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Behavioral Risk Measurement: Empirical Evidence From NYSE

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ABSTRACT

This study aims to create a risk measure based on systematic investor behavior. For this purpose, as an alternative to the classical risk measure, volatility, the empirical validity of the downside risk measure, which includes skewness and kurtosis values, was tested. Standard deviation, skewness, and kurtosis differences are used to explain the returns of portfolios created using data from stocks listed on the New York Stock Exchange (NYSE) between 1982 and 2020 depending on different risk concepts. Risk definitions are based on the previous period's skewness and kurtosis coefficients of stock returns. Based on the determined measures, stocks are classified according to their risk level. The relationship between returns and risk measures was examined by regression analysis. According to the results, negative skewness did not provide a higher return than positive skewness. In addition, a higher kurtosis value did not provide higher returns than a lower kurtosis value. As a result, the concept of risk, which represents the loss of the investor, emerges as a result of irrational systematic investor behavior and can be modeled with the skewness coefficient of the return distribution. However, taking a risk in this sense does not promise a reward.

Keywords
Systematic Investor Behavior, Psychological Biases, Skewness and Kurtosis

JEL Classification
G11, C30, C58

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Davranışsal Risk Ölçüsü: NYSE'den Ampirik Kanıtlar

ÖZ

Bu çalışmanın amacı sistematik yatırımcı davranışlarına dayalı risk ölçüsü oluşturmaktır. Bu amaç doğrultusunda, klasik risk ölçüsü olan volatiliteye alternatif olarak, çarpıklık ve basıklık değerlerinin dahil olduğu aşağı yönlü risk ölçüsünün ampirik olarak geçerliliği test edilmiştir. 1982 – 2020 yılları arasında NYSE'de listelenen hisse senetlerine ait verilerden yararlanarak ve farklı risk kavramları baz alınarak oluşturulan portföylerin getirilerini açıklamak için standart sapma, çarpıklık ve basıklık farklılıkları kullanılmıştır. Risk tanımlamaları, hisse senetleri getirilerinin bir önceki dönem ait çarpıklık ve basıklık katsayıları üzerinden yapılmıştır. Belirlenen ölçüler üzerinden hisse senetleri risklerine göre sınıflandırılmıştır. Getiriler ile riski tanımlayan ölçüler arasındaki ilişki regresyon analizi ile incelenmiştir. Elde edilen sonuçlara göre negatif çarpıklığın pozitif çarpıklığa göre, daha yüksek basıklık değerinin de daha düşük basıklık değerine göre daha yüksek getiri sağlamadığı görülmüştür. Sonuç olarak, yatırımcının kaybını temsil eden risk kavramı, irrasyonel sistematik yatırımcı davranışının sonucu olarak ortaya çıkmakta ve getiri dağılımının çarpıklık katsayısı ile modellenebilmektedir. Ancak bu anlamdaki riskin üstlenilmesi bir ödül vaat etmemektedir.

Anahtar Kelimeler
Sistematik Yatırımcı Davranışı, Psikolojik Yanılsamalar, Çarpıklık ve Basıklık

JEL Kodu
G11, C30, C58

1. Introduction

Investors create portfolios through asset selection, capital distribution, and portfolio revision based on evaluations. Investors aim to obtain the highest return at a given level of risk or a certain return at the lowest risk. Depending on the defined risk measure, the portfolio's success or failure is evaluated. Standard deviation is the most commonly used risk measure in this context. However, this measure has some drawbacks. First of all, the standard deviation considers positive and negative deviations together. Accordingly, the current results that high risk does not provide high returns suggest standard deviation is not an appropriate measure of risk. This study investigates the effect of investors' use of risk measures reflecting the effects of systematic investor behavior on portfolio management while choosing assets in the first stage of portfolio management.

There is a lack of attention given to the impact of systematic investor behavior on portfolio management. The risk criteria used by the investor at the stage of securities selection are traditional risk-return measures (standard deviation, alpha, beta coefficient, sharp ratio, Value at Risk, etc.) and superficial financial data of the firm (B/M ratio, Market Cap., price to earnings ratio, etc.). These traditional risk-return measures only reflect the real risk-return profile under the assumptions of the efficient market hypothesis. Several studies have refuted the thesis that stock returns have a normal distribution as assumed in the efficient market hypothesis. In fact, many studies (Bowman, 1980; Fiegenbaum and Thomas, 1988; Andersen et al., 2007; Chou et al., 2009), prove that the most basic assumption of the theory expressed as " high-risk high return" is violated, in other words, there is a negative relationship between risk and return. Therefore, it is necessary to use measures based on the prospect theory, which explains investor behavior rather than the expected value theory based on the efficient market hypothesis. However, risk measures based on the prospect theory are based on investor behavior. It is clear that investor behavior alone cannot be used to measure risk. On the other hand, a risk measure can be obtained assuming that there are systematic behaviors that lead all investors. These behaviors affect stock prices and returns. Therefore, it will be necessary to obtain measures whose relationship with return can be determined based on actual data. In this study, the portfolio performances will be compared with respect to standard deviation (the current risk measure) and the skewness and kurtosis of the return distribution (which we assume to reflect systematic investor behavior). Thus, we will try to determine how robust and in what direction the relationship between risk and return is for which risk measure. The study assumes that risk is shaped by investor behavior. Therefore, using statistical measures that take into account the effect of systematic investor behavior on returns will provide an optimal risk-return tradeoff.

Economists have observed individuals' economic behavior since the mid-1700s (Jeremy Bentham 1748 – 1832). First, expected utility theory (economic man) and prospect theory (irrationality) are two major theories that contradict each other. Behavioral finance and the efficient market hypothesis were developed as alternatives to each other in the context of this development. While the efficient market hypothesis assumes "the investor is completely informed, infinitely sensitive and rational", the prospect theory underlying behavioral finance has the hypothesis of the "investor has psychological biases". However, behavioral finance progress on investor characteristics was divided into two main branches. The first of these deals with the explanation of unpredictable individual investor behaviors through cognitive biases and heuristics. Studies in this direction base investors' irrational decisions on the illusions they fall into while making decisions and argue that it is therefore unpredictable. The other side argues that investor behavior has systematic characteristics. Scientific studies on individual investors' systematic irrational investment decisions have been published for the last 60 years. According to

De Bondt (1998), expert investors determine an opposite investment strategy using this systematic behavior.

Individual investors' perceptions of price processes and stock value, risk-return management, and trading strategies create a systematic effect on stock prices. As a result, the risk is determined by the systematic effect of behavior. The modern portfolio theory makes the important contribution of considering risk from a portfolio perspective rather than from an asset perspective. In other words, the effect of the relationship between diversification and assets on risk should be considered. For this reason, we chose to build portfolios instead of dealing with assets individually. Portfolios are created after stocks have been ranked according to some characteristics in order to assess the effects of risk measurement on portfolios. It has been attempted, through the analysis of the differences between the performance of the different portfolios, to determine which indicator represents risk the best among those that move in the same direction as the return.

