Skewed Greed: Realized Skewness or Maximum returns, which statistical anomaly is better at capturing greed in financial markets?

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Abstracts

Skewed Greed: Realized Skewness or Maximum returns, which statistical anomaly is better at capturing greed in financial markets?

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Investors like to have the possibility of very high returns, even if they are highly unlikely. Because of this, they prefer positively skewed assets, which are consequently overvalued generating lower returns. This work studies the implications of extraordinarily skewed returns in the cross-sectional pricing of stocks in light of previous evidence that investors favor assets with lottery-like payoffs and the fact that many investors are inadequately diversified. Analyzing data from US stocks since 1927 I found that, realized skewness has an economically important and statistically significant negative relationship with expected stock returns. This realized-skewness sorted strategy rewards its investors with an average monthly return of 0.7% with a corresponding t-stat of 27.2 and a Sharpe Ratio of 0.89, with certain unexpected calendar months – April and July – outperforming the market with Sharpe ratios of 1.5 and 2.24, respectively. My findings are of interest to investors as this strategy is easy to implement and this work lays out the path for further academic research regarding skewness related trading strategies.

Keywords: Realized Skewness; Statistical Anomalies; Extreme returns; Lottery-like payoffs; Cross-sectional return predictability.

Ganância enviesada: Enviesamento realizado ou retornos máximos, qual anomalia estatística é que é melhor a capturar ganância nos mercados financeiros?

João Rafael Pereira Gaspar Mendes Abrantes

Os investidores gostam de ter a possibilidade de retornos muito elevados, mesmo que sejam altamente improváveis. Por isso, eles preferem ativos positivamente assimétricos, que consequentemente são sobrevalorizados, o que gera retornos inferiores. Este trabalho estuda as implicações de retornos extraordinariamente assimétricos de ações, de acordo com estudos anteriores que concluíram que muitos dos investidores estão inadequadamente diversificados e preferem ativos com retornos semelhantes aos de uma loteria. Ao analisar os dados de ações dos EUA desde 1927, descobri que a assimetria realizada tem uma relação negativa economicamente importante e estatisticamente significativa com os retornos esperados das ações. Essa estratégia recompensa seus investidores com um retorno mensal médio de 0,7% com um t-stat correspondente de 27,2 e um índice de Sharpe de 0,89, com alguns meses do calendário inesperados – abril e julho – a baterem o mercado com os índices de Sharpe de 1,5 e 2,24, respetivamente. O presente trabalho tem relevância para os investidores, dado que esta estratégia é fácil de implementar e estabelece a base para estudos académicos adicionais sobre estratégias de investimento relacionadas à assimetria.

Keywords: Assimetria realizada; Retornos extremos; Retornos semelhantes aos de uma lotaria; Previsibilidade dos retornos.

Table's Index

Figure’s Index

Table of Contents

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1. Introduction

"Be fearful when others are greedy. Be greedy when others are fearful." – Warren Buffet, Chairman and CEO of Berkshire Hathaway.

Driven by my newfound knowledge in data science and its applications on empirical finance, I decided to study how I could develop quantitative strategies to capture statistical anomalies in financial markets and exploit their "greed". Greediness in finance goes hand in hand with investors' wishful thinking that gives them enough confirmation bias in order to, naively, believe their luck is about to change. Put simply, people like to believe in their luck, that they are the exception to the rule, and they bet on it. Although the chances of winning the lottery are millions to one, people are still willing to spend money for the small chance of hitting the jackpot. Overall, people like the possibility of a big win, even if it is very unlikely. Financial markets are no exception to this phenomenon. Luck, in empirical finance, is often proxied by certain statistical measures in a returns' distribution such as maximum returns and skewness.

Building on the findings of (Bali, Cakici, and Whitelaw 2011) who show that extremely favorable returns (maximum returns) are a proxy for skewness, this study aims to test if the negative relationship between forward returns with maximum returns and realized skewness still holds, and if it has become weaker or stronger. I analyze this relationship to evaluate what would be the best anomaly that beats the market. This thesis seeks to study both the aforementioned investor's preferences by investing in assets with the highest maximum returns, as a proxy for right-tail events in their return's distribution, and, conversely, exploit that same exact preference for positively skewed assets by investing in assets with the lowest skewness and determine which strategy performs best at beating the market.

Empirical finance literature is overflowing with evidence of the predicting power of realized skewness and its variations, namely idiosyncratic skewness, on forward returns in the cross-sectional asset returns space, at all levels (firm, industry, sector, asset class). Nevertheless, there has never been true consensus across, the relevant literature, over the relationship between skewness and forward returns. In other words, is skewness positively or negatively related with forward returns? Results are mixed, for instance, (Rehman and Vilkov 2011) examine the link between expected stock returns and ex-ante skewness finding that positively skewed stocks outperform negatively skewed stocks by 45 basis points per month. In addition, (Chen, Li, and Worthington 2021), also find a positive relationship between the two, and find excess returns of 4.596% per annum, significant at a 5% level. Notwithstanding, looking at commodity futures' skewness, (Fernandez-Perez et al. 2018) obtain an 8.01% yearly excess return on average and find an alpha of 6.21% when controlling for risk factors with a Sharpe Ratio of 0.78, giving evidence of a strong negative relation between skewness and expected returns. Furthermore, (Han et al. 2020) and (Baltas and Salinas 2019) have confirmed that realized skewness is negatively related to future returns and yield diversification gains, driving up risk adjusted returns from a Sharpe Ratios of 0.35 to 0.72. Moreover, using high-frequency stock data, (Amaya et al. 2015) confirm the negative relation between skewness and expected returns of stocks finding a difference of 34 basis points in outperformance of negatively positively skewed stocks.

I, however, take a more holistic view of this research question by focusing on the US stock market from 1927 to 2021 and analyzing different sub-samples such as 1962 to 2005 and 1962 to 2021. Extending (Amaya et al. 2015)'s methodology, but in higher timeframes (monthly formation and holding periods), I sorted stocks in deciles from lowest to highest realized skewness to form different equal-weighted and value-weighted long/short portfolios as well as long-only portfolios with monthly rebalancing. Analyzing these strategies, I find that skewness is negatively correlated with 1-month forward returns, in line with the majority of academia and empirical studies. On average, I find that the equal-weighted lowest skewness (LOW SKEW) decile outperforms by 70 basis points the highest skewness decile (HIGH SKEW), with a corresponding t-statistic of 27.21, and the equivalent (Fama and French 1993) (Carhart 1997) 4FF alpha difference of 0.71 basis points with a corresponding t-statistic of 9.01, every month. Therefore, my strategy yields out-of-sample returns more statistically significant and economically important than the abovementioned literature and higher risk-adjusted returns with annualized Sharpe Ratios of 0.89. However, when looking into sub-samples of my data I find that this relationship is losing some of its predicting power, as between 1962 and 2021, the outperformance decreases to 0.44, with a corresponding t-statistic of 21.83 and an alpha of 0.44 with an equivalent t-statistic of 5.02. I studied how the combination of different formation and holding periods might affect this strategy's predicting power and, by extension, its statistical and economical implications. With formations periods either of 1 month, 1 year and 5 years and holding periods either of 1 month, 3 months or 6 months, I find overwhelming evidence that the lower (higher) the timeframes chosen the higher (lower) will the outperformance be of the LOW SKEW portfolios, meaning that skewness is negatively (positively) correlated with forward returns. By answering this question, I find evidence as to why the topic of extreme returns has always been so polarizing in empirical finance and why both schools of thought can be right depending on the combination of holding and formation periods chosen. Therefore, filling such an important gap in literature and bringing consensus to this academic debate.

Moreover, to cover a gap in literature, I show that this strategy is able to generally withstand market turmoil and economic woes and uncertainty better than the market. This ability to preserve capital is demonstrated, on one hand, by the cumulative out-of-sample excess returns being more than triple of the excess market returns. On the other hand, I find that this strategy boasts strong seasonality in months less favorable to investors, more specifically, in an annualized total return basis its best calendar month yields, on average, 17.05%, in July with a 2.24 Sharpe Ratio and its second-best calendar month yields, on average, 13.35%, in April with a 1.5 Sharpe Ratio. Finally, to add to the literature, I also study the time-series of the spread between LOW SKEW's and HIGH SKEW's realized skewness (SKEW SPREAD), finding out that it is statistically significant, on all levels, to mean revert using both Dickey-Fuller and Augmented Dickey-Fuller tests, opening up significant research opportunities towards statistical arbitrage strategies.

Extending (Bali, Cakici, and Whitelaw 2011)'s methodology I corroborate their major findings: extreme (maximum) returns are negatively correlated with 1-month forward returns. Using the same sample and data previously mentioned, I sorted stocks in deciles from lowest (LOW MAX) to highest (HIGH MAX) daily maximum returns to form different equal-weighted and value-weighted long/short portfolios as well as long-only portfolios with monthly rebalancing. With a t-statistic of 6.25, the LOW MAX outperforms HIGH MAX by 35 basis points, with a t-statistic of 4.78 and an equivalent difference in 4FF alphas of 80 basis points, per month. By updating (Bali, Cakici, and Whitelaw 2011)'s data sample to 2021 I, therefore, added to the literature and found that their strategy has underperformed significantly as of late, meaning that this strategy might have become too crowded or fell victim to noise in its predicting power.

My findings are of interest to investors as this strategy is easy to implement and this work lays out the path for further research regarding skewness related trading strategies.

This thesis is organized as follows: section 2 gives an overview of the underlying theories and relevant literature, section 3 explains the data and research methodology, section 4 discusses the results and future research ideas, section 5 lists the limitations, and section 6 concludes.

2. Literature Review

All investors are constantly trying to predict future returns through educated guesses, empirically proven assumptions, theories, and models. While one of the most critical assumptions across the world of finance is the normality of financial returns, there are known deviations. Knowing about these anomalies, investors are persistently looking to exploit discrepancies between normality and non-normality to make a profit. Generally, a distribution with high excess kurtosis that is positively skewed (meaning that it has a longer tail on the positive side) therefore, its maximum returns may be higher than in a normal distribution, because there is a higher probability of extreme positive returns occurring in that distribution, and vice-versa.

One of these anomalies is skewness. Skewness deviates from normality by shifting the returns' distribution to the left or right, thus taking extremes into account, also known as Kurtosis, rather than just the average. These extremes promise big returns which attract investors that are willing to bet on their luck, or skill, for a chance of hitting the jackpot. Since the 1990s, asset returns have become increasingly skewed to the right (negative skewness), meaning that in financial markets there have been increasingly more positive returns coupled with more extremely negative returns (black swan events). Events of high volatility, starting with the internet bubble of the late 90s, followed by the terrorist attacks of September 11th, 2001, the financial crisis, and subsequent years of quantitative easing have been detrimental to the shift in the distribution of returns. Skewness is also of particular importance for investors in the short- to medium-term, as they cannot rely on the average as a measure of returns. For positively skewed returns the mean is higher than the median and mode of the distribution, implying higher average returns. But while low or even negative returns are limited and more likely, very high returns are possible but rare. Therefore, investors betting on their luck, prefer positively skewed assets. This preference overvalues positively skewed assets, which in turn reduces their returns.

How knowledge is absorbed into asset pricing is one of finance's greatest fundamental questions. Due to the unique features of various markets, knowledgeable traders may choose to trade in certain markets, and information is likely to be absorbed into asset values in these markets first. If other markets do not immediately assimilate new information, a lead-lag relationship may arise between asset values across markets. In financial markets, two schools of thought exist. The first one believes in market efficiency, in other words investors are unable to consistently earn abnormal returns, not predicted by the standard pricing model. The second view encompasses investors believing that abnormal returns can be extracted through the use of forecasting/predicting models. The two views divide investors into one relying only on the Efficient Market Hypothesis (E. F. Fama 1970), investing in a broad market index to replicate market returns, and one aiming to consistently beat the market by predicting future returns for different asset classes. To this end, different market anomalies have been uncovered. These anomalies, not explained by the standard pricing model, provide evidence against a fully efficient market, as investors have shown the ability to gain consistent returns based on forecasting metrics.

The function of the asymmetry (or skewness) of a distribution can be regarded from two complementary perspectives. Negative skewness, on the one hand, gauges the likelihood of big negative realizations and can be considered as a source of tail risk Kelly and Jiang (2014) Bollerslev, Todorov, and Xu (2015) or crash risk (Kozhan, Neuberger, and Schneider 2013). Alternatively, inclination for skewness reflects the speculative tendency of investors (Barberis et al. 2008) (Bordalo, Gennaioli, and Shleifer 2012). Investor judgments are likely to be extremely sensitive to the extent of skewness for these two reasons (B. Boyer, Mitton, and Vorkink 2010) (Kumar 2009). In other words, theoretical work confirms the skewness anomaly with different theories, based on investors' preference for positively skewed assets. (Barberis et al. 2008) study the cumulative prospect theory by Amos Tversky Daniel Kahenman (1992) to find that investors tend to falsely evaluate risk and subsequently overestimate the value of stocks with small probabilities of large positive returns. (B. Boyer, Mitton, and Vorkink 2010) also found that investors prefer high skewness for the possibility to earn high returns and forego diversification in return. As a result, retail investors' interest inflates the price of positively skewed assets, which leads to overpriced assets with lower expected returns. This is in line with empirical evidence that investors prefer lottery-like assets that promise large payoffs but with a small probability, thus being positively skewed as defined by (Kumar 2009) **.** Additionally, the optimal beliefs framework by (Brunnermeier et al. 2006) states that investors choose to believe in the optimal outcome and thus distort actual probabilities to maximize their return. Because of their optimal expectations, investors prefer positive skewness in assets, increasing demand, which subsequently decreases average returns. This belief in the optimal outcome is supported by (Bali, Cakici, and Whitelaw

2011), who find that extreme returns in stocks are reoccurring, meaning that "stocks with extreme positive returns in a given month should also be more likely to exhibit this phenomenon in the future" (Bali, Cakici, and Whitelaw 2011). Thus, investors that choose to believe in their luck think they will repeatedly earn high returns after hitting the jackpot once, while the findings by (Bali et. al. 2011) can also be interpreted oppositely - that extreme negative returns are recurring as well. Two noteworthy instances are the favorite longshot bias in horse track betting, in which the expected return per dollar gambled tends to increase uniformly with the likelihood of the horse winning on the one hand the prevalence of negative expected returns in lottery games on the other hand, despite their popularity (Thaler and Ziemba 1988). Intriguingly, there is growing evidence that the degree of skewness in the payoffs attracts players in the latter instance (A Garrett and S. Sobel Russell 1999) (Walker and Young 2001). In light of the aforementioned, (Bali, Cakici, and Whitelaw 2011) find that extremely favorable returns are a proxy for skewness. I extend their data and methodology towards sorting stocks in deciles based on their realized skewness, to investigate such relationship (maximum returns and realized skewness) and determine which methodology presents higher total and risk-adjusted returns.

