavior during investment. It is observed that from 2000 to 2001, 2002 to 2006, and 2007 to 2009, the investors display myopic loss behavior. The reasons for displaying such myopic behavior during these periods are the 9/11 terrorist attacks in 2001 and Financial Global Crisis in 2007–2008. In 2000–2001, the 9/11 terrorist attack on the United States also affected the US economy negatively. Due to this, there was high uncertainty and volatility in the market and investors were reluctant to make new investments in the US Stock Market. Moreover, they already made investments in the stocks and other assets showed losses, and it remained a challenge to show any substantial recovery in a considerable period.

Several studies show the same findings that after the 9/11 attacks, the New York Stock Exchange become more volatile because of the high level of uncertainty and many key market elements were damaged or destroyed in the attack. The economic loss was much more than anything else at that period. Due to the sudden change, the profits of the firms decreased, thus fueling the individual investor's fear to invest because of high fluctuations in the stock prices (Lacker 2004; Chen and Siems 2004; Nedelescu and Johnston 2005).

From 2007–2009, the financial global crisis also impacted economic activities adversely, and many developed economies including the United States of America experienced liquidity problems and recession that led ultimately to financial stress. In the financial global crises, the investments by individual investors are also greatly decreased because of the fear of an uncertain future (Olbrys 2021). Moreover, the results of the current findings also coincide with the previous existing studies due to the behavioral biases; the investors show contradictory behavior, and the market becomes adaptive (Blavatskyy and Pogrebna 2009). Furthermore, the results also show the same findings as shown by Lee and Veld-Merkoulova (2016) that the investors who evaluate their investments more frequently are likely to suffer less losses irrespective of any economic events.

Table 2. Recovery Probabilities for LPM ratio of Six Types of Stocks for Different Time Periods.

Panel A: Recovery Probabilities for LPM Ratio of Big–High Book-to-Market Stocks					**Panel B: Recovery Probabilities for LPM Ratio of Small–Low Book-to-Market Stocks**				
	Benchmark Recovery (%)					**Benchmark Recovery (%)**			
Year	**25**	**50**	**75**	**Full**	**Year**	**25**	**50**	**75**	**Full**
1995–1999	96.68	0.77	0.69	1.85	**1995–1999**	56.03	6.11	3.85	34.01
2000–2001	78.78	5.78	3.11	12.33	**2000–2001**	97.90	0.53	0.51	1.07
2002–2006	89.09	0.00	1.53	9.38	**2002–2006**	1.87	0.51	0.51	97.11
2007–2009	87.60	3.79	2.22	6.39	**2007–2009**	99.57	0.06	0.09	0.27
2010–2014	26.54	3.00	2.76	67.70	**2010–2014**	29.68	4.46	3.94	61.92
2015–2020	5.02	0.91	0.88	93.20	**2015–2020**	2.00	0.27	0.25	97.49
Panel C: Recovery Probabilities for LPM Ratio of Big–High Investment Stocks					**Panel D: Recovery Probabilities for LPM Ratio of Small–Low Investment Stocks**				
	Benchmark Recovery (%)					**Benchmark Recovery (%)**			
Year	**25**	**50**	**75**	**Full**	**Year**	**25**	**50**	**75**	**Full**
1995–1999	33.24	4.88	2.89	58.98	**1995–1999**	3.50	0.84	0.83	94.83
2000–2001	98.70	0.27	0.40	0.63	**2000–2001**	95.17	1.24	1.27	2.32
2002–2006	4.25	1.33	0.97	93.45	**2002–2006**	99.99	0.00	0.00	0.01
2007–2009	97.32	0.55	0.55	1.58	**2007–2009**	95.96	1.38	1.19	1.46
2010–2014	20.24	3.61	3.30	72.85	**2010–2014**	6.83	1.39	1.35	90.43
2015–2020	2.34	0.33	0.33	97.00	**2015–2020**	0.55	0.45	2.00	97.00