This paper is organized as follows: Section 2 examines the relationship between systematic investor behavior and risk, and explains the role of the skewness and kurtosis coefficients in defining this relationship. In Section 3, regression models and the variables used in these models are introduced. Section 4 presents and discusses empirical results. Section 5 concludes the paper and draws on implications for future studies.

2. Systematic Investor Behavior and Risk

Investors make investment decisions based on financial information and price movements. There are some arguments that each investor makes distinct decisions and therefore investor behavior is unpredictable. It has been empirically demonstrated, however, that misconceptions that investors often fall into have a significant impact on stock returns.

Due to the confirmatory bias caused by factors affecting investors (especially the commentaries on charts), the trade volume of investors and the volatility in prices are systematically affected. This affects the skewness and kurtosis of stock returns distribution. According to Bowden (2015), investors interact through sharing information and act as if there is a network between them. It impacts the kurtosis and skewness of stock returns.

De Bondt (1998) argues that investors tend to take higher risks day by day, therefore, irrational investment decisions are gradually increasing. Over time, more and more investors will show similar behaviors and instincts. Investors' systematic effects due to similar misconceptions reduce volatility. Because investors agree. Baker et al. (2016) have shown that volatility increases when investors disagree. Kim et al. (2014), on the other hand, argue that the effect of disagreement between investors on stock return estimates varies depending on investor behaviors. As a result, low volatility will result in a market in which investors agree to a large extent. However, high losses experienced by investors who fall into similar misconceptions will prove a behavioral risk factor. This contradiction can be eliminated with an alternative perspective on risk. Our study aims to eliminate this contradiction by measuring the systematic effects of investors' behavior on risk.

Arditti (1967) was the first to study that skewness could be used as a risk measure. In this study, it is concluded that the second and third moments of the probability distribution for stock returns can be regarded as a reasonable risk measure. Levy (1969), criticizing Arditti (1967) that higher-order moments cannot be neglected, stated that not only skewness but also kurtosis should be used as a measure of risk. In addition, by first associating skewness with investor behavior, he concluded that the investor prefers positive asymmetric distributions (like a lottery) and dislikes negative asymmetric distributions (hence buying insurance policies). Although these two studies are criticized by some studies (e.g. Francis (1975)) that support the mean-variance model and therefore argue that the third and higher moments do not affect investor preferences, studies based on these remarks (Jean, 1971; Arditti and Levy, 1973; Simkowitz and Beedles, 1978, etc.) provide evidence that investors' portfolio preferences are affected by the degree of skewness of returns.

Peiro (1999), argues that stock returns have a skewed distribution, claims that the skewness arises from the sample distribution, and although there are short-term skewnesses, the normal distribution is valid when a sufficiently long-term analysis is made. Studies on the skewness preference of investors in the following years however, (Tversky and Kahneman, 1992; Brunnermeier and Parker, 2005; Mitton and Vorkink, 2007; Barberis and Huang, 2008; Goetzmann and Kumar, 2008; Kumar, 2009; Luchtenberg and Seiler, 2014) clarified the issue of skewness by revealing the effects of investor behavior on the distribution of returns and handling the skewness preference based on the expectation theory. Empirical evidence from these studies (for or against) shows that investors behave according to the expectation theory rather than the classical risk-return profile. However, the results are inconsistent in terms of investor types.

Therefore, it has become widely accepted that skewness affects risk preferences. This effect is related to investors' psychological illusions while making decisions. Birru and Wang (2016) have found evidence that investors' preferences for skewness to the right are very high for low-priced stocks due to the illusion of nominal price. Wen et al. (2013) argue that there is a bidirectional relationship between investors' behaviors toward risk and return distribution. They state that when the risk desire of investors increases (decreases) the skewness of the return distribution will increase (decrease) and as a result of the reverse operation of this relationship, the risk attitude will be affected by the results (gains and losses). Dillenberger and Rozen (2015) obtained a similar result. They concluded that risk attitudes are affected by past experiences, and risk aversion behavior increases after disappointments. These two studies argue that investors' risk attitudes are shaped by each investor's success and failure. This result may suggest the impossibility of detecting a systematic pattern of behavior reflected in the stock price. However, investors fall into the same misconceptions when making investment decisions as if there is a communication network between them. Systematic investors' behavior affects the future price due to repetitive errors caused by decisions made using past price data (by graphical analysis).

Albuquerque (2012), states that there is negative skewness in market returns and positive skewness in stock returns. This model has shown that the heterogeneous structure at the firm level causes contradictions. Even if stocks have different return distributions individually, negative skewness dominates a portfolio. Albuquerque (2012) provides strong evidence for investors' systematic behavior's effect on prices. The right skewness preference of investors causes stock returns to be skewed to the right in certain periods. However, in the long run, this effect disappears or even reverses. Additionally, Simkowitz and Beedles (1980) concluded that positive and negative skewness on a stock basis alone is not a consistent distribution. In parallel with this result, this study assumes that behavioral patterns with systemic effects can be used as a risk measure. Continuous and repetitive investment decisions, reflected in asset prices, become systematic, creating a measurable empirical risk measure.

Another contradiction in skewness is related to individual stock and portfolio returns. Several studies (e.g. Aggarwal et al., 1989) support that the positive skewness of individual stocks disappears in portfolios. Sun and Yan (2003), however, state that if skewness is taken into account in portfolio optimization, it lasts longer. This result indicates that there are non-permanent positive skewed effects created by investors' preferred skewness in individual stocks and that investors can obtain permanent positive skewness only through portfolio optimization that takes skewness into account. Therefore, factors that motivate investors to systematically invest in individual stocks with positive skewness are not a coincidence. Professional investors follow individual investors' behavior and produce investment strategies based on the positions they take contrary to individuals.

Studies on investors' skewness preferences have not been limited to a single asset. Studies have shown that investors' skewness preferences affect portfolio composition during portfolio creation. It is one of the factors that investors consider most in asset selection. In fact, this clearly shows that investors' risk perception is not only based on a single asset price. Therefore, the skewness preference should be analyzed by considering the relationship of the assets in the portfolio to one another. In other words, a risk measure based on investor behavior should be associated with portfolio risk. In one of the first studies on the effect of skewness preference on portfolio return and risk Simkowitz and Beedles (1978), concluded that diversification would reduce positive skewness. Singleton and Wingender (1986), however, showed that skewness is not permanent over periods for stocks and portfolios consisting of these stocks. The findings suggest portfolios consisting of stocks with positively skewed returns in one period are unlikely to be positively skewed in the next. Prakash et al. (2003) examined whether the skewness in international markets affected investors' portfolio decisions. They empirically verified Levy (1973)'s theoretical inferences with the investment strategies they established by creating portfolios based on the mean, variance, and skewness of investment returns.