A vast body of research stresses the ability of idiosyncratic risks to forecast future returns. Theoretically, prior research suggests that investors with loss aversion utility are concerned about idiosyncratic risk (Barberis, HUANG, and SANTOS 2001), which would explain why investors maintain under-diversified portfolios. This line of reasoning is utilized to explain the function of idiosyncratic volatility (MERTON 1987). More recently, the function of idiosyncratic skewness (Barberis et al. 2008) (Kumar 2009) (B. Boyer, Mitton, and Vorkink 2010) demonstrates that investors with a predisposition for skewness invest disproportionately in assets with positive idiosyncratic skewness. As a result, equities with significant idiosyncratic skewness pay a premium at equilibrium. Moreover, several empirical studies have proven, at the firm level, the significance of skewness, and its strong forecasting ability for future individual stock returns and equity option returns (B. Boyer, Mitton, and Vorkink 2010) (Bali and Murray 2013) (Conrad, Dittmar, and Ghysels 2013) (B. H. Boyer and Vorkink 2014) (Amaya et al. 2015) (Byun and Kim 2016) .

Nonetheless, empirical results on the relation between skewness and expected returns are mixed. (Rehman and Vilkov 2011) investigate the relation between *ex-ante* skewness and expected stock returns. According to their assumption that forward-looking information is incorporated in option prices and is not yet reflected in stock prices, they compute the *ex-ante* skewness from option data. They find that positively skewed stocks outperform negatively skewed stocks by 45 basis points per month. Additionally, (Chen, Li, and Worthington 2021) investigate the relation between industry skewness and expected returns, also finding a positive relationship between the two. They create equally weighted portfolios with 12 months formation and 3 months holding periods and find excess returns of 4.596% per annum, significant at a 5% level.

However, most academic research finds a negative relation between skewness and expected returns, which is confirmed over multiple asset classes with the use of future, forwards, options, and equity return data. (Fernandez-Perez et al. 2018) conducted a study to provide proof of a negative relation between skewness and expected returns. Looking at commodity futures, they created equally weighted portfolios with a 12-month formation period and sorted them on skewness, investing long in the bottom 20% of the stock and short in the top 20% of the stock. They obtain an 8.01% yearly excess return on average and find an alpha of 6.21% when controlling for risk factors with a Sharpe Ratio of 0.78, giving evidence of a strong negative relation between skewness and expected returns. Another study by (Han et al. 2020) looks at commodities' future returns, in which idiosyncratic skewness is used to rank stocks and create portfolios. With monthly rebalancing, they invest in the bottom and top 30% of securities and find an average return spread of -6.72% per annum, significant at any level. Their findings confirm the negative relation documented by (Fernandez-Perez et al. 2018). Similarly, (Baltas and Salinas 2019) conducted research looking at future and forward contracts for different asset classes. They find that creating a strategy that combines different asset classes can yield diversification benefits and can yield a Sharpe Ratio of 0.72, compared to 0.35 when securities are treated individually. They confirm that realized skewness is negatively related to future returns, for the different asset classes, meaning that lower skewness yields higher future returns.

As discussed, the vast majority of literature shows extensive proof of the negative relation between skewness and asset returns, for different asset classes. But how does skewness relate to stock returns? (Vojtko and Lievaj 2021) look at equity, bonds, and currency markets. In their study, they find that longing equity indexes with the most negative and shorting the ones with the most positive skewness yields an annual return of 0.96% in an equally weighted portfolio. While their results need to be considered with caution, as no statical test of significance was performed, their study provides a broad view regarding the direction of the relation, which is found to be positive for the bond and currency market. Using high-frequency stock data, (Amaya et al. 2015) confirm the negative relation between skewness and expected returns of stocks. Creating deciles based on realized skewness, they find a difference of 34 bps in returns for equal-weighted portfolios with a one-week formation and holding period, with the lowest skewness decile outperforming the highest.

3. Data and Methodology

3.1. Research plan

In this section, I describe where and how I screened and collected the data and subsequently demonstrate how the daily and monthly returns, monthly maximum returns, monthly skewness, and all other relevant metrics were calculated. Moreover, I explain how I formed and held portfolios by univariate sorting the stocks into deciles for a plethora of strategies, including Long/Short and Long-only portfolios. Lastly, I explain how I investigated limiting proprieties and their effects on the aforementioned portfolios along with their descriptive statistics of these portfolios.

3.2. Data

I examined the US Market as my primary data set from the Center for Research in Security Prices (CRSP) which contains all New York Stock Exchange (NYSE), American Stock Exchange (Amex), and Nasdaq (NQ) financial and nonfinancial enterprises (CRSP share codes: 10 and 11), from January 1926 to December 2021. The total number of firms observed over the period was 26,240 with a total number of of 1,152 months.

Using daily stock returns (CRSP: RET) to calculate the maximum daily returns, for each stock in each month, and monthly skewness of the daily stock returns for each firm, in each month. Furthermore, I pull the monthly stock returns (CRSP: RET) to compute 1 month, 3 month and 6 month returns for each firm. Moreover, I use month-end shares outstanding (CRSP: SHROUT) and month-end share price (CRSP: PRC) to compute monthly market capitalizations for each firm, to compute value-weighted returns. The second data source is the Fama French Library in order to extract the Fama, French and Carhart factors (4FF)so as to compute excess returns and determine, on one hand, the statistical significance and, on the other, the economic importance of the findings. The third data source was the Federal Reserve Economic Data (FRED) to pull official American recession periods, according to National Bureau of Economic Research (NBER), in order to investigate how sensitive are this thesis findings to the economic cycle. The fourth data source was Yardeni Research's historical Bull/Bear US Stock Markets, as to research how sensitive or robust are this thesis' findings to the financial market's sentiment and overall performance. The last data source is Bloomberg L.P. in regard to screening and selecting certain control variables such as the VIX Index, MOVE Index, and many other standard economic variables.

3.3. Methodology

This thesis, firstly, aims at replicating (Bali, Cakici, and Whitelaw 2011) in order to, on one hand, corroborate their results and update them with the latest data available, and on the other hand, provide a robust data validation to base this thesis' main research question – which statistical anomaly in extreme returns beats the market. I extended their sample period, which started in 1962 and ended in 2005 to begin in 1927 and finish in 2021. To that extent, I also examined three separate sample periods: first and foremost, the 1st sample period ranges from 1927 to 2021, the 2nd sample period spans across 1962 until 2021 and last but not least, the 3rd sample period covers the period between 1962 and 2005. The purpose for this decomposition aims at completing (Bali, Cakici, and Whitelaw 2011)'s sample and observe if their findings are still relevant (i.e., statistically significant and/or economically important) in the current landscape of financial markets, and it builds a robustness check for the subsequent findings in my skewness strategy.

Therefore, by replicating their approach, for each stock, I calculated the maximum daily return in every given month (hereinafter MAX, as in (Bali, Cakici, and Whitelaw 2011)), in the abovementioned data section. After the formation period (1 trading month) of this strategy is over, for each of month of the sample period, I rebalance all 10 MAX-ranked portfolios, by allocating every stock to its respective MAX decile, where Portfolio 1 holds the firms with the lowest maximum returns and, conversely, Portfolio 10 invests in the firms with the highest maximum returns, for any given trading month. Subsequently, each MAX-ranked portfolio is held for 1 trading month, with no subsequent trading actions within the holding period, in line with (Bali, Cakici, and Whitelaw 2011). For every MAX-ranked portfolio, monthly returns were calculated using the two approaches in (Bali, Cakici, and Whitelaw 2011), which are the most widely used in empirical finance research: value-weighted and equal-weighted. The latter approach, also known in academia as the "1/N methodology", weights each security its respective decile. The approach was chosen for various reasons. Firstly, the method is easy to implement. Secondly, some securities see their corresponding market cap fluctuate between a wide range of values during short timespans making it difficult to implement a value-weighted methodology if the allocation frequently and drastically changes compared to the previous month. Lastly and most importantly, empirical evidence as in (DeMiguel, Garlappi, and Uppal 2009) shows that no asset allocation model is consistently better than the 1/N rule. Moreover, for each trading month, I formed a Long/Short Portfolio, where Portfolio 10 was held, and Portfolio 1 was sold. Following those steps, for every portfolio, I computed all relevant descriptive statistics to determine this strategy's economic importance, and most importantly, I calculated their 4FF alphas in order to estimate its statistical significance.

Subsequently, once my results validated the ones obtained by (Bali, Cakici, and Whitelaw 2011) for the same sample period, I felt confident in diving in the exact same data and extrapolate the abovementioned methodology. However, instead of ranking stocks based on their monthly maximum daily return, I instead ranked each stock on their monthly daily returns' realized skewness (hereinafter SKEW). While (Amaya et al. 2015) use intraday data to calculate weekly realized moments for stock returns, I chose daily data to calculate daily stock returns, to compute the monthly skewness. The intuition in this strategy is that the bottom deciles (1st, 2nd) are the deciles for the stocks with the highest cumulative returns. Thus, these percentiles include securities that show a higher concentration of returns on the right side of the distribution and a larger tail on the left side of the distribution, meaning that an investor may expect frequent small gains but a few large losses. Whereas the top deciles (e.g 9th, 10th) include the companies with the highest skewness, which inversely, means that an investor may expect frequent small losses but a few large gains, explained by a higher concentration of returns on the left of the distribution of results and a fat tail on the right side. Not only did I calculate 1-month formation periods, but I also got each firm's 1-year daily returns' realized skewness and 5-year daily returns' realized skewness to take into account future robustness tests and hypothesis testing. Following that, I also compute 3-month and 6-month returns for each firm to allow for two additional holding periods.

As shown in Figure 1, the 1M1M strategy consists of forming portfolios based on the realized skewness of their holdings' one-month daily returns and holding them for the subsequent month. Within this strategy, the first formation period for the full sample was January 1927 with the corresponding holding period of February 1927, whereas the last formation period for the same timeframe was November 2021 with the last holding period being December 2021.

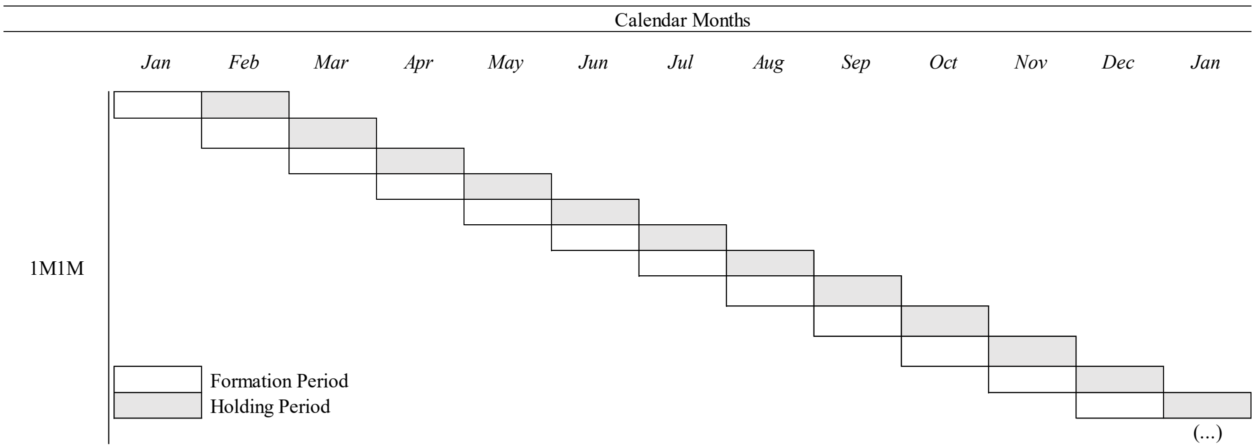

Figure 1 - A graphical illustration of the process of constructing stock portfolios based on the realized skewness of the stocks' one-month (1M) daily returns and then holding such portfolios for one month (1M).

The 1M3M strategy consists of forming portfolios based on the realized skewness of their holdings' one-month daily returns and holding them for the next three months. Within this strategy, the first formation period within the full sample was January 1927 with the corresponding holding period being between February 1927 and April 1927. The last formation period for the same timeframe was September 2021, with the last holding period being between October 2021 and December 2021.

The 1M6M strategy consists of forming portfolios based on the realized skewness of their holdings' one-month daily returns and holding them for the next six months. Within this strategy the first formation period within the full sample was January 1927, with the corresponding holding period being between February 1927 and July 1927. The last formation period for the same timeframe was September 2021, with the last holding period being between July 2021 and December 2021.

Moreover, the 1Y1M strategy consists of forming portfolios based on the realized skewness of their holdings' one-year daily returns and holding them for the next month. Within this strategy the first formation period within the full sample was between January 1927 and December 1927, with the corresponding holding period being January 1928, whereas the last formation period for the same timeframe was between December 2020 and November 2021, with the last holding period being December 2021.

