Return-forecasting Signals in Australia, Brazil and United States' Equity Markets

Zijian Zou[1,a,*]
[1]*University of Southern California, 3470 Trousdale Parkway, Los Angeles, United States*
a. kevinzou@usc.edu
**corresponding author*

Abstract: This paper offers an in-depth analysis of the role various signals play in equity indices within Australia, Brazil, and the United States. Utilizing statistical methods, particularly single-variate regression analysis, I examine the relationship between the monthly return rates of these indices alongside various signals. A noteworthy finding of my research is that certain trading signals exhibit statistical significance within the context of individual nations, yet this significance does not translate across borders. This difference could be attributed to distinct economic factors inherent to each country, such as varying inflation rates and market microstructures. This study sheds light on multiple financial literatures by offering a comparative cross-sectional perspective on equity markets, and it laid the foundation for more nuanced financial research in the future. Despite the significant insights gained from this study, it also acknowledges the potential for further enhancement of the dataset, emphasizing the quest for a deeper understanding of these complicated relationships.

Keywords: return forecasting, stock market, global macro

1. Introduction

Trade signals, encompassing technical indicators, mathematical algorithms, and economic indexes, are pivotal in deciphering market behavior across global financial landscapes. These signals, varying in form and function, have long captivated research interests due to their profound influence on market trends. For instance, the seminal work of Jegadeesh and Titman [1] underscored the effectiveness of a momentum strategy in the stock market, highlighting the potential of upward trend-based asset purchases. In contrast, Hu [2] revealed a negative interplay between stock market volatility and real fixed investment in the U.S., illustrating the broader impact of market signals beyond direct equity market metrics. With a focus on the diverse economic landscapes of Australia, Brazil, and the United States, this study aims to build upon these foundational insights, exploring the nuanced roles of trade signals in these varying markets and providing an updated perspective in the ever-evolving realm of financial analysis.

While extensive research has been conducted on signals emanating directly from equity markets, a notable gap exists in understanding the influence of signals from other areas, such as fixed income, foreign exchange markets, and broader economic indicators. Furthermore, much of the existing literature has concentrated on the U.S. equity markets, often overlooking the intricate dynamics of developed and developing countries' markets. Recognizing this limitation, this study aims to bridge

DOI: 10.54254/2754-1169/83/20240725

these gaps by investigating the effects of diverse trading signals across different national economies. This approach promises a more holistic understanding of the global financial landscape and seeks to uncover the unique impacts these signals may have in varying economic contexts. By employing a comprehensive methodological framework, this research provides insights that could inform investors and policymakers worldwide, enhancing the strategic navigation of complex market environments.

In preparation for my regression analysis, I initially conducted a detailed examination of the equity markets in Brazil, Australia, and the United States. This preliminary step reveals distinct characteristics: Brazil's market is notably characterized by higher volatility, whereas Australia exhibits a relatively steady equity growth trend. The U.S. market's dynamics, distinct in their own right, further enrich this comparative analysis. To ensure the reliability of my dataset, I implemented the Augmented Dickey-Fuller (ADF) root test to assess data stationarity, an essential step in validating the data for regression analysis. In cases of non-stationarity, I apply the first differencing to transform the data. This meticulous data cleansing process eliminates non-stationary data and datasets with insufficient frequency, ensuring that my regression analysis is grounded in the most robust and reliable data. These methodological steps are critical in laying a solid foundation for my analysis, allowing me to draw meaningful and accurate conclusions about the impact of trading signals across these diverse equity markets.

As a final step in preparing the dataset, I perform standard normalization to ensure uniformity and comparability of the data, a critical process given the diverse nature of the markets under study. Subsequent regression analysis, employing a rigorous approach tailored to assess the impact of trading signals, reveals an intriguing pattern: only a select few signals exhibit statistical significance within a 5% confidence interval. Moreover, these significant signals show variation across the markets of Brazil, Australia, and the United States. This initial finding, aligning partially with existing literature while also uncovering new insights, underscores the need for a deeper dive into the distinct factors that uniquely influence each nation's market. My study thus pivots to a more granular investigation, exploring economic, regulatory, and market-specific variables that might account for these variations in signal significance.

Running single variate regression using the monthly data of 62 signals over 3 nations, I have found 12 signals display statistical significance in 3 nations, varying in multiple fields from equity technical analysis to fixed income sentiment. This study demonstrates that the effectiveness of economic and financial signals in forecasting equity index performance significantly differs across Australia, Brazil, and the United States, underscoring these countries' distinct economic environments and market behaviors. While specific indicators like the Real Effective Exchange Rate (REER) and fixed income signals are impactful in individual nations, their relevance is not universally consistent. This highlights the intricacies of global equity markets and the importance for investors to tailor their analysis to the unique economic and market contexts of each country. The research further shows that even among developed economies like Australia and the United States, different factors influence market trends, whereas Brazil's emerging market status brings unique predictive signals, mainly from the fixed income domain, indicating the relationship between a market's maturity and its key economic indicators. The quantitative analysis is complemented by a review of relevant financial literature, seeking explanations for my findings. My research contributes to existing knowledge by validating the relevance of momentum as a trading signal in Australia's capital market and by illuminating the role of Brazil's economic structure in explaining its unique market signals.

My study makes several significant contributions to the finance literature, particularly in understanding the Real Effective Exchange Rate (REER) and its impact on equity markets. The regression analysis, detailed in Table 2, reveals positive coefficients for both *CitiBroadREER* and *CitiNarrowREER*. This suggests that an increase in REER is associated with a slight rise in the AS51

Index. Such a finding offers a new perspective compared to previous research, which often emphasizes the negative implications of REER volatility. For instance, Bagella, Becchetti, and Hasan [3] demonstrated that REER volatility negatively affects per capita GDP growth.

Similarly, AbuDalu [4] explored REER's impact on financial markets, primarily using Asian data, and reported multiple effects, often negative. In contrast, my study contributes to the literature that posits a positive correlation between REER increases and equity markets, providing statistical evidence to support this view. For example, Lim [5] found that the appreciation of the Australian dollar positively affects the Basic Materials sector, a significant part of Australia's export GDP. This aligns with my results and supports the theory of a positive interaction between stock prices and exchange rates, specifically in the Australian context. My study thus enriches the discourse by offering empirical evidence on the nuanced effects of REER changes on equity markets.

Secondly, my study significantly advances the understanding of fixed income's role in equity-market return forecasting. The regression results in Table 3 indicate that increases in fixed income volatility and capital exposure positively correlate with monthly returns in Brazil's IBOV Index. This finding contrasts with historical perspectives, such as Hu's study [2], which identified a negative correlation between stock market volatility and real fixed investment in the U.S. Similarly, Sharma's research in India [6] observed that increased equity market volatility typically leads to a decline in bond yields, as investors seek refuge in fixed income securities. Chiang's 2020 study [7] further explored this dynamic, noting that while stock-bond correlations vary over time, they often exhibit a negative trend, especially during periods of high market risk, as indicated by a rising Volatility Index (VIX). My study diverges from this traditional view by suggesting that, at least in the context of the Brazilian market, heightened fixed-income volatility and capital exposure can positively influence equity returns. This highlights a unique aspect of the stock-bond interrelation, suggesting that investor behavior might not always follow the traditional flight-to-quality pattern in certain market conditions. My research thus contribute to a more nuanced understanding of the complex interactions between fixed-income and equity markets.

