Comparing the differences in stock and metal prices before and after Brexit: Study on Germany and the United States

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Abstract

The focus of the research is to analyze the consequence of Britain's exit from the European Union on uncertainities of stock markets and returns. The study also analyses Brexit's consequences on metal prices. The S&P 500 faced high volatility before Brexit (standard deviation of monthly returns 3.38%) that has increased slightly (4.28%) during post-Brexit. In the case of DAX, a little less volatility is noticed from pre-Brexit to post-Brexit (5.27% to 4.9%). Independent sample t-test resulted in insignificant mean monthly returns values for both S&P500 and DAX. Linear regression results effect of Brexit on stock returns was also insignificant indicating no notable change caused because of Brexit on the monthly returns of stock.

In the case of metals, the volatility of gold showed a moderate increase post-Brexit (standard deviation increased from 211.78 to 251.37) and was significant. The volatility in the case of silver was reduced largely (the standard deviation decreased from 8.96 to 4.39). The change in price from pre-Brexit to post-Brexit was significant in the case of silver. Linear regression of gold and silver prices during the Brexit period was significant indicating a significant effect of Brexit on gold and silver prices.

To compare the volatility and stability of the stock market between the US and Germany further analysis of Log returns and the Moving average of log returns was constructed. The standard deviation of log returns decreased during post-Brexit in both the stocks (S&P500:0.31 to 0.04; DAX:0.05 to 0.04) but was not significant as indicated by independent sample t-test and Linear regression.MA_Log return was significant in the case of the S&P 500.

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Thank you all for being a part of this journey

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1. Introduction

Global financial markets faced significant economic and political uncertainties as a consequence of the United Kingdom's choice to exit from the European Union, an event widely known as Brexit. (Hohlmeier & Fahrholz, 2018; Nagarakatte & Natchimuthu, 2022). On June 23rd, 2016 the referendum happened, and A total of 51.9% of voters opted to leave the European Union. (Hobolt, 2016). This resulted in uncertainties in stock and commodity markets. As a consequence of this, there was a sudden fall in stock indices, a fall in the value of the Pound Sterling, and volatility in the prices of metals (Baker et al. 2016; Nagarakatte & Natchimuthu, 2022; Kierzenkowski et al., 2016).

As mentioned in the European Commission report Brexit has had a substantial economic effect on the European Union, there was a significant trade relationship between the UK, France, and Germany in 2015. Service exports by France to the UK were €18 billion and with Germany, it was €12 billion. The same trend was seen in imports where France and Germany played major roles. Germany was the top supplier of goods to the United Kingdom, exporting goods worth €68 billion, followed by the Netherlands with €34 billion and France with €28 billion. In terms of imports, Germany also held the leading position at €34 billion, with France following at €20 billion. The European Union was a key trading partner for the UK, contributing to around 45% of its total exports and 53% of its total imports.

Due to Brexit the movement of merchandise, funds, and labor between the UK and EU countries was affected leading to economic fragmentation. This breakdown also spread to financial market operations as a result of capital flow restrictions. On the day of the Brexit vote, there was a decline in FTSE 20 by 7.2% while the British pound experienced a steep decline. Declining by more than 8% against the US dollar and 6% against the euro..

The changing relationship between financial markets in reaction to changes in major geopolitical events was analyzed by many studies (Jawadi et al 2015; Yang et al,2003). The cross-market dependencies occurred due to the external event defined as contagion (Forbes and Rigobon,2002) hypothesis was tested in various contexts. Following the stock market crash of October 1987, Arshanapalli and Doukas (1993) observed a rise in market interdependence between the US and European markets.

Similarly, Yang et al. (2003) noted an increase in the correlation between Asian and US markets after the 1997 Asian Financial Crisis. Similarly, Jawadi et al. (2015) analyzed the increased volatility spill over between the US and other three major (Frankfurt, London, and Paris)financial centers both during and after the crisis. The recent study by Aristeidis and Elias

(2018) employed a copula-based approach to analyze global market reactions to the outcome of the UK's Brexit referendum. The analysis revealed that a temporary price reversal after the referendum allowed the stock market to get back to clear its losses. Ben Ameur and Louhichi (2021) identified deep insights into market dynamics during the phase of market uncertainties. They identified how Brexit-influenced uncertainties affected financial markets significantly causing high volatility and spillover.

By taking perspectives from the above studies the current study explores how stock price trends in countries evolved about major geo-political events. These studies focused on multiple European markets. Our focus of the study is narrower as analysis of stock price movements in selected countries is done. However, the underlying concept of uncertainty-driven fluctuations remains a key consideration, helping us understand potential spillover effects and structural shifts in share market behavior.

The research aims to analyze the differences in stock and metal prices before and after Brexit by comparing Germany and the United States. Both nations have a significant economic influence, making it essential to comprehend their reactions to Brexit helps to draw deep insights into financial shock transmission and how the market will respond to these geo-political changes.

1.1 Background and Rationale

Macroeconomic shocks and political events result in highly sensitive stock and metal markets. Brexit emerged as one of the primary important financial episodes in the latest financial history, resulting in raising concerns about business agreements, regulatory frameworks, and investor's attitudes (Hohlmeier & Fahrholz). Both the US and German stock markets experienced significant volatility, with a sudden price decline followed by a recovery phase through market adjustment to new changes (Ren, 2022). Metal prices especially gold, silver, and industrial metals like copper and aluminum reflected the transfer of investor attitude and hedging mechanism.

The US and Germany are chosen for this current study because of their economic significance and well-defined financial structures. Due to the closer association of Germany with the UK and being the largest economy in the European Union faced direct consequences of Brexit. The uncertainties in trade negotiations, potential tariffs, and financial service disruption resulted in a direct impact on German industries and investors' behavior (Bartkowiak & Ratajczak, 2019; Sampson, 2017). The United States is the world financial leader with notable financial influence. Though far from the European Union acknowledged the Brexit shock due to investors' bother about international trade, the likelihood of economic development, and current uncertainties (Mix, 2022).

Valuable insights into market resilience, investor attitude, and economic interdependencies can be obtained by understanding the behavior of stock and metal prices in these two countries before and after Brexit (Galán-Gutiérrez & Martín-García, 2021). The study will contribute to existing research by focusing on cross-market differences, financial adjustment pattern recognition, and analyzing wider economic implications of geopolitical disruptions.

1.2 Consequence of Brexit on Stock Markets

The immediate market response to the Brexit referendum was marked by heightened volatility. The DAX index in Germany experienced a steep drop in the immediate aftermath of the vote, reflecting investor concerns over potential economic disruptions. German multinational corporations, particularly those in the automotive, banking, and industrial sectors, saw significant stock price declines due to fears of restricted access to the UK market. Financial institutions, in particular, were vulnerable, as many German banks had strong ties with London's financial hub (Andrikopoulos, Dassiou, & Zheng, 2019).

Similarly, the U.S. stock market witnessed a temporary decline, affecting major indices such as the S&P 500 and Dow Jones registering notable losses. The uncertainty surrounding trade relationships and potential economic slowdowns triggered risk aversion among investors. However, compared to European markets, the U.S. market demonstrated a relatively quicker recovery, connected to the Federal Reserve's monetary policies, strong domestic economic fundamentals, and the perception of the U.S. economy as a haven for investments (Qiao, Liu, Huang, et al., 2021).

1.3 Consequence of Brexit on Metal Prices

Metals, particularly gold, have historically functioned as safe-haven assets during times of financial uncertainty(Baur and McDermott, 2010; Hapau, R. G. 2023)). In the immediate aftermath of Brexit, gold prices increased suddenly as investors sought stability amid market turmoil(Mackenzie and Platt,2016; Chan et al., 2011). The rise in gold prices indicated a flight to safety, as shareholders shifted away from volatile assets such as equities. Silver also experienced gains, although to a lesser extent compared to gold (Money Morning, 2016).

In contrast, industrial metals such as copper and aluminum exhibited downward movement due to concerns over financial slowdowns and potential disruptions in trade (Arezki & Matsumoto, 2017). Gold and silver functions as a shield against price escalation and exchange rate variations. The British pound experienced significant volatility during post-Brexit leading to investment in gold and silver by investors (The Pure Gold Company, 2019). The dual role played by silver in industrial applications and as an investment commodity imparts a unique outlook on the impact of financial uncertainty on its demand and price compared to gold (USA Gold, 2024).

Gold and silver are among the most liquid and actively traded metals in global markets, making them more reflective of investor sentiment compared to other commodities that may have lower trading volumes. Germany, being a major exporter of industrial goods, saw fluctuations in metal prices impacting its manufacturing sector. The United States, with its strong industrial base, also experienced shifts in commodity prices, although the impact was moderated by domestic economic policies and global market dynamics (Galán-Gutiérrez & Martín-García, 2021).

1.4 Objectives of the study

Brexit, one of the most significant political and economic events in recent history, has had far-reaching effects on global financial markets. The uncertainty surrounding the United Kingdom's departure from the European Union affected investor confidence, trade relationships, and overall market stability. Due to the interconnectedness of the global economy, its impact was especially noticeable in major economies such as Germany and the United States. This study aims to examine the financial implications of Brexit by addressing the following objectives:research attempts to find the financial repercussions of Brexit by focusing on the following objectives:

1. Comparative analysis of stock price changes before and after Brexit in Germany and the United States
2. Consequence of Brexit on prices of key metals like Gold and Silver in both countries
3. Analyse stock market volatility and stability in both countries due to events related to Brexit

1.5 Hypothesis:

1. NH (H_0): There is no significant difference in mean monthly stock returns pre-and post-Brexit

   AH (H_1): There is a significant difference in mean monthly stock returns pre- and post-Brexit

2. NH (H_0): There is no significant difference in the mean price of gold and silver pre and post-Brexit

   AH (H_1): There is a significant difference mean price of gold and silver pre and post-Brexit
3. NH (H_0): There is no significant difference in stock market volatility before and after Brexit.

   AH (H_1): There is a significant difference in stock market volatility before and after Brexit.

1.6 Overview of Methodology

The study undertakes a quantitative approach by making use of historical stock and metal price data. Data sources for the study are financial databases. Statistical techniques like paired t-tests, regression analysis, and volatility models are used. To give contextual understanding and theoretical support review of the studies on Brexit's economic impact is carried out.

1.7 Significance of the Research

The UK's departure from the EU marked a notable move in its economic ties with the block. While the country will reduce its close integration and collaboration with neighboring nations, it may also create new opportunities to establish business deals directly with countries external to the EU. Beyond the direct financial effects of Brexit, withdrawing from the EU could catalyze significant domestic policy reforms. Significant government events, such as Brexit, have the potential to disrupt the security and forex markets of economically advanced nations (Stoupos & Kiohos, 2021).

The findings of this research will be relevant for policymakers, shareholders, and financial analysts seeking to understand the implications of geopolitical events on financial markets (Smales, 2016). By comparing Germany and the United States, this report will highlight the differential impacts of Brexit on a major EU economy and a non-EU global financial powerhouse. Furthermore, the insights gained can inform future policy decisions, risk mitigation strategies, and investment planning in the appearance of similar geopolitical uncertainties.

Brexit was a defining moment in modern economic history, influencing financial markets worldwide. Understanding the differences in stock and metal price behaviors before and after Brexit is crucial for comprehending broader market dynamics and investor reactions to uncertainty. This study helps to narrow down the knowledge gap by providing real-world evidence and comparative examination of the German and U.S. financial markets, offering valuable contributions to financial research and economic policy discussions.

2 Review of Literature

2.1 Introduction

The withdrawal of Britain from the European Union commonly called "Brexit" happened on 23rd June 2016 and is a leading example of economic and political events. This resulted in large uncertainties in financial markets, and a huge loss of around two trillion dollars was incurred by the global stock market in a single day (Quaye et al., 2016) that the market had never seen before.

