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Emerging Growth Industries: Small-Cap vs. Large-Cap Volatility Divergence from Traditional Patterns

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ABSTRACT

Although there is comprehensive research on sensitivity of large-cap and small-cap stocks to macroeconomic shocks, a significant gap remains regarding whether these relationships persist within emerging high-growth industries that are increasingly significant in the modern economy. This study analyzes lead-lag relationships between macroeconomic factors (Federal Funds Rate (FFR) and Consumer Price Index (CPI)) and three prominent emerging industries: biotechnology, clean energy, and robotics from 2005 to 2025 (macroeconomic factors only 2013-2021). It also tracks the relationship between the same macroeconomic indicators and volatility of stocks based on capitalization (small-cap and large-cap, represented by the Russell 2000 Volatility Index (RVX) and the CBOE Volatility Index (VIX)). Using Granger causality and cross-correlation analyses on daily returns, I find that VIX consistently leads RVX, confirming the information flow hypothesis from liquid large-caps to less efficient small-caps. However, the Autoregressive Distributed Lag Model (ARDL) reveals that broad market volatility does not consistently drive the emerging sectors of the economy. Instead, it identifies such interdependencies as a strong bidirectional relationship between robotics and clean energy and robotics leading biotech. These findings suggest that emerging growth industries are primarily driven by technological innovations and policies rather than broad market trends, questioning conventional approaches to creating and managing portfolios and challenging the traditional view of this newly established sector as a uniform asset class.

Introduction

While there is a comprehensive research record regarding sensitivity of large-cap and small-cap stocks to macroeconomic shocks, there's a gap on whether these relationships remain within the emerging high-growth sectors that are ever-more pivotal to the modern economy and global events.

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In finance, volatility is the statistical measure that shows variation, or fluctuation, of the price of a financial instrument over certain periods of time. It is a product of standard deviation and square root of the number of time periods. It is one of the core characteristics of financial markets, demonstrating a degree of uncertainty about the size and direction of changes in the value of a given stock. Volatility is crucial for assessing risk and creating trading strategy, but is most often used to identify instability signals. It captures reaction intensity to released information and may be caused by various economic (interest rate changes, data reveal), financial (mergers and acquisitions, speculation), and political events; this is why correctly identifying these reasons early provides a clear advantage for financial institutions, firms, and private investors.

For instance, during the 2008 recession, investors carefully tracked CBOE Volatility Index (VIX) leading up to the individual bank failures and local stock market crashes. A popular measure of volatility expectations on the stock market, VIX showed its predictive power in the months leading up to the collapse of Lehman Brothers and the ensuing market crash when it showed sustained climb from a historically low level. In other words, massive increase in the cost of insuring against market losses through options that VIX signaled served as a leading indicator of immense panic and systematic risk building up long before they were revealed.

Implying expected 30-day forward-looking S&P 500 Volatility, VIX represents only blue chip, or large-cap stocks that have more diversified revenue streams and easier access to capital, thereby resistance to macroeconomic shocks as well. For stocks and indices that are capitalized on a smaller scale, the Russell 2000 Volatility Index (RVX) measures the same implied volatility and is derived from the Russell 2000 Index that represents small-cap stocks. As Bauman et al. (1998) showed, small-caps generally outperform large-caps but present higher risk.Therefore, they are more exposed to credit rates and demand shocks in the economy. Similarly, indices and Exchange-Traded Funds (ETFs) often serve as sectoral benchmarks like the ones analyzed throughout this study: Nasdaq Biotechnology Index (XBI) for biotech, the iShares Global Clean Energy ETF (ICLN) for renewable energy, and Global Robotics and Automation Index ETF (ROBO) for robotics.

In other words, this study focuses on several representatives of a stock market sector—emerging growth industries. It consists of a large scope of industries and companies that are characterized by an above-average growth rate (exceeding GDP growth of 2-3%) and being relatively recently established (majority in the 21st century).

The aim of this study is to analyze emerging industries differences in sensitivity to economic shocks (e. g. changes in inflation and interest rate) based on capitalization by using market data and time series methods. I hypothesize that RVX will show greater sensitivity (the coefficient in

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a regression model will be significantly larger) to changes in the FFR and CPI than VIX as both VIX and RVX react to the same macroeconomic conditions. I also assume that among emerging industries, biotech (XBI) will be more sensitive to interest rate changes than clean energy (ICLN) or robotics (ROBO), because biotechnology is usually more associated with bigger investments. My third hypothesis is that the lead-lag relationship from VIX to RVX will strengthen (cross-correlation between VIX and lagged RVX will be significantly higher) during recessionary periods than during expansion as the stock market as a whole reacts to major economic shifts more than to positive news.

Determining these relationships and dynamics would help private investors, portfolio managers, and other specialists and corporations in the financial sector build clear risk behavior models when allocating capital to the increasingly more popular high-growth sectors during economic shifts. Eventually, additional clarification whether these industries move with the broad market trends or independently can add crucial understanding for creating effective diversification and risk strategies.

Many studies have analyzed how stock volatility differs across industries, economies, and recessions, based on capitalization. However, there's not enough material to tell if this is also true for emerging growth industries—biotech, fintech, and clean energy. This paper concerns the evolution of small-cap versus large-cap stocks sensitivity in emerging growth industries in the US since 2005. It addresses issues of Consumer Price Index (CPI) and Federal Funds Rate (FFR) impact on small-cap and large-cap stocks and the lead-lag relationship between the last two (represented by VIX and RVX) in recessions, as well as whether small-caps in these three industries ever outperform large-caps in recessions, or just lose less.

Literature Review

The relationship between stock market volatility and macroeconomic factors has been comprehensively documented in financial research, as well as its behavior across recessions and sectors. Existing literature has shown that large-caps lead small-caps because of lower risk, higher liquidity, and reduced sensitivity to credit conditions. Specifically, small-cap stocks outperform, with earnings excessing 5.2% annually (Bauman et al., 1998). Building on Bauman et al.'s findings, Altay (2003) demonstrated that small-caps take 3 days to fully react to macro news, whereas large-caps take only 1 because the information flows from liquid (large-cap) to illiquid (small-cap) segments (Altay, 2003). Thus, small-cap volatility is highly procyclical (0.45 GDP correlation), and 72% of small-cap outperformance in value happens in early-cycle recoveries (Bauman et al.,1998).

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This procyclical nature of the stock market itself has been analyzed as well. Vatsa et al. (2024) note that equity markets have consistently lagged industrial production by 1-3 months over recent decades. Their research also identifies an important temporal shift: the correlation between inflation and stock market cycles was negative in the late 20th century, but became positive in the 21st. Given the major change in the predictive relationship between market and the real economy, they questioned if including the S&P 500 in the Composite Index of Leading Indicators was justified.

The role volatility plays in both preceding and signaling economic problems is critical; it is another necessary theme that should be taken into account when analyzing the relationship between stocks and macroeconomic indicators. Sarosh (2014), for instance, demonstrates that in the US and in the EU, a bidirectional and non-linear relationship between volatility and recessions is recorded. It is stated that while increasing volatility leads to escalation of the recession risk, the outbreak of a recession, in turn, boosts volatility by 40-60%. In fact, after 2008, particularly high volatility jumps extended recessionary periods by 3-6 months, implying that volatility indices could be integrated into central bank systems identifying these warning signals early.