Another measure that shows investor behavior's systematic effects on prices is kurtosis. As kurtosis increases, the risk increases due to the thick tails in the distribution. Consistent with the preference for right-skewness, investors prefer stocks with high kurtosisLai (2012) concluded that hedgers are more conservative or less speculative than three-moment and mean-variance models if they invest in a strategy that considers the fourth moment. Investors look for low kurtosis when they want to avoid risk, and they prefer high kurtosis when they want to take risks to increase their high return probability. In other words, when they invest with gamble-like behavior, they prefer stocks with high kurtosis return distribution (thick-tailed distribution). Premaratne and Bera (2000) presented a flexible parametric approach to skewness and excessive kurtosis. In addition to an autoregressive model, they argue that Pearson type IV distribution can produce a better risk explanation for different components of the risk premium. This includes variance, skewness, and kurtosis. Therefore, skewness and kurtosis were analyzed in this study and used to define risk. This study proved a systematic effect on skewness and kurtosis. In addition, the concept of risk created by investor behaviors is modeled.

Investors' systematic effects on prices by using gambling-like investment strategies have been discussed in the literature for a while. According to the findings, systematic investor behaviors are generally caused by gambling-like investment strategies. Conrad et al. (2014) state that stock prices of companies with high default potential and abnormally low expected returns increase due to excessive demand from investors. Investors can influence the price in a way that dominates the effect of all other variables on the price. This is done by choosing a skewed return distribution due to a lottery-like investment strategy.

Jondeau and Rockinger (2003) concluded that the third and fourth moments vary with time, but do not affect volatility dynamics. The fact that the problem experienced in variance, which is used as a traditional risk measure, is valid for both the third and fourth moments shows the impossibility to estimate these properties by fixed parameter methods. In this case, the characteristics of the returns created by price movements arising from systematic investor behavior should be modeled with associated methods based on empirical data. Jurczenko et al. (2005) propose a non-parametric method to find a solution to portfolio optimization by considering skewness and kurtosis. Their empirical study of hedge funds led them to develop a portfolio optimization model based on the first four moments. Thus, skewness and kurtosis can be used to determine the distribution of assets in the portfolio. In other words, they can be considered elements of a risk-return trade-off.

Two influential studies guiding our study are Harvey and Siddique (2000) and Yang and Zhou (2015). Both studies investigate investor behavior's systematic effect on stock prices. Harvey and Siddique (2000) evaluated systematic skewness as a risk factor. They concluded that it was still significant even after removing the size effect and B/M effect from the return. The residual return that could not be explained by the market factor could be explained by conditional skewness reflecting investors' expectations. Similar to Harvey and Siddique (2000), we created portfolios based on investors' skewness preferences. Additionally, by creating portfolios according to skewness and kurtosis preferences, we used investors' attitudes toward risk as variables explaining returns.

Yang and Zhou (2015) also examine the effects of investors’ trading strategies and attitudes on asset prices. One of the most revealing findings of their study is that investor behavior is more effective at the prices of small stocks. This evidence suggests that a different measure of risk than volatility may be behaviorally based. The study also shows that behavior prevails over sentiment. Unlike other studies, this study tests the explanatory power of behavioral factors by eliminating market risk from the Fama-French three-factor model. In the study, the irrational behavior of the stock market is explained by using the composite investor sentiment index created by Baker and Wurgler (2006) using technical analysis indicators for investor sentiment. In addition, the investor buying and selling behavior index was created using Lee and Ready's (1991) algorithm for investor behavior. The most remarkable difference and innovation of our study is the complete elimination of the market factor to explain stock return. In other words, risk completely reflects the investor's risk behavior.

3. Regression Models

This study redefines the factors on which risk is based, due to the effect of systematic investor behavior on stock prices. The most well-known study in this context was carried out by Fama and French (1992), Fama and French (1993), Fama and French (1995), and Fama and French (1996). They explained stock returns by size, B/M ratio, and market factors, then added operating profitability and investment to these factors to the Fama–French Five-factor Model (Fama and French, 2015). In these models, stock returns are explained by economic variables. They argue that the issuing company's economic activities have long-term effects on the stock price (the authors use a five-year period), so these variables with continuous effects can be defined as risk components. However, studies show that risk factors perceived by investors and directing investments are more likely to affect investment decisions. Psychological factors rather than economic factors dominate short-term investment decisions. Therefore, the variables that affect investment decisions in the short term and which are the systematic result of investors' motivation to win were handled. The method used by Fama and French (1993) was applied by using the variables that we chose as risk components in our study.

In order to determine the systematic effects of investors' investment decisions on stock prices, one can examine the third and fourth moments (skewness and kurtosis). Skewness and kurtosis enable us to differentiate between negative and positive factors that affect the price and returns, although the first and second moments are the result of all factors (positive and negative). Studies on the relationship between skewness and stock returns have a recent history. Statistically, negative skewness increases the probability of loss and positive skewness increases the probability of gain. Barberis and Huang (2008) argue that securities can be priced by their own skewness. Their conclusion was that positively skewed securities may be overpriced and have a negative average excess return. Brunnermeier and Parker (2005) argue that investors tend to make decisions to maximize their happiness due to their utility-based biases, so they overestimate their returns and prefer skewness in portfolio selection. Other empirical studies support this result. Boyer et al. (2010), Bali et al. (2011), and Kumar (2009) show that investors' preferences for skewness have a lasting effect on prices. They create excessive gambling-like behaviors which create a valuation illusion that shows negative returns. Harvey and Siddique (2000) argue that the momentum effect is associated with systematic skewness, with winners having significantly lower skewness than losers.

The fourth moment (kurtosis), another factor in which systematic investor behavior can be observed, measures the size of the distribution peak. The increase in kurtosis degree causes the distribution to be steeper and the tails thicker. Therefore, in parallel with investors' skewness preferences, high kurtosis preferences also lead to gambling-like behaviors. For this reason, studies on skewness and kurtosis in the literature deal with the effects of these two moments together. Parallel to the literature, we focused on whether high skewness (negative or positive) and kurtosis explain the risk arising from systematic investor preferences.

We use a model consisting of two risk components and a market factor, which we think reflects investor psychology related to stock returns. Our main hypothesis is: "The skewness and kurtosis of stock return distributions are variables that explain risk". Time series regression models were created using market-related factors, standard deviation, skewness, and kurtosis from the previous year's data as explanatory variables.

