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Portfolio Diversification of Global Stock Indices and the Predictive Power of Macro-Economic Signals on the SPX Index

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Abstract

This study presents and analyzes the performance dynamics of NIFTY, SPX, and HSI indices from September 2011 to October 2022. Meanwhile, it also sheds light on the correlation between the major stock market indexes and macroeconomic signals (SPX and US macroeconomic signals here, for example). I employ a robust analytical framework and statistical tests to evaluate performance metrics and assess the performance of various diversified portfolios. Moreover, I apply regression techniques to explore the predictive power of macroeconomic signals on SPX movements. My key findings are: 1) specific diversification strategies significantly improve performance compared against individual indices, and 2) certain macroeconomic indicators demonstrate predictive power to the SPX index's performance.

Keywords

Stock Market, Macroeconomic Indicator, Return Forecasting, Portfolio Diversification

1. Introduction

1.1. Portfolio Diversification

In the dynamic landscape of global finance, the stock market plays an increasingly important role in ensuring this environment's liquidity and steady growth, which also indicates a more and more significant correlation between financial development and economic growth (Restis et al., 2001). Therefore, equity indices in different countries have become standard tools to evaluate the value of investing in specific environments. At this moment, to further develop stability and increase revenue, portfolio diversification based on the equity indices is one of those most critical and necessary methods. Though heterogeneity appears in the diversification choice because of factors such as age, wealth, or other behavioral biases, diversification still behaves to be able to help most investors improve their portfolios (Goetzmann & Kumar, 2008).

My research provides a novel approach to understanding the intricate effect of portfolio diversification by comparing and analyzing the combination of three key stock indices: the SPX, NIFTY, and HSI in terms of USD over the past two decades. The choice of these indices is not random, and each plays a unique and significant role in the global financial picture. The study aims to uncover the hidden patterns and connections that can influence investment performances across different regions and economic environments by analyzing these specific markets.

The SPX, which represents the performance of the largest publicly traded companies in the USA, is always considered a benchmark for the overall health of the U.S. stock market and economy, commonly considered the world's largest and most influential. While the US market is characterized by its depth, liquidity, and the presence of major global corporations, it's becoming apparent how the growth or any fluctuations in the US economy might influence the rest of the world. Followed by the study of Arora and Vamvakidis (2006), the influence of the growth of the US economy is not only different from but also exceeds that of any other common global shocks. In this case, I aim to conduct a reproducibility or replicability study about the role of SPX in the index portfolio to explore further how the US equity indexes performed in the diversified portfolio under the modern global economic shocks that might seriously influence the results of investments.

In contrast, the Indian market represented by the NIFTY index in my model resembles a rapidly developing yet unstable emerging entity. By carefully analyzing the unique performance of the NIFTY index over the past decade during major global economic fluctuations, comparing it with other equity indices in the model, and examining its impact when combined with other specific indices, I aim to figure out the characteristics of this high potential yet still developing economy. Meanwhile, a unique feature of the Indian market is that its integration with other markets largely depends on the currency it's measured by, and measuring in terms of the USD instead of local currencies would be more likely to cause the integration. In this case, when my research compares the Indian, US, and Hong Kong markets in terms of USD and calculates the return of the combination of them, the Indian market will have a closer relationship with the other markets (including both regional and global markets). Indian market will then play a special role in my portfolio diversification research since, in the long run, it is commonly influenced by the global market (US, UK market, etc.), and while in the short run, it will be more significantly affected by the regional market such as Hong Kong and Singapore market due to various financial and economic shocks. Such a market can effectively bridge the other components in my portfolio, Hong Kong SAR and the US (Dhal, 2009).

In addition to the SPX and NIFTY, the Hang Seng Index (HSI), which represents the Hong Kong market in my model, also plays a pivotal role in the diversified portfolio analysis. Just like the two indices above, HSI also tracks the performance of the most prominent and liquid companies listed on the Hong Kong Stock Exchange. Such an index can generally reflect the health of companies not just in Hong Kong SAR and mainland China but also in other Asian countries or regions. Meanwhile, as one of Asia's leading financial hubs, Hong Kong SAR also blends Western and Asian financial practices, which makes the HSI an even more crucial indicator for the economic connection between Western and Asia. Therefore, such a market has a strategic position and is like a gateway to mainland China. It also provides all investors unique access to the potential and dynamic Chinese economy while benefiting from the robust regulatory environment established in Hong Kong SAR. According to Meyer (2008), integrating Hong Kong's market with the global financial system has already made the Hong Kong market a significant player in the international finance game. Thus, its performance is influenced by both regional and global economic trends, as reflected in the dramatic increase in the value of the real net exports of services from Hong Kong SAR. Finally, in my diversified portfolio model, the Hong Kong market is more mature than the Indian market and less stable than the US market. It builds the connection between developed and emerging markets, which can balance the other two equity indices in my diversified portfolio, making it an indispensable component of a comprehensive investment strategy.

In conclusion, a diversified portfolio that combines the adjusted SPX, NIFTY, and HSI indices provides investors with a more flexible way of investing. Analyzing all of them together will also make the understanding of different markets more comprehensive. Over the past twenty years, a period marked by numerous significant events (such as the Mumbai hotel terrorist attacks, the 2007 global financial crisis, and the 2020 COVID-19 pandemic), investments have become especially uncertain, which further enhances the research value of this portfolio. My study aims to determine what the stability and global influence represented by SPX, the potential and volatility embodied by NIFTY, and the strategic position of the pioneer economy represented by HSI will be like when they interact.

1.2. Macroeconomic Signals and Equity Index (Using the SPX as an Example)

Having established the importance of my model of portfolio diversification through the analysis of the key global indices I choose to use, it is also necessary to understand what will influence the various global indices. It's also necessary to determine how macroeconomic signals predict stock market movements and, thus, the market's return in a particular period. Therefore, in order to optimize the investment plan and anticipate the market trends, it is crucial to find out the relationship between macroeconomic indicators and stock market indices.

Numerous studies have questioned the predictive relationship between macroeconomic signals and equity indices, and such a topic has always been controversial in the early times. According to one of Bernanke and Kuttner's (2005) studies, changes in federal reserve policy, especially unexpected monetary policy actions, substantially impact stock prices. However, Flannery and Protopapadakis (2002) noted that most previous studies have merely found little evidence to prove that equity market returns respond to macroeconomic developments. Even when some evidence was found, these studies typically focused solely on the effects of inflation and money supply on equity returns, similar to the focus of Bernanke and Kuttner's study. Hence, to determine if the relationship between macroeconomic signals still exhibits a similar time-varying coefficient with the equity returns like before, and to assess whether this relationship still remains difficult to detect with the constant coefficient model, I decided to focus on the US market and filter the signals from border to narrower categories.

In my research, I start with various macroeconomic signals that are recorded by the City Bank, which can possibly influence equity index performance and are always used by City Bank to evaluate the economy of countries. Since all these indicators offer incredibly valuable insights into the health of a country's market, it's quite possible that investors might want to use these signals to predict the future trends of a particular market. And finally, analyzing the correlation between these signals and the equity indices is especially appropriate here. According to around fifty macroeconomic signals about the United States economy in the Bloomberg terminal, some might not have a significant correlation with the SPX index (the equity index I chose here to represent the US Market). To find those typical data that are relatively more important and enlightened, I apply different tests to finally only keep the signals that have sufficient data recorded for study. Consequently, I can find out the correlation between the US macroeconomic signals and SPX to further understand what types of signals are more time-varying.

The remainder of my paper is written as follows. Section 2 examines data collection, individual index performance, the impact of significant global events, and various portfolio strategies. Section 3 explores the relationship between macroeconomic indicators and equity indices, including data preparation and regression analysis. Finally, Section 4 summarizes key findings, discusses implications for investors and financial analysts, and suggests areas for future research.

2. Diversified Portfolio Study

2.1. Data and Methodology

My study analyzes the performance of the adjusted three key equity indices, which are the SPX (S&P 500), the NIFTY (Nifty 50 Index), and the HSI (Hang Seng Index), over the period from September 2000 to October 2022. Initially, I collected adjusted[1] equity index data from 122 countries to evaluate the global market comprehensively, and each country was assigned a unique list number for identification, ranging from 1 (ANGOLA) to 122 (ASIA EX JAPAN). These three indices (NIFTY, SPX, and HSI) are selected because they represent major global markets and their unique roles in the global economy, as stated in the introduction. Finally, I collected the adjusted daily closing prices from the Bloomberg terminal to observe them more straightforwardly.