Finally, the shock of the COVID-19 pandemic proved to be one of the last resistance testings for financial markets and economies, further shedding light on the factors impacting volatility and recovery. Uddin et al. (2021) observed 200–300% volatility during the beginning of the pandemic. Their cross-country analysis revealed that macroeconomic resilience wasn't the same everywhere; nations with higher-quality infrastructure, lower oil dependency, and more diversified economies experienced lower return variance and recovered 30–50% faster, underscoring the importance of fundamental economic structure in mitigating volatility.

Though Bauman et al. (1998) and Altay (2003) established the lead-lag relationship between large and small caps broadly, and Uddin et al. (2021) showed sectoral differences during COVID-19, no study has examined if this relationship remains within emerging growth industries. Biotech, fintech, and clean energy—may correlate differently with global trends compared to bluechip sectors (more reliable large-cap stocks). This study aims to fill this gap: it analyzes the sensitivity of small-cap versus large-cap stocks within these emerging growth industries to inflation and changes in interest rates.

Data

I used VIX, RVX, and NASDAQ Biotechnology Index (XBI) from 2005 to 2025; Global Clean Energy ETF (ICLN) from 2008 to 2025; Global Robotics & Automation Index (ROBO) from 2013 to 2025. RVX and VIX were pulled from Federal Reserve Economic Data, whereas

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emerging industries indices were pulled from Yahoo Finance. In the table below, you can see a full list of variables' tickers, sources, and time periods.

Table 1: Variables Used

Variable	Symbol	Source	Time Period
CBOE Volatility Index	VIX	FRED	2005-01-01 to 2025-08-27
Russell 2000 Volatility Index	RVX	FRED	2005-01-01 to 2025-08-27
NASDAQ Biotechnology Index	XBI	Yahoo Finance	2005-01-01 to 2025-08-27
iShares Global Clean Energy ETF	ICLN	Yahoo Finance	2008-01-01 to 2025-08-27
Robo Global Robotics ETF	ROBO	Yahoo Finance	2013-01-01 to 2025-08-27
Federal Funds Rate	FFR	FRED	2013-11-01 to 2021-10-01
Consumer Price Index	CPI	FRED	2013-11-01 to 2021-10-01

In figure 1 and 2 you can see the original and differenced out variables.

Methods

In order to determine what tests I could run with what variables, I first made a correlation matrix to see how volatility correlates with small-cap, large-cap, and macroeconomic factors. Figure 3 reveals a strong positive relationship between CPI and small-cap (0.81), a weaker relationship between CPI and large-cap (0.43), and even weaker relationships between RVX and FFR (-0.27), VIX and large-cap and RVX and small-cap.

1. Using daily data, I then tested the price series for stationarity with the Augmented Dickey-Fuller (ADF) test (visualized in the data section) to ensure the validity of the time series models used. Crucial for producing meaningful results in other tests, stationarity is a statistical trait stating that a series doesn't have a trend. Since all series were non-stationary in levels, I

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converted them to daily returns (5,173 observations after differencing and alignment) for analysis.

2. Next, I employed two methods to analyze relationships between VIX, RVX, and emerging industries: Cross-Correlation Function (CCF) analysis and Granger causality tests. The first was used to identify the strongest correlation lags, or, in other words, if past values of one variable (e.g., VIX) provide statistically significant information about the future values of another (e.g., RVX). While it doesn't prove true causality, Granger test examines predictive power of the variables on each other. The second examined predictive patterns and determined identifiable lead-lag relationships, with optimal lag length selected using the Akaike Information Criterion (AIC). You can see the results in figures 4-15.

3. After Granger Causality tests and Cross-Correlation Function analysis I attempted to model relationships between emerging industries and macroeconomic variables (FFR, CPI) with Autoregressive Distributed Lag (ARDL) models.

ARDL is a flexible linear time series model, where values of yt (dependent variable) explain current yt, and both the dependent and independent variables are related both contemporaneously and across historical (lagged) values. Used in forecasting, macroeconomics, climate studies, and finance, ARDL delivers coefficients of the variables after combining lagged levels of the dependent variable and distributed lags of regressors.

The general formula is:

$$y_t = a_0 + a_1 t + \sum_{i=1}^{p} \psi_i y_{t-i} + \sum_{j=1}^{k} \sum_{l_j=0}^{q_j} \beta_{j,l_j} x_{j,t-l_j} + \epsilon_t$$

Where p is the lag order of the dependent variable, qi is the lag order of the i-th regressor, and εt is an error term.

However, statistical issues made the results unreliable for drawing conclusions about macroeconomic sensitivities. Signs of overfitting and perfect multicollinearity (occurs when two or more independent variables are too highly correlated) made it impossible for the model to isolate their individual effects.

4. Lastly, I conducted diagnostic tests (e. g. residual analysis and correlation checks) conducted to prove model validity. They revealed negative residual correlations, signaling potential model misspecification or omission of some of the necessary variables.

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Results

Volatility Transmission Patterns

To test my hypothesis that information flows from large-cap to small-cap, I examined the lead-lag relationship between the VIX (large-cap volatility) and RVX (small-cap volatility). Cross-Correlation Analysis Between RVX and VIX showed strongest correlation lag of 0.170 at 0 ($r = 0.85$, $p < 0.001$), suggesting the two variables are contemporaneous, meaning they move together most strongly on the same day without lead/lag relationship (Figure 5).

Using Granger Causality test with AIC-chosen lag p=20, I found that RVX-VIX relationship is not significant (F=1.1364, p=0.3029), whereas vice-versa is (F=15.835, p=2.2e-16), implying that VIX granger-causes RVX and confirming the hierarchical information flow hypothesis. Clean energy lags RVX by 1 day, and robotics lags VIX and RVX by 5 days. Below you can see the table summarizing the results. Most significant findings from the two tests are visualized in figure 4.

Table 2: Significant Granger Causality Relationships ($p < 0.05$)

Relationship	F-Statistic	P-Value	Lag order
VIX → RVX	15.84	<0.001	20
Robotics → Biotech	8.92	<0.001	5
Robotics → Clean Energy	4.17	0.043	5
Clean Energy → Robotics	3.85	0.028	3

Sectoral Interdependencies

While including lags of VIX/RVX is statistically significant in the ARDL models for robotics and clean energy, granger test results here show that there is no predictable, lag-linear granger causality in either of the volatility variables and any of the emerging growth industries, implying volatility is not their primary driver. The only granger causality occurs bidirectionally with VIX and RVX (p=0.0211 and p=0.0213, expected because they show volatility of the same industries, just varying based on capitalization). It shows that fear in small-caps spills over into large-caps with a 3-6 day lag. Robotics/AI is also a powerful leading indicator for clean energy and biotech

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sentiment ($p=0.0427$ and $p<0.00001$, which is more surprising and can tell that third factors play a major role in this relationship). One-directional causality occurs between robotics and biotech ($p=0.0004$), meaning that robotics granger-causes, or leads, biotech, implying interdependence of the industries on the same technology, for example. The test reveals a lot of unexplained shocks.