Third, the paper significantly contributes to the literature on general market dynamics, focusing on exchange rates and their impact on stock markets. Huang [8] highlights the short-term negative effect of exchange rate depreciations on stock prices in BRICS countries, with markets typically recovering after a quarter. In Brazil, stock market returns are primarily influenced by financial account movements due to exchange rate changes. Jeon [9] further supports this by showing that foreign exchange rate fluctuations systematically affect stock returns, particularly in export-oriented emerging markets. This correlation is attributed to the export-led growth strategy prevalent in these economies, where home currency depreciation can boost exports, impacting stock returns positively.

Additionally, my study sheds light on the role of implied volatility in equity markets. Hsiao [10] found that high implied volatility indicates future market reversals during significant market downturns, but it can signal continued losses in cases of moderate drops. Mateus [11] identifies implied idiosyncratic volatility as a potent predictor of stock returns. Thimmaraya [12] delves into the speculative behavior of market participants, highlighting how speculation in implied volatility can cause deviations in asset prices from their fundamental values, often driven by an overestimation of this volatility.

Furthermore, this research aligns with findings on the relationship between volatility spreads and expected market returns. Atilgan [13] presents evidence of a negative link between volatility spreads and expected returns, a relationship especially pronounced during specific periods like earnings announcements. This study also suggests that trading strategies based on this intertemporal relationship can outperform passive strategies. On the Advance/Decline line, while Zakon [14] posits its predictive capabilities, Patel [15] counters this view, especially in the context of the Indian stock market, aligning with the theory of market efficiency. Lastly, exploring the price-to-cash flow ratio, Lei [16], Estep [17], Jansen [18], and Tomaso [19] collectively underscore its predictive power for stock market returns, each adding a unique perspective on the relationship between cash flows and stock performance.

The remainder of the paper is organized as follows. Section 2 delves into the economic structures of Australia, Brazil, and the United States, highlighting significant events that have impacted their financial markets. Section 3 describes the data and methodology used in my study. Section 4 discusses the research findings and interpretations of the signals in each nation. Finally, Section 5 summarizes the key insights and conclusions of my research.

2. Background of Australia, Brazil, and the United States

2.1. Australia

In Figure 1, the financial crisis precipitated by the collapse of Lehman Brothers on September 2008 marked significant global market turbulence, as evidenced by a 7.2% decline in the AS51 index on the day of the collapse, followed by continued downturns. In response, the Australian government implemented a fiscal intervention on October 1, 2008, introducing an $10 billion stimulus package. This multifaceted package, comprising tax reductions and augmented government spending, aimed to rejuvenate the economy and restore investor confidence by signaling governmental proactive measures against the crisis.

Concurrently, the Reserve Bank of Australia (RBA) engaged in monetary policy adjustments, initiating a sequence of interest rate reductions beginning with a 0.50% cut on October 8, 2008. These reductions, intended to spur economic growth by lowering borrowing costs, further bolstered the stock market and reinforced investor trust in the central bank's commitment to crisis management.

The onset of the COVID-19 pandemic in December 2019, which unleashed a global economic downturn and a consequential stock market crash, presented a new challenge. March 2020 saw the AS51 index plunge by 20.2%, marking the most significant monthly decrease since the 1987 crash. In an unprecedented move, the RBA executed a substantial 0.75% interest rate cut on March 19, 2020, to foster economic recovery through more accessible borrowing. The market responded positively to this intervention, reflecting investor confidence in the RBA's aggressive stance.

Additionally, on March 25, 2020, the Australian government announced an A$130 billion stimulus package, encompassing tax relief and increased government expenditures. This announcement was pivotal in uplifting investor sentiment, indicating the government's dedication to combating the pandemic's economic ramifications.In May 2020, the decision by the Organization of the Petroleum Exporting Countries (OPEC) and its allies to reduce oil production marked a strategic effort to stabilize the oil market, adversely affected by the pandemic. This move elicited a favorable market response, demonstrating investors' appreciation of OPEC+'s concerted efforts.

The year 2020 also witnessed the exacerbation of market volatility due to the ongoing US-China trade war, further stressing the global economy. However, a significant positive development occurred in July 2020 with Pfizer's announcement of its COVID-19 vaccine's 95% efficacy, fostering investor optimism about the vaccine's potential economic impact and offering a glimmer of hope in the pandemic's resolution.

DOI: 10.54254/2754-1169/83/20240725

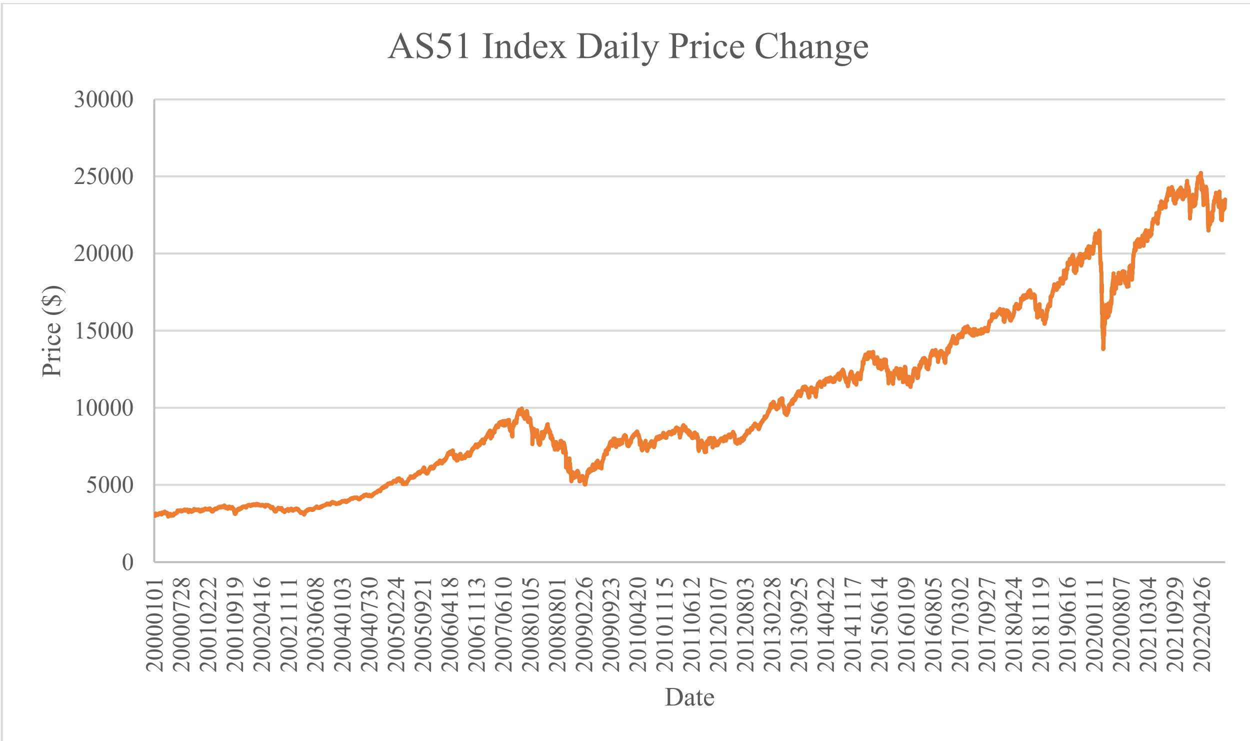

Figure 1: AS51 Daily Index Price Change.

