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When to Hedge Downside Risk?

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Abstract: Hedging downside risk before substantial price corrections is vital for risk management and long-only active equity manager performance. This study proposes a novel methodology for crafting timing signals to hedge sectors' downside risk. These signals can be integrated into existing strategies simply by purchasing sector index put options. Our methodology generates successful signals for price corrections in 2000 (dot-com bubble) and 2008 (global financial crisis). A key innovation involves utilizing sector correlations. Major price swings within six months are signaled when a sector exhibits high valuation alongside abnormal correlations with others. Utilizing the price-to-earnings ratio for identifying sectors' high valuations is more beneficial than the bond–stock earnings yield differential. Our signals are also more efficient than those of standard technical analyses.

Keywords: market timing; risk management; risk hedging; equity market crashes; bond–stock earnings yield differential

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1. Introduction and Literature Review

Our proposed methodology provides timely alerts for the two most significant market crashes in recent market history. Whitehouse et al. (2023) emphasize the importance of the early forecasting of a financial bubble for investors. One way to take advantage of an early warning is to buy sector index put options when the signal is observed. The signal can overlay easily with a portfolio manager's existing strategy. Therefore, an equity portfolio manager can use it to hedge potential downside risk due to a portfolio's exposure to a certain sector. In addition to these crashes, our timing signal has also been effective in identifying notable price corrections across major S&P 500 sectors over the past few decades.

We evaluate our signals using bootstrapped pseudo p-values and finally compare our results with signals derived from commonly used technical analyses among practitioners, demonstrating their efficiency. Previous research on predicting market crashes using a single-variable approach suggests that the bond–stock earnings yield differential (BSEYD) model may offer better predictions for equity market corrections compared to price-earnings ratio (PE) models. However, the results of our generalized methodology challenge these findings. In the future, our suggested approach could be extended by utilizing more valuation metrics.

The literature dedicated to market crashes is extensive. The primary focus of numerous studies concerns the identification of bubble conditions and volatility spillovers and undertaking crash forecasts (Lleo and Ziemba 2019; Yousaf and Hassan 2019). Tran et al. (2023) highlight that there is still a lack of a clear-cut definition of a bubble crash in the literature. Sornette (2009) defines crashes based on anomalous price patterns. In a seminal paper, Abreu and Brunnermeier (2003) characterize a crash as a sudden plummet in price from an inflated level which, driven by a bubble, descends to its fundamental value.

Rational arbitrageurs recognize that the market will eventually collapse, yet they aim to capitalize on the expanding bubble and its lucrative returns in the interim. Of course, this behavior further increases the price and patterns of the herding behavior of noise traders. Tran et al. (2023) define bubbles that are primarily driven by irrational investor behavior as classical. Ideally, rational arbitrageurs aim to exit the market just before the crash occurs. Recent studies explore different approaches for predicting endogenous financial asset bubbles (Deng et al. 2022; Focardi and Fabozzi 2014; Guan et al. 2022). Accurate forecasts provide valuable insights for mitigating their impact and devising effective crisis management strategies.

One early study by Ausloos et al. (2002) mentions that log-periodic oscillations are found before crashes in several financial indices. In a study about stock market crashes from 2007 to 2009, Lleo and Ziemba (2012) utilized the BSEYD model to predict stock market crises in different countries. This model can easily predict stock market crashes with high interest rates relative to earnings but not others related to political reasons (the European debt crisis and the political stalemate in Washington). The literature rigorously investigates many ratios as predictors of equity corrections using methodology such as the PE ratio, the cyclically adjusted PE ratio, and the ratio of the market value of all publicly traded stocks to the current level of the GNP (Lleo and Ziemba 2019). Dichtl et al. (2023) utilize many ratios, including book-to-market and dividend-to-price ratios, for predicting crashes in major European Union countries. In another study, Focardi and Fabozzi (2014) utilize the ratio of financial to operational profits in corporations. Their study criticizes the approach that considers a bubble a deviation from fundamental/rational price because, in practice, future cash flows cannot be precisely forecasted, and deviations from rational prices cannot be clearly identified. Based on their framework, bubbles can be identified based on the excess growth of financial markets with respect to the real economy. Moreover, financial flows should be evaluated based on the real economy and inflation.

Continuing the line of investigation in the literature on log-periodic power law models, Cajueiro et al. (2009) investigate whether crashes in the Brazilian stock market could be identified using intraday observations. Another econophysics approach presented by Munoz Torrecillas et al. (2016) suggests that the dot-com bubble can be identified. Within this framework, the primary focus is to find the moment in stock trading at which the transition between efficient market behavior and herding behavior occurs. A power-law distribution of stock-price changes within a segment indicates herding behavior and the start of the dot-com bubble. Fu et al. (2021) construct a firm-specific investor sentiment index by using the PE ratio and find a positive relation with the stock price crash risk. Recent studies in the literature also explore the role of social media in herding behavior and market crashes. Guan et al. (2022) focus on the brief market collapse during the COVID-19 pandemic. The authors show how market sentiments affect prices and how negative market sentiments are mitigated in digitally intense sectors. Sul et al. (2017) argue that positive and negative sentiments are spread through tweets, affecting daily investment decisions and prices for firms in the S&P 500. Deng et al. (2022) use machine learning approaches to predict individual stocks' price crashes in the Chinese stock market, one of the most compelling equities markets, for various capitalizations. Also, some studies use theoretical stochastic processes and other probabilistic models to study financial crashes (Jarrow 2012).

In a separate strand of research on this topic, options are utilized to study financial market crises. Leiss et al. (2015) constructed risk-neutral return probability distributions from S&P 500 options data over 2003–2013. During the pre-crisis period, increasing option implied returns were observed. The study found that the realized-minus-implied risk premium was approximately 8% in the pre-crisis period and doubled to 16% in the post-crisis period. Using a similar approach, Xu et al. (2020) utilize S&P 500 calls and puts to predict upside (downside) uncertainty related to upward (downward) movements in the US equity market. Also, the authors show the spillover of these risks to international markets. On the other hand, Xiong et al. (2016) focus on forecasting only forward-looking left tail risk using a series of multiple regression analyses. Other studies have utilized

GARCH stable models (Molina-Muñoz et al. 2020). Also, Molina-Muñoz et al. (2020) enrich their framework by incorporating tail index measures. Boubaker et al. (2022) encompass data from 27 countries from 1918 to 2019 to identify a structural turning point associated with each bubble following a burst. In another study, Tsakonas et al. (2022) introduce an innovative method to predict major downturns in financial markets. This method performs a nonlinear analysis of the logarithmic returns of the index and then uses the moving Lyapunov exponent as a signal for financial market crashes.

Our study contributes to the literature by further investigating how financial ratios can accurately predict financial market bubbles. Investors' ability to time major price corrections and crashes can improve their risk-adjusted performance (Berge et al. 2008). Individuals are incentivized to time market outcomes in the persistence of bubbles. Moreover, our work provides a framework for investors with respect to the timing of hedging the risk of losses from a market crash while maintaining the potential for gains. A situation with an exceptionally high sector PE ratio with out-of-historical norm correlations with other sectors indicates substantial price swings in the index within the subsequent six months. Finally, although the previous literature provides frameworks that are based on a stock market index or individual stocks (Lleo and Ziemba 2019; Deng et al. 2022; da Silva 2022), our analysis utilizes data on a sector level and provides a valuable tool for practitioners to implement an appropriate hedging strategy on the sector level.

We also contribute to the literature by incorporating the dynamic of correlation in our analysis in addition to the standard statistical measures that are used in the univariate approach (Lleo and Ziemba 2019; Dichtl et al. 2023). The proposed methodology can provide a timing signal for various GICS sector indexes. Our work can also contribute to the strand of the literature addressing the pricing of downside risk (Farago and Tédongap 2018; Galsband 2012; Mercik 2023). For example, the criteria used in formulating the timing signal can be utilized as extra tools in studying the tail risk measures from Mercik (2023). Farago and Tédongap (2018) discuss the notion of downstate factors. Our methodology can support potential new frameworks for disappointment-related factors.

The rest of the study is organized as follows: Section 2, we discuss how the data were collected and the methodology based on the sector PE ratio and sector correlation matrix. Section 3, we briefly discuss the intuition behind the signal and how it can benefit investors' investment processes, such as enhancing performance or managing risk. This is illustrated through various examples, in particular the dot-com bubble crash in 2000 and the global financial crisis of 2008. Finally, Section 4, we provide some concluding remarks.

2. Data and Research Methods

We collected sector-level data for each of the S&P 500 GICS sector indexes. The historical data were downloaded from the Bloomberg terminal. The S&P 500 GICS sectors used in this study were Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, and Utilities[1]. The first sector-level data item is the daily total return for each sector index. The historical return data started in January 1990. The second data item is the sector index's daily PE ratio[2]. The historical PE ratio started in April 1990[3]. In summary, there are two sets of daily historical data series. The first set comprises daily returns, and the second comprises PE ratios.