Methodological Challenges

When running ARDL, negative residual correlations showed that the model residuals are negatively correlated over time, implying overfitting or multicollinearity issues (VIF > 10). This indicates that the model fits the data too well, is incorrect, or has crucial explanatory variables missing, suggesting that linear models may be insufficient to capture the complex relationships between these emerging sectors and macroeconomic indicators.

Discussion/Conclusion

The analysis revealed several key patterns in emerging growth industries. The bidirectional Granger causality between robotics and clean energy suggests a feedback loop, likely driven by shared technological drivers and policy environments. These sectors appear to move together as part of a broader technological transformation ecosystem. This is something investors can take into account when determining how to diversify their portfolios across sectors.

For financial corporations and specialists, this study proves robotics and AI as a foundational technology influencing other sectors and underlines the appearance of strong independent trends on the emerging industries market. For instance, an investor in solar energy can monitor technological breakthroughs in industrial robotics to detect early signals for their holdings, as these sectors depend on each other's technology. A venture capital firm with a focus on biotech, similarly, should track advancements in automation as well, because they may broaden the scope of opportunities in high-throughput drug screening or personalized medicine, for example. Finally, a portfolio manager should conduct a comprehensive, sector-specific analysis before making decisions instead of relying on the broad market.

Specifically, the volatility analysis shows clear hierarchical patterns, with VIX Granger-causing RVX but not vice versa. This supports the information flow hypothesis from liquid large-cap markets to less efficient small-cap segments. The strongest correlation at lag zero indicates they primarily move concurrently, with small-caps showing delayed response over 3-6 days. In the context of business cycles, this means that investors could consider when correcting their strategy or making decisions.

Although the attempted macroeconomic analysis using ARDL models proved statistically unreliable due to perfect multicollinearity issues, each industry demonstrated distinct

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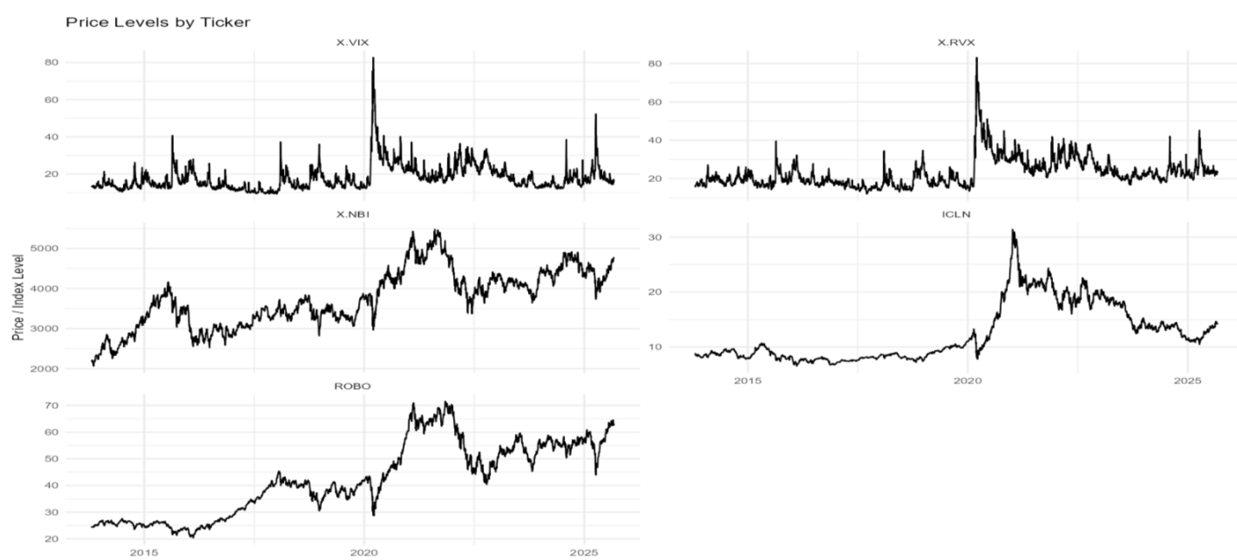
characteristics, implying that some sectors, such as robotics and clean energy (with bidirectional relationship), should be analyzed as a holistic technological ecosystem. This relationship, likely driven by shared reliance on manufacturing, automation, and supportive policies, tell investors that they should monitor the other industry if they're involved in one of them. Similarly, the finding that robotics Granger-causes biotech leads to an assumption that advances in robotics and AI, a foundational technology, may drive innovation in biotech areas, major application domain, like lab-grown tissues or drug screening.

As for volatility sensitivity, biotech showed complex internal dynamics with its negative values, whereas clean energy had a simpler structure with moderate relationship, and robotics demonstrated mixed effects. In general, the lack of predictability power of broad market volatility (VIX/RVX) in these sectors suggests that their performance is mostly influenced by sector-specific factors—such as technological breakthroughs or policy changes—underscoring the need for deeper sectoral expertise when investing in the high-growth industries.

For investors, these results explain that emerging industries cannot be treated as a homogeneous sector. Small-cap and large-cap segments within it show different volatility levels, and cross-sector correlations are significant. Future research should explore alternative modeling approaches to better capture the complex, non-linear relationships in these newly established but rapidly evolving sectors.