Due to the interconnection between global economies, Brexit's impact was not only confined to the UK but also extended to other economies. Burdekin et al. (2018) analyzed the short-lived consequence of the exit of Britain from the EU on international stock markets and found that a 10 percent decline in the UK FTSE 100, 8.4 percent decline in the German DAX, a 9.6 percent decline in French CAC, 5.5 percent in the case of the US S&P and 181.85 points in case of India's Nifty 50.

In response to numerous political and economic incidents and emergencies, financial studies have explored the transmission of shocks across global markets. This literature review analyses the consequences of Brexit on stock and metal rates by reviewing relevant studies, theoretical perspectives, and empirical findings.

2.2 Repercussions of political events on the stock and commodity market

In Financial markets stock and commodity prices are highly uncertain and also influenced by political situations. Hui and Chan (2021) noted that the Brexit poll generated potential instability and unpredictability in the world financial market. The uncertainty associated with political events such as Brexit influenced various trades and the world stock market.

Pastor and Veronesi (2013) suggested the theoretical model depicting how political events and uncertainties come up with risk premiums in the stock market. And also increasing volatility in returns and correlations among stocks. Research studies additionally examined the impact of political uncertainties on the financial market.

Given the importance of political events and financial uncertainties, many studies (Chou et al.2014; Egger and Zhu,2020) analyzed the economic and financial integration between countries., as well as the spillover effects of political uncertainties across borders. According to Chou et al.2014 the effect of political instability caused by to Arab Spring upsprings revealed varying stock market volatility across the nations. Similarly, Egger and Zhu (2020) investigate the stock market reactions to the U.S.-China trade war, finding that protectionist tariffs negatively impact firms not only in the involved countries but also in third-party nations. Their findings reinforce the idea that political uncertainty is a crucial factor in contemporary global financial markets.

Building upon the work of Pastor and Veronesi (2013), Brogaard et al. (2020) examine data from the 2016 and 2020 U.S. presidential elections to assess the impact of global political uncertainty.Their study demonstrates that uncertainty stemming from the U.S. election cycle influences not only domestic stock markets but also has significant repercussions on international financial markets.

Existing research highlights a connection between political uncertainty and climate risk. Stroebel and Wurgler (2021) recognize regulatory uncertainty as the most significant climate-related concern for investors. Ramelli et al. (2021) found that during Donald Trump’s 2016 election, the stock market rewarded carbon-intensive firms. Similarly, Ilhan, Sautner, and Vilkov (2021) provide evidence that the cost of hedging against the downside risk of carbon-intensive companies declined following Trump’s election. Chen and Kettunen (2017) demonstrate that uncertain carbon policies can impact corporate profitability, consumer surplus, and the costs businesses incur to meet carbon emission targets. Additionally, Brogaard et al. (2020) use timeframes of three and six months before U.S. presidential elections to assess international political uncertainty.

In the opinion of Guedes et al. (2019), political risk has an impact on government bonds, foreign exchange, and commodity markets. Gu & Hibbert, (2021) also mentioned acute fluctuations in the international market as a result of Brexit. According to Stoupos and Kiohos (2021), in developed countries, notable political events like Brexit could fluctuate stock and forex markets. The UK will have long-term effects due to financial instability caused due to Brexit.

Kara et al., (2021) mentioned due to Brexit UK will have to face uncertain investment decisions for the future, fiscal policies, and also product regulation. According to Stoupos & Kiohos (2021), Brexit has increased uneasiness among investors forthcoming involvement of the UK in the European internal market.

Driffield and Karoglou (2019) raised concerns about disadvantages for the UK in terms of the obtainability of wandering labor and business dealings of the UK with the EU. UK’s banking sector will also have a negative as a result of moving its headquarters from the UK to the EU due to Brexit (Kara et al.,2021). The US treasury yields are regarded as investor's attitudes about the economy. The decreased US treasury yield indicates market instability. Political conditions impact the demand for US treasury yields. Treasury yields are regarded as haven investments sought by investors (McCormack & Regan,2021) during market uncertainties as the US government returns them.

According to Reuters (2016) government bonds like the German 10-year government bond and French 10-year government bonds safeguard investors in case of market instability. Brexit uncertainty also influenced the commodity market in addition to currency and government bonds (Breinlich et al.,2018). During the Brexit referendum period, crude oil and gold served as effective hedging instruments for UK stocks (Abuzayed et al., 2022).

2.3 Consequence of Brexit on Stock and Metal Prices in Germany and UK

Commodity markets serve as financial instruments for investors seeking diversification from securities (Aepli et al., 2017). Market conditions are influenced by both local (microeconomic) factors affecting specific securities and broader geopolitical and macroeconomic indicators, fundamentals, and financial elements. These influences vary depending on market cycles, such as bull and bear phases or fluctuations in supply and demand. Paraschiv et al. (2015) examined the varying impact of financialization and market fundamentals, highlighting that commodity prices are sometimes dictated by financialization and, at other times, by structural breaks. Similarly, Figuerola-Ferretti et al. (2015) noted that periods of low volatility often align with financial bubbles, whereas price fluctuations are sometimes driven by physical market constraints.

Gu and Hibbert (2018) discovered that stocks exhibiting higher volatility were more susceptible to market disturbances triggered by Brexit compared to more stable stocks. Conversely, Bohdalová and Greguš (2017), who examined indices such as EPUCCEUM, EPUCUK, and EPUCBREX, did not establish a strong correlation between Brexit and fluctuations in the FTSE 100. Meanwhile, Davies and Studnicka (2018) found that firms with extensive exposure to both the UK and EU, as well as those reliant on imported intermediate goods, experienced the most significant drops in daily performance following the referendum. Breinlich et al. (2018) highlighted that both stock prices and the British pound declined as expectations around UK-EU trade policies, including tariffs and non-tariff barriers, evolved. The impact of Brexit extended to exchange-traded funds (ETFs), as noted by Alkhatib and

Harasheh (2018), while Nasir and Morgan (2018) emphasized its influence on the British pound. Skrinjarić (2019) identified mixed effects of Brexit-related events on abnormal cumulative returns in Central and Eastern European (CEE) and South and Eastern European (SEE) stock markets, although a significant impact on volatility trends was evident.

The Brexit referendum had a significant impact on the global foreign exchange market, as Dao et al. (2019) identified a strong link between intraday currency fluctuations and volatility transmission to specific currencies. Shaikh (2018) examined key implicit volatility indices across various regions, including the Eurozone, Asia-Pacific, Africa, Canada, and the United States, revealing that while volatility indices experienced positive abnormal returns, most global equity markets responded negatively. Furthermore, economies with high debt-to-GDP ratios, such as Greece, Ireland, Italy, Portugal, and Spain, faced more severe negative effects from Brexit (Burdekin et al., 2018), as did businesses primarily reliant on domestic rather than international revenue (Oehler et al., 2017). In the long run, European financial markets displayed a negative correlation following Brexit (Bashir et al., 2019), while volatility contagion spread across 43 emerging market stock exchanges after the June 2016 referendum (Aristeidis & Elias, 2018).

Much literature is available to see the consequence of Brexit on the UK markets but there are only a few literature available that explore the effect of Brexit on Germany and the United States. Being a key member of the European Union Germany faced uncertainties in stock and commodity prices as a result of Brexit. The United States which is regarded as a global financial hub also faced significant indirect Impact due to Brexit.

Burdekin et al. (2018) analyzed the immediate consequence of Brexit on global equity markets and found that 8.4 percent decline in the German DAX and 5.5 percent in the case of the US S&P. Banking shares were squeezed in Europe as a result of Brexit. Germany's Deutsche Bank saw a 14 percent decline in its shares, affecting the UK's largest bank (Riley & Long, 2016).

The U.S. banks also experienced significant losses, reflecting the negative impact of the US-UK "special relationship." Morgan Stanley dropped by more than 10 percent, Citigroup declined by above 9 percent, and Goldman Sachs fell by 7 percent. Additionally, Invesco (IVZ), a U.S.-based investment firm having a strong existence in the UK, was the less-performing stock in the whole S&P 500, plummeting nearly 14 percent (Riley & Long, 2016).

Following the referendum results, which unsettled financial markets, investors redirected their funds toward traditionally secure assets. According to Mackenzie & Platt (2016), Gold prices initially surged by 8.1 percent before stabilizing slightly above $1,300 per ounce, reflecting an almost 5 percent increase on June 24, 2016. As noted by Mackenzie & Platt (2016), gold had already been one of the year's most successful financial assets before Brexit, having risen by 24 percent.

In contrast, oil prices dropped by around 5 percent due to worry about a potential financial slowdown that could decrease demand. U.S. crude (CLc1) declined by $2.51, reaching $47.60 per barrel, while Brent (LCOc1) fell by 4.9 percent to $48.42 per barrel. Similarly, industrial metals experienced a downturn, with copper (CMCU3) decreasing by 1.7 percent (Lash & Krudy, 2016).

2.4 Theoretical and Methodological Outlook

Many studies (Chan, Frankel, & Kothari, 2004; Borges, 2010; Ozdemir, 2011; Mlambo & Biekpe, 2015 have used the Efficient Market Hypothesis and Behavioural Finance Theory. The widely used study to examine market or single firm reaction to any shock/event is the event study which evolved from the efficient market hypothesis (Fama,1970).

Fama (1970) suggested capital market should reflect all the available information thoroughly to be efficient. This indicates the impact of Brexit would be fully reflected immediately in asset prices if financial markets incorporated all new information efficiently. However, according to Shiller (2003), this theory often leads to misinterpretations of events like in the case of important stock market bubbles. According to behavioral finance theory, prolonged market fluctuation is impacted by investors' attitudes, irrational behavior, and uncertainties (Shiller,2003).

2.5 Economic and Financial Impact

Bernanke, Bloom, and McDonald and Siegel suggest that uncertainty negatively impacts economic activity(Bernanke, 1983; Bloom, 2009; McDonald & Siegel, 1986). From a demand perspective, businesses often delay investment decisions during uncertain economic conditions, while households tend to reduce their spending (Carroll, 1997). On the supply side, uncertainty leads to higher labor costs, which can hinder firm productivity (Bloom, 2009;Bernanke, 1983; Dixit and Pindyck ;2012 McDonald & Siegel, 1986). These economic disruptions may, in turn, influence business environments and stock market performance(Schwert, 1990). Research indicates that the impact of macroeconomic uncertainty on stock prices is primarily driven by shifts in the required rate of return or fluctuations in expected future dividends(Boyle & Peterson, 1995; Abel, 1988). Such unfavorable effects can weaken business confidence and ultimately suppress stock market performance(Bloom, 2009).

The literature presents diverse perspectives on the economic and financial indications of Britain's withdrawal and its possible consequences. Taylor (2016) suggests that the United Kingdom's departure from the EU could weaken the process of European integration, potentially prompting other countries within the EU to request special agreements or opt out of certain policies governed by supranational institutions. Moreover, Brexit could usher in an extended period of uncertainty, division, and introspection within the EU, especially during the transition phase as both parties negotiate the respect of their separation.

Given the UK's considerable influence in foreign and defense policy, its exit may weaken the EU's position as a global power. However, some analysts contend that Brexit could instead foster a more cohesive European bloc, facilitating greater unification without resistance from Britain (Archick, 2016, p. 12). There was an argument by Pisani Ferry et al. (2016) that financial and political power across geographical dynamics could shift considerably in the coming years, with dominance likely moving toward nations with large populations and powerful economies.

In this changing global environment, it remains undetermined in case traditionally influential European nations such as Germany, France, and the United Kingdom will emerge as primary beneficiaries. Additionally, the EU must navigate Britain's departure carefully to minimize its impact on member states, all while addressing existing challenges related to security, migration, and citizens' well-being.