2.1. Data Transformation Methodology

The rest of this section will describe the methodology used for constructing the timing signal. The first step is to transform the ten sectorial daily PE data series into series expressed in z-scores. We adopted a robust version of the z-score suggested by Rousseeuw and Hubert (2011). For the rest of the paper, we mean the robust version when we refer to the z-score. The z-score is constructed as follows, and x_i is an observation:

$$z_i = \frac{(x_i - Median_{j=1,\ldots,n}(x_j))}{MAD} \tag{1}$$

where *MAD* (the median of all absolute deviations from the median) is defined as follows:

$$MAD = 1.438 \times median_{i=1,\dots n}\left(\left|x_i - median_{j=1,\dots,n}(x_j)\right|\right) \tag{2}$$

According to Rousseeuw and Hubert (2011), the constant 1.438 is a correction factor that makes the MAD unbiased at the normal distribution. Outliers tend to have z_i values greater than two (or less than negative two). The robust version of the z-score plays an important role in our timing signal methodology, and discussing its computing in more detail is worthwhile. One of the motivations for adopting this robust z-score calculation is its ability to detect outliers when the traditional score fails to do so. Detecting outliers plays a vital role in our methodology. We use the same example in Rousseeuw and Hubert (2011) to illustrate this point. Consider the following five observations: 6.27, 6.34, 6.25, 63.1, and 6.28. The sample mean is $\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$. In this case, the sample mean is 17.65. The classic estimator of standard deviation is $s = \sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2/(n-1)} = 25.42$. The traditional z-score calculation is $z_i = (x_i - \overline{x})/s$. The z-scores for the above five observations are -0.45, -0.45, -0.45, 1.79, and -0.45. In this case, the traditional z-score fails to detect the outlier 63.1.

The form of distribution and the existence of outliers and fat tails can impact the effectiveness of specific measures to detect outliers. The main concerns in the literature regarding methodologies and measures for detecting outliers are masking effects and swamping (Rousseeuw and Hubert 2018). Masking effects refer to the characterization of large-deviation observations as "normal", while swamping occurs when "normal" observations are characterized as having large deviations. The robustness of a measure concerns its consistency. So, after removing outliers, the results should closely fit the results with the outliers. The robustness of our z-score comes with a cost. For symmetric distributions, the traditional z-score is more efficient (Rousseeuw and Hubert 2011). However, the data utilized in this study are not symmetrical.

The following is the calculation of the robust z-score for the same five observations according to Equations (1) and (2). The median of these five observations is 6.28. The absolute deviations from the median are 0.01, 0.06, 0.03, 58.82, and 0. The median of these five absolute deviations from the median is 0.03. In this case, $MAD = 1.483 \times 0.03 = 0.044$. The robust z-scores for these five observations are -0.22, 1.35, -0.67, 1277.14, and 0.00. The robust z-score can detect the outlier 63.1, which has a robust z-score of 1277.14. This example illustrates an important concept that makes the robust version of the z-score more suitable for detecting outliers in our case. The traditional z-score is based on the mean and standard deviation of the observations. Both the mean and standard deviation are sensitive to the influence of outliers (which the z-score tries to detect). On the contrary, the robust z-score is based on the median and MAD, which are less sensitive to the influence of outliers.

We transform the ten sectorial daily PE series into ten z-score series. There are two reasons for this z-score transformation. The first reason is to use the z-score to detect extremely high valuations. Empirical observation indicates that extremely high valuations usually precede major price tumbles. The second reason is that the z-score standardizes the PE data across ten sectors. Such standardization makes z-scores comparable across different sectors. The Information Technology sector typically has a higher PE ratio than the Utilities sector. For example, a PE ratio of 20 is high for the Utilities sector, but this is not the case for the Information Technology sector. However, a z-score above two indicates a high PE ratio regardless of the sector.

A z-score series is constructed iteratively as the PE data series grows at a daily frequency. The z-score as of a specific date is built by gathering PE data up to the given date. The PE data are converted into z-scores using Equations (1) and (2). The PE z-score is the z-score as of the given date. This process repeats for the next day, when we have one more new observation of PE data. This approach prevents the construction of a PE z-score as of a specific date using PE data that are not available yet as of the given date. In this way, there is no look-ahead bias in constructing a PE z-score, making the methodology more realistic when conducting a backtest.

The following is an example illustrating the first step of the methodology for constructing the timing signal. The example we use is the signal date 3 January 2000 for the Information Technology sector index. The solid line in Figure 1 is the Information Technology sector PE ratio between 1 July 1999 and 3 January 2000. The PE ratio as of 3 January 2000 is 63.27. Then, we construct a z-score series of the PE ratio as of 3 January 2000 (the dotted line in Figure 1), using PE data from 3 December 1990 up to 3 January 2000. The z-score as of 3 January 2000 is 3.63. There are two points we would like to elaborate on further. First, a high PE level (and PE z-score) can last a while. As shown in Figure 1, the PE remains at a relatively high level throughout the time period of the plot. Second, the notion that the PE z-score is "as of a certain date" is essential. One day after 3 January 2000, we have one more observation of the PE ratio for 4 January 2001. We re-construct a new PE z-score series up to 4 January 2001. In other words, the PE z-score as of 4 January 2001 is computed from the most recent and longer (one observation longer) PE series (which ends on 4 January 2001).

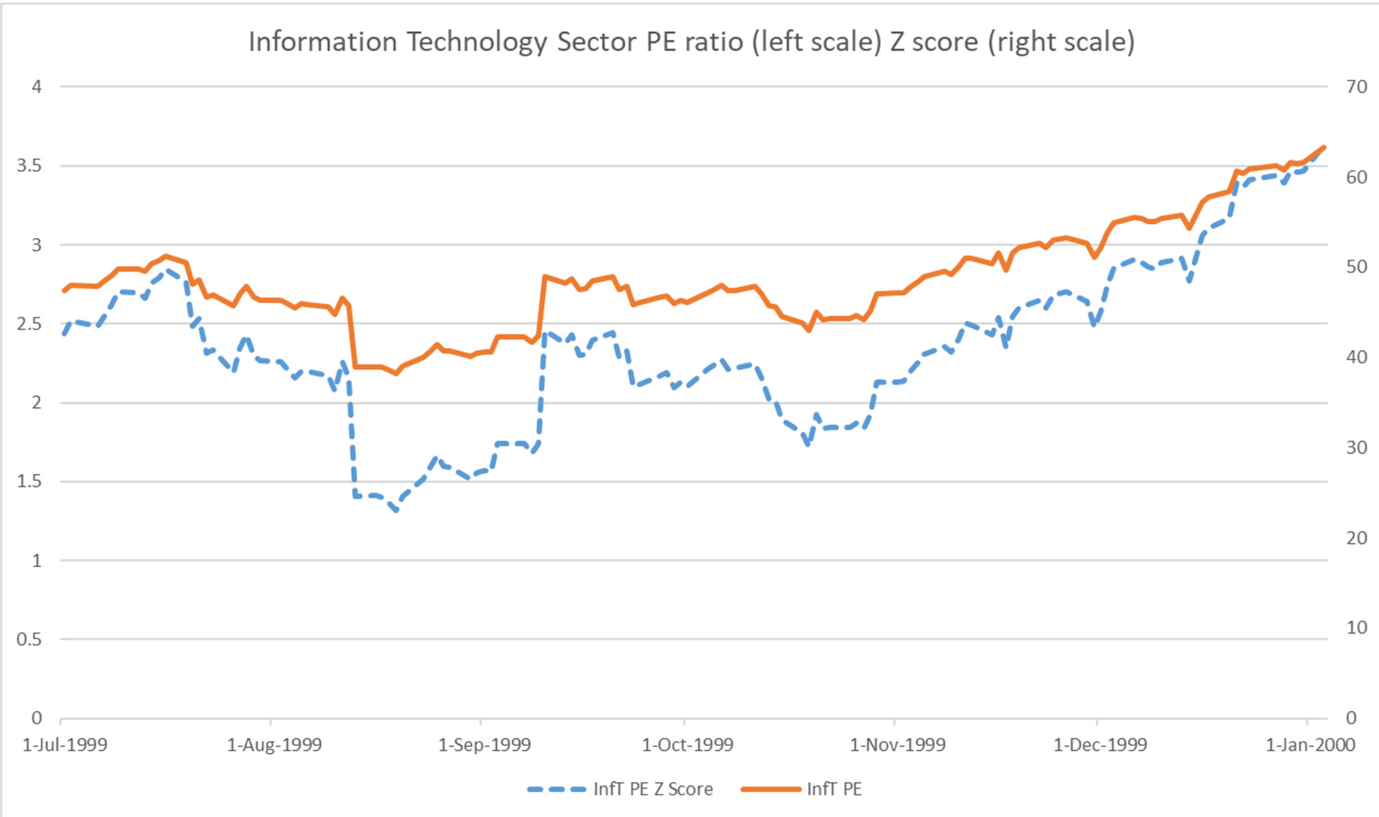

Figure 1. The solid line is a time series plot of the Information Technology sector index PE ratio (right scale). The dotted line is a plot of the PE z-score as of 3 January 2000 (left scale). Both plots end on 3 January 2000.

The second step involves building a daily series of a ten-by-ten sector correlation matrix. Starting from January 1995, as of each trading day and using all the available daily return history up to the given day, we estimate an exponentially weighted moving average (EWMA) correlation matrix. Following Chapter 23 of Hull (2018), we set the decline rate parameter (λ) to 0.94.