Meanwhile, I also gathered the exchange rate for most currencies against the world's USD (US Dollar) to ensure a comparability and accurate analysis. Every single currency was matched with its corresponding country by using the same list of numbers assigned during the equity index collection process above. For example, I collected the exchange rates between the INR (Indian Rupee) and USD (US Dollar) at the end of each day from 2011-2022 to normalize the NIFTY index values into USD terms to further compare and analyze the performance of the portfolio, which contains both of them. Although I also collected the exchange rate for the HKD (Hong Kong Dollar) against USD, I didn't actually complete a day-by-day HSI value match to USD like what I did to NIFTY because of the unique modified currency board mechanism. Such a mechanism linked the HKD to the USD since October 1983 in order to maintain confidence in the HKD's exchange rate. Even if there were always some tiny fluctuations in the exchange rate, I still decided to apply the exchange rate of 7.8 HKD per USD as I expect that these tiny fluctuations are usually minimal and constrained by the intervention bounds set by HKMA and to reduce the volatility typically associated with freely floating currencies (Harrison & Xiao, 2019).

Admittedly, it is indeed equally significant to acknowledge the existence of these fluctuations and the potential impact such a fluctuation might cause, and ignoring it might introduce slight errors in the final valuation of the portfolio diversification. But by not normalizing the HSI values daily in this particular research, I aimed to simplify the data processing without compromising the accuracy and comparability of the research results since the exchange rate fluctuations were not expected to influence the analysis materially. Intentionally neglecting the fluctuations is also actually a realization of the broader and more stable impact of government interventions on the overall economy and financial markets. For instance, if the US implements a monetary policy that affects the value of the USD quickly, the HKMA will have to respond with some types of

[1]Adjusted Prices: The equity prices collected from Bloomberg here are not just the closing prices of the indices each day but are some adjusted prices, which incorporate dividends and stock splits. Bloomberg uses a starting point for its price series, and if you divide any two prices to get returns, they should match, except on dividend days. For example, if an index is 1000 and pays a 1 dividend, it will drop to 999 in traded price, but in reality, investors receive that 1 dividend. You will get 1000/1000 in my adjusted price series instead of 1000/999. Depending on the days you pull the data from Bloomberg, it starts at a given point and adjusts accordingly, so it differs from the traded price. This adjustment ensures a more accurate reflection of investors' returns, considering the actual payouts from dividends and other factors and isolate the result from the effects of dividents or stock splits (Johnson, 1966).

corresponding policies to adjust the HKD value to maintain the peg with the USD. Such policies affect the exchange rate and have broader implications for the Hong Kong economy, stock market, and capital inflows. Adopting an approach like this will also enable me to focus more on the general trends and alleviate the impacts of the policies implemented by HKMA on the value of HSI.

Although I have data for the NIFTY, HSI, and SPX from 2000-2022, the exchange rate for the INR against the USD is only available from 2011 onwards. In this case, in order to keep a consistent time frame for the diversified portfolio return analysis, my calculation for the portfolio returns also started in 2011. And before doing the return calculation, there is also a local performance analysis and an event study based on this, which examines the impact of the significant events on these three indices. These two studies span from 2000 to 2022 as well because such a study does not involve aligning the indices to a single currency standard, and thus I am able to conduct the event study better from the outset and account for the impact of significant events on a country's currency value by only focusing on using local equity indices values for analysis at the beginning. The evaluation completed using local currency should also be more valuable for reference by local investors.

2.2. Single Index Performance Evaluation

The first step of the portfolio diversification analysis is to evaluate each selected equity index's performance comprehensively. This is done by conducting a general statistical analysis of the NIFTY, SPX, and HSI. The analysis includes calculating monthly returns, annualized returns, standard deviations, skewness, kurtosis, and the Sharpe ratio and finally combining them into **Table 1** and **Table 2**. All the data I used in this analysis are the same as those used for the later return calculation, as discussed above in the data description.

Table 1. Descriptive statistics of NIFTY, SPX, and HIS.

Metric	NIFTY	SPX	HSI
Mean Monthly Return	0.0125	0.0063	0.0046
Standard Deviation of Monthly Returns	0.0653	0.0445	0.0589
Annualized Mean	0.1601	0.0779	0.0560
Annualized Standard Deviation	0.2261	0.1540	0.2040
Skewness	−0.3394	−0.5065	−0.2982
Kurtosis	5.2412	3.8394	3.7636
Sharpe Ratio (Rf = 0)	0.7079	0.5057	0.2745

This table shows summary statistics for the NIFTY, SPX, and HSI indices. The data spans from September 2000 to October 2022, and the metrics include mean monthly return, standard deviation of monthly returns, annualized mean, annualized standard deviation, skewness, kurtosis, and the Sharpe ratio (Rf = 0). Additionally, I present the monthly return frequency distribution for each index across various return intervals.

Table 2. Monthly return frequency distribution.

Monthly Return Interval	NIFTY	SPX	HSI
−1 to −0.1	9	4	12
−0.1 to −0.05	24	29	36
−0.05 to −0.03	28	14	19
−0.03 to −0.01	32	37	26
−0.01 to 0	20	13	20
0 to 0.01	19	34	18
0.01 to 0.03	34	63	55
0.03 to 0.05	37	43	35
0.05 to 0.1	55	33	40
0.1 to 1	15	3	12

This table presents the frequency of monthly returns within specific intervals for the NIFTY, SPX, and HSI indices from September 2000 to October 2022.

2.2.1. NIFTY Index Performance

During the time period from 2000-2022, the NIFTY index exhibits a range of monthly return frequencies, and there are some notable occurrences within various return intervals. After using R to generate and classify the data, I got a distribution that spans widely from negative returns (such as those between −1 to −0.1 with 9 occurrences) to positive returns (like those in the range of 0.1 to 1 with 15 occurrences). Overall, the intermediate ranges demonstrate a well-balanced distribution, as 24 occurrences for returns are between −0.1 to −0.05, 55 occurrences for returns are between 0.05 to 0.1, and the mean monthly return for NIFTY is 0.0125 here. Although the data shows an overall positive performance over the examined period and looked promising and fine, the standard deviation of 0.0653 actually reflects the relatively serious volatility of the investment in NIFTY. Likewise, when the analysis is annualized, the mean return of 0.1601 and the standard deviation of 0.2261 also kind of underscore the high-risk, high-reward nature of the growing Indian market. Therefore, the investment in only the NIFTY from 2000-2022 should be beneficial, but it can also be risky.

Another important data point that needs to be noted is the skewness of −0.3394 here, which indicates a distribution with a longer left tail. A distribution like this suggests that there is a higher likelihood for extreme negative returns to appear. The kurtosis value is 5.2412, which is significantly higher than the normal distribution of 3, and this value implies fat tails and extreme returns are more likely to exist. Finally, the Sharpe ratio of 0.7079 (calculated with a risk-free rate of zero) demonstrates that the NIFTY has a relatively favorable risk-adjusted return despite the inherent volatility in the market.

2.2.2. SPX Index Performance

Though the SPX index also has many negative returns like NIFTY does, the extreme negative values between the range of −1 to −0.1 are rare for SPX, with only 4 occurrences. For the SPX index, the negative returns, which are between -0.03 and −0.01, are most frequent, with 37 occurrences. From 2000 to 2022, the SPX index had 63 monthly returns between 0.01 and 0.03, and 33 of them were between 0.05 and 0.1. In this case, SPX seems to be more stable and consistent than NIFTY, and although SPX has a 0.0063 monthly return and 0.0779 annual return, the monthly standard deviation of 0.0045 and annualized standard deviation of 0.154 completely makes up for the disadvantage of relatively low returns.

The SPX index's skewness is −0.5065, which reflects a more pronounced left tail than the NIFTY indices. Such a distribution suggests that SPX might have a relatively higher frequency of extreme negative returns than NIFTY when using local currency to invest. The kurtosis value is 3.8394, which is less than that of NIFTY, which means that the fat tails for SPX should also be less pronounced than that of NIFTY. At last, a Sharpe ratio of 0.5057 still signifies a commendable risk-adjusted return, although it's slightly lower than NIFTY's.

2.2.3. HSI Index Performance

The HSI index presents a more nuanced monthly return frequency distribution. It reveals some unique characteristics while maintaining certain parrallels with the NIFTY and SPX indices. For HSI's negative returns, there are 12 occurrences between −1 to −0.1, 36 occurrences between −0.1 to −0.05, 19 occurrences between −0.05 to −0.03, 26 occurrences between −0.03 to −0.01, and 20 of them between −0.01 to 0. A distribution like this obviously reflects the fact that it's more likely that HSI will have a negative return in the past two decades than both NIFTY and USD. Additionally, a mean monthly return value of 0.0046 further indicates that HSI has moderate growth, which is lower than that of both NIFTYs (0.0125) and the SPX (0.0063)[2]. The standard deviation of 0.0589, which is lower than that of NIFTY but greater than that of SPX, also shows the pioneer role of the Hong Kong market, which might be more risky than the Western market but more mature than other Asian markets.