Figures



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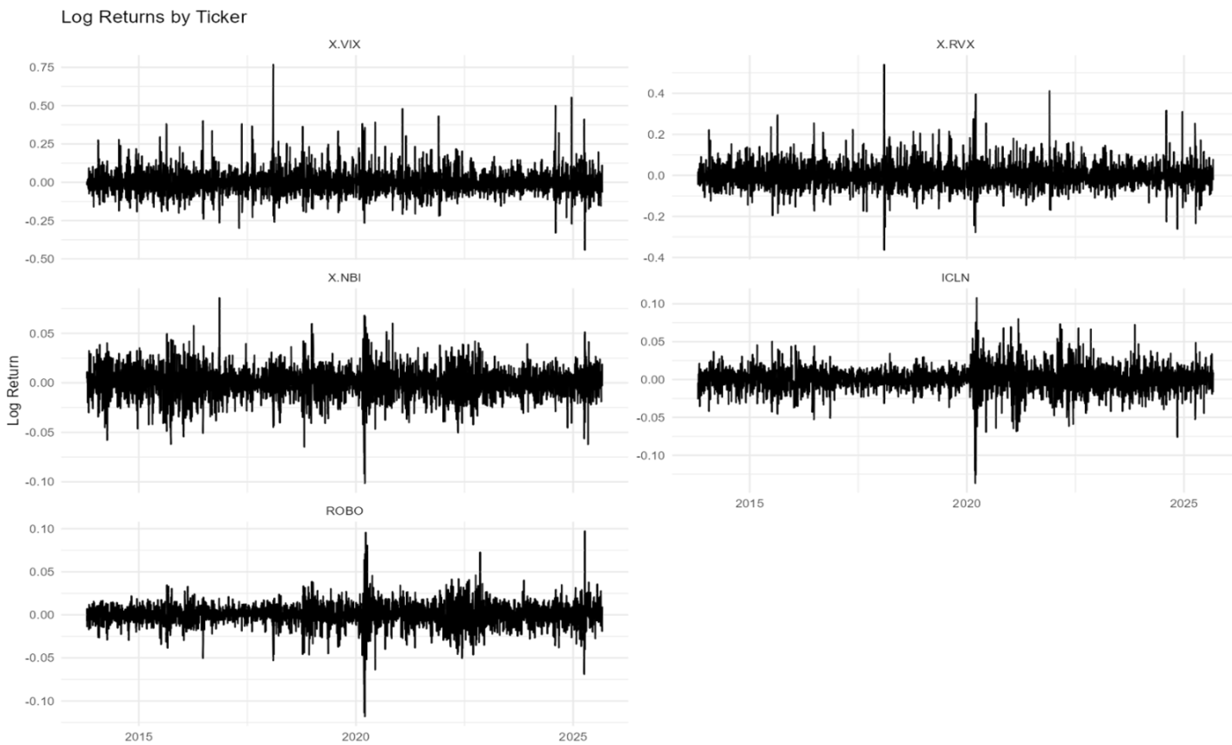
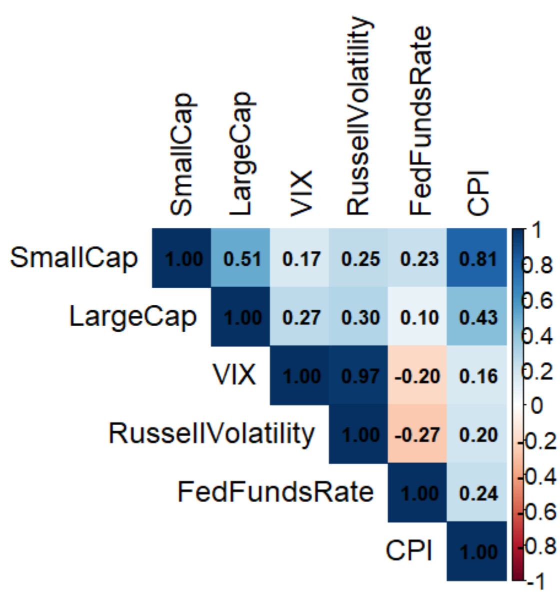
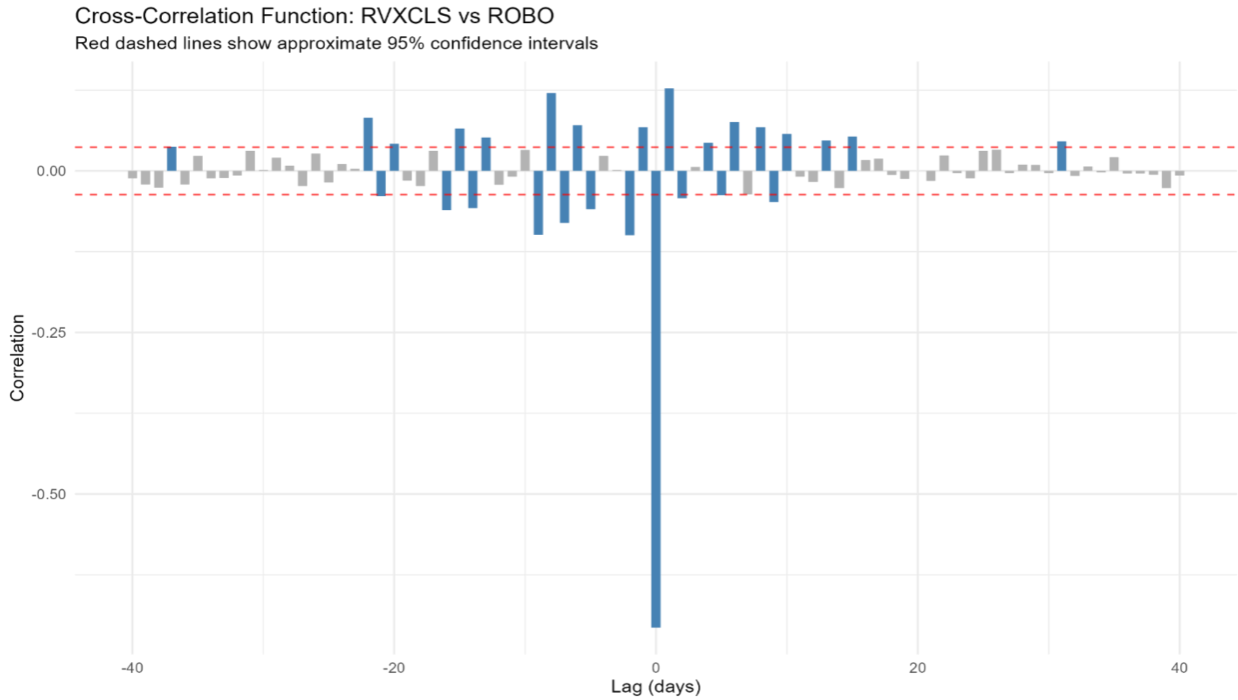
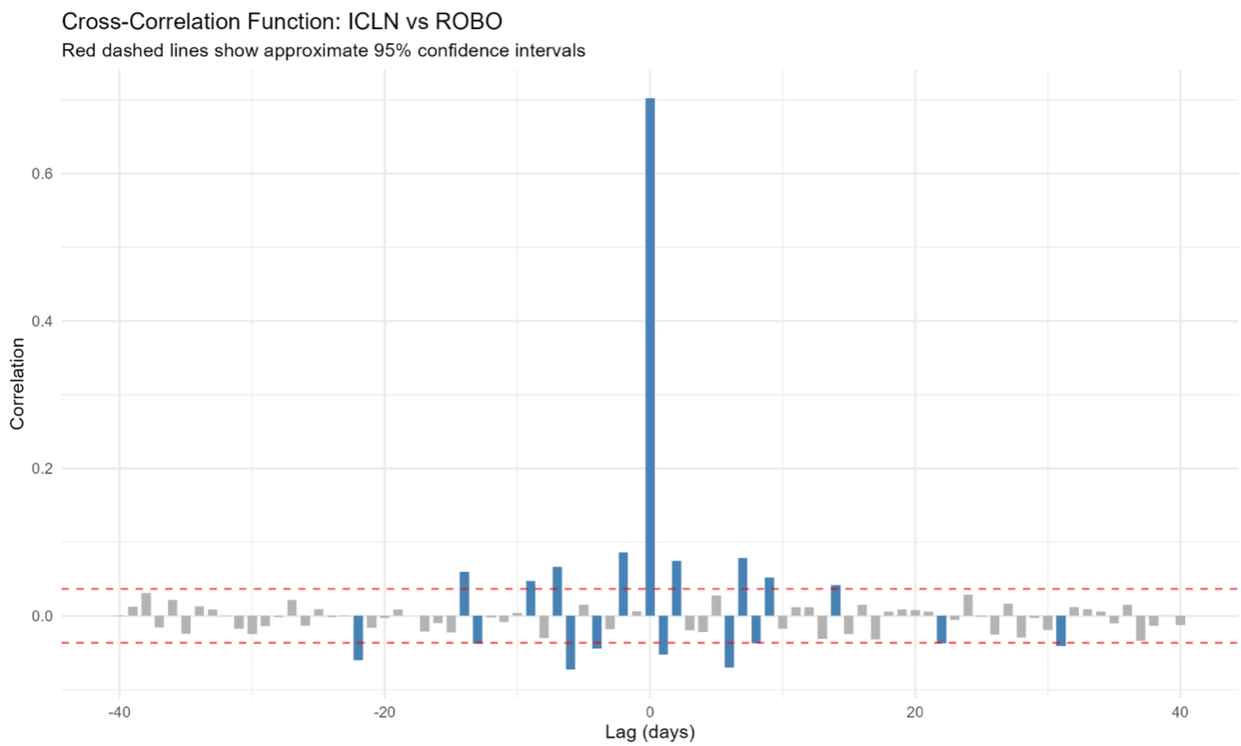





