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**Article**

## Volatility implications for asset returns correlation

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## Volatility Implications for Asset Returns Correlation

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### Abstract

Although there is an extensive literature on the impact of volatility on asset returns correlation, investigating this in relation to broad asset selection and in perspective of different timelines has received less attention. In comparison to the previous papers, we use a much broader set of 35 selected asset classes and used rolling returns for five different periods ranging from 3 months to 5 years to calculate rolling correlations, which was used further for regression analysis between rolling correlation and volatility index (VIX). Results showed more impact of volatility on the mid-term horizon, such as 1 year, possibly meaning that for longer periods, structural economic factors impact correlation significantly, while for shorter periods, immediate market reactions to events and short-term fluctuations reduce the impact of the correlation. Autocorrelation of residuals suggests that correlation follows trends, which is evidenced more in longer periods. The study contributes to existing literature by comparing the volatility impact across a broad range of assets and multiple time horizons, revealing that correlation is sensitive to time horizons – overall and in terms of responses to heightened volatility. Also, the impact of volatility is different over different time periods, with most impact for the mid-time horizon, such as 1 year.

### Keywords

Asset correlation | volatility | market stress | diversification | portfolio management

### JEL Codes

G11, G12, G14

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## 1. Introduction

In today's investment environment, effective portfolio management requires a deep understanding of numerous factors influencing performance. Historical asset dynamics, explored in numerous works, constitute one such factor. However, analysis of historical data alone only provides a partial picture. To achieve optimal results, investors must consider the entirety of portfolio assets and how they interact with each other, especially in the context of crises. Recent research demonstrates that correlations between assets can fluctuate significantly during different periods, often encompassing crisis periods (Allard et al., 2020; Molenaar et al., 2023). These fluctuations significantly impact overall portfolio risk and return. Understanding these changes empowers investors to make more informed decisions and adapt their strategies to ensure stable performance.

If there is a systematic pattern of correlation changes during crises across assets, it would imply that a diversification approach needs to consider the nature of these changes in order to be effective. Numerous existing studies explore certain aspects of how different assets interact during crises. For example, Sandoval & Franca (2012) examined the correlation of equity market indices in different countries during crises and concluded that markets tend to behave similarly during high volatility. According to another study, systemic crises are characterised by a general breakdown in the correlation structure rather than an increase in co-movement (Melkuev, 2014), although only 4 asset classes represented by 4 indices were studied in this research. Tronzano (2020) focuses on the 'defensive assets' as defined by the authors themselves (such as gold, oil and the Swiss franc) and demonstrates that financial crises led to a significant increase in all pairwise correlations between these assets, but correlations with other assets were not considered.

While extensive research has explored the impact of volatility on asset return correlations (Akhtaruzzaman et al., 2021; Dutta et al., 2021; Sun, 2024; X. Wang et al., 2023), we concluded that each individual research paper considers a separate aspect of the research question and does not provide an overall systematic overview of the research question: either only a part of assets (or tickers) is considered, or the behaviour of assets is studied only during a specific period (e.g., the 2008 crisis), or the single return period is used (whether short, medium or long term).

Considering this, in this paper we aim to analyse the volatility implication on correlation across the wide range of asset classes, which covers substantial historic range, and multiple return periods. Firstly, we will define the broad range of asset classes, which will expand the commonly recognised list of equities, bonds, commodities, and so on, to subclasses, to ensure we cover enough asset classes that can be used for portfolio diversification. Secondly, we will calculate returns of the selected asset classes for different holding periods, to further investigate whether volatility affects assets differently over different periods of time. Finally, we will calculate the correlations for all possible pairs for different return periods and will apply regression analysis to the volatility index to evaluate its implications for correlations.

