Financial Risk Analytics and Management

(ECON F342)

Abnormal Returns or Mismeasured Risk? Network Effects and Risk Spillover in Stock Returns with special reference to India

Group Members

Harshal Anand Badgujar 2018B3A40771G
Katanguri Koushik 2018B3A40745G
Dhruv Setia 2018B3A40772G
Nirvan Mundra 2018B3A40718G

Keywords:
Fama-French factor model; market microstructure; trading behaviour; panel data factor model; risk spillover; abnormal returns

Introduction

In the recent development in Econometric models, we have seen improvements in major models, improvements in the model's efficiency, accuracy, and reliability. These models are also improved to study the abnormal returns in the current financial markets and find the reasons for such abnormalities. Despite using the popular models being robust, there is a need for change in those models as the markets are now influenced by many factors. One such factor is the Network effect, which then creates risk spillover or volatility spillover. In one of the recent economic studies, it is shown that Social Network and Price discovery have a significant role in stock price and stock return. The sudden Shocks in the markets are sometimes correlated to these networks. For example, Reddit users influence the stock price of GameStop, and a Tweet for Elon Musk influenced Cryptocurrency prices, i.e., Bitcoin and Dogecoin. Thus, Considering the newer influences on the markets, the models we are using to estimate here are FF-type factor models; these models are adjusted to network dependence structure, applied to the adjusted daily data to monthly stock prices on the stock returns for the NSE Stocks (NIFTY 50), to find the evidence of networks effects in NSE, the adjusting of the current model to address the underlying influences and external factors for the factor model. Further, we will also see whether this is a mismeasured risk and network effects on stocks listed in NSE with risk and volatility spillover over the past two decades. Their degree and at what time frame they were at peak and briefly describing the scene during the 2008 financial crisis by these terms using charting and statistical tests.

We try to bring out the returns more related to risks, as risk and recovery go hand in hand; we also try to provide a structural understanding of risk spillovers. Sudden shocks in the market are mostly aligned with these abnormal returns. We have considered the CAPM model as a benchmark, and we also factor in the FF- factor adjusted model for the study.

Literature Review:

Dynamic return and volatility spillovers among S&P 500, crude oil, and gold

Mehmet Balcilar | Huseyin Ozdemir | Zeynel Abidin Ozdemir

They have done investigation of the return and volatility spillovers in the S&P 500 index and the two most common commodities, oil and gold. Data sets were the realized volatility with the monthly return on a monthly series covering the period January 1986 to the August 2018.
The methodology used in this study was quantile-VAR models, vector autoregression with variance decomposition.
And they have finally concluded that return spillover is relatively higher for the extremely negative and large positive shocks as compared to the average shocks, while the spillover due to volatility is relatively larger only for the large positive shocks as compared to the average shocks.

A robust and powerful test of abnormal stock returns in long-horizon event studies

Anupam Dutta, James W. Kolari, Seppo Pynnönen, Johan Knif

This article has conducted a handful of robustness tests of abnormality stock returns in long horizon event study. Some of the test-statistics they have used are ASR-T, BHAR-T, BHAR-TSA, CCAR-T and CALENDAR-T. For each test-statistic, we can define a-ratio and test the hypothesis formed initially. Data sets were the samples containing NYSE, AMEX, and also from the NASDAQ stocks covering the time-period from July 1973 and ending in December 2009.

Dynamic relations between oil and stock markets: Volatility spillovers, networks and causality

Jose E Gomez-Gonzalez, Sebastian Sanín-Restrepo Jorge Hirs-Garzon 2020

Their main area of focus was to draw a relation between oil dynamics and equity market returns for largely participating countries in commodity markets. After this regression, the article also expressed volatility, spillover, network effects through modelling and indexing the individual factors of these effects and had also done a granger causality test between oil commodity prices and equity stock returns. Data were taken on a monthly basis on top 7 largely valued indices which are the S&P 500, S&P Toronto Stock Exchange, Moscow Exchange, Norway's Oslo Stock exchange, SENSEX of India, Chinese SSE Composite Index from Shanghai Stock Exch., and the UK's FTSE 100 index and were covering the timeline from the month of July 2002 upto April 2018.

Networks of volatility spillovers among stock markets

Eduard Baumöhl, Tomáš Výrost 2017, Štefan Lyócsa, Evžen Kočenda

Volatility spillover models have become much more fascinated in the 21st century, and this article is a network analysis of volatility spillover models taken from the 40 stock markets around the globe. Volatility spillover models help to see the degree of interconnectedness of 2 different markets. And by high spatial autocorrelation, this was confirmed that indirect changes/effects were more severe than the direct changes in any market alone, which simply implies one can't ignore the spatial effects to test the interconnectedness or relationships among the stock markets. Rather than using a GARCH model, they have used modified types like AVGARCH, APARCH, EGARCH, GJR-GARCH, NAGARCH etc. Datasets were of high frequency ranging from January 2, 2006, to December 31, 2014. The article concluded with the interconnectedness that markets peaked at the time of the financial crisis of the year 2008: 40% of the total of 1560 volatility.

Modeling and forecasting abnormal stock returns using the nonlinear gray Bernoulli model

Mahdi Salehi and Bahar Doryab

Abnormality in stock returns is a part of an investors journey. And this article has focused on forecasting and modelling abnormality in stock returns by applying the gray's Bernoulli model. Datasets were taken from the list companies of the Tehran stock exchange from 2005 to 2015. This model is subdivided into three parts which are the gray's model, the nonlinear gray's Bernoulli model, and the Nash nonlinear gray's Bernoulli model. The former one is the simplest model and then going to become much more advanced. The study concluded that the later one could predict abnormal stock returns.

Examining the evidence of risk spillovers between Shanghai and London non-ferrous futures markets: a dynamic Copula-CoVaR approach

Hong Shen, Ying Xing, Yue Tang

Shen 2020: The objective of the paper is to find out evidence of the stock spillovers which created or popped up between the Shanghai stock exchange and London's futures market; it's focused on the non ferrous metals market of the Future segment. The model used to investigate the spillover is Copula-CoVar. The data used for this is the daily data, and for marginal distributions with the optimal Copula functions are deduced using the kernel's estimation method with the squared distance test as propped under Euclidean regime. Copula-CoVar is used to find the Conditional particular Value at Risk and also the Value at Risk rate; with this, the correlation coefficient between Shanghai stock dynamics and London's Future segment market. The results have shown that the risk spillover effect is exerted from London to Shanghai and also vice versa. The effect is mostly caused by the changes occurring in the Global Economy system across the worldwide. Moreover, the degree of the risk spillover is most significant in the case of Shanghai from London, mostly on zinc and copper.

Spatial linkage of volatility spillovers and its explanation across G20 stock markets: A network framework

Weiping Zhang, , Yang Lu, Jian Wang, Xintian Zhuang

Zang 2020: This research paper aims to find the correlation between spillovers due to volatility and the influence on the G20 Stock market. The model used in the research here is the GARCH-BEKK; it is used to establish an estimate of the volatile spillover and construct a dynamic on volatility networks. Data used in the study is the daily spot price for the G20 index (both opening and closing are paired). The observation time period covers the month of January 2, 2006 upto December 31, 2018. A Complex network theory is used to construct a relationship between the parts of the real financial system across a conceived network.

Here, to gain the empirical results of the analysis, they have used BEKK (1,1) GARCH model to predict or to make an estimation of the volatility relationship over the five periods; in the process of estimation, the significance of the Wald test at the 1% is considered, considering all the estimates this gave the general result, the developed markets are found to be more influential as compared to the current emerging markets during the period of shocks rapid changes, while the emerging markets are prone to be more sensitive to the volatility shocks, during a randomly selected period. The end of the paper also introduces the QAP(Quadratic assignment procedure) to deduce or to identify the majority of factors influencing the spatial linkage of the spillovers induced by volatility

Results from QAP show that because of geography influence and the correlation across the economic cycles and also the centrality of structure factors and some external economic factors.

The Influence Of Social Network Structure On Stock Price Disclosure

Zhaoyuan Wanga, Haijun Yang, Shancun Liu

Wang 2020: The is proposing a new heterogeneous model to investigate the influence of different structures of network on the equity stock disclosure of the multiple social networks. This model used different networks to construct a scale-free random network to test out the influence of stock prices. The paper relies on the fact that social networks and main source of price discovery of the stocks and the influential articles of the markets and the companies related. The main four channels of the information exchange are preferential network, randomly connected, weighted randomly plus the network and random connection. Economists have also demonstrated the significant influence of Social Networks with the price discovery; this model is an improvement on HAM of Chiarella; the paper has embedded multiple social networks into the old model and also added agents which will incorporate private information. The structure and construct are given in the paper. After all the necessary additions to the model, the results show significant influences on the price discovery in the dynamic stock market, and this also has a significant effect on the private through informational and contagion. On comparing the simulation results on various networks, networks with small-world properties have sped up the contagion of the information and price discovery and obstructed the information, decelerating the speed of the pricing discovery and also then may also cause failure in the market.

Interrelation And Spillover Effects Between Stocks And Bonds: Crossmarket And Cross-asset Evidence

David G. McMillan

Mcmillan 2020: The purpose of this research paper is to determine the behaviour of both the interrelation and spillover effects on contemporaneous and casual, of the stock and the money mkt i.e. bond markets of the four major global nations. The paper uses Realized volatility approach and a generalised vector autoregressive approach to examine the causality and spillover effects. The empirical model used for the study focuses on the VAR model, Granger causality tests and the Spillover index. Data used for the model is of the bond and stock return data of Japan, Germany, the UK and the USA particularly. The data is taken over a period of 1980 to May 2018. The modelling is frequented monthly, and the daily data is used to construct the monthly returns with the volatility, covariance and the correlations.

The results of the tests and the model reveal that return correlation and spillovers for one same asset/commodity across global markets will raised over time, while the return correlation and spillovers for different assets in international markets exhibit substantial variation, the rise and fall of the return correlation and spillovers are most significant during the 2000's. The equivalent spillovers results are prominent in indicating the large effect of the time variation but a little or with no given direction. The most influential stock market is the US Stock market. This exhibits a leading role for other bond return markets. Bonds also showed a higher degree of interaction among these markets as each of them influence one another.

This paper also points out a key result as the stock returns also points out(lead) movements in the bond markets. This pattern is also proved in the paper. This paper also includes the various influences across the markets(Cross-Market behaviour) within the countries.

These results are useful to build interest in the investors, policymakers, and information flows across the markets alike.

Volatility Spillover From Oil Prices To Precious Metals Under Different Regimes

Ayşegül Kırkpınar

Kirkpınar 2020: The paper's main objective is to study the volatility spillovers from oil to the precious metals under both high and also low volatile regimes and analyze the association with the increasing prices and the volatility in financial markets. Here in the paper, the analysis is done on time-varying co-movements of the commodity prices. The model used in the paper is GARCH (1,1); data taken into consideration is the daily closing prices of the assets such as oil and precious metals. The time period of the data considered is from Jan 2010 to Dec 2018. GARCH is considered the most appropriate model for the study since it is the most appropriate for the volatility structure with The Markov Switching model is also used for the study for the spillover analysis. For the analysis of both the models, the results show that there was volatility spillover from oil to the palladium and platinum in the low regime and oil to palladium in the high regime. Thus investors, when investing in oil and palladium, will have a diverse portfolio and diverse benefits in a low regime. This analysis is beneficial for the long term investors, decisive policymakers,and also for the risk managers for the financial portfolio management.

A social network model of investment behaviour in the stock market(Bakker2010)

L. Bakker a, W. Hare b,∗, H. Khosravi a, B. Ramadanovic c

This paper explores the social and psychological variables that affect the market valuation, the instability within the stock market due to social impacts affecting investor decisions to buy ,sell or hold stock. The author develops a social network model of stock market which incorporates the effects of trust network, superinvestors ,investor decisions that drive stock price,etc and shows that social trust network can cause highly stochastic behavior in stock value and investment behavior which can essentially delay the adjustment of the market.

On equity risk prediction and tail spillovers(pouliasis2017)

Panos Pouliasis Ioannis Kyriakou Nikos Papapostolou

This paper studies the impact of modelling time-varying variances of stock returns in terms of risk measurement and extreme risk spillover. The univariate model used to estimate conditional volatility dynamics is shown and describes the criteria used to evaluate forecasting performance and the method used to measure the economic value of forecasts in terms of VaR and extreme risk.Models like MRS and Mix-N models suits the data well and capture volatility persistence better than the standard GARCH and also constitutes some applications based on stock return volatility modelling and gauge the anticipating potential of regime-dependent models in the sector.

Abnormal Returns from Takeover Prediction Modelling: Challenges and Suggested Investment Strategies (danbolt2016)

This paper is inspired by finding target prediction models that have some anticipating ability. It discovers the basic factors that affect the stock returns of predicted target portfolios and look into potential strategies for reducing the effects of these factors.It begins by selecting a representative sample of all companies that have been listed on the same market.The results show that the predicted target portfolios do not earn positive abnormal returns because of the tendency of uneven number of underperforming firms

THE PERSISTENCE OF ABNORMAL RETURNS f--(jacobsen1988)

ROBERT JACOBSEN

This paper examines time-series behavior of ROI to investigate the persistence of normal returns,Strategic factors are examined to work out the extent to that they assist to sustain a comparative advantage.The behavior of ROI series indicates a slow convergence process A number of factors such as vertical integration, market share etc if increased by implementing strategies by firms that influence these factors will tend to earn longer term profits.