The following illustrates the second step of the methodology, using the same 3 January 2000 signal date as an example. It is about the construction of the nine correlation z-scores. In this example, we focus on the correlation between the Information Technology sector index and the nine other sector indexes (i.e., there are nine correlation pairs). Table 1 shows the ten-by-ten sector correlation matrix estimated as of 3 January 2000. The nine correlation pairs are highlighted in the table (i.e., the row labeled as InfT). This particular correlation matrix is estimated using the sector's total daily return from January 1990 up to 3 January 2000. We estimate the correlation matrix for each trading day with an expanding data window. Therefore, we have a time series of the correlation matrix. Let us focus on the row of correlations between the Information Technology sector index and the nine other sector indexes. Figure 2 is a time series plot of these nine correlations as of 3 January 2000. By design, the series ends on 3 January 2001 (as of date). For illustration purposes, Table 2 shows the first few rows and last few rows of correlation used in the plot. For example, the column labeled Enrs is a time series for the correlation between Energy and Information Technology from 3 January 1995 up to 3 January 2000 (i.e., as of date). Using the time series of these nine correlation pairs, we construct nine correlation z-score series as of 3 January 2000. Figure 3 is a time series plot of these nine z-scores as of 3 January 2000. By design, the series ends on 3 January 2001 (as of date). For illustration purposes, Table 3 shows the first few rows and last few rows of z-scores used in the plot. The nine correlation pairs as of 3 January 2000 are the last row in Table 2 (highlighted). As we discussed earlier, the notion of a certain date is very important. For example, one day after 3 January 2000, we have one more observation of an estimated correlation matrix and a new row of the nine correlation pairs. We re-construct a new correlation z-score series up to 4 January 2001. The correlation z-score as of 4 January 2001 is from the newly constructed series.

Table 1. Sector correlation matrix as of 3 January 2000. The following is an estimated ten-by-ten sector correlation matrix.

	Enrs	**Matr**	**Indu**	**ConD**	**ConS**	**Hlth**	**Finl**	**InfT**	**Tels**	**Util**
Enrs	1.000	0.454	0.322	0.546	0.238	0.182	0.373	−0.051	0.345	0.353
Matr	0.454	1.000	0.339	0.337	0.198	0.202	0.418	−0.103	0.267	0.445
Indu	0.322	0.339	1.000	0.602	0.481	0.093	0.594	−0.020	0.255	0.455
ConD	0.546	0.337	0.602	1.000	0.525	0.351	0.592	−0.060	0.409	0.440
ConS	0.238	0.198	0.481	0.525	1.000	0.665	0.552	−0.125	0.176	0.437
Hlth	0.182	0.202	0.093	0.351	0.665	1.000	0.267	0.053	−0.006	0.276
Finl	0.373	0.418	0.594	0.592	0.552	0.267	1.000	−0.058	0.452	0.610
InfT	**−0.051**	**−0.103**	**−0.020**	**−0.060**	**−0.125**	**0.053**	**−0.058**	**1.000**	**0.087**	**−0.134**
Tels	0.345	0.267	0.255	0.409	0.176	−0.006	0.452	0.087	1.000	0.169
Util	0.353	0.445	0.455	0.440	0.437	0.276	0.610	−0.134	0.169	1.000

Table 2. Time series of the correlation between the Information Technology sector index and nine other sector indexes. For illustration purposes, the table only shows the beginning and ending of the time series. The series ends on 3 January 2000.

Date	**Enrs**	**Matr**	**Indu**	**ConD**	**ConS**	**Hlth**	**Finl**	**InfT**	**Tels**	**Util**
3 January 1995	0.298	0.482	0.694	0.669	0.577	0.667	0.421	1.000	0.191	0.122
4 January 1995	0.303	0.483	0.691	0.650	0.562	0.669	0.418	1.000	0.195	0.133
5 January 1995	0.302	0.482	0.683	0.640	0.536	0.667	0.419	1.000	0.195	0.143
6 January 1995	0.265	0.515	0.684	0.616	0.510	0.599	0.419	1.000	0.115	0.154
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
27 December 1999	0.122	0.045	0.270	0.286	0.049	0.057	0.211	1.000	0.307	0.130
28 December 1999	0.088	−0.049	0.267	0.260	0.057	0.090	0.187	1.000	0.210	0.118
29 December 1999	0.109	−0.009	0.259	0.219	0.033	0.070	0.211	1.000	0.175	0.099
30 December 1999	0.127	0.025	0.266	0.212	0.015	0.063	0.195	1.000	0.179	0.076
31 December 1999	0.113	0.005	0.257	0.187	0.016	0.076	0.193	1.000	0.162	0.077
3 January 2000	**−0.051**	**−0.103**	**−0.020**	**−0.060**	**−0.125**	**0.053**	**−0.058**	**1.000**	**0.087**	**−0.134**

Table 3. Time series of the correlation z-score between the Information Technology sector index with nine other sector indexes as of 3 January 2000. For illustration purposes, the table only shows the beginning and ending of the time series. The nine correlation pairs as of 3 January 2000 are in the highlighted row (last row) in the table.

Date	Enrs	Matr	Indu	ConD	ConS	Hlth	Finl	InfT	Tels	Util
3 January 1995	0.192	0.279	0.511	0.428	0.904	0.625	−0.240		−0.673	−0.554
4 January 1995	0.218	0.285	0.499	0.336	0.828	0.629	−0.254		−0.656	−0.501
5 January 1995	0.216	0.280	0.455	0.291	0.700	0.624	−0.249		−0.656	−0.450
6 January 1995	0.019	0.455	0.462	0.177	0.568	0.380	−0.251		−1.000	−0.391
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮		⋮	⋮
27 December 1999	−0.746	−2.039	−1.648	−1.357	−1.765	−1.562	−1.115		−0.173	−0.514
28 December 1999	−0.926	−2.536	−1.666	−1.475	−1.727	−1.445	−1.216		−0.590	−0.572
29 December 1999	−0.816	−2.328	−1.706	−1.669	−1.844	−1.517	−1.118		−0.742	−0.668
30 December 1999	−0.718	−2.147	−1.672	−1.698	−1.940	−1.541	−1.183		−0.725	−0.783
31 December 1999	−0.792	−2.249	−1.718	−1.818	−1.930	−1.497	−1.192		−0.799	−0.778
3 January 2000	**−1.667**	**−2.824**	**−3.130**	**−2.964**	**−2.646**	**−1.579**	**−2.236**		**−1.124**	**−1.834**

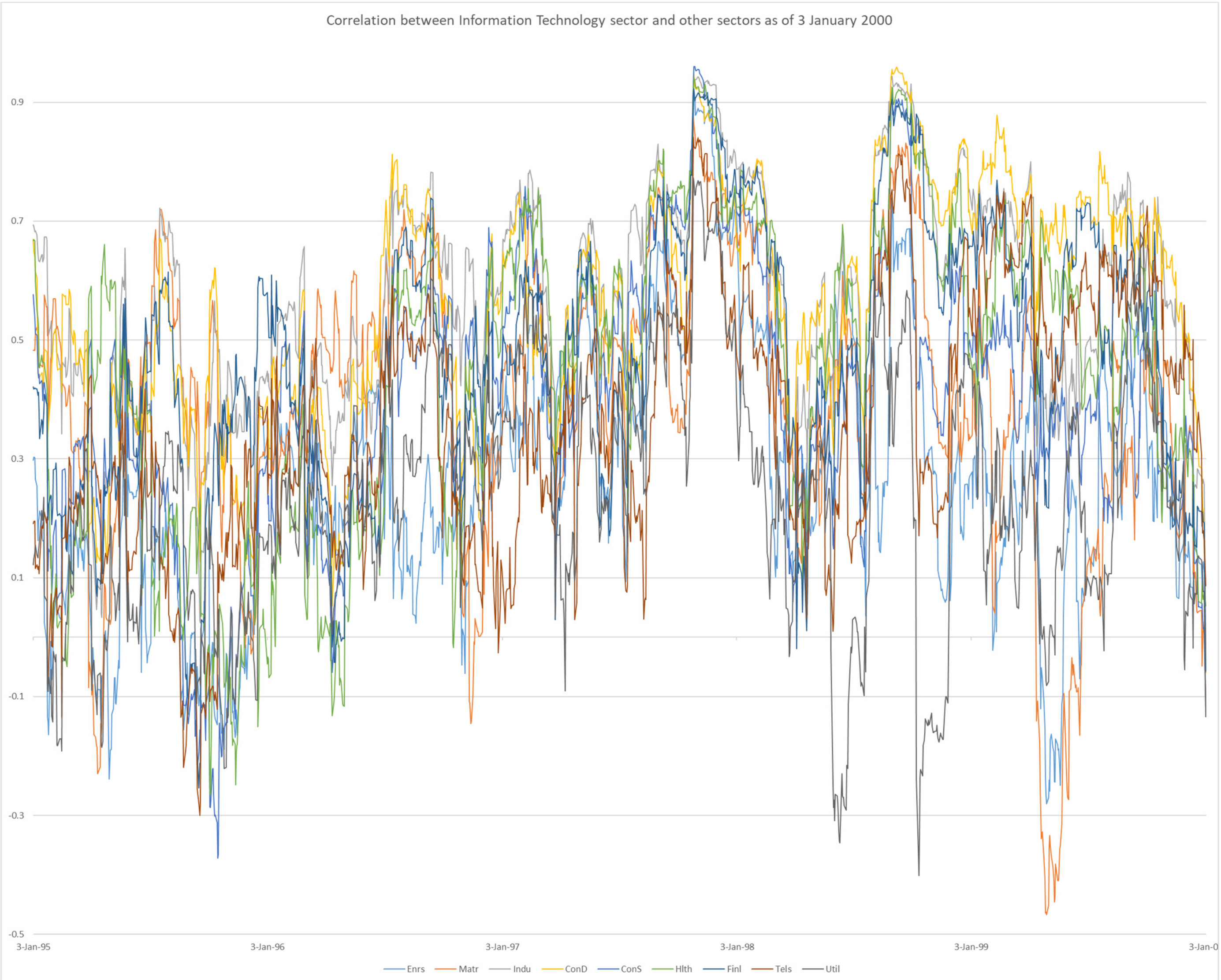

Figure 2. Time series plot of correlations between the Information Technology sector and the other sectors as of 3 January 2000.