The skewness here is −0.2982, the largest among these three indices. This value shows that HSI has had fewer extreme negative returns for the last twenty decades, which might be surprising to some extent as it has so many negative values. This indicates that although the Hong Kong stock market has certain volatility and may experience extended periods of negative returns due to signif-

[2]The mean monthly return differences: The observed higher mean monthly return for the NIFTY index compared to the HSI and SPX can be attributed to the distinct characteristics of the Indian market. Unlike Hong Kong SAR, which operates under a pegged exchange rate system with the USD, the Indian Rupee (INR) follows a floating exchange rate regime. This allows for greater volatility and the potential for higher returns in the Indian market. Additionally, the maturity of the Hong Kong market, one of the most developed in Asia, results in more stable and moderate returns. The pegged HKD and the mature market environment contribute to the closer performance figures of the HSI and SPX, while India's floating INR and emerging market status drive the higher returns observed in the NIFTY index. As evidenced by the exchange rate analysis, a floating rate like that of the INR is characterized by high variability and low R^2 values, reflecting true trade and financial linkages, which can result in more significant fluctuations and potentially higher returns.

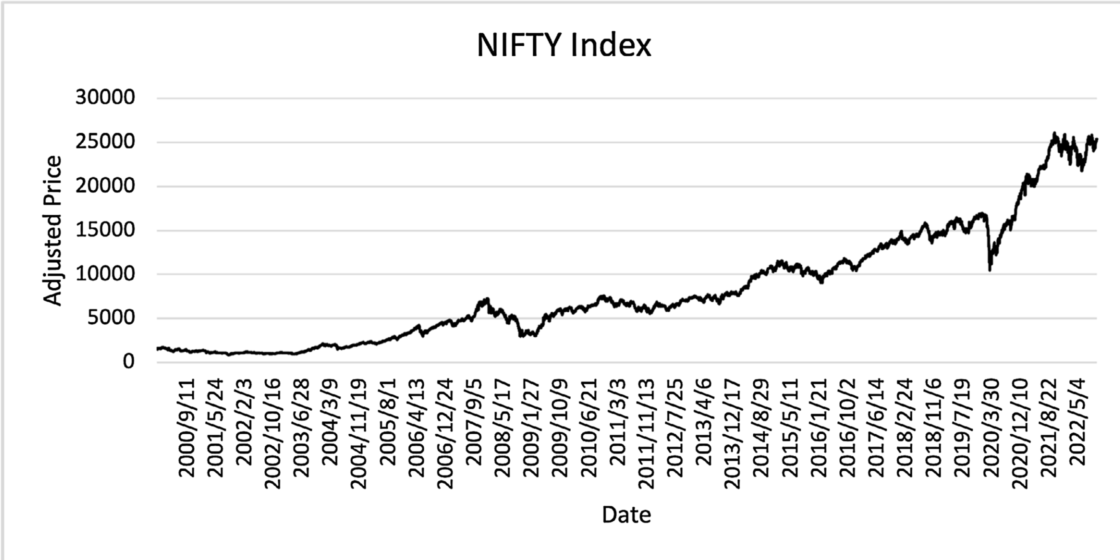
icant events, rapid and substantial short-term losses are not as severe as imagined. The kurtosis value is 3.7636 for HSI, suggesting fat tails but to a lesser extent than the NIFTY index, which fits the assumptions above. Finally, the Sharpe ratio of 0.2745 is the lowest among the three indices, indicating that the Hong Kong market has the least attractive risk-adjusted return for local investors. These results indeed reflect the complex interplay of Western and Asian financial practices impacting market performance.

2.3. Events Study: Integrating Historical Data and Single Index Performance

The topic of what influences the behavior of the stock market is always controversial, and most of the time, there should be a lot of factors that exist together to influence the performance of the indices commonly. However, for most people, before they make investment decisions and apply their investment strategies or quantitative models, they must first make a rough decision about the direction of their investments and the markets they are targeting. Hence, it becomes necessary to understand significant global events that could potentially impact investment returns before analyzing data. My event study serves this purpose. In my research, I aim to identify and briefly introduce those events that significantly affect return levels before conducting more detailed data analysis, thus avoiding confusion when encountering unexpected data. Therefore, the event study here is not highly detailed, in-depth, or heavily data-oriented. The data provided merely connects with the single index performance evaluation mentioned above.

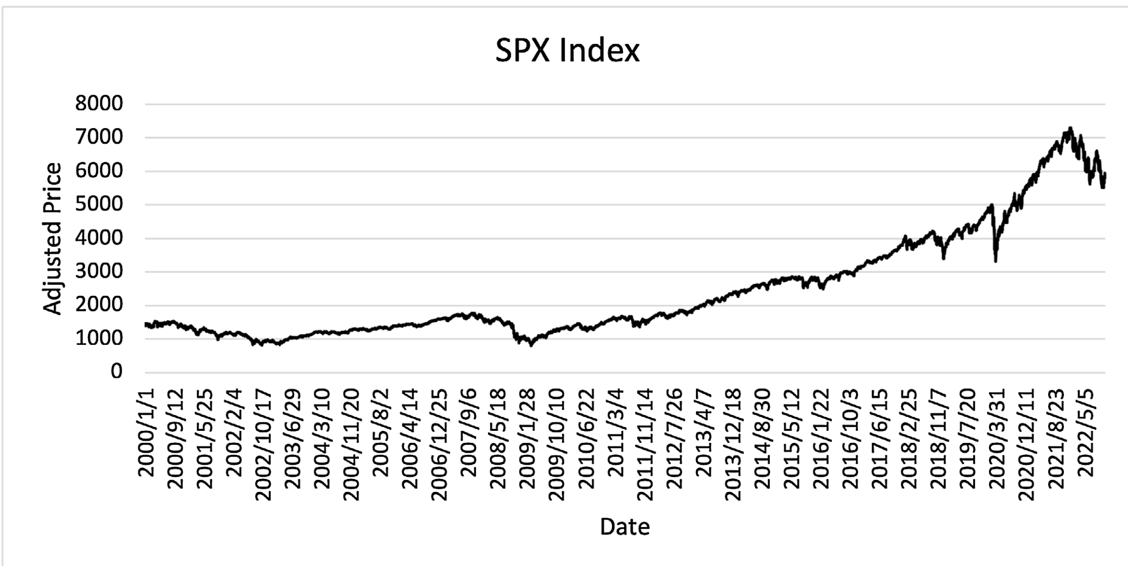
The Global Financial Crisis (2007-2009) significantly influenced the performance of the global markets, and this impact is clearly reflected in the HSI, SPX, and NIFTY indices as well. Here are three figures that can clearly present the situation during that time period. From **Figure 1**, the HSI index experienced a sharp decline, dropping from around 32,000 in late 2007 to below 15,000 by early 2009. This aligns with the historical data, indicating significant volatility during this period. The SPX index similarly saw a severe decline, with **Figure 2** showing a drop from approximately 1500 in late 2007 to around 700 in early 2009, losing nearly 50% of its value. The NIFTY index also demonstrated considerable fluctuations, and it dropped from about 6000 in early 2008 to below 3000 by early 2009, mirroring the interconnected nature of global economies and the impact of the crisis on the Indian market. These observations correspond with the single index performance data, where the NIFTY exhibited high standard deviation (0.0653) and negative skewness (−0.3394), indicating its susceptibility to extreme negative returns during crises.

The COVID-19 Pandemic (2020) led to another sharp decline across all three indices. The HSI index faced significant drawdowns starting in January 2020, plummeting from around 30,000 to nearly 20,000 by March 2020, exacerbated by global economic shutdowns. The SPX index underwent one of the fastest bear markets in history, with the graph showing a drop from about 3400 in early 2020



This figure shows the adjusted price of the NIFTY index in INR from 2000 to 2022. The graph highlights the index's performance over two decades and also reflects some important volatility and growth points. Reading the study events with this graph makes it easier to see the index's responsiveness to different types of global economic shocks.