Table 2. *Cont.*

Panel E: Recovery Probabilities for LPM Ratio of Big–High Operating Profit Stocks					Panel F: Recovery Probabilities for LPM Ratio of Small–Low Operating Profit Stocks				
	Benchmark Recovery (%)					Benchmark Recovery (%)			
Year	**25**	**50**	**75**	**Full**	**Year**	**25**	**50**	**75**	**Full**
1995–1999	6.14	1.52	1.58	90.76	**1995–1999**	3.09	0.57	0.56	95.79
2000–2001	97.95	0.63	0.62	0.80	**2000–2001**	98.52	0.51	0.33	0.64
2002–2006	85.72	2.48	2.45	9.35	**2002–2006**	88.11	3.30	1.35	7.24
2007–2009	97.09	0.96	0.95	0.99	**2007–2009**	98.72	0.48	0.47	0.33
2010–2014	6.70	2.11	2.02	89.17	**2010–2014**	7.45	1.82	1.76	88.96
2015–2020	1.12	0.50	0.34	98.00	**2015–2020**	0.48	0.07	0.45	99.00

Tables 3 and 4 show the cumulative results by considering Table 1 (Sharpe ratio) and Table 2 (LPM ratio). According to the recovery probabilities by using the Sharpe ratio, the market becomes efficient during 1995–1999, 2002–2006, and 2010–2020 and myopic behavior is not present during this period. However, during 2000–2001 and 2007–2009, the market follows the adaptive market hypothesis and investors exhibit myopic loss aversion behavior. By using the LPM ratio, from 1995 to 2009, the market follows the adaptive market hypothesis; this means that the market is neither efficient nor inefficient. Between 2010 and 2020, the NYSE is less adaptive and more efficient, thus following the efficient market hypothesis. The reasons for this are: firstly, the period from 2010 to 2020 is considered a booming period in the history of the NYSE; secondly, during this period, profitable mergers and acquisitions take place, which positively influences NYSE; lastly, in 2013, NYSE joined the United Nations Sustainable Stock Exchange initiatives, which also positively influences the NYSE and makes it more efficient; as opposed to its previous adaptive period from 1995 to 2009. The practical implications of the results give an understanding to the financial analysts, investors, and policymakers related to the financial markets, especially when it follows the efficient market hypothesis and when it follows the adaptive market hypothesis. Moreover, these results also demonstrate how individual investors deal with the losses and make better investment decisions.

Table 3. Overall results in terms of myopic loss aversion, Efficient Market Hypothesis, and Adaptive Market Hypothesis by using Sharpe ratio.

Years	Myopic Behavior	Efficient Market Hypothesis (EMH)	Adaptive Market Hypothesis (AMH)
1995–1999	Myopic behavior is not present	Supported	Not supported
2000–2001	Myopic behavior present	Not Supported	Supported
2002–2006	Myopic behavior is not present	Supported	Not supported
2007–2009	Myopic behavior present	Not Supported	supported
2010–2014	Myopic behavior is not present	Supported	Not supported
2015–2020	Myopic behavior is not present	Supported	Not supported

Table 4. Overall results in terms of myopic loss aversion, Efficient Market Hypothesis, and Adaptive Market Hypothesis by using LPM ratio.

Years	Myopic Behavior	Efficient Market Hypothesis (EMH)	Adaptive Market Hypothesis (AMH)
1995–1999	Myopic behavior present	Not supported	supported
2000–2001	Myopic behavior present	Not Supported	Supported
2002–2006	Myopic behavior is not present	Supported	Not supported
2007–2009	Myopic behavior present	Not Supported	supported
2010–2014	Myopic behavior is not present	Supported	Not supported
2015–2020	Myopic behavior is not present	Supported	Not supported

According to the overall results, the acceptance and rejection of the hypothesis in terms of Sharpe and LPM ratio are presented in Table 5:

Table 5. Overall acceptance and rejection of Hypothesis.

Sharpe Ratio	LPM Ratio
✓ The H_1 is accepted for the periods 2000–2001 and 2007–2009. This means that investors show myopic behavior, and the market follows the adaptive market hypothesis. ✓ During 1995–1999, 2002–2006, and 2010–2020, the market becomes efficient, thus H_1 is rejected in this case.	✓ The H_1 is accepted for the periods 2000–2009. This means that investors show myopic behavior, and the market follows the adaptive market hypothesis. ✓ During 1995–1999 and 2010–2020, the market becomes efficient, thus H_1 is rejected in this case.