Cross-Correlation Function: RVXCLS vs ROBO
Red dashed lines show approximate 95% confidence intervals
Correlation
0.00
-0.25
-0.50
-40
-20
0
20
40
Lag (days)


Cross-Correlation Function: ICLN vs ROBO
Red dashed lines show approximate 95% confidence intervals
Correlation
0.6
0.4
0.2
0.0
-40
-20
0
20
40
Lag (days)

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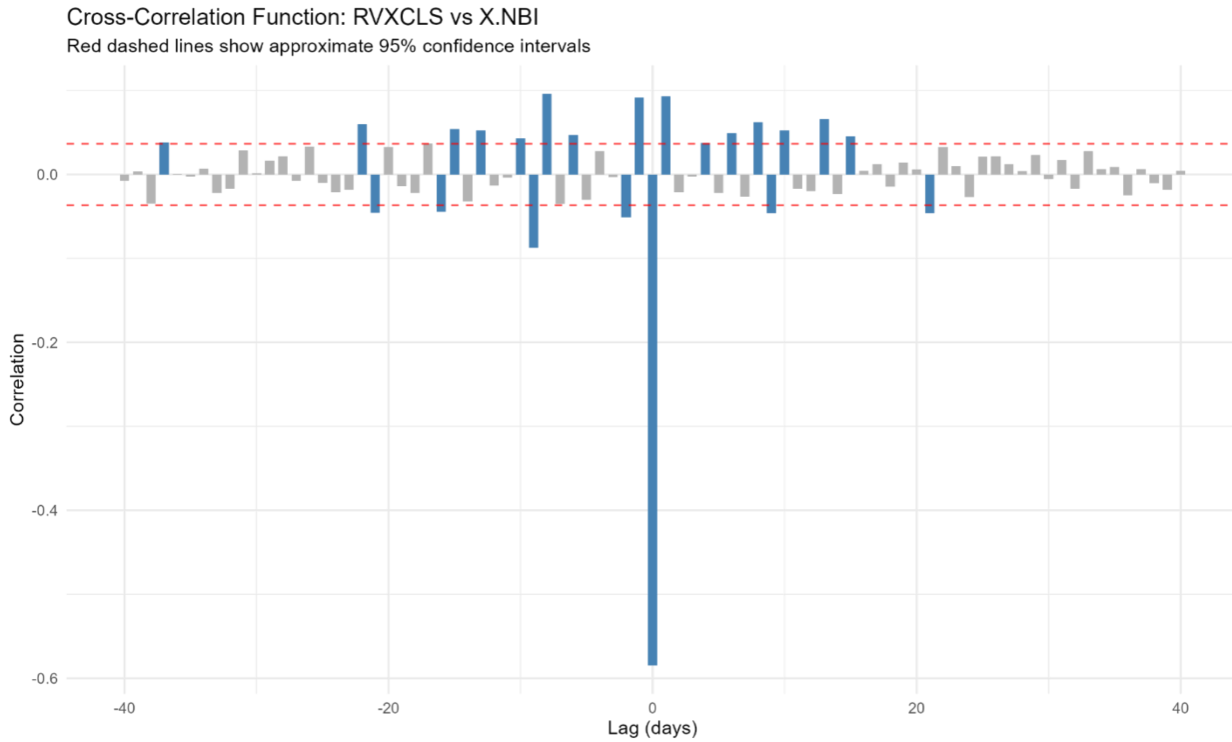