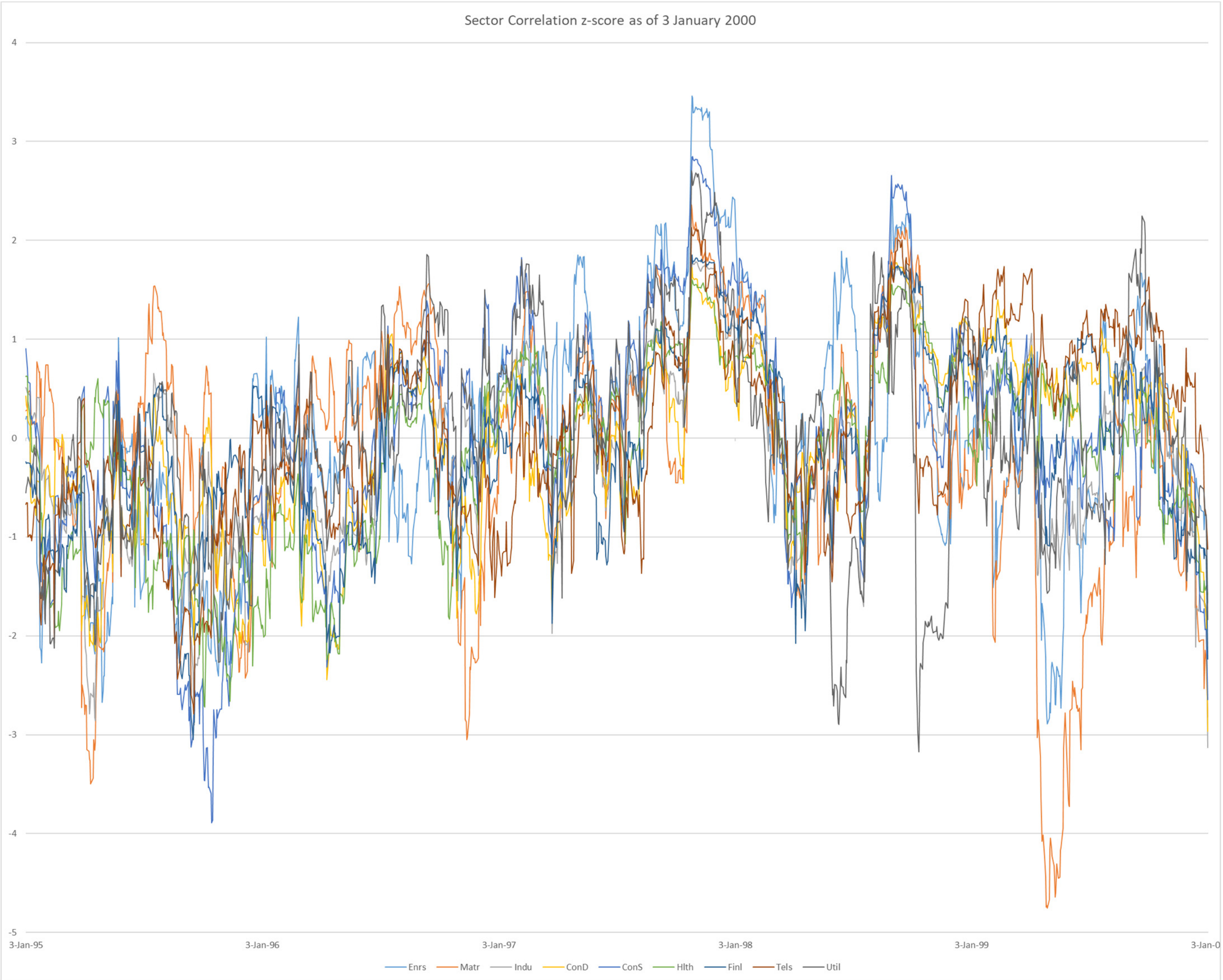

Figure 3. Time series plot of correlation z-scores as of 3 January 2000.

2.2. Timing Signal Construction

After completing the two steps mentioned above, we are ready to describe the construction of the timing signal for hedging downside risk. This process applies to each of the sectors separately. We construct the timing signal for each of the sectors individually. Whenever a sector's PE z-score is above 2.5 (i.e., the valuation for the sector index is high), we also check this sector's correlation with the other nine sectors. Using the daily series of the correlation matrix, we have a daily historical series of a particular correlation up to the date when we are performing the checking. From the daily historical series of nine different correlations, we can transform these nine correlations into nine different z-scores (based on each correlation's history up to this point). Then, from these nine different correlation z-scores (as of the date we are checking), we count how many are less than negative two (i.e., which two sectors are less correlated or even become negatively correlated). When this count is more than three (and the sector's PE z-score is above 2.5), we have a timing signal for hedging downside risk. The following is an empirical justification for considering a number of counts more than three. The occurrence of such an event, across all sectors, constitutes less than 10% of the time, conditional upon the 2.5 PE z-score threshold[4]. The sector index tends to exhibit big price swings in the following six months after the timing signal appears.

Finally, the following illustrates how the methodology generates the signal date, 3 January 2000. Figure 1 shows that the Information Technology sector's PE z-score was above 2.5 for a while. As of 3 January 2000, the PE z-score is 3.63. As of 3 January 2001, we observe the very "first" instance of five correlation z-scores less than negative two. As shown in the last row of Table 3, these five correlation z-scores are −2.82 (Materials/Information Technology), −3.13 (Industrials/Information Technology), −2.96 (Consumer Discretionary/Information Technology), −2.65 (Consumer Staples/Information Technology), and −2.24 (Financials/Information Technology). Our methodology proposes a threshold that the number of correlation z-scores less than negative two is three. In this example, we have five. Therefore, according to our methodology, 3 January 2001 is an early warning signal date for the Information Technology Index.

3. Results and Discussion

The intuition behind the signal is the following. Based on historical observations, when the equity market crashes as a bubble deflates, the stocks related to the bubble tend to exhibit high valuations before the crash. Therefore, we focus on the days for which the PE z-score is above 2.5 when constructing the timing signal. The PE z-score's ability to identify outliers helps us identify days with high valuation. However, history also teaches us that one can observe high valuation for a long time before a crash happens (Lleo and Ziemba 2019). Hence, we need a second piece of information to narrow our focus when formulating a timing signal. In this case, the second piece of information is the correlation between the sector with high valuation and the other nine sectors. Suppose some of these nine correlations exhibit extremely low correlations (or extreme negative correlations). Once again, we use the correlation z-score to identify instances in which correlations are extremely low. In that case, it may indicate that a sector index with a high valuation has been behaving "out of line" compared to its historical norm. Assuming these extreme correlations will revert to the norm, this phenomenon may be used as a leading indicator for the upcoming major price corrections of the sector with high valuation. As defined in the previous section, when the count of correlation z-scores below −2 is more than three, this criterion signals the time to consider hedging the downside risk for the sector index with a high valuation, especially for long-only managers. There are typically multiple significant up-and-down price swings after seeing the signal. Therefore, buying one (or more) put option(s) is an excellent way to put on the hedge when using this timing signal by asset managers (or investors). A put option allows an investor to participate in the upside of a price swing while protecting the loss from the downside of a price swing.

3.1. Two Major Market Crashes

The following are two case studies illustrating our proposed timing signal. The first case study is the dot-com bubble crash of 2000. The second case study is the crash of the global financial crisis in 2008. These are the main booms that can be characterized as bubbly until 2017 (Guerron-Quintana et al. 2023). On 3rd January 2000, we obtained a timing signal. The results related to this signal date are shown in Table 4. On this signal date, the information technology sector index PE z-score was 3.63. The PE z-score had been above 2.5 for a while. However, it was the first time that the number of correlation z-scores below negative two was more than three. Five z-score correlations were below negative two: −2.82 (Materials/Information Technology), −3.13 (Industrials/Information Technology), −2.96 (Consumer Discretionary/Information Technology), −2.65 (Consumer Staples/Information Technology), and −2.24 (Financials/Information Technology). We calculated the return of the Information Technology sector index after we observed the signal.

Table 4. Timing signal for the Information Technology sector. The signal date represents the date on which the timing signal was observed. The PE z-score is the PE ratio of the S&P 500 Information Technology sector index expressed as a z-score. The count represents the number of sectors correlated with the Information Technology sector index with a z-score less than negative two. The first date of the return calculation is the signal date plus two trading days. The sector label represents the correlation z-score. Our methodology provides a beneficial timing signal for the dot-com bubble crash.

