Open Journal of Business and Management, 2025, 13(3), 2099-2119
https://www.scirp.org/journal/ojbm
ISSN Online: 2329-3292
ISSN Print: 2329-3284

Portfolios, Stock Market Indices and Investment Strategies

Yihan Wu

School of Mathematical Sciences, Shanghai Jiao Tong University, Shanghai, China
Email: caracalla@sjtu.edu.cn

How to cite this paper: Wu, Y. H. (2025). Portfolios, Stock Market Indices and Investment Strategies. *Open Journal of Business and Management, 13,* 2099-2119.
https://doi.org/10.4236/ojbm.2025.133109

Received: April 7, 2025
Accepted: May 19, 2025
Published: May 22, 2025

Abstract

Introduction: In an increasingly interconnected global economy, investors seek strategies to preserve capital and enhance growth, particularly during financial crises. This study investigates capital hedging strategies and stock market index prediction, focusing on the distinct behaviors of stock markets in India, Singapore, and Qatar. Despite globalization, these markets exhibit unique trends influenced by factors such as exchange rates and commodity prices. **Methods:** We utilize a dataset from Bloomberg containing daily stock market indices and macroeconomic signals from major global markets. Time series analysis, including stationarity tests and regression modeling, is applied to identify key economic indicators that impact stock market performance. Additionally, we conduct portfolio simulations to determine optimal asset allocations under different crisis scenarios. The study quantitatively analyzes three major financial crises—the 2008 global financial crisis, the 2015-2016 market downturn, and the 2020 COVID-19 crash—to assess market responses and recovery patterns. **Results:** Empirical findings reveal that stock markets retain regional characteristics despite global integration. The Indian stock market's prolonged bull run correlates strongly with exchange rate trends, while Qatar's market is significantly influenced by oil prices. Portfolio analysis suggests that diversification across regions reduces risk and enhances stability during crises. **Conclusion:** This study contributes to the literature on regional market performance, crisis-driven market dynamics, and stock market prediction. The findings offer valuable insights for investors in designing resilient portfolios and understanding key economic factors driving stock market fluctuations.

Keywords

Stock Market Prediction, Financial Crises, Portfolio Analysis, Time Series Analysis, Emerging Markets

1. Introduction

Many people are concerned about the profits and losses in the stock market. Especially in the unpredictable global economic environment of the 21st century, investors worldwide are contemplating how to preserve their assets and promote capital growth. This paper conducts research in two areas: capital hedging during economic crises and the prediction of stock market indices, with the aim of providing valuable references for global investors.

A series of empirical studies have explored the P/S ratio and its impact on stock prices. The earliest study by Brown (1967) introduced the concept of the P/S ratio. Subsequently, Nicholson, Smith, & Willis (1979) argued that the importance of the P/S ratio is not as significant as the P/E ratio. Senchack Jr. and Martin (1987) studied the impact of the P/S ratio pricing strategy on stock prices, finding that low P/S ratio stocks performed better in terms of absolute and risk-adjusted returns, outperforming high P/S ratio stocks and the equally weighted market portfolio, and were effective even for loss-making companies. Suzuki (1998) studied simple investment factors on the Tokyo Stock Exchange, finding that over 14 years, low P/S ratio stocks outperformed low P/B and low P/E portfolios, allowing investors to choose from a broader range of industries and reduce portfolio risk. Nathan, Sivakumar, & Vijayakumar (2001) demonstrated that trading strategies based on the P/S ratio yield significantly higher excess returns than those based on the P/E ratio, and that combining both ratios yields even higher excess returns. However, these studies primarily focus on the overall market without distinguishing the impact of the P/S ratio on different groups. Therefore, it is necessary to analyze the P/S ratio patterns of different groups and their impact on market prices.

Other studies have explored the P/E ratio and its determinants over time. The earliest study by Johnson and Shirer (1930) examined the relationship between the P/E ratio and market behavior. Subsequently, Pari et al. (1989) studied the correlation of the P/E ratio with short-term and long-term growth rates, as well as its negative correlation with expected return rates. Ramcharran (2002) focused on emerging markets and identified growth (earnings potential) as a determinant of cross-country variations in P/E ratios. Leibowitz (2002) explored how higher leverage leads to a decrease in the P/E ratio. Anderson and Brooks (2006) found that long-term calculations of the P/E ratio significantly enhanced the value premium. Bodhanwala (2014) studied portfolios constructed based on low P/E ratios outperforming benchmark market returns. Most recently, Park (2021) highlighted how cyclically adjusted P/E ratios better reflect market mispricing.

Persson & Ståhlberg (2007) pointed out that it is possible to outperform the overall stock market by investing in undervalued stocks according to the EV/EBITDA. Iltas, Arslan, & Kayhan (2017) argue that a decline in EV/EBITDA increases stock returns.

Öztürk & Karabulut (2018) in "The Relationship between Earnings-to-Price, Current Ratio, Profit Margin and Return: An Empirical Analysis on Istanbul Stock Exchange" concluded that stocks with higher profit margins generate higher returns in the next period. Handayani and Winarningsih (2020) in "The Effect of Net Profit Margin and Return on Equity Toward Profit Growth" demonstrated that Net Profit Margin (NPM) has an impact on profit growth and calculated its coefficient of determination.

Gupta & Banerjee (2019) in "Does OPEC news sentiment influence stock returns of energy firms in the United States?" concluded that PTBV is positively correlated with excess market returns.

I have obtained a dataset collected by Bloomberg containing daily stock market indices and daily macroeconomic signals from the world's major stock markets, providing us with an opportunity to study the aforementioned indicators. By analyzing the data, I can observe the relationship between major stock market events of the 21st century and the rise and fall of stock markets. I also explored the top-performing portfolios across different markets. Additionally, I can use mathematical tools to analyze the relationship between macroeconomic signals and stock market indices.

Firstly, I selected the composite stock indices of three stock markets: India, Singapore, and Qatar, and conducted a study on their gains and losses over the past 20 years. I found that although many stock market news and historical events have global impacts, the stock markets of these three Asian countries have retained their unique characteristics. India's Nifty index has been known for its prolonged bull market, reflecting both the strong confidence of Indian investors in the stock market and the exchange rate of the Indian Rupee. However, some analysts argue that the Nifty50 only represents large-cap stocks and cannot reflect the situation of mid-cap and small-cap stocks. As a developed country, Singapore's stock index is relatively stable overall. Meanwhile, Qatar's stock index is significantly influenced by oil prices.