The option of British voters to withdraw from the EU is anticipated to make a significant impact on both parties, primarily due to disruptions in trade flows, labor mobility, and shifts in investment behavior (Lawless & Morgenroth, 2016). Pisani Ferry et al. (2016) emphasize the deep interdependencies on either side of the EU and the United Kingdom, making it improbable that either economy will achieve full independence shortly.

Additionally, a major economic uncertainty for the UK stems from the stability and growth prospects of the Eurozone. Meanwhile, the successful implementation of ongoing reforms at the EU level remains crucial for the Union's future, regardless of how Brexit unfolds.

Emerson et al. (2017) indicate that while both the EU and the UK will face financial losses due to Brexit, the burden will be disproportionately higher for the UK. Given the 1:5 ratio between the UK’s GDP and that of the EU, the EU’s losses are estimated to be 10-15 times smaller. The projected losses for the EU range from 0.11 percent of GDP in optimistic scenarios to 0.52 percent in pessimistic ones, translating to an annual average of 0.01 percent to 0.05 percent of GDP until 2030. In contrast, the UK's GDP is anticipated to shrink by 1.31 percent to 4.21 percent by 2030, with econometric models incorporating foreign direct investment (FDI) impacts suggesting potential losses of up to GDP by 7.5 percent.

Sampson (2017) experimentally demonstrates that EU member states will experience reduced trade with the UK post-Brexit, though the UK's losses will be more severe, except for Ireland, which is expected to be more significantly affected. In a best-case scenario, Brexit could reduce EU per capita consumption by 0.14 percent, whereas in a worst-case scenario, the decline could reach 0.35 percent. Additionally, third countries might gain from trade distortions caused by Brexit, but these benefits are expected to be minor compared to the losses for the UK and EU.

Roja-Romagosa (2016, pp. 9-10) further quantifies Brexit’s trade impact, estimating that the EU overseas market to the UK could decrease by 1.7 percent if a free business agreement is established, or by 3 percent under World Trade Organization (WTO) terms. Conversely, UK exports are predicted to drop significantly by 12.5 percent under free trade.

3 Methodology

The below methodology helps to outline the research design, data sources used to get relevant data, analytical techniques used to tackle the research questions, ethical considerations, and limitations in examining the consequence of Brexit on stock and metal prices in the USA and Germany. Through the use of strong qualitative techniques, the study aims to identify meaningful insights about financial market reactions to geo-political events. And also helps to understand the market adjustment to such events.

3.1 Method of Research

This investigation employs a Quantitative technique to analyze the consequence of Brexit on Stock and Metal prices in the US and Germany. This is a comparative study conducted using historical data on stock and metal prices. Analyzed using statistical techniques to know the trend and volatility pattern pre- and post-Brexit referendum. This study highlights the dissimilarities in market behavior between the two countries. Different data sources are identified and compared thoroughly using the manual observation method so has to be certain the trustworthiness of the data sources used for the study.

Studies have shown that investors shift towards gold and silver during crises as a hedge against currency depreciation and stock market downturns (Baur & Lucey, 2010). Brexit was a major geopolitical event that caused global financial instability, making it relevant to examine how these metals responded. Unlike a broad commodity index, which includes multiple commodities affected by various unrelated factors (e.g., oil prices depend on supply shocks and geopolitical conflicts), gold and silver prices are more directly influenced by economic and political uncertainty (Mackenzie & Platt, 2016). Prior research often analyzes gold and silver individually rather than using broad commodity indices when examining financial crises (Hood & Malik, 2013).

3.2 Data Preparation

Market data comprises historical, time-series numerical information related to financial markets. It serves as a crucial resource for analysts and traders to evaluate past trends and monitor real-time stock prices, offering valuable insights into market dynamics. This data is generally accessible for free and can be directly obtained from financial market websites. Researchers have extensively leveraged market data to predict price fluctuations using machine learning techniques. Prior studies have primarily focused on two key areas: stock index forecasting, which includes major indices like the Dow Jones Industrial Average (DJIA) (Ranco et al., 2015), Nifty (Bharadwaj et al., 2015), Standard & Poor's (S&P) 500 (Zhang & Wu, 2009), NASDAQ (Guresen et al., 2011), and the Deutscher Aktien Index (DAX) (Lugmayr et al., 2012), as well as studies examining multiple indices (Porshnev et al., 2015; Nti et al., 2020). Others have concentrated on forecasting individual stock prices for specific companies like Apple (Weng et al.,2017) and Google ((Di Persio & Honchar, 2017) or groups of companies(Nair & Mohandas, 2015; Hagenau, Liebmann, Hedwig, & Neumann, 2012).

Additionally, research has explored time-specific stock market predictions, including intraday(Huang & Li, 2017), daily (Peachavanish, 2016), weekly(Shah, Isah, & Zulkernine, 2019), and monthly(Nayak, Pai, & Pai, 2016)forecasts. Most prior studies have focused on categorical predictions, where stock movements are classified into discrete categories such as up, down, positive, or negative(Devi & Bhaskaran, 2015; Makrehchi, Shah, & Liao, 2013). Technical indicators have been extensively applied in stock market prediction (SMP) due to their ability to summarize trends in time-series data. Various studies have examined different types of technical indicators, including trend, momentum, volatility, and volume indicators(Devi & Bhaskaran, 2015; Ghanavati, Wong, Chen, Wang, & Fong, 2016; Bustos, Pomares, & Gonzalez, 2017). Moreover, several researchers have combined multiple types of technical indicators to enhance the accuracy of SMP(Weng, Ahmed, & Megahed, 2017; Dey, Kumar, Saha, & Basak, 2016).

The research analysis is carried out using secondary data sources. The historical data of stock and metal prices are collected from financial databases available forthrightly like financial databases, stock, and commodity exchange platforms. The data is collected from the following data sources.

Stock Price data was taken from investing.com and Yahoo Finance. Gold and Silver are used as a proxy for the metal. Metal Price (Gold and Silver) data was taken from The London Bullion Market Association(LBMA), Data Hub, and Chicago Mercantile Exchange(COMEX). While metal prices are influenced internationally by country-specific factors like local demand, taxation, and currency movement may also create fluctuations (Boulamanti and Moya,2016). In this study, international gold and silver prices are used to capture global trends.

The complete analysis of price fluctuations and market stability is done by taking a data span of 5 years before and after the Brexit referendum. The Brexit referendum date June 23, 2016, has been considered as the base date.

3.3 Variables and Measures

To meet the objectives of the study the following variables are identified.

1. DAX 30 stock index for Germany
2. S&P500 stock indices for the US
3. Historical data on international prices of Golden and Silver
4. The standard deviation of monthly return as a volatility measure

3.4 Statistical Analysis

Statistical analysis is crucial for understanding the impact of Brexit on stock and metal prices in Germany and the United States. It allows for the identification of significant trends, patterns, and relationships within financial data. By employing techniques such as time-series analysis, event study methodology, and regression analysis, researchers can quantify the Brexit effect and distinguish it from other market influences. This analysis enhances decision-making for investors, policymakers, and economists by providing empirical evidence on market behavior. To analyze the data collected exploratory data analysis using descriptive statistics, regression methods, and Volatility analysis will be used. The analysis was carried out using SPSS software.

3.4.1 Descriptive Statistics

To study the trends in stock and metal prices before and after the Brexit event basic statistical measures like mean, median, standard deviation, and Percentage measures are used.

3.4.2 Comparative Study

The paired t-test is used to compare the means stocks before and after Brexit. As we are observing the same stocks before and after Brexit(i.e.matched pair), this test will help to compare the mean returns within each stock over the two time periods. The following formula is used to calculate the test statistic.

$$t = \bar{X}_{diff} / (\frac{S_{diff)}}{\sqrt{n}})$$

Where,

$\bar{X}_{diff}$: Mean of the difference

S: Standard deviation

N: Size of the sample(i.e number of pairs of observation)

The H_0 and H_1 for the Paired sample t-test is

H_0: Population 1 Mean(Mean1)= Population 2 Mean(Mean 2)

H_1: Population 1 Mean(Mean1) ≠ Population 2 Mean(Mean 2)

In case if normal assumption is violated Wilcoxon signed-rank test is used to examine the mean difference between two paired samples.

$$W = \sum_{i=1}^{N_r} [sgn(r_{2,i} - r_{1,i}). R_i]$$

Where,

N_r=Size of the sample

Sgn=signum function

$r_{1,i}$,r2$_{,I}$ =ranked pairs from two distribution

R_i =rank i

The H_0 and H_1 for the Wilcoxon signed rank test is

H_0: $m=m_0$ Population median of paired difference is equal to 0

H_1: $m \neq m_0$ Population median of paired difference does not equal to 0

3.4.3 Volatility Study

To study stock price fluctuation and market stability following methods will be employed

3.4.3.1 Standard Deviation of Returns

Monthly percentage returns of stock indices and metal prices can be calculated using the following formula. The choice of using monthly stock return data is supported by its widespread availability and relevance in capturing market trends. A higher standard deviation value indicates greater volatility, making monthly returns a suitable measure for analyzing stock price behavior.

Ben-Ahmed et al. (2022) analyzed how COVID-19 affected the stock returns of digital companies by utilizing monthly stock return data. Similarly, Bansal et al. (2021) investigated the impact of real earnings management on cross-sectional stock returns, incorporating the moderating effects of market, size, value, and momentum factors, also using monthly stock return data. These studies highlight the suitability of employing monthly returns for evaluating stock price behavior.

$$Monthly\ Return = \frac{Price_t - Price_{\ t-1}}{Price_{t-1}} * 100$$

3.4.3.2 Log Returns

It is a metric used to determine an asset's return over a given period. Logarithmic returns are preferred for statistical analysis and hypothesis testing since they tend to follow a normal distribution more closely than simple returns. Many studies(Schewert,1989; Engle,1982; Bollersv,1986) used log returns to conduct market volatility studies. The sharp increase in log return indicates financial crises or unstable markets. Nelson's (1991) EGARCH model uses log returns to capture market volatility. Campbell, Lo & MacKinlay's (1997) study also indicates the role of log return in predicting financial stability.

The natural logarithm of the ratio of consecutive prices is calculated.

$$Log\ Returns = \ln(\frac{P_t}{P_{t-1}})$$

Where,

P_t's stock price at the time of t

P_{t-1} is the stock price at the time t-1

Ln is a natural logarithm

3.4.3.3 Moving Average of Log Return

For assessing market stability the well-established technique in financial time series analysis is the use of moving averages of lagged log returns. The financial time series does not reflect the overall trend as it often exhibits short-term fluctuations. So it is necessary to smooth out the variations. To focus on meaningful trends over time filtering of daily noise can be done by computing a three-period moving average of past log returns. Log returns are preferred over simple percentage changes because they normalize price variations, allowing for a more constancy and comparable measure across different periods and asset classes.

MEAN(LAG(Log_Return,1), LAG(Log_Return,2), LAG(Log_Return,3)) This formula calculates three-period average returns by reducing noise and highlighting underlying trends.

Look ahead bias is prevented by using lagged values as it incorporates only past returns into the analysis. This technique is aligned well with broadly accepted financial stability models like Bollerslev's (1986) GARCH model and Engle's (1982) ARCH model, which rely on past returns to estimate volatility. Rolling window techniques of risk assessment and trend analysis were also highlighted by Fama(1970) in his market efficiency study.

In finding the consequence of Brexit on stock returns this method is specifically useful for comparing pre-and post-Brexit market stability. Applying the moving average separately in both periods helps to identify whether there is a significant shift in market volatility and behavior. If there are significant changes in moving averages post-Brexit then there is an increase in market instability caused due to Brexit-related changes.