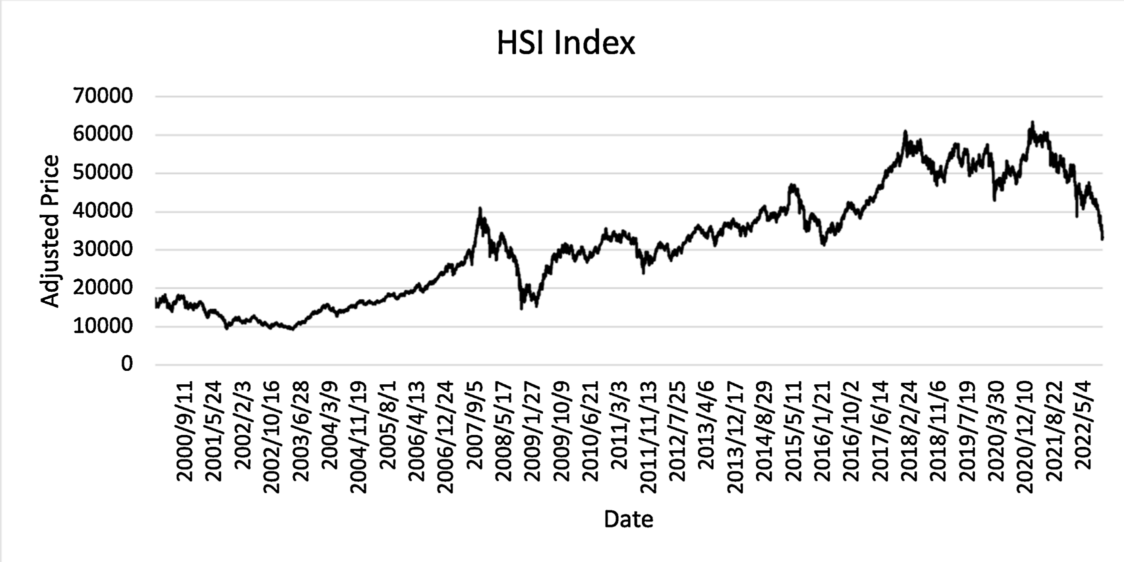
Figure 1. NIFTY index adjusted price from 2000 to 2022 in local currency.



This figure presents the adjusted price of the SPX index in USD from 2000 to 2022. Since the SPX index represents the performance of the largest publicly traded companies in the USA, this graph can visibly show the overall trend of the US economy.

Figure 2. SPX index adjusted price from 2000 to 2022 in local currency.

to around 2200 in March 2020, highlighting the high volatility caused by the pandemic's uncertainty. The NIFTY index also dropped sharply, falling from about 12,000 in early 2020 to below 8000 by March 2020, reflecting the global economic impact and frequent occurrence of negative returns during such crises.



This figure illustrates the adjusted price of the HSI index in HKD from 2000 to 2022. As the pioneer of the rapidly growing Asian economy, Hong Kong's market can always tell investors plenty of information about the status of the Asian economy. The HSI index, after adjustment, is a great tool for seeing the performance.

Figure 3. HSI index adjusted price from 2000 to 2022 in local currency.

This event aligns with the single index performance evaluation, where the HSI had a mean monthly return of only 0.0046 and a relatively low Sharpe ratio of 0.2745, indicating its limited risk-adjusted return amidst high volatility.

Other notable periods of drawdown include the 2001-2003 downturn, influenced by events like the Gujarat Earthquake (2001), the September 11 attacks (2001), and the Iraq War (2003). These events caused significant market volatility, with the NIFTY index particularly affected. The graph shows the NIFTY index experiencing fluctuations during this period, with noticeable dips around these major events. This is consistent with the performance data, where the NIFTY's standard deviation and negative skewness indicate its vulnerability to such shocks. The 2008-2010 period saw multiple shocks, including the global financial crisis, the Mumbai attacks (2008), the H1N1 pandemic (2009), and the European debt crisis (2010). Each of these events contributed to increased volatility and drawdowns in the HSI, SPX, and NIFTY indices. As shown in Figure 3, The HSI graph shows a substantial drop from over 30,000 in late 2007 to around 15,000 in early 2009 and another dip during the 2010 European debt crisis. The SPX and NIFTY indices also show similar patterns of significant declines during these events.

In conclusion, this event study reveals the substantial impact of major global events on the performance of the HSI, SPX, and NIFTY indices. These indices exhibit significant volatility and skewness during periods of economic and geopolitical crises, underscoring the interconnected nature of global markets. Understanding these historical events is crucial for effectively anticipating and managing market risks in portfolio diversification strategies. The provided graphs clearly illustrate these events' dramatic effects on the indices, emphasizing the need for robust risk management practices in investment strategies. The single index performance evaluation analysis supports these findings, highlighting the indices' high volatility and susceptibility to extreme negative returns during such periods.

2.4. Diversified Portfolio Analysis

This section presents a comprehensive analysis of diversified portfolios composed of the NIFTY, SPX, and HSI indices. The performance metrics are based on daily prices converted to USD from September 2011 to October 2022. The analysis aims to evaluate the benefits of diversification in terms of returns, volatility, Sharpe ratios, and drawdowns, providing insights into optimal asset allocation strategies.

The individual performance of the NIFTY, SPX, and HSI indices from September 2011 to October 2022, when priced in USD, reveals significant differences in returns, volatility, and risk-adjusted performance. The NIFTY index achieved an accumulated return of 221.36%, with an annualized return of 9.85%. However, it also exhibited an annualized volatility of 22.95%, resulting in a Sharpe ratio of 0.43 and a maximum drawdown of 36.54%. The SPX index stood out with the highest accumulated return of 389.38% and an annualized return of 13.61%, combined with a lower annualized volatility of 15.85%, yielding a Sharpe ratio of 0.86 and a maximum drawdown of 23.67%. In contrast, the HSI index demonstrated an accumulated return of 128.54%, with an annualized return of 3.89%. Its annualized volatility was 17.91%, leading to a Sharpe ratio of 0.22 and a maximum drawdown of 39.19%.

Several differences emerge when comparing these USD-adjusted figures to the previously analyzed data from 2000 to 2022, which did not standardize for USD. The earlier data reflected local currency valuations, adding a layer of complexity due to currency risk and fluctuations. The USD adjustment standardizes the comparison, highlighting the intrinsic performance characteristics of each index without the additional volatility from currency changes (Campbell & Viceira 2010). The NIFTY index shows a high return but also substantial volatility and drawdowns, reflecting the dynamic and high-growth nature of the Indian market. The SPX index stands out with the highest returns and Sharpe ratio, underscoring the stability and growth of the US market. In contrast, while showing moderate returns and high volatility, the HSI index indicates the challenges and risks associated with the Hong Kong market.

When converted to USD, the differences in performance metrics underscore the impact of exchange rate fluctuations. The USD-adjusted data clarifies each index's inherent performance and risk attributes, facilitating a more accurate comparison. This adjustment is particularly important in a global investment context, where currency risk can significantly influence portfolio performance (De Santis & Gerard, 1998; Solnik et al., 1996).

At this time, to more comprehensively see how these three indexes are related and if they can have a better performance when they are all invested in one portfolio, especially for the US investors, I decided to conduct a classification of different portfolio diversification plans and here are how they are classified and behave in different portfolios. And to provide a clearer view of the impact of portfolio diversification on various return metrics, Table 3 presents the performance of three indices measured in USD from 2010 to 2022.

Table 3. Portfolios of one type of index.

Index	Accumulated Return	Annualized Return	Annualized Volatility	Sharpe Ratio	Maximum Drawdown
NIFTY (India)	221.36%	9.85%	22.95%	0.43	36.54%
SPX (USA)	389.38%	13.61%	15.85%	0.86	23.67%
HSI (Hong Kong)	128.54%	3.89%	17.91%	0.22	39.19%

Here is the individual performance of these three indices from 2010 to 2022.

2.4.1. Balanced Portfolios

Balanced portfolios are commonly constructed by equally allocating investments among the three indexes in the study. This catalog aims to moderate risk and thus provide more stable returns, and the data in Table 4 just perform such a feature.

Table 4. Balanced portfolio's performances.

Portfolio	Accumulated Return	Annualized Return	Annualized Volatility	Sharpe Ratio	Maximum Drawdown
1/3 NIFTY, 1/3 SPX, and 1/3 HSI	236.36%	9.12%	16.17%	0.56	25.71%
1/2 NIFTY and 1/2 SPX	306.84%	11.73%	17.54%	0.67	29.63%
1/2 NIFTY and 1/2 HSI	178.21%	6.87%	18.04%	0.38	28.41%
1/2 SPX and 1/2 HSI	231.14%	8.74%	15.15%	0.58	26.06%

Balanced portfolios have an approximately equal allocation to the indices, aiming to provide moderate returns with balanced risk. It also typically exhibits moderate returns and risk profiles. The portfolio with equal allocation to NIFTY, SPX, and HSI provides a diversified approach with lower volatility and drawdowns. The 50% NIFTY and 50% SPX portfolios show the highest accumulated return among the balanced portfolios, demonstrating the strong performance of the US market combined with India's growth potential.