Signal Date	3 January 2000	3 April 2000	7 August 2000
PE z-score	3.63	3.50	2.56
Count	5	4	4
1st month return (%)	−2.36	−6.41	6.09
2nd month return (%)	10.60	−6.30	−19.57
3rd month return (%)	14.00	7.53	−2.54
4th month return (%)	−15.32	2.00	−15.80
5th month return (%)	−15.03	1.10	−13.02
6th month return (%)	24.65	−5.12	17.26
Pseudo-pvalue [95% Confidence Interval]	0.0149 [0.0124, 0.0175]	0.0647 [0.0594, 0.0701]	0.0072 [0.0054, 0.0091]
Energy	−1.67	−2.46	−2.03
Materials	−2.82	−2.77	−2.16
Industrials	−3.13	−1.42	−0.49
Consumer Discretionary	−2.96	−2.37	−0.65
Consumer Staples	−2.65	−3.25	−2.81
Health Care	−1.58	−1.77	−2.67
Financials	−2.24	−1.43	−0.22
Information Technology			
Communication Services	−1.12	−0.01	0.15
Utilities	−1.83	−0.82	−0.75

We computed six different monthly returns for each signal date. The first date used for the return calculation is 5th January 2000 (i.e., signal date + two trading days); this extra lag simulates the implementation delay. This is because it takes time to put on a hedge. Then, we calculate the first, second, third, fourth, fifth, and sixth monthly returns after observing the signal[5]. Table 4 shows that the fourth and fifth monthly returns are both about −15%. Berge et al. (2008) also document the lag between observing their BSEYD signal and the actual price correction. The BSEYD entered the danger zone in May 1987, and the correction occurred four months later in October 1987. However, the second, third, and sixth monthly returns are positive. These kinds of big up-and-down price swings are expected to be observed while a bubble is deflating. Suppose a long-only strategy manager can hold options in their portfolio. In that case, the manager can consider buying put options to protect the downside risk while still being able to capture the potential upside. The timing signal presented itself again on 3 April 2000. If a manager had put on a long-term hedge during the first signal date, this new signal date would be less critical. Table 4 shows that the price swings are less intense than we observed during the first signal date. Nevertheless, this particular signal date can still provide some downside protection. The sum of all negative returns is still more significant than that of all positive returns. After more than six months since the first signal date, the timing signal appeared again on 7 August 2000. The information technology index turned significantly downward after this signal date. The returns for the second, fourth, and fifth months are big negative numbers (i.e., −19.57%, −15.80%, and −13.02). After this signal date, the signal did not appear again for the rest of the time during our analysis. Our analysis ended at the end of September 2023. In summary, the timing signal could help managers (or investors) avoid significant losses while the dot-com bubble deflates. Figure 4 shows the information technology index and the three signal dates (the three vertical lines on the chart).

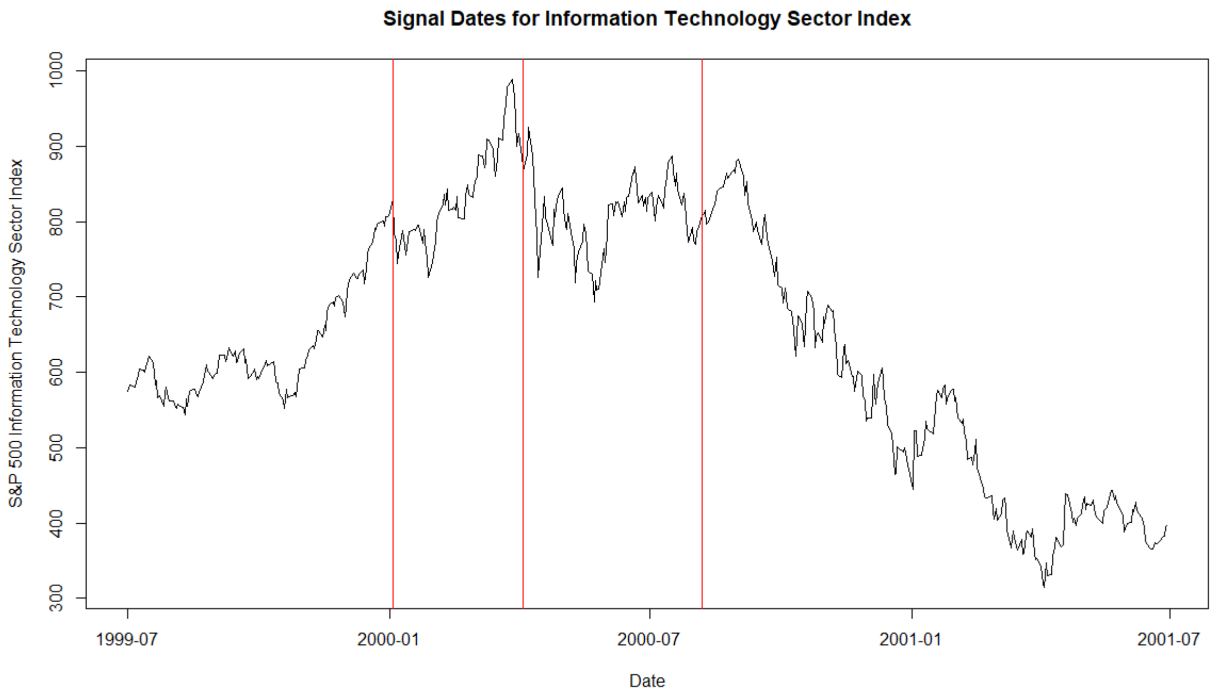

Figure 4. Signal dates for the Information Technology sector index. The three signal dates are 3 January 2000, 3 April 2000, and 7 August 2000.

The following discusses how to conduct a statistical analysis to test whether the signal does really provide information for hedging downside risk. Let us use the signal date 3 January 2000 as an example to illustrate the analysis. As mentioned earlier, we compute six different monthly returns following this particular signal date. To conduct the analysis, we compute six different monthly returns following each trading date in our data sample, and there are 8377 trading dates. For this signal date, there are three months (out of six) with a negative return. The sum of these three negative returns is −32.71% (i.e., the sum of −2.36,−15.32, and −15.03, as shown in Table 4). There are only 125 dates out of the 8377 trading dates followed by three months (out of six months) with negative returns, and the sum of these three negative returns is less than or equal to −32.71%. If one randomly picks a date from these 8377 dates, there is only a 0.0149 (i.e., 0.0149 ≈ 125/8377) probability that the chosen date can provide the same or better hedging benefit. The hedging benefit refers to the magnitude of the sum of the negative returns. If our methodology generates random signal dates (i.e., the methodology does not provide useful hedging benefits), it is very unlikely to pick a date with such a good hedge benefit as the signal date, 3 January 2001. In other words, the signal date 3 January 2000 is statistically significant. For presentation purposes, we use the term pseudo-pvalue to describe the 0.0149 probability. Based on the usual convention, the corresponding signal date is significant if the pseudo-pvalue is less than 0.05. We only have one sample of 8377 trading dates. However, we can use the bootstrapping technique to compute a more robust version of the pseudo-pvalue and its corresponding 95% confidence interval. In this example, the bootstrapped pseudo-pvalue is 0.0149, with a confidence interval of [0.0124, 0.0175]. The pseudo-pvalues and confidence intervals are reported in Table 4. Table 4 shows that both the first and third signal dates have pseudo-pvalues less than 0.05. The pseudo-pvalue for the second signal is 0.06, which is still less than 0.1.

The second case study is the crash of the global financial crisis in 2008. On average, a decline greater than the largest one-day drop during the global financial crisis is expected to occur approximately once every 27 years (Aboura 2014. The results of the timing signal for the financial sector index are shown in Table 5. The first signal for the financial sector index appeared on 23 July 2008. According to the pseudo-pvalue, this signal date is highly significant. The third, fourth, and fifth monthly returns are −21.55%, −15.98%, and −11.17%. This particular signal date provides an early warning signal for the upcoming price corrections. The timing signal comes up again on 12 April 2021. The index drops −4.27% during the third month after observing the signal. However, there are no significant price swings in this case. The pseudo-pvalue also indicates that this signal date is not significant. The signal date falls within the global COVID-19 pandemic, and the financial sectors did not appear to be in a bubble. The index was still recovering from its bottom in March 2020. The financial sector index might exhibit very different behavior before and during the pandemic. This may explain the false alarm for this particular signal date. Figure 5 shows the financial index and the first signal date (the chart's first vertical line from the left). The second vertical line is the signal date based on the BSEYD. We will discuss the BSEYD in more detail later in this section.

Table 5. Timing signal for the Financials sector. The signal date represents the date on which the timing signal was observed. The PE z-score is the PE ratio of the S&P 500 financials sector index expressed as a z-score. The count represents the number of sectors correlated with the Financials sector index with a z-score less than negative two. The first date of return calculation is the signal date plus two trading days. The sector label represents the correlation z-score. Our methodology provides a beneficial timing signal for the global financial crisis.