The 1Y3M strategy consists of forming portfolios based on the realized skewness of their holdings' one-year daily returns and holding them for the next three months. Within this strategy the first formation period within the full sample was between January 1927 and December 1927, with the corresponding holding period being between January 1928 and March 1928, whereas the last formation period for the same timeframe was between October 2020 and September 2021, with the last holding period being between October 2021 and December 2021.

The 1Y6M strategy consists of forming portfolios based on the realized skewness of their holdings' one-year daily returns and holding them for the next six months. Within this strategy the first formation period within the full sample was between January 1927 and December 1927, with the corresponding holding period being between January 1928 and June 1928, whereas the last formation period for the same timeframe was between July 2020 and June 2021, with the last holding period being between July 2021 and December 2021.

The 5Y1M strategy consists of forming portfolios based on the realized skewness of their holdings' five-year daily returns and holding them for the next month. Within this strategy, its first formation period, within my full sample, was between January 1927 and December 1931 with the corresponding holding period being January 1932, whereas the last formation period, for the same period, was between December 2017 and November 2021 with the last holding period being December 2021.

Moreover, the 5Y3M strategy consists of forming portfolios based on the realized skewness of their holdings' five-year daily returns and holding them for the next three months. Within this strategy, its first formation period, within my full sample, was between January 1927 and December 1931 with the corresponding holding period being between January 1932 and March 1932, whereas the last formation period, for the same period, was between October 2017 and September 2021 with the last holding period being between October 2021 and December 2021.

Finally, the 5Y6M strategy consists of forming portfolios based on the realized skewness of their holdings' five-year daily returns and holding them for the next three months. Within this strategy, its first formation period, within my full sample, was between January 1927 and December 1931 with the corresponding holding period being between January 1932 and June 1932, whereas the last formation period, for the same period, was between July 2017 and June 2021 with the last holding period being between July 2021 and December 2021.

In total, I computed 3 different formation periods and 3 different holding periods allowing for 9 separate ways of testing this strategy's statistical significance and economic importance as well as confirming or denying this thesis research question and its main theory behind it.

4. Results and Discussion

4.1. Maximum Returns (MAX)

Table 1 displays the 1M1M value-weighted and equal-weighted average monthly returns of decile portfolios built by sorting NYSE/Amex/Nasdaq companies from lowest to highest daily returns during the preceding month (MAX). Results are provided for the sample period of January 1927 to December 2021. Portfolio 1 (LOW MAX) is the portfolio of stocks with the lowest maximum daily returns over the last month, whereas portfolio 10 (HIGH MAX) is the portfolio of stocks with the highest maximum daily returns over the past month. The value-weighted average difference in monthly raw return between decile 10 (HIGH MAX) and decile 1 (LOW MAX) is -0.6% each month, with a t-statistic of -6.95. In addition to the average raw returns, Table 1 also displays the intercepts (Fama-French-Carhart four-factor alphas) from the regression of the value-weighted portfolio returns on a constant, the excess market return, a size factor (SMB), a book-to-market factor (HML), and a momentum factor (MOM) in accordance with (Fama and French 1993) (Carhart 1997). The t-statistic for the difference in alphas between the HIGH MAX and LOW MAX portfolios is -3.99, as seen in the final row of Table 1. This difference is economically and statistically significant at all conventional significance levels. Upon careful inspection of the value-weighted average returns and alphas across deciles, it becomes apparent that the pattern is not a linear decrease as MAX grows. The average value-weighted returns of deciles 1–8 are comparable, ranging from 0.95%–1.09%, per month. However, from decile 9 to decile 10, the average returns decline significantly, from 0.8%, then to 0.35%, each month. Albeit, as MAX increases the alphas for the first seven deciles, which are also similar, decrease to near to zero, but for deciles 8 through 10, they drop substantially to negative figures. Intriguingly, the inverse of this pattern can be observed across deciles in the average monthly maximum daily return of equities inside each decile. It rises monotonically from deciles 1 to 10, but the rise is much more significant for deciles 8, 9, and 10. These deciles include stocks with corresponding average maximum daily returns of 9%, 13%, and 23%. All deciles are, on average, composed of 320 companies with a monthly turnover ratio equivalent to 84% across the board. Furthermore, of those 320 companies, on average, the higher the MAX decile the lower the corresponding average market cap each month. Intuitively, this trend is warranted given the inverse correlation between a company's size and its implied volatility which should account for the extreme equity returns in any given month. Therefore, given a predisposition for such an upside possibility, investors may be willing to pay a premium for assets with exceptionally high positive returns and tolerate lower predicted returns. In other words, it is possible for investors to see these equities as attractive lottery-like assets with a small possibility of a significant profit. As demonstrated in the third column of Table 1, the returns on equal-weighted portfolios are comparable, although considerably less economically and statistically significant. With a t-statistic of -6.25, the average raw return difference between the LOW MAX and HIGH MAX portfolios is -0.35%, each month. With a t-statistic of -4.78, the equivalent difference in alphas is -0.8 percentage points every month. As with value-weighted returns, the deciles with the lowest future returns and negative alphas are the extreme deciles, in this case, deciles 9 and 10.

Table 1 - Returns and alphas on portfolios of stocks sorted by MAX. In order to construct decile portfolios on a monthly basis between January 1927 and December 2021. Stocks were ranked according to their highest daily return (MAX) throughout the course of the previous month. Portfolio 1 (10) is comprised of the equities that have generated the lowest (greatest) maximum daily returns over the course of the previous month. The data shown in the table are the value-weighted (VW) and equal-weighted (EW) average monthly OOS returns, the four-factor Fama-French-Carhart alphas on the value-weighted and equal-weighted portfolios, the average maximum daily return of stocks during the previous month, the average number of stocks and their average size in each portfolio every month. The final two rows indicate the differences in monthly returns and the differences in alphas with regard to the four-factor Fama-French-Carhart model that were calculated between portfolios 10 and 1, as well as the related t-statistics for each of these comparisons and are shown below with * if statistically significant to the 10% level, ** if statistically significant to the 5% level and *** if statistically significant to the 1% level.

Decile	VW Portfolios		EW Portfolios		Average MAX	Average # of Stocks	Average SIZE
	Average Return	Four-factor alpha	Average Return	Four-factor alpha			
LOW MAX	0.95	0.18	1.23	0.41	2.07	322	421.06
2	1.01	0.16	1.33	0.39	2.89	321	411.53
3	1.24	0.27	1.43	0.41	3.61	321	301.93
4	1.08	0.04	1.39	0.32	4.35	321	244.20
5	1.11	0.06	1.42	0.25	5.20	321	200.18
6	1.20	0.08	1.38	0.20	6.22	321	163.82
7	1.21	0.06	1.28	0.06	7.56	320	140.29
8	1.09	-0.06	1.24	-0.03	9.56	321	121.50
9	0.80	-0.41	1.15	-0.14	13.49	319	103.00
HIGH MAX	0.35	-0.87	0.89	-0.39	22.89	317	92.85
10-1	-0.60	-1.05	-0.34	-0.80	20.82		
	*-6.95****	*-3.99****	*-6.25****	*-4.78****			

For the study in Table 1, I begin the sample in January 1927 since this is the starting point of my data sample. Nevertheless, the results are comparable whether I begin the sample in July 1927 or for different subsamples. For instance, for the subsample spanning July 1962 to December 2005, which is the most commonly used time-series used throughout the majority of the literature on the cross-section of expected returns, the average value-weighted monthly returns for the difference between HIGH MAX and LOW MAX portfolios is -0.51, with a corresponding t-statistic of -5.64 and an alpha of -0.77 with an equivalent t-statistic of -1.82. The average equal-weighted monthly returns, however, is -0.72, with a corresponding t-statistic of -14.34 and an alpha of -0.73 with an equivalent t-statistic of -3.12. In this timeframe, the average market cap difference between HIGH MAX and LOW MAX was lower than the one across the entire sample. Last but not least, in order to extend the most commonly used time-series sample with more recent data, in the subsample starting at July 1962 and ending in December 2021, the average value-weighted monthly returns for the difference between HIGH MAX and LOW MAX portfolios is -0.64, with a corresponding t-statistic of -6.93 and an alpha of -0.92 with an equivalent t-statistic of -2.57. However, the average equal-weighted monthly returns are -0.67, with a corresponding t-statistic of -13.33 and an alpha of -0.81 with an equivalent t-statistic of -4.16. In the remainder of this thesis, I continue to give data for the full sample spanning January 1927 to December 2021.

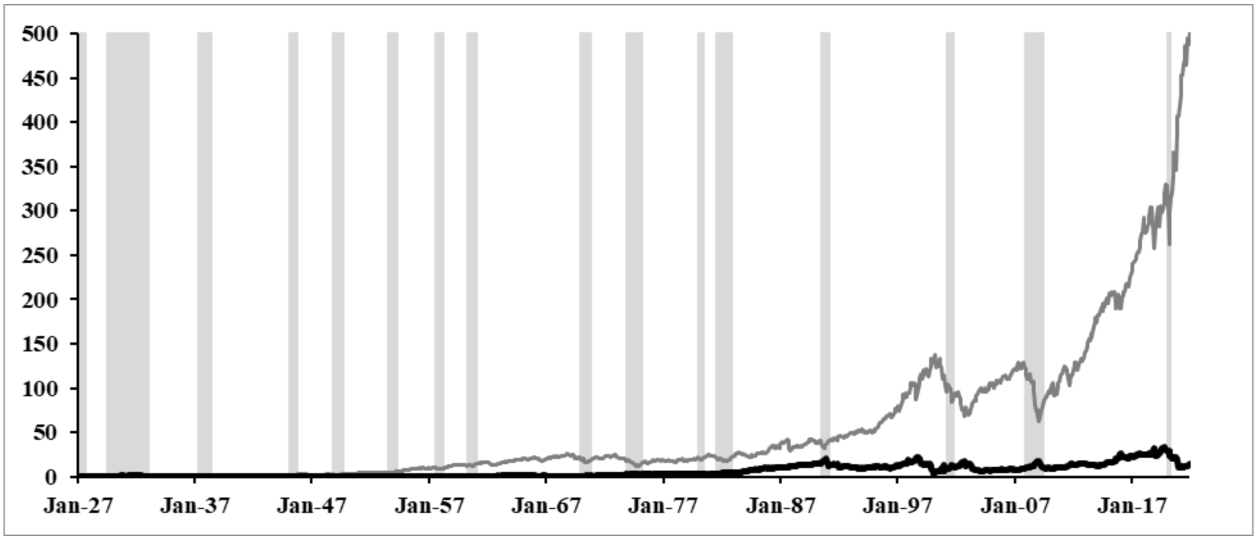

Figure 2 - Comparison of the cumulative out-of-sample monthly excess returns between the Fama-French MRK-RF factor, in grey, and the 1-10 strategy, in black, which went long on the LOW MAX portfolios and shorted the HIGH-MAX portfolios. Returns are not net of fees and are based on the equal-weight methodology. Shaded regions represent NBER recessions and/or periods of US stock market corrections. The sample period is between January 1927 and December 2021.

(Bali, Cakici, and Whitelaw 2011) findings, boasted that a MAX-sorted trading strategy stood the test of time and between 1962 and 2005 frequently beat the market in total returns and risk-adjusted returns as well. By updating the same out-of-sample returns to 2021, I find that this strategy's superiority has taken a dive as, for one thing, its risk-adjusted returns decreased to just 0.14 annualized Sharpe Ratio and, for the other, it has recently started to underperform the market as shown in Figure 3. This strategy's recent underperformance may be a consequence of the longer time period that the MAX Spread, measured by the monthly difference between the average maximum daily returns, in a month, of HIGH MAX's stocks and LOW MAX's stocks. As shown in Figure 4, whenever the MAX Spread had formed an up-trend, such as between 1962 and 2002, the MAX strategy might have considerable amount of information, unbeknownst to regular strategies, wherein it was able to capture the most statistically significant alpha and economic importance, in line with my above-mentioned findings between different sample periods, fueling its outperformance of the overall market, as shown in Figure 3. Nevertheless, during times where the MAX Spread is in a down-trend, such as between 1927 and 1962 or now, between 2002 and 2021, the strategy is less effective at generating alpha and prone to underperform the broader market.

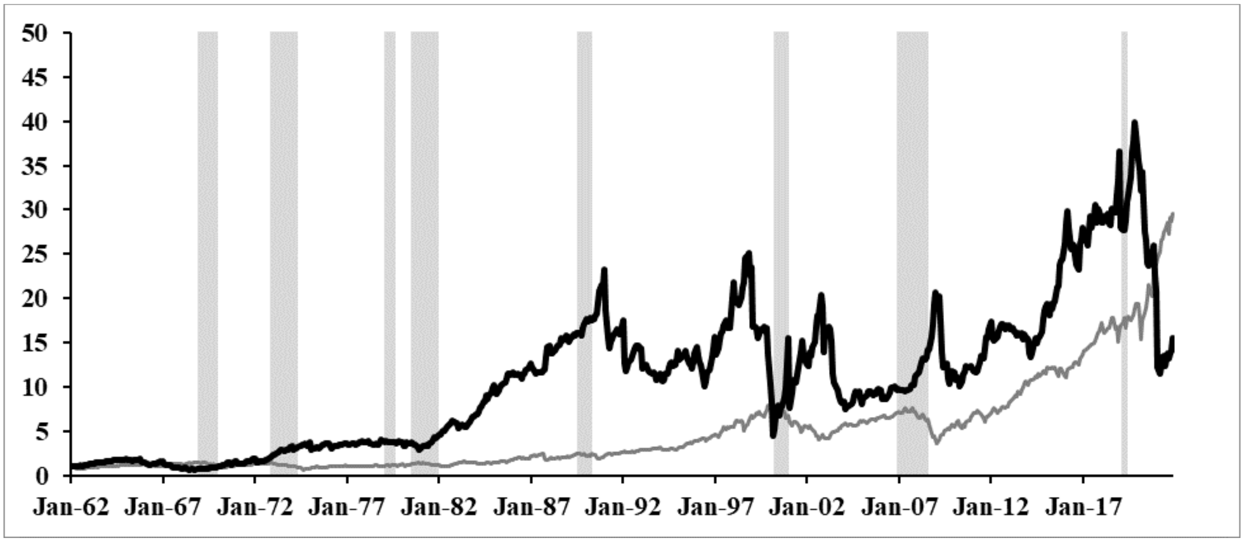

Figure 3 - Comparison of the cumulative out-of-sample monthly excess returns between the Fama-French MRK-RF factor, in grey, and the 1-10 strategy, in black, which went long on the LOW MAX portfolios and shorted the HIGH-MAX portfolios. Returns are not net of fees and are based on the equal-weight methodology. Shaded regions represent NBER recessions and/or periods of US stock market corrections. The sample period is between January 1962 and December 2021.