The balanced portfolio, which comprises equal allocations to NIFTY, SPX, and HSI, shows a cumulative return of 236.36% with an annualized return of 9.12%. Its annualized volatility is 16.17%, which finally results in a Sharpe ratio of 0.56. The maximum drawdown in this portfolio is 25.71%. All of these metrics reflect the fact that a well-balanced portfolio can achieve moderate returns with controlled risk.

Another balanced portfolio here is constructed by allocating half to NIFTY and half to SPX. In this portfolio, the highest accumulated return is 306.84%, and the annualized return also increases to 11.73%. Therefore, despite a slightly higher annualized volatility of 17.54% and a larger maximum drawdown of 29.63%, this portfolio has a more favorable risk-adjusted return with a Sharpe ratio of 0.67. Meanwhile, the portfolios with equal allocations to NIFTY and HSI, and SPX and HSI, respectively, show cumulative returns of 178.21% and 231.14%. While the NIFTY&HSI portfolio has a higher volatility (18.04%) and a lower Sharpe ratio (0.38), the SPX&HSI portfolio presents a more attractive risk-adjusted return with a Sharpe ratio of 0.58 and lower annualized volatility of 15.15%.

Finally, among these balanced portfolios, the half NIFTY half SPX portfolio stands out with the highest returns, indicating that a balanced approach leveraging the stability of the US market and the growth potential of the Indian market can achieve favorable risk-adjusted performance.

2.4.2. SPX-Dominant Portfolios

Table 5. SPX-Dominant portfolios' performances.

Portfolio	Accumulated Return	Annualized Return	Annualized Volatility	Sharpe Ratio	Maximum Drawdown
10% NIFTY and 90% SPX	373.89%	13.23%	15.80%	0.84	24.63%
20% NIFTY and 80% SPX	357.75%	12.86%	15.95%	0.81	25.78%
30% NIFTY and 70% SPX	341.10%	12.48%	16.30%	0.77	27.08%
10% HSI and 90% SPX	352.62%	12.64%	15.42%	0.82	22.59%
20% HSI and 80% SPX	318.52%	11.66%	15.13%	0.77	22.45%
30% HSI and 70% SPX	286.97%	10.69%	14.99%	0.71	22.53%

SPX-dominant portfolios have a higher proportion of SPX, leveraging the stability and high return of the US market. Portfolios with a dominant allocation to SPX generally exhibit high returns with relatively low volatility. The highest return is observed in the 10% NIFTY and 90% SPX portfolios, showcasing the benefits of leveraging the stability and performance of the US market. These portfolios also display high Sharpe ratios, indicating favorable risk-adjusted returns.

As shown in **Table 5**, The SPX-dominant portfolios amplify the stability and high returns of the US market by allocating a larger proportion to the SPX index. The first portfolio includes a 10% NIFTY and 90% SPX portfolio, and such a combination exhibits the highest accumulated return of 373.89%, while the annualized return is 13.23%. Compared to the other portfolios in this category, an annualized volatility of 15.8% and a Sharpe ratio of 0.84 just indicate strong favorable risk-adjusted returns., and a maximum drawdown of 24.63% also reflects the phenomenon that, at most of the time, the global economy crisis seem to undermine the SPX's performance the least.

Other SPX-dominant portfolios that include NIFTY, such as 20% NIFTY and 80% SPX and 30% NIFTY and 70% SPX, show representative cumulative returns of 357.75% and 341.10%. It becomes obvious that the larger the proportion of NIFTY allocated in this particular combination, the worse the whole portfolio behaves. Though the returns are still considerable and risks manageable, their results are unfavorable.

When the superiority of the SPX-NIFTY portfolio scheme is evident at a glance, the SPX-dominated portfolio plan containing HSI and SPX shows some differences. Although the inclusion of HSI relatively lowers the overall return, it effectively reduces investment volatility. The 10% HSI and 90% SPX portfolio achieve an accumulated return of 352.62%, an annualized return of 12.64%, a Sharpe ratio of 0.82, a volatility of 15.42%, and a maximum drawdown of 22.59%. As the proportion of HSI increases, the volatility decreases as well. The 20% and 80% SPX portfolio has a cumulative return of 318.52, an annualized return of 11.66%, a Sharpe ratio of 0.77, an annualized volatility of 0.77, and a maximum drawdown of 22.45%. The 30% HSI and 70% SPX combination show a cumulative return of 286.97%, an annualized return of 10.69, a Sharpe ratio of 0.71, an annualized volatility of 14.99%, and a maximum drawdown of 22.53%. However, it's also easy to notice that the annualized and accumulated returns narrowed significantly as a trade-off for increased stability. When the HSI proportion reaches a certain level, this trade-off becomes more substantial, even resulting in a higher maximum drawdown. Therefore, in this case, a certain amount of HSI holds significant value for return analysis. However, when HSI occupies too much weight in the SPX combination, the negative impacts become increasingly evident.

2.4.3. NIFTY-Dominant Portfolios

Table 6. NIFTY-Dominant portfolios' performances.

Portfolio	Accumulated Return	Annualized Return	Annualized Volatility	Sharpe Ratio	Maximum Drawdown
90% NIFTY and 10% SPX	237.98%	10.23%	21.67%	0.47	34.60%
80% NIFTY and 20% SPX	254.94%	10.60%	20.48%	0.52	33.38%
70% NIFTY and 30% SPX	272.15%	10.98%	19.38%	0.57	32.14%
90% NIFTY and 10% HSI	213.85%	9.26%	21.70%	0.43	34.27%
80% NIFTY and 20% HSI	205.68%	8.66%	20.56%	0.42	32.32%
70% NIFTY and 30% HSI	196.95%	8.06%	19.56%	0.41	30.64%

NIFTY-dominant portfolios have a higher proportion of NIFTY, focusing on the high growth potential of the Indian marker. While these portfolios demonstrate high growth potential, they also have relatively higher volatility and drawdowns. The 90% NIFTY and 10% SPX portfolio show a significant return but with increased risk, highlighting the trade-off between return and risk for investors focusing on the Indian market.

According to Table 6, as NIFTY plays a more and more dominant role, the decline in performance has also become more and more distinct. The more the NIFTY is allocated, the lower the cumulative returns, annualized returns, and Sharpe ratios are. The volatility and drawdowns also increase all the time. Such a contrast is more pronounced when it's compared to local currency performance, where NIFTY shows a generally much better return.

The significant difference between returns in INR and USD can be simply attributed to currency fluctuations and those complicated factors that cause the exchange rate to fluctuate. The INR has depreciated against the USD over the study period, which negatively impacts the USD-denominated returns. Factors such as India's inflation rate, fiscal policies, and economic instability just all contribute to such a result. Future research should delve into the specific macroeconomic and currency factors affecting the NIFTY index. By exploring this area, investors all over the world might be able to measure their diversified portfolios easier.

2.4.4. HSI-Dominant Portfolios

Table 7. HSI-Dominant portfolios' performances

Portfolio	Accumulated Return	Annualized Return	Annualized Volatility	Sharpe Ratio	Maximum Drawdown
90% HSI and 10% SPX	145.31%	4.86%	17.13%	0.28	36.59%
80% HSI and 20% SPX	163.84%	5.83%	16.45%	0.35	33.93%
70% HSI and 30% SPX	184.24%	6.80%	15.89%	0.43	31.24%
90% NIFTY and 10% HSI	213.85%	9.26%	21.70%	0.43	34.27%
80% NIFTY and 20% HSI	205.68%	8.66%	20.56%	0.42	32.32%
70% NIFTY and 30% HSI	196.95%	8.06%	19.56%	0.41	30.64%

HSI-dominant portfolios have a higher proportion of HSI, aiming to capture the stability and strategic position of the Hong Kong market. They generally have lower returns and higher volatility while they are compared to SPX-dominant portfolios. The 90% HSI and 10% SPX portfolios exhibit the lowest return and highest drawdown among the analyzed portfolios, reflecting the stability yet limited growth potential of the Hong Kong market.

According to Table 7, HSI-dominant portfolios also exhibit declining performance as the HSI proportion increases. Generally, higher HSI allocations always result in lower cumulative returns and Sharpe ratios. Volatility and maximum drawdowns increase, like those in the NIFTY-dominant portfolios. When the HSI plays a dominant position, the Hong Kong market's stability only starts to offer limited growth potential. Consequently, the existence of HSI only brings limited benefits to the portfolio. Such a result might be caused by Hong Kong's economy being tied to mainland China, and frequent regional political uncertainties can also undermine its performance.