THE PERSISTENCE OF ABNORMAL RETURNS AT INDUSTRY AND FIRM LEVELS: EVIDENCE FROM SPAIN(bou2007)

This paper focuses on whether it is firms or industries where differences in profits arise and time dependency of profit rates, the convergence process of the firms. It analyzes the whole influence in firms and industry and segregating the influence arising from transient and permanent components. It uses a variance component specification approach in which abnormal returns are broken down into random effects related to time, industry, and firm by year components.

The Fama-French five-factor model and emerging market equity returns. Selebogo Mosoeu and Odongo Kodongo

The paper investigates the markets to find efficiency, fairness and to provide most diverse markets. This gives the portfolio managers, traders fair knowledge while investing in a market. This paper tries to find the Risk involved in the market via a means of investigating different elements involved in an organization.The paper uses Fama & French (2015) model, which gives a set of 5 elements/factors whose suitability for pricing.The paper covers influential markets and geographically specific markets of, Australia, Chinese, and South African data comparing to America and Japanese Data for empirical studies, to use as a benchmark in the new literature.

Observations made paper are the relationships between firm-size, firm value, profits, and investment size and value, no of portfolios, and although the patterns are not uniform but in general are similar. In general all the markets with high average firm-size have high stock price irrespective of risk when compared to the low average firm-size which have low stock price even with less stock price.The profitability generating high returns are inconsistent and weaker and which generate less returns are consistent and stronger portfolios. This result are consistent in every market tested data.

Detecting Abnormal Returns Using The Market Model With Pre-Tested Data Steven Graham, Wendy L. Pirie, William A. Powell

The current literature suggests numerous various procedures for increasing the ability of tests to find abnormal returns in event studies. The authors simulate events mistreatment arbitrarily generated portfolios and compare check outcomes mistreatment 3 completely different procedures: typical, cross-sectional, and cross-sectional with standardized residuals. We have a tendency to compare the results of every check once all observations are enclosed with the results once the high mercantilism volume observations are excluded from the estimation amount.

Both the standard approach with excluded observations and therefore the cross-sectional approach with uniform residuals with all observations turn out just about the proper check sizes and greatly increase the capability of tests to find abnormal returns, in line with the simulation results. The cross-sectional technique with uniform residuals, on the opposite hand, is clearly the foremost common of the 3 procedures.

The arrival of firm-specific news adversely affects the ability of tests to find abnormal returns in event studies. Empirical money analysis offers many alternatives for up the ability of such tests. 2 suggestions are to drop observations for days on that the best volume is according or to use standardized market model residuals. During this paper, we have a tendency to develop a model that shows that the quality errors of the market model area unit, in general, heteroskedastic. The idea of political economy suggests that indiscriminately dropping observations, the same as pre-testing the information, might build the quality check statistics invalid. The parameter estimates area unit found to be considerably completely different once five p.c of the observations area unit omitted, compared with mistreatment of all of the observations.

Research Gaps:

A small drawback in Dutta 2018 one can see is that this paper has not considered the after the time of 2007-08 crisis which is from 2009 to 2018, which can give us more close approximation of the robustness of the latest abnormalities in stocks.
Jose E Gomez-Gonzalez, Jorge Hirs-Garzon, Sebastian Sanín-Restrepo 2020**.** Since this article has only taken the top 7 indices there are much more emerging markets across the world like the Gulf countries and some from Singapore, Malaysia which are also a prime part of the international market. To get a more accurate degree of spillover these can be included.
In Doryab 2018 Since Tehran stock exchange is an emerging market we can expect a higher degree of randomness in abnormality in other developed markets like NYSE, NSE, TYO etc.
In the Shen 2020 Copula-CoVar model can only accurately show significance in Risk Spillover over two markets when it's between more than two markets results can be insignificant. Multiple variables on the Copula - CoVar model are not accurate.
This paper provides theoretical Support for Risk Management. The global economy here gave a Macro factor to the overall study and provided a connection over a large range of the Risk Spillovers in the non-ferrous metal future market.

Objectives:

Using the monthly stock prices of Nifty 50 as market index and 30 major components of the market, the paper aims to focus and find evidence on the abnormalities in return, of a particular stock by time series analysis of the market. Further we have also considered the network effects i.e. dependence of particular stock on its similar other firm specific stocks(eg TataMotors and Bajaj Auto).

Methodology:

Here we have used the **Fama French model** to analyse the risk return given by any stock over a period of time.

$$r = r_f + \beta_1(r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \varepsilon_{it} \quad \text{..............................}(1)$$

r = returns for (i = 1,2,....n) stocks

r_m-r_f = Excess returns

β_1 = beta-factor or sensitivity of a stock / market coefficient

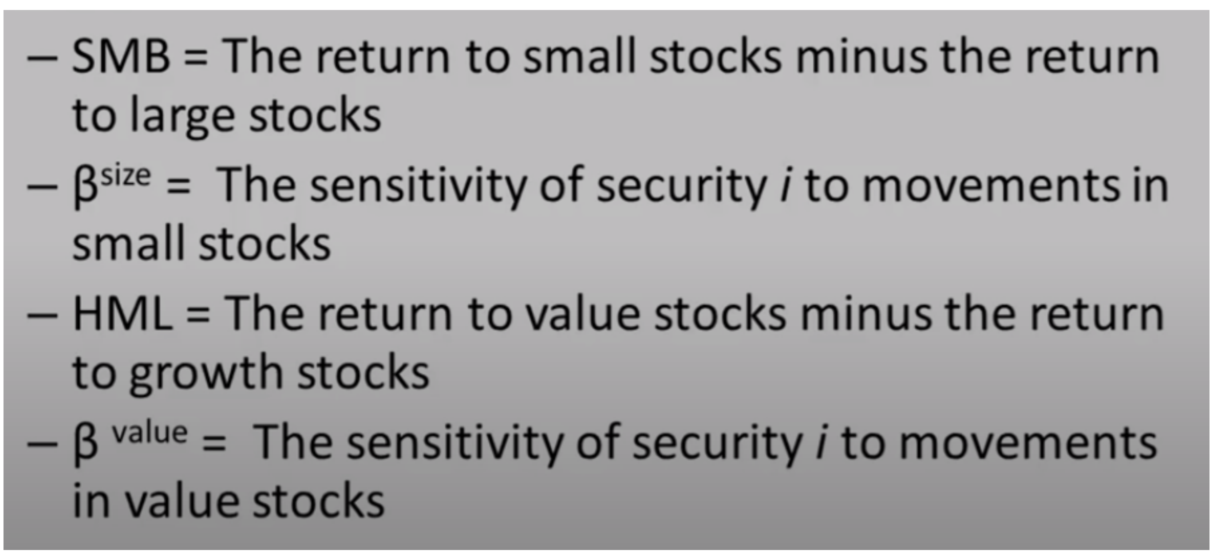
β_2= Size Risk Coefficient

β_3 = Value Risk Coefficient

SMB = Size premium

HML = Value Premium

ε_{it} = idiosyncratic error term



After all, the parameters will be beta $\beta_1, \beta_2, \beta_3$ to be estimated from the data sets by regression analysis over a financial time series.
However, the FF model is not taking any network effects into consideration, and hence these estimates will be biased and inefficient in measuring the risk leading to abnormal expected returns.
Since the CAPM model is not truly efficient in predicting the return we will also include network effects.
Further we are adding another term to increase the efficiency of the model, the term is the β_4 *(WML)

$$r = r_f + \beta_1(r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \beta_4(WML) \quad \ldots\ldots\ldots\ldots\ldots(2)$$

Finally the equation 2 will be used for doing the expected return analysis which is simply the classification of low alpha low beta, high alpha high beta accordingly with the Nifty 50's top 30 stocks.

Here **CAPM model** is also used to estimate beta and alpha values to find the relationship between Market Returns and Underlying Asset Returns, Equation used for CAPM model

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

$E(R_i)$ = capital asset expected return
R_f = risk-free rate of interest
β_i = sensitivity
$E(R_m)$ = expected return of the market

CAPM model Empirical Analysis is done on Nifty 50, 30 major components.

Data and Estimated Model

We collected monthly stock pricing from yahoo finance, on the stocks included in Nifty 50, we have considered 30 major components.We are using the adjusted Close price of each stock every month adjusted for splits, dividends and distributions. The period under analysis is from 1st Jan’ 2010 to 1st Jan’ 2020.(Exception of COALINDIA.NS and HDFC LIFE.NS which are later added to Nifty 50). Historical monthly factors of Fama French 4-factor are collected from the web “Sobhesh K. Agarwalla, Joshy Jacob & Jayanth R. Varma (2013)”,This is a working paper on the required values for FF-Model, This constitutes our Data Analysis.

First, To find the Trends in Returns of the Stocks, we have plot graph comparing to Returns on market index (Returns are in %)

Then, We estimate by a CAPM 2-Factor model including only an intercept(Alpa) and Excess return on market,This is used as a Benchmark test.As, only CAPM model is not efficient enough to capture the overall Network effect we use in the next model.

Then, We also estimate Fama-French Model including Rm, SMB, HML, WML, Rf.
The CAPM model exhibits strong network dependence. Risk spillovers are related to Networks effects, Capm model is used to correlate Market(Nifty 50 Index) to its major components to see the variance effects of the total Index on the underlying values, this is significant and we can see this in beta values of the CAPM analysis(Table

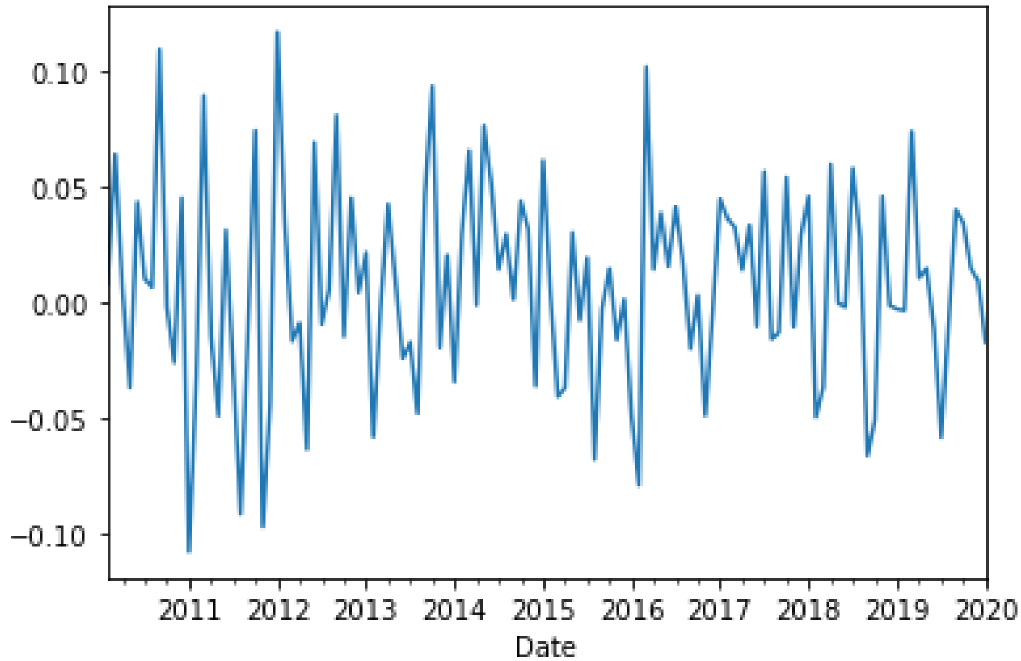
Trading activity and Structural Interpretations are also related, thus we use FF-type model, Trading activity can be done using FF-type model whereas in Structural Interpretations are beyond Fama-French model, thus we use CAPM model(as this only has Market Return Factor) and for better explantation we use CAPM as benchmark and cluster points.

To Study further we can also use a Variance Ratio test for the Efficiency of the market, this can be significant as Indian market usually has weak efficiency and this can be used to conclude the abnormal return in the market.