5. Conclusions

Predictably, the share prices in financial markets are mispriced due to behavioral influences. This study has attempted to determine the adaptiveness st of the US market by using the proxy of myopic loss behavior. Investors make sound decisions by getting all the knowledge available in and from the market; however, the financial behavioral theory is contrary to the principle of conventional theory due to psychological influences and their effect on trade decision making. This study particularly focuses on the premise that generally, investors who are exposed to lose myopia start selling their stock when there is a downward trend in the market.

The performance of portfolios is measured in terms of the Sharpe and LPM ratio. Following this step, ordinal logistic regression is used for calculating the probability that investors will recover 25%, 50%, 75%, or 100% of the ratios of their investments during the specified time. The results show that for both Sharpe and LPM ratios from 2010 to 2020 a full recovery of losses can be noticed. This means that investors do not need to panic in times of downward trends in the US market and that calmness may be a winning tool for investors. Thus, we reject the theory of myopic loss aversion and the hypothesis. For 2000–2001, 2002–2006, and 2007–2009 we have shown that losses are not fully recovered, hence the hypothesis is accepted during the recession and global financial crisis in the United States.

Another conclusion drawn from this study is that New York Stock Exchange is consistent with the adaptive market hypothesis during the following different periods: 1995–1999, 2000–2001, 2002–2006, and 2007–2009; after the downward trend, the U.S. market starts the process of recovery of losses and investors show myopic behavior. Interestingly, the NYSE is more efficient during the period from 2010–2020, and as such, it does not support the adaptive market hypothesis; this is due to the boom period faced by the NYSE, and several mergers and acquisitions that have taken place on the NYSE that have pushed the market towards increased efficiency.

This study helps to predict the probabilities of recovering past performance. It enables investors to get a better understanding of the behavior necessary to obtain the best stock returns and to devise profitable investment strategies according to market conditions. The study has theoretical and practical implications for researchers, individual and institutional investors, policymakers, and economic analysts. Theoretically, this study is a valuable addition to Behavioral and Standard finance. The phenomenon of myopic loss aversion is linked with the adaptive market hypothesis to determine whether the market is efficient or adaptive. Moreover, the study provides insight into how to control emotions to avoid further losses when there is a downward trend in the market.

The practical implication of this study included through AMH is that the profitability of following a particular investment strategy produces cyclical profits or losses over time. Similarly, another implication is that it allows one to view market efficiency as changing over time. There are some limitations and recommendations for a future study, as this study was limited to the New York Stock Exchange, which is a developed market; further investigations may be done on other developed or developing countries. There was another limitation in that the study was based on the Sharpe ratio and LPM ratio. Further research will be conducted by using other performance measures such as the value-at-risk ratio, the Sortino ratio, and the Treynor Index. Furthermore, this study used a one-month frequency of data; future studies will also be based on daily, weekly, quarterly, or yearly data frequency. Finally, other stock categories, such as momentum and growth, will also be tested in the future as this study was only considering three stock categories.

Author Contributions: A.S. and U.A. contributed to the literature review, the conceptualization and writing of the original article, and prepared the first draft. U.N. and S.K.S. contributed to the research design, revised, and approved the final manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: The authors would like to acknowledge the support of Prince Sultan University for paying the article processing charges (APC) of this publication.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are available at Kenneth R. French-Data Library https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (accessed on 1 July 2022).

Conflicts of Interest: The authors declare no conflict of interest.