3.4.3.4 Rolling Standard deviation

Schwert (1989) used rolling standard deviation to analyze the stock market volatility. Many studies (Andersen et al,.2003; Engel 1982) calculated rolling standard deviation in their studies related to stock market volatility. The standard deviation of log returns is calculated over the rolling window to capture the time-varying volatility. The rolling standard deviation at time t with a rolling window of size N is calculated by the formula.

$$\sigma_t = \sqrt{\frac{1}{N-1}\sum_{i=t-N+1}^{t}(r_i - \bar{r})^2}$$

Where,

$$\sigma_t = rolling\ standard\ deviation\ at\ time\ t$$

r_i = log return at time i

$\bar{r}$= mean of log return over the time window

N is window time

Volatility and rolling standard deviation values are directly correlated

3.4.4 Regression Analysis

In financial analysis, Regression is a commonly employed econometric technique to understand the behavior of the market. A previous study by Nelson and Kim (1993) highlighted the role of the regression model in predicting stock returns. Busch and Matthes (2016) used a similar technique to analyze Brexit's impact. In a study by Baumhol and Lyocsa (2009) importance of stationarity of time series to avoid false results was highlighted.

A simple linear regression analysis is used to test the extent of Brexit's effect on stock and metal prices. Two separate regression for stock and metal prices using stock indices(DAX, S&P 500, NASDAQ) and metal prices (Gold and Silver) and dependent variables respectively. Independent variables constitute the Brexit dummy variable (0=Pre Brexit,1=Post Brexit) while controlling for other economic factors thus allowing for a statistical assessment of Brexit’s direct effect on the financial market and separating it from broader economic trends.

The regression equation is given by

$$Price_t = \beta_0 + \beta_1 Brexit_t + \epsilon_t$$

Where: $Price_t$=Stock/Metal Price at time t

$Brexit_t$=Takes the value of 1 in case of Post Brexit,0 in case of Pre Brexit

β_1 Measures Brexit’s impact

ε_t is the Error Term

3.5 Reliability of Data and validation

The trustworthiness of the data is taken care of by comparing stock and metal prices in multiple data sources like Yahoo Finance, Bloomberg, etc. Outliers caused due to extreme events other than Brexit like the financial crisis, are identified and removed. Also, the consistency of the results is checked using different timeframes and control variables.

3.6 Ethical Considerations

Ethical considerations play a crucial role in conducting research on the differences in stock and metal prices before and after Brexit, particularly when examining the cases of Germany and the United States. Ensuring ethical integrity in such a study requires careful attention to data accuracy, transparency, confidentiality, and the responsible use of financial information. Researchers must adhere to ethical guidelines to ensure that their findings are reliable, unbiased, and contribute meaningfully to financial market research.

One key ethical consideration is the accuracy and transparency of data sources. Since this study relies on historical financial data, it is essential to use reputable and publicly available sources, such as stock exchanges, central banks, and financial institutions. Misrepresentation or selective use of data could lead to biased conclusions, which might misinform investors and policymakers. Previous studies, such as those by Breinlich et al. (2018) and Davies and Studnicka (2018), have emphasized the importance of using robust statistical methods to avoid misleading interpretations in financial market research. Ensuring data reliability strengthens the validity of the study and maintains ethical research standards.

Another ethical concern is the potential impact of the findings on financial markets and investors. While research on Brexit's effects is valuable, it must be conducted with caution to avoid creating unnecessary panic or speculation. The work of Shaikh (2018) highlights how investor sentiment and market reactions can be influenced by media reports and research studies. Therefore, researchers must present their findings objectively and avoid exaggerated claims that could lead to market instability. Additionally, any recommendations derived from the study should be clearly stated as based on historical data rather than predictive claims about future market behavior.

Confidentiality and data protection are also essential ethical aspects, particularly when dealing with financial information. While this study primarily relies on publicly available data, researchers must ensure that any proprietary or sensitive information is handled appropriately. According to Nti, Adekoya, and Weyori (2020), ethical research in financial markets should respect data ownership and ensure that no private or insider information is disclosed. Furthermore, if any third-party databases or proprietary datasets are used, proper permissions must be obtained, and data usage must comply with legal regulations such as the General Data Protection Regulation (GDPR) in the European Union.

The objectivity and impartiality of the research process are also crucial ethical considerations. Financial studies must be free from conflicts of interest, ensuring that researchers do not have personal or financial stakes that could influence their analysis. According to Weng, Ahmed, and Megahed (2017), studies on financial markets should disclose any potential conflicts of interest to maintain credibility. If the research is funded by an external organization, transparency regarding sponsorship and potential biases must be maintained. Researchers should also strive to avoid confirmation bias by using multiple methodologies and diverse datasets to cross-validate findings.

Data collected for the study is publicly available. Therefore, there is no ethical consideration related to human participants. However, data usage is made by considering academic integrity guidelines, proper referencing, and a transparent approach. All sources of data are acknowledged and any biases are discussed.

3.7 Limitations

The historical price data collected may have missing values and they have to be imputed using suitable techniques(Haryono et al., 2024). The study employs a small sample size, which can reduce statistical power in turn affecting the reliability of the result (Nelson & Kim, 1993).

Stock and Metal prices are also influenced by factors other than Brexit like global economic trends, Business policies, and other factors that will distort the true impact of Brexit (Busch & Matthes, 2016).

Due to the non-stationarity character of stock and metal prices, there will be a breach of the assumption of t-tests and regression(Baumohl & Lyocsa, 2009). Many statistical tests assume a normal distribution, but financial data often show skewness and heavy tails, requiring transformations or non-parametric tests(Qiu,2024).

The study helps find the associations between Brexit and market movements but may not identify direct causality. Gradual market adjustments that happened before or after the Brexit referendum may be overlooked due to arbitrary event windows (Henderson, 1990). For better accuracy, structural Breaks in time-series data should be studied using advanced econometric modeling.

The study has selection bias and market sentiment as it only focuses on S&P 500, DAX, gold, and silver. However, investors' sentiments will be affected by other asset classes differently (Baker and Wurgler,2007).

4 Findings and Discussions

4.1 Performance of Stock Market pre-and post-Brexit

Table 4.1:Summary Statistics of Monthly Return[1]

Brexit Period	Statistic		S&P 500	DAX
Pre-Brexit	Mean		0.84% (0.41%)	0.65% (0.64%)
	95% CI of Mean	LL	-0.003%	-0.65%
		UL	1.66%	1.95%
	5% Trimmed Mean		0.82%	0.78%
	Median		0.95%	0.94%
	Variance		11.44	27.79
	Std. Deviation		3.38%	5.27%
	Minimum		-7.18%	-19.19%
	Maximum		10.77%	12.32%
	Range		17.95%	31.51%
	Interquartile Range		4.40%	7.06%
	Skewness		0.001 (0.295)	-0.65 (0.295)
	Kurtosis		0.69 (0.582)	2.09 (.582)
Post-Brexit	Mean		1.34% (0.53%)	0.87% (0.60%)
	95% CI of Mean	LL	0.29%	-0.33%
		UL	2.39%	2.07%
	5% Trimmed Mean		1.47%	0.98%
	Median		1.83%	0.78%
	Variance		18.29%	24.03
	Std. Deviation		4.28%	4.90%
	Minimum		-12.51%	-16.44%
	Maximum		12.68%	15.01%
	Range		25.19%	31.45%
	Interquartile Range		3.69%	5.81%
	Skewness		-0.62% (0.295)	-0.41 (0.29)
	Kurtosis		1.95% (0.58)	2.08 (0.58)

[1]Figures in Parenthesis indicates Standard Error

The monthly returns of the S&P 500 and DAX indices for the period 2011 to 2021(pre-Brexit: Jan 2011 to Jun 2016,post-Brexit: July 2016 to Dec 2021) were analyzed. The sole purpose of the analysis is to gain insights into market behavior during periods of economic uncertainty. The summary statistics of the S&P 500 and DAX indices for the Before and after Brexit times are shown in Table 4.1.

The average returns in both stocks increased during post-Brexit (S&P500:1.34%, DAX:0.87%) when compared to pre-Brexit (S&P500:0.84%, DAX:0.65%). Standard deviation (measure of volatility) increase for the S&P500 (pre-Brexit: 3.38%, post-Brexit: 4.28%), and though DAX displayed a decrease in standard deviation (pre-Brexit: 5.27%, post-Brexit: 4.90%) volatility remained high compared to the S&P500. Greater fluctuation in return was observed for S&P500 (Pre-Brexit: 17.95%, Post-Brexit: 25.19%) compared to DAX (Pre-Brexit: 31.51%, Post-Brexit: 31.45%) though high fluctuation but value is little stable.

Thus according to descriptive statistics, the average returns of both stocks increased after Brexit (S&P500:1.34%, DAX:0.87%) compared to pre-Brexit (S&P500:0.84%, DAX:0.65%). However, standard deviation as a measure of volatility yields mixed results. In the case of the S&P 500 volatility increased during post-Brexit (pre-Brexit:3.38%,post-Brexit:4.28%) whereas in the case of DAX volatility decreased (pre-Brexit:5.27%,post-Brexit:4.90%). Volatility in stock returns remained higher in the case of DAX compared to S&P500. We can infer from this that Brexit-induced market uncertainty in terms of fluctuations was more in the case of US markets compared to German markets.

The shift in the distribution of return in the S&P500 is indicated by negative skewness value during the post-Brexit period (from 0.001% to -0.62%) whereas DAX returns remained a little stable (from -0.65% to -0.41%). The S&P 500 kurtosis shot up from 0.69% to 1.95%, indicating a greater probability of extreme returns, while DAX remained relatively stable (Pre-Brexit: 2.09, Post-Brexit: 2.08).

Skewness measures the symmetry of data distribution. In the case of the S&P 500, the returns were slightly positively skewed (0.001) during pre-Brexit while during post-Brexit distribution was moderately skewed towards the left (-0.62) indicating downside risk post-Brexit. The kurtosis value indicates curve distribution is platykurtic and it increased post-Brexit for S&P 500 (pre-Brexit:0.69, Post-Brexit:1.95) and was stable for DAX (pre-Brexit:-2.09, Post-Brexit:2.08). These findings are a key indicator of heightened market volatility post-Brexit, particularly for the S&P 500, with an increased likelihood of extreme market movements. These findings align with research on financial markets during political events, where increased uncertainty often leads to fatter tails in return distributions (Lux, 1998).

Table 4.2 Paired Sample t-Test of Monthly_Return

Stock Name	Pre-Brexit		Post-Brexit		t(65)	p	Cohen's d
	M	SD	M	SD			
S&P-500	0.84%	3.38%	1.34%	4.27%	-0.754	0.45	-0.093
DAX	0.65%	5.27%	0.87%	4.90%	-0.246	0.80	-0.030

To see whether the mean returns of the S&P 500 and DAX differ notably in pre- and post-Brexit paired sample t-test was carried out. Table 4.2 depicts the outcome of a paired samples t-test comparing the average monthly returns from the S&P 500 and DAX indices pre and post-Brexit. There is an increase in the mean return of both stocks during the post-Brexit period (S&P 500: 0.84% to 1.34%, DAX: 0.65% to 0.87%). There is greater volatility in the S&P 500 compared to DAX as indicated by the increased standard deviation value of S&P stocks (S&P 500: 3.38% to 4.27%, DAX: 5.27% to 4.90%).

The t-values (-0.754 for S&P 500, -0.246 for DAX) and p-values (0.45, 0.80) suggest that the differences in returns between the before and after Brexit periods were not statistically significant. Hence we do not reject the null hypothesis of no difference. Cohen's d values (-0.093, -0.030) show small effect sizes, implying that Brexit had a negligible impact on stock returns despite increased volatility.

This indicates that Brexit had minimal impact on stock returns despite heightened volatility. This finding matches with literature that suggests global equity markets often adjust rapidly to major geopolitical events, leading to short-term fluctuations but no lasting impact on returns (Ali et al., 2023; Taimur & Khan, 2013).