2.2. Brazil

In Figure 2, IBOV index underwent substantial volatility during May 2000, driven by factors. The dot-com bubble burst was a pivotal event that reverberated across global financial markets. In 2000, the IBOV index bore witness to a staggering decline of over 50%, reflecting the erosion of investor confidence in the technology sector. Simultaneously, political instability in Brazil further exacerbated the index's turbulence during this period.

In the subsequent period of August 2002, the IBOV index continued to grapple with heightened volatility, influenced by several key factors. The Brazil debt crisis emerged as a defining event, profoundly impacting the country's economic landscape. The government's default on its debt in 2002 necessitated implementing a series of stringent austerity measures. Concurrently, speculation against the Brazilian real exacerbated the index's fluctuations as concerns grew about the nation's economic prospects. The election of Luiz Inácio Lula da Silva as president in 2002 introduced further uncertainty regarding the Brazilian economy, as his leftist political stance raised investor apprehensions about potential economic policies.

The period between 2010 to 2016 witnessed another chapter of significant volatility for the IBOV index, attributed to various influential factors. The global financial crisis of 2008 left an indelible mark on global financial markets, with the IBOV index enduring a steep drop of over 50%. Investor confidence in the worldwide economy was deeply shaken. The impeachment of President Dilma Rousseff in 2016 introduced a fresh wave of uncertainty regarding Brazil's economic trajectory. As the first Brazilian president to be impeached, her removal from office ushered in a period of political instability. Furthermore, corruption scandals that came to light during this period eroded investor trust in the Brazilian government.

Finally, in the turbulent years of 2020, the IBOV index experienced pronounced volatility, influenced by a set of impactful factors. The outbreak of the COVID-19 pandemic sent shockwaves throughout global financial markets, with the IBOV index plummeting by more than 30% in 2020 as

DOI: 10.54254/2754-1169/83/20240725

investors grappled with the pandemic's economic repercussions. The impeachment proceedings against President Jair Bolsonaro in 2022 introduced fresh uncertainty, primarily stemming from his handling of the COVID-19 pandemic. This political turmoil contributed to a period of political instability. Additionally, the war in Ukraine amplified the index's volatility, as it drove up commodity prices, negatively impacting the Brazilian economy.

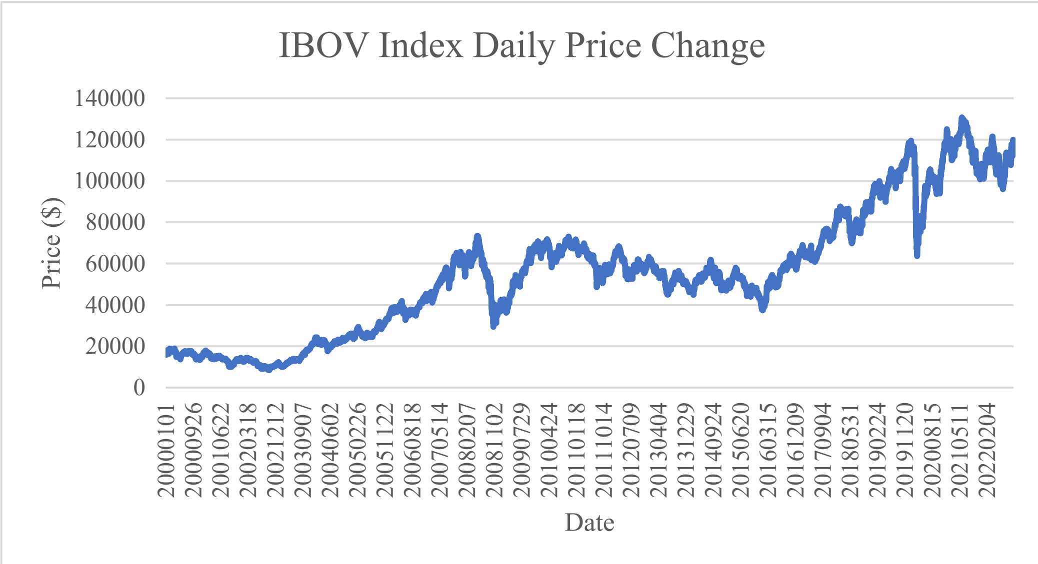

Figure 2: IBOV Daily Index Price Change.

2.3. United States

In Figure 3, the collapse of Lehman Brothers in September 2008 marked a pivotal moment in the financial crisis, sending shockwaves through the financial markets. As the fourth-largest investment bank in the United States, Lehman Brothers' downfall triggered a significant sell-off in the stock market, with the SPX index experiencing a 4.4% decline on the day of the collapse. This decline persisted in the following days. To address the crisis, the US government introduced the Troubled Asset Relief Program (TARP) in October 2008, a $700 billion bailout plan to stabilize the financial system. TARP included various measures, such as purchasing distressed assets from banks, and its announcement induced a stock market rally, reassuring investors that the government was taking action.

In a parallel development, Fannie Mae and Freddie Mac, government-sponsored enterprises, faced financial difficulties in September 2008, prompting the US government to intervene. This takeover led to concerns among investors about its impact on the mortgage market, contributing to a decline in the stock market.

December 2008 witnessed the worst single-day decline in the history of the SPX index, with a staggering 7.77% drop on December 1, 2008. This crash was precipitated by a combination of factors, including the Lehman Brothers collapse and the government takeover of Fannie Mae and Freddie Mac. Furthermore, the government's intervention in American International Group (AIG) on September 16, 2008, a major insurance company with significant exposure to the subprime mortgage market, added to the stock market's volatility, as investors expressed concerns about its impact on the broader financial system.

The inauguration of Barack Obama as the 44th president of the United States on January 20, 2009, was met with optimism by many Americans, leading to a rally in the stock market, with the SPX index rising by 3.4% on that day. Subsequently, in February 2009, the US Congress passed a $787 billion stimulus package to revitalize the economy. This comprehensive package featured measures such as tax cuts and increased government spending, and its passage further buoyed investor confidence as they looked forward to its positive impact on the economy.

The stock market reached its lowest point in March 2009, with the SPX index closing at 6,624.95 on March 9, 2009, marking the conclusion of the most severe bear market in history. In May 2009, the Federal Reserve conducted bank stress tests to assess the banking system's health. The results revealed that ten of the largest US banks required additional capital, causing concerns among investors about the implications of these capital shortfalls for the banks. Moreover, in June 2009, the US government extended a bailout to General Motors, grappling with financial difficulties stemming from the decline of the auto industry. While the bailout averted the company's bankruptcy, it also prompted concerns among investors regarding its impact on the government's finances, leading to a decline in the stock market.

The onset of the COVID-19 pandemic in December 2019 and its global spread profoundly impacted economic activity and triggered a stock market crash. To address the financial challenges, OPEC and its allies agreed to cut oil production in May 2020, aiming to stabilize the oil market, which had been severely affected by the pandemic. The announcement of these production cuts generated optimism among investors, who welcomed the proactive measures taken by the OPEC+ countries.