Future studies should investigate the US and mainland China's regional political stability and economic relationship. While the exchange rate is relatively fixed because of the peg, future studies should quantify the influence of policies and the global financial environment.

2.4.5. Summary and Event Study Analysis

The analysis of diversified portfolios reveals several key findings. Portfolios with a dominant allocation to the S&P 500 (SPX) exhibit the highest returns and the most attractive risk-adjusted performance, as indicated by their Sharpe ratios. This is largely due to the stability and robust performance of the US market (Dimson, Marsh, & Staunton, 2021). In contrast, NIFTY-dominant portfolios offer high growth potential but come with significantly higher volatility and drawdowns, reflecting the emerging market risks associated with India (Bekaert & Harvey, 2003). HSI-dominant portfolios show lower returns and higher volatility than SPX-dominant portfolios, mirroring the stability yet limited growth potential of the Hong Kong market (Engle & Rangel, 2008). The impact of exchange rate fluctuations is evident when compared to the non-USD adjusted data from section 2.2. The conversion to USD standardizes the comparison, emphasizing each index's intrinsic performance and risk characteristics without the added complexity of currency risks. This adjustment highlights the benefits of diversification more clearly by reducing the additional volatility introduced by currency fluctuations (Solnik & McLeavey, 2009).

Meanwhile, the drawdowns observed in the diversified portfolios correlate with significant global events discussed in the event study. For example, the COVID-19 pandemic led to sharp declines across all indices, resulting in substantial drawdowns during this period (Baker et al., 2020). The pandemic caused global economic disruptions, supply chain issues, and market uncertainty, severely impacting market performance. Similarly, inflation concerns, interest rate hikes, and geopolitical tensions in 2022 led to notable market declines, influencing the diversified portfolios' performance (Forbes & Rigobon, 2002). These events underscore the interconnected nature of global markets and the importance of diversification in mitigating risks associated with large economic and geopolitical shocks (Longin & Solnik, 2001).

3. Macroeconomic Signals and Equity Index

In this section, I delve into the relationship between macroeconomic signals and the performance of the SPX index by focusing on their predictive power. I employ a robust methodology that encompasses data collection, signal selections, and regression analysis to achieve this purpose. The primary objective here is to identify which specific macroeconomic indicators will have relatively significant predictive relationships with the monthly returns of the SPX index.

3.1. Data and Methodology

3.1.1. Data Collection

The study focuses on several macroeconomic indicators recorded by Citibank, including Fixed Income Leveraged Positioning, Trade Balance, Economic Surprise, Inflation Surprise, Consumer Price Index (CPI), Producer Price Index (PPI), and Budget Balance Forecast, etc. These indicators were all chosen due to their relevance in assessing the economic health of the United States, and the data for these indicators spans from September 2011 to October 2022. The adjusted daily closing prices for the SPX index were sourced from the Bloomberg terminal, which thus ensured consistency and accuracy in capturing the SPX's performance over the study period. Similarly, macroeconomic indicators were collected from Bloomberg and Citibank's economic databases to provide the same purpose.

3.1.2. Signal Selection

I employed both frequency and duration tests to refine the list of macroeconomic indicators. The purpose was to filter out indicators with insufficient data or inadequate recording frequency. The initial list of indicators was extensive, but many were excluded due to inconsistent historical records or inadequate data points for meaningful analysis during signal selection. The selection criteria for the frequency and duration tests were as follows: Indicators with less than 93 data points were excluded from the frequency test, and indicators with less than five years of data were excluded from the duration test. As a result, only indicators that passed both the frequency and duration tests were retained for further analysis.

3.1.3. Data Adjustment and Testing

By filtering the indicators, I ensured the stationarity of the remaining data series, which is crucial for time series analysis to avoid spurious regression results. Non-stationary data can lead to unreliable and invalid inferences. To test for stationarity, I used the Augmented Dickey-Fuller (ADF) test, a standard statistical test used to check for the presence of unit roots in a time series sample. The ADF test assesses whether a time series is stationary by evaluating if it has a unit root. The ADF test results were summarized with key statistics, including the Test Statistic and Critical Values at 1%, 5%, and 10% levels. After this, I also applied the first difference adjustment to indicators that were not stationary. This transformation helps stabilize the time series' mean by removing trends and seasonality. The ADF test was then retaken after applying the first difference adjustment to ensure the data's stationarity.

3.1.4. Data Normalization

Before performing the regression analysis, I normalized the data of all the signals left to ensure comparability and to remove the effects of different scales among the variables. Normalization involves transforming the data with a mean of zero and a standard deviation of one. This process allows for a more accurate comparison of the impact of different macroeconomic signals on the SPX index. The normalization was done by using R to scale each column of the data, excluding the date column, using the z-score normalization method, and the normalized data was then saved for subsequent analysis.

3.1.5. Regression Analysis

With a refined list of stationary and normalized macroeconomic signals, I then proceeded to the regression analysis to examine these indicators' predictive power on the SPX index's monthly returns, and the regression model used can be represented as follows:

$$\text{SPX Return}_t = \alpha + \beta * \text{Signal}_t + \varepsilon_t \tag{1}$$

where SPX Return_t is the monthly return of the SPX index at time t, α is the intercept term, β is the coefficient representing the relationship between the macroeconomic signal and the SPX return, Signal_t is the value of the macroeconomic indicator at time t, and ε_t is the error term. Each macroeconomic signal was regressed individually against the SPX monthly returns to determine its predictive significance. The regression analysis was performed using ordinary least squares (OLS) estimation. The significance of each coefficient β was evaluated using t-tests, and the overall model fit was assessed using the R-squared statistic.

3.2. Results and Interpretation

Table 8. Regression results.

Variable	Coefficient	T-stat	P-value	Significant (P < 0.1)
First Difference of Terms Trade	−0.0052	−1.8437	0.0663	TRUE
First Difference of 1-Month Call Implied Volatility at 50 Delta Default	−0.0074	−1.9926	0.0478	TRUE
First Difference of 1-Month Put Implied Volatility at 50 Delta Default	−0.0064	−1.7321	0.0850	TRUE
First Difference of Best Price to Sales Ratio	0.0063	1.9132	0.0571	TRUE
First Difference of Current Ratio	0.0060	2.0504	0.0414	TRUE
First Difference of Estimated Price to Cash Flow	0.0091	2.8080	0.0055	TRUE
First Difference of Index Estimated Dividend Yield	−0.0056	−1.7137	0.0881	TRUE
First Difference of Implied Volatility Moneyness	−0.0067	−1.8031	0.0731	TRUE
First Difference of Total Debt to EBITDA	0.0049	1.7315	0.0845	TRUE

This table reflects the regression test results. It shows how the significant macroeconomic variables impact SPX returns with their coefficients, t-statistics, p-values, and R-squared values.

3.2.1. Overview of The Regression Results

The regression analysis reveals several key findings regarding the relationship between various macroeconomic signals and the monthly returns of the SPX index. The analysis employed a first-difference adjustment to ensure stationarity and then used ordinary least squares (OLS) regression to determine the predictive power of each macroeconomic signal. The results are all summarized in **Table 8**. I focus on those indicators with a p-value less than 0.1, which reveals statistical significance at the 10% level. By conducting such a regression, I can find those signals with relatively significant coefficients with adjusted SPX index prices.

The regression result suggests that several macroeconomic signals have statistically significant relationships with SPX returns. Below, I will discuss each signal in detail and compare my findings with existing literature to validate or contrast my results.

3.2.2. Regression Outcomes

Terms of Trade

The regression analysis shows a negative coefficient of −0.0052 for the first difference of terms of trade, with a t-statistic of −1.8437 and a p-value of 0.0663. This suggests that an increase in the terms of trade negatively impacts SPX returns. According to Burstein, Neves, and Rebelo (2003), terms of trade shocks can significantly influence the economy, particularly through their impact on inflation and output. My findings align with their conclusion that adverse terms of trade shocks can negatively affect equity returns due to increased costs and reduced profitability. Similarly, Gruss and Kebhaj (2019) found that terms-of-trade volatility significantly affects inflation in commodity-exporting economies, which can, in turn, impact stock market performance. While their study focused on inflation and economic growth in commodity-exporting countries, my research quantifies the impact on SPX returns, emphasizing the broader applicability of terms-of-trade effects on equity markets.