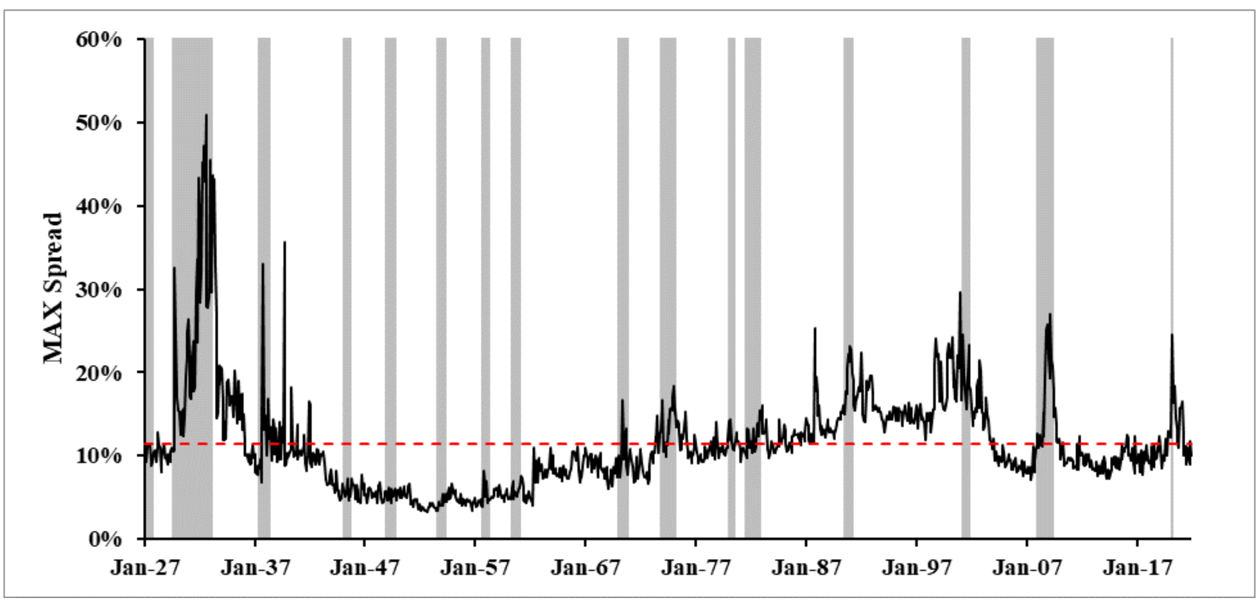

Figure 4 - Visual representation of the MAX Spread time-series. This figure represents, in black, the MAX Spread data-series along with its long-term average, in a dotted red line. Shaded regions represent NBER recessions and/or periods of US stock market corrections. The sample period is between January 1927 and December 2021.

4.2. Realized-Skewness (SKEW)

By observing this strategy's behavior and motivated by the findings of all relevant abovementioned literature - that investors may pay high prices for stocks that have exhibited extreme positive returns in the past in the expectation that this behavior will be repeated in the future – and noting the fact that (Bali, Cakici, and Whitelaw 2011) showed that MAX is empirically proven to have a strong positive correlation with skewness, I investigate if realized monthly skewness-sorted strategies can serve as a better proxy for lottery like payoffs. The SKEW strategy, as shown in the Table 2, has its pros as well as its cons when compared to the MAX strategy. Nonetheless it is undeniably true that they hold a great deal of similarities which drove my curiousness of how much better or worse the SKEW strategy could be to maximize total returns and optimize risk adjusted returns.

Table 2 - Returns and alphas on portfolios of stocks sorted by SKEW. In order to construct decile portfolios on a monthly basis between January 1927 and December 2021, stocks were ranked according to their daily return's realized monthly skewness (SKEW) throughout the course of the previous month. Portfolio 1 (10) is comprised of the equities that have generated the lowest (greatest) monthly skewness over the course of the previous month. The data shown in the table are the value-weighted (VW) and equal-weighted (EW) average monthly OOS returns, the four-factor Fama-French-Carhart alphas on the value-weighted and equal-weighted portfolios, the average maximum daily return of stocks during the previous month, the average number of stocks and their average size in each portfolio every month were taken into consideration in this study. The final two rows indicate the differences in monthly returns and the differences in alphas with regard to the four-factor Fama-French-Carhart model that were calculated between portfolios 10 and 1, as well as the related t-statistics for each of these comparisons and are shown below with * if statistically significant to the 10% level, ** if statistically significant to the 5% level and *** if statistically significant to the 1% level.

	VW Portfolios		EW Portfolios		Average	Average #	Average
Decile	**Average Return**	**Four-factor alpha**	**Average Return**	**Four-factor alpha**	**SKEW**	**of Stocks**	**SIZE**
LOW SKEW	0.89	0.25	1.55	0.73	-0.80	318	522.83
2	1.03	0.30	1.48	0.65	-0.39	317	629.78
3	1.00	0.30	1.43	0.59	-0.15	319	640.94
4	1.04	0.33	1.38	0.50	0.03	319	620.99
5	0.94	0.22	1.33	0.48	0.21	315	597.79
6	0.95	0.24	1.27	0.37	0.39	317	594.34
7	0.91	0.26	1.23	0.37	0.60	317	554.69
8	0.99	0.30	1.11	0.20	0.88	317	509.75
9	0.96	0.28	1.08	0.21	1.36	317	432.59
HIGH SKEW	0.79	0.09	0.85	0.02	1.88	318	331.38
10-1	-0.10	-0.15	-0.70	-0.71	2.68		
	*-3.37****	*-1.72***	*-27.21****	*-9.01****			

Table 2 displays the 1M1M value-weighted and equal-weighted average monthly returns of decile portfolios built by sort in NYSE/Amex/Nasdaq companies by their daily return's realized monthly skewness (hereinafter SKEW). Results are provided for the sample period of January 1927 to December 2021. Portfolio 1 (LOW SKEW) is the portfolio of stocks with the lowest SKEW over the last month, whereas portfolio 10 (HIGH SKEW) is the portfolio of stocks with the highest SKEW over the past month. The value-weighted average difference in monthly raw return between decile 10 (HIGH SKEW) and decile 1 (LOW SKEW) is -0.1% each month, with a t-statistic of -3.37, both lower than the in their MAX counterparts. In addition to the average raw returns, Table 2 also displays the intercepts Fama-French-Carhart four factor alphas. The t-statistic for the difference in alphas between the HIGH SKEW and LOW SKEW portfolios is -1.72, as seen in the final row of Table 2. This difference is still economically important but not statistically significant. Upon careful inspection of the value-weighted average returns and alphas across deciles, it becomes apparent that the pattern is not a linear decrease as SKEW grows. The average value-weighted returns of deciles 1 through 9 are comparable, ranging from 0.89% to 1.04% per month. However, in decile 10, the average returns decline significantly, to 0.79%. Furthermore, each portfolio's alphas appear to hold no relationship with the level of SKEW, confirming that SKEW, at least compared to MAX, fails to bring relevant information for this model. In fact, it appears to be adding noise to it, justifying its poor performance against MAX. Likewise in MAX, the average realized monthly skewness, in the previous month, within each portfolio's holdings rises from deciles 1 to 10, according to its definition, but the rise is much more significant for deciles 2, 9, and 10. These deciles include stocks with corresponding SKEW of -0.39, 1.36 and 1.88. I find that all deciles are, on average, composed of 318 companies with a monthly turnover ratio equivalent to 88% across the board, higher than the MAX strategy. Furthermore, similarly to MAX, I find that, on average, the higher the SKEW decile the lower will the corresponding average market cap be, each month. Intuitively, this trend is warranted given the positive correlation between a company's size and its returns. For a company to be of such size it should have more trading days of positive and consistent returns, therefore, the bigger the company the more negatively skewed its stock. As demonstrated in the third column of Table 2, the returns on equal-weighted portfolios are comparable, although considerably more economically and statistically significant, unlike in MAX. With a t-statistic of -27.7, the average raw return difference between the HIGH SKEW and LOW SKEW portfolios is -0.70%, each month, double that of in MAX. With a t-statistic of -9.01, the equivalent difference in alphas is -0.71 percentage points every month. As with value-weighted returns, the decile with the lowest average returns and negative alpha is the extreme deciles, in this case, decile 10.

Extending the methodology in the MAX strategy, for the subsample spanning July 1962 to December 2005, the average value-weighted monthly returns for the difference between HIGH SKEW and LOW SKEW portfolios is 0.25, with a corresponding t-statistic of 9.69 and an alpha of 0.22 with an equivalent t-statistic of -1.86. However, the average equal-weighted monthly returns are -0.52, with a corresponding t-statistic of -24.38 and an alpha of -0.51 with an equivalent t-statistic of -5.12. In this timeframe, the average market cap difference between HIGH SKEW and LOW SKEW was higher than the one across the entire sample. Last but not least, in order to extend the most commonly used time-series sample with more recent data, in the subsample starting at July 1962 and ending in December 2021, the average value-weighted monthly returns for the difference between HIGH SKEW and LOW SKEW portfolios is 0.17, with a corresponding t-statistic of 6.61 and an alpha of 0.15 with an equivalent t-statistic of 1.5. However, the average equal-weighted monthly returns are -0.44, with a corresponding t-statistic of -21.83 and an alpha of -0.44 with an equivalent t-statistic of -5.02. I note that there is overwhelming empirical evidence, across all samples, for every significance level, to support that SKEW is an overall better proxy for predicting future returns than MAX. As a consequence, its cumulative returns are superior and astoundingly better than the overall market, as shown in Figure 5.

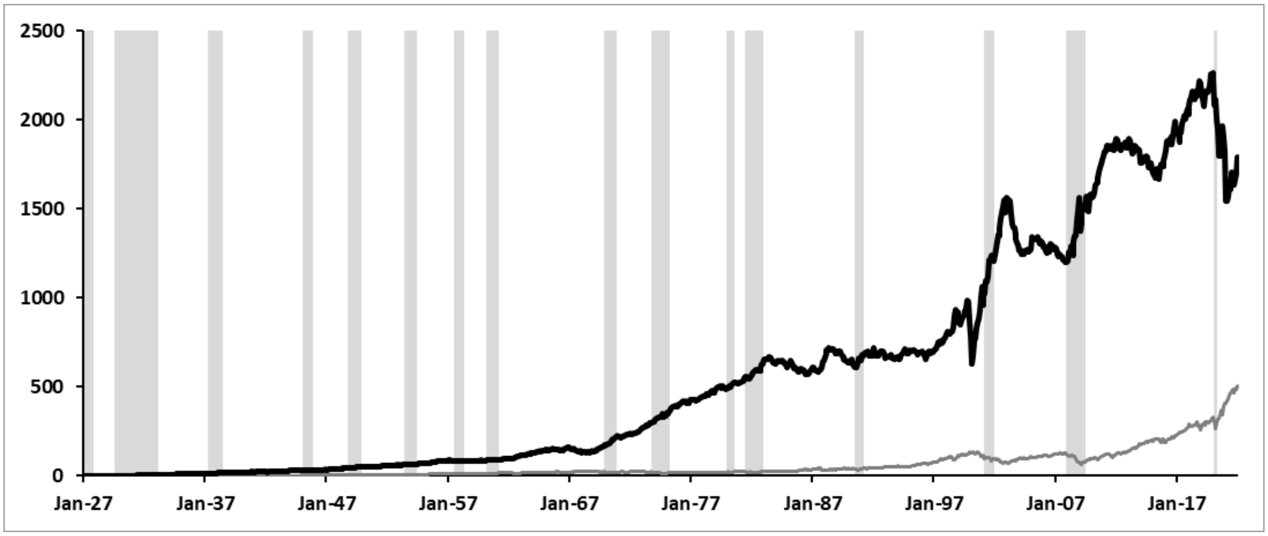

Figure 5 - Comparison of the cumulative out-of-sample monthly excess returns between the Fama-French MRK-RF factor, in grey, and the 1-10 strategy, in black, which went long on the LOW SKEW portfolios and shorted the HIGH SKEW portfolios. Returns are not net of fees and are based on the equal-weight methodology. Shaded regions represent NBER recessions and/or periods of US stock market corrections. The sample period is between January 1927 and December 2021.