In July 2020, Pfizer announced the efficacy of its COVID-19 vaccine, a significant breakthrough in the fight against the pandemic. This announcement catalyzed a stock market rally, as investors expressed optimism about the vaccine's potential impact on the economy and were relieved that a promising treatment for the disease had emerged. Following in December 2020, the US Food and Drug Administration (FDA) approved the Pfizer COVID-19 vaccine, a momentous milestone in the pandemic battle. This decision further fueled optimism among investors, who saw the vaccine as a crucial tool in reviving the economy and were reassured by the availability of a safe and effective treatment.

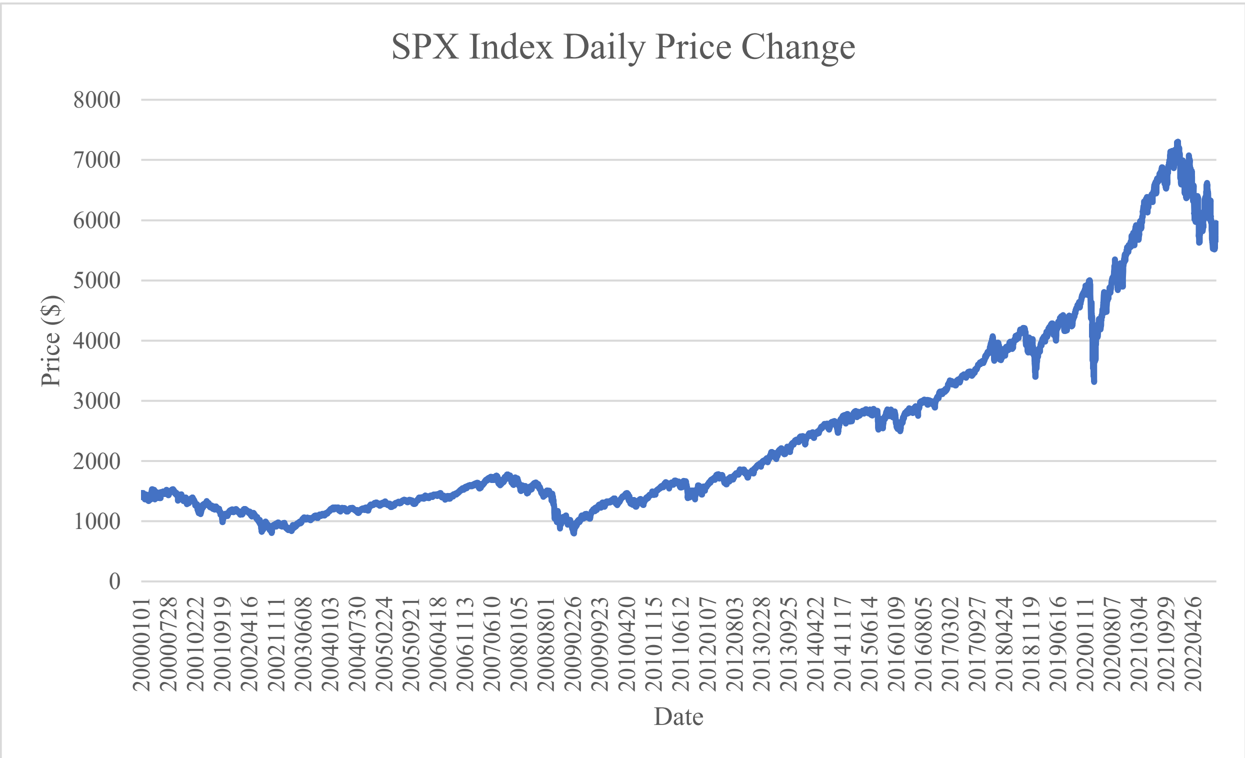

Figure 3: SPX Daily Index Price Change.

DOI: 10.54254/2754-1169/83/20240725

3. Dataset and Methodology

3.1. Data Description

The dataset, sourced from the Bloomberg Financial Terminal®, comprises a comprehensive range of data points essential for my analysis. The equity index dataset includes 8,336 price points, covering January 1, 2000, to October 27, 2022. I supplement this with a dataset of 62 distinct signal indices to provide a holistic view, paralleling the same timeframe. This dual dataset approach enables a robust analysis of market dynamics.

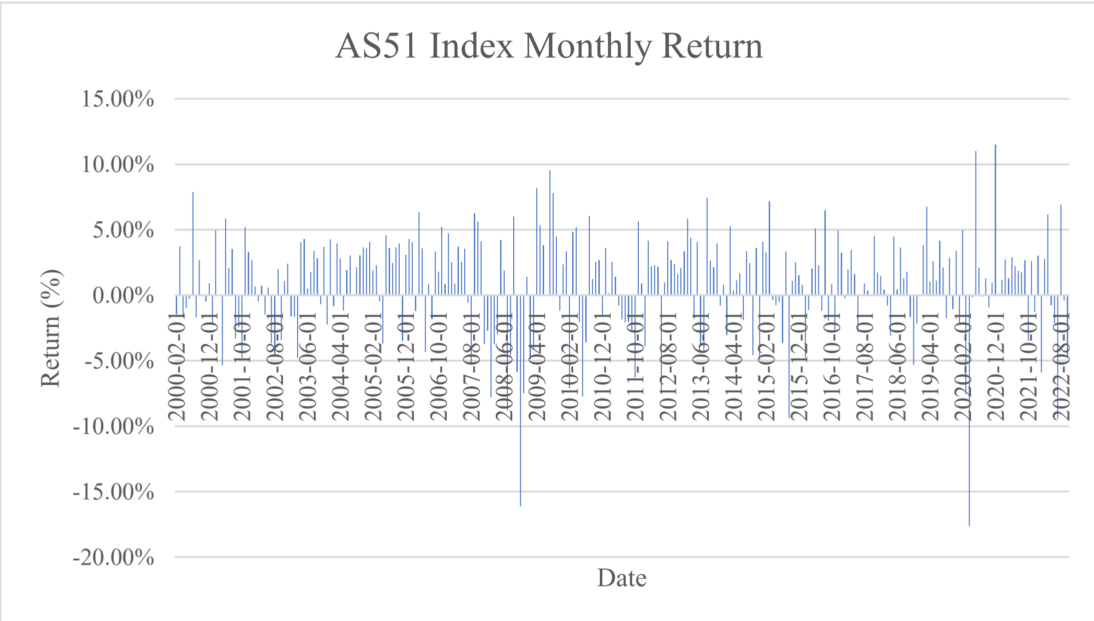

Figure 4: AS51 Index Monthly Return.