1-Month Call Implied Volatility at 50 Delta Default (1M_CALL_IMP_VOL_50DELTA_DFLT)

The first difference of 1-Month Call Implied Volatility at 50 Delta Default has a negative coefficient of −0.0074, with a t-statistic of −1.9926 and a p-value of 0.0478. This indicates that higher implied volatility of call options correlates with lower SPX returns. Dennis, Mayhew, and Stivers (2006) suggest that implied volatility is a forward-looking measure of market uncertainty, which typically inversely correlates with market returns. Additionally, Atilgan, Bali, and Demirtas (2015) found that implied volatility indices are significant predictors of future stock returns, with a notably strong relationship during periods of substantial informational events, such as earnings announcements, large cash flow and discount rate news, and extreme values in the consumer sentiment index during the periods of financial distress. They also mentioned that the spread between the implied volatilities of out-of-the-money put (OTM put) and at-the-money call (ATM call) options written on the SPX index has a robust relation with expected returns. While their study highlights the role of implied volatility during crisis periods and focuses more on the comprehensive relationship between OTM put, ATM call, and the return, my research generalizes this relationship across a broader time frame of more than ten years. It demonstrates call option implied volatility's consistent and comprehensive impact on SPX returns.

1-Month Put Implied Volatility at 50 Delta Default (1M_PUT_IMP_VOL_50DELTA_DFLT)

Similarly, the first difference of 1-Month Put Implied Volatility at 50 Delta Default shows a negative coefficient of −0.0064, with a t-statistic of −1.7321 and a p-value of 0.0850. This suggests that higher implied volatility of put options is associated with lower SPX returns. Research by Cremers and Weinbaum (2010) shows that put option implied volatility often spikes market stress and reflects investor concerns about downside risks, which is consistent with my results. Coincidentally, when I combined such results with the above regression results of the implied volatility of 1-month call options at 50 delta and compared them with SPX return data, I also found that their spread had some correlation with SPX returns, which corroborates the second point made by Demirtas and others (2015) mentioned in the previous section. Likewise, Xing, Zhang, and Zhao (2010) demonstrated that the difference between implied volatilities of puts and calls (volatility skew) could predict future stock returns, which further enhances the argument that not only put or call but the combination of both them has a relatively strong relationship with the stock or equity returns. So, my study here specifically isolates the predictive power of put option volatility, and it added granularity to understanding how implied volatility impacts SPX returns. When the separate regressions on these signals are combined and observed, new findings can also be revealed in this research.

Best Price to Sales Ratio (BEST_PX_SALES_RATIO)

The first difference of Best Price to Sales Ratio has a positive coefficient of 0.0063, with a t-statistic of 1.9132 and a p-value of 0.0571. This suggests that a higher price-to-sales ratio predicts higher SPX returns. Early in 2005, O'Shaughnessy (2005) had already found that the price-to-sales ratio strongly predicted future stock performance and recorded down in his book, and he also mentioned that higher ratios often indicate growth potential. Similarly, Loughran and Ritter (1997) investigated the impact of seasoned equity offerings (SEOs) on stock returns. They discovered that firms issuing new equity tend to underperform non-issuing firms in the long run. Since they also observed that issuers often exhibit high sales growth rates relevant to the denominator of the price-to-sales ratio I study here, this research also supports my regression result. Loughran and Ritter indicate a correlation between sales growth and long-term stock performance, which can finally conclude that firms with higher sales growth and, consequently, higher price-to-sales ratios tend to have better future stock returns.

While this research focuses on the long-term impact of equity issuance on individual stock returns, I offer a different perspective by examining the predictive power of the price-to-sales ratio on a more frequent and monthly basis for SPX returns. Even though there are many differences between individual stocks and equity, long-term and short-term, Loughran and Ritter's research still provides my research with a future developing direction, which is that potential overvaluation and market correction are also some derived factors from the sales growth that can influence the returns of the stocks and thus the equity.

Current Ratio (CUR_RATIO)

The first difference of Current Ratio shows a positive coefficient of 0.0060, with a t-statistic of 2.0504 and a p-value of 0.0414, indicating that a higher current ratio predicts higher SPX returns. Such a result is not surprising and is supported by many previous studies, such as Bali, Peng, Shen, and Tang's (2014) study, which concluded a significant positive relationship between stock-level liquidity shocks and future returns. Their research result suggests that the market underreacts to these shocks. Their study observed that decile portfolios long on stocks with positive liquidity shocks and short on stocks with adverse liquidity shocks generate a raw and risk-adjusted return of 0.70% to 1.20% per month.

My study aligns with their findings on the importance of liquidity but differs in focus and methodology. While my research examines the current ratio's impact on SPX returns, Bali et al. focus on stock-level liquidity shocks and their effects on individual stock returns. This difference highlights how various measures of liquidity can influence stock performance. Bali et al. emphasize market underreaction to liquidity shocks, whereas my study demonstrates a direct positive relationship between the current ratio and SPX returns. Both studies underscore the critical role of liquidity in financial markets, suggesting that understanding liquidity's impact requires considering both steady-state measures like the current ratio and dynamic factors like liquidity shocks.

Estimated Price to Cash Flow (EST_PX_CASHFLOW_FY3_AGGTE)

The regression model here indicates a significant positive relationship between the first difference of the Estimated Price to Cash Flow Ratio and the SPX return. To be more specific, the coefficient of 0.0091, a t-statistic of 2.8080, and a p-value of 0.0055 generally suggest that an increase in the price-to-cash flow ratio can predict higher returns for the SPX. Such a finding aligns well with the broader literature, and Jansen's (2021) forthcoming study is just a great example. He posits that cash flow growth (CFG) is a critical driver of stock returns. He used various analysis methods such as Fama-Macbeth and Fama-french regression to test his hypothesis.

Though Jasen's study about cash flow seems to support my regression result and is very relevant to my study, it is still significant to distinguish between cash flow growth and the price-to-cash-flow ratio. Cash flow growth refers to the increase in the cash generated by a company over time, impacting stock returns by enhancing the firm's value creation capability (Jansen, 2021). In contrast, the price-to-cash-flow ratio (P/CF) measures the price of a company's stock relative to its cash flow generation, providing insight into market valuation (Pinkasovitch, 2023). While Jansen emphasizes the direct relationship between CFG and stock returns at the firm level, my study highlights the importance of market-level valuation metrics. Future research could integrate firm-level CFG data with macroeconomic indicators to develop a comprehensive model of market returns.

Index Estimated Dividend Yield (IDX_EST_DVD_YLD)

My study's first difference of Index Estimated Dividend Yield has a negative coefficient of 0.0056, a t-statistic of -1.7137, and a p-value of 0.0881. Regression results like this show that higher dividend yield estimates predict lower SPX returns. This finding is similar to Fama and French (1988), who observed that higher dividend yields often correlate with lower future returns, which is potentially due to market corrections. While Fama and French demonstrated that dividend yields have more substantial predictive power over longer horizons due to the autocorrelation of expected returns, my study focuses on the short-term implications. The results indicate that higher dividend yield estimates negatively impact SPX returns in the immediate term, highlighting the short-term predictive power of dividend yields and providing immediate investment insights.

This study complements the work of Campbell and Shiller (1988) too, who found that dividend yields can predict long-term stock returns but not short-term fluctuations. By showing that higher dividend yield estimates are associated with lower immediate SPX returns, my research adds a new dimension to understanding dividend yield predictability. This negative short-term relationship suggests that anticipated market corrections and adjustments in investor expectations play a significant role. Overall, this study contributes to the literature by demonstrating the short-term predictive capacity of dividend yields on SPX returns, offering more immediate insights than previous research's long-term focus.

Implied Volatility Moneyness (IVOL_MONEYNESS)

The first difference of Implied Volatility Moneyness shows a negative coefficient of -0.0067, with a t-statistic of -1.8031 and a p-value of 0.0731. This reveals that higher implied volatility across different moneyness levels predicts lower SPX returns. Research by Bakshi, Kapadia, and Madan (2003) demonstrates that implied volatility spreads provide information about future market movements and often negatively correlate with returns. Their findings support the result of my regression here regarding the relationship between implied volatility moneyness and SPX monthly returns. Doran, Peterson, and Tarrant (2007) show that implied volatility across different strike prices can predict stock returns, particularly in periods of market stress. My study expands on this by focusing on the predictive power of implied volatility across moneyness levels in a broader context. By not just limiting the survey to stress periods, my research adds another comprehensive view of its impact on SPX returns.

Total Debt to EBITDA (TOT_DEBT_TO_EBITDA)

The first difference of Total Debt to EBITDA shows a positive coefficient of 0.0049 (t-statistic of 1.7315, p-value of 0.0845), indicating that higher debt levels relative to earnings forecast increased SPX returns. This finding supports the arguments of Titman and Wessels (1988), who suggest that high debt levels can signal financial risk and aggressive growth strategies that may enhance returns. Similarly, Graham, Leary, and Roberts (2015) emphasize the benefits of high leverage through tax shields and growth strategies, which can contribute to higher stock returns. My findings provide clearer evidence of the positive impact of total debt to EBITDA on SPX returns, highlighting how leverage influences market performance beyond general firm-level analysis.