References

Abu Bakar, Azizah, Antonios Siganos, and Evangelos Vagenas-Nanos. 2014. Does mood explain the Monday effect? *Journal of Forecasting* 33: 409–18. [CrossRef]

Aggarwal, Divya, and Uday Damodaran. 2020. Ambiguity attitudes and myopic loss aversion: Experimental evidence using carnival games. *Journal of Behavioral and Experimental Finance* 25: 100258. [CrossRef]

Alevy, Jonathan E., Michael S. Haigh, and John A. List. 2007. Information cascades: Evidence from a field experiment with financial market professionals. *The Journal of Finance* 62: 151–80. [CrossRef]

Almudhaf, Fahad. 2018. Predictability, Price bubbles, and efficiency in the Indonesian stock-market. *Bulletin of Indonesian Economic Studies* 54: 113–24. [CrossRef]

Alrabadi, Dima Waleed Hanna, Shadi Yousef Al-Abdallah, and Nada Ibrahim Abu Aljarayesh. 2018. Behavioral biases and investment performance: Does gender matter? Evidence from Amman Stock Exchange. *Jordan Journal of Economic Sciences* 5: 77–92.

Asur, Sitaram, and Bernardo A. Huberman. 2010. Predicting the future with social media. Paper presented at 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, Toronto, ON, Canada, August 31–September 3, vol. 1, pp. 492–99.

Baltagi, Badi H. 2008. Forecasting with panel data. *Journal of Forecasting* 27: 153–73. [CrossRef]

Barberis, Nicholas, and Richard Thaler. 2003. A survey of behavioral finance. *Handbook of the Economics of Finance* 1: 1053–128.

Bawa, Vijay S. 1975. Optimal rules for ordering uncertain prospects. *Journal of Financial Economics* 2: 95–121. [CrossRef]

Benartzi, Shlomo, and Richard H. Thaler. 1995. Myopic loss aversion and the equity premium puzzle. *The Quarterly Journal of Economics* 110: 73–92. [CrossRef]

Benartzi, Shlomo, Richard H. Thaler, Stephen P. Utkus, and Cass R. Sunstein. 2004. Company Stock, Market Rationality, and Legal Reform. *Market Rationality, and Legal Reform* Olin Working Paper. Available online: https://ssrn.com/abstract=573504 (accessed on 1 July 2022).

Black, Fischer, and Myron Scholes. 1973. The valuation of options and corporate liabilities. *Journal of Political Economy* 81: 637–54. [CrossRef]

Blavatskyy, Pavlo, and Ganna Pogrebna. 2009. Myopic loss aversion revisited. *Economics Letters* 104: 43–45. [CrossRef]

Borges, Maria Rosa. 2010. Efficient market hypothesis in European stock markets. *The European Journal of Finance* 16: 711–26. [CrossRef]

Boya, Christophe M. 2019. From efficient markets to adaptive markets: Evidence from the French stock exchange. *Research in International Business and Finance* 49: 156–65. [CrossRef]

Chen, Andrew H., and Thomas F. Siems. 2004. The effects of terrorism on global capital markets. *European Journal of Political Economy* 20: 349–66. [CrossRef]

Chen, Gong-Meng, Kenneth A. Kim, John R. Nofsinger, and Oliver M. Rui. 2004. *Behavior and Performance of Emerging Market Investors: Evidence from China*. Working Paper. Pullman: Washington State University, January, unpublished.

Chitenderu, Tafadzwa T., Andrew Maredza, and Kin Sibanda. 2014. The random walk theory and stock prices: Evidence from Johannesburg Stock Exchange. *International Business & Economics Research Journal (IBER)* 13: 1241–50.

Corredor, Pilar, Elena Ferrer, and Rafael Santamaria. 2015. Sentiment-prone investors and volatility dynamics between spot and futures markets. *International Review of Economics & Finance* 35: 180–96.

Costa, Raone Botteon. 2018. A systematic test for myopic loss aversion theory. *Review of Behavioral Finance* 10: 320–35. [CrossRef]

Dougherty, Christopher. 2011. *Introduction to Econometrics*. Oxford: Oxford University Press.

Elton, Edwin J., Martin J. Gruber, Stephen J. Brown, and William N. Goetzmann. 2009. *Modern Portfolio Theory and Investment Analysis*. New York: John Wiley & Sons, chp. 237.