Figure 5 illustrates the predictability, reliability, and superiority of the SKEW strategy as it appears to reward its investors with both low volatility and high returns providing their risk-adjusted returns even during periods of economic recessions and/or market corrections. That being said, it came as no shock that the individual descriptive statistics of both the individual portfolios and SKEW strategy's monthly returns are even more statistically important and economically important than MAX, as shown in Table 3. The clear overperformance against the overall market can be evidence of the complete lack of awareness of this factor within market participants. It is apparent why it has become such a niche strategy to exploit this factor in the high frequency trading industry, however, with this thesis I find that even by extending timeframes, the SKEW strategy can pose a serious contender for new factor-based investing approaches. One begs the question of how much more can one extend this methodology and still generate robust results. Intuitively, if the stock market is very efficient in incorporating fresh information from the market, predictability would be ephemeral and unlikely to endure for a more extended period. Whether the prediction persists over a longer horizon may also depend on the nature of the data. If the information is a passing trend and has nothing to do with fundamentals, predictability would likewise decline very rapidly. I find that the 1M1M SKEW-ranked portfolios have, throughout the entire sample, the most economically important and statistically significant returns. LOW SKEW stands out with 18.61 annualized average return, with an equivalent 7.38 t-stat which provided a 0.76 annualized

Sharpe ratio. The SKEW strategy, by going long the LOW SKEW and shorting the HIGH SKEW portfolios manages an inferior 8.35 annualized average return, with an equivalent 8.71 t-stat which provided an improved 0.89 annualized Sharpe ratio. Furthermore, I find that by increasing the formation periods, the lowest SKEW portfolios generally lose their edge, leading to lower total returns as well as risk adjusted returns. Inversely, the highest SKEW portfolios capture the alpha which the lowest SKEW portfolios tend to lose. Moreover, I show that by increasing the holding period the same trend shows up, only more pronounced. Interestingly, with this matrix of holding and formation periods strategies, I note that one could come up to very different conclusions. This shines some light as to why there is such a great deal of conflicting evidence in the relevant literature, where some authors find that skewness is negatively correlated with future returns and other find the opposite. By in large, based on Table 3, I find that skewness related strategies are positively correlated with their own timeframes. More precisely, the lower the timeframes the higher are the total and risk-adjusted returns of portfolios composed of the lowest skewness. As to why there is such a dramatic shift in conclusions, depending on the timeframe, I theorize that the longer the formation period, stocks with the highest skewness are more the more "prone" to overperform in the near future relative to their peers. Moreover, the longer the holding period, the more noise there will be in the portfolios' holdings which dilutes or even destroys the edge that the SKEW factor brings to those portfolios. Another way of looking at it is that stocks with extremely negative SKEW are more "prone" to crash (i.e., its left-tail kurtosis), likewise in most momentum-related strategies. This poses an incredible future research opportunity to study such relationship between skewness and momentum strategies.

Table 3 - The table reports the equal-weighted out-of-sample annualized average returns (Panel A), their equivalent t-stats (Panel B) and the corresponding annualized Sharpe Ratios (Panel C) of each portfolio. K is the number of months for the formation period and J is the number of months for the holding period of such portfolios. The sample period is between January 1927 and December 2021.

		Equal-Weighted OOS Returns			
K=	*J*=	1	3	6	Δ
		Panel A1			
1	LOW SKEW	18.61	14.42	13.62	-4.99
12		14.66	12.26	12.61	-2.05
60		16.88	12.92	13.17	-3.70
Δ		-1.73	-1.51	-0.44	

		Equal-Weighted OOS Returns			
K=	*J*=	1	3	6	Δ
		Panel B1			
1	LOW SKEW	*7.38*	*7.78*	*11.16*	3.77
12		*5.29*	*8.37*	*12.10*	6.81
60		*5.90*	*8.96*	*13.08*	7.18
Δ		-1.48	1.17	1.93	

		Equal-Weighted OOS Returns			
K=	*J*=	1	3	6	Δ
		Panel C1			
1	LOW SKEW	0.76	0.46	0.47	-0.29
12		0.55	0.50	0.51	-0.04
60		0.62	0.54	0.56	-0.06
Δ		-0.14	0.08	0.09	

		Equal-Weighted OOS Returns			
K=	*J*=	1	3	6	Δ
		Panel A2			
1	HIGH SKEW	10.26	13.53	14.29	4.03
12		15.23	17.94	17.83	2.60
60		15.28	17.76	17.80	2.52
Δ		5.03	4.23	3.51	

		Equal-Weighted OOS Returns			
K=	*J*=	1	3	6	Δ
		Panel B2			
1	HIGH SKEW	*3.74*	*7.56*	*10.96*	7.21
12		*5.47*	*8.01*	*11.22*	5.76
60		*5.40*	*7.51*	*10.90*	5.50
Δ		1.66	-0.05	-0.06	

		Equal-Weighted OOS Returns			
K=	*J*=	1	3	6	Δ
		Panel C2			
1	HIGH SKEW	0.38	0.45	0.46	0.08
12		0.56	0.48	0.47	-0.09
60		0.57	0.46	0.47	-0.10
Δ		0.18	0.01	0.01	

		Equal-Weighted OOS Returns			
K=	*J*=	1	3	6	Δ
		Panel A3			
1	L/S	-8.35	-0.89	0.68	9.03
12		0.57	17.05	31.34	30.77
60		-1.59	4.85	4.63	6.22
Δ		6.76	5.74	3.95	

		Equal-Weighted OOS Returns			
K=	*J*=	1	3	6	Δ
		Panel B3			
1	L/S	*-8.71*	*-1.03*	*1.06*	9.77
12		*0.35*	*4.83*	*6.23*	5.88
60		*-1.21*	*3.51*	*4.93*	6.14
Δ		7.50	4.54	3.87	

		Equal-Weighted OOS Returns			
K=	*J*=	1	3	6	Δ
		Panel C3			
1	L/S	-0.89	-0.06	0.04	0.94
12		0.04	0.50	0.64	0.61
60		-0.13	0.21	0.21	0.34
Δ		0.77	0.27	0.17	

Figure 6 visualizes this strategy's cumulative performance against the overall market, which has underperformed as of late, but showed that time and time again it is capable of withstanding economic woes and market crashes.

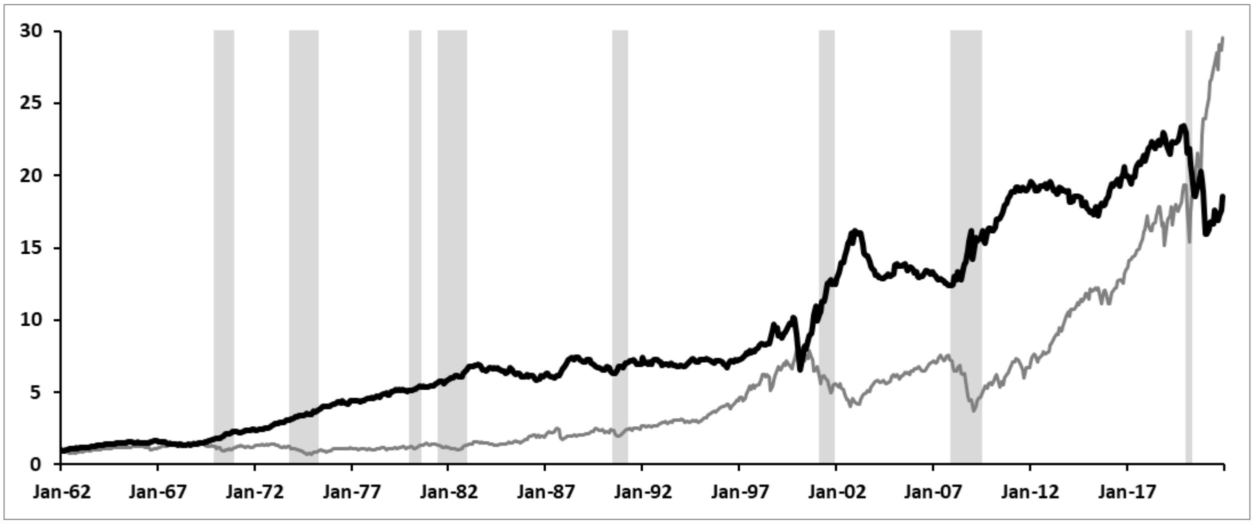

Figure 6 - Comparison of the cumulative out-of-sample monthly excess returns between the Fama-French MRK-RF factor, in grey, and the 1-10 strategy, in black, which went long on the LOW SKEW portfolios and shorted the HIGH SKEW portfolios. Returns are not net of fees and are based on the equal-weight methodology. Shaded regions represent NBER recessions and/or periods of US stock market corrections. The sample period is between January 1962 and December 2021

Extending the methodology, I did with the MAX strategy I also computed the SKEW Spread, measured by the monthly difference between the average realized daily returns' skewness in a month, of HIGH SKEW's stocks and LOW SKEW's stocks as shown in Figure 7. The recent upswing in the spread's volatility as well as the underperformance that it brought into the SKEW strategy are, to the best of my knowledge, unfounded by the leading robustness checks such as default yield spread, inflation, stock variance, long-term yield, term spread, short-term yield, market dividend yield or market earnings-to-price ratio. I went as far as regressing this strategy with newer, more relevant robustness checks such as the VIX Index, MOVE Index and SKEW Index only to find no statistically significant factor that might be able to justify this strategy's uncharacteristic recent performance. Additionally, I noted that within the entire data sample, the spread between the highest and lowest skewness-ranked deciles steadily increased by 0.002% per month. I proceeded to study which decile contributed most to this discovery and found that the 1st skewness-ranked decile (LOW SKEW) had the most influence on this trend as it decreased at a much higher rate than the 10th skewness-ranked decile increased (HIGH SKEW).

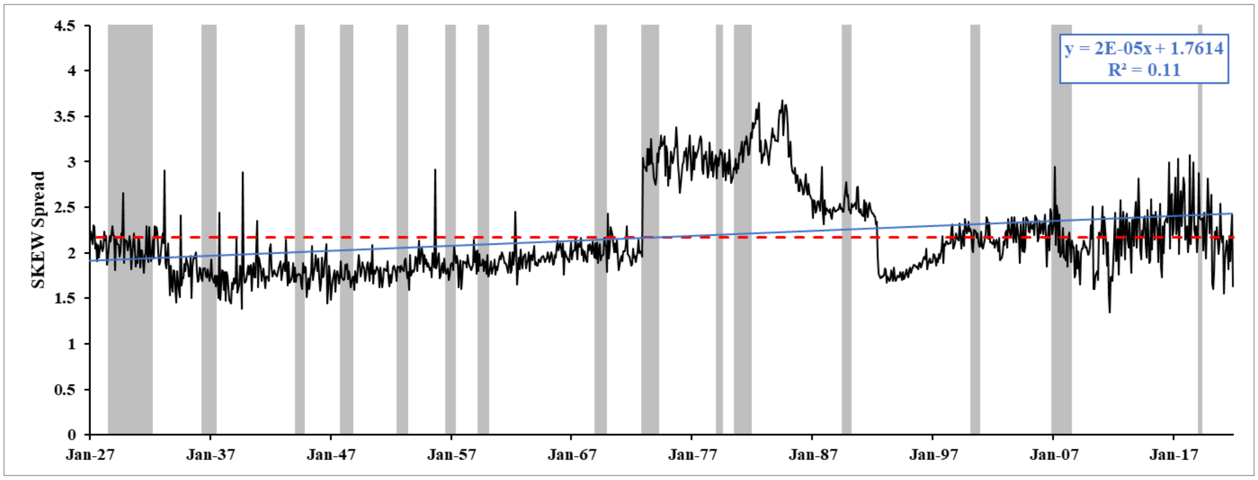

Figure 7 - Visual representation of the SKEW Spread time-series. This figure represents, in black, the SKEW Spread data-series along with its long-term average, in a dotted red line, and its linear trendline, in blue. Shaded regions represent NBER recessions and/or periods of US stock market corrections. The sample period is between January 1927 and December 2021.

According to Figure 8, I can identify the abovementioned trend as well as a clear decline for the 1st decile while the 10th appears to have remained stable. Some reasons for such asymmetric behavior might be: Firstly, risk profiles have overall increased which is a result of the decrease in risk-free yields and other fixed-income yields across investors as they are forced to resort to riskier investment strategies, like betting on returns, to generate yields and match or beat benchmarks. Furthermore, the overall tendency of the skewness percentiles becoming more negative could be explained by the general state of the stock market throughout the last two decades, where investors experienced frequent small gains but few large losses, evidencing negative skewness.

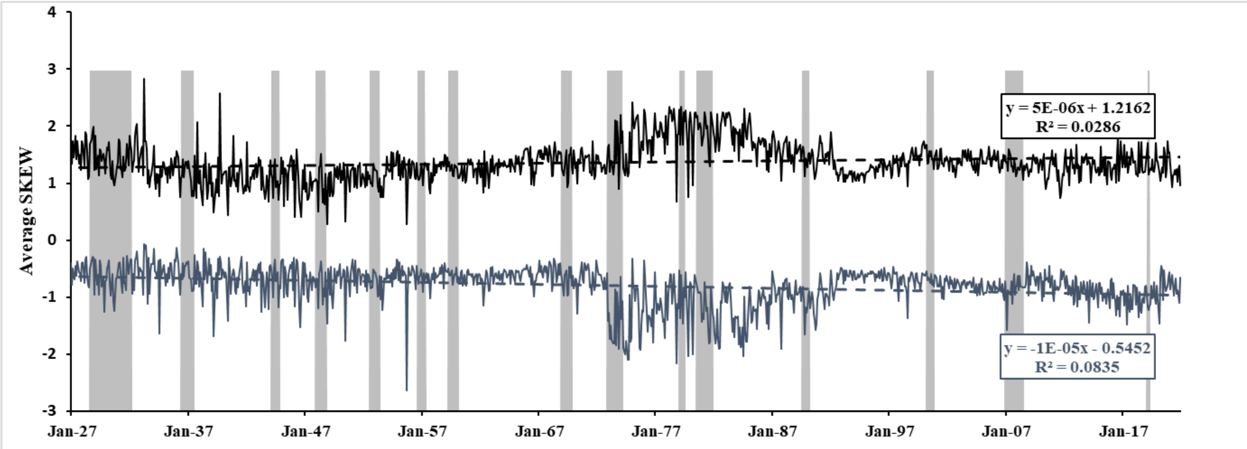

Figure 8 - Visual representation of the average SKEW time-series. This figure represents, in black, the average SKEW for the HIGH SKEW portfolio, along with its long-term trendline, in a dotted black line, and he average SKEW for the LOW SKEW portfolio, in blue, along with its long-term trendline, in a dotted blue line. Shaded regions represent NBER recessions and/or periods of US stock market corrections. The sample period is between January 1927 and December 2021.