Next, I conducted a quantitative study on three major stock market recessions: the financial crisis of 2008, the 2015-2016 stock market crash, and the global stock market crash caused by the COVID-19 pandemic in 2020. I quantitatively compared the consequences of these three stock market crashes.

Following this, I attempted to identify the portfolio with the highest returns or the lowest risks under different scenarios. I simulated the portfolios I obtained using the three crises of the 21st century, each with different causes and processes, as well as the recovery periods following these crises. From the perspective of U.S. investors, I identified the most suitable portfolio.

Finally, I sought to analyze the relationship between the composite stock indices and the stock market signatures. First, I applied time series analysis methods to identify those series that are stationary or have unit roots. I then performed regression analysis between all the series that had their unit roots removed and the time series of the stock indices, identifying the signatures that are correlated. This allowed us to analyze the factors that most influence the major stock markets.

I contribute to the following finance literatures. Firstly, my research contributes to the literature exploring regional market performance differences in the context of globalization. While existing studies often focus on the overall trends and volatility of global stock markets, my analysis of the long-term gains and losses in the Indian, Singaporean, and Qatari markets provides empirical evidence of the unique behaviors and driving factors of specific national markets. Although globalization has influenced stock markets worldwide, I found that these markets retain distinct regional characteristics, particularly in terms of their performance and potential for long-term investment. This discovery offers a new perspective for understanding investment opportunities in different markets and fills a gap in the study of regional markets under globalization.

Secondly, my research contributes to the existing literature on market behavior during financial crises. In these studies, market reactions are typically explored through the analysis of single crisis events, whereas I provide a quantitative comparison of the 2008, 2015-2016, and 2020 global stock market crashes, revealing patterns in market responses and recovery paths during different crises. Despite the complexity and diversity of market crisis behavior, my study demonstrates that there are certain regularities in how different markets respond to crises. This provides an empirical foundation for investors to develop strategies to cope with future crises, filling a gap in the cross-crisis comparative analysis in market crisis research.

Thirdly, my research contributes to the literature exploring the relationship between stock market indicators and market factors. Existing studies on time series analysis and the identification of market factors often focus on the overall volatility of the market, lacking in-depth exploration of specific market impact factors. By employing time series analysis and regression analysis, I identified key market signatures related to stock indices, revealing the major factors influencing several significant stock markets. This finding not only enriches the application of time series analysis in market research but also provides empirical support for better understanding the driving factors behind market fluctuations, filling a gap in the detailed identification of market prediction research.

The remainder of this paper is organized as follows. Section 3 discusses the fluctuations and causes of the three stock market indices in this century. Section 4 discusses the portfolio options available to U.S. investors. Section 5 discusses the relationship between the fluctuations of the three stock market indices and various financial signatures. Section 6 concludes the paper.

2. Analysis of Asian Stock Indices' Dynamics

2.1. Composite Stock Index Trend

In this chapter, I have selected India's NIFTY Index, Singapore's STI Index, and Qatar's DSM Index as the main objects of study. Since India is a developing country, Singapore is a developed country, and Qatar is a wealthy Middle Eastern country rich in oil and gas resources, I expect their stock price indices to reflect their unique characteristics. The indices of these three stock markets are updated daily on weekdays according to their respective statutory operating hours: NIFTY and STI are generally updated from Monday to Friday, while DSM is typically updated from Sunday to Thursday.

By studying my unique dataset, I can plot the rise and fall trends of the three stock markets from January 1, 2000, to October 27, 2022 as in Figures 1-3.

Figure 1. Trends of DSM Stock Index (2000-2022). Data source: Bloomberg. **X-axis:** Time (Years from 2000 to 2022). **Y-axis:** DSM Stock Index Value.

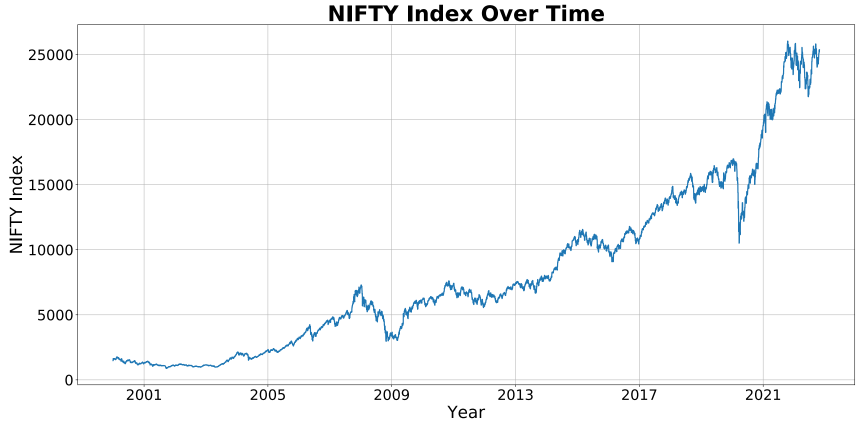

Figure 2. Trends of NIFTY Stock Index (2000-2022). Data source: Bloomberg. **X-axis:** Time (Years from 2000 to 2022). **Y-axis:** NIFTY Stock Index Value.

Figure 3. Trends of STI Stock Index (2000-2022). Data source: Bloomberg. **X-axis:** Time (Years from 2000 to 2022). **Y-axis:** STI Stock Index Value.

India's stock index has exceeded 25,000 points at its peak and is now over 60,000 points. Over the past 20 years, it has generally maintained a trend of rapid growth with some fluctuations, earning the reputation of being an enduring bull market.

Singapore's stock index has been relatively stable overall, with its peak not surpassing 6000 points. The general trend shows slow growth amid fluctuations, with faster growth in the 2000s and slower growth in the 2010s.

Qatar's stock index has also grown rapidly, but with very large swings.

Due to the unique characteristics of the stock indices of India and Qatar, I will conduct some qualitative analysis. Some evidence indicates that in countries that have experienced severe inflation in the 21st century, stock market indices tend to be correlated with FX indices. An increase in the FX index often indicates a depreciation of the domestic currency relative to a basket of currencies, which may signal inflation. As a result, the market may have greater confidence in the companies reflected in these indices (Ülkü & Demirci, 2012). So, I found India's FX index and made some comparisons with India's composite stock price index (**Figures 2-4**).