Empirical Results

1. Trends in Returns of Stocks(in %)

NiFTY 50



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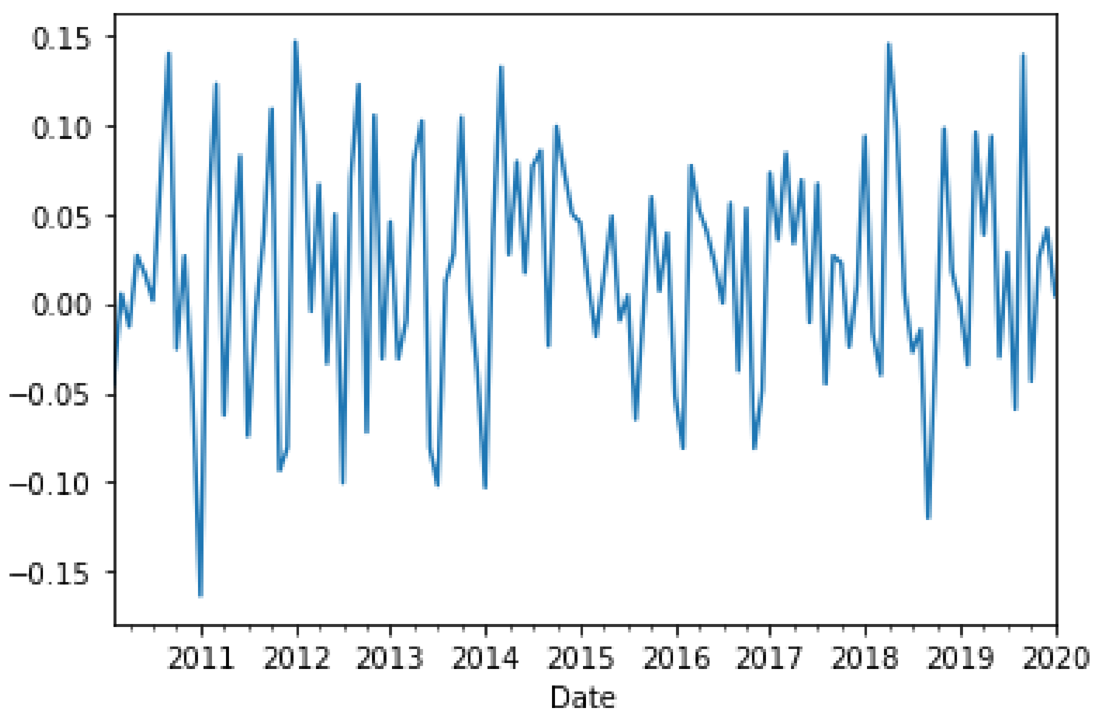

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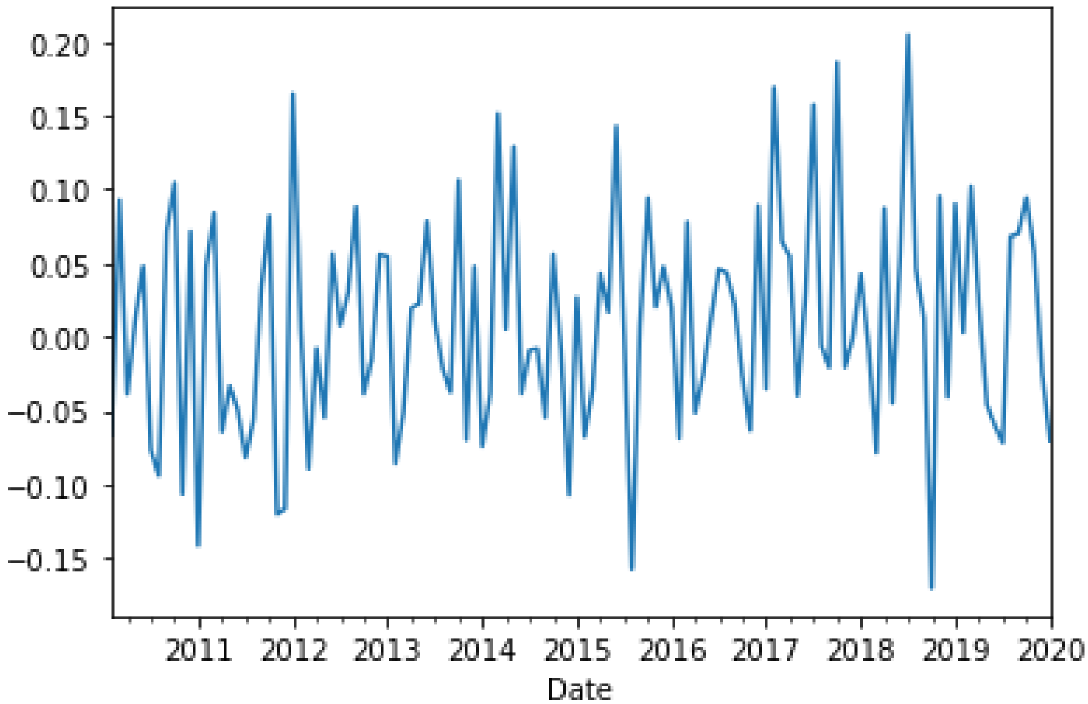

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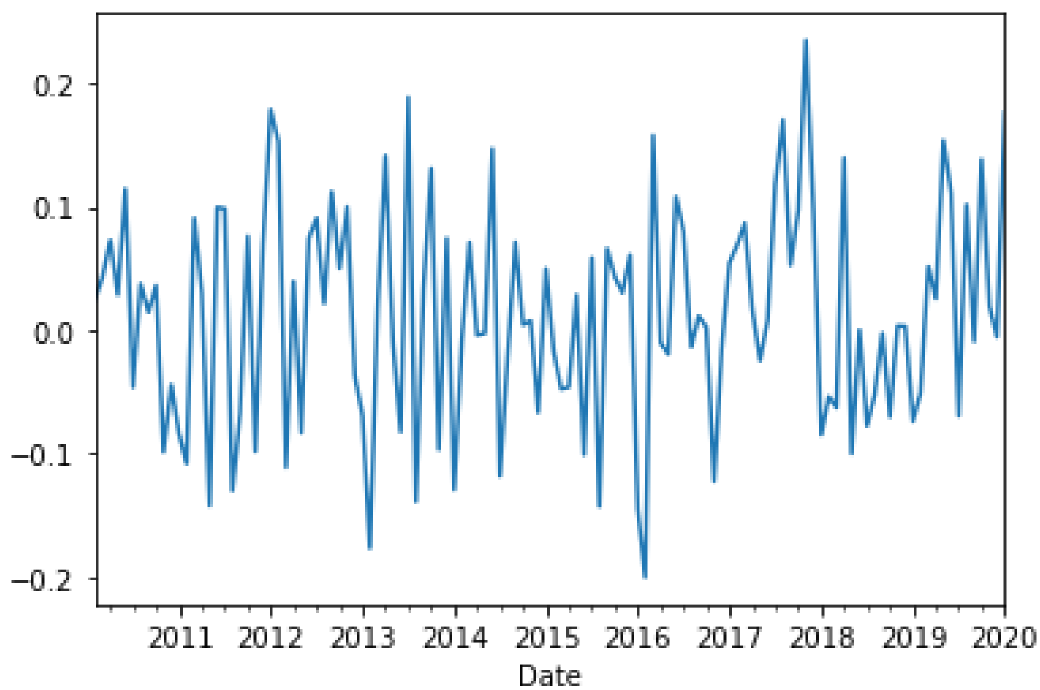

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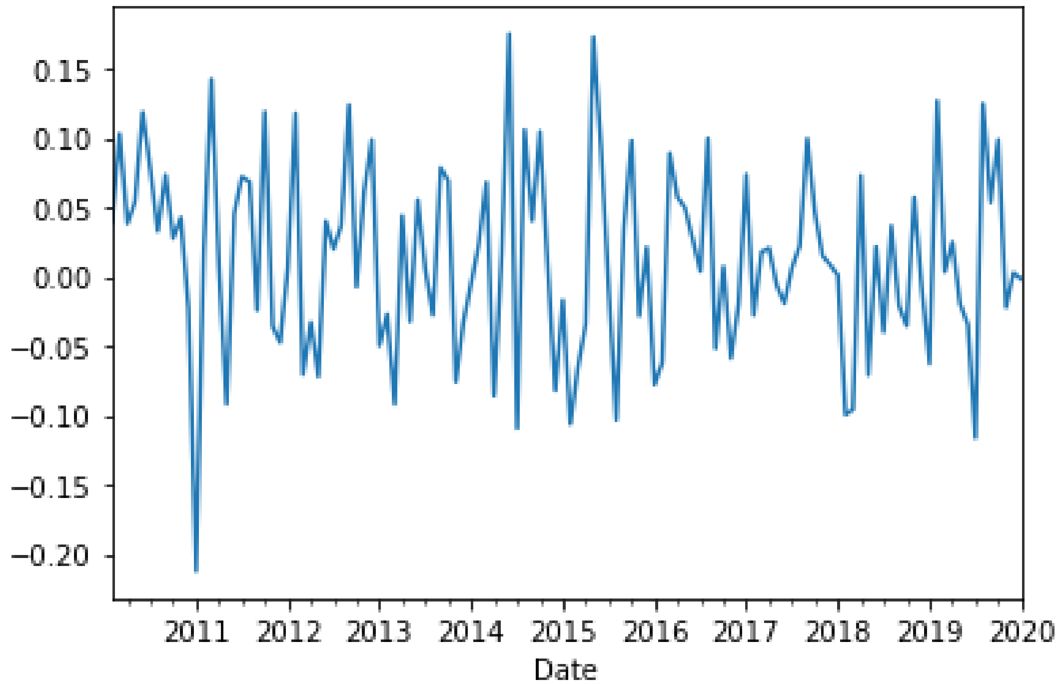

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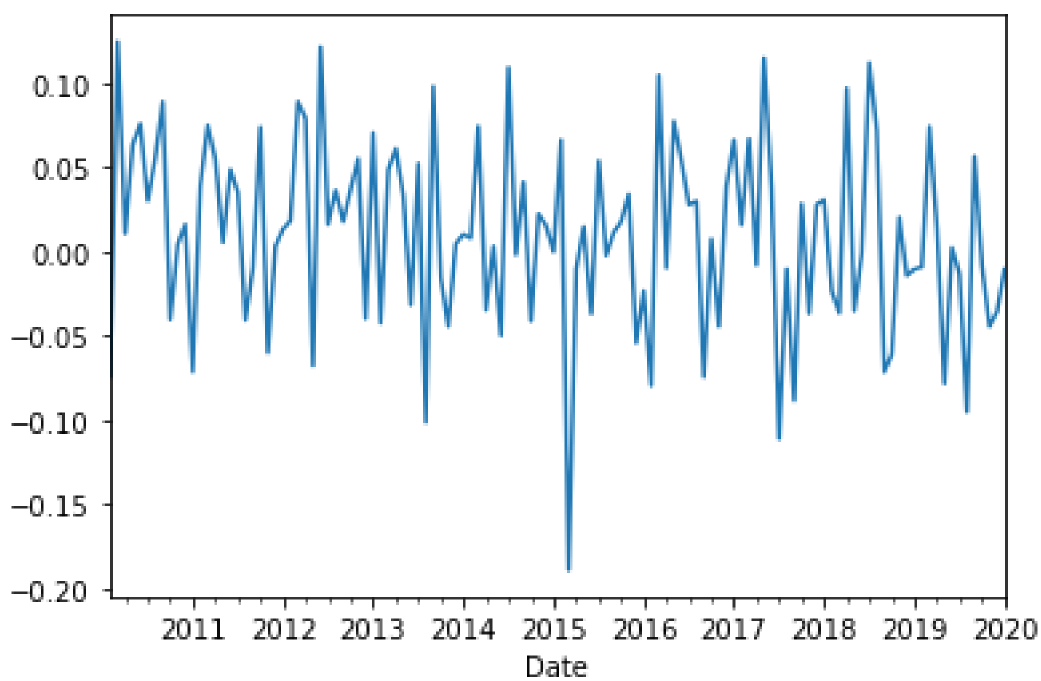

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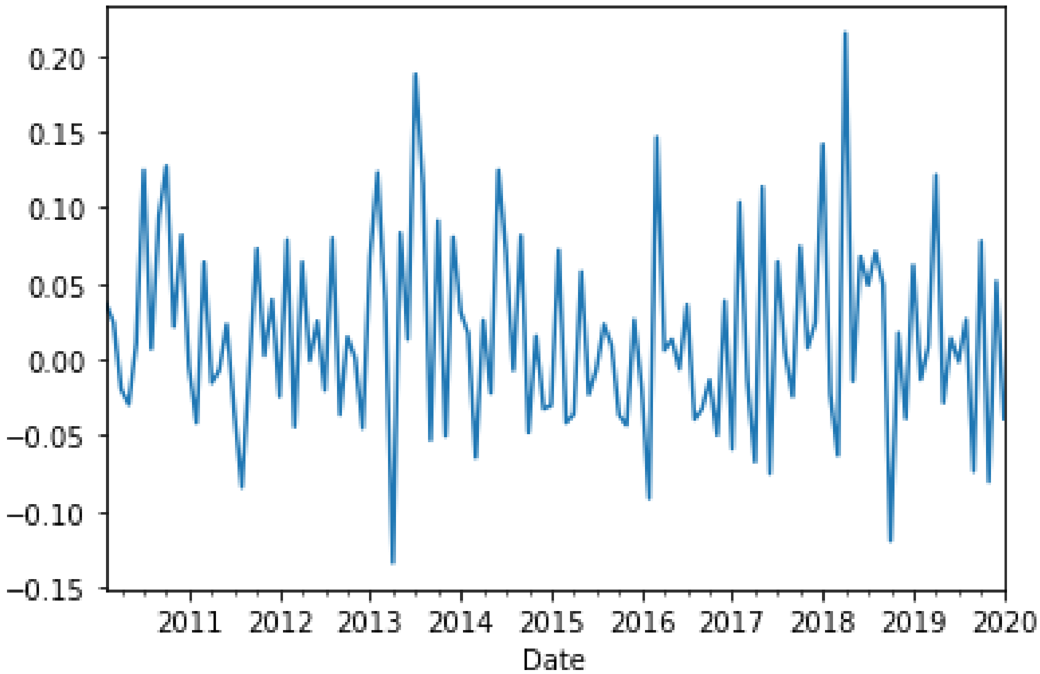