Fama, Eugene F., and Kenneth R. French. 1995. Size and book-to-market factors in earnings and returns. *The Journal of Finance* 50: 131–55. [CrossRef]

Feldman, Todd. 2010. A more predictive index of market sentiment. *Journal of Behavioral Finance* 11: 211–23. [CrossRef]

Fishburn, Peter C. 1977. Mean-risk analysis with risk associated with below-target returns. *The American Economic Review* 67: 116–26.

Frazzini, Andrea, and Owen A. Lamont. 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics* 88: 299–322. [CrossRef]

Haritha, P. H., and Abdul Rishad. 2020. An empirical examination of investor sentiment and stock market volatility: Evidence from India. *Financial Innovation* 6: 1–15.

He, Xue Dong, and Xun Yu Zhou. 2014. Myopic loss aversion, reference point, and money illusion. *Quantitative Finance* 14: 1541–54. [CrossRef]

Hirshleifer, David. 2001. Investor psychology and asset pricing. *The Journal of Finance* 56: 1533–97. [CrossRef]

Hsiao, Cheng. 2022. *Analysis of Panel Data*. Cambridge: Cambridge University Press.

Kahneman, Daniel, and Amos Tversky. 1979. Prospect theory: An analysis of decision under risk. In *Handbook of the Fundamentals of Financial Decision Making: Part I*. Singapore: World Scientific, pp. 263–92.

Kaplanski, Guy, and Haim Levy. 2010. Sentiment and stock prices: The case of aviation disasters. *Journal of Financial Economics* 95: 174–201. [CrossRef]

Kaustia, Markku, Eeva Alho, and Vesa Puttonen. 2008. How much does expertise reduce behavioral biases? The case of anchoring effects in stock return estimates. *Financial Management* 37: 391–412. [CrossRef]

Lacker, Jeffrey M. 2004. Payment system disruptions and the federal reserve following September 11, 2001. *Journal of Monetary Economics* 51: 935–65. [CrossRef]

Larson, Francis, John A. List, and Robert D. Metcalfe. 2016. *Can Myopic Loss Aversion Explain the Equity Premium Puzzle? Evidence from a Natural Field Experiment with Professional Traders*. NBER Working Paper. Cambridge: National Bureau of Economic Research.

Lee, Boram, and Yulia Veld-Merkoulova. 2016. Myopic loss aversion and stock investments: An empirical study of private investors. *Journal of Banking & Finance* 70: 235–46.

Leibowitz, Martin L., Anthony Bova, and P. Brett Hammond. 2010. *The Endowment Model of Investing: Return, Risk, and Diversification*. Hoboken: John Wiley & Sons, vol. 534.

Levy, Moshe. 2017. Measuring Portfolio Performance: Sharpe, Alpha, or the Geometric Mean? *Journal of Investment Management* 15: 1–17. [CrossRef]

Lim, Kian-Ping, Weiwei Luo, and Jae H Kim. 2013. Are US stock index returns predictable? Evidence from automatic autocorrelation-based tests. *Applied Economics* 45: 953–62. [CrossRef]

Lintner, John. 1965. Security prices, risk, and maximal gains from diversification. *The Journal of Finance* 20: 587–615.

Liu, Lin, and Qiguang Chen. 2020. How to compare market efficiency? The Sharpe ratio based on the ARMA-GARCH forecast. *Financial Innovation* 6: 1–21. [CrossRef]

Lo, Andrew W. 2004. The adaptive markets hypothesis. *The Journal of Portfolio Management* 30: 15–29. [CrossRef]

Lo, Andrew W. 2005. Reconciling efficient markets with behavioral finance: The adaptive markets hypothesis. *Journal of Investment Consulting* 7: 21–44.