I discovered a pattern that aligns with my hypothesis. As one of the countries whose currency has experienced the most severe depreciation this century, I attempted to find the same pattern in Argentina's stock market, and indeed, I did (**Figure 5** and **Figure 6**).

As for Qatar, it is a Middle Eastern country whose primary industry is oil. During the period from 2007 to 2009, DSM first surged, then plummeted, and surged again, lagging somewhat behind other economies. The reason is likely that global oil prices continued to rise until July 2008, after which they began to fall sharply, and then quickly rose again in 2009, which closely matches DSM's trend. Therefore, I hypothesize that the fluctuations in Qatar's stock market are closely related to oil prices. I compared the global oil price trends with Qatar's composite stock index, and the conclusion confirmed my hypothesis (**Figures 1-7**).

Figure 4. FX Index of India (2000-2022). **X-axis:** Time (Years from 2000 to 2022). **Y-axis:** FX Index of Indian Rupee.

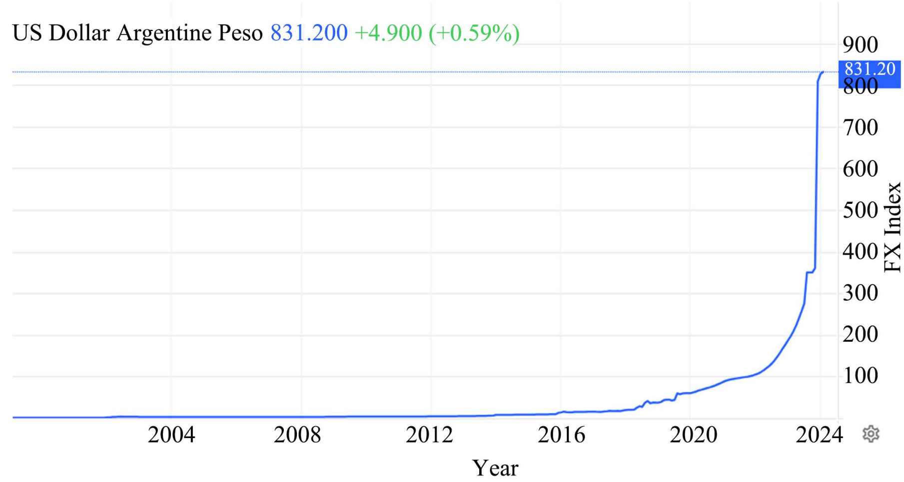

Figure 5. FX Index of Argentina (2000-2022). **X-axis:** Time (Years from 2000 to 2022). **Y-axis:** FX Index of Argentine Peso.

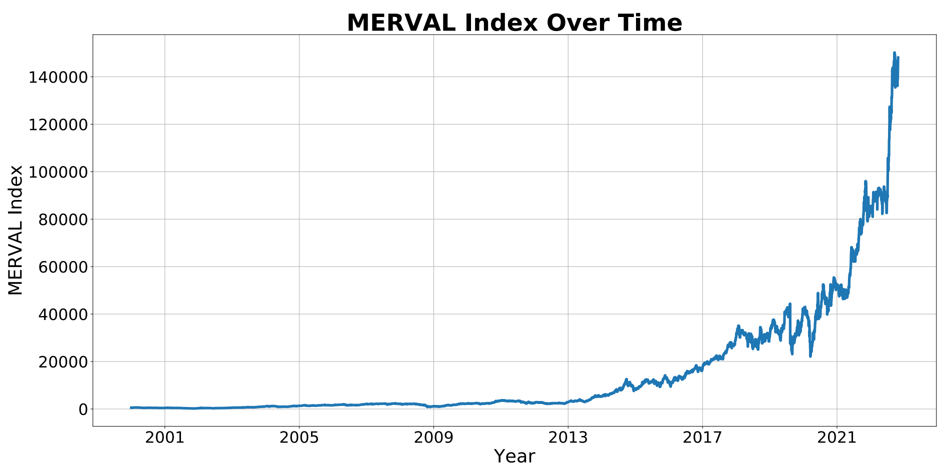

Figure 6. Trends of MERVAL Stock Index (2000-2022). Data source: Bloomberg. **X-axis:** Time (Years from 2000 to 2022). **Y-axis:** MERVAL Stock Index Value.

Figure 7. Crude Oil Price Index (2000-2022). **X-axis:** Time (Years from 2000 to 2022). **Y-axis:** Crude Oil Price (USD per Barrel).

2.2. Three Major Crisis

In the next phase of my research, I will study and attempt to identify the best-performing investment portfolios during times of crisis. To establish benchmarks, I will identify three major global stock market crashes in the 21st century and precisely define them within my dataset. The first one is the subprime mortgage crisis, which had the most far-reaching impact.

In early 2008, concerns about a U.S. recession, the uncontrollable U.S. subprime mortgage crisis, and the massive unwinding activities following Société Générale trader Jérôme Kerviel's alleged unauthorized large trades on European stock index futures triggered a global stock market crash (Acharya & Richardson, 2009). On January 21, 2008, global stock markets, except for the U.S. (which was closed), saw a significant drop, with an average decline of 5%. India's market fell by 9%, Qatar's by 5.5%, and Singapore's by 4.3%. The following day, Asian markets continued to plunge, with India dropping 6% and Singapore 7.8%. However, the Federal Reserve's sharp interest rate cut before the market opened partially alleviated the downturn, though volatility in Asian markets remained severe.

In the second half of 2008, as the crisis spread through credit derivatives impacting other companies, global stock markets experienced several rounds of sharp declines. Several trading days saw drops that exceeded those of Black Monday on January 21, although there were also days of strong market rallies amid the crashes.

From June 2015 to June 2016, the world stock markets went through another crash, with the A-share circuit breaker mechanism causing a crash in early 2016, low oil prices, and Brexit being identified as key causes. It wasn't until July 2016 that global stock markets largely recovered (Cassis & Wójcik, 2018).

In early 2020, the rapid global spread of the COVID-19 pandemic led governments to implement large-scale lockdowns, restrict travel, and curtail economic activities. Fears over the severe economic impact of these measures—such as business shutdowns, supply chain disruptions, and rising unemployment—further exacerbated market panic.

After bottoming out in March 2020, the stock market began to rebound, driven by economic recovery and a surge in tech stocks in the latter half of the year.