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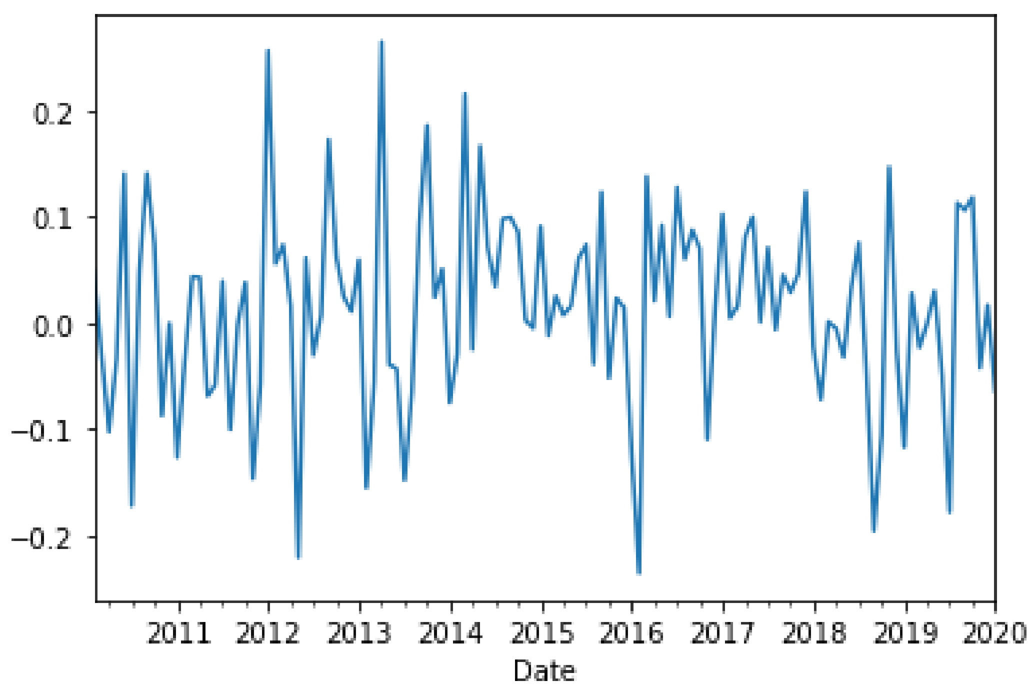

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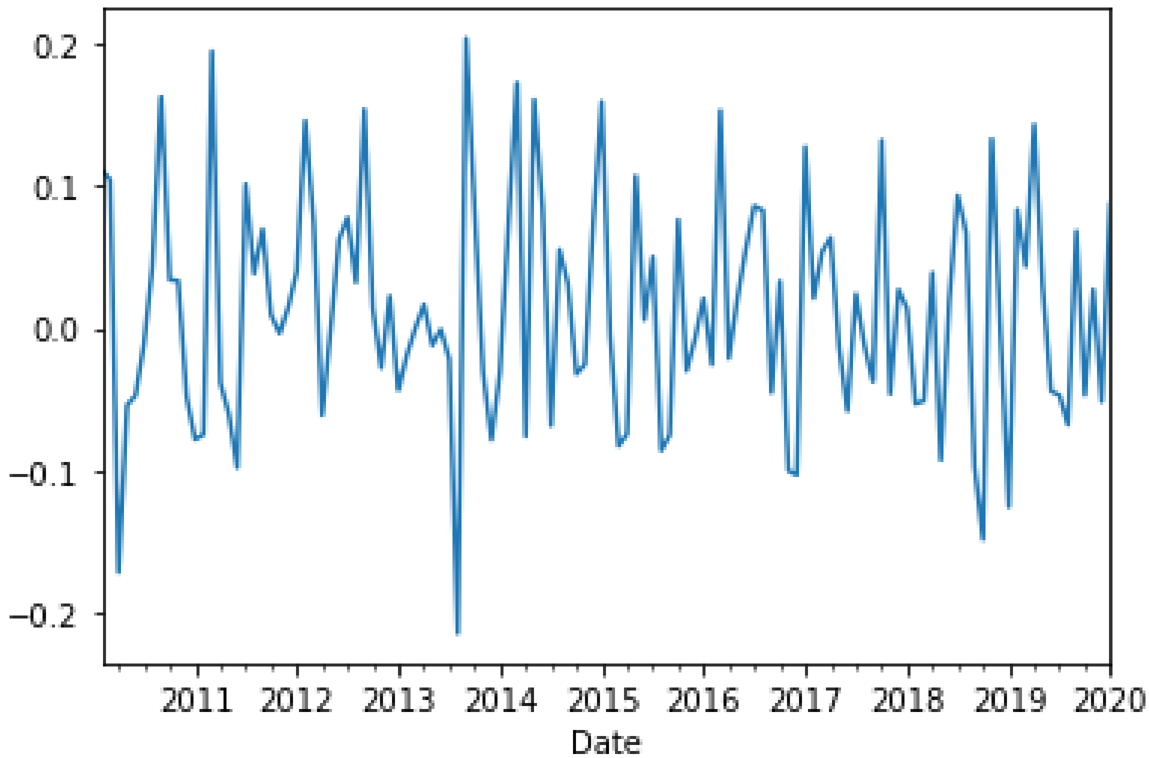

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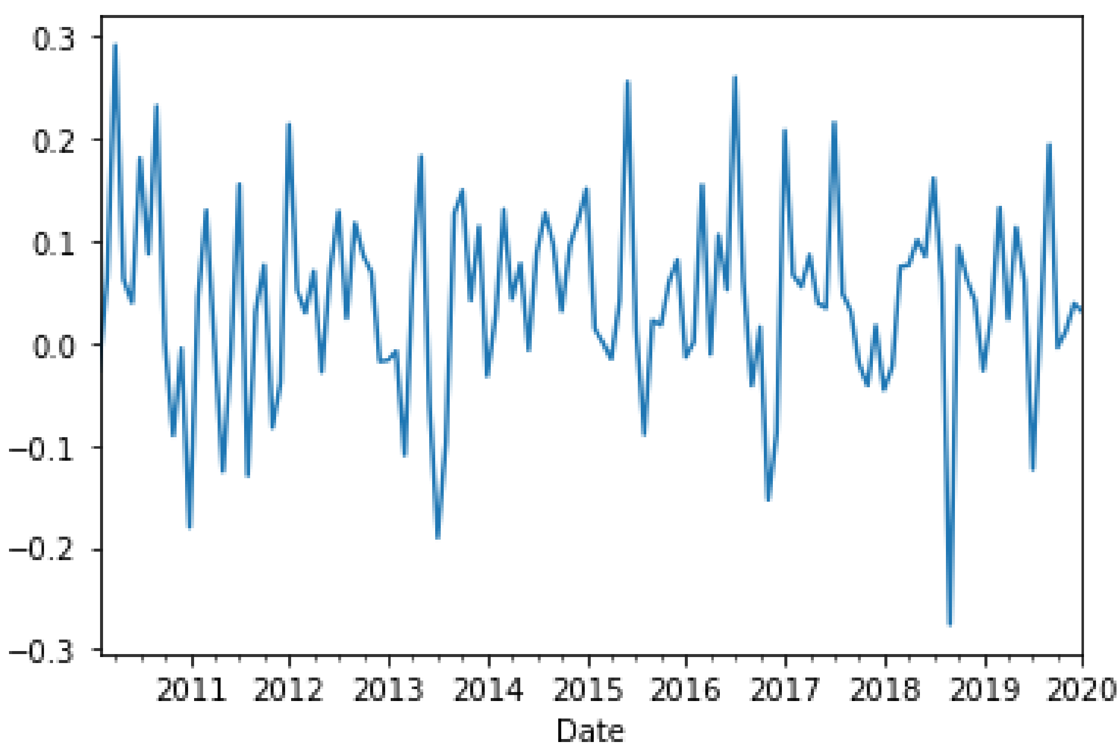

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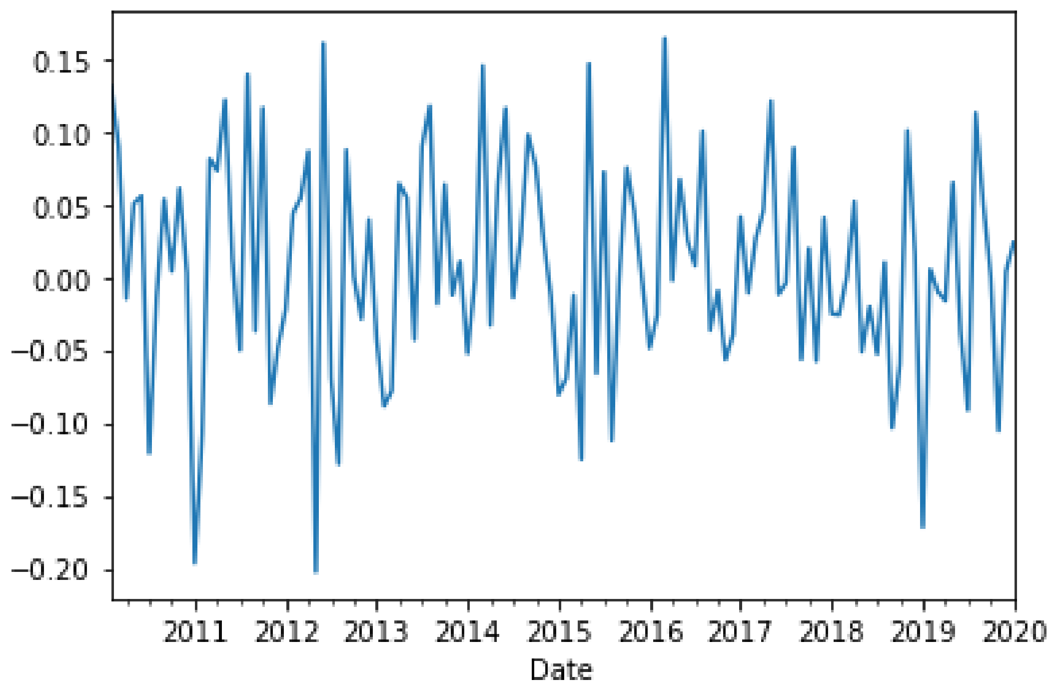

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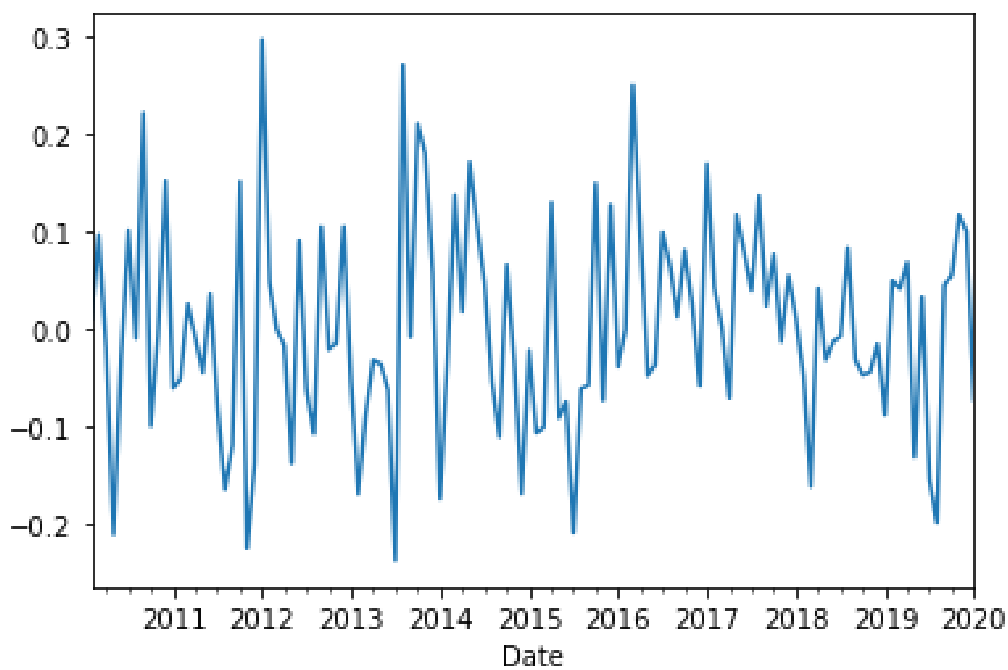

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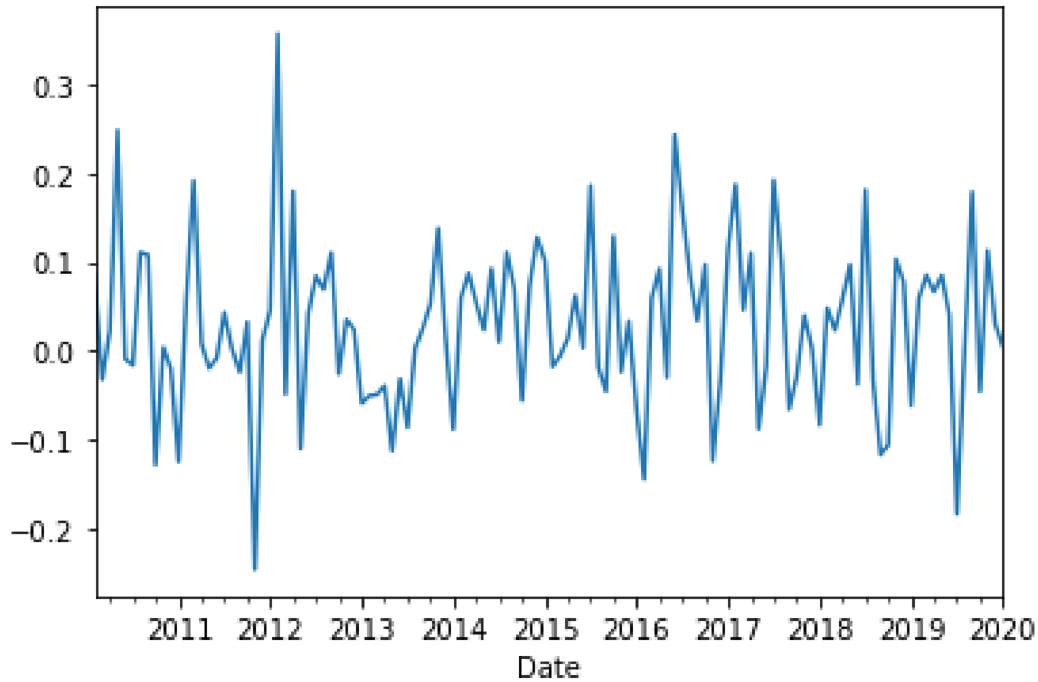