Signal Date	23 July 2008	12 April 2021
PE z-score	2.54	2.50
Count	4	5
1st month return (%)	−4.35	6.14
2nd month return (%)	2.00	2.81
3rd month return (%)	−21.55	−4.27
4th month return (%)	−15.98	1.54
5th month return (%)	−11.17	4.05
6th month return (%)	2.27	−0.32
pseudo-pvalue	0.0058	0.2175
[95% Confidence Interval]	[0.0043, 0.0075]	[0.2087, 0.2265]
Energy	−2.63	−0.07
Materials	−2.35	−0.04
Industrials	−0.04	0.24
Consumer Discretionary	0.70	−4.97
Consumer Staples	−0.75	−2.07
Health Care	−0.77	−2.03
Financials		
Information Technology	−0.06	−3.30
Communication Services	−2.13	−2.55
Utilities	−3.77	−1.77

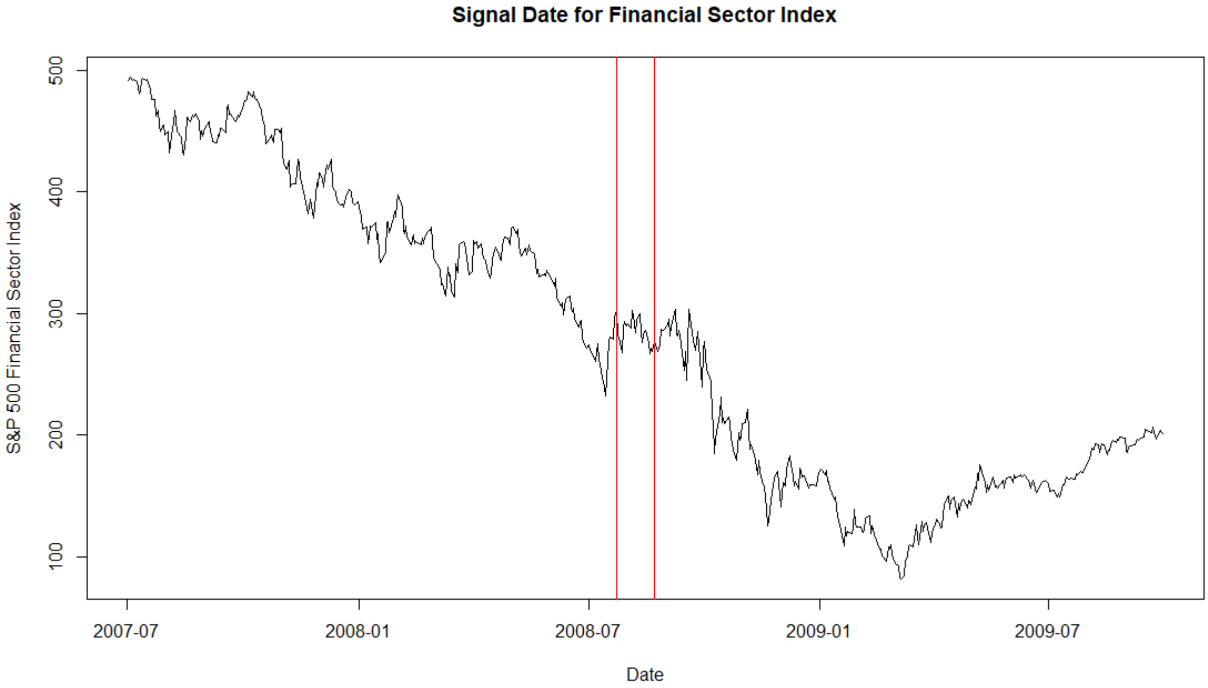

Figure 5. Signal dates for the Financials sector index. The first vertical line on the left is the signal date based on the PE z-score. The second vertical line on the right is the signal date based on the BSEYD z-score. The signal dates are 23 July 2008 and 22 August 2008.

3.2. Other Sectors' Timing Signals

In addition to providing early warnings for the two major well-known crashes in recent financial history, the timing signal also managed to catch some significant price corrections in the following three sectors: Utilities, Energy, and Health Care. Table 6 shows the timing signal results for the Utility sector. For the signal that appeared on 16 January 2020, the Utility sector index dropped about 18% during the second month after observing the signal. The pseudo-pvalue for this signal is 0.0074, which is highly significant. However, it is reasonable to assume that this 18% drop could be related to the COVID-19 crisis and not the burst of a bubble in the Utilities sector. There was no Utilities sector bubble before the pandemic crisis. For the other two signal dates, 11 June 1998 and 9 October 1998, the price swings were less violent than those discussed earlier. The pseudo-pvalues for these dates are only fairly significant. Table 7 shows the timing signal results for the Health Care sector. There is only one signal date that appeared on 19 April 1999. The Health Care sector index returns for the second, fourth, and sixth months are −5.08%, −10.98%, and −6.80. The signal did provide an asset manager the chance to hedge the downside risk. The pseudo-pvalue also indicates that this signal date is significant. Table 8 shows the timing signal results for the energy sector. There are four signal dates. The first signal date, 21 April 1999, is significant. However, this is not the case for the other three signal dates.

Table 6. Timing signal for the Utilities sector. The signal date represents the date on which the timing signal was observed. The PE z-score is the PE ratio of the S&P 500 Utility sector index expressed as a z-score. The count represents the number of sectors whose correlation with the Utilities sector index correlates with a z-score less than negative two. The first date of the return calculation is the signal date plus two trading days. The sector label represents the correlation z-score.

Signal Date	**11 June 1998**	**9 October 1998**	**16 January 2020**
PE z-score	2.56	2.52	2.51
Count	7	5	4
1st month return (%)	−1.21	−1.14	5.40
2nd month return (%)	−4.26	1.36	−18.14
3rd month return (%)	0.73	1.03	6.57
4th month return (%)	12.07	−4.38	−7.70
5th month return (%)	−3.88	−3.81	9.04
6th month return (%)	3.08	1.64	−4.65
Pseudo-pvalue [95% Confidence Interval]	0.1207 [0.1138, 0.1277]	0.1214 [0.1144, 0.1284]	0.0074 [0.0056, 0.0093]
Energy	−2.62	−0.24	2.87
Materials	−2.33	−1.96	−0.52
Industrials	−2.78	−3.53	−2.71
Consumer Discretionary	−1.82	−3.60	−2.31
Consumer Staples	−2.67	−1.09	0.46
Health Care	−3.17	−2.92	−0.75
Financials	−2.57	−4.74	−2.65
Information Technology	−3.23	−2.39	−1.29
Communication Services	−1.76	0.57	−1.78
Utilities			

Table 7. Timing signal for the Health Care sector. The signal date represents the date on which the timing signal was observed. The PE z-score is the PE ratio of the S&P 500 Health Care sector index expressed as a z-score. The count represents the number of sectors whose correlation with the utilities sector index has a correlation z-score less than negative two. The first date of the return calculation is the signal date plus two trading days. The sector label represents the correlation z-score.

Signal Date	**19 April 1999**
PE Z-score	3.19
Count	4
1st month return (%)	−1.99
2nd month return (%)	−5.08
3rd month return (%)	8.46
4th month return (%)	−10.98
5th month return (%)	11.17
6th month return (%)	−6.80
Pseudo-pvalue [95% Confidence Interval]	0.0137 [0.0113, 0.0162]
Energy	−2.34
Materials	−2.82
Industrials	−2.13
Consumer Discretionary	0.99
Consumer Staples	−1.06
Health Care	
Financials	−0.85
Information Technology	0.35
Communication Services	1.09
Utilities	−2.37

Table 8. Timing signal for the Energy sector. The signal date represents the date on which the timing signal was observed. The PE z-score is the PE ratio of the S&P 500 utilities sector index expressed as a z-score. The count represents the number of sectors whose correlation with the Utilities sector index correlates with a z-score less than negative two. The first date of the return calculation is the signal date plus two trading days. The sector label represents the correlation z-score.

Signal Date	21 April 1999	7 March 2000	14 June 2017	6 November 2017
PE z-score	5.03	3.84	8.10	4.32
Count	4	4	4	6
1st month return (%)	0.82	2.41	−0.31	−1.00
2nd month return (%)	4.26	−0.16	−0.96	6.45
3rd month return (%)	1.50	9.99	1.10	1.90
4th month return (%)	2.67	−3.32	6.67	−8.65
5th month return (%)	0.60	−7.74	−0.14	−0.79
6th month return (%)	−11.63	15.45	0.98	8.31
Pseudo-pvalue	0.0122	0.1402	0.3100	0.1546
[95% Confidence Interval]	[0.0099, 0.0146]	[0.1327, 0.1477]	[0.3002, 0.3200]	[0.1469, 0.1623]
Energy				
Materials	−0.13	−2.23	−0.28	−2.06
Industrials	−1.85	−3.01	−1.39	−1.89
Consumer Discretionary	−2.19	−1.98	−2.19	−0.23
Consumer Staples	−1.70	−3.55	−2.27	−2.30
Health Care	−3.37	−2.24	−1.73	−2.05
Financials	−1.81	−1.82	−0.50	−2.08
Information Technology	−2.09	−1.88	−2.25	−0.92
Communication Services	−2.27	−0.80	−0.84	−2.08
Utilities	−0.47	0.08	−3.47	−3.72

Table 9 shows the timing signal results for the Consumer Discretionary and Industrials sectors. The three columns on the left are for the Consumer Discretionary sector index. The three columns on the right are for the Industrials sector index. Unlike the other signal dates we have discussed, there were no substantial price swings within six months after observing the timing signal. After a closer inspection, we noticed that all these signal dates for these two sectors fall within the time of the COVID-19 global pandemic. These two sectors were not in a bubble before the pandemic. As we conjectured earlier, these two sector indexes might exhibit very different behaviors before and during the pandemic. Like other systematic risk factors, such as war, the pandemic can result in price behavior that cannot be easily predicted (Deng et al. 2022). Finally, there is no timing signal for the Materials or Consumer Staples sector indexes.