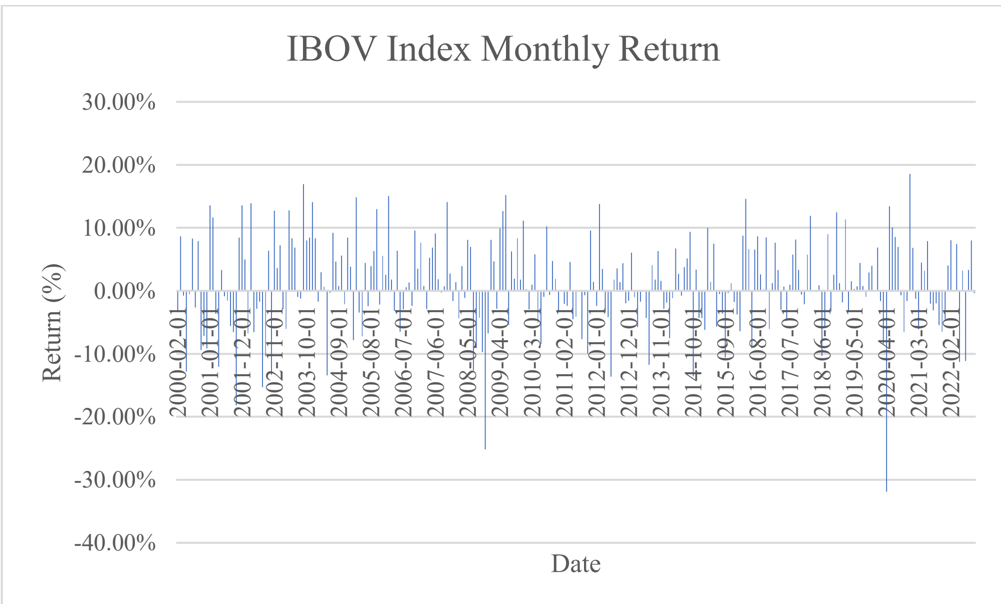

Figure 5: IBOV Index Monthly Return.

DOI: 10.54254/2754-1169/83/20240725

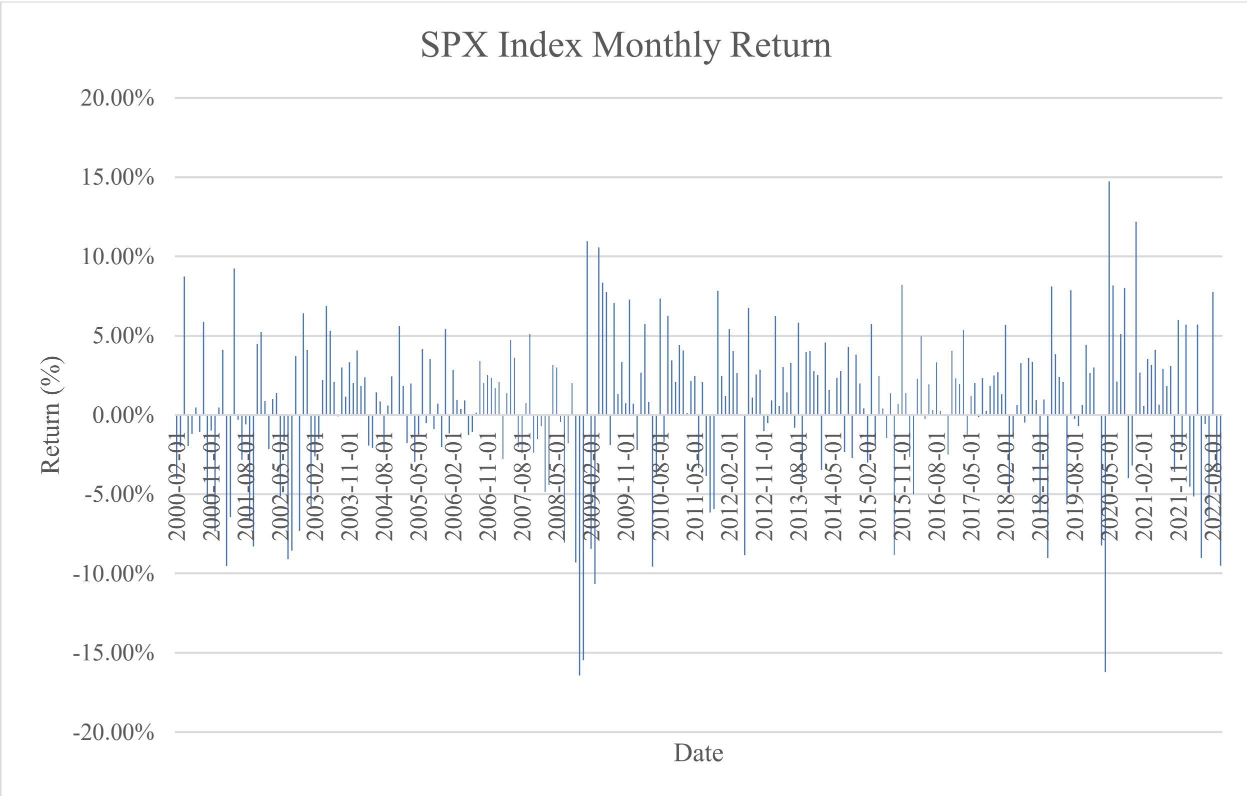

Figure 6: SPX Index Monthly Return.

In Figure 4, and 5 and 6, I compute the monthly price returns of these equity indexes, expressing them in percentage terms. These returns serve as the dependent variable in my regression analyses, allowing me to gauge the impact of various market signals accurately. By comparing the current month's signal values against the subsequent month's stock returns, my aim is to unravel the predictive power of these signals. This temporal alignment is crucial in understanding the cause-and-effect relationship in financial markets and assessing whether these signals can provide investors with a proactive understanding of market movements.

This approach, inspired by the detailed and precise analysis in the sample paper, enables us to delve deep into the nuances of financial markets. These data handling and analytical techniques are designed to ensure that my findings are statistically valid and practically relevant for market participants.

3.2. Data Cleaning and Filtering

In this research, I strongly emphasize rigorous data preparation before proceeding with regression analysis, ensuring both the integrity and appropriateness of the dataset. This process begins with applying the Augmented Dickey-Fuller (ADF) Test, a crucial step in time series analysis, to ascertain the stationarity of signal data. Stationarity is fundamental in statistical models as it implies consistent statistical properties like mean and variance over time. For data exhibiting non-stationarity, I apply the first-difference transformation, a method essential for stabilizing the mean by removing trends and seasonality, thereby converting non-stationary series into stationary ones. This transformation enhances the reliability of the regression analysis by ensuring that the relationships modeled reflect authentic underlying patterns rather than spurious correlations.

Furthermore, I meticulously exclude any non-stationary data even after this transformation. Including persistently non-stationary data can introduce biases and distort relationships in time series

DOI: 10.54254/2754-1169/83/20240725

models, leading to erroneous conclusions. My study also incorporates a frequency filter to maintain analytical robustness, eliminating data points with excessively sparse occurrences. This step is instrumental in preventing overfitting, where the model might inaccurately capture noise instead of the proper signal. Ensuring a consistent frequency of data points is critical for improving the generalizability and reliability of the predictive models.

Finally, I apply standard normalization to the data that met the stationarity and frequency criteria. This normalization, scaling the data to have a mean of zero and a standard deviation of one, is crucial. It puts different variables on a comparable scale, significantly aiding in identifying influential predictors and enhancing the interpretability of the regression model coefficients. Each of these steps is meticulously undertaken to ensure that my regression analysis is accurate and yields valid and reliable insights.

3.3. Statistical Output

There are only a few signals that exhibit statistical significance in the single-variate regression. Besides the United States, most of the signals that are statistically significant are non-equity signals that come from fixed-income markets or are purely strong macroeconomic indicators.

To ensure the reliability of my data for regression analysis, I conducted the Augmented Dickey-Fuller (ADF) test to check for stationarity in my time series data. This step was crucial to avoid spurious results in my regression models. Variables were processed to align with the monthly frequency of my data, considering that analyzing daily fluctuations would lead to an overwhelming data volume and potential noise in my results.