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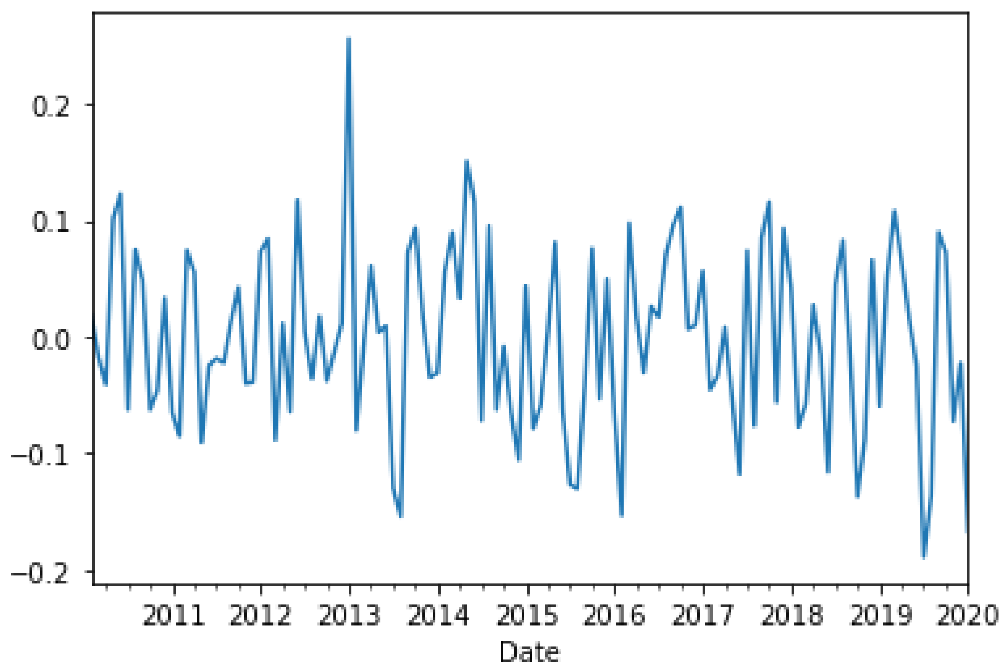

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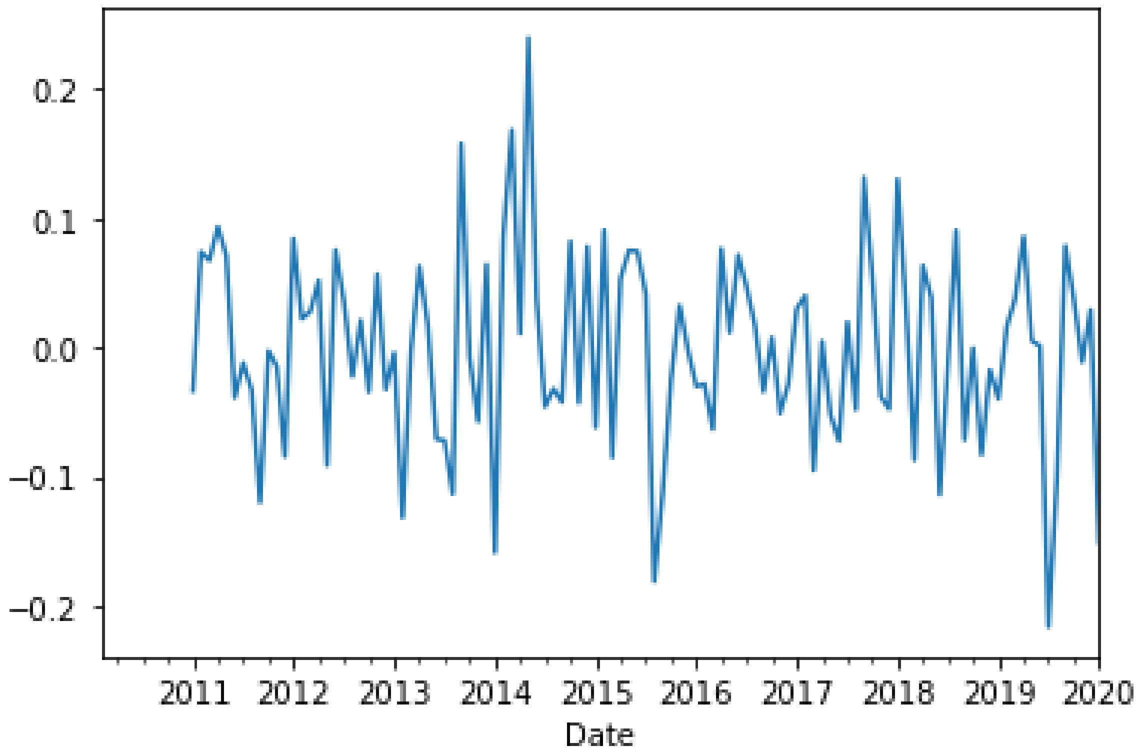

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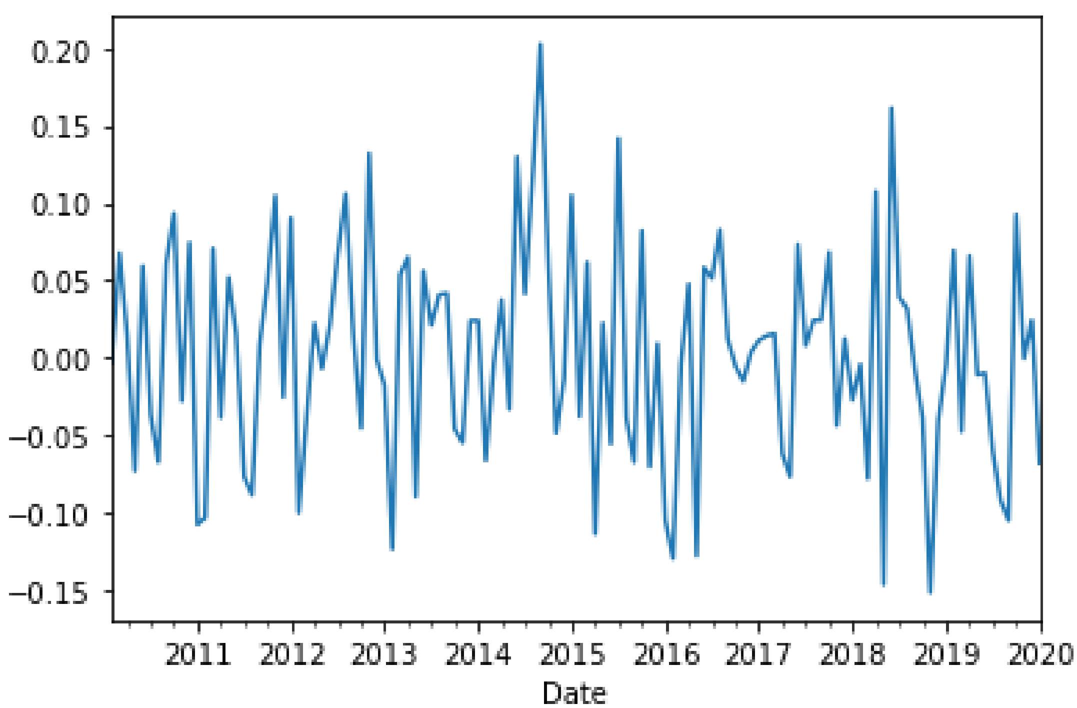

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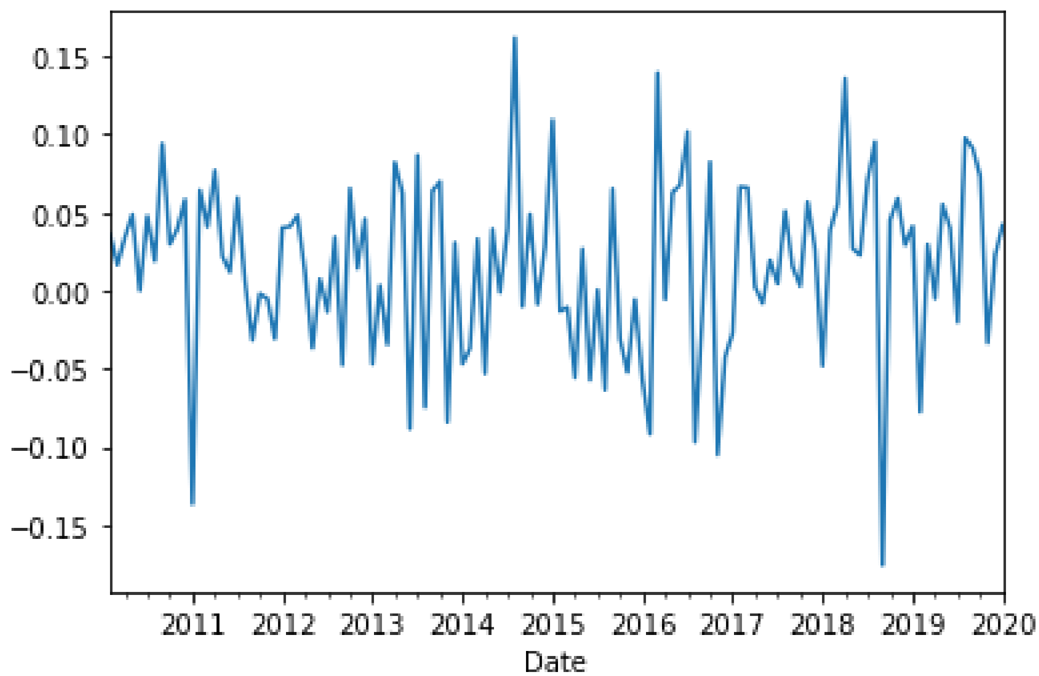

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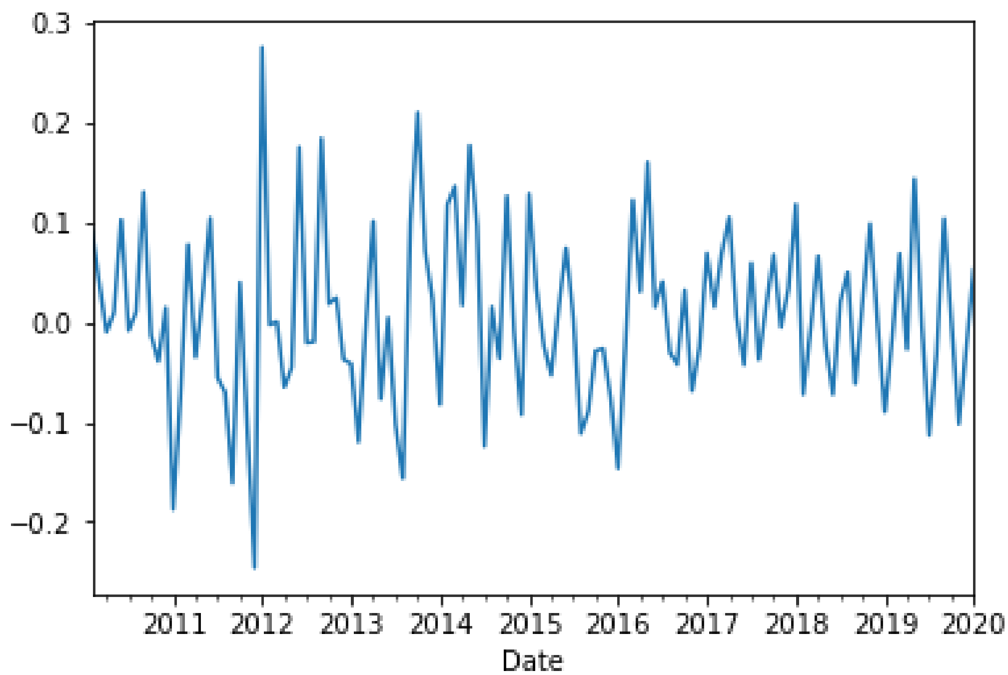