The regression analysis (Table 4.3) further corroborates these findings. The regression analysis explores the effect of the Brexit period on stock market returns for the S&P 500 and DAX indices. The constant term for S&P 500 ($B = 0.791$, $p = 0.118$) and DAX ($B = 0.650$, $p = 0.301$) suggests that pre-Brexit returns were not notably different from zero. The Brexit period variable has a small, insignificant effect on both indices (S&P 500: $B = 0.503$, $p = 0.482$; DAX: $B = 0.222$, $p = 0.802$), indicating no strong relationship. The low R^2 values (S&P 500: 0.004, DAX: 0.000) suggest that the Brexit period explains the slightest variance in stock returns. This indicates that Brexit explained only a negligible portion of the variance in stock returns, reinforcing the conclusion that other macroeconomic and geopolitical factors played a more dominant role.

Table 4.3 Linear Regression[2] of Monthly_Return

Variables	S&P500					DAX				
	B	**β**	**SE**	**t**	**sig**	**B**	**β**	**SE**	**t**	**sig**
Constant	0.791		0.502	1.576	0.118	0.650		0.627	1.038	0.301
Brexit_Period	0.503	0.065	0.713	0.706	0.482	0.222	0.022	0.886	0.251	0.802
R^2	0.004					0.000				

[2]Dependent Variable: Monthly Return

4.2 Gold and Silver Price Trends Before and After Brexit

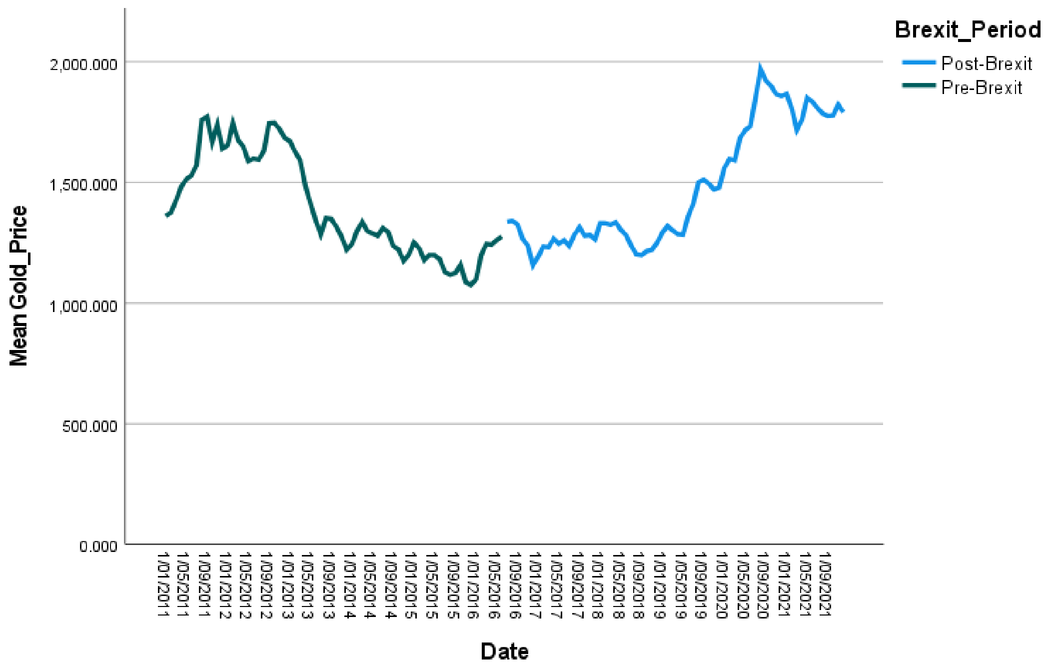

Figure 4. 1 Gold Price over the Time

Figure 4.1 displays the average gold price trend over the year. The dark green line represents the pre-Brexit period showing fluctuations and decreasing trends in mean gold price until the Brexit event. The post-Brexit period represented by the blue line begins with the stable phase before experiencing a sharp increase, indicating increased market volatility and investor uncertainty following Brexit. This rush in gold prices reflects about haven asset role played by gold indicating a shift in investment behavior toward gold despite financial turmoil.

The descriptive statistics in Table 4.4 provide insights into how Brexit influenced the international prices of Gold and Silver. During Pre-Brexit the average gold price was $1397.57 with a standard deviation of $211.78 showing moderate fluctuations. The average price value increased to $ 1477.81 during the post-Brexit period with a standard deviation of $251.37 indicating greater volatility. The minimum price jumped to $1157.36 from $1075.74, while the maximum price jumped to $ 1772.14 from $ 1968.63, showing wider price fluctuations.

The distribution of gold prices was positively skewed during post-Brexit with a skewness value of 0.54 (skewness value of 0.37 during pre-Brexit). The kurtosis value remained negative (pre-Brexit:-1.28 and post-Brexit:-1.34) indicating gold prices had relatively flatter distribution both before and after Brexit.

The average price of silver declined to $ 19.77 post-Brexit from $25.68 pre-Brexit. There was reduced volatility in silver price during post-Brexit as indicated by a decline in standard deviation value to 4.39 from 8.96 prevailed during pre-Brexit. Increase in Positive skewness of silver prices from 0.59 to 0.92. The kurtosis value of silver price during post-Brexit is 0.58 which indicates more peakedness of the normal curve compared to the post-Brexit kurtosis value of -0.74.

***Table 4.4 Descriptive Statistics of Metal Prices*[3]**

Brexit Period	Statistic		Gold	Silver
Pre-Brexit	Mean		1397.57 (26.07)	25.68 (1.102)
	95% Confidence Interval for Mean		1345.50	23.48
			1449.63	27.88
	5% Trimmed Mean		1394.66	25.22
	Median		1326.33	22.33
	Variance		44850.22	80.27
	Std. Deviation		211.78	8.96
	Minimum		1075.74	14.38
	Maximum		1772.14	48.70

	Range		696.40	34.20
	Interquartile Range		380.03	15.81
	Skewness		0.37 (0.295)	0.59 (0.295)
	Kurtosis		-1.28 (0.582)	-0.74 (0.582)
Post-Brexit	Mean		1477.81 (30.94)	19.77 (0.54)
	95% Confidence Interval for Mean		1416.02	18.69
			1539.61	20.85
	5% Trimmed Mean		1469.30	19.55
	Median		1335.71	18.16
	Variance		63187.69	19.28
	Std. Deviation		251.37	4.39
	Minimum		1157.36	14.53
	Maximum		1968.63	29.58
	Range		811.27	15.06
	Interquartile Range		497.02	7.59
	Skewness		0.54	0.92 (0.295)
	Kurtosis		-1.34	0.58 (0.582)

[3]Figures in Parenthesis indicate Standard Error

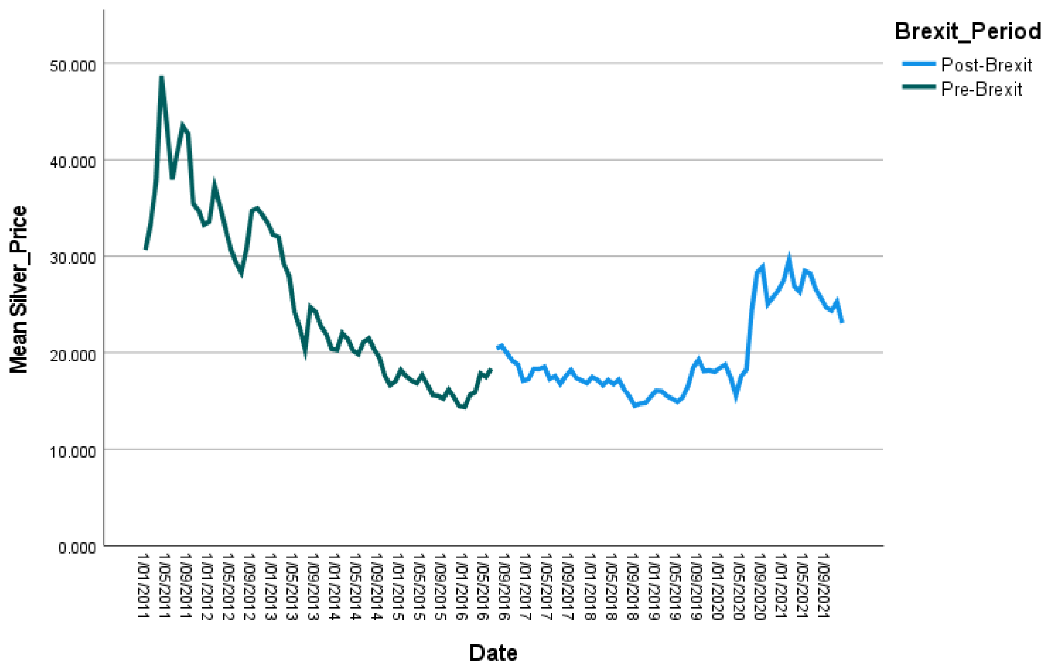

Figure 4. 2 Silver Prices over the time

Figure 4.2 illustrates the behavior of average silver prices over the year. During the pre-Brexit period(dark green line) there was a sharp decline in silver prices followed by stabilization. The post-Brexit period(blue line) starts with relatively stable prices followed by an immediate rush showing high volatility. This behavior of silver supports the notion of investor demand for precious metals as safe-haven assets, driven by market instability surrounding Brexit's economic impact.

Table 4.5 Paired Sample t-Test for Metal Prices

Stock Name	**Pre-Brexit**		**Post-Brexit**		**T(65)**	**p**	**Cohen's d**
	M	**SD**	**M**	**SD**			
Gold	1397.56	211.78	1477.81	251.37	-1.49	0.142	-0.183
Silver	25.69	8.96	19.77	4.39	4.04	<0.001	0.497

The output of the Paired sample t-test to see whether there is any notable difference in gold and silver prices before and after Brexit is presented in Table 4.5. There is a notable increase in the average price of gold (The average price in pre-Brexit is \$1397.56 with SD=211.78 and in post-Brexit \$1477.81 with SD=251.37) with a t-value of -1.49 (p=0.142). Hence we do not reject the null hypothesis of no difference.

Cohen's d value of -0.183 suggests a small effect size, implying that Brexit had a modest impact on gold prices. In the case of silver, the mean price dropped significantly from \$ 25.69 (SD=8.96) pre-Brexit to \$19.77(SD=4.39) post-Brexit with a t-value of 4.04(p <0.001). Hence we reject the null hypothesis of no difference. The Cohen's d value of 0.497 suggests a large effect size, meaning Brexit had a considerable impact on silver prices.

The analysis of Gold and Silver prices helps to understand the insights into investor behavior during the Brexit period. Prices of gold increased during post-Brexit (\$1397.57 to \$1477.81), with greater volatility (standard deviation rising from \$211.78 to \$251.37), showing a shift toward gold as a safe-haven asset. The positive skewness value of 0.54 during post-Brexit suggests increased demand-driven price spikes.

In contrast, the mean silver price declined to \$19.77 during post-Brexit from \$25.68 during pre-Brexit with reduced volatility(standard deviation drops from \$8.96 to \$4.39). The paired t-test revealed that Brexit has significantly affected silver prices(t 4.81, p < 0.001). Cohen; 's D value of 0.838 also showed a higher effect size indicating a substantial impact of

Brexit on silver prices. Comparative analysis revealed that silver has much financial uncertainty compared to gold.

Table 4.6 Linear Regression of Metal Prices

Linear Regression of Metal Prices

Variables	**Gold**					**Silver**				
	B	**β**	**SE**	**t**	**sig**	**B**	**β**	**SE**	**t**	**sig**
Constant	1397.57		28.61	48.86	<0.00	25.69		0.87	29.58	<0.001
Brexit_ Period	80.25	0.17	40.46	1.98	0.045	-5.91	-0.39	1.23	-4.81	<0.001
R^2	0.029					0.151				

To know the consequence of Brexit on gold and silver prices a linear regression model is fitted (Table 4.6). The coefficient of the Brexit period ($\beta = 0.17$, $p = 0.045$) indicates a significant positive relationship at a 0.05 level of significance, suggesting gold prices increased slightly due to Brexit. However, $R^2 = 0.029$ shows that Brexit explains only 2.9% of the variation in gold prices and other variables affect gold prices that are not taken in the model.