## 2. Data and methods

In selecting the appropriate number of asset classes, we analysed papers that studied some issues which require defining asset classes, such as asset allocation strategies, reactions of asset classes to geopolitical events, and so on, and found that the approach to defining asset classes differs among these papers. For example, Nystrup et al. (2017), exploring whether regime-based asset allocation can effectively respond to changes in financial regimes at the portfolio level, selected 10 asset classes, while Bellu & Conversano (2020), presenting new tactical asset allocation model, selected 20 asset classes, and Będowska-Sójka et al. (2022) and Mensi et al. (2022) selected different numbers of asset classes as well. Thus, it is evident that the choice of asset classes is largely influenced by the specific objectives of each study. Our decision to include 35 asset classes was motivated by the aim of capturing a wide array of assets that are likely to respond differently under various economic and market conditions. This broad selection ensures

that the analysis covers a diverse range of asset types, including equities, bonds, commodities, and alternative investments, each of which has distinct risk and return profiles across different economic scenarios.

While selecting 35 asset classes, we carefully balanced the need for diversification with the practical constraints of data analysis, ensuring that our list is comprehensive yet manageable. This approach helps to ensure that the assets chosen can represent key sectors, regions, and economic cycles, allowing us to explore how these assets perform under varying conditions. The goal for choice of 35 asset classes is to strike a balance between providing comprehensive coverage and maintaining focus on the study's core objectives, allowing us to assess the implications of volatility for asset returns correlations effectively.

The raw data was obtained from various sources, including Yahoo Finance, Federal Reserve Economic Data (FRED), Kaggle, and Stock Analysis. The source choice is based on the data availability of the specific asset class. For each asset class, we primarily selected data from the most liquid and widely used Exchange-Traded Fund (ETF) that tracks the performance of the respective index or asset class. In instances where multiple ETFs exist for the same asset class, we conducted a comparative analysis and selected the ETF with the longest historical record and lowest tracking error, as this ensures better data continuity and reliability. This approach ensures that the results obtained are reflective of what an investor can realistically achieve by holding the selected ETF, thereby maintaining practical relevance when considering portfolio allocation. In other words, the returns analysed will represent the actual returns which can be obtained by holding the ETF, which gives exposure to the asset class. The next consideration is the available historical period for the ETF. In some cases, the ETF emerged much later than the index tracked by this ETF; therefore, there are many more data points for the index itself. In this case, we compared the daily returns of the ETF and the index, using the methodology of calculating the tracking error, as defined by Satchell & Hwang (2016), specifically 'ex-post' tracking error. We applied a threshold of 10%, meaning that if the tracking error exceeded this value, we retained only the ETF's data, even if the index had a longer historical record. In some cases, such as with commodities like gold, we used the direct price of the commodity to calculate tracking error instead of the index returns. This

approach ensures that the data used for analysis reflects the actual performance an investor would experience when holding the ETF, rather than relying on historical index data that might not fully capture real-world investable returns. This makes the analysis more realistic and applicable for investors who would be using the ETF to gain exposure to the asset class.

Table 1 presents selected asset classes and their corresponding ETF tickers or indices, the data of which is used in this work. All data obtained is daily, except for the price of copper, which is provided on a monthly basis. Considering all other data is daily, linear approximation was applied to the monthly price of copper to convert it to a daily price. Please note that series WILL5000PR, representing data of Wilshire 5000 Total Market Index is no longer available on FRED; instead, data can be accessed via Yahoo Finance by series code ^W5000.

Using collected data, we calculated rolling returns for periods of 3 months, 6 months, 1 year, 2 years, and 5 years. A rolling return is a method used to evaluate the performance of an asset over overlapping time periods. Instead of calculating returns just from fixed start and end dates, rolling returns look at a series of time periods, ‘rolling’ forward – in our case, day-by-day. This approach helps capture the impact of any changes that occur during the analysed period, offering a dynamic view of performance across different time frames. The total return for each period consists of two components: (1) price change (capital appreciation or depreciation) and (2) dividends (income from distributions). To calculate the first component, which is price change in percentage (for example, 20%, or 0.2 in the case where price increased from \$10 to \$12), for each date entry, the corresponding price at this date, and the price at the date of the beginning