Titman and Wessels (1988) note that high research and development expenditures, low employee quit rates, and high selling expenses are associated with lower debt ratios due to increased uniqueness and potential liquidation costs. This uniqueness negatively impacts debt levels but aligns with observed market trends. Graham, Leary, and Roberts (2015) extend this by showing that corporate leverage has grown significantly since 1945, driven by reduced government borrowing and increased financial sector development. This supports the positive relationship between leverage and returns. The interaction of macroeconomic factors and firm-specific characteristics in these studies underscores the complex role of leverage in predicting SPX returns.

3.2.3. Analysis of Fluctuations and Their Impact on Investment Returns

This section analyzes some specific periods of significant fluctuations and their effects on NIFTY, SPX, and HSI to provide a more comprehensive understanding of how fluctuations in macroeconomic signals impact the indices in terms of investment returns.

First of all, using the NIFTY index as an example, during the COVID-19 pandemic in early 2020, the NIFTY index experienced a sharp decline of approximately 30% in a matter of weeks. This period of heightened volatility was characterized by significant changes in macroeconomic indicators such as GDP growth rate and inflation rate. Since the sharp decline can be attributed to the sudden economic slowdown and subsequent negative investor sentiment, analyzing the return data during this period can actually reveal that macroeconomic signals such as the unemployment rate and consumer confidence index had a predictive relationship with the downturn in NIFTY returns (Mamilla et al., 2023).

Similarly, there was also a significant drawdown of nearly 50% of the SPX index during the Global Financial Crisis (2007-2009). This specific fluctuation was closely linked to macroeconomic indicators like housing starts, interest rates, and credit spreads. The regression analysis indicates that during periods of financial stress, increases in implied volatility and changes in the federal funds rate were strong predictors of the SPX's downward movements. Understanding these relationships helps in predicting future SPX performance under similar economic conditions.

Finally, the HSI index experienced several periods of volatility due to regional economic and political events too. The analysis shows that changes in all these various macroeconomic signals might have more or less impact on HSI returns. The regional political instability and its economic repercussions were reflected in decreased investor confidence and subsequent sell-offs in the stock market.

By analyzing these specific periods of significant fluctuations, we can better understand the dynamic relationship between macroeconomic signals and index performance. This deeper analysis provides insights into how macroeconomic changes can predict index movements and help investors and policymakers make informed decisions in the face of economic uncertainty.

4. Conclusion

In this study, I explored the dynamics of portfolio diversification using the NIFTY, SPX, and HSI indices and examined the predictive power of macroeconomic signals on the SPX index. My research spanned from September 2011 to October 2022, comprehensively analyzing individual index performances, the impact of significant global events, and various diversified portfolio strategies. Additionally, I applied regression techniques to investigate the relationship between specific macroeconomic indicators and SPX movements.

My key findings are twofold. Firstly, I discovered the specific performance of each index in their local currencies and then evaluated the diversified portfolios, which include them. While these indices are individually assessed in their local currency, NIFTY surprisingly exhibited the highest returns and the most attractive risk-adjusted performance, and the performance of SPX and HSI follows. In contrast, when these indices are priced in USD during the diversification strategy evaluation section, it's common to see a phenomenon in which SPX achieves overwhelmingly higher returns when combined with other indices in this research, which means that the larger the proportion of SPX in the investment portfolio, the greater the returns. I thus noticed that the performance of NIFTY when denominated in USD is way worse than when denominated in INR. And the performance of HSI denominated in USD does not differ much from its performance when denominated in HKD due to the peg between the HSD and the USD. In this case, the combination of Hong Kong's HSI and SPX is an exception to this trend. Although the inclusion of HSI still reduces the overall return, this slight reduction also decreases volatility and the maximum drawdown. Such a result reveals that exchange rate fluctuations should be one of the critical factors that might significantly influence performance. It also presents a different investment direction for American investors, who can invest in the long-term development of the leading US stock market and may exhibit domestic investment preference when assets are denominated in USD.

Therefore, at the end of section two, I conducted robustness checks and event studies to clarify the reasons behind the above findings and enrich my understanding. I confirmed that significant global events, such as the Global Financial Crisis and the COVID-19 pandemic, substantially impacted the performance of the HSI, SPX, and NIFTY indices. These events highlighted the interconnected nature of global markets and emphasized the importance of diversification in mitigating risks associated with large economic and geopolitical shocks.

This first part demonstrates that a balanced approach, leveraging the stability of developed markets like the US and the growth potential of emerging markets like India, can achieve favorable risk-adjusted performance. Moreover, understanding the predictive power of macroeconomic indicators can help investors anticipate market trends and optimize their portfolios accordingly.

Secondly, my regression analysis revealed that several macroeconomic signals have statistically significant relationships with SPX returns. Notable indicators include terms of trade, the implied volatility of call and put options, price-to-sales ratio, current ratio, estimated price-to-cash flow ratio, index estimated dividend yield, implied volatility moneyness, and total debt to EBITDA. These findings underscore the importance of macroeconomic indicators in predicting equity index performance and provide valuable insights for optimizing investment strategies. Some of these macroeconomic signals have been studied in relation to the market, while others have not. However, even for those signals that have yet to be directly explored for their relationship with stock indices, various related studies have examined similar indicators and talked about their correlations with the financial market or the economy. In the second part of my study, I compare my regression data with past research to analyze and determine the changes in the relationship between these indices and the SPX over the past dozen of years.

In conclusion, my study contributes to the existing literature by providing a novel approach to portfolio diversification and macroeconomic signal analysis. I hope my findings will aid investors in making informed decisions and encourage further research in this area. Future studies could explore integrating firm-level cash flow growth data with macroeconomic indicators to develop a comprehensive model of market returns, enhancing the understanding of the intricate relationships between market performance and economic signals.

Conflicts of Interest

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

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Appendix A: Variable Definitions

Signal	Description
Terms Trade	**Terms Trade** refers to the conditions and terms under which trade agreements are made, including the agreed prices, quantities, delivery schedules, and other aspects of the trade contract between parties.
1M_CALL_IMP_VOL_50DELTA_DFLT	**1M_CALL_IMP_VOL_50DELTA_DFLT (1-Month Call Implied Volatility at 50 Delta Default)**: This represents the implied volatility of 1-month call options that are at-the-money, with a delta of 0.50. Implied volatility is a measure of the market's expectation of the volatility of the underlying asset over the life of the option.
1M_PUT_IMP_VOL_50DELTA_DFLT	**1M_PUT_IMP_VOL_50DELTA_DFLT (1-Month Put Implied Volatility at 50 Delta Default)**: This represents the implied volatility of 1-month put options that are at-the-money, with a delta of 0.50. Like call implied volatility, this measure reflects the market's expectations of future volatility for the underlying asset.
BEST_PX_SALES_RATIO	**BEST_PX_SALES_RATIO (Best Price-to-Sales Ratio)**: This is a financial metric that compares a company's stock price to its sales per share. It is used to determine the value the market places on each dollar of the company's sales.
CUR_RATIO	**CUR_RATIO (Current Ratio)**: This is a liquidity ratio that measures a company's ability to pay short-term obligations or those due within one year. It is calculated as current assets divided by current liabilities.
EST_PX_CASHFLOW_FY3_AGGTE	**EST_PX_CASHFLOW_FY3_AGGTE (Estimated Price-to-Cash Flow for Fiscal Year 3 Aggregate)**: This ratio represents the estimated price-to-cash flow ratio for the company aggregated over the next three fiscal years. It provides insight into the valuation of a company based on its projected future cash flows.
IDX_EST_DVD_YLD	**IDX_EST_DVD_YLD (Index Estimated Dividend Yield)**: This refers to the estimated dividend yield for an index, calculated by dividing the projected annual dividends by the current index level. It indicates the expected return from dividends for the index constituents.
IVOL_MONEYNESS	**IVOL_MONEYNESS (Implied Volatility by Moneyness)**: This term describes the implied volatility of options based on their moneyness, which is the relationship between the strike price of the option and the current price of the underlying asset. Moneyness categories include in-the-money, at-the-money, and out-of-the-money.
TOT_DEBT_TO_EBITDA	**TOT_DEBT_TO_EBITDA (Total Debt to EBITDA)**: This leverage ratio compares a company's total debt to its earnings before interest, taxes, depreciation, and amortization (EBITDA). It is used to assess a company's ability to pay off its incurred debt.

In this table, I list the definitions of those macroeconomic signals that pass the regression and have a relatively significant impact on the SPX index.