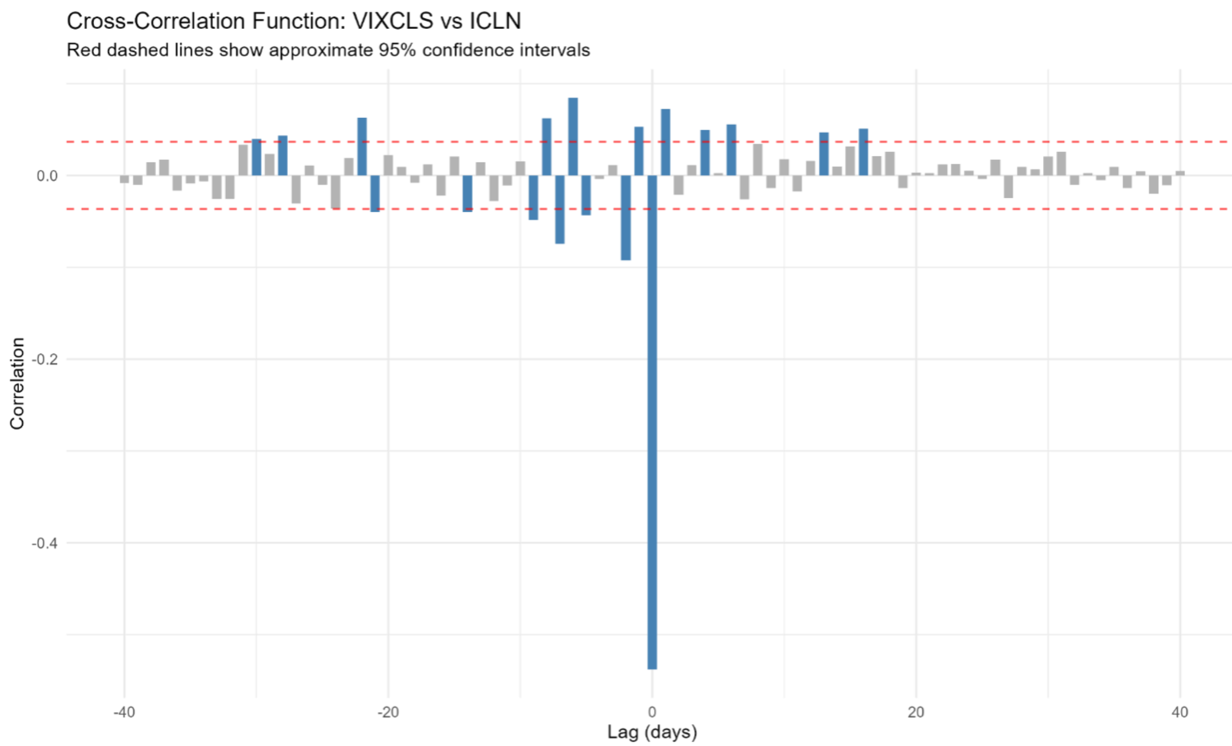

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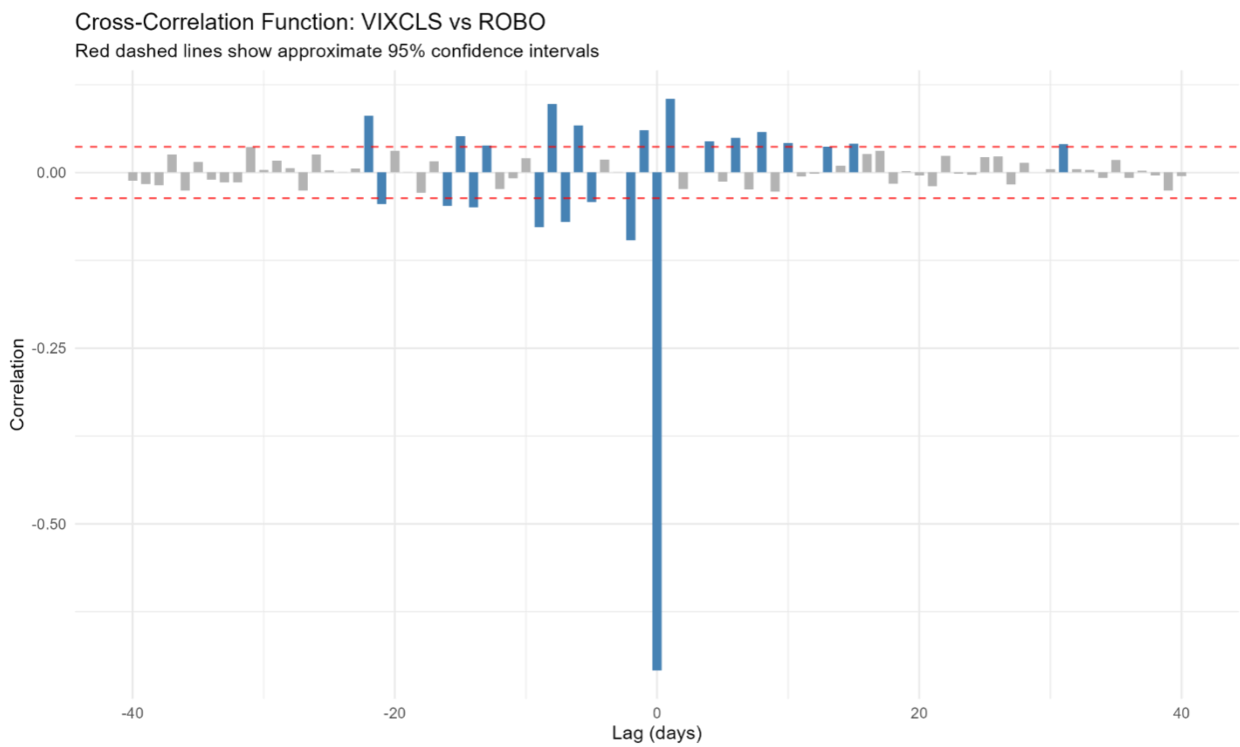