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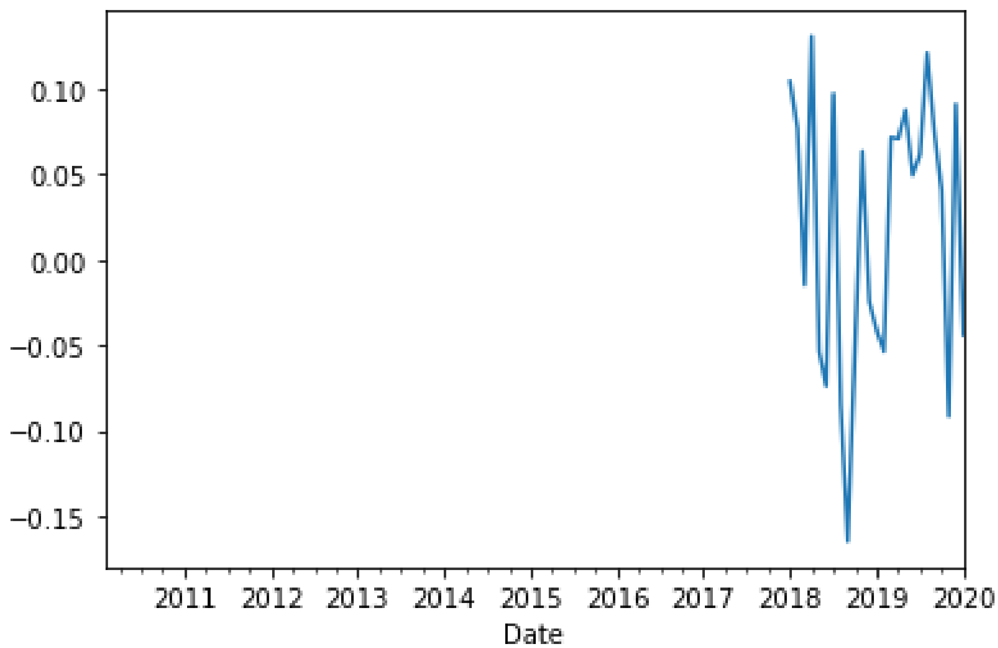

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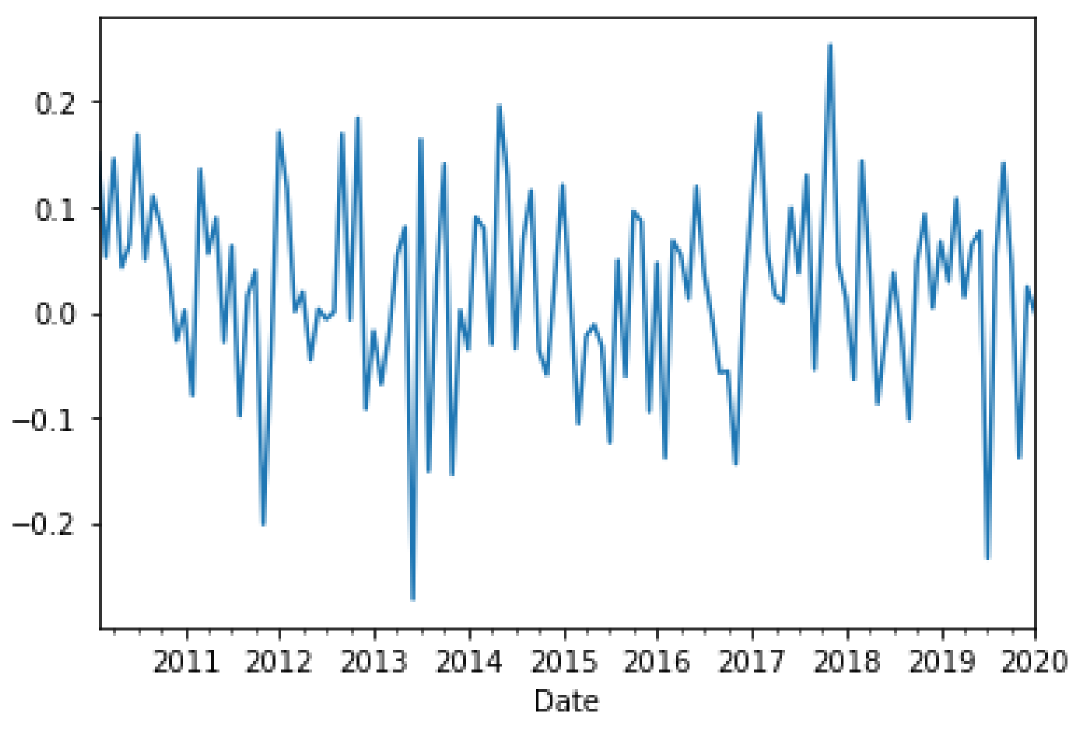
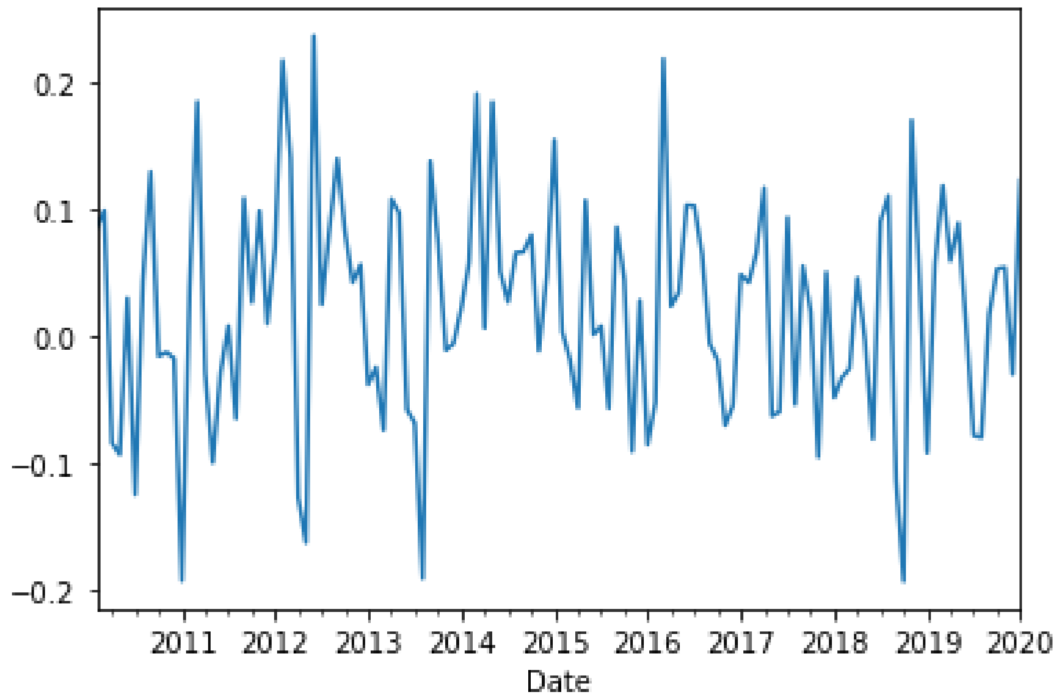
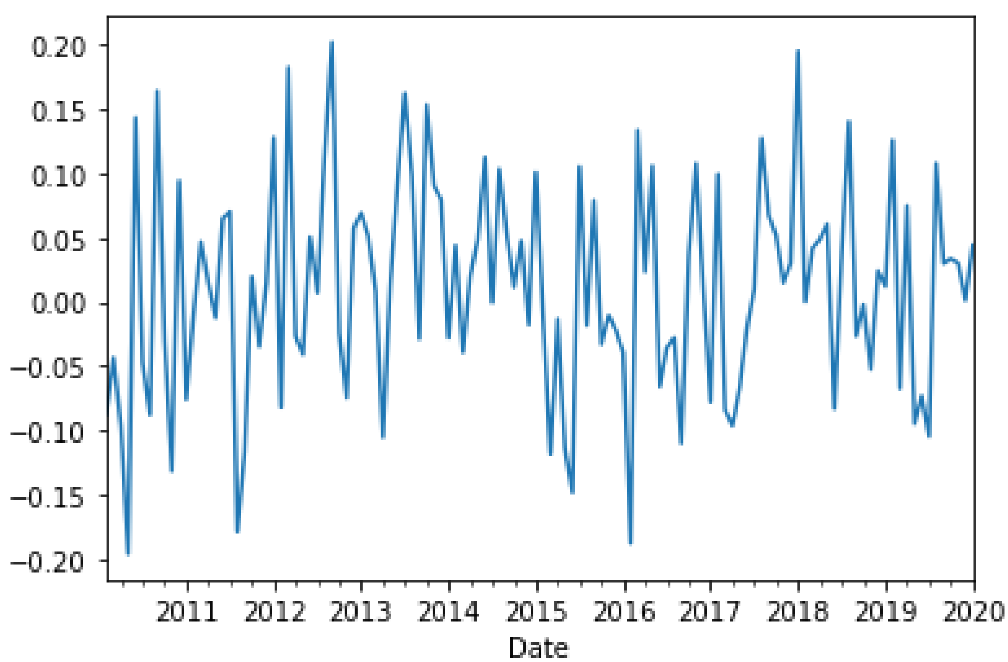