As observable in Figure 11, I found evidence of the SKEW spread swinging around the mean (red line), suggesting a reversion towards the mean when studying long timespans. To prove the reversion to the mean, I evaluate whether the model follows a random walk or is stationary according to the Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests. Table 4 shows that all stationarity tests are statistically significant on all relevant significance levels. Additionally, for the same period, I computed the KPSS unit root test in order to filter out any doubts on the previous findings, as one of the most important best practices in empirical finance. This test did not reaffirm my DF and ADF tests' findings, mainly due to the period between 1970 and 1990 where the SKEW spread jumped so inexplicably. Nevertheless, I do note when taking into consideration smaller sub-sample periods, mainly of 5 to 7 years of data (intriguingly similar to the standard length of normal economic and financial cycles), all stationarity tests and unit root tests come statistically significant on all levels. This poses a great opportunity to perform statistical arbitrage strategies based on this statistical anomaly and, therefore, sets the stage for future research focused on this topic.

Table 4 - Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) stationarity tests' descriptive statistics. T-stats are in bold if they are statistically significant on all relevant significance levels.

SKEW	DF Statistics			ADF Statistics
Spread	*No Drift*	*Drift*	*Drift + Trend*	*Lag(2)*
β	-1.46	-1.46	-1.46	-2.06
t-stat	***-55.18***	***-55.44***	***-55.42***	***-26.95***

The SKEW-ranked portfolios were tested for their seasonality and behavior during well-known and widely accepted calendar effects in financial academia by analyzing and singling out each calendar month's descriptive statistics and economic performance, throughout the entire 1927-2021 sample period. I noted that this strategy has counter-intuitive seasonality, as for one, in an annualized total return basis its best calendar month yields, on average, 17.05%, in July and its second-best calendar month yields, on average, 13.35%, in April. When taking risk-adjusted performance into account, in an annualized basis, its best calendar month is also July with a 2.24 Sharpe Ratio, and its second-best calendar month is April as well with a 1.5 Sharpe Ratio. These months are widely known in empirical finance as less rewarding for investors however, once again, I find that this strategy is able to shine bright specially in harder circumstances and periods.

5. Limitations

Like all empirical finance research, this thesis faced several limitations, some of which, however, might just be excellent opportunities for further research. More specifically, some of the limitations include the availability and quality of data – as not every data point was available for the entire sample period, invalidating some robustness' checks feasibility/effectiveness. Therefore, the divergence in data and its sources enabled sampling and selection biases as the results of this thesis may have been influenced by the samples and sub-samples chosen for analysis, as well as the methods used to select and weight those samples. Additionally, some of this study's conclusions may be found guilty of extrapolation and generalization as in the findings of this thesis may not be easily applicable or generalizable to other markets or time periods. Furthermore, throughout this study's data discussion I shined some light on the fact that some data cannot fully and/or easily find or establish strong and significant causal relationships.

Moreover, during this study, and given the sheer size of data that had been used called for the use of programming languages, most notably python, which, on one hand, excelled at going through all the data by cleaning it, preparing it and computing it extremely fast and efficiently. On the other hand, it put a considerable amount of "black boxes" throughout this thesis' methodology.

It is essential to point out that I did not take into account transaction expenses on my strategies' performance, which may be broken down into three categories: fees, commissions, and spreads.

6. Conclusion

In capital markets with no inefficiencies or arbitrage restrictions, all assets should be valued fairly at any given moment using the information that is publicly accessible at that time. In actuality, however, prices are known to vary from fundamentals, perhaps over lengthy time periods. This thesis intended to identify a trading strategy that outperforms the market and maximizes risk-adjusted returns based on the realized skewness of North American stocks. Previous literature implies that investors choose favorably positively skewed assets because they offer very high returns, which in turn causes these assets to be overvalued and decrease their returns. Thus, I attempted to capitalize on this tendency by emphasizing on negative realized skewness. I observed that the negative correlation between realized skewness and forward returns remained high, statistically, and economically significant. This relationship has, however, diminishing predicting power when higher timeframes are considered. This outcome is unaffected by a large number of other possible risk factors and control variables. My findings are interpreted within the context of a market with poorly diversified, risk-averse investors that choose lottery-like products. In fact, the propensity for lottery-like returns may be the root cause of under diversification, as well-diversified equities portfolios lack this characteristic. The opposite certainly suggests that equities with severe negative returns display the opposite impact, i.e., investors find them unattractive, and as a result, they promise greater future returns as they become a less crowed trade.

How has this anomaly not been captured by other, more sophisticated, investors? The difficulty and/or reluctance of several investors to participate in short selling has been extensively studied in the literature. In addition, equities with exceptional positive returns are often tiny and illiquid, as showcased within this thesis' discussion, indicating that transaction costs may provide a significant barrier to adopting the applicable trading strategy. Lastly, these small-cap equities are often owned and traded by individual investors, as opposed to institutions that may seek to exploit this occurrence. These limitations may play a role in this study's observations, mainly on the strategies discussed, which have, during the course of the entire sample, outperformed the overall market and performed relatively well during periods of market corrections and/or economic downturns.
Furthermore, the volatility within realized skewness spread has increased from 1990 onwards, nonetheless throughout the entire data sample, the spread itself is experiencing statistically significant mean-reversion patterns, on all critical levels. This observation could be used as a

reliable predictor of returns for future trading strategies involving statistical arbitrage opportunities within realized skewness-ranked stocks and thus presents an interesting topic for further research. The aforementioned spread has, additionally, increased throughout the entire sample. A possible explanation for the increase in the realized skewness spread could be higher risk-taking due to decreases in risk-free yields and investment time-horizons.

Lastly, intriguingly, I found that these skewness-ranked strategies fare exceptionally better in months that the majority of relevant literature deemed to be, on average, less seasonally rewarding to investors. Given the scope and reliability of my findings, this suggests a potentially rewarding area for further investigation to pinpoint the exact causes for such calendar event.

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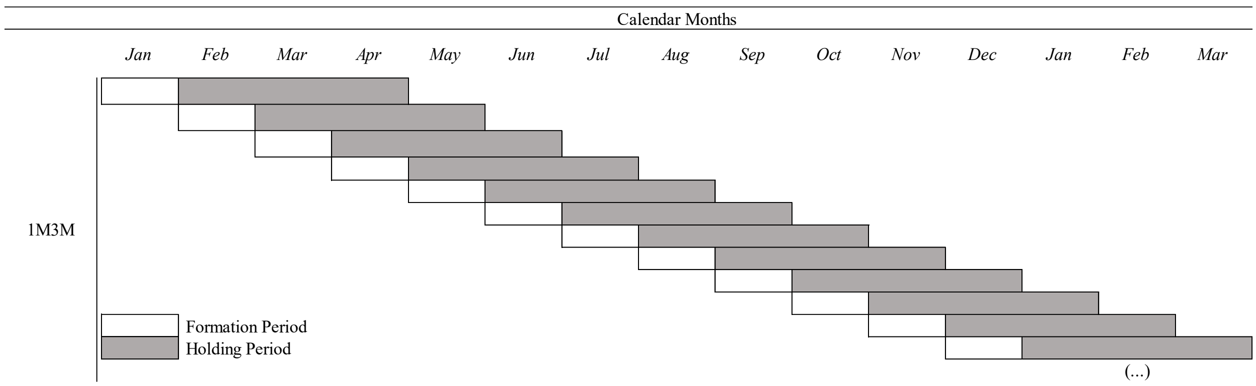
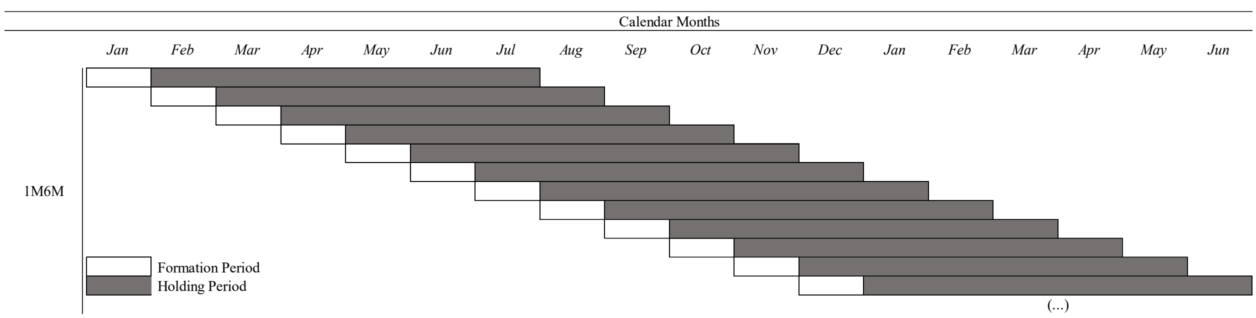
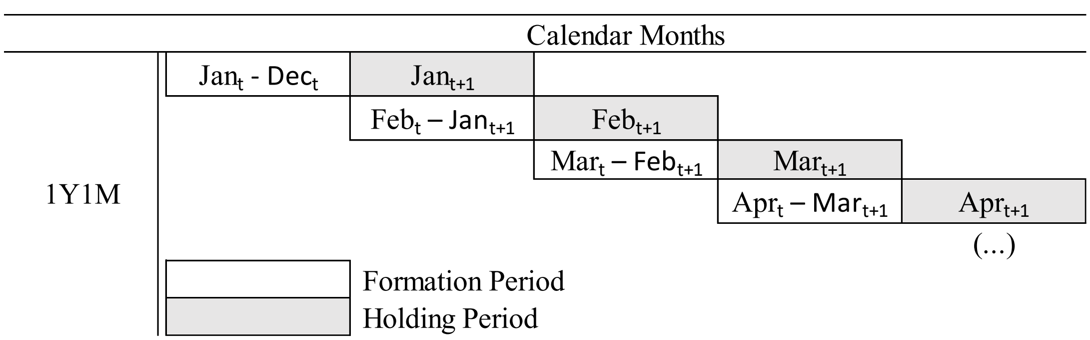
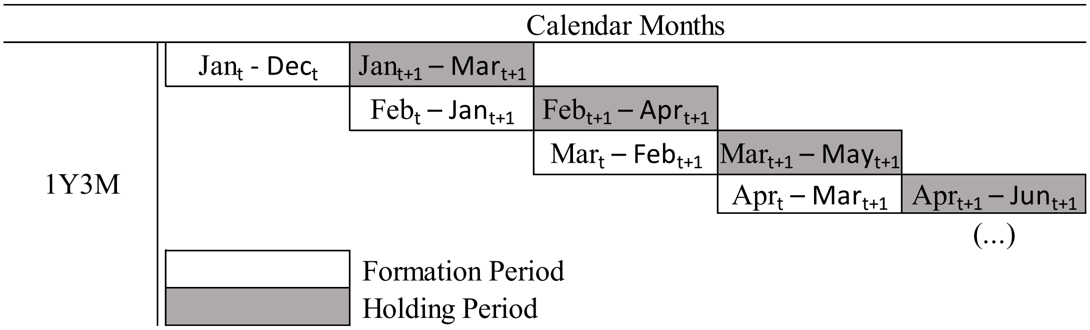
8. Appendix

Graphical illustrations of the process of constructing stock portfolios based on the realized skewness of the stocks.