The following is a discussion on how to integrate the early warning signal we propose into a manager's investment process. We have demonstrated that the signal provides an early warning of major price downturns in the next six months. In fact, the signal also indicates a higher-volatility regime for the next six months. Higher volatility implies substantial price swings in both up and down directions. One possible way to take advantage of this timing signal is to buy put options a few months out to hedge downside risk while keeping upside potential. There are many possible ways to implement this kind of put option hedge. For example, a manager can roll over the put option hedge each month over the next six months[6]. If a manager specializes in a sector rotation strategy, this timing signal can enhance the performance of the strategy. The manager can overlay the timing signal with the existing strategy by putting on the put option hedge (when the timing signal indicates they should do so) for various sector exposures of the strategy. By a similar argument, a traditional long-only active equity manager can also take advantage of this timing signal[7]. Based on the timing signal, the manager can put on the downside risk hedge for their portfolio's sector exposures. However, the conditions for implementing the methodology in various equity markets are as follows: First, sufficient data history is needed on the sector level for the daily PE ratio and total daily return for building the timing signal. Second, sector index options must be available for trading.

Table 9. Timing signal for the Consumer Discretionary and Industrials sectors. The signal date represents the date on which the timing signal was observed. The BSEYD z-score is the PE ratio of the S&P 500 Consumer Discretionary (or Industrials) sector index expressed as a z-score. The count represents the number of sectors whose correlation with the utility sector index correlates with a z-score less than negative two. The first date of the return calculation is the signal date plus two trading days. The sector label represents the correlation z-score. The three columns on the left are for the Consumer Discretionary sector index. The three columns on the right are for the Industrials sector index.

Signal Date	10 November 2020	12 January 2021	14 April 2021	26 January 2021	21 April 2021	25 August 2021
PE z-score	4.92	5.90	7.95	4.23	7.07	4.24
Count	4	4	4	4	4	4
1st month return (%)	1.88	1.74	−6.02	9.34	2.10	−3.07
2nd month return (%)	3.19	−4.41	3.04	2.30	−1.63	3.75
3rd month return (%)	4.23	6.15	5.88	6.15	2.23	1.75
4th month return (%)	−6.22	1.08	−0.54	1.34	2.45	−1.91
5th month return (%)	5.26	−2.12	0.93	0.19	−2.75	2.52
6th month return (%)	6.66	4.37	−2.50	0.42	−1.12	−5.20
Pseudo-pvalue	0.0276	0.1296	0.1378	0.0425	0.2180	0.1151
[95% Confidence Interval]	[0.0241, 0.0312]	[0.1226, 0.1369]	[0.1304, 0.1452]	[0.0382, 0.0469]	[0.2091, 0.2268]	[0.1083, 0.1220]
Energy	−2.03	−1.18	−2.16	0.38	−0.60	0.42
Materials	−2.29	−2.51	−1.84	0.58	0.45	0.54
Industrials	−5.32	−4.59	−4.40			
Consumer Discretionary				−4.41	−3.12	−2.42
Consumer Staples	−0.76	−0.92	−2.19	−2.88	−1.63	−2.32
Health Care	−0.33	−2.52	−1.17	−1.61	−1.20	−3.20
Financials	−6.74	−4.93	−5.82	0.03	0.50	0.57
Information Technology	1.11	−0.83	0.13	−4.09	−2.42	−2.07
Communication Services	1.37	−0.01	0.32	−2.14	−2.04	−0.54
Utilities	−1.02	−0.65	−0.77	−0.71	−2.36	−1.46

The BSEYD is another well-studied predictor for market corrections (Berge et al. 2008; Lleo and Ziemba 2015, 2017). The definition of the BSEYD is the nominal treasury bond yield minus earnings yield. Our analysis used the 10-year treasury yield downloaded from the FRED database. We repeated a similar analysis using the BSEYD rather than PE ratios to construct the timing signals based on the earlier methodology. We used 2.0 as the BSEYD z-score cutoff[8]. The analysis period was the same as before, from January 1995 to September 2023. No timing signal was found for the following eight sectors: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Communication Services, and Utilities. For the Information Technology sector, only one signal date was found using the BSEYD when the dot-com bubble was deflating. The signal date was 3 January 2000, which is the same signal date obtained based on the PE ratios we presented earlier. Table 10 is a summary of this signal date[9]. There was only one signal date for the financial sector using the BSEYD. The signal date was 22 August 2008. The signal date obtained when using PE ratios was 23 July 2008. This signal date is significant, with a pseudo-pvalue of 0.0032. Table 11 is a summary of this signal date. This signal date can be beneficial to investors. We found that the maximum count of extreme sector correlation is three while the BSEYD z-score is above 2.0. The second vertical line from the left in Figure 5 corresponds to this signal date. When comparing these two predictors (PE ratio vs. BSEYD), the BSEYD produces fewer signal dates than the PE ratio.

Table 10. Timing signal for the information technology sector using BSEYD. The signal date represents the date on which the timing signal was observed. The BSEYD z-score is the BSEYD of the S&P 500 information technology sector index expressed as a z-score. The count represents the number of sectors correlated with the Information Technology sector index with a z-score less than negative two. The first date of return calculation is the signal date plus two trading days. The sector label represents the correlation z-score.

Signal Date	**3 January 2000**
BSEYD z-score	2.12
Count	5
1st month return (%)	−2.36
2nd month return (%)	10.60
3rd month return (%)	14.00
4th month return (%)	−15.32
5th month return (%)	−15.03
6th month return (%)	24.65
Pseudo-pvalue	0.0149
[95% Confidence Interval]	[0.0124, 0.0175]
Energy	−1.67
Materials	−2.82
Industrials	−3.13
Consumer Discretionary	−2.96
Consumer Staples	−2.65
Health Care	−1.58
Financials	−2.24
Information Technology	
Communication Services	−1.12
Utilities	−1.83

Table 11. Timing signal for the Financials sector using the BSEYD. The signal date represents the date on which the timing signal was observed. The PE z-score is the PE of the S&P 500 financials sector index expressed as a z-score. The count represents the number of sectors correlated with the Financial sector index with a z-score less than negative two. The first date of return calculation is the signal date plus two trading days. The sector label represents the correlation z-score.

Signal Date	**22 August 2008**
BSEYD z-score	2.05
Count	3
1st month return (%)	9.92
2nd month return (%)	−31.02
3rd month return (%)	−18.46
4th month return (%)	−4.39
5th month return (%)	−3.21
6th month return (%)	−15.33
Pseudo-pvalue	0.0032
[95% Confidence Interval]	[0.0020, 0.0045]
Energy	−2.06
Materials	−2.01
Industrials	0.43
Consumer Discretionary	0.54
Consumer Staples	0.03
Health Care	−0.23
Financials	
Information Technology	0.39
Communication Services	0.25
Utilities	−2.05

We can also compared our methodology with commonly used technical analyses (Neely et al. 2014). One of the well-known indicators among practitioners is the death cross

(Dolvin 2014; Smith 2017). The concept revolves around identifying temporal occurrences wherein the short-term moving average intersects with the longer-term average, thereby delineating strategic entry and exit points. The most common short- and long-term comparisons are between the 50-day moving average (MA) and 200-day moving average (MA). Initially, there is buying momentum. The price increases, and eventually the 50-day MA crosses above the 200-day MA. When the price starts falling, the 50-day MA falls below the 200-day MA; this is a signal of a long-term bearish trend. If the downward momentum is only temporary and the stock rebounds to the upside trend, then the death cross is deemed to be a false alarm. We compare this approach based on the simple moving averages with our methodology. Table 12 summarizes the death-cross analysis[10]. As shown in Table 12, there are more signal dates than in our methodology for each of the ten sectors. However, substantial downward price swings have not followed many of these signal dates.

Table 12. Performance summary of technical indicators.

Death Cross Analysis	Number of Signals	Average Number of Negative Monthly Returns within Six Months Period after Signal	Percentage of Significant Signal Pseudo-Pvalue
Consumer Discretionary	17	2.0	35.3%
Consumer Staples	18	2.0	22.2%
Energy	17	2.4	0.0%
Financial	16	2.6	56.3%
Health	18	2.2	33.3%
Industrials	16	2.4	25.0%
Information Technology	17	2.6	29.4%
Materials	19	2.3	31.6%
Communications	19	2.4	15.8%
Utilities	17	2.7	17.6%

4. Conclusions

In this research article, we proposed a new systematic signal that can be used to time the hedging of downside risk at the sector level. The timing signal only uses two data items as inputs, sector-level daily PE ratios and daily total returns. First, we focus on time periods in which a sector index exhibits high valuation. For the purpose of this signal, we regard a sector index as having high valuation when its price-to-earnings z-score is greater than 2.5. Then, we check the correlation between the high-valuation sector and nine other sector indexes. These nine correlations are transformed into nine z-scores based on each correlation's own historical daily data. If more than three correlation z-scores are less than negative two, then we have a timing signal. During the six-month period after the signal appears, there will usually be substantial up-and-down price swings. The signal is able to provide beneficial timing information during the collapse of the dot-com bubble and global financial crisis (housing bubble). This methodology can also generate beneficial timing information for other S&P 500 sector indexes. Most existing studies focus on the equity market index rather than sector indexes. We are filling a gap in the literature. We also generalize the classic univariate crash prediction approach by including the correlation dynamic among different sectors in formulating the timing signal. Moreover, using the PE ratio to determine instances of high valuation can identify more beneficial hedging opportunities than using the bond–stock earnings yield differential. Our methodology generates more efficient signals than other commonly used technical analyses such as the death cross technical indicator. Another strength of this signal is that the methodology is easy to implement and maintain. Moreover, the data requirement for the signal is not demanding. Daily total returns and price-to-earnings ratios are the two data inputs required for building the signal. For risk management purposes, one can also interpret the signal as an indicator for the beginning of a high-volatility regime for a sector index. One weakness of the proposed signal could be its performance during the COVID-19 pandemic. The limitation of this signal could be related to specific, simultaneous formations of bubbles across sectors, making the correlation criterion less effective. A future research project is to improve the current signal by incorporating other hedging signals or more market metrics as indicators of high valuation. Another possible extension to investigate is this methodology's potential application to timing the crash of an individual stock.