Based on the data and insights gathered from the previous two sections, I will design the portfolio to be studied in the next chapter.

3. Portfolio Research and Construction

In this chapter, I attempt to identify the most effective portfolio to ensure minimal losses and the most stable structure during the financial crisis mentioned in the previous chapter. This typically means achieving higher and more stable returns, a higher Sharpe ratio, and relatively smaller maximum drawdowns during global stock market downturns. I approach this issue from the perspective of U.S. investors.

3.1. Statistical Characteristics of a Specific Market

To achieve the aforementioned goals, I first need to calculate the statistical characteristics of the stock markets of the three selected countries. I will begin by defining the concept of returns. Since the indices of each stock market differ in terms of update times and frequencies, in order to standardize, I set: $MI_n \triangleq$ stock index on 1th this month $MI_{n+1} \triangleq$ stock index on 1th next month, and monthly return M_n is calculated as:

$$M_n = \frac{MI_{n+1} - MI_n}{MI_n}$$

When calculating annual statistics, I typically multiply the statistics calculated from monthly data by a specific coefficient.

Using this method, I calculated the data for the three stock markets of monthly return. I provide an illustration to give readers a more intuitive understanding (Figures 8-10).

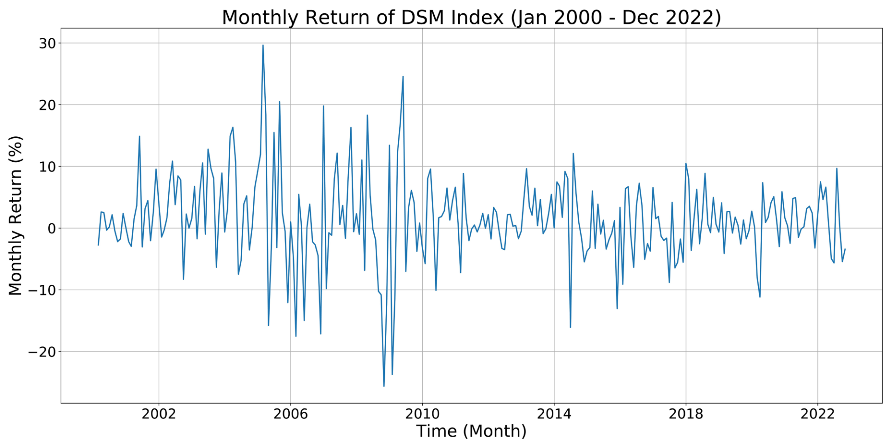

Figure 8. DSM's return by month **X-axis:** Time (Months from January 2000 to December 2022). **Y-axis:** Monthly Return of DSM Index (%).

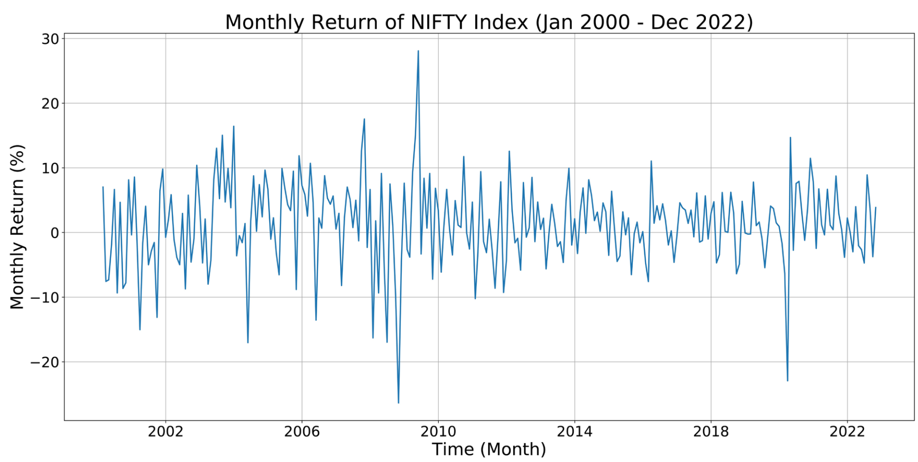

Figure 9. NFITY's return by month **X-axis:** Time (Months from January 2000 to December 2022). **Y-axis:** Monthly Return of NIFTY Index (%).

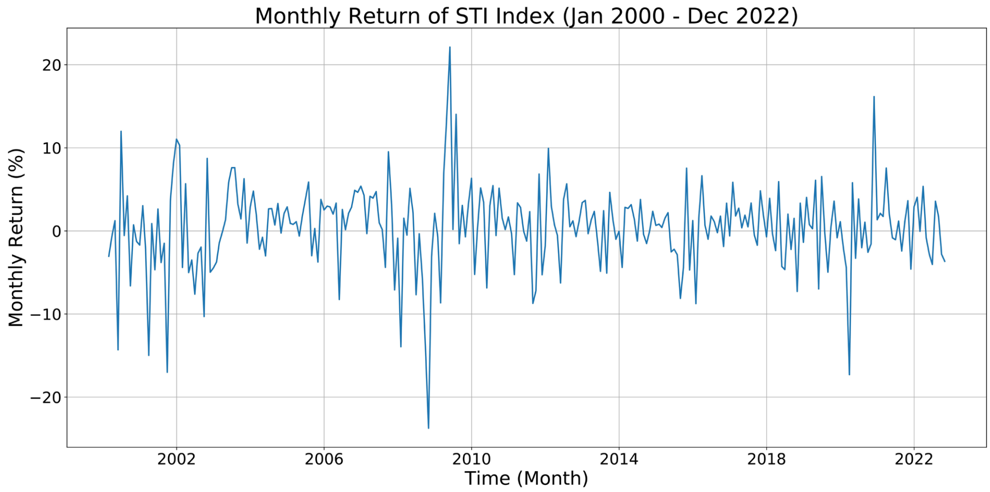

Figure 10. STI's return by month **X-axis:** Time (Months from January 2000 to December 2022). **Y-axis:** Monthly Return of STI Index (%).

For these data, I selected the mean, standard deviation, skewness, kurtosis, Sharpe ratio, and maximum drawdown as the statistical measures for my study. Among them, the Sharpe ratio is a measure of risk-adjusted return. It is used to assess how much excess return an investor can earn for each unit of risk taken. Specifically:

$$\text{Sharpe Ratio} = \frac{R_p - R_f}{\sigma_p}$$

while:

- R_p: The expected return of the portfolio;
- R_f: Risk-free return (commonly approximated using government bond yields);
- σ_p: The standard deviation of the portfolio's returns, representing the investment's risk or volatility.