Table 1 shows the results of a single linear regression for Australia's stock market. The four signals that are statistically significant at the 5% level are *CitiBroadREER.fd*, CitiNarrowREER.fd, *LONG_TERM_PRICE_EARNINGS_RATIO.fd*, and *PX_TO_CASH_FLOW*. Three of these signals have positive coefficients, which means that they are positively correlated with the AS51 Index’s return, and PX_TO_CASH_FLOW has negative coefficients, which means it is negatively correlated with the AS51 Index’s return. Specifically, a one-unit increase in *CitiBroadREER.fd* is associated with a 0.00503 increase in the AS51 Index’s monthly returns. A one-unit increase in *CitiNarrowREER.fd* is associated with a 0.0052 increase in the AS51 Index’s monthly returns. A one-unit increase in *LONG_TERM_PRICE_EARNINGS_RATIO.fd* is associated with a 0.0064 increase in the AS51 Index’s monthly returns. A one-unit increase in *PX_TO_CASH_FLOW* is associated with a 0.0061 decrease in the AS51 Index’s monthly returns.

Table 1: Australia’s Selected Signals after Single Linear Regression.

	Coefficient (2 digit)	T-Stat	R-Squared	P-value
CitiBroadREER.fd	0.00503	2.12	1.65%	0.03
CitiNarrowREER.fd	0.0052	2.20	1.77%	0.03
LONG_TERM_PRICE_EARNINGS_RATIO.fd	0.0064	2.68	2.63%	0.01
PX_TO_CASH_FLOW	-0.0061	-2.58	2.43%	0.01

Note: Table 2 presents regression statistics for selected signals that significantly predict the monthly return of the AS51 Index. It details the coefficients (to two decimal places), T-statistics, R-squared values, and P-values for signals, including CitiBroadREER.fd, CitiNarrowREER.fd, LONG_TERM_PRICE_EARNINGS_RATIO.fd, and PX_TO_CASH_FLOW. These statistics offer insight into the strength, reliability, and significance of each signal's relationship with the AS51 Index's performance.

Table 2 shows the results of a single linear regression for Brazil's stock market. The five signals that are statistically significant at the 5% level are *Fixed Income Uncertainty*, *Fixed Income Total Positioning*, *Fixed Income Real Money Positioning*, *AGGR Sentiment*, and *BEST_EPS*. *Fixed Income Uncertainty*, *Fixed Income Total Positioning*, and *Fixed Income Real Money Positioning* have positive coefficients, which means that they are positively correlated with the IBOV Index’s monthly returns. *AGGR Sentiment* and *Best_EPS* have negative coefficients, which means that they are negatively correlated with the IBOV Index's monthly return. Specifically, a one-unit increase in *Fixed Income Uncertainty* is associated with a 0.015 increase in Brazil's stock market returns. A one-unit increase in *Fixed Income Total Positioning* is associated with a 0.017 increase in the IBOV Index's monthly returns. A one-unit increase in *Fixed Income, Real Money Positioning,* is associated with a 0.017 increase in the monthly returns of the IBOV Index. A one-unit increase in *AGGR Sentiment* is associated with a 0.018 decrease in the IBOV Index's monthly returns. A one-unit increase in *BEST_EPS* is associated with a 0.012 decrease in the monthly returns of the IBOV Index.

Table 2: Brazil's Selected Signals after Single Linear Regression.

	Coefficient (2 digit)	T-Stat	R-Squared	P-value
Fixed Income Uncertainty	0.015	3.12	4.96%	0.00
Fixed Income Total Positioning	0.017	2.56	6.00%	0.01
Fixed Income Real Money Positioning	0.017	2.59	6.11%	0.01
AGGR Sentiment	-0.018	-2.14	6.40%	0.04
BEST_EPS	-0.012	-2.43	2.79%	0.02

Note: Table 3 showcases the regression analysis results for selected signals that significantly predict the monthly return of Brazil's IBOV Index. It includes the regression coefficients (to two decimal places), T-statistics, R-squared values, and P-values for various signals such as Fixed Income Uncertainty, Fixed Income Total Positioning, Fixed Income Real Money Positioning, Aggregate Sentiment, and Bloomberg's estimated Earnings Per Share (BEST_EPS). This table offers insights into the predictive power and statistical significance of each signal in relation to the IBOV Index's performance.

Table 3 shows the results of single linear regression for the United States stock market. The three signals that are statistically significant at the 5% level are *1M_PUT_IMP_VOL_50DELTA_DFLT.fd*, *EST_PX_CASHFLOW_FY3_AGGTE.fd*, and *INDX_ADV_VOL.fd*. Two of these signals have positive coefficients (*EST_PX_CASHFLOW_FY3_AGGTE.fd* and *INDX_ADV_VOL.fd*), while one signal has a negative coefficient (*1M_PUT_IMP_VOL_50DELTA_DFLT.fd*). Specifically, a one-unit increase in *1M_PUT_IMP_VOL_50DELTA_DFLT.fd* is associated with a -0.0077 decrease in the SPX Index's monthly~ returns. A one-unit increase in *EST_PX_CASHFLOW_FY3_AGGTE.fd* is associated with a 0.0067 increase in the SPX Index's monthly returns. A one-unit increase in *INDX_ADV_VOL.fd* is associated with a 0.0066 increase in the SPX Index's monthly returns.

Table 3: United States' Selected Signals after Single Linear Regression.

	Coefficient (2 digit)	T-Stat	R-Squared	P-value
1M_PUT_IMP_VOL_50DELTA_DFLT.fd	-0.0077	-2.07	2.37%	0.04
EST_PX_CASHFLOW_FY3_AGGTE.fd	0.0067	2.03	1.99%	0.04
INDX_ADV_VOL.fd	0.0066	2.26	2.05%	0.02

Note: Table 4 displays regression results for selected signals that effectively predict the monthly return of the United States' SPX Index. The table provides a concise overview of the regression coefficients (accurate to two decimal places), T-Statistics, R-Squared values, and P-values for key signals including 1st month put implied volatility at 50 delta, Estimated Price to Cash Flow for Fiscal Year 3 Aggregate, and Advance Volumes. These statistics are instrumental in understanding the extent and significance of each signal's influence on the SPX Index's market performance.

4. Major Findings

This section delves into the intricate dynamics of trade signals and their varying impacts on the stock markets of Australia, Brazil, and the United States. Each section presents a nuanced analysis of how specific economic indicators and models, such as the *Real Effective Exchange Rate* (REER) and the Discounted Cash Flow (DCF), influence market trends and investor behavior in these distinct economies. This section explores the complex relationship between various financial signals and

DOI: 10.54254/2754-1169/83/20240725

market performance, highlighting the unique economic characteristics and market sensitivities of each country. Through this comparative analysis, the chapter aims to shed light on the multifaceted nature of global financial markets and the differing roles that economic indicators play across diverse economic landscapes.

4.1. Australia

Australia's economy, heavily reliant on commodity exports and foreign capital inflows, places a unique emphasis on the role of REER. Studies such as those by Bagella, Becchetti, and Hasan [3] demonstrate that REER volatility can significantly impact economic growth. In the Australian scenario, the fluctuating REER directly influences commodity prices, affecting the nation's export competitiveness. A rise in REER indicates that exports become costlier, potentially leading to reduced trade competitiveness, while a decrease in REER makes exports more competitive, boosting the nation's economic growth.