In the case of silver prices, Brexit had a significant negative impact implying a decline in silver price due to Brexit. R^2 value of 0.15 specifies that 15 percent of the variation in silver prices is described by Brexit. This result indicated more effect of Brexit is seen in the case of silver prices compared to Gold Prices. The silver price was more sensitive to uncertainties caused due to Brexit, while the price of gold showed little upward trend proving its role as a safe-haven asset.

These findings align with studies indicating that gold is a preferred safe-haven asset at the time of financial crises (Manohar & Guntur, 2021; Baur and McDermott, 2010), while silver's behavior is more complex, often reacting differently to macroeconomic shocks (Abidi et al., 2025).

4.3 Comparative stock market volatility and stability Analysis Between the US and Germany

The standard deviation of log returns is calculated to measure the volatility of the stock returns and the results are presented in Table 4.7. The standard deviation of S&P 500 log returns was 0.31 indicating high volatility in stock returns before Brexit. The log returns of DAX had a much lower standard deviation of 0.05 indicating relatively stable returns compared to the S&P500 before Brexit.

Table 4.7 Standard Deviation of Log Returns

Statistic	**Brexit Period**	**S&P 500**	**DAX**
Standard Deviation	Pre-Brexit	0.31	0.05
	Post-Brexit	0.04	0.04
	Total	0.22	0.05

The standard deviation of the S&P 500 dropped significantly to 0.04**,** suggesting reduced market fluctuations after Brexit. The DAX also exhibited a slight decrease in standard deviation (0.04) indicating only a marginal reduction in volatility. Over the complete study period, the S&P 500 had a total standard deviation of 0.22, indicating that the overall market instability was mainly driven by the pre-Brexit period. The DAX, with a total standard deviation of 0.05, remained relatively stable throughout the study period.

Table 4.8 Paired Sample T-test of Log_Return

Stock Name	**Pre-Brexit**		**Post-Brexit**		**T(64)**	**p**	**Cohen's d**
	M	**SD**	**M**	**SD**			
S&P 500	-0.030	0.31	0.012	0.042	-1.11	0.85	0.08
DAX	0.004	0.54	0.007	0.049	-0.67	0.51	-0.02

To see whether there are significant differences in average log returns before and after Brexit the paired sample t-test was carried out (Table 4.8). In the case of the S&P 500 negative average return(-0.030) seen during pre-Brexit shifted to a positive (0.012) during post-Brexit. The pre-Brexit period exhibited high volatility (0.31) and there was a significant reduction in volatility (0.04) during the post-Brexit period. The T-test ($t(64)=-1.11, p=0.85$) indicated no significant differences between pre-and post-Brexit log returns. Cohen's d value of 0.08 indicates a small size effect and this indicates the change in log returns is less and may not have a notable impact on market behavior.

In the case of the DAX positive average return(0.004) in pre-Brexit slightly increased to 0.007 during post-Brexit. The pre-Brexit period exhibited slightly high volatility(0.54) compared to the post-Brexit(0.05) period. The T-test ($t(64)=-0.67, p=0.51$) indicated no significant differences between pre-and post-Brexit log returns, and hence null hypothesis is not rejected. Cohen's d value of -0.02 indicates a negligible size effect and this indicates the change in log returns is less and no meaningful difference between pre- and post-Brexit periods.

Table 4.9 Linear Regression of Log Returns

Variables	S&P500					DAX				
	B	**β**	**SE**	**t**	**sig**	**B**	**β**	**SE**	**t**	**sig**
Constant	-0.03		0.03	-1.12	0.27	0.01		0.01	0.75	0.45
Brexit_ Period	0.04	0.09	0.04	1.11	0.27	0.00	0.03	0.01	0.30	0.77
R^2	0.009					0.001				

Table 4.9 presents the linear regression results of log returns for the S&P 500 and DAX by considering the Brexit period as the independent variable. The intercept term for the S&P 500 is -0.03, while for DAX, it is 0.01, neither of which is statistically significant. The regression coefficient for the Brexit period is 0.04 ($\beta = 0.09$, $p = 0.27$) for S&P 500 and 0.00 ($\beta = 0.03$, $p = 0.77$) for DAX, indicating that Brexit had a minimal and statistically insignificant effect on log returns**.** The R^2 values (0.009 for S&P 500, 0.001 for DAX) suggest that Brexit explains very little of the variation in log returns.

The pairedsample t-test results specify that the shift in average log returns for both indices was not statistically significant. The S&P 500 moved from a negative return (-0.030) pre-Brexit to a positive return (0.012) post-Brexit, accompanied by a significant decline in volatility. However, the t-test ($p = 0.269$) and Cohen's d (0.233) suggest a small effect size, implying that Brexit did not substantially impact market behavior. Similarly, the DAX's average return showed a slight increase (0.004 to 0.007), with an insignificant effect size (Cohen's d = 0.05) and an insignificant t-test result ($p = 0.766$), indicating no meaningful difference.

Regression results confirm these findings, as Brexit's impact on log returns was statistically insignificant for both indices (S&P 500: $\beta = 0.09$, $p = 0.27$; DAX: $\beta = 0.03$, $p = 0.77$). The low R^2 values (0.009 for S&P 500, 0.001 for DAX) indicate that Brexit explains little variation in returns. While S&P 500 volatility declined sharply post-Brexit, DAX exhibited more frequent but moderate fluctuations, suggesting that the European market was more responsive to external economic changes. Overall, Brexit had a minimal impact on stock returns, with greater implications for market volatility rather than returns themselves.

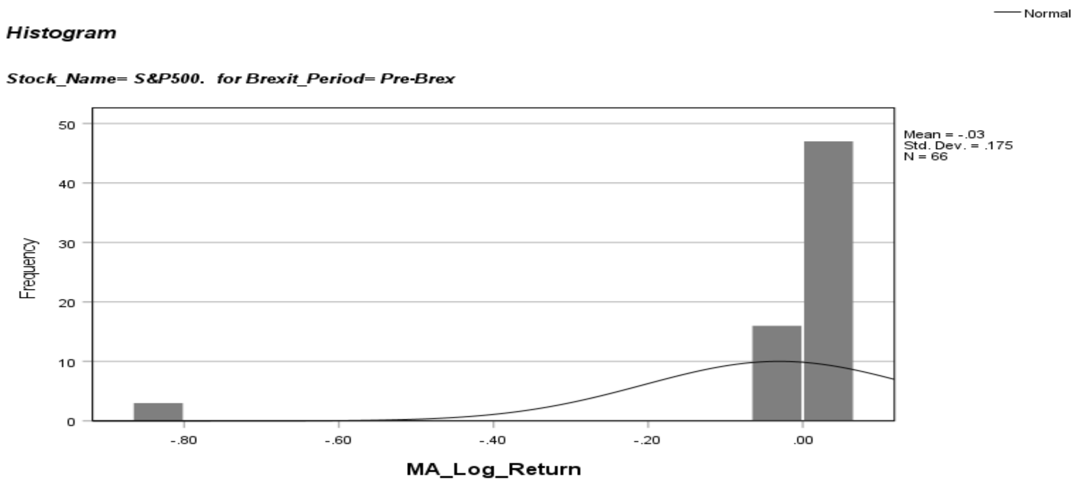

Figure 4. 3 Histogram of Moving Average of Log Return for S&P500 during the pre-Brexit period

The before-Brexit moving average of log return for the stock S&P 500 is displayed in Figure 4.3. The Mean of the moving average log return is -0.03 with a standard deviation of 0.175. The distribution is skewed to the left with most returns concentrated near 0. The outlier on the left indicates an unusual negative return, possibly caused by a significant market event.

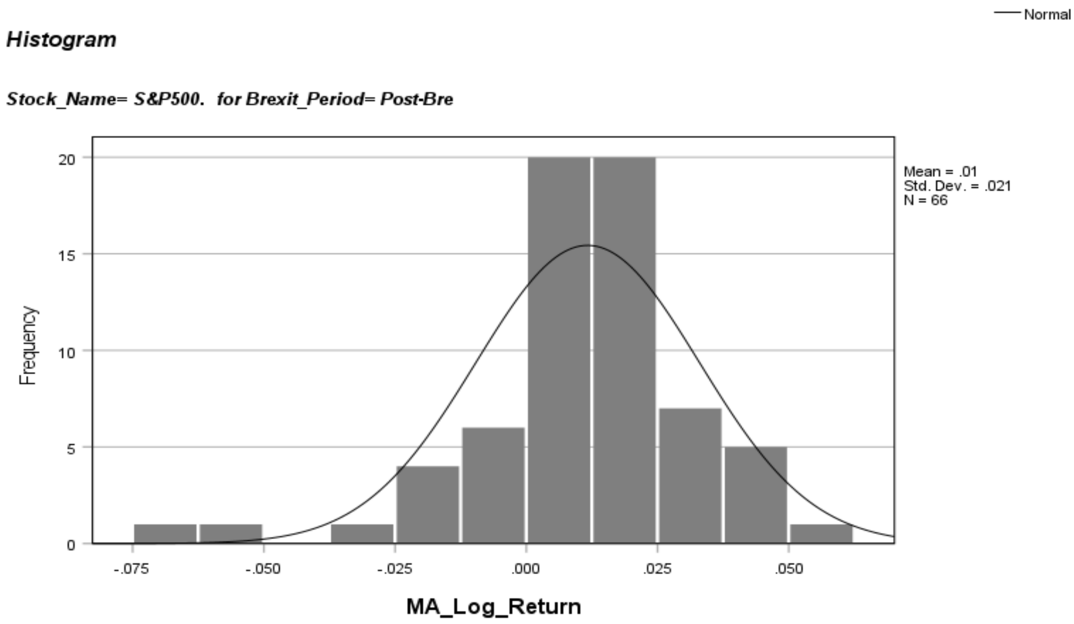

Figure 4. 4 Histogram of Moving Average of Log Return for S&P500 during the post-Brexit period

The post-Brexit moving average of log return for the stock S&P 500 is displayed in Figure 4.4. The Mean of the moving average log return is 0.01 with a standard deviation of 0.021. The distribution is slightly left skewed with most of the returns falling between 0.000 to

0.025.