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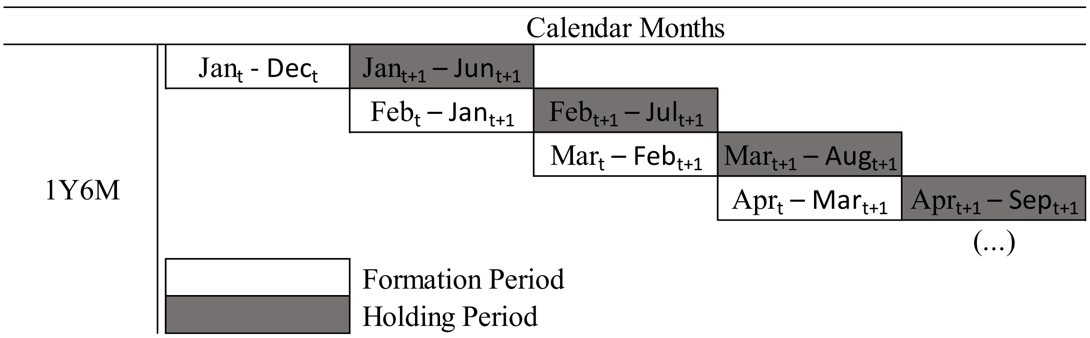
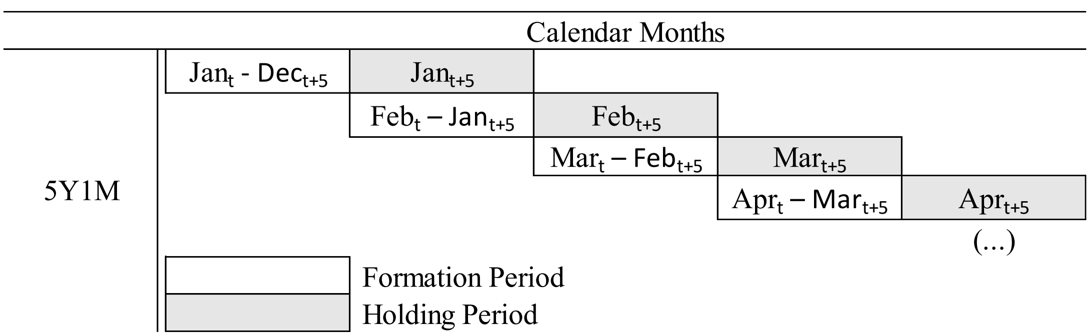
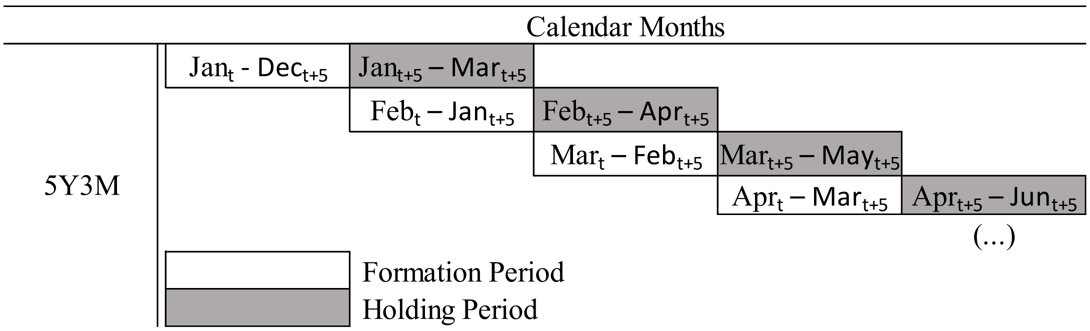
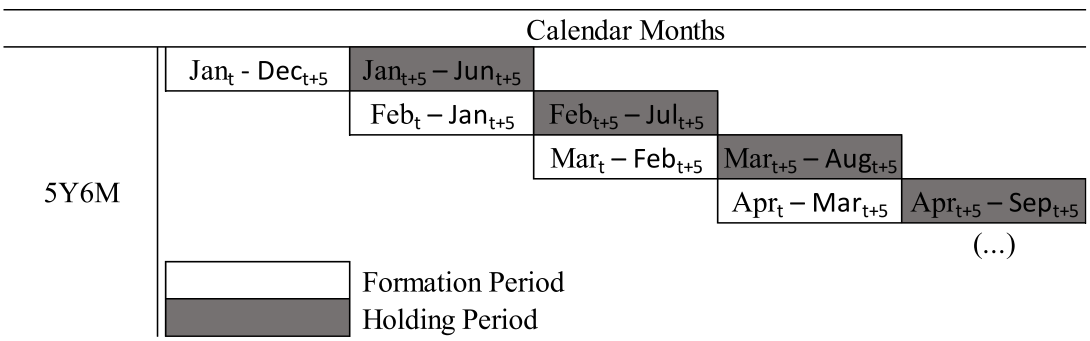
1Y3M
Jan_t - Dec_t
Jan_t+1 – Mar_t+1
Feb_t – Jan_t+1
Feb_t+1 – Apr_t+1
Mar_t – Feb_t+1
Mar_t+1 – May_t+1
Apr_t – Mar_t+1
Apr_t+1 – Jun_t+1
(…)
Formation Period
Holding Period


Calendar Months
1Y6M
Jan_t - Dec_t
Jan_t+1 – Jun_t+1
Feb_t – Jan_t+1
Feb_t+1 – Jul_t+1
Mar_t – Feb_t+1
Mar_t+1 – Aug_t+1
Apr_t – Mar_t+1
Apr_t+1 – Sep_t+1
(…)
Formation Period
Holding Period


Calendar Months
5Y1M
Jan_t - Dec_t+5
Jan_t+5
Feb_t – Jan_t+5
Feb_t+5
Mar_t – Feb_t+5
Mar_t+5
Apr_t – Mar_t+5
Apr_t+5
(…)
Formation Period
Holding Period





MAX strategy OOS monthly returns, 4FF alphas and t-stats between 1962 and 2021.

1962-2021

	VW Portfolios		**EW Portfolios**		**Average**	**Average #**	**Average**
Decile	**Average Return**	**Four-factor alpha**	**Average Return**	**Four-factor alpha**	**MAX**	**of Stocks**	**SIZE**
LOW MAX	0.98	0.14	1.19	0.32	1.94	460	658.33
2	0.99	0.14	1.32	0.35	2.82	458	645.62
3	1.15	0.22	1.40	0.38	3.57	458	473.28
4	1.11	0.13	1.39	0.33	4.35	458	382.54
5	1.06	0.08	1.36	0.29	5.24	458	313.62
6	1.19	0.16	1.28	0.21	6.33	458	256.85
7	1.20	0.19	1.21	0.14	7.75	457	219.98
8	1.06	0.07	1.14	0.09	9.89	458	190.79
9	0.70	-0.35	0.92	-0.13	14.09	456	161.84
HIGH MAX	0.34	-0.78	0.51	-0.49	23.15	452	146.17
10-1	-0.64	-0.92	-0.67	-0.81			-512.16
	-6.93	***-2.57***	***-13.33***	***-4.16***			

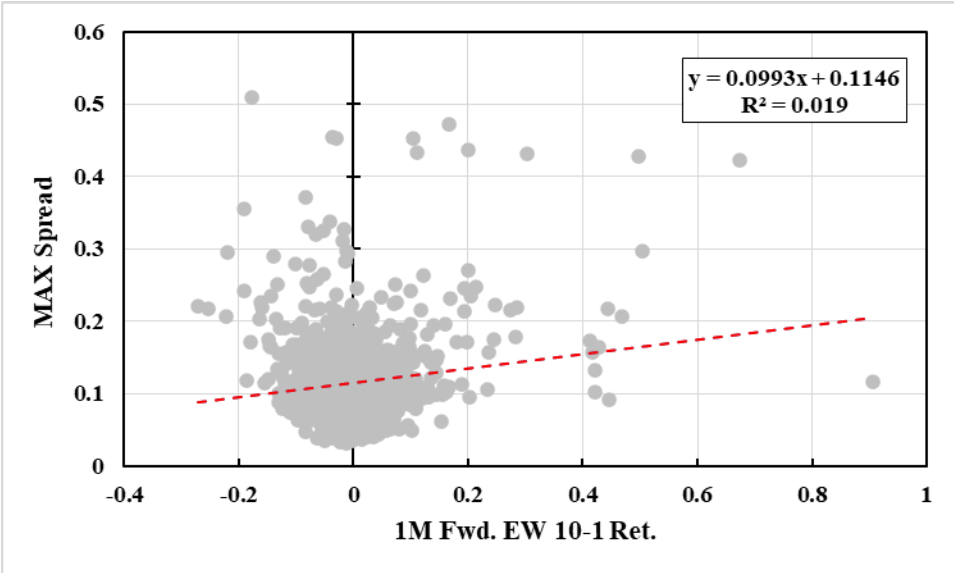
MAX strategy equal-weighted deciles' descriptive statistics between 1927 and 2021.

Descriptive Statisitics	Deciles										L/S
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**(10-1)**
Count	1140	1140	1140	1140	1140	1140	1140	1140	1140	1140	1151
Annualized Mean (%)	14.73	15.95	17.19	16.73	17.00	16.56	15.37	14.87	13.75	10.66	-4.03
t-stat	*32.53*	*29.79*	*27.97*	*24.88*	*22.45*	*20.46*	*17.73*	*15.81*	*13.61*	*9.37*	*-4.79*
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Annualized St. Dev. (%)	15.29	18.08	20.76	22.71	25.58	27.33	29.27	31.75	34.12	38.41	28.52
Annualized Sharpe ratio	0.96	0.88	0.83	0.74	0.66	0.61	0.52	0.47	0.40	0.28	-0.14
t-stat	*7.76*	*7.30*	*6.97*	*6.37*	*5.86*	*5.43*	*4.80*	*4.33*	*3.78*	*2.65*	*-1.38*
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.17)*
Skewness	0.43	0.09	0.64	0.68	1.29	1.59	1.55	1.72	2.12	2.52	3.33
Excess kurtosis	9.72	8.35	11.63	10.45	14.67	16.52	15.41	15.58	18.23	17.42	24.12
JB test statistic	*4518.83*	*3314.36*	*6497.40*	*5280.44*	*10540.66*	*13444.78*	*11732.74*	*12101.50*	*16645.27*	*15611.33*	*30012.47*
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Minimum (%)	-20.55	-28.57	-31.30	-30.86	-34.82	-33.79	-35.28	-34.11	-34.88	-30.75	-27.21
Percentile 25 (%)	-0.81	-0.98	-1.26	-1.65	-2.06	-2.27	-2.68	-3.04	-3.49	-4.68	-4.23
Median (%)	1.47	1.76	1.82	1.64	1.66	1.62	1.48	1.23	0.91	0.32	-1.16
Percentile 75 (%)	3.36	3.93	4.37	4.56	4.66	4.92	5.10	5.23	5.18	4.99	1.86
Maximum (%)	38.07	36.48	55.09	57.20	62.45	76.77	82.88	80.57	98.56	101.61	90.67
AR(1)	0.22	0.18	0.17	0.17	0.20	0.19	0.18	0.22	0.20	0.16	0.11
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
AR(2)	0.03	0.00	0.01	0.00	0.00	0.00	-0.01	0.01	0.01	0.02	0.00
p-value	*(0.37)*	*(0.94)*	*(0.77)*	*(1.00)*	*(0.91)*	*(0.90)*	*(0.70)*	*(0.65)*	*(0.76)*	*(0.48)*	*(0.99)*
AR(3)	-0.08	-0.09	-0.10	-0.12	-0.10	-0.11	-0.09	-0.08	-0.06	-0.04	-0.01
p-value	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.04)*	*(0.16)*	*(0.84)*
Q	62.58	45.90	44.00	48.80	57.29	54.68	48.52	59.88	52.51	32.36	12.81
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*

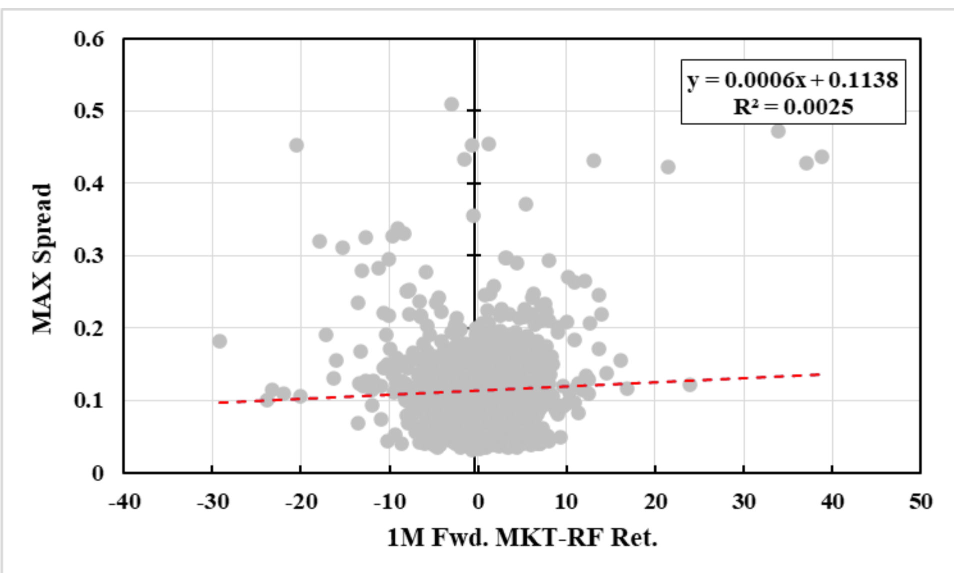
MAX strategy value-weighted deciles' descriptive statistics between 1927 and 2021.

Descriptive Statisitics	Deciles										L/S
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**(10-1)**
Count	1140	1140	1140	1140	1140	1140	1140	1140	1140	1140	1151
Mean (%)	11.39	12.11	14.82	12.95	13.32	14.34	14.47	13.07	9.56	4.23	-7.10
t-stat	*24.41*	*23.88*	*25.26*	*19.23*	*18.45*	*17.79*	*16.40*	*14.52*	*9.35*	*3.61*	*-6.89*
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
St. Dev. (%)	15.76	17.12	19.82	22.74	24.37	27.22	29.80	30.38	34.50	39.56	34.94
Sharpe ratio	0.72	0.71	0.75	0.57	0.55	0.53	0.49	0.43	0.28	0.11	-0.20
t-stat	*6.27*	*6.16*	*6.44*	*5.15*	*4.97*	*4.81*	*4.48*	*4.01*	*2.65*	*1.04*	*-1.97*
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.30)*	*(0.05)*
Skewness	0.94	-0.19	0.43	0.76	1.08	1.45	1.30	0.76	1.33	1.95	2.07
Excess kurtosis	14.44	6.56	8.78	10.50	13.28	13.50	11.76	7.05	9.04	13.27	14.17
JB test statistic	*10074.38*	*2051.13*	*3699.33*	*5344.81*	*8601.34*	*9061.18*	*6891.17*	*2469.98*	*4215.04*	*9084.18*	*10447.90*
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Minimum (%)	-20.61	-27.49	-29.92	-27.58	-34.43	-32.89	-36.44	-35.97	-38.34	-39.34	-47.80
Percentile 25 (%)	-1.20	-1.42	-1.62	-2.12	-2.21	-2.53	-3.27	-3.35	-4.29	-6.01	-5.80
Median (%)	1.02	1.25	1.32	1.32	1.27	1.38	1.04	0.98	0.43	-0.45	-1.53
Percentile 75 (%)	3.23	3.92	4.27	4.48	4.53	4.87	5.22	5.42	5.44	5.28	3.23
Maximum (%)	49.57	31.68	49.96	55.42	62.63	65.68	72.74	63.91	73.36	105.21	87.48
AR(1)	0.10	0.07	0.08	0.11	0.11	0.14	0.14	0.13	0.15	0.07	0.04
p-value	*(0.00)*	*(0.01)*	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.02)*	*(0.13)*
AR(2)	-0.01	-0.03	-0.02	-0.03	-0.04	-0.04	-0.04	0.03	0.00	0.01	0.01
p-value	*(0.62)*	*(0.36)*	*(0.46)*	*(0.26)*	*(0.16)*	*(0.23)*	*(0.21)*	*(0.29)*	*(0.91)*	*(0.64)*	*(0.84)*
AR(3)	-0.06	-0.15	-0.08	-0.10	-0.12	-0.09	-0.10	-0.05	-0.08	-0.01	0.00
p-value	*(0.05)*	*(0.00)*	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.08)*	*(0.00)*	*(0.64)*	*(0.96)*
Q	16.30	32.20	16.30	25.53	32.48	32.82	35.14	22.75	33.38	5.78	2.32
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.12)*	*(0.51)*

MAX Spread and 1 month forward equal-weight 10-1 returns' scatterplot.