In the Discounted Cash Flow (DCF) analysis, I observe that fluctuations in *REER* critically affect assumptions about future cash flows, discount rates, and growth projections for Australian companies. A depreciating *REER* can enhance the revenues of export-oriented companies, leading to higher projected cash flows in the DCF model. Conversely, an appreciating *REER* can increase import costs, affecting companies reliant on imports and leading to lower projected cash flows. These dynamics underscore the sensitivity of the Australian market to *REER* changes.

Unlike Australia, the U.S. has a highly diversified economy, reducing the impact of *REER* fluctuations on any single sector. Moreover, the U.S. dollar serves as the world's primary reserve currency, making the American market less susceptible to exchange rate fluctuations. In contrast, Brazil's equity market is influenced more by internal political and economic factors than by *REER*. Brazil's high inflation rates and political instability often overshadow the impact of *REER* on its equity market.

The data analysis, which provides similar results to Bali, Demirtas, and Atilgan [13], shows that *REER* has a statistically significant positive relationship with Australia's AS51 Index, though it only partly explains the index's variability. This finding resonates with Jeon [9], who noted the systematic impact of exchange rate movements on stock returns in export-driven economies.

The correlation between *REER* and equity markets varies globally due to each nation's unique economic environment. In Australia, *REER*'s impact is more apparent due to its commodity-driven, export-oriented economy. The U.S.'s diversified nature and Brazil's complex economic environment make the correlation less evident in these countries. AbuDalu et al. [4] demonstrate the diverse impacts of REER across different economies, echoing the findings of Bali, Demirtas, and Atilgan [13] on the Australian AS51 Index.

This study contributes to a more nuanced understanding of global financial markets, highlighting the need for a comprehensive approach to financial market analysis. The varying impacts of *REER* across different economies underscore the importance of context-specific strategies for investors and policymakers.

4.2. Brazil

The observed negative correlation between aggregate sentiment and the IBOV index's monthly return in Brazil's market aligns with Huang's findings [8] on the impact of exchange rate fluctuations. While temporary depressions in stock markets due to exchange rate depreciations are common, a rebound is often seen after a quarter, especially in Brazil, where financial investments drive these movements. This supports the notion that in export-heavy economies, a weaker currency can bolster stock returns by enhancing the profitability of the tradable sector and attracting foreign investments. Melo and

Gomes [20] in their study 'The Impact of Monetary Policy on the Brazilian Stock Market' highlight the influence of Brazil's monetary policy on stock market dynamics, which resonates with the observed correlation between aggregate sentiment and the IBOV index's monthly return, akin to Huang's observations [8] on exchange rate impacts.

Further aligning with this perspective, Melo and Gomes [20] emphasize how currency depreciation can spur foreign investment and positively affect stock market valuations in Brazil, echoing the dynamics outlined in the Discounted Cash Flow(DCF) model. The DCF model's application in this context underscores how a depreciated currency can spur foreign investment and elevate stock market valuations. As currency depreciation increases expected cash flows, it positively affects asset valuations, reflecting the intricate relationship between currency movements, foreign investment, and stock performance in Brazil.

The single-variate regression analysis reveals that three fixed income signals—uncertainty, total positioning, and real money positioning—are significant predictors of the IBOV Index's monthly returns. This finding is in line with the broader understanding of fixed-income instruments as stable return providers, as suggested by Estep [17]. Their positive influence on equity markets, seen through increased fixed-income volatility and investment positions correlating with higher stock returns, highlights Brazil's distinct economic landscape, characterized by currency volatility and inflation.

In Brazil, central bank interventions, a response to these economic factors, significantly impact bond yields and corporate borrowing costs, thereby influencing the equity market. This contrasts with the more stable dynamics of developed economies and indicates a strong linkage between fixed-income and equity markets in Brazil. While much of the historical research, like that of Sharma, Chhabra, and Saxena [6], has focused on the equity market's influence on fixed income, the reverse relationship—how fixed income market volatility can drive equity demand and market sentiment—remains underexplored. This gap presents an opportunity for future research to explore Brazil's unique financial interdependencies and the significant role of fixed income in shaping the IBOV Index's performance.

4.3. United States

In an expanded analysis of the SPX Index, the paper delves deeper into the implications of various financial signals within the U.S. market. My investigation suggests that while certain signals like 1st month implied volatility and Estimated Price to Cash Flow for Fiscal Year 3 Aggregate show a statistically significant correlation with the SPX Index's monthly returns, their overall impact on the market's variability is modest. This aligns with the insights of Bali, Demirtas, and Atilgan [13], who emphasize the nuanced relationship between implied volatility and market returns, and Estep [17], who investigates the influence of cash flow metrics on stock performance.

My findings illustrate that these signals, though indicative, cannot be solely relied upon for a comprehensive market analysis. This is consistent with the Efficient Market Hypothesis, as explored by Eugene Fama, which posits that markets efficiently incorporate all available information into stock prices. The study by Hsiao and Li [10] also suggests that the relationship between implied volatility and market returns is not uniformly consistent, supporting my discussion on the complexities of interpreting financial signals within the U.S. market. The U.S. market, characterized by high liquidity and a robust regulatory framework, offers a complex environment where multiple factors interplay to influence stock performance.

Moreover, the relationship between these financial signals and market performance raises intriguing questions about market efficiency and investor behavior. Are these signals capturing unassimilated market information, or are they merely reflections of broader economic trends? This discussion leads us to consider the role of investor sentiment, market speculation, and macroeconomic factors in shaping market dynamics.

Furthermore, this paper highlights the importance of adopting a multifaceted approach to financial market analysis. Given the complexity of the U.S. market, it is imperative to utilize advanced analytical methods, including multivariate regression and machine learning models, to discern the true drivers of market movements. The complexities of market dynamics, as discussed by Chiang [7], reinforce the importance of a multifaceted approach to financial analysis in highly liquid and regulated markets like the U.S., supporting my emphasis on advanced analytical methods. Such an approach should integrate a broader spectrum of financial variables, encompassing not only traditional economic indicators but also newer metrics that reflect the evolving nature of financial markets.

In summary, my analysis contributes to a nuanced understanding of the U.S. financial market, underscoring the need for a comprehensive and sophisticated analytical framework. This approach is vital for investors, policymakers, and market analysts aiming to navigate the intricacies of one of the world's most advanced financial markets. By recognizing the limited explanatory power of individual signals and the need for a holistic analysis, our investigation paves the way for more informed and strategic decision-making in the financial sector.

5. Conclusion

In conclusion, my research underscores the diverse roles of the economy and signals in forecasting equity index performance across Australia, Brazil, and the United States. These differences are not merely incidental but are deeply rooted in each nation's unique economic fabric and market mechanisms. My findings reveal that while specific signals, such as the Real Effective Exchange Rate (REER) and various fixed income indicators, significantly impact equity markets in certain countries, their applicability is not universally extendable. The study by Roehner [21] on stock market behavior following crashes supports the view that market-specific factors, such as interest rate spreads, are critical in understanding equity index performance, aligning with the findings of diverse signals influencing markets in countries like Australia and Brazil. This highlights the intricate and heterogeneous nature of global equity markets and underscores the necessity for investors to tailor their analyses to the specific economic and market contexts of each country.