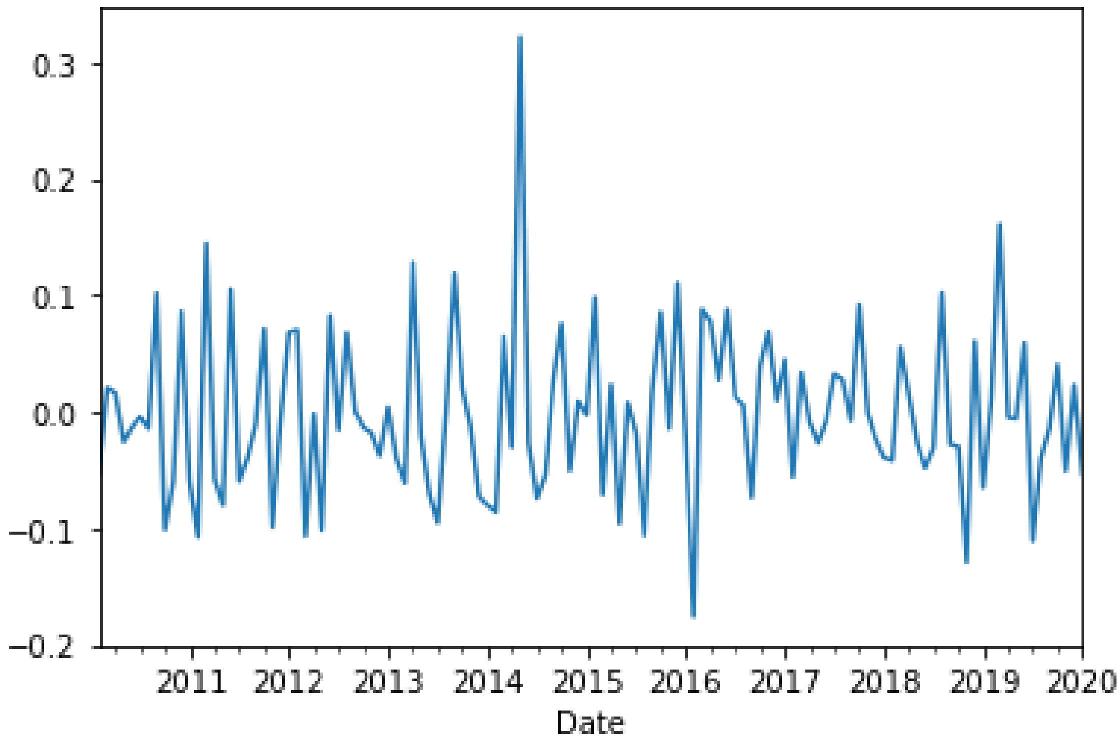
SHREECEM.NS



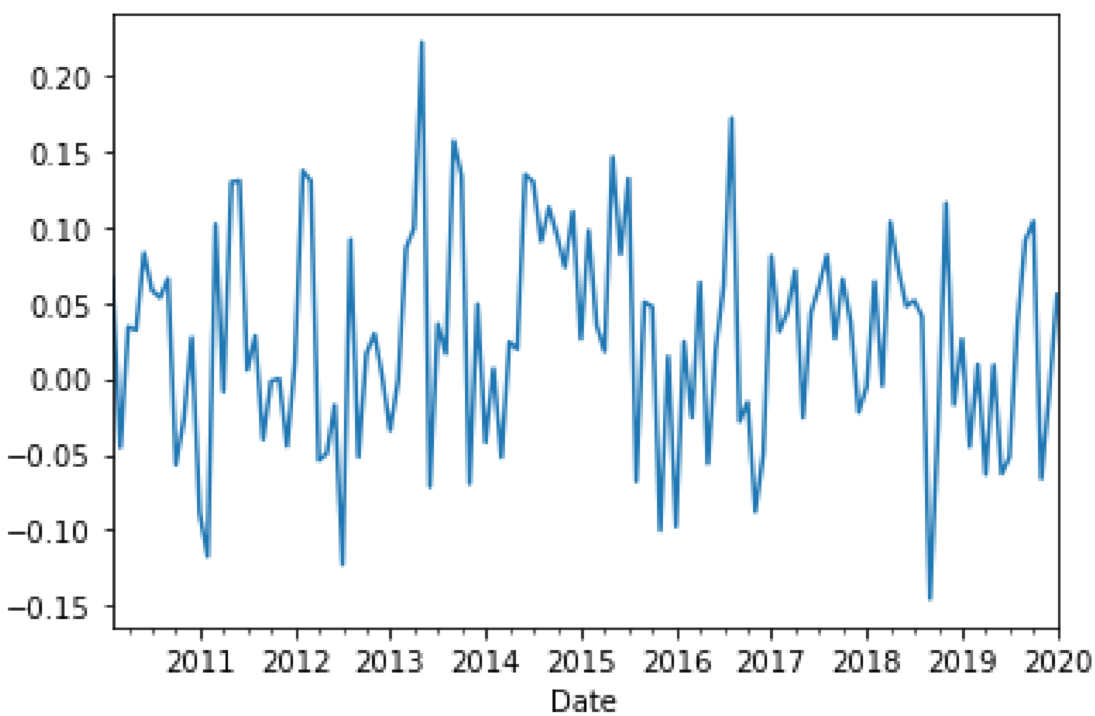
Tech.Ns



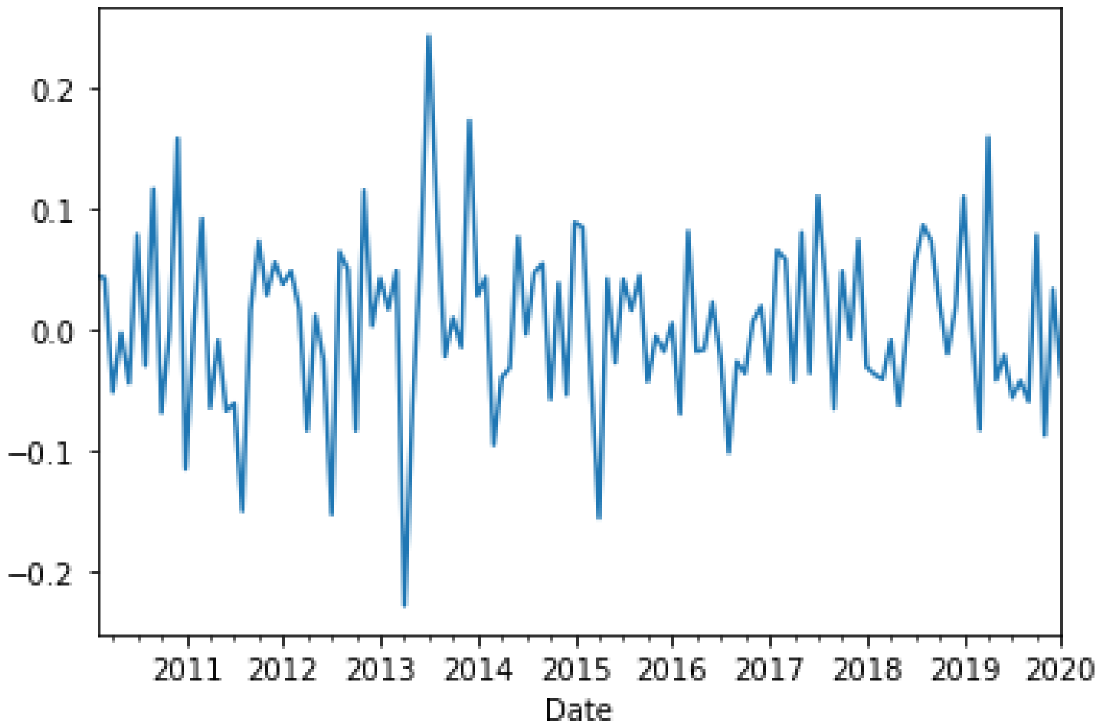
NTPC.NS



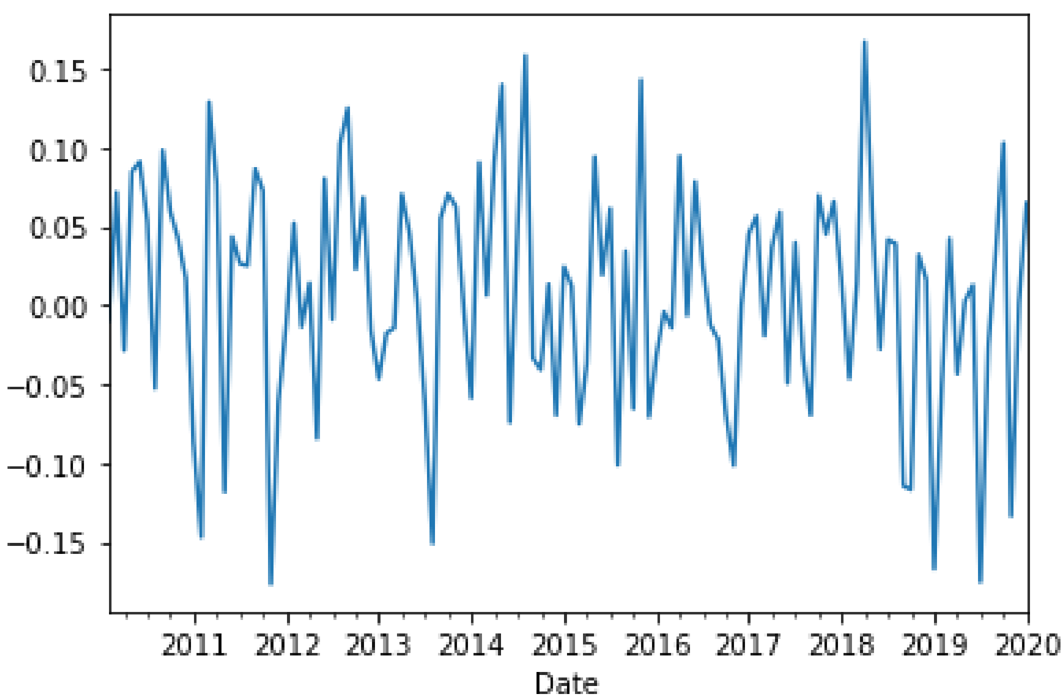
BRITANNIA.NS



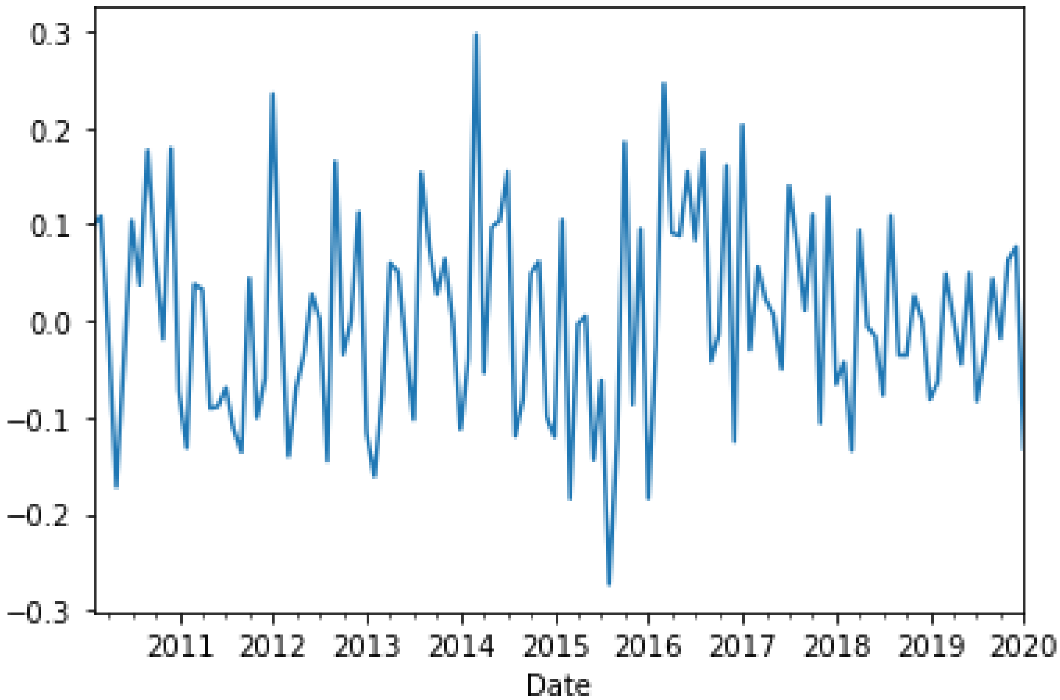
Wipro.NS



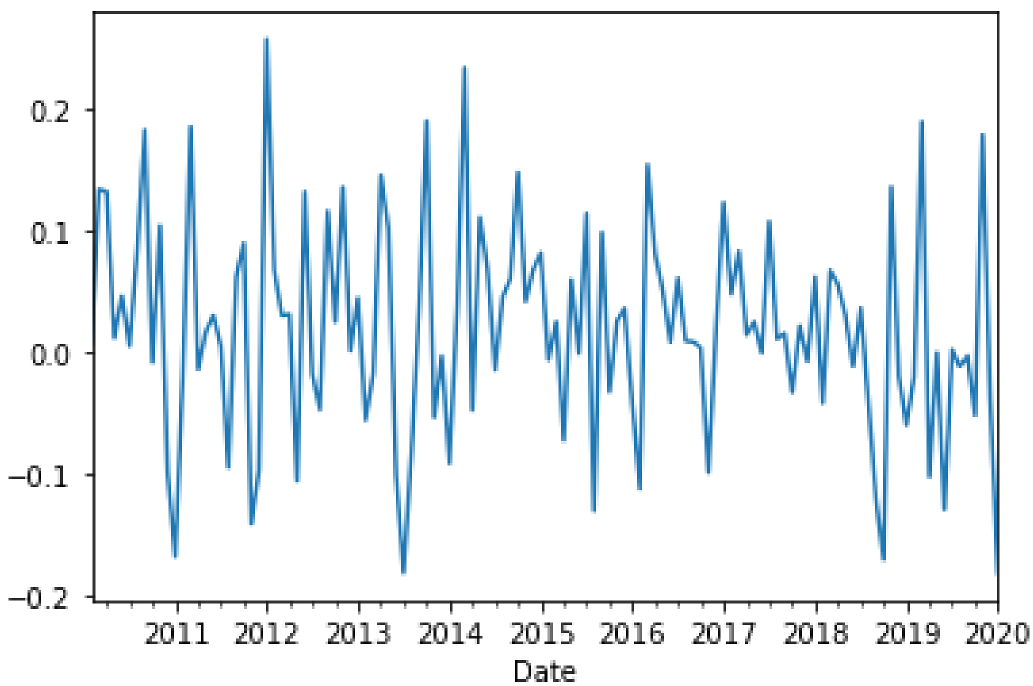
M&M.NS



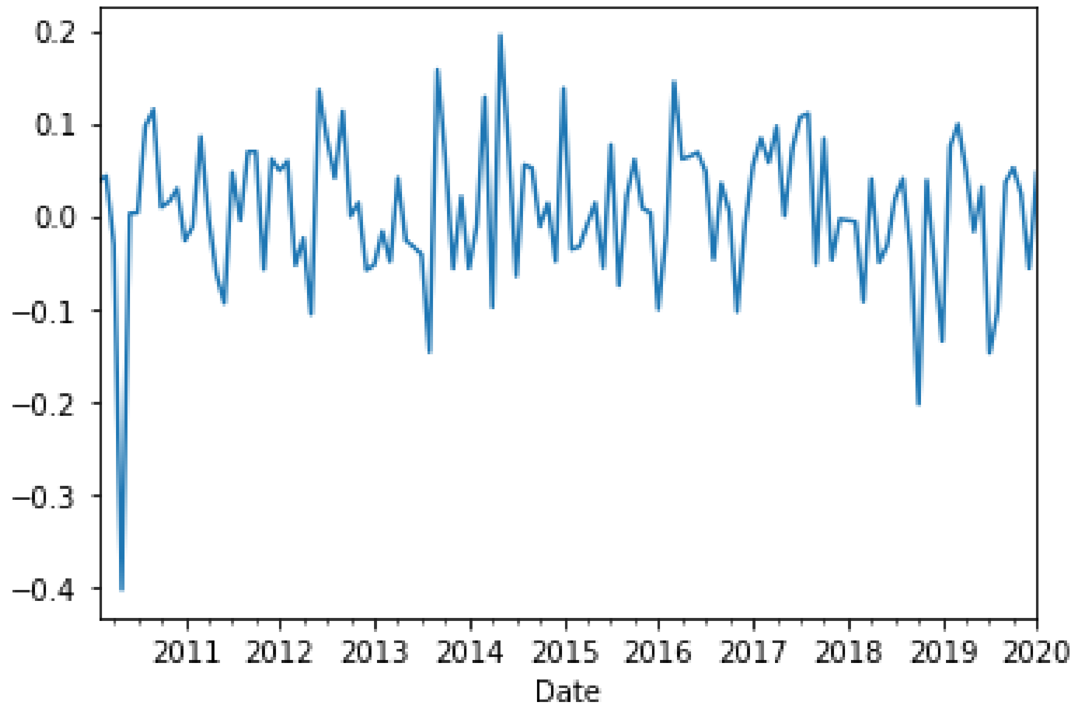
Hindalco.NS



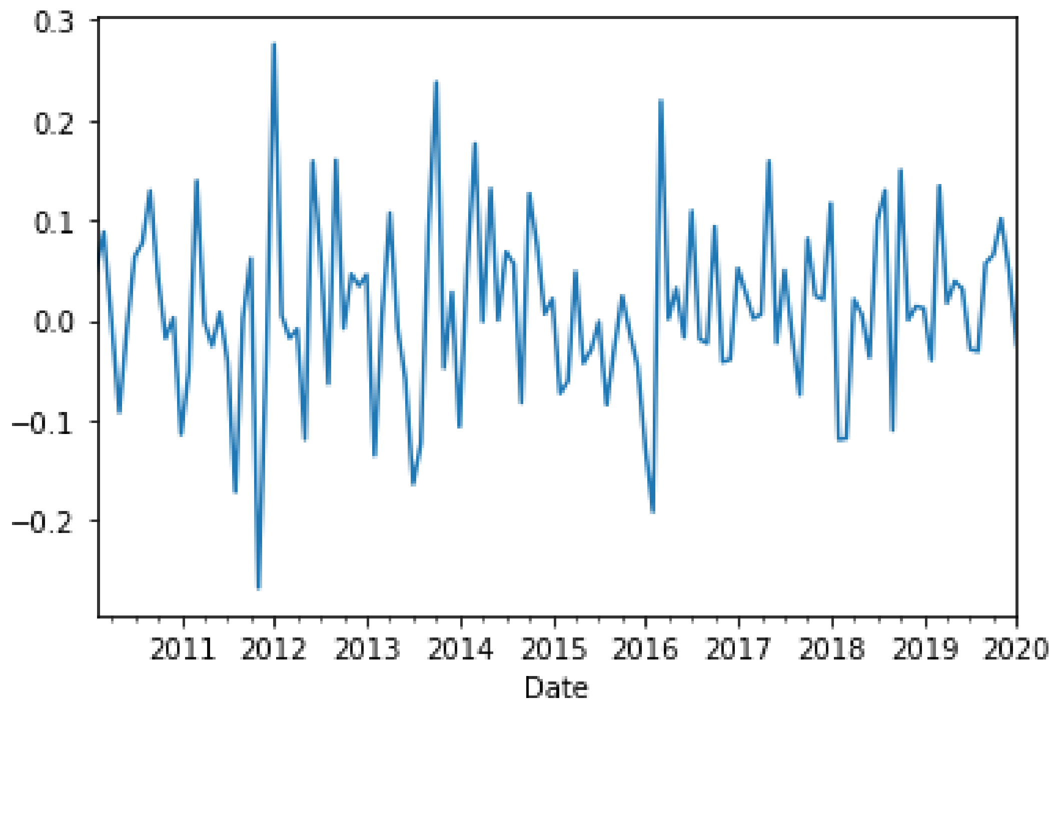
INDUSIND BANK.NS



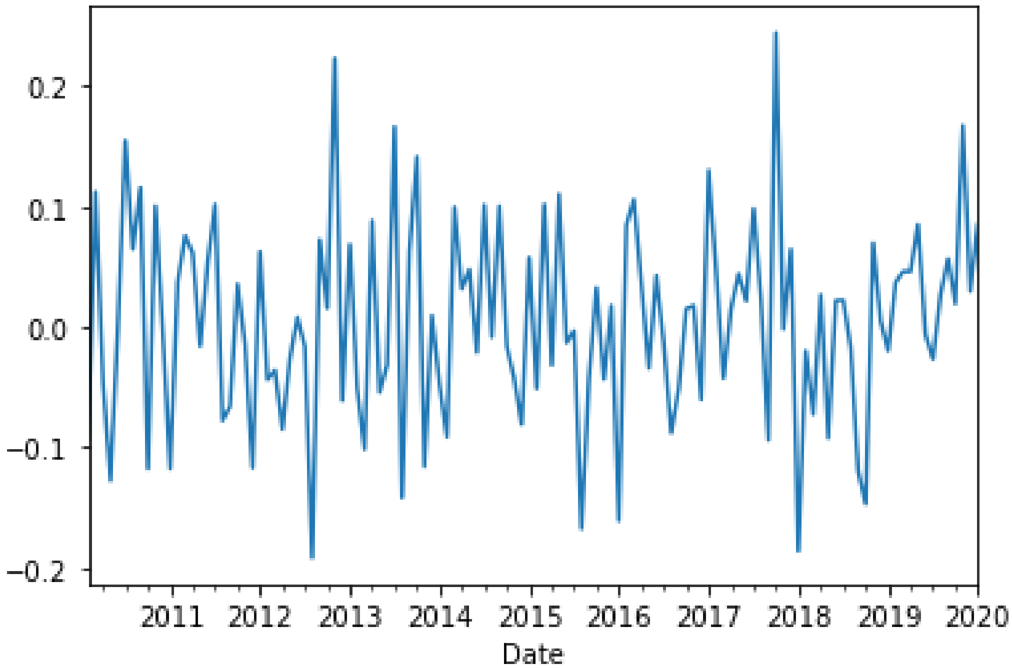
GRASIM.NS



ICICIBANK.NS



BHARTIARTL.NS



2. Estimated CAPM

	Estimated CAPM	
	CAPM Beta	CAPM (Expected Returns in %)
	Beta	Alpha
NiFTY 50	1	
KOTAKBANK.NS	1.009208687	9.42%
RELIANCE.NS	1.088485828	10.11%
TATACONSUM.NS	1.116654277	10.36%
BAJAJ-AUTO.NS	0.8484252189	8.01%
ITC.NS	0.6558025864	6.32%
TCS.NS	0.3805834728	3.91%
MARUTI.NS	1.465865778	13.42%
ULTRACEMCO.NS	1.010885253	9.43%
BAJFINANCE.NS	1.273864833	11.74%
HEROMOTOCO.NS	0.7576027038	7.22%
TATASTEEL.NS	1.375251254	12.63%
BAJAJFINSV.NS	0.9234412164	8.67%
ONGC.NS	1.010983992	9.44%
COALINDIA.NS	0.7608844671	7.25%
CIPLA.NS	0.4896761189	4.87%
NESTLEIND.NS	0.5670129277	5.55%
LT.NS	1.477065831	13.52%
HDFCLIFE.NS	0.9737039114	9.11%
TITAN.NS	1.043632353	9.72%
SHREECEM.NS	1.284895183	11.83%
TECH.NS	0.6777415572	6.52%
NTPC.NS	0.8569778671	8.09%
BRITANNIA.NS	0.5219052218	5.15%
Wipro.NS	0.3855021661	3.96%
M&M.NS	0.9137663357	8.58%
Hindalco.NS	1.341774391	12.33%
INDUSBANK.NS	1.464172623	13.40%
GRASIM.NS	1.063350642	9.89%
ICICIBANK.NS	1.609756863	14.68%
BHARTIARTL.NS	0.8755388145	8.25%

3. FF-Model

	FF (4 factor) MODEL Beta				FF Model Effeciency (R^2) (In %)
	Market risk coefficient (Rm-Rf) Beta	Size risk coefficient (SMB)	Value risk coefficent (HML)	WML coefficient	
NiFTY 50					
KOTAKBANK.NS	1.09	-0.15	-0.30	-0.05	0.47089
RELIANCE.NS	1.13	-0.34	-0.26	-0.12	0.437308
TATACONSUM.NS	1.250558	0.127733	0.311733	0.394	0.443715
BAJAJ-AUTO.NS	1.03924	0.039218	-0.12247	0.227143	0.324305
ITC.NS	0.763485	-0.13393	-0.17163	0.131264	0.248276
TCS.NS	0.616101	-0.18249	-0.24627	0.333386	0.143398
MARUTI.NS	1.56946	0.215729	-0.20669	-0.13109	0.563529
ULTRACEMCO.NS	1.280196	-0.25094	-0.08384	0.35217	0.381999
BAJFINANCE.NS	1.458428	0.197573	-0.15518	0.084137	0.397263
HEROMOTOCO.NS	0.951316	0.067737	-0.14971	0.124439	0.234223
TATASTEEL.NS	0.962236	-0.32246	-0.02976	-0.73544	0.450828
BAJAJFINSV.NS	1.21756	0.639803	-0.19359	0.091697	0.32491
ONGC.NS	0.968368	-0.14564	0.017707	-0.08677	0.364263
COALINDIA.NS	0.66071	0.04658	0.134583	-0.15593	0.285844
CIPLA.NS	1.543344	1.013861	1.121643	1.516755	0.140996
NESTLEIND.NS	0.872123	0.010661	-0.14068	0.298077	0.303944
LT.NS	1.543344	-0.167	-0.08675	0.058622	0.572242
HDFCLIFE.NS	1.013861	0.828599	-0.07968	0.585417	0.507509
TITAN.NS	1.121643	0.143094	0.035363	0.035964	0.296806
SHREECEM.NS	1.516755	-0.25731	-0.22428	0.162058	0.452496
TECH.NS	0.633562	-0.21726	0.270601	-0.18057	0.109802
NTPC.NS	0.700989	-0.08927	-0.06481	0.082813	0.398522
BRITANNIA.NS	0.858522	-0.01497	-0.12233	0.341889	0.198912
Wipro.NS	0.473689	-0.2232	-0.1421	0.16879	0.064053
M&M.NS	1.041511	0.120103	-0.10398	0.119505	0.327514
Hindalco.NS	0.998324	-0.60912	0.338677	-0.29907	0.442099
INDUSBANK.NS	1.489095	-0.03503	-0.29259	-0.11375	0.526825
GRASIM.NS	1.221375	0.004749	0.051515	0.259586	0.407224
ICICIBANK.NS	1.447208	-0.45163	-0.00628	-0.14035	0.633546
BHARTIARTL.NS	0.884345	-0.36679	0.141093	0.128598	0.267336

1. Cluster Analysis

Low Alpha & low beta < 1		
Stocks	Beta	Alpha
TCS.NS	0.3805834728	0.0391
Wipro.NS	0.3855021661	0.0396
CIPLA.NS	0.4896761189	0.0487
BRITANNIA.NS	0.5219052218	0.0515
NESTLEIND.NS	0.5670129277	0.0555
ITC.NS	0.6558025864	0.0632
TECH.NS	0.6777415572	0.0652
HEROMOTOCO.NS	0.7576027038	0.0722