**Table 1.** Selected asset classes and data series and source description

Broad asset classes	Selected asset class	Representative ticker(s) or index	Sample period and frequency
U.S. equities	U.S. broad equity	Index: Wilshire 5000 Total Market Index, Close; Data series: WILL5000PR – FRED	1970-12-31 to 1979-11-30 – monthly, 1979-12-03 to 2024-03-28 – daily
	U.S. Large cap (S&P 500 index)	Ticker: SPY - SPDR S&P 500 ETF Trust, Close; Data series: SPY – Yahoo Finance	1980-01-02 to 2024-05-10 – daily
	U.S. sectoral equities	Tickers: XLE, XLU, XLK, XLB, XLP, XLY, XLI, XLV, XLF - Select Sectors SPDR Funds, all Close; Data series: all – Yahoo Finance; IYR - iShares U.S. Real Estate ETF, all Close; Data series: all – Yahoo Finance Index: S&P Communication Services Select Sector Index, Close; Data series: ^SP500-50 – Yahoo Finance	XLE, XLU, XLK, XLB, XLP, XLY, XLI, XLV, XLF - 1998-12-22 to 2024-04-05 – daily; IYR - 2000-06-19 to 2024-04-05 – daily; ^SP500-50 - 1993-05-04 to 2024-04-05 – daily.
	U.S. growth equities	Ticker: IUSG - iShares Core S&P U.S. Growth ETF, Close; Data series: IUSG - Yahoo Finance	2000-07-28 to 2024-04-08 – daily
	U.S. value equities	Ticker: IUSV - iShares Core S&P U.S. Value ETF, Close; Data series: IUSV – Yahoo Finance	2000-08-04 to 2024-04-05 – daily
International equities	Developed countries' equities ex.-U.S.	Ticker: VEA - Vanguard FTSE Developed Markets Index Fund ETF Shares, Close; Data series: VEA – Yahoo Finance	2007-07-26 to 2024-04-05 – daily
	EU equities	Ticker: EZU - iShares MSCI Eurozone ETF, Close; Data series: EZU – Yahoo Finance	2000-07-31 to 2024-04-05 – daily
	Japan equities	Ticker: EWJ - iShares MSCI Japan ETF, Close; Data Series: EWJ – Yahoo Finance	1996-03-18 to 2024-04-05 – daily
	Developing countries' equities ex.-China	Ticker: EMXC - iShares MSCI Emerging Markets ex China ETF, Close; Data Series: EMXC – Yahoo Finance	2017-07-26 to 2024-04-05 – daily

Continued **Table 1.** Selected asset classes and data series and source description