First, the regression was created to show the extent to which skewness and kurtosis simultaneously explain returns. In other words, how investor behavior can be explained by the combination of these two moments. In order to test the explanatory power of both moments individually, two more regressions were constructed. In these regressions, the standard deviation and skewness and the standard deviation and kurtosis values were used as explanatory variables, respectively.

$$R_t - r_f = \beta_0 + \beta_1 \left(R_{Mt} - r_f \right) + \beta_2 HKMLK_t + \beta_3 SNMSP_t + \varepsilon_t \tag{1}$$

$$R_t - r_f = \beta_0 + \beta_1 \left(R_{Mt} - r_f \right) + \beta_2 H\sigma ML\sigma_t + \beta_3 SNMSP_t + \varepsilon_t \tag{2}$$

$$R_t - r_f = \beta_0 + \beta_1 \left(R_{Mt} - r_f \right) + \beta_2 H\sigma ML\sigma_t + \beta_3 HKMLK_t + \varepsilon_t \tag{3}$$

Where

$R_t - r_f$; residual returns of the portfolios,

$R_{Mt} - r_f$; residual returns of the market,

$HKMLK_t$; The portfolio comparing the returns of the portfolios with high and low kurtosis for the period *t.* It was obtained as a result of ranking according to the kurtosis of the stock returns in the t-1 period,

$SNMSP_t$; The portfolio comparing the returns of the portfolios with high and low skewness for the period *t.* It was obtained as a result of ranking according to the skewness of the stock returns in the *t*-1 period,

$H\sigma ML\sigma_t$: The portfolio comparing the returns of the portfolios with high and low standard deviations for the period *t.* It was obtained as a result of ranking according to the standard deviation of the stock returns in the *t* -1 period.

Since the constant term (β_0) and the coefficient (β_1) of the variable (R_{Mt}-r_f) that shows the market effect in equations (1), (2) and (3) are negligible, the following regression models are handled:

$$R_t - r_f = \beta_2 HKMLK_t + \beta_3 SNMSP_t + \varepsilon_t \tag{4}$$

$$R_t - r_f = \beta_2 H\sigma ML\sigma_t + \beta_3 SNMSP_t + \varepsilon_t \tag{5}$$

$$R_t - r_f = \beta_2 H\sigma ML\sigma_t + \beta_3 HKMLK_t + \varepsilon_t \tag{6}$$

Stock returns obtained by using daily stock prices and market value data at the end of the previous period were used for regression models. Regression results were obtained by using the data from 1982 to 2020 on an annual basis. As in the Fama-French (1993) model, the residual returns were sorted according to the kurtosis value calculated from the data of the previous year on June 30 of each year to create the explanatory variables and then divided into two equal parts. Thus, stocks are divided into 2 classes namely high kurtosis (HK) and low kurtosis (LK). Then, the classes called HK and LK for equation (1) are reordered according to their skewness values (skewed left, normal, and skewed right). The portfolios obtained after the rankings are High Kurtosis-Skewed Negative (HKSN), High Kurtosis-Normal (HKN), High Kurtosis-Skewed Positive (HKSP); Low Kurtosis-Skewed Negative (LKSN), Low Kurtosis-Normal (LKN) and Low Kurtosis-Skewed Positive (LKSP). For equation (2), a similar ranking was performed based on first the standard deviation and then the skewness. The resulting portfolios are High Std Dev.-Skewed Negative (HσSN), High Std Dev.-Normal (HσN), High Std Dev.-Skewed Positive (HσSP); Low Std Dev.-Skewed Negative (LσSN), Low Std Dev.- Normal (LσN), and Low Std Dev.-Skewed Positive (LσSP). Finally, for equation (3), portfolios were created by ordering based on standard deviation and kurtosis, respectively. Portfolios obtained as a result of this ranking are High Std Dev.-High Kurtosis (HσHK), High Std Dev.-Normal (HσN), High Std Dev.-Low Kurtosis (HσLK); Low Std Dev.-High Kurtosis (LσHK), Low Std Dev.- Normal (LσN) and Low Std Dev.-Low Kurtosis (LσLK). While creating explanatory variables following equations were used:

$HKMLK = [(HKSN + HKN + HKSP) - (LKSN + LKN + LKSP)]/3$

$SNMSP = [(HKSN + LKSN) - (HKSP + LKSP)]/2$

$H\sigma ML\sigma = [(H\sigma SN + H\sigma N + H\sigma SP) - (L\sigma SN + L\sigma N + L\sigma SP)]/3$

The dependent variables of the regression models were obtained by developing another ranking criterion similar to the rankings above. For equation (1), the stocks were first divided into 5 equal parts according to their kurtosis values, then each of these 5 parts was divided into 5 parts again according to the degree of skewness, and a total of 25 portfolios were obtained. Similarly, for equation (2), the stocks were divided into 5 according to their standard deviation values, and then 25 portfolios were created by arranging each according to their skewness values. Finally, for equation (3), 25 portfolios were created based on the standard deviation and kurtosis values, respectively. The regression models were used to determine to what extent the 25 portfolio returns are explained by the differences in skewness and kurtosis. Assuming that the investment horizon of the investors in the market is one year, the standard deviation, skewness, and kurtosis values of the returns are calculated by using the daily data of one year before the investment start date, and the portfolios described above are created. The reason for choosing this period is the habit of retail investors to predict the future price of the stock using charts from the past year. The reason for this habit is that it is a feature of technical analysis, which is the type of analysis that such traders use. This approach shows that investors are prone to take high risk because they set short-term investment horizon if they act according to the rules of technical analysis.

A negative degree of skewness was considered high risk. The variance (standard deviation), which is used as a risk measure, is far from being a risk phenomenon that reflects the investor's perception alone, as it includes all negative and positive deviations. The investor's describing a situation as risky means the "probability of losing". Therefore, in equation (1), negative skewness is accepted as a risky situation. In terms of kurtosis, high kurtosis values that cause the thick tail problem represent risky situations. As a result, investors who risk high loss probabilities (in other words, gamble-like behaviors) to catch rare high gains prefer stocks with negative skewness and high kurtosis, meaning that they hold the portfolio with the highest risk. In equation (1), the explanatory power of both risk variables (skewness and kurtosis) is tested, while in equations (2) and (3), their ability to explain the return alone as an extension of the standard deviation is tested.

4. Data and Emprical Results

Data of stocks listed on NYSE provided by the Thomson Reuters Eikon Database (Refinitiv) were used in our analyses. The daily closing prices of the stocks registered to the NYSE between 1982 and 2020 are used and each investment period is between the 1st of July and the 30th of June. Daily returns data from the previous year are used for ranking the stocks. Some stocks are not included in the analysis since there is a significant number of NAs in the data for some stocks. We exclude these stocks from our data set to prevent biases. We assume that investors decide on the stocks that they will invest in the next year by analyzing the data of the stock for the past year.

In Table 1, the returns and standard deviations of the portfolios are given. The values in the table were obtained by taking the average for the period (1982-2020) of equally weighted stocks in the corresponding portfolio. Regarding the portfolio returns, no significant difference was found between returns for kurtosis-skewness-based portfolios (see Table 2). The following statements are true for the other two: for standard deviation-skewness-based portfolios (the riskiest portfolio is the portfolio with the highest standard deviation and the lowest skewness), the return increases from the riskiest portfolio to the less risky portfolios. The same is true for other portfolios. For the standard deviation and kurtosis-based portfolios (the riskiest portfolio is a portfolio consisting of stocks with high standard deviation and high kurtosis), returns have higher values from the riskiest portfolio to the less risky portfolio.