Maximum drawdown is an important indicator for measuring the largest potential loss that an investment or trading strategy may experience over a specific period. It represents the maximum decline in asset price from its peak to its lowest point during a given time frame and is one of the commonly used metrics in risk management. The calculation formula is as follows:

$$\text{MDD} = \frac{\text{Peak Value} - \text{Trough Value}}{\text{Peak Value}}$$

while:

- **Peak Value** The highest value of the asset's net worth during a specific period;
- **Trough Value** The lowest net worth of the asset during the same period.

Without detailing my calculation process, I present the results in Table 1.

This table reports the general statistical characteristics of the three stock markets and USA's stock market we studied. We primarily calculated the means, standard deviation, skewness, kurtosis, Sharpe ratio, and maximum drawdown.

Table 1. General statistic characteristics.

	Statistic	Monthly	Annualized
NIFTY			
	Mean	1.2%	14.4%
	Standard Deviation	6.5%	22.5%
	Skewness	−0.335	
	Kurtosis	2.226	
	Sharpe Ratio	18.9%	
	Maximum Drawdown	54.6%	
DSM			
	Mean	1.4%	16.8%
	Standard Deviation	7.1%	29.6%
	Skewness	0.016	
	Kurtosis	2.355	
	Sharpe Ratio	20.3%	
	Maximum Drawdown	61.0%	
STI			
	Mean	0.4%	4.9%
	Standard Deviation	5.1%	17.7%
	Skewness	−0.508	
	Kurtosis	3.752	
	Sharpe Ratio	8.7%	
	Maximum Drawdown	56.0%	
SPX			
	mean	0.6%	7.3%
	std	4.4%	15.4%
	skewness	−0.504	
	kurtosis	0.852	
	Sharpe ratio	13.7%	47.6%
	maximum drawdown	50.9%	

3.2. Statistical Characteristics of Constructed Portfolios

Next, I will attempt to diversify the virtual capital to study the impact of the portfolio on investment returns and asset stability. I will conduct the following two sets of experiments: In the first set, I will evenly split the virtual capital and invest in the two selected markets, calculating the statistics for the three combinations.

In the second set, I will divide the virtual capital into three equal parts and invest in the three selected markets, observing the statistics. I will only analyze the standard deviation, Sharpe ratio, and maximum drawdown. Similarly, I present the results in **Table 2**. This table reports the Standard deviations, Sharpe ratios and Maximum drawdowns reflected in the portfolios constructed from the three markets we have researched, where the data in the first and second rows do not differentiate between selected countries.

Table 2. Statistical metrics of the portfolios.

std				
	One Country	6.5%	7.1%	5.1%
	Two Countries	5.6%	5.3%	5.1%
	Three Countries			
sharpe_ratio				
	One Country	18.9%	20.3%	8.7%
	Two Countries	23.8%	15.8%	18.5%
	Three Countries			
mdd				
	One Country	54.6%	61.0%	56.0%
	Two Countries	35.7%	37.3%	32.8%
	Three Countries			

It can be observed that the monthly return standard deviation of the portfolio with three countries is significantly lower than that of one or two countries. Additionally, the standard deviation of the portfolio returns for two countries is also lower than the arithmetic average of the individual standard deviations of the two countries. This suggests that the portfolio approach is beneficial in reducing risk.

The Sharpe ratio measures the cost-effectiveness of stock returns. It can be seen that the Sharpe ratio of the portfolio with three countries is greater than the average Sharpe ratio of the two-country portfolio, which is also greater than the Sharpe ratio of the single country.

The data on maximum drawdown is quite unique. I believe that a portfolio consisting of more than one stock is likely to lead to trend intermingling, thereby reducing the maximum drawdown value. Further increasing the number of stocks may have a less significant effect.

3.3. American Situation

First, I plot the fluctuations and the index of the American stock market (**Figure 11**).

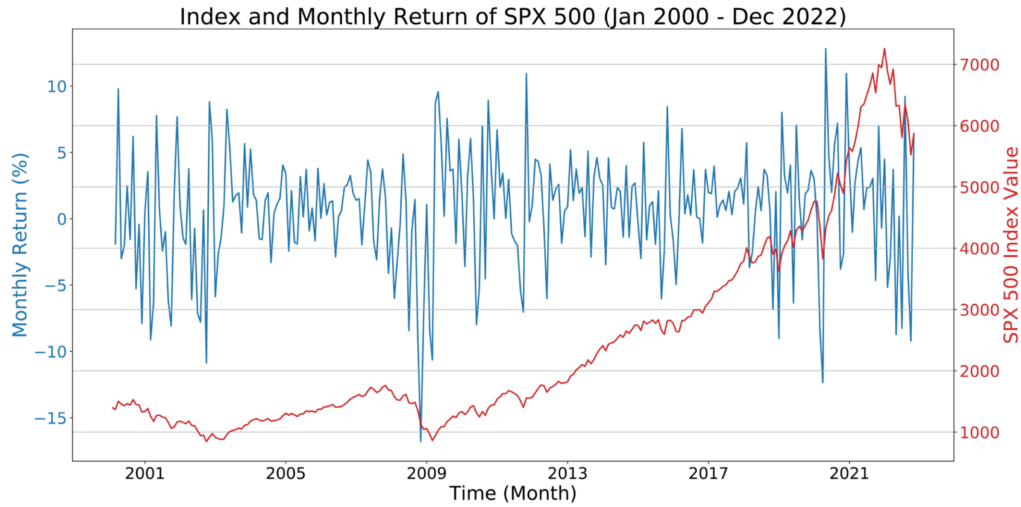

Figure 11. Index and Monthly Return of SPX 500. This figure presents the historical trend of the SPX 500 index along with its monthly return. The data illustrates major downturns during the 2008-09 financial crisis and the COVID-19 pandemic, followed by strong recovery phases. **X-axis:** Time (Months from January 2000 to December 2022). **Y-axis (Left):** Monthly Return of SPX 500 (%). **Y-axis (Right):** SPX 500 Index Value.

I first calculated some basic statistics of the American stock market, which can be found in **Table 1**.