In developed economies like Australia and the United States, the influencing signals on their equity indices show marked differences. This suggests that even within similar economic tiers, diverse underlying factors and market-specific nuances drive market behaviors. On the other hand, Brazil, with its emerging market status, exhibits a distinct set of predictive signals, largely emanating from the fixed income domain. This distinction not only demonstrates the varied impact of market maturity on signal relevance but also emphasizes the intricate relationship between a country's stage of economic development and the effectiveness of different economic indicators.

As a result, this paper provides valuable insights for market participants, offering a nuanced understanding of how diverse economic signals interplay with market dynamics in different national contexts. This enhanced understanding is pivotal for investors, policymakers, and market analysts in making informed decisions and developing strategies that are attuned to the complexities of global financial markets. As the world's economic landscape continues to evolve, the importance of such tailored and context-specific analysis becomes ever more critical.

References

[1] *Jegadeesh, N., Titman, S., & Kong, H. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. Bauer.uh.edu. Retrieved from https://www.bauer.uh.edu/rsusmel/phd/jegadeesh-titman93.pdf*

[2] *Hu, Z. (1995). Stock market volatility and corporate investment. SSRN Electronic Journal. Retrieved from https://doi.org/10.2139/ssrn.883249*

[3] Bagella, M., Becchetti, L., & Hasan, I. (2006). Real effective exchange rate volatility and growth: A framework to measure advantages of flexibility vs. costs of volatility. Journal of Banking & Finance, 30(4), 1149–1169. Retrieved from https://doi.org/10.1016/j.jbankfin.2005.05.012
[4] AbuDalu, A. (2014). The real effective exchange rate impact on ASEAN-5 economic growth. International Journal of Economics & Management Sciences, 03(02). Retrieved from https://doi.org/10.4172/2162-6359.1000174
[5] Lim, L. K. (n.d.). Asymmetric foreign exchange exposure: a sector analysis. Org.au. Retrieved from http://mssanz.org.au/modsim2011/D8/lim.pdf
[6] Sharma, S. C., Chhabra, B., & Saxena, N. (2020). Empirical study on the factors affecting bond market returns-evidence from Indian markets. International Journal of Bonds and Derivatives, 4(2), 114. Retrieved from https://doi.org/10.1504/ijbd.2020.109335
[7] Chiang, T. (2020). Risk and policy uncertainty on stock–bond return correlations: Evidence from the US markets. Risks, 8(2), 58. Retrieved from https://doi.org/10.3390/risks8020058
[8] Huang, Q., Wang, X., & Zhang, S. (2021). The effects of exchange rate fluctuations on the stock market and the affecting mechanisms: Evidence from BRICS countries. The North American Journal of Economics and Finance, 56(101340), 101340. Retrieved from https://doi.org/10.1016/j.najef.2020.101340
[9] Jeon, B. (2017). Exchange Rate Exposure - JSTOR.
[10] Hsiao, P., & Li, M. (2010). Implied Volatility and Future Market Return. Insurance Markets and Companies. Business Perspectives.
[11] Mateus, C., & Konsilp, W. (2014). Implied idiosyncratic volatility and stock return predictability. Journal of Mathematical Finance, 04(05), 338–352. Retrieved from https://doi.org/10.4236/jmf.2014.45032
[12] Thimmaraya, R., & Masuna, V. (2017). Implied volatility and stock market speculation. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3040470
[13] Bali, T. G., Demirtas, K. O., & Atilgan, Y. (2011). Implied volatility spreads and expected market returns. SSRN Electronic Journal. Retrieved from https://doi.org/10.2139/ssrn.1782625
[14] Zakon, A. J., & Pennypacker, J. C. (1968). An analysis of the advance-decline line as a stock market indicator. Journal of Financial and Quantitative Analysis, 3(3), 299. Retrieved from https://doi.org/10.2307/2329815
[15] Patel, J. (2015). An Analysis of the Advance-Decline Indicator in the Indian Stock Market. Journal of Finance Issues. Retrieved from https://doi.org/10.58886/jfi.v14i1.2291
[16] Lei, Q. (2006). Cash distributions and returns. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.687276
[17] Estep, P. W. (2003). Cash flows, asset values, and investment returns. The Journal of Portfolio Management, 29(3), 17–26. Retrieved from https://doi.org/10.3905/jpm.2003.319880
[18] Jansen, B. (2016). Cash Flow Growth and Stock Returns. In SSRN.
[19] Tomaso, D. (2020). Stock Returns and Cash Flows: A New Asset Pricing Approach." By Sonia Di Tomaso. SSRN.
[20] De Melo, M., & Miranda, J. W. F. (2023). The Impact of Monetary Policy on the Brazilian Stock Market - Researchgate. Research Gate.
[21] Roehner, B. M. (2000). Identifying the bottom line after a stock market crash. International Journal of Modern Physics. C, Physics and Computers, 11(01), 91–100. https://doi.org/10.1142/s0129183100000092

Apendix A: Signal Definitions

In this table, I provide a list of the signals with definitions that are statistically significant in single-variate regression.

Signals	Definitions
Aggregate Sentiment (AGGR_Sentiment)	Measures the collective mood of investors in the Brazilian forex market, influencing buying or selling pressures on foreign exchange.
BEst EPS (BEST_EPS)	Bloomberg's estimation of a company's earnings per share (EPS) for a given period. This metric can significantly impact investor sentiment, driving buying or selling activity in individual stocks as well as the broader market.
Citi Broad Real Effective Exchange Rate (CitiBroadREER.fd)	Measures the value of Australia's currency against a wide basket of currencies, adjusted

DOI: 10.54254/2754-1169/83/20240725

	for inflation. It impacts exports, imports, and investor sentiment in the Australian stock market.
Citi Narrow Real Effective Exchange Rate (CitiNarrowREER.fd)	Similar to CitiBroadREER.fd but focuses on a narrower set of trading partners. It's particularly relevant to specific sectors in Australia that trade heavily with this.
Estimated Price to Cash Flow for Fiscal Year 3 Aggregate (EST_PX_CASHFLOW_FY3_AGGTE.fd)	A forward looking valuation metric focused on expected cash flows, influencing stock valuations in the U.S.
Fixed Income Real Money Positioning	Reflects the bond holdings of institutional investors, affecting both the bond and stock markets in Brazil.
Fixed Income Total Positioning	Indicates the overall exposure of Brazilian investors in fixed income assets, impacting liquidity in the equity market.
Fixed Income Uncertainty	Reflects the level of unpredictability in Brazil's bond market, which can have a spillover effect on the equity market.
Advance Volumes (INDX_ADV_VOL.fd)	Reflects the trading volume of advancing stocks in the U.S., serving as an indicator of market momentum and sentiment.
Long Term Price Earnings Ratio (LONG_TERM_PRICE_EARNINGS_RATIO.fd)	A valuation metric for Australian stocks that considers earnings over an extended period, offering a gauge of market sentiment and valuation.
Price to Cash Flow Ratio(PX_TO_CASH_FLOW)	Compares a company's stock price to its cash flow, serving as another valuation metric in the Australian market.
1st month put implied volatility at 50 dealta by the Listed Implied Volatility Engine (1M_PUT_IMP_VOL_50DELTA_DFLT.fd)	A measure of expected volatility in U.S. stocks, based on the pricing of one-month put options.