When the risk measures of the portfolios are analyzed in terms of standard deviations, there is no obvious pattern between portfolio standard deviations for the kurtosis-skewness-based portfolios. For the other two groups, however, the standard deviations of portfolios defined as riskier are higher than portfolios defined as less risky. Therefore, there is a negative linear relationship between the degree of risk and the standard deviation value for these two groups.

The regression coefficients and other statistical data for each group are given in Tables 3 through 8. The portfolios created according to the skewness and kurtosis in Table 4 and Table 5 aim to reveal the risk perception of the investor in case the two factors are evaluated together as a risk factor. The strict risk definition is used in these regression equations in this sense. We have ranked portfolios from high kurtosis and negative skewness (highest risk) to positive skewness and low kurtosis (lowest risk). Therefore, we assume that investors employ the riskiest investment strategies when they expect high returns with low probability (i.e. gambling-like behavior). The fact that almost all of the coefficients of the skewness and kurtosis variables are significant indicates that the relationship is consistent (see Table 3). The same is not valid for the coefficients of the market variable. Since the constant and the coefficient of the market variable were negligible in all the years, a second regression consisting of only the skewness and kurtosis factors was used (see Table 4). This had a significant impact on R^2 values. We accept that the market variable fails to explain short-term stock returns using daily data.

Another interesting situation about R^2 values is that all portfolios with low kurtosis (regardless of skewness) have higher R^2 values than portfolios with high kurtosis. In other words, kurtosis alone can explain an investor’s risk behavior at a higher rate only in stocks with low financial risk. This leads to the conclusion that kurtosis alone does not qualify as a risk factor. However, this is not reflected in the returns. In other words, low probability and high returns do not occur at the investor's request. The kurtosis coefficient being negative for all years is strong proof that investors cannot achieve their dreams. Thus, a consistent negative relationship between kurtosis and returns indicates that gambling-like behavior results in frustration for all stocks. Finally, by examining residual returns, the hypothetical same-directional relationship between risk and return does not stand out. Therefore, investors' investment in risky assets through gambling-like behaviors does not affect the return.

It will not be difficult for the big fish to predict an investor's systematic trading behavior if the investor largely follows a market-dominant behavior pattern. As emphasized by De Bondt (1998), after individual investors determine a certain reference point and start trading, they can obtain a lot of data from past price movements. This will confirm the frameworks they have created and support their excessive confidence. This point is a boon to proving an investor's overconfidence by buying and selling stocks whose past price movements have rarely yielded high returns. The regression models (2), (3), (5), and (6) were used to demonstrate this situation more powerfully with a more flexible approach to risk. This approach evaluates standard deviation, skewness, and kurtosis separately as risk factors which are summarized in Tables 5, 6, 7, and 8. Instead of considering standard deviation as a risk factor alone due to handicap, it creates positive deviations, we believe that by associating the standard deviation with the third and fourth moments separately, we bring a perspective that is more appropriate to investor psychology.

Tables 5 and 6 contain the results obtained by regression models of 25 portfolios on risk factors consisting of standard deviation and kurtosis. It is assumed that portfolios consisting of stocks with high standard deviation and high kurtosis are perceived as the riskiest portfolios for investors. Investors call stocks with high volatility but low probability extreme values risky. The regression coefficients are consistent and almost all are statistically significant. The fact that the R^2 values are significantly higher than the previous regression results indicates that the power of the standard deviation and kurtosis factors together in explaining stock returns is much higher. However, the main point of interest is in the residual returns with R^2 values. Portfolios with low kurtosis have higher returns regardless of standard deviation. Having the riskiest portfolios (i.e., high volatility and positive skewness) means the investor settles for the lowest return. This result reveals the inevitable result of gambling behavior for investors more clearly and strongly. Considering the R^2 values, the coefficients of the standard deviation and kurtosis variables are at the highest level in stocks with positive kurtosis and low volatility. This finding leads to the conclusion that it is possible to earn high returns from stocks with consistent price movements, even with low probability. This seems to be possible only with positive news about the firm that impacts expectations.

Table 1

Descriptive Statistics of Portfolios (Averages of 39 years)

Portfolio Returns (×10⁻⁴)

Skewness Quantiles	Kurtosis Quantiles: High	2	3	4	Low
Negative	0,2052	1,8913	1,3217	1,4986	1,3008
2	1,6542	1,9697	1,2938	1,3468	1,8475
3	1,7482	1,9028	1,9493	1,8804	1,7319
4	2,3614	2,2699	1,6504	1,1689	1,8088
Positive	2,3484	1,8815	2,0883	1,5610	0,7528

Skewness Quantiles	Std Dev. Quantiles: High	2	3	4	Low
Negative	-0,3173	0,6153	1,8801	2,9814	2,2685
2	-0,4788	0,9817	1,9745	2,9722	1,9185
3	-1,1696	1,3301	2,0099	2,2470	2,6055
4	-0,1871	1,2296	2,1132	2,4875	3,0406
Positive	0,6495	2,6533	2,3557	2,8774	2,6149

Kurtosis Quantiles	Std Dev. Quantiles: High	2	3	4	Low
High	0,3072	1,9741	2,3788	3,0053	2,2423
2	0,3534	2,2827	2,2240	3,2154	2,8082
3	-0,5185	1,0960	2,3964	2,5458	2,4904
4	-0,3736	0,8136	1,7641	2,3331	2,3881
Low	-1,3053	0,6387	1,5370	2,3065	2,5410

Portfolio Std. Dev. (×10⁻²)

Skewness Quantiles	Kurtosis Quantiles: High	2	3	4	Low
Negative	1,0835	0,9544	1,0758	1,0285	1,1181
2	1,0058	1,0243	0,9951	1,0767	1,1509
3	0,9951	1,0120	1,0337	1,0765	1,1350
4	1,0869	0,9814	1,0460	1,1123	1,1981
Positive	0,9262	1,0263	1,0932	1,1137	1,2012

Skewness Quantiles	Std Dev. Quantiles: High	2	3	4	Low
Negative	1,3505	1,1482	1,0208	0,8379	0,6602
2	1,6500	1,2488	1,1311	0,9650	0,7477
3	1,4896	1,2460	1,1244	0,9964	0,7341
4	1,3744	1,2082	1,1020	0,9661	0,7284
Positive	1,2519	1,1018	1,0168	0,8497	0,6512

Kurtosis Quantiles	Std Dev. Quantiles: High	2	3	4	Low
High	1,2723	1,0301	0,9248	0,7891	0,6024
2	1,3921	1,1396	1,0361	0,8270	0,6543
3	1,4031	1,2021	1,0900	0,9396	0,7137
4	1,4250	1,2590	1,1485	1,0230	0,7520
Low	1,6367	1,3354	1,2085	1,0477	0,8040

Table 2

Kruskal-Wallis H test for portfolio returns

Portfolio	Test Statistics	Probability
Kurtosis-Skewness Based	7.207	0.125
Std Dev-Skewness Based	17.250	0.002*
Std Dev-Kurtosis Based	18.956	0.001*

*H_0:Population medians are equal rejected at α=0.05 level

Negatively skewed stocks often produce negative or low returns and rarely yield lottery-like high returns (see Table 7 and Table 8). In this sense, skewness is a sharper risk measure than kurtosis. If investing in positive kurtosis means playing poker, investing in negative skewness means playing craps. It can be seen clearly in residual returns. Regardless of standard deviation, portfolios with negative skewness have negative or low returns. We can see from the R^2 values that this relationship is consistent and has much higher power to explain returns than other portfolios. The regression coefficient for the skewness factor is positive (with the exception of two values), once again proving that negative skewness is a harbinger of low returns. The fact that regression coefficients are more significant for portfolios with negative skewness also supports this result. It indicates that investors who make gambling-like investment decisions are determined and consistent in falling into overconfidence, framing, and reference point mistakes.