It can be clearly seen that the American stock market has been mostly in a bull market over the past 20 years, with the only significant declines occurring during the 08-09 financial crisis and the COVID-19 pandemic period. So next, I will analyze these two stock market downturn events separately.

In the 08-09 stock market crash, my research method is to first find the highest point before the crash, then find the date when it returns to the highest point after the crash, and consider the period in between as the time of the crash outbreak and recovery.

Through calculation, the American stock market reached its highest point before the crash on October 31, 2007, at 1762.2373 points, dropped to 845.0403 points on February 27, 2009, and finally surpassed the high point from over four years ago on March 19, 2012.

It can be seen that the downturn lasted exactly 14 months, and the recovery period was longer, reaching 36 months. The maximum drawdown during this downturn reached 50.91%.

The stock market crash caused by the COVID-19 pandemic began on February 19, 2020, when the stock index was at 5004.825 points. On March 23, just one month later, the US stock market fell to 3313.683 points, with a retracement rate of 33.790%. By August 10, 2020, the US stock market had returned to 5000 points, which I believe can be considered the end of the aftermath of the stock market crash.

I organized some statistics for the two events, including skewness and kurtosis, which represent the situation over the entire period. Some characteristics can be observed in **Table 3**. This table reports the key statistics of the U.S. stock market during the two financial crises, including the six key statistics primarily studied in the table above.

Table 3. Summary statistics for different crisis periods.

Stats				
period	crash	recovery	crash	recovery
mean	−0.1%	0.1%	−0.9%	0.2%
std	2.0%	1.1%	3.1%	2.2%
skewness				
kurtosis				
Sharpe_ratio		6.3%		10.4%
drawdown				

In terms of similarities, both crises experienced a significant drop in stock indices followed by a gradual recovery, with the rate of decline during the downturn being faster than the rate of recovery. As for differences, the stock market crash caused by the pandemic unfolded and recovered more quickly than the financial crisis, had better profitability during the recovery phase, and overall, the impact of COVID-19 on the stock market was somewhat less severe than that of the financial crisis.

For an American, it is a reasonable idea to reduce risk and earn returns by investing in other stock markets during the downturn and recovery periods following a financial crisis. Therefore, I plan to determine the investment strategy for American investors by simulating investment portfolios during two crises.

3.4. Constructing Portfolios as American Investors

I set the investment portfolio as A, with each market represented as n_i, and the weight of each market within the portfolio as p_i.

$$A = \sum_{i=1}^{k} p_i n_i$$

The investment process I simulate is as follows: at a certain moment t_1, buy investment portfolio A with dollars, and then at another moment t_2, sell A to convert back into dollars.

Assuming temporarily that exchange rates remain unchanged, then at time t_1, I invest mi dollars in market n_i. Through this algorithm, I can calculate my actual wealth for each day between t_1 and t_2. I can then use this wealth to perform further statistical analyses. Simultaneously, I can also calculate the wealth based on this type of investment portfolio versus the wealth based on investing in the U.S. stock market alone, and make a comparison.

3.4.1. The Crash in 08-09 Financial Crisis

I first design the investment portfolio based on the stock market downturn period of the 2008-2009 crisis. During this process, I aim to have the highest possible mean, the smallest possible variance, and the smallest possible maximum drawdown.

In terms of means, through calculation (which proved to be of limited significance), it was discovered that the two stock markets that performed the best and the worst during this major downturn were the COLCAP index of Colombia, which showed a −0.03% downward, and the ICEXI index of Iceland, which experienced a −0.46% decline, more than that of the United States.

I discovered that, in a 1:1 portfolio, the stock markets of Malaysia and New Zealand demonstrated the best numerical stability during the 2007-2009 crisis: their standard deviation was only 0.84%. By contrast, U.S. stocks exceeded 2% (In the following chart, the situation of the Icelandic stock market is so outlandish that it affects the presentation of the data).

The portfolio with the smallest maximum drawdown was achieved by the combination of the Chilean and Argentine stock markets, suggesting that diversifying funds into South American stock markets might be a good strategy during the onset of a crisis.

3.4.2. The Recovery after 08-09 Financial Crisis

I will not elaborate further on the research method. At this stage, the Peruvian stock market exhibited the most remarkable recovery speed, which reached 0.12% while the Portuguese stock market was the slowest, which is 0.01%. Surprisingly, in terms of stability, the portfolio of Malaysia and New Zealand remained the most stable, with a standard deviation of 0.46%.

The portfolio of Colombia and the Philippines contributed the best Sharpe ratio, which is 13.6%, making it a very prosperous investment during the recovery period.

3.4.3. COVID-19

I'll follow suit and provide the results directly in **Table 4** without further elaboration on the thought process. **Table 4** reports the best and worst performing two markets during the COVID-19 pandemic, both in the market crash and recovery phases, along with the portfolios with the smallest standard deviation and maximum drawdown.

We conducted some experiments and exhausted various scenarios, discovering some patterns: For American investors, the Latin American stock markets often perform relatively well, while the economies of Southern Europe always tend to disappoint. The combination of developed countries and developing countries is often more stable. If one is pursuing a high Sharpe ratio during recovery periods, the performance of East Asian economies tends to be impressive. There are also some distinctions: The strong performance of Latin American countries' stock markets during the subprime mortgage crisis was weakened during the COVID-19 period, during which oil economies performed better.

Table 4. Extremes of figures during the COVID-19.

Period		
best means	CHINA	−0.31%
worst means	COLOMBIA	−1.77%
lowest std	MEXICO + NEW ZEALAND	1.44%
lowest mdd	CHINA + QATAR	12.12%
Period		
best means	ARGENTINA	0.33%
worst means	SPAIN	0.04%
lowest std	MALAYSIA + QATAR	0.63%
highest Sharpe_ratio	TAIWAN REGION OF CHINA + SAUDI ARABIA	20.52%

4. Test for Predictive Factors

In Chapter Five, I will face a unique task. My dataset contains a large number of economic indicators that reflect certain situations in various stock markets or economies. This chapter will focus on analyzing the economic factors that are most closely related to the three selected stock markets, thereby fulfilling the idea of serving stock market predictors.

4.1. Data Filtering

I have a complex dataset, and some data clearly cannot help in predicting stock market indices. Some of these data are updated annually, which may not adapt to the daily changes in stock price indices. Some have significant missing data, appearing for less than a year over twenty years, and the instability of data registration can also affect others' use.