Malkiel, Burton G. 1973. *A Random Walk Down Wall Street*. New York: W. W. Norton & Co.
Malkiel, Burton G. 2003. The efficient market hypothesis and its critics. *Journal of Economic Perspectives* 17: 59–82. [CrossRef]
Markowitz, Harry. 1952. The utility of wealth. *Journal of Political Economy* 60: 151–58. [CrossRef]
Markowitz, Harry M. 2010. Portfolio theory: As I still see it. *Annual Review of Financial Economics* 2: 1–23. [CrossRef]
Miller, Merton H., and Franco Modigliani. 1958. The cost of capital. Corporate Finance and the Theory of Investment. *American Economic Review* 48: 261–97.
Mlambo, Chipo, and Nicholas Biekpe. 2007. The efficient market hypothesis: Evidence from ten African stock markets. *Investment Analysts Journal* 36: 5–17. [CrossRef]
Nawrocki, David N. 1991. Optimal algorithms and lower partial moment: Ex post results. *Applied Economics* 23: 465–70. [CrossRef]
Ndubuisi, Paul, and Kingsley Okere. 2018. Stock Returns Predictability and the Adaptive Market Hypothesis in Emerging Markets: Evidence from the Nigerian Capital Market. (1986–2016). *Asian Journal of Economic Modelling* 6: 147–56. [CrossRef]
Nedelescu, Oana, and R. Barry Johnston. 2005. The Impact of Terrorism on Financial Markets. *The Impact of Terrorism on Financial Markets* 2005: 1–22.
Olbrys, Joanna. 2021. The Global Financial Crisis 2007–2009: A Survey. SSRN 3872477. Available online: https://ssrn.com/abstract=3872477 (accessed on 1 July 2022).
Pakes, Ariel, and Zvi Griliches. 1984. Estimating distributed lags in short panels with an application to the specification of depreciation patterns and capital stock constructs. *The Review of Economic Studies* 51: 243–62. [CrossRef]
Ritter, Jay R. 2003. Behavioral finance. *Pacific-Basin Finance Journal* 11: 429–37. [CrossRef]
Samuelson, Paul A. 1994. The long-term case for equities. *Journal of Portfolio Management* 21: 15. [CrossRef]
Schwaiger, Rene, and Laura Hueber. 2021. Do MTurkers exhibit myopic loss aversion? *Economics Letters* 209: 110137. [CrossRef]
Schwert, G. William. 2003. Anomalies and market efficiency. In *Handbook of the Economics of Finance*. Amsterdam: Elsevier, vol. 1, pp. 939–74.
Shafique, Attayah, Usman Ayub, and Muhammad Zakaria. 2019. Don't let the Greed catch you! Pleonexia rule applied to Pakistan stock exchange. *Physica A: Statistical Mechanics and Its Applications* 524: 157–68. [CrossRef]
Sharpe, William F. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance* 19: 425–42.
Sharpe, William F. 1966. Mutual fund performance. *The Journal of Business* 39: 119–38. [CrossRef]
Shefrin, Hersh, and Meir Statman. 2000. Behavioral portfolio theory. *Journal of Financial and Quantitative Analysis* 35: 127–51. [CrossRef]
Thaler, Richard H., Amos Tversky, Daniel Kahneman, and Alan Schwartz. 1997. The effect of myopia and loss aversion on risk taking: An experimental test. *The Quarterly Journal of Economics* 112: 647–61. [CrossRef]
Tversky, Amos, and Daniel Kahneman. 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5: 297–323. [CrossRef]
Urquhart, Andrew, and Frank McGroarty. 2016. Are stock markets really efficient? Evidence of the adaptive market hypothesis. *International Review of Financial Analysis* 47: 39–49. [CrossRef]
Urquhart, Andrew, and Robert Hudson. 2013. Efficient or adaptive markets? Evidence from major stock markets using very long run historic data. *International Review of Financial Analysis* 28: 130–42. [CrossRef]
Urquhart, Andrew, Bartosz Gebka, and Robert Hudson. 2015. How exactly do markets adapt? Evidence from the moving average rule in three developed markets. *Journal of International Financial Markets, Institutions and Money* 38: 127–47. [CrossRef]
Wesslen, Ryan, Alireza Karduni, Douglas Markant, and Wenwen Dou. 2021. Effect of uncertainty visualizations on myopic loss aversion and the equity premium puzzle in retirement investment decisions. *IEEE Transactions on Visualization and Computer Graphics* 28: 454–64. [CrossRef]
Wooldridge, Jeffrey M. 1995. Selection corrections for panel data models under conditional mean independence assumptions. *Journal of Econometrics* 68: 115–32. [CrossRef]