5. Discussion and Conclusion

It would be wrong and incomplete to consider individual investors' irrational investment decisions only in terms of their own investments' success. Investors' trade in a market will affect prices when they are considered a significant part of the market. However, this situation cannot be limited to individual investors only. We cannot limit irrational investment decisions to unprofessional investor behavior. The data and news about professional fund managers' success reveal that their success is not constant and there are failures up to scandals. Therefore, it would not be wrong to talk about the existence of common reasons that affect all investors in the investment world and cause irrational decisions. We think that it is an original study because it is a study that tries to explain the systematic behavior of investors with the statistical characteristics of stock returns. Therefore, we think that this study will lead to a detailed examination and modeling of systematic investor behavior in terms of causes and effects.

Systematic investor behavior first requires reflection on risk concepts and risk measures. We define risk as the "probability of loss" and risk premium as the "reward for risking loss" and try to find a measure of risk that fits this definition. At this point, we need arguments to model all or almost all of the market in order to include the systematic effects of investor behavior in the concept of risk. Therefore, we can explain investor behavior according to the second type of chaos theory (market order consists of the sum of expected and spontaneous actions based on both rational and irrational behavior). In other words, a model should be created to obtain results from searching for random patterns. This study takes a step forward by finding statistical measures (skewness and kurtosis) and using empirical evidence for systematic investor behavior. The main output of the study is that differences in skewness and kurtosis are expressed as sources of risk without violating the assumption of randomness (the normality of returns). Parallel to the other studies in the literature, it becomes clear with this study that the relationship between risk and return is not in the same direction when the standard deviation is used as a traditional risk measure. Therefore, only loss-based risk measures should be used.

Within the scope of this study, portfolios have been created by a systematic approach based on the tools we use to define investor risk. As a result, the findings are consistent as they were obtained by the same method over 39 years of data. However, to model stock prices by creating a risk concept based on systematic investor behavior, data from multiple markets should be used. In addition, stronger evidence for the validity of the findings can be obtained by making the classification based on the skewness and kurtosis coefficients starting from different months of the year.

The most important result of this study for investors is that they should consider that the factors that they are systematically affected during their buy and sell decisions will not have the same results for every stock. It would be beneficial to pay attention to the more advanced statistical properties (such as skewness and kurtosis of the returns) of stock returns, different from the mean and standard deviations.

Table 3

Regression Results of $R_t - r_f = \beta_0 + \beta_1(R_{Mt} - r_f) + \beta_2 HKMLK_t + \beta_3 SNMSP_t + \varepsilon_t$ *Model*

β_1

Skewness Quantiles	Kurtosis Quantiles: High	2	3	4	Low
Negative	0.0010	0.0010	0.0009	0.0008	0.0008
(prob)	51.28%	58.97%	56.41%	6.15%	48.72%
2	0.0011	0.0009	0.0011	0.0010	0.0010
(prob)	56.41%	51.28%	53.85%	51.28%	51.28%
3	0.0009	0.0010	0.0010	0.0011	0.0011
(prob)	64.10%	64.10%	66.67%	58.97%	53.85%
4	0.0009	0.0011	0.0010	0.0010	0.0011
(prob)	64.10%	58.97%	53.85%	56.41%	56.41%
Positive	0.0008	0.0009	0.0009	0.0009	0.009
(prob)	46.15%	43.59%	43.59%	46.15%	48.72%

β_2

Skewness Quantiles	Kurtosis Quantiles: High	2	3	4	Low
Negative	-0.2767	-0.4003	-0.2094	-0.0188	-0.2420
(prob)	79.49%	69.23%	71.79%	84.62%	76.92%
2	-0.6481	-0.5069	-0.3285	-0.4981	-0.4827
(prob)	74.36%	79.49%	76.92%	76.92%	74.36%
3	-0.7570	-0.8849	-0.8808	-0.9377	-0.9254
(prob)	84.62%	87.18%	82.05%	89.74%	82.05%
4	-1.2830	-1.3051	-1.2819	-1.3550	-1.3419
(prob)	97.87%	94.87%	97.44%	92.31%	92.31%
Positive	-1.5667	-1.6165	-1.5794	-1.6605	-1.6179
(prob)	92.31%	97.44%	94.87%	92.31%	94.87%

β_3

Skewness Quantiles	Kurtosis Quantiles: High	2	3	4	Low
Negative	0.5661	0.4062	0.0852	-0.3044	-0.5955
(prob)	74.36%	66.67%	58.97%	74.36%	71.79%
2	0.4701	0.1982	0.0335	-0.2321	-0.5631
(prob)	69.23%	56.41%	53.85%	66.67%	76.92%
3	0.5616	0.2378	0.0152	-0.2485	-0.5417
(prob)	64.10%	61.54%	61.54%	74.36%	71.79%
4	0.5456	0.2697	0.0176	-0.3320	-0.4479
(prob)	76.92%	56.41%	69.23%	79.49%	79.49%
Positive	0.5974	0.3466	0.0283	-0.1663	-0.5788
(prob)	82.05%	64.10%	51.28%	51.28%	76.92%

R^2

Skewness Quantiles	Kurtosis Quantiles: High	2	3	4	Low
Negative	0.1026	0.1026	0.0513	0.0769	0.0256
2	0.1282	0.0769	0.1026	0.1026	0.0769
3	0.2051	0.2051	0.2308	0.2051	0.2051
4	0.1282	0.1282	0.1282	0.1282	0.1282
Positive	0.3077	0.2821	0.2051	0.2821	0.2564

* The coefficients and R^2 values in the table are the averages for 1982-2020. Prob values are the ratios of the ones that are significant according to the 0.01, 0.05, and 0.10 significance levels within the total.