MAX Spread and 1 month forward excess market returns' scatterplot.



SKEW strategy OOS monthly returns, 4FF alphas and t-stats between 1962 and 2021.

1962-2021

	VW Portfolios		**EW Portfolios**		**Average**	**Average #**	**Average**
Decile	**Average Return**	**Four-factor alpha**	**Average Return**	**Four-factor alpha**	**SKEW**	**of Stocks**	**SIZE**
LOW SKEW	0.75	0.20	1.28	0.66	-0.89	457	822.41
2	0.98	0.38	1.39	0.72	-0.42	457	991.47
3	0.89	0.31	1.35	0.68	-0.17	459	1009.34
4	0.99	0.40	1.31	0.64	0.03	459	977.86
5	0.88	0.28	1.27	0.60	0.20	453	941.08
6	0.93	0.33	1.16	0.46	0.39	456	935.67
7	0.96	0.38	1.12	0.44	0.62	457	872.76
8	0.96	0.39	1.02	0.35	0.92	457	801.96
9	1.01	0.46	0.96	0.30	1.46	457	680.06
HIGH SKEW	0.92	0.35	0.84	0.23	1.88	457	520.37
10-1	0.17	0.15	-0.44	-0.44	2.35		-302.04
	6.61	*1.50*	***-21.83***	***-5.02***			

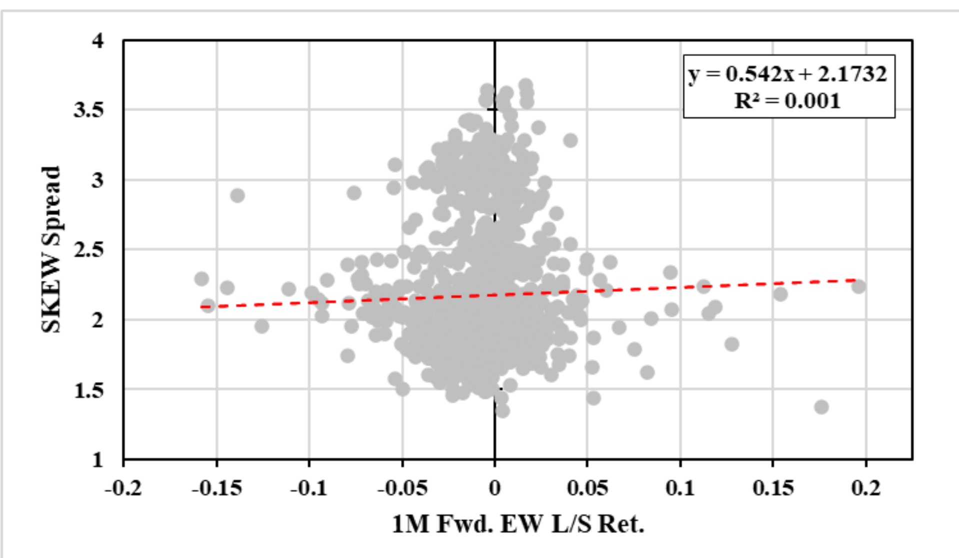
SKEW strategy equal-weighted deciles' descriptive statistics between 1927 and 2021.

Descriptive Statisitics	**Deciles**										**L/S**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**(10-1)**
Count	1140	1140	1140	1140	1140	1140	1140	1140	1140	1140	1140
Annualized Mean (%)	18.61	17.75	17.21	16.57	15.97	15.23	14.79	13.30	13.01	10.26	-8.35
t-stat	*7.38*	*7.05*	*6.82*	*6.37*	*6.26*	*5.76*	*5.50*	*4.78*	*4.58*	*3.74*	*-8.71*
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Annualized St. Dev. (%)	24.56	24.52	24.59	25.34	24.85	25.78	26.20	27.15	27.67	26.70	9.35
Annualized Sharpe ratio	0.76	0.72	0.70	0.65	0.64	0.59	0.56	0.49	0.47	0.38	-0.89
t-stat	*6.51*	*6.28*	*6.12*	*5.79*	*5.70*	*5.31*	*5.11*	*4.51*	*4.35*	*3.61*	*-7.36*
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Skewness	1.94	1.17	0.96	1.57	0.77	1.27	1.37	1.39	1.95	1.69	0.45
Excess kurtosis	18.75	13.10	10.71	16.25	8.55	12.94	12.78	13.52	19.06	16.24	10.42
JB test statistic	*17408.19*	*8415.18*	*5627.74*	*13006.12*	*3589.99*	*8257.11*	*8110.23*	*9053.57*	*17978.66*	*13069.33*	*5194.49*
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Minimum (%)	-26.47	-33.39	-31.84	-32.75	-33.00	-31.82	-28.90	-32.38	-32.18	-30.18	-15.81
Percentile 25 (%)	-1.85	-1.83	-1.94	-1.82	-2.05	-2.09	-2.50	-2.57	-2.80	-2.64	-1.84
Median (%)	1.54	1.67	1.71	1.58	1.43	1.32	1.41	1.28	1.31	1.07	-0.61
Percentile 75 (%)	4.48	4.76	4.64	4.61	4.67	4.78	4.78	4.60	4.70	4.21	0.47
Maximum (%)	69.57	65.73	64.23	69.47	54.49	64.71	63.47	66.91	83.17	75.22	19.63
AR(1)	0.22	0.19	0.18	0.21	0.18	0.18	0.19	0.20	0.21	0.21	0.10
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
AR(2)	0.03	0.01	0.00	0.01	0.00	0.00	0.02	-0.01	0.00	0.03	0.08
p-value	*(0.28)*	*(0.79)*	*(0.93)*	*(0.77)*	*(0.91)*	*(0.87)*	*(0.60)*	*(0.74)*	*(1.00)*	*(0.27)*	*(0.01)*
AR(3)	-0.08	-0.10	-0.10	-0.10	-0.09	-0.08	-0.09	-0.10	-0.08	-0.09	0.08
p-value	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.00)*	*(0.00)*
Q	61.63	50.81	45.95	60.38	44.62	45.56	50.10	56.54	56.85	61.74	27.32
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*

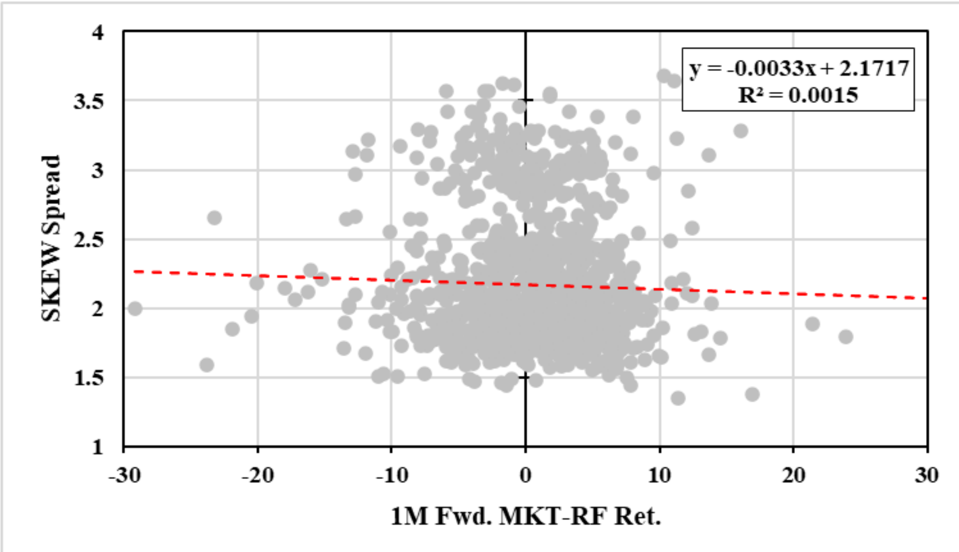
SKEW strategy value-weighted deciles' descriptive statistics between 1927 and 2021.

Descriptive Statisitics	Deciles										L/S
	1	2	3	4	5	6	7	8	9	10	
Count	1140	1140	1140	1140	1140	1140	1140	1140	1140	1140	1140
Annualized Mean (%)	10.69	12.38	11.97	12.54	11.33	11.44	10.95	11.90	11.56	9.53	-1.16
t-stat	*5.80*	*6.35*	*6.27*	*6.41*	*5.70*	*5.56*	*5.50*	*5.55*	*5.50*	*4.66*	*-1.12*
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.26)*
Annualized St. Dev. (%)	17.96	19.01	18.61	19.07	19.37	20.03	19.41	20.88	20.49	19.94	10.12
Annualized Sharpe ratio	0.60	0.65	0.64	0.66	0.59	0.57	0.56	0.57	0.56	0.48	-0.12
t-stat	*5.35*	*5.76*	*5.71*	*5.81*	*5.27*	*5.16*	*5.11*	*5.15*	*5.11*	*4.41*	*-1.12*
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.26)*
Skewness	-0.10	0.42	0.10	-0.25	-0.08	0.38	0.21	0.92	0.84	0.28	-0.65
Excess kurtosis	5.65	9.41	6.49	4.61	6.18	8.77	7.51	15.89	12.52	10.51	9.70
JB test statistic	*1520.31*	*4238.30*	*2001.35*	*1019.97*	*1815.18*	*3680.49*	*2688.73*	*12149.64*	*7574.72*	*5259.93*	*4549.23*
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Minimum (%)	-27.36	-27.24	-27.79	-29.31	-32.84	-29.93	-27.22	-34.07	-30.04	-31.26	-24.22
Percentile 25 (%)	-1.76	-1.78	-1.66	-1.63	-1.82	-1.75	-1.93	-1.96	-1.96	-1.90	-1.51
Median (%)	1.28	1.41	1.27	1.39	1.34	1.21	1.21	1.26	1.21	1.19	-0.01
Percentile 75 (%)	3.89	3.94	3.96	4.08	4.02	4.05	4.01	4.05	3.98	3.90	1.46
Maximum (%)	31.27	48.67	37.11	34.04	37.30	48.57	47.72	58.28	55.55	53.29	22.53
AR(1)	0.12	0.10	0.09	0.09	0.08	0.08	0.07	0.11	0.13	0.12	-0.07
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.01)*	*(0.02)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*
AR(2)	-0.02	0.01	-0.01	-0.01	-0.02	-0.01	-0.04	-0.07	-0.04	0.02	0.08
p-value	*(0.56)*	*(0.80)*	*(0.80)*	*(0.65)*	*(0.57)*	*(0.62)*	*(0.14)*	*(0.03)*	*(0.14)*	*(0.45)*	*(0.01)*
AR(3)	-0.10	-0.07	-0.08	-0.08	-0.08	-0.11	-0.10	-0.11	-0.09	-0.08	-0.02
p-value	*(0.00)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.57)*
Q	30.09	17.18	16.96	15.57	15.72	20.59	18.50	33.70	32.26	26.41	13.90
p-value	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*

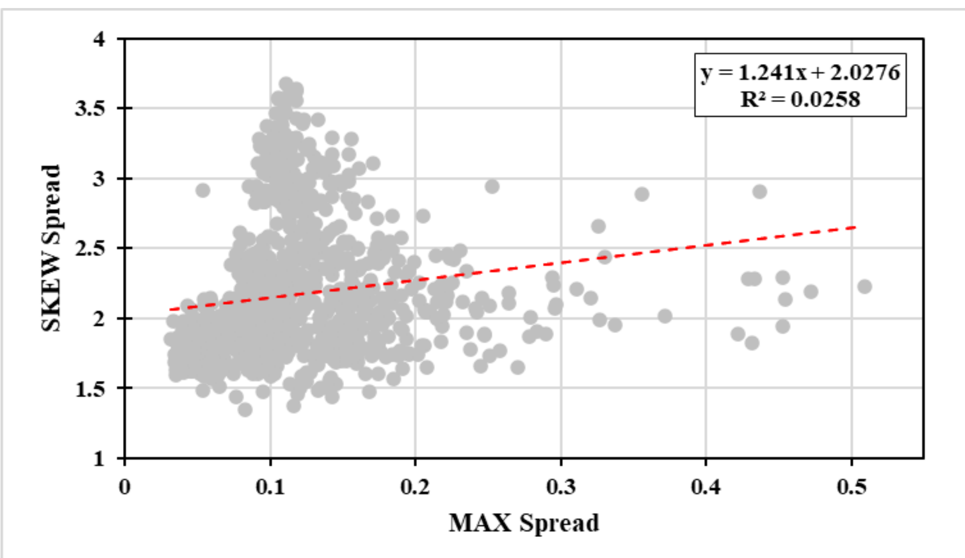
SKEW Spread and 1 month forward equal-weight 10-1 returns' scatterplot.



SKEW Spread and 1 month forward excess market returns' scatterplot.



SKEW Spread and MAX Spread scatterplot.



SKEW Spread and 1 month forward MAX Spread scatterplot.