I need to study the frequency of changes in these data, but such a large dataset appears to be chaotic, so I decided to use an algorithm to address this issue. I categorize the data into three types: daily, monthly, and annual data. The classification is executed based on the following algorithm: the number of data points divided by the number of times the data changes. If the result is close to 5, it is classified as daily data; if close to 30, as monthly data; and if close to 365, as annual data. Specifically, data with fewer than 1826 data points are not included in the calculation. There are 1573 factors which was recognized as daily updated.

I hope that this data consists of stationary series to facilitate the upcoming experiments. In time series analysis, a **stationary series** refers to a sequence whose statistical properties (such as mean, variance, and autocovariance) do not change over time. Analyzing and predicting stationary series is generally simpler than non-stationary series because their behavior is more predictable.

4.2. ADF Test and Standardizing

Next, to ensure that these data are stationary series, I will conduct unit root tests on each of them. The unit root test is a statistical test in time series analysis used to determine whether a time series is stationary or has a unit root. If a time series has a unit root, it is non-stationary and will exhibit long-term trends, with random shocks (such as economic events or policy changes) having permanent effects on the series. Conversely, if there is no unit root, the time series is stationary, and the effects of random shocks are temporary, causing the series to revert to the long-term mean.

I use the ADF test to determine the presence of a unit root. The ADF test, or Augmented Dickey-Fuller test, is a statistical method used to determine whether a time series has a unit root, thereby assessing if it is non-stationary. Developed by David Dickey and Wayne Fuller, this test is a crucial tool for detecting the presence of unit roots in time series data, and it is widely used in the analysis of economic and financial data.

The ADF test specifically targets the following model to test for a unit root:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \cdots + \delta_{p-1} \Delta Y_{t-p+1} + \epsilon_t$$

where:

- Y_t is the time series data.
- Δ is the first difference operator, i.e., $\Delta Y_t = Y_t - Y_{t-1}$.
- α represents a constant term (if present).
- βt is a trend component (if present).
- γ is the coefficient to be tested; the heart of the unit root test is testing the hypothesis $\gamma = 0$ (presence of a unit root) against $\gamma < 0$ (absence of a unit root).
- δ_i are coefficients of the autoregressive part.
- ϵ_t is the error term.
- p is the lag order, determined by the autocorrelation structure of the data.

And the steps are as follows:

1) Select Lag Length: The lag length p in the ADF test must be determined, which can be selected using information criteria such as AIC or BIC to choose the most appropriate number of lags.

2) Perform Regression Analysis: Based on the selected lag length, estimate the above ADF regression model.

3) Calculate Test Statistic: The core ADF statistic is the t-statistic of the γ coefficient in the regression. Theoretically, this statistic should be compared to specific critical values (from the distribution of unit root processes) rather than the critical values from a standard normal distribution.

The hypothesis testing is:

- **Null Hypothesis (H0)**: The series has a unit root ($\gamma = 0$).
- **Alternative Hypothesis (H1)**: The series does not have a unit root ($\gamma < 0$).

For each array, select the longest valid segment for the ADF test. I use the built-in adfuller function from statsmodels.tsa.stattools in Python, with a confidence interval of 5 percent.

I implemented the ADF test for these signal data using Python. For those signals that were not stationary, I also conducted the ADF test on their differences. Only one signal did not pass the test. All the data from the countries I are interested in (Singapore, India, Qatar, and the USA) passed both tests. I have also designed a program to standardize these signals.

4.3. Regression

I finally arrive at the last step: regression testing. I perform multiple linear regression tests on the previous n months of data for each series that passed the Filtering and ADF test against the stock index of the $n + 1$ month, as described in the algorithm below:

Set X_{mat} = The arrays of factors Set Y = The array of returns one month forward Set X_{mat} = df[the name of the factors] $X_{\text{mat}} = \text{sm.add\_constant}\left(X_{\text{mat}}\right)$

Build the linear model $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$ model = sm.OLS (Y , X_{mat}).fit()

The results indicate the related factors as follows in Table 5. This table reports some of the indices that are considered to have the strongest correlation with the three major stock markets. Markets and their most related factors (the value of $p > |t|$ is below 0.05.

Table 5. Results of the ADF test.

NIFTY	STI	DSM
CitiNarrowREER	BEST_EPS	CitiBroadREER
PROF_MARGIN	IDX_EST_DVD_YLD	BEST_PX_SALES_RATIO
	LONG_TERM_PRICE_ EARNINGS_RATIO	EST_PX_CASHFLOW_FY3_AGGTE
		PX_TO_TANG_BV_PER_SH

5. Robustness Check

In this robustness check, we include a comprehensive set of commonly used financial and macroeconomic indicators from the Citi dataset. These parameters encompass all frequently tracked signals in global financial analyses. Through extensive stationarity testing and regression modeling, we observe that the conclusions drawn from our model remain highly consistent and reliable. This indicates that the methodology developed in this study is not only valid within the present sample but also robust enough to support future research in financial market behavior. Furthermore, the experimental procedure and regression framework employed here are broadly applicable across global stock markets, demonstrating strong generalizability and scalability.

6. Conclusion

In conclusion, this study provides valuable insights into the unique characteristics and behaviors of the stock markets in India, Singapore, and Qatar over the past two decades. By examining the impact of major financial crises and employing quantitative methods to identify optimal portfolios, I contribute to the understanding of market dynamics in a globalized context. My analysis reveals that, despite globalization, these markets retain distinct regional traits that influence their performance and investment potential. Additionally, by comparing multiple market downturns, I highlight regularities in market responses, offering empirical foundations for future investment strategies. Furthermore, my exploration of the relationship between stock market indicators and underlying market factors enhances the existing literature by identifying key influences on market fluctuations. This research not only enriches my comprehension of regional market behaviors but also fills significant gaps in the study of market performance, providing a framework for further exploration and strategic investment decision-making.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Acharya, V. V., & Richardson, M. (2009). Causes of the Financial Crisis. *Critical Review, 21,* 195-210. https://doi.org/10.1080/08913810902952903

Anderson, K., & Brooks, C. (2006). The Long-Term Price-Earnings Ratio. *Journal of Business Finance & Accounting, 33,* 1063-1086. https://doi.org/10.1111/j.1468-5957.2006.00621.x

Bodhanwala, R. J. (2014). Testing the Efficiency of Price-Earnings Ratio in Constructing Portfolio. *IUP Journal of Applied Finance, 20,* 111-118.