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Notes

1. The real estate sector is excluded from this study because it has a shorter data history than the other ten sectors.
2. According to the description provided by Bloomberg, the price is an index's "Last Price" (i.e., Bloomberg code PX_Last). A constituent stock's EPS (earnings per share) are based on the trailing 12-month EPS aggregate. The sector index EPS are calculated by summing up each constituent's weight in the index multiplied by the constituent stock's EPS.
3. Not all sectors have PE data from April 1990. However, all sectors have daily PE data starting from August 1991.
4. The empirical conditional distribution tables are available upon request.
5. For the monthly return calculation, we define a monthly return as the return during four weeks. For example, the first monthly return is from 5 January 2000 to 1 February 2000.
6. The discussion of various option implementations and the cost of downside risk hedging will be a separate topic beyond the scope of this study. This is because many possible hedging implementations depend on investors' risk management objectives and policies. We gathered the put option premium from the Bloomberg terminal to achieve a sense of the hedging cost. On the signal dates, the six-month premiums of at-the-money put options average about 7% of the underlying sector index value.
7. Assuming the manager can hold sector index options in his/her strategy.
8. It is very rare for z-score to be bigger than 2.5.
9. The result is the same as the first signal date in Table 4.
10. The detailed results of this analysis are available upon request.

References

Aboura, Sofiane. 2014. When the US stock market becomes extreme? *Risks* 2: 211–25. [CrossRef]

Abreu, Dilip, and Markus K. Brunnermeier. 2003. Bubbles and crashes. *Econometrica* 71: 173–204. [CrossRef]

Ausloos, Marcel, Kristinka Ivanova, and Nicolas Vandewalle. 2002. Crashes: Symptoms, diagnoses and remedies. In *Empirical Science of Financial Fluctuations*. Tokyo: Springer, pp. 62–76.

Berge, Klaus, Giorgio Consigli, and William T. Ziemba. 2008. The predictive ability of the bond-stock earnings yield differential model. *The Journal of Portfolio Management* 2008: 63–80. [CrossRef]

Boubaker, Sabri, Zhenya Liu, Tianqing Sui, and Ling Zhai. 2022. The mirror of history: How to statistically identify stock market bubble bursts. *Journal of Economic Behavior & Organization* 204: 128–47.

Cajueiro, Daniel O., Benjamin M. Tabak, and Filipe K. Werneck. 2009. Can we predict crashes? The case of the Brazilian stock market. *Physica A: Statistical Mechanics and its Applications* 388: 1603–9. [CrossRef]

da Silva, Paulo Pereira. 2022. Crash risk and ESG disclosure. *Borsa Istanbul Review* 22: 794–811. [CrossRef]

Deng, Shangkun, Yingke Zhu, Shuangyang Duan, Zhe Fu, and Zonghua Liu. 2022. Stock Price Crash Warning in the Chinese Security Market Using a Machine Learning-Based Method and Financial Indicators. *Systems* 10: 108. [CrossRef]

Dichtl, Hubert, Wolfgang Drobetz, and Tizian Otto. 2023. Forecasting Stock Market Crashes via Machine Learning. *Journal of Financial Stability* 65: 101099. [CrossRef]

Dolvin, Steven D. 2014. The Efficacy of Trading Based on Moving Average Indicators: An Extension. *The Journal of Wealth Management* 17: 52–57. [CrossRef]

Farago, Adam, and Roméo Tédongap. 2018. Downside risks and the cross-section of asset returns. *Journal of Financial Economics* 129: 69–86. [CrossRef]

Focardi, Sergio M., and Frank J. Fabozzi. 2014. Can We Predict Stock Market Crashes? *The Journal of Portfolio Management* 40: 183–95. [CrossRef]

Fu, Junhui, Xiang Wu, Yufang Liu, and Rongda Chen. 2021. Firm-specific investor sentiment and stock price crash risk. *Finance Research Letters* 38: 101442. [CrossRef]

Galsband, Victoria. 2012. Downside risk of international stock returns. *Journal of Banking & Finance* 36: 2379–88.

Guan, Chong, Wenting Liu, and Jack Yu-Chao Cheng. 2022. Using social media to predict the stock market crash and rebound amid the pandemic: The digital 'haves' and 'have-mores'. *Annals of Data Science* 9: 5–31. [CrossRef]

Guerron-Quintana, Pablo A., Tomohiro Hirano, and Ryo Jinnai. 2023. Bubbles, crashes, and economic growth: Theory and evidence. *American Economic Journal: Macroeconomics* 15: 333–71. [CrossRef]

Hull, John C. 2018. *Options Futures and Other Derivatives*, 10th ed. New York: Pearson Education.

Jarrow, Robert. 2012. Detecting asset price bubbles. *The Journal of Derivatives* 20: 30–34. [CrossRef]

Leiss, Matthias, Heinrich H. Nax, and Didier Sornette. 2015. Super-exponential growth expectations and the global financial crisis. *Journal of Economic Dynamics and Control* 55: 1–13. [CrossRef]

Lleo, Sebastien, and William T. Ziemba. 2012. Stock market crashes in 2007–2009: Were we able to predict them? *Quantitative Finance* 12: 1161–87. [CrossRef]

Lleo, Sebastien, and William T. Ziemba. 2015. Some historical perspectives on the bond-stock earnings yield model for crash prediction around the world. *International Journal of Forecasting* 31: 399–425. [CrossRef]

Lleo, Sebastien, and William T. Ziemba. 2017. Does the bond-stock earnings yield differential model predict equity market corrections better than high P/E models? *Financial Markets, Institutions & Instruments* 26: 61–123.

Lleo, Sebastien, and William T. Ziemba. 2019. Can Warren Buffett forecast equity market corrections? *The European Journal of Finance* 25: 369–93. [CrossRef]

Mercik, Aleksander R. 2023. Is tail risk priced in the cross-section of international stock index returns? *Modern Finance* 1: 17–29. [CrossRef]

Molina-Muñoz, Jesús, Andrés Mora-Valencia, and Javier Perote. 2020. Market-crash forecasting based on the dynamics of the alpha-stable distribution. *Physica A: Statistical Mechanics and Its Applications* 557: 124876. [CrossRef]

Munoz Torrecillas, Maria Jose, Rossitsa Yalamova, and Bill McKelvey. 2016. Identifying the Transition from Efficient-Market to Herding Behavior: Using a Method from Econophysics. *Journal of Behavioral Finance* 17: 157–82. [CrossRef]

Neely, Christopher J., David E. Rapach, Jun Tu, and Guofu Zhou. 2014. Forecasting the equity risk premium: The role of technical indicators. *Management Science* 60: 1772–91. [CrossRef]

Rousseeuw, Peter J., and Mia Hubert. 2011. Robust statistics for outlier detection. *Wiley Interdisciplinary Reviews: Data mining and Knowledge Discovery* 1: 73–79. [CrossRef]

Rousseeuw, Peter J., and Mia Hubert. 2018. Anomaly detection by robust statistics. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 8: e1236. [CrossRef]

Smith, C. Michael. 2017. Trading moving average crossovers: Further testing of risk-adjusted and after-tax returns. *The Journal of Wealth Management* 20: 94–100. [CrossRef]

Sornette, Didier. 2009. *Why Stock Markets Crash: Critical Events in Complex Financial Systems*. Princeton: Princeton University Press.

Sul, Hong Kee, Alan R. Dennis, and Lingyao Yuan. 2017. Trading on twitter: Using social media sentiment to predict stock returns. *Decision Sciences* 48: 454–88. [CrossRef]

Tran, Kim Long, Hoang Anh Le, Cap Phu Lieu, and Duc Trung Nguyen. 2023. Machine Learning to Forecast Financial Bubbles in Stock Markets: Evidence from Vietnam. *International Journal of Financial Studies* 11: 133. [CrossRef]

Tsakonas, Stefanos, Michael Hanias, Lykourgos Magafas, and Loukas Zachilas. 2022. Application of the moving Lyapunov exponent to the S&P 500 index to predict major declines. *Journal of Risk* 24. [CrossRef]

Whitehouse, Emily J., David I. Harvey, and Stephen J. Leybourne. 2023. Real-Time Monitoring of Bubbles and Crashes. *Oxford Bulletin of Economics and Statistics* 85: 482–513. [CrossRef]

Xiong, James X., Thomas M. Idzorek, and Roger G. Ibbotson. 2016. The economic value of forecasting left-tail risk. *The Journal of Portfolio Management* 42: 114–23. [CrossRef]

Xu, Yahua, Jun Xiao, and Liguo Zhang. 2020. Global predictive power of the upside and downside variances of the US equity market. *Economic Modelling* 93: 605–19. [CrossRef]

Yousaf, Imran, and Arshad Hassan. 2019. Linkages between crude oil and emerging Asian stock markets: New evidence from the Chinese stock market crash. *Finance Research Letters* 31. [CrossRef]