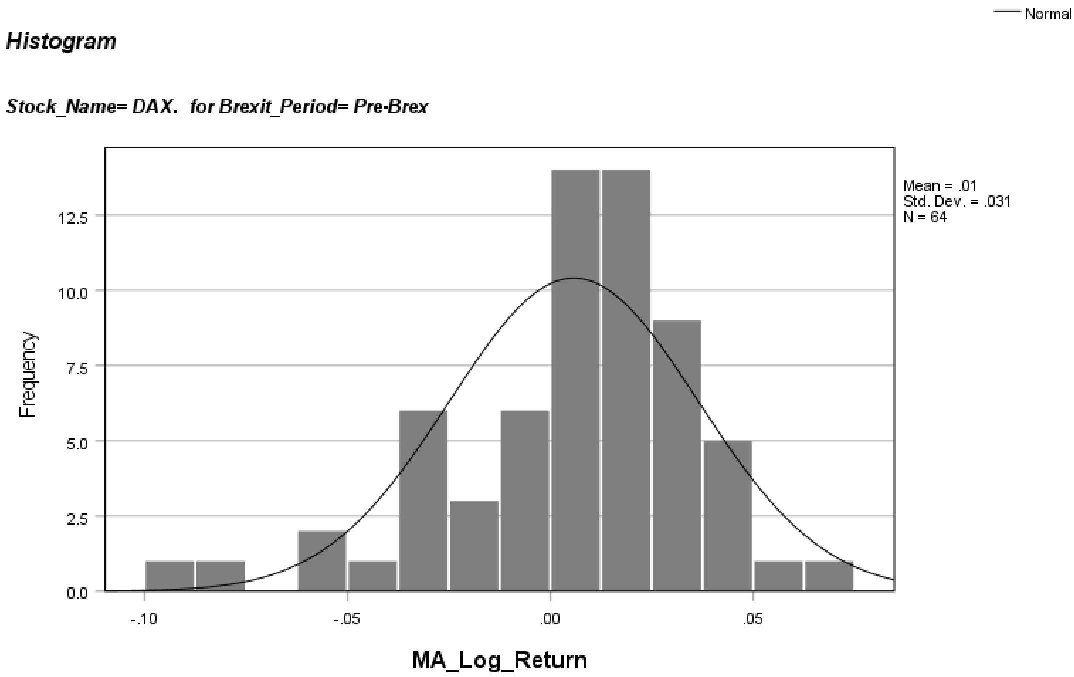

Figure 4. 5 Histogram of Moving Average of Log Return for DAX during the pre-Brexit period

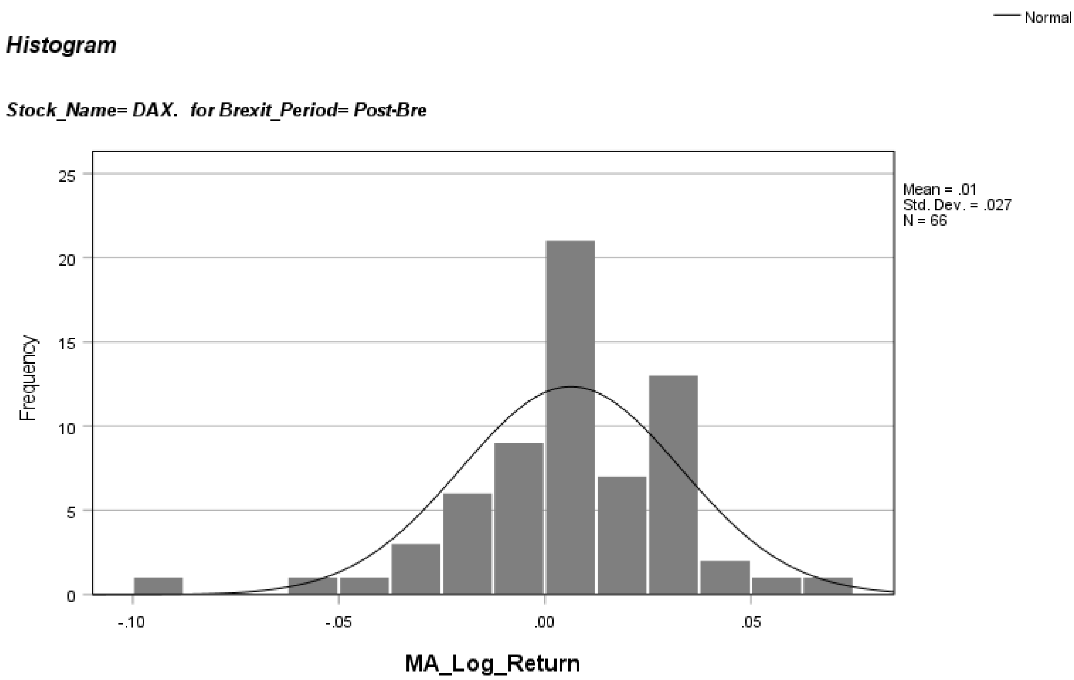

Figure 4. 6 Histogram of Moving Average of Log Return for DAX during the post-Brexit period

The moving average log returns of the DAX index before and after Brexit are displayed in Figure 4.5 and Figure 4.6 respectively. Both distributions have a mean of 0.01, indicating that the average returns remained unchanged across the periods. However, differences in standard deviation suggest a shift in volatility. Before Brexit, the standard deviation was 0.031, while post-Brexit, it decreased to 0.027, indicating slightly reduced volatility.

The pre-Brexit distribution is slightly left-skewed with a broader spread, suggesting more negative returns and higher risk. Post-Brexit, the distribution appears more peaked, with a higher frequency of returns clustering around zero, implying lower variability. Brexit led to a decrease in volatility and a tighter return distribution, indicating a potentially more stable market environment for DAX after Brexit.

The paired sample t-test of the mean moving average of the log return of the S&P 500 stocks before and after Brexit is provided in Table 4.10. The mean moving average of the log return remained constant during post-Brexit(0.01) with the mean moving average of the log return in pre-Brexit (0.01). The test is a not significant 5% significance level. Cohen's d (-0.14) indicated a small impact.

Table 4.10 Paired T-test of MA_ Log_Return

Stock Name	**Pre-Brexit**		**Post-Brexit**		**T(66)**	**p**	**Cohen's d**
	M	**SD**	**M**	**SD**			
S&P 500	0.01	0.02	0.01	0.02	-1.93	-1.21	-0.14
DAX	0.00	0.03	0.01	0.03	-0.10	-0.56	-0.07

The paired sample t-test of the mean moving average of the log return of the DAX stocks before and after Brexit is provided in Table 4.10. The mean moving average of the log return remains the same in both periods with a consistent standard deviation of 0.03 showing market stability. The test is not significant (p=-0.56) Very low Cohen's d value of -0.07 showed a minimal impact.

The linear regression results further again confirm these findings (Table 4.11). For the S&P 500, Brexit had a statistically notable effect on returns ($p = 0.05$), with a beta coefficient (β) of 0.17, explaining 3% of the variance ($R^2 = 0.03$). This suggests a small but notable Brexit-related shift in S&P 500 returns. In contrast, for the DAX, Brexit's impact was insignificant ($p = 0.91$), with a near-zero beta ($\beta = 0.01$) and $R^2 = 0.000$, indicating no meaningful effect on returns.

Table 4.11 Linear Regression of MA_Log Returns

Variables	**S&P500**					**DAX**				
	B	**β**	**SE**	**t**	**sig**	**B**	**β**	**SE**	**t**	**sig**
Constant	-0.03		-0.01	-1.97	0.05	0.01		0.00	1.62	0.11
Brexit_ Period	0.04	0.17	0.02	1.93	0.05	0.00	0.01	0.01	0.11	0.91
R^2	0.03					0.000				

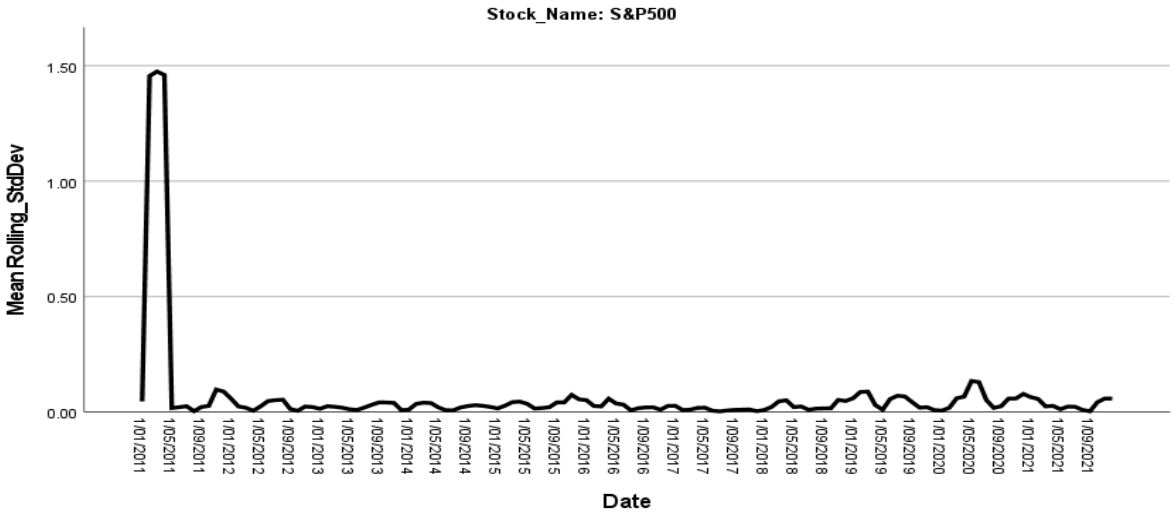

Figure 4. 7 Rolling Standard Deviation for the S&P 500 over the year

The rolling standard deviation of log returns of S& P 500 and DAX for the study period is displayed in Figure 4.7 and Figure 4.8 respectively. In the case of the S&P 500 sharp spike in volatility around 2011, reaching over 1.5, followed by a prolonged period of stability with minor fluctuations. This suggests that the S&P 500 underwent a notable market event during that time, after which volatility subsided and remained relatively low. In contrast, DAX displayed more frequent fluctuations without single extreme values. DAX displayed multiple peaks indicating DAX has been more susceptible to market uncertainty, with persistent periods of increased volatility.