Brown, R. D. (1967). *An Analysis of Market Behavior of Daily Newspapers.* Doctoral Dissertation, University of Illinois at Urbana-Champaign.

Cassis, Y., & Wójcik, D. (2018). *International Financial Centres after the Global Financial Crisis and Brexit.* Oxford University Press.

Gupta, K., & Banerjee, R. (2019). Does OPEC News Sentiment Influence Stock Returns of Energy Firms in the United States? *Energy Economics, 77,* 34-45. https://doi.org/10.1016/j.eneco.2018.03.017

Handayani, N., & Winarningsih, S. (2020). The Effect of Net Profit Margin and Return on Equity toward Profit Growth. *Moneter-Jurnal Akuntansi dan Keuangan, 7,* 198-204. https://doi.org/10.31294/moneter.v7i2.8701

Iltas, Y., Arslan, H., & Kayhan, T. (2017). The Stock Return Predictability: Comparing P/E and Ev/Ebitda. *Pressacademia, 4,* 262-274. https://doi.org/10.17261/pressacademia.2017.694

Johnson, N. O., & Shirer, J. T. (1930). Certain Aspects of the Interpretation of Price-Earnings Ratios. *Journal of the American Statistical Association, 25,* 106-110. https://doi.org/10.1080/01621459.1930.10503096

Leibowitz, M. L. (2002). The Levered P/E Ratio. *Financial Analysts Journal, 58,* 68-77. https://doi.org/10.2469/faj.v58.n6.2487

Nathan, S., Sivakumar, K., & Vijayakumar, J. (2001). Returns to Trading Strategies Based on Price-to-Earnings and Price-to-Sales Ratios. *The Journal of Investing, 10,* 17-28. https://doi.org/10.3905/joi.2001.319458

Nicholson, S. F., Smith, M., & Willis, R. B. (1979). Investment Perspectives—150 Years. *Financial Analysts Journal, 35,* 33-37. https://doi.org/10.2469/faj.v35.n6.33

Öztürk, H., & Karabulut, T. A. (2018). The Relationship between Earnings-to-Price, Current Ratio, Profit Margin and Return: An Empirical Analysis on Istanbul Stock Exchange. *Accounting and Finance Research, 7,* 109-115. https://doi.org/10.5430/afr.v7n1p109

Pari, R., Carvell, S., & Sullivan, T. (1989). Analyst Forecasts and Price/Earnings Ratios. *Financial Analysts Journal, 45,* 60-62. https://doi.org/10.2469/faj.v45.n2.60

Park, S. (2021). The P/E Ratio, the Business Cycle, and Timing the Stock Market. *The Journal of Portfolio Management, 47,* 165-183. https://doi.org/10.3905/jpm.2021.1.270

Persson, E., & Ståhlberg, C. (2007). *PE and Ev/Ebitda Investment Strategies vs. the Market: A Study of Market Efficiency.* Master's Thesis, Linköping University.

Ramcharran, H. (2002). An Empirical Analysis of the Determinants of the P/E Ratio in Emerging Markets. *Emerging Markets Review, 3,* 165-178. https://doi.org/10.1016/s1566-0141(02)00004-3

Senchack Jr., A., & Martin, J. D. (1987). The Relative Performance of the PSR and per Investment Strategies. *Financial Analysts Journal, 43,* 46-56. https://doi.org/10.2469/faj.v43.n2.46

Suzuki, M. (1998). PSR—An Efficient Stock-Selection Tool? *International Journal of Forecasting, 14,* 245-254. https://doi.org/10.1016/s0169-2070(98)00030-2

Ülkü, N., & Demirci, E. (2012). Joint Dynamics of Foreign Exchange and Stock Markets in Emerging Europe. *Journal of International Financial Markets, Institutions and Money, 22,* 55-86. https://doi.org/10.1016/j.intfin.2011.07.005

Appendix: List of Index

CitiNarrowREER: CitiNarrowREER is a Real Effective Exchange Rate (REER) index calculated by Citi, which measures a country's currency competitiveness relative to its narrow set of major trading partners, adjusted for inflation differences.

BEST EPS: BEST (Bloomberg Estimates) EPS reflects the consensus estimate of Earnings Per Share (EPS). The consensus estimate is the average of sell-side analyst projections.

CitiBroadREER: CitiBroadREER is a Real Effective Exchange Rate (REER) index calculated by Citi, which measures a country's currency competitiveness relative to a broader set of its trading partners, adjusted for inflation differences.

PROF_MARGIN: PROF_MARGIN refers to the 'profit margin', a financial metric that indicates the percentage of revenue a company retains as profit after expenses. It measures how effectively a company is managing its costs relative to its revenue. A higher profit margin means the company is able to keep a larger portion of its revenue as profit, signaling greater operational efficiency.

IDX_EST_DVD_YLD: IDX_EST_DVD_YLD is the Index Estimated Dividend Yield for the current year, calculated as the Estimated Dividends for Year 1 divided by the Last Price.

BEST_PX_SALES_RATIO: BEST_PX_SALES_RATIO is a financial metric that compares a company's stock price to its sales per share. It is used to assess the relative valuation of a company, evaluating how much investors are willing to pay for each unit of sales generated by the company. A higher ratio suggests strong future growth expectations, while a lower ratio may indicate undervaluation or lower growth prospects.

LONG_TERM_PRICE_EARNINGS_RATIO: The Long-Term Price-to-Earnings (P/E) ratio is calculated using the company's last price and the 10-year average real earnings per share (EPS). Real EPS is adjusted for inflation using the consumer price index (CPI) of the company's country. The 10-year average real EPS is computed from 40 quarters, 20 semi-annual periods, or 10 annual figures.

EST_PX_CASHFLOW_FY3_AGGTE: EST_PX_CASHFLOW_FY3_AGGTE is the Index Estimated Price-to-Book ratio for Fiscal Year Three (FY3), calculated as the Last Price divided by the Estimated Book Value for FY3 Aggregate.

PX_TO_TANG_BV_PER_SH: PX_TO_TANG_BV_PER_SH is a ratio that compares a company's stock price to its tangible book value per share, indicating how much investors are willing to pay for each unit of the company's tangible assets.