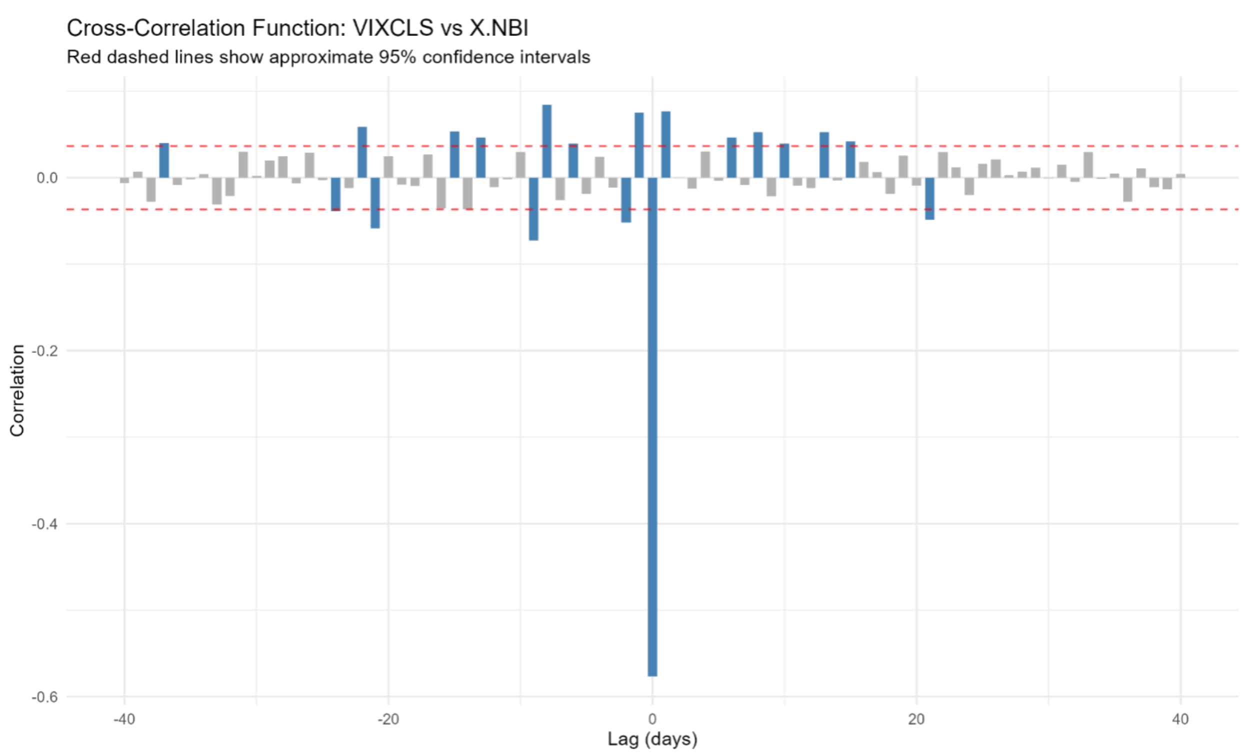

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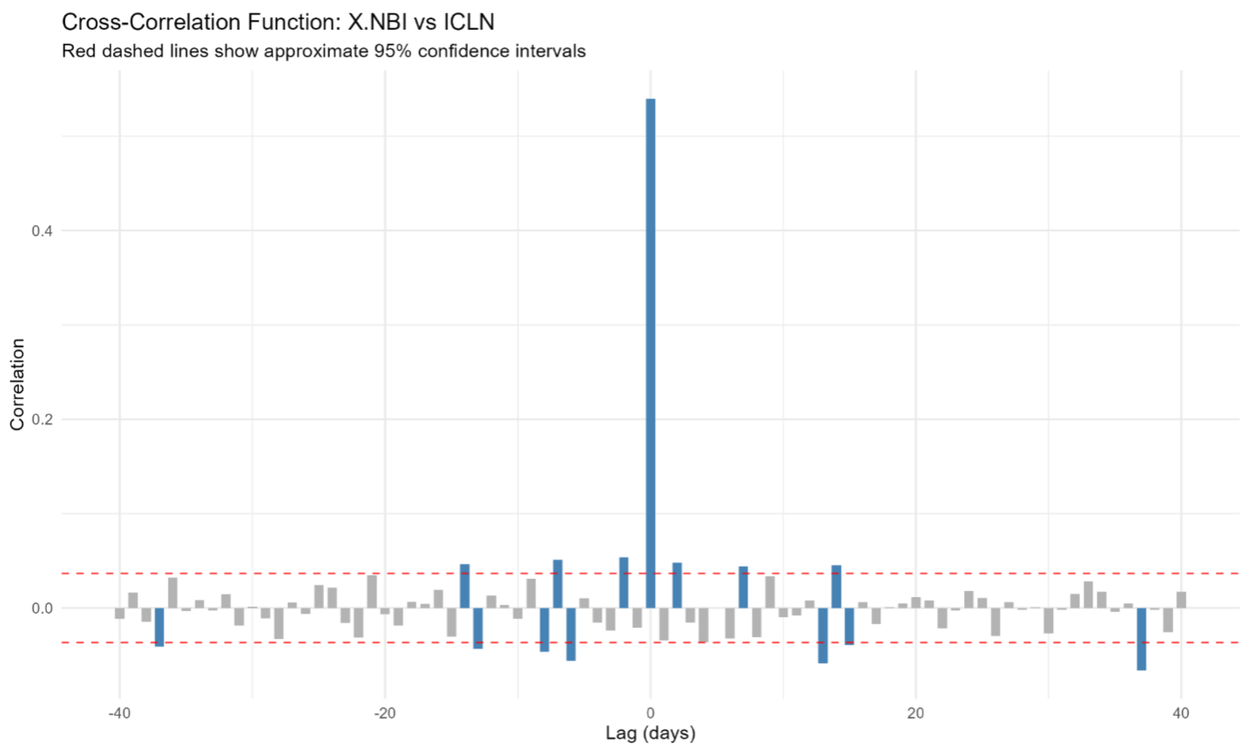
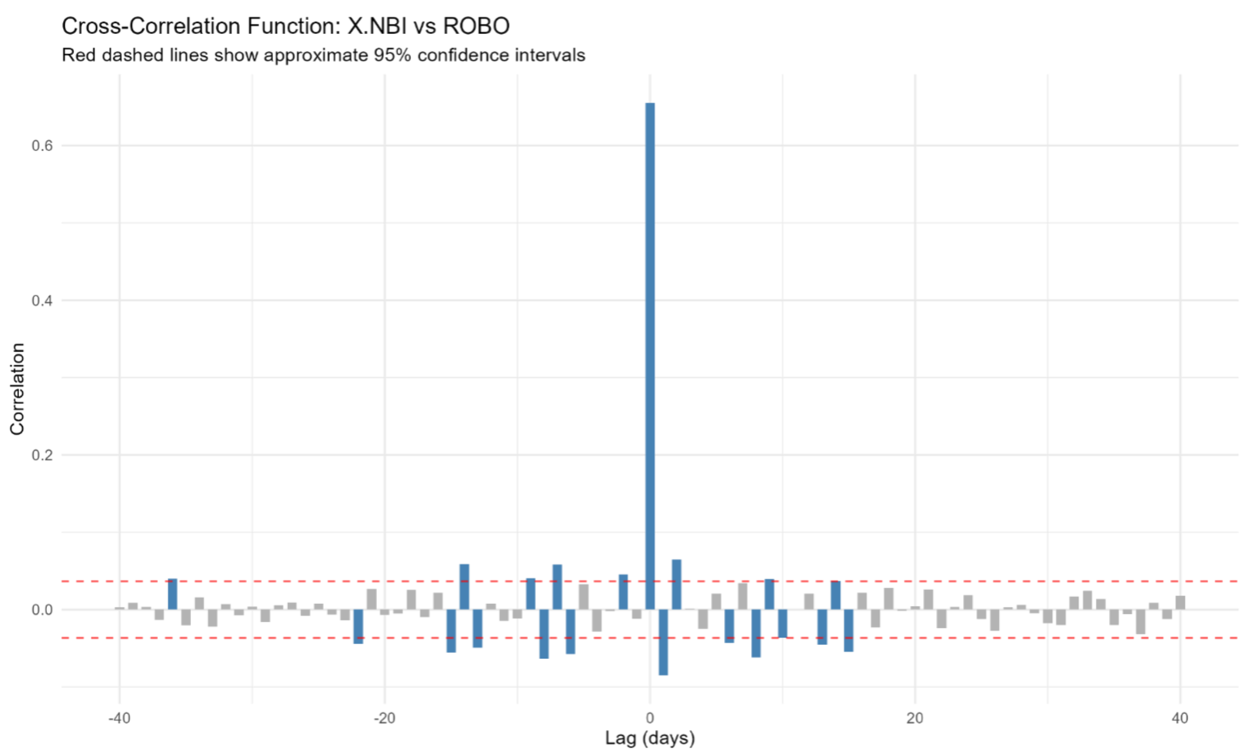
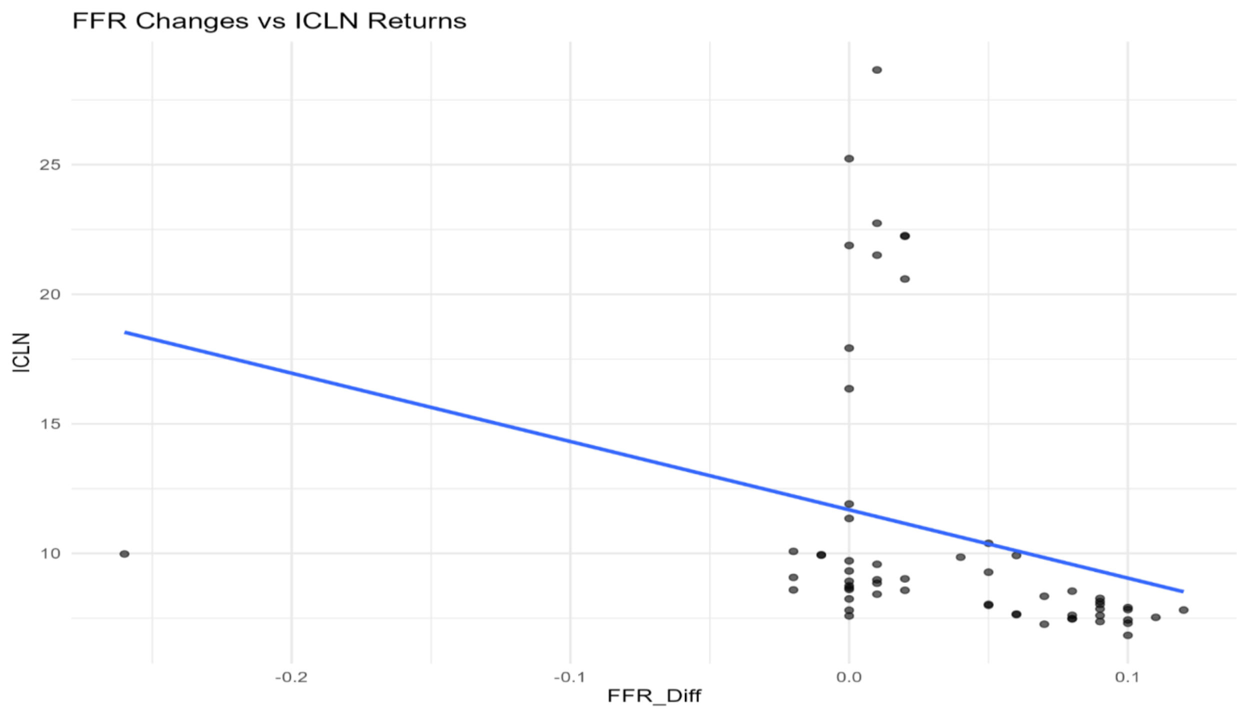
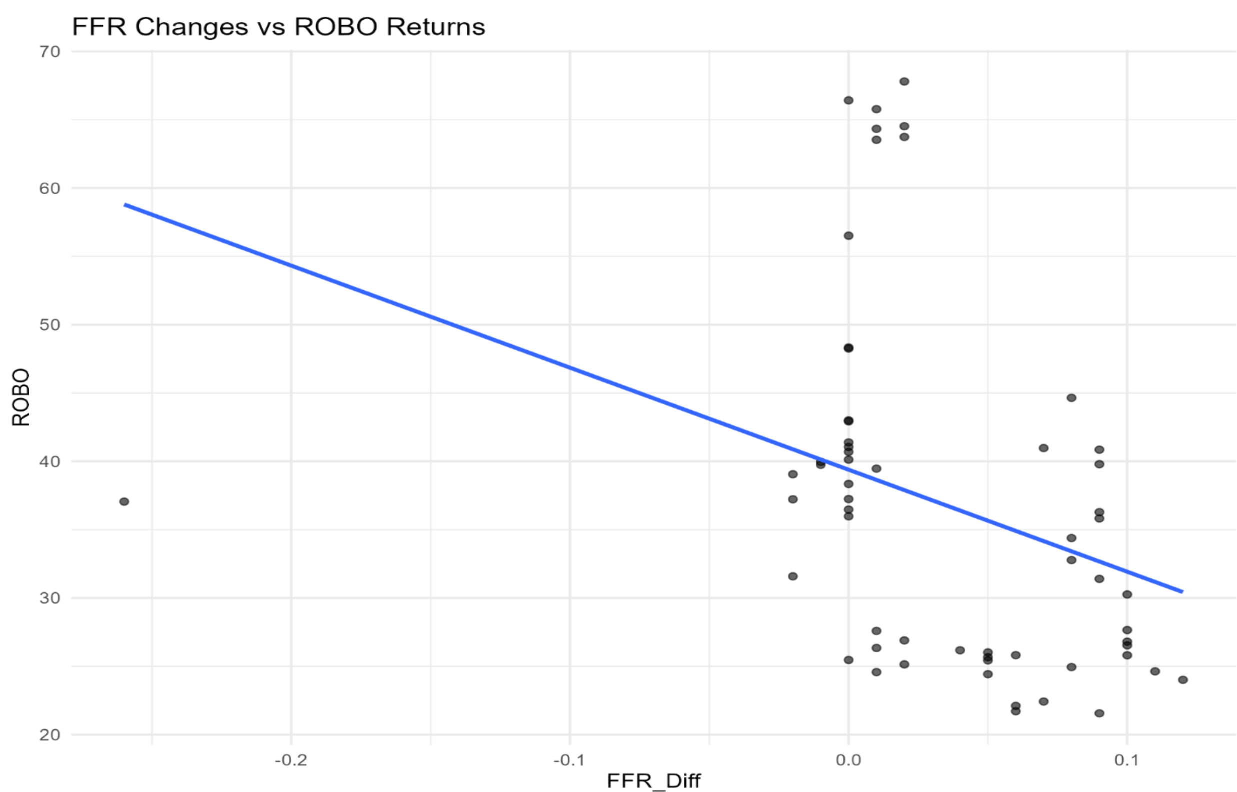