Table 4

Regression Results of $R_t - r_f = \beta_2 HKMLK_t + \beta_3 SNMSP_t + \varepsilon_t$ *Model*

		β_2						β_3				
		Kurtosis Quantiles						Kurtosis Quantiles				
Skewness Quantiles		High	2	3	4	Low		High	2	3	4	Low
	Negative	-0.2656	-0.3887	-0.1968	-0.0104	-0.2333	Negative	0.5238	0.3669	0.0479	-0.3425	-0.6341
	(prob)	74.36%	66.67%	76.92%	82.05%	76.92%	(prob)	76.92%	71.79%	64.10%	74.36%	76.92%
	2	-0.6336	-0.4954	-0.3162	-0.4838	-0.4692	2	0.4269	0.1585	-0.0156	-0.2731	-0.6007
	(prob)	71.79%	76.92%	76.92%	74.36%	74.36%	(prob)	69.23%	53.85%	51.28%	71.79%	84.62%
	3	-0.7491	-0.8770	-0.8717	-0.9237	-0.9087	3	0.5163	0.1963	-0.0278	-0.2940	-0.5840
	(prob)	82.05%	84.62%	84.62%	87.18%	82.05%	(prob)	66.67%	56.41%	66.67%	79.49%	74.36%
	4	-1.2716	-1.2910	-1.2691	-1.3481	-1.3261	4	0.5090	0.2272	-0.0264	-0.3730	-0.4963
	(prob)	94.87%	94.87%	94.87%	92.31%	92.31%	(prob)	76.92%	58.97%	69.23%	82.05%	82.05%
	Positive	-1.5549	-1.6039	-1.5687	-1.6471	-1.6071	Positive	0.5580	0.3100	-0.0159	-0.2096	-0.6158
	(prob)	92.31%	97.44%	97.44%	92.31%	94.87%	(prob)	84.62%	66.67%	56.41%	58.97%	79.49%

		R^2				
		Kurtosis Quantiles				
Skewness Quantiles		High	2	3	4	Low
	Negative	0.1973	0.1942	0.1556	0.1787	0.1698
	2	0.2163	0.1880	0.1671	0.1709	0.1964
	3	0.2623	0.2371	0.2139	0.2357	0.2340
	4	0.3108	0.2923	0.2977	0.3091	0.2988
	Positive	0.3604	0.3334	0.3220	0.3374	0.3444

* The coefficients and R^2 values in the table are the averages for 1982-2020. Prob values are the ratios of the ones that are significant according to the 0.01, 0.05, and 0.10 significance levels within the total.

Table 5

Regression Results of $R_t - r_f = \beta_0 + \beta_1(R_{Mt} - r_f) + \beta_2 H\sigma ML\sigma_t + \beta_3 HKMLK_t + \varepsilon_t$ Model

β_1 (Std Dev. Quantiles)

Kurtosis Quantiles	High	2	3	4	Low
High	0.0001	0.0003	0.0006	0.0007	0.0005
(prob)	33.33%	35.90%	33.33%	43.59%	38.46%
2	0.0006	0.0007	0.0005	0.0007	0.0005
(prob)	56.41%	53.85%	53.85%	53.85%	51.28%
3	0.0006	0.0008	0.0007	0.0006	0.0005
(prob)	53.85%	56.41%	48.72%	53.85%	48.72%
4	0.0006	0.0007	0.0006	0.0006	0.0005
(prob)	64.10%	43.59%	56.41%	48.72%	51.28%
Low	0.0006	0.0006	0.0005	0.0004	0.0002
(prob)	56.41%	58.97%	56.41%	56.41%	51.28%

β_2 (Std Dev. Quantiles)

Kurtosis Quantiles	High	2	3	4	Low
High	1.6434	1.8008	1.7815	1.7669	1.9337
(prob)	100%	100%	100%	100%	100%
2	1.0273	1.1365	1.1896	1.2046	1.2459
(prob)	100%	100%	100%	100%	100%
3	0.6968	0.8187	0.8248	0.7862	0.7802
(prob)	94.87%	100%	100%	92.31%	92.31%
4	0.4132	0.4708	0.4738	0.4710	0.4183
(prob)	79.49%	87.18%	82.05%	84.62%	69.23%
Low	0.1912	0.1720	0.1237	0.1016	0.1094
(prob)	58.97%	56.41%	48.72%	56.41%	56.41%

β_3 (Std Dev. Quantiles)

Kurtosis Quantiles	High	2	3	4	Low
High	0.2822	0.2777	-0.4796	-1.0363	-1.8174
(prob)	69.23%	76.92%	82.05%	94.87%	100%
2	-0.3704	-0.6042	-0.8089	-1.1206	-1.4466
(prob)	76.92%	84.62%	94.87%	89.74%	97.44%
3	-0.4140	-0.6629	-0.8428	-1.0973	-1.2774
(prob)	74.36%	94.87%	92.31%	89.74%	92.31%
4	-0.4419	-0.5865	-0.7908	-1.0349	-1.1860
(prob)	76.92%	89.74%	89.74%	92.31%	92.31%
Low	-0.2985	-0.4463	-0.6136	-0.7845	-0.9012
(prob)	76.92%	94.87%	94.87%	92.31%	94.87%

R^2 (Std Dev. Quantiles)

Kurtosis Quantiles	High	2	3	4	Low
High	0.2564	0.2821	0.4103	0.6667	0.8462
2	0.1795	0.2821	0.3846	0.5897	0.7179
3	0.1795	0.2308	0.2308	0.4615	0.4872
4	0.1282	0.1282	0.1795	0.2821	0.3846
Low	0.1026	0.1026	0.1282	0.1282	0.1795

Table 6

Regression Results of $R_t - r_f = \beta_2 H\sigma ML\sigma_t + \beta_3 HKMLK_t + \varepsilon_t$ Model

β2 (*Std Dev Quantiles*)

Kurtosis Quantiles	*High*	*2*	*3*	*4*	*Low*
High	*1.6540*	*1.8276*	*1.8133*	*1.8065*	*1.9608*
(prob)	*100%*	*100%*	*100%*	*100%*	*100%*
2	*1.0591*	*1.1731*	*1.2224*	*1.2361*	*1.2735*
(prob)	*100%*	*100%*	*100%*	*100%*	*100%*
3	*0.7293*	*0.8592*	*0.8612*	*0.8161*	*0.8076*
(prob)	*97.44%*	*100%*	*100%*	*92.31%*	*94.87%*
4	*0.4459*	*0.5115*	*0.5057*	*0.5070*	*0.4467*
(prob)	*79.49%*	*92.31%*	*84.62%*	*82.05%*	*79.49%*
Low	*0.2187*	*0.2028*	*0.1543*	*0.1236*	*0.1262*
(prob)	*74.36%*	*58.97%*	*58.97%*	*58.97%*	*58.97%*

β3 (*Std Dev Quantiles*)