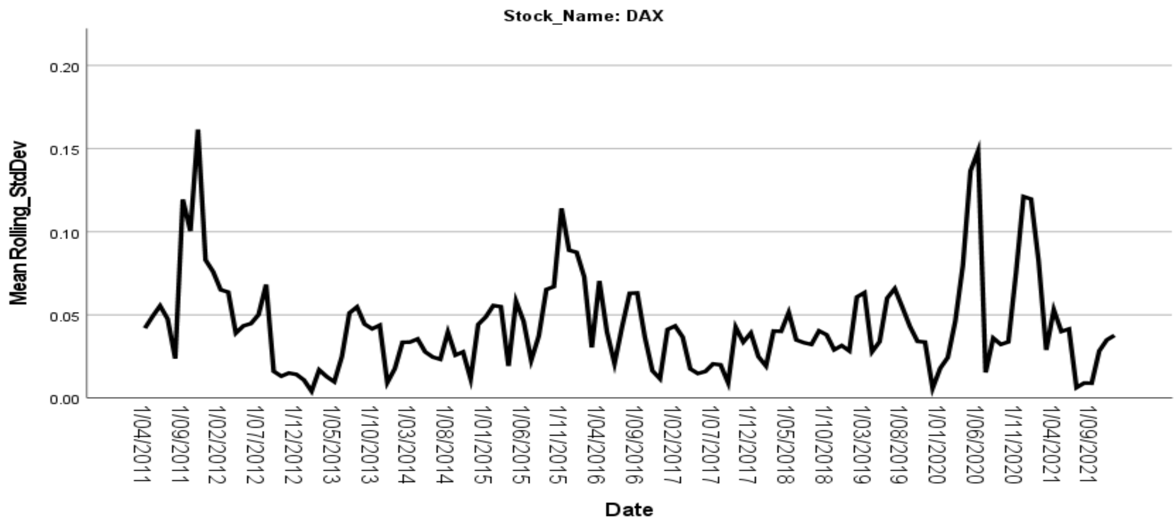

Figure 4. 8 Rolling Standard Deviation for the DAX over the year

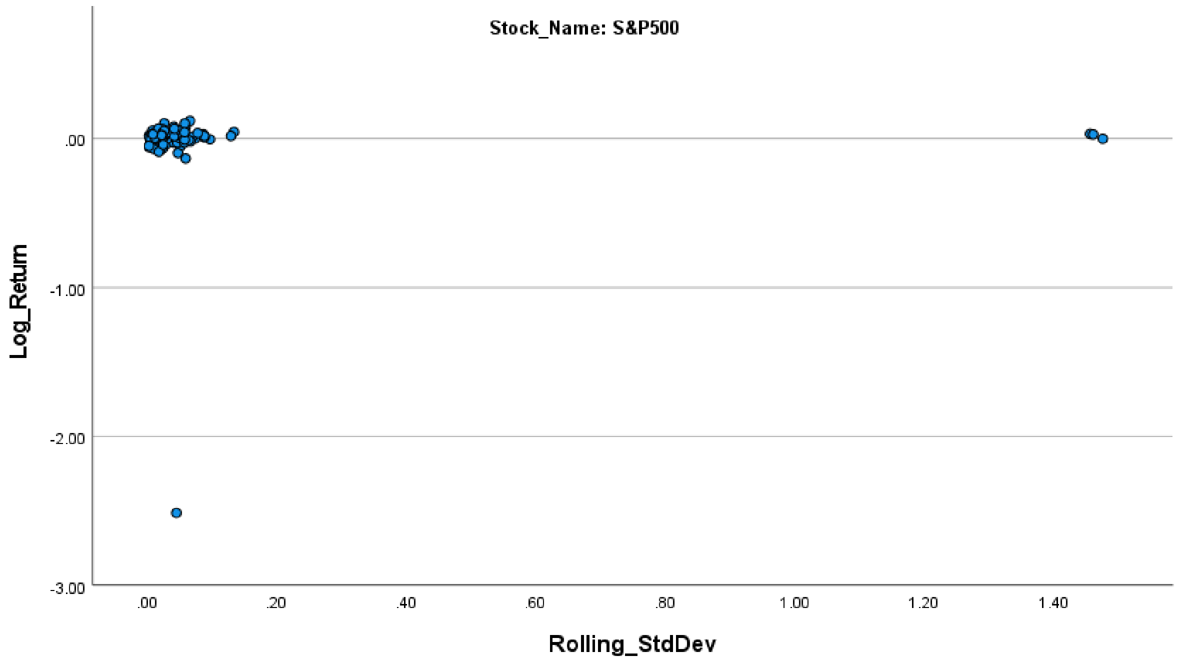

Figure 4. 9 Scatter Plot of Log Return and Rolling_StdDev for S&P 500

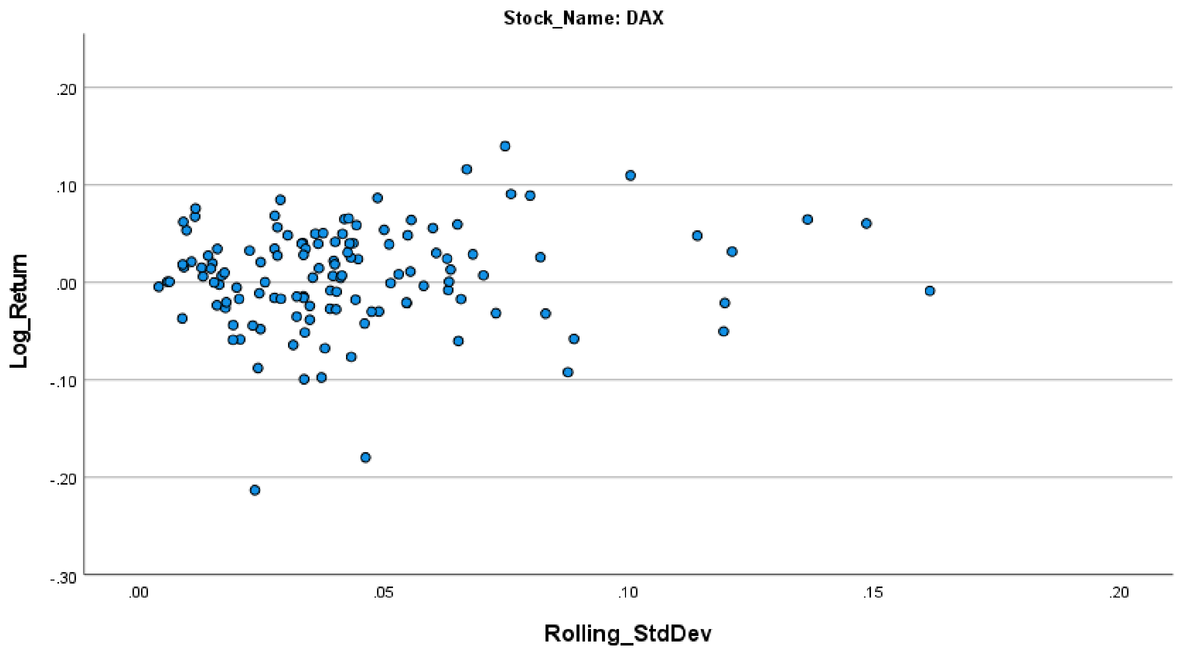

Figure 4. 10 Scatter Plot of Log_Return and Rolling_StdDev for DAX

To know the relationship between fluctuations and volatility shifts the scatter plots depicting the relationship between the rolling standard deviation of log returns and log return for S&P 500 and DAX are presented in Figure 4.9 and Figure 4.10 respectively. In the case of the S&P 500 majority of the data points clustered around low standard deviation values indicating a more stable market with less volatility during most of the period. The presence of a market crash or an abrupt shift in price movement is indicated due to the presence of an outlier having a high negative log return. Occasional period of heightened volatility is indicated by the presence of data points with high rolling standard deviation.

Whereas, in DAX the log returns are scattered around different rolling standard deviation values. DAX data points are evenly distributed unlike S&P 500 clustered tightly. A clear relationship can be identified between the rolling standard deviation and log returns. As volatility increases higher price fluctuation becomes more common. The DAX appears to be highly reactive to variations in market conditions, which happen due to the economic structure of the European market and external influences such as currency fluctuations and international trade policies.

The findings reveal significant differences in volatility and return patterns between the S&P 500 and DAX indices pre- and post-Brexit. Before Brexit, the S&P 500 exhibited high volatility with a standard deviation of 0.31, while the DAX was proportionately stable at 0.05. Post-Brexit, the volatility of the S&P 500 dropped significantly to 0.04, indicating reduced market fluctuations, whereas the DAX saw only a slight decline (0.04), reflecting minimal change. The overall standard deviation of the S&P 500 (0.22) suggests that market instability was primarily driven by the pre-Brexit period, whereas the DAX remained stable throughout (0.05).

5 Conclusion

5.1 Summary

The study analyses the effect of Brexit on USA and Germany stock (S&P 500 and DAX) and commodity (Gold and Silver) markets by collecting monthly data from different financial databases for the period from 2011 to 2021. The stock analysis revealed that the mean return of stocks increased after the Brexit period (S&P 500: 1.34%, DAX: 0.87%) compared to pre-Brexit (S&P 500: 0.84%, DAX: 0.65%). However, the volatility measure standard deviation revealed mixed results. The S&P 500 exhibited an increased standard deviation(3.38% to 4.28%) while DAX showed a slight decline in standard deviation (from 5.27% to 4.90%). These findings indicate high uncertainty in US markets after the Brexit period compared to German markets.

In the case of the S&P 500, there was a shift in the distribution of return post-Brexi t (skewness value of -0.62 %) implying downside risk. The increase in kurtosis value from 0.69% to 1.95% also indicated a higher probability of extreme returns. Whereas, DAX displayed relatively stable values with minor changes in skewness (-0.65 to -0.41) and kurtosis value(2.09 to 2.08). These findings align with the study by Lux (1998) where he stated major geopolitical events result in extreme market movements like increased volatility.

From the t-test, it is confirmed that the mean monthly returns increased after Brexit but it was not significant (S&P 500: $p = 0.45$; DAX: $p = 0.80$). The negligible effect size was also indicated by Cohen's d values (-0.093 for S&P 500, -0.030 for DAX) which further boosted the understanding that Brexit had less impact on stock returns. Regression results also indicated a small proportion of variance in stock returns due to Brexit (-0.093 for S&P 500 with an R^2 value of 0.004, -0.030 for DAX with an R^2 value of 0.000).

The analysis of international prices of gold and silver before and after Brexit revealed investor behaviors due to changes in market conditions. The price of gold increased($1,397.57 to $1,477.81) post-Brexit with a high standard deviation ($211.78 to $251.37) resulting in greater volatility. The price increase reinforces the role of gold as a safe haven asset during market uncertainty. In contrast to this silver prices significantly declined ($25.68 to $19.77) with a decreased standard deviation ($8.96 to $4.39) indicating less volatility. According to the t-test, Brexit had a significant impact on silver prices ($p < 0.001$, Cohen's d = 0.838), and only a medium effect is seen in the case of Gold (p = 0.142, Cohen's d = -0.183). Regression results indicated Brexit had a significant positive effect on gold prices($\beta = 0.17$, p = 0.045) while the impact on silver prices is more pronounced($R^2 = 0.15$) implying high sensitivity of silver prices due to Brexit uncertainties.

Further, the analysis of log returns and the moving average of log returns confirmed that Brexit had no significant impact on long-term stock returns. The log return of the S&P 500 shift from negative (-0.030) during pre-Brexit to positive(0.012) during post-Brexit. Minor changes in log returns are observed in the case of DAX (0.004 to 0.007). These changes are non-significant (S&P 500: p = 0.85; DAX: p = 0.51) with a small effect as indicated by Cohen's d value (S&P 500:0.08, DAX:-0.02). This is further confirmed through regression results ($R^2 = 0.009$ for S&P 500, $R^2 = 0.001$ for DAX) of the minimal effect of Brexit on log returns.

The T-test of the moving average of log return before and after Brexit was not significant and small size effect as indicated by Cohen's value(S&P500:-0.14, DAX:-0.07). Regression analysis of the Moving average of log returns resulted in a significant coefficient for S&P 500(β:0.17,p:0.05, R^2:0.03) but was insignificant in the case of DAX (β:0.17,p:0.05, R^2:0.00) implying there are other variables influences stock behavior in addition to Brexit.

The Brexit referendum has the minimum impact on stock returns. However, there is increased volatility in the case of the S&P 500. The results indicated world financial market reacts to major political events quickly through short-term fluctuations but in the long term, they adjust (Ali et al., 2023; Taimur & Khan, 2013). Gold and Silver react to Brexit impact significantly reflecting their role as haven assets. The results help to a wider understanding of market movements during major geopolitical events and show the resilience of the world financial market during such uncertainties.

5.2 Implications

5.2.1 Political Implications

For policy formulation, the results highlight the resilience of financial markets to geopolitical shocks. Despite initial uncertainty, markets adjust quickly, mitigating prolonged adverse effects on returns. Regulatory bodies should, however, remain vigilant in monitoring market stability and ensuring adequate liquidity during such periods. Policies aimed at reducing uncertainty, such as clear communication regarding economic policies post-Brexit, could further minimize volatility.

5.2.2 Implication on investors

The findings suggest that while Brexit led to increased volatility, its long-term impact on stock returns was minimal. This emphasizes the significance of diversification and risk mitigation tactics for investors. The heightened volatility in the S&P 500, indicated by an increase in standard deviation and kurtosis, suggests that investors should consider hedging strategies, such as options or alternative assets like gold, to mitigate downside risks during periods of political uncertainty.

5.3 Limitation of the Study

The study has taken into account only the pre-and post-Brexit period but other global economic events US-China trade relations(Li et al., 2022) /indicators like GDP growth, unemployment rates, consumer spending behavior inflation rate, etc. have influenced market trends (Zakhidov, 2024). Li et al.,(2022) analyzed sectoral stock market analysis of Chinese geopolitical risk and provided deep insights. This study is limited to only one sector and the Brexit effect may vary across sectors. Much deeper insight is obtained by sectoral analysis.

5.4 Future Line of Work

Future lines of work should include longer-term analysis to check whether the Brexit effect is transient or long-term. More deeper understanding of market response can be obtained if we include different industries in the analysis. Brexit impact can be compared with other geopolitical events to differentiate from other geo-political events. Future studies should focus on isolating Brexit-specific impact on broader economic trends by including macroeconomic variables in the analysis.

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