FFR Changes vs ICLN Returns
ICLN
25
20
15
10
-0.2
-0.1
0.0
0.1
FFR_Diff


FFR Changes vs ROBO Returns
ROBO
70
60
50
40
30
20
-0.2
-0.1
0.0
0.1
FFR_Diff

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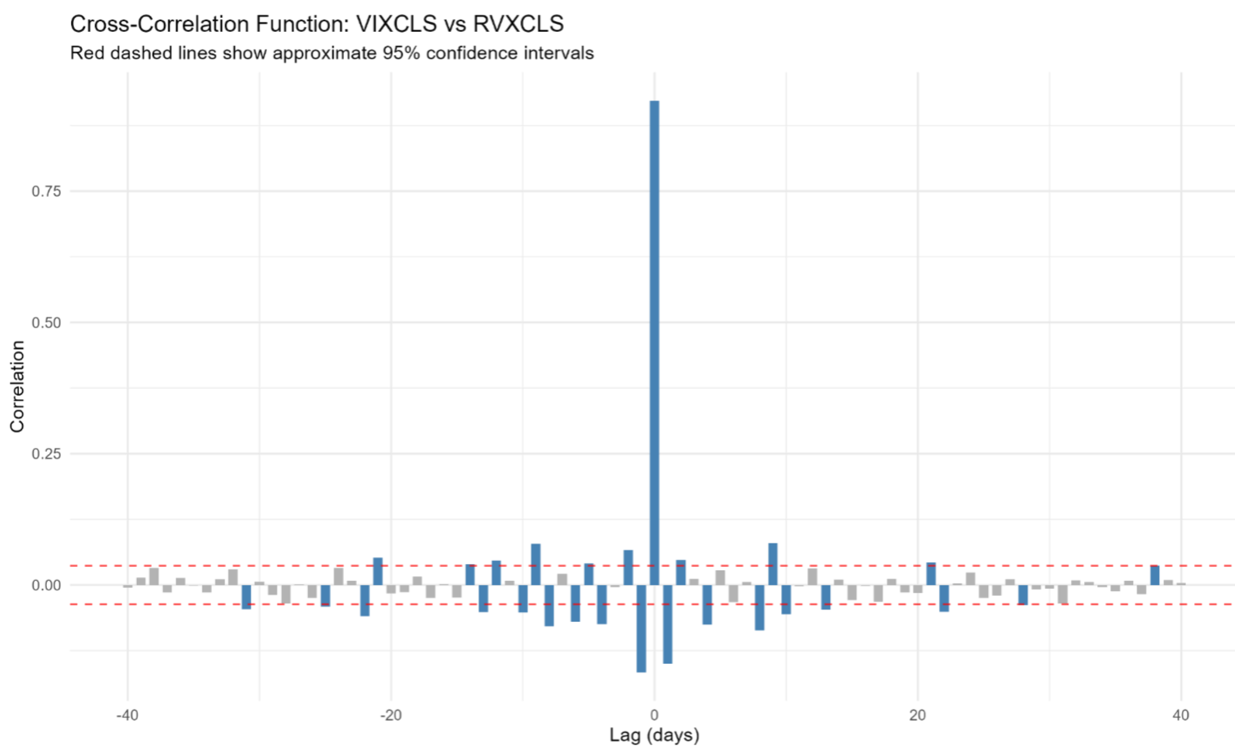

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