Kurtosis Quantiles	*High*	*2*	*3*	*4*	*Low*
High	*0.2828*	*0.2829*	*-0.4688*	*-1.0250*	*-1.8077*
(prob)	*71.79%*	*76.92%*	*82.05%*	*92.31%*	*100%*
2	*-0.3602*	*-0.5927*	*-0.8002*	*-1.1122*	*-1.4377*
(prob)	*76.92%*	*84.62%*	*94.87%*	*89.74%*	*97.44%*
3	*-0.4058*	*-0.6503*	*-0.8325*	*-1.0884*	*-1.2695*
(prob)	*74.36%*	*94.87%*	*94.87%*	*89.74%*	*87.18%*
4	*-0.4318*	*-0.5746*	*-0.7834*	*-1.0256*	*-1.1776*
(prob)	*76.92%*	*89.74%*	*92.31%*	*92.31%*	*92.31%*
Low	*-0.2883*	*-0.4364*	*-0.6044*	*-0.7790*	*-0.8982*
(prob)	*76.92%*	*94.87%*	*94.87%*	*92.31%*	*94.87%*

R2 (*Std Dev Quantiles*)

Kurtosis Quantiles	*High*	*2*	*3*	*4*	*Low*
High	*0.2564*	*0.2564*	*0.3846*	*0.6667*	*0.8462*
2	*0.1795*	*0.2564*	*0.4103*	*0.5897*	*0.7179*
3	*0.1795*	*0.2051*	*0.2308*	*0.4359*	*0.4872*
4	*0.1026*	*0.1282*	*0.1795*	*0.2821*	*0.3590*
Low	*0.1026*	*0.1026*	*0.1026*	*0.1282*	*0.1795*

** The coefficients and R2 values in the table are the averages for 1982-2020. Prob values are the ratios of the ones that are significant according to the 0.01, 0.05, and 0.10 significance levels within the total.*

Table 7

Regression Results of $R_t - r_f = \beta_0 + \beta_1(R_{Mt} - r_f) + \beta_2 H\sigma ML\sigma_t + \beta_3 SNMSP_t + \varepsilon_t$ *Model*

β_1

Skewness Quantiles	Std Dev. Quantiles: High	2	3	4	Low
High	0.0006	0.0004	0.0002	0.0005	0.0002
(prob)	38.46%	46.15%	33.33%	41.03%	46.15%
2	0.0005	0.0005	0.0004	0.0004	0.0005
(prob)	51.28%	53.85%	48.72%	38.46%	46.15%
3	0.0005	0.0006	0.0004	0.0005	0.0005
(prob)	48.72%	53.85%	43.59%	56.41%	53.85%
4	0.0005	0.0005	0.0004	0.0005	0.0005
(prob)	53.85%	56.41%	51.28%	53.85%	56.41%
Low	0.0004	0.0003	0.0003	0.0004	0.0005
(prob)	48.72%	46.15%	53.85%	64.10%	53.85%

β_2

Skewness Quantiles	Std Dev. Quantiles: High	2	3	4	Low
High	1.8186	2.2364	2.1092	1.8857	1.6335
(prob)	100%	100%	100%	100%	100%
2	1.3106	1.5003	1.4893	1.4739	1.2740
(prob)	100%	100%	97.44%	100%	100%
3	0.9323	1.1036	1.0672	1.0474	0.9824
(prob)	89.74%	94.87%	100%	92.31%	92.31%
4	0.6125	0.6939	0.7076	0.7172	0.6527
(prob)	82.05%	82.05%	87.18%	87.18%	84.62%
Low	0.2528	0.2881	0.3434	0.3629	0.3412
(prob)	69.23%	79.49%	74.36%	69.23%	76.92%

β_3

Skewness Quantiles	Std Dev. Quantiles: High	2	3	4	Low
High	1.2553	1.3748	0.2205	-0.5582	-0.9669
(prob)	87.18%	87.18%	58.97%	79.49%	94.87%
2	0.8509	0.8376	0.4347	0.2296	-0.0415
(prob)	79.49%	79.49%	66.67%	64.10%	71.79%
3	0.6916	0.6981	0.4827	0.2226	0.0764
(prob)	82.05%	79.49%	82.05%	66.67%	66.67%
4	0.6585	0.6176	0.4348	0.2668	0.0574
(prob)	69.23%	74.36%	74.36%	74.36%	64.10%
Low	0.5188	0.5290	0.3886	0.2207	0.0526
(prob)	82.05%	69.23%	71.79%	64.10%	51.28%

R^2

Skewness Quantiles	Std Dev. Quantiles: High	2	3	4	Low
High	0.5128	0.6154	0.4615	0.4359	0.4615
2	0.3077	0.4359	0.3333	0.2821	0.1282
3	0.1538	0.1538	0.1026	0.1282	0.1026
4	0.1282	0.1026	0.0769	0.0769	0.0769
Low	0.0513	0.0769	0.0769	0.07.69	0.0769

* The coefficients and R^2 values in the table are the averages for 1982-2020. Prob values are the ratios of the ones that are significant according to the 0.01, 0.05, and 0.10 significance levels within the total.

Table 8

Regression Results of $R_t - r_f = \beta_2 H\sigma ML\sigma_t + \beta_3 SNMSP_t + \varepsilon_t$*Model*

β_2

Skewness Quantiles	Std Dev Quantiles: High	2	3	4	Low
High	1.8478	2.2710	2.1262	1.9098	1.6483
(prob)	100%	100%	100%	100%	100%
2	1.3371	1.5349	1.5172	1.5031	1.3043
(prob)	100%	100%	97.44%	100%	100%
3	0.9611	1.1389	1.0941	1.0768	1.0148
(prob)	94.87%	94.87%	100%	92.31%	94.87%
4	0.6414	0.7230	0.7393	0.7467	0.6862
(prob)	82.05%	84.62%	87.18%	87.18%	87.18%
Low	0.2723	0.3072	0.3641	0.3901	0.3707
(prob)	74.36%	79.49%	82.05%	69.23%	79.49%

β_3

Skewness Quantiles	Std Dev Quantiles: High	2	3	4	Low
High	1.2382	1.3516	0.2068	-0.5751	-0.9753
(prob)	87.18%	87.18%	58.97%	79.49%	92.31%
2	0.8318	0.8178	0.4182	0.2125	-0.0639
(prob)	79.49%	76.92%	69.23%	69.23%	71.79%
3	0.6756	0.6802	0.4669	0.2013	0.0582
(prob)	79.49%	76.92%	74.36%	61.54%	58.97%
4	0.6404	0.5980	0.4159	0.2442	0.0368
(prob)	69.23%	71.79%	74.36%	74.36%	66.67%
Low	0.5073	0.5158	0.3737	0.2029	0.0326
(prob)	82.05%	66.67%	66.67%	61.54%	58.97%

R^2

Skewness Quantiles	Std Dev Quantiles: High	2	3	4	Low
High	0.4615	0.6154	0.4615	0.4103	0.4103
2	0.2821	0.4359	0.3077	0.2564	0.1026
3	0.1282	0.1282	0.1282	0.1282	0.1026
4	0.1282	0.1026	0.0769	0.0769	0.0769
Low	0.0513	0.0769	0.0769	0.0769	0.0769

* The coefficients and R^2 values in the table are the averages for 1982-2020. Prob values are the ratios of the ones that are significant according to the 0.01, 0.05, and 0.10 significance levels within the total.

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