COALINDIA.NS	0.7608844671	0.0725
BAJAJ-AUTO.NS	0.8484252189	0.0801
NTPC.NS	0.8569778671	0.0809
BHARTIARTL.NS	0.8755388145	0.0825
M&M.NS	0.9137663357	0.0858
BAJAJFINSV.NS	0.9234412164	0.0867
HDFCLIFE.NS	0.9737039114	0.0911
High Beta >1 & alpha from 0.094 upto 0.15		
Stocks	Beta	Alpha
KOTAKBANK.NS	1.009208687	0.0942
ULTRACEMCO.NS	1.010885253	0.0943
ONGC.NS	1.010983992	0.0944
TITAN.NS	1.043632353	0.0972
GRASIM.NS	1.063350642	0.0989
RELIANCE.NS	1.088485828	0.1011
TATACONSUM.NS	1.116654277	0.1036
BAJFINANCE.NS	1.273864833	0.1174
SHREECEM.NS	1.284895183	0.1183
HINDALCO.NS	1.341774391	0.1233
TATASTEEL.NS	1.375251254	0.1263
INDUSBANK.NS	1.464172623	0.134
MARUTI.NS	1.465865778	0.1342
LT.NS	1.477065831	0.1352
ICICIBANK.NS	1.609756863	0.1468

Conclusions & Inferences

1)From the Trends of the Return of the Stocks, We can see the Stock returns nearly follow the stock return of the markets, To check this we use FF and CAPM model to compare the Trends and Check whether the Underlying Stocks Components of the market have an effect on the market and vice versa

2) A CAPM model is the most simple regression to calculate the expected return incorporating only risk free rate and beta of the stock and other is the market return. And hence this model is inefficient in predicting the market return more accurately or we can say statistically less explained by the r_f and beta. Due to this we incorporated Fama French to see the more explained returns due to other market factors such as SMB, HML, WML. etc. (5 factor model)

2)The Fama-French, CAPM, Variance Ratio, ARCH model and similar models and tests are important models and significant models in Economic Finance,as these provide good understanding of the risk, returns and price information and also for finding efficiency in the Market. This helps in understanding the underlying Risk Spillovers in the market.

3) In the Paper we found confirmation/facts of the abnormal returns, auto-correlation dependence in returns of stocks from Benchmark CAPM model and FF-Model.

4)From the CAPM Empirical analysis we can see that there is a significant interdependence of the Stock Returns inherently Stock prices, this concludes that there is network effect of the stock pricing across the market, and The high beta values(>1) are highly influential in stock value pricing of the market thus affecting other indirectly in the process

4) The Fama French Model having an R^2 value average of 35.74% is not very accurate, even adding the 4 factor has less average to conclude any statement. This could suggest that that market is inherently inefficient and thus the Nifty market is weaker but it does conclude that Markets have High Network Effects and once the larger player in the market is hit that influences the whole markets thus leading to Risk-Spillovers.

5) The Risk-Spillovers and Network effects cause abnormal returns, Risk Calculations cannot be accurate as many of them do not capture the whole Network in the Underlying Assets in the whole market.

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Data Sources:

However the data is taken from NSE we are taking it from the pre arranged manner from this data science website.
Nifty50 companies opening and closing price is taken from
https://www.kaggle.com/rohanrao/nifty50-stock-market-data
https://in.finance.yahoo.com/quote/%5ENSEI?p=%5ENSEI
https://in.finance.yahoo.com/quote/%5ENSEI/components?p=%5ENSEI
For Cluster selection of low alpha, high beta etc we are referring NSE website
https://www1.nseindia.com/products/content/equities/indices/strategic_indices.htm
https://www.rbi.org.in/Scripts/BS_NSDPDisplay.aspx?param=4