Broad asset classes	Selected asset class	Representative ticker(s) or index	Sample period and frequency
Metals such as gold, silver, platinum and copper	Gold	Index: LBMA Gold Price PM (\$/ozt); Data Series: Global Gold price - Historical Data (1979-Present) – Kaggle	1985-01-01 to 2023-10-06 - daily
	Silver	Index: LBMA Silver Price (\$/ozt); Data Series: Daily Silver prices (1968 - 2022) – Kaggle	1968-01-02 to 2022-04-21 - daily
	Platinum	Index: Platinum London PM Fix (\$/ozt); Data Series: Daily London Fix Prices 1990 – 2024 – Kaggle	1990-04-02 to 2023-10-09 - daily
	Copper	Index: FRED Global price of Copper (\$/ton); Data Series: PCOPUSDM – FRED	1991-01-01 to 2024-02-01 - monthly
Oil, Energy, and Agriculture commodities – exposure	Oil	Ticker: DBO - Invesco DB Oil Fund, Close; Data Series: DBO – Yahoo Finance	2007-01-05 to 2024-04-05 - daily
	Uranium	Ticker: URA - Global X Uranium ETF, Close; Data Series: URA – Yahoo Finance	2010-11-05 to 2024-04-05 - daily
	Agriculture commodities	Ticker: DBA - Invesco DB Agriculture Fund, Close; Data Series: DBA – Yahoo Finance	2007-01-05 to 2024-04-05 - daily
Alternative investment – exposure	Cryptocurrency – Bitcoin	Ticker: GBTC - Grayscale Bitcoin Trust ETF (BTC), Close; Data Series: GBTC – Yahoo Finance	2015-05-11 to 2024-04-08 - daily
Government bonds – exposure	U.S. Long-term bonds	Ticker: TLT - iShares 20+ Year Treasury Bond ETF, Close; Data Series: TLT – Yahoo Finance	2002-07-30 to 2024-04-19 - daily
	U.S. Mid-term bonds	Ticker: IEF - iShares 7-10 Year Treasury Bond ETF, Close; Data Series: IEF – Yahoo Finance	2002-07-30 to 2024-04-19 - daily
	U.S. Inflation-linked bonds	Ticker: TIP - iShares TIPS Bond ETF, Close; Data Series: TIP – Yahoo Finance	2003-12-05 to 2024-04-19 - daily
	Developing countries' government bonds	Ticker: EMB - iShares J.P. Morgan USD Emerging Markets Bond ETF, Close; Data Series: EMB – Yahoo Finance	2007-12-19 to 2024-04-19 - daily
Corporate bonds - exposure	U.S. Corporate bonds	Ticker: VCIT - Vanguard Intermediate-Term Corporate Bond Index Fund ETF Shares, Close; Data Series: VCIT – Yahoo Finance	2009-11-23 to 2024-04-19 - daily
	International corporate bonds	Ticker: CEMB - iShares J.P. Morgan EM Corporate Bond ETF, Close; Data Series: CEMB – Yahoo Finance	2012-04-19 to 2024-04-19 - daily
Mixed bonds – exposure	T-Bills, Corporate, MBS and Agency Bonds	Ticker: BND - Vanguard Total Bond Market Index Fund, Close; Data Series: BND – Yahoo Finance	2007-04-10 to 2024-04-19 - daily
	Broad-based short-term investment grade	Ticker: BSV - Vanguard Short-Term Bond Index Fund ETF Shares, Close; Data Series: BSV – Yahoo Finance	2007-04-10 to 2024-04-19 - daily

of the corresponding lookback period, were taken. For example, it means that 1-year return calculated at the date of January 1, 2010, corresponds to the return from price change for holding an asset from January 1, 2009, to January 1, 2010. The second component, return from dividends, was calculated as follows: first, we calculated the sum of dividends received during the lookback period. After this, this sum was divided

by the price at the beginning of the lookback period, which gives us a return from dividends at per purchase price. Using the previous example of 1-year rolling return, if from January 1, 2009, to January 1, 2010, there was \$1 of dividends, and the price on January 1, 2009, was \$20, the dividend returns by January 1, 2010, were 5%. On other hand, if dividends were paid on January 2, 2009, the rolling return for period of

**Table 2.** Summary statistics of asset yearly rolling returns

	Count	Mean	Std	Min	Max
<b>BND</b>	4,036	0.028	0.050	-0.168	0.180
<b>BSV</b>	4,034	0.020	0.029	-0.077	0.135
<b>CEMB</b>	2,770	0.026	0.070	-0.187	0.294
<b>DBA</b>	4,091	0.002	0.185	-0.470	0.642
<b>DBO</b>	4,091	0.027	0.363	-0.646	1.374
<b>EMB</b>	3,859	0.046	0.102	-0.257	0.644
<b>EMXC</b>	1,433	0.041	0.199	-0.319	0.875
<b>EWJ</b>	6,809	0.036	0.204	-0.434	0.854
<b>EZU</b>	5,707	0.062	0.227	-0.591	0.814
<b>GBTC</b>	1,990	1.835	3.404	-0.891	33.085
<b>gold</b>	9,854	0.059	0.150	-0.292	0.709
<b>IEF</b>	5,218	0.033	0.066	-0.181	0.205
<b>IUSG</b>	5,709	0.092	0.192	-0.513	0.825
<b>IUSV</b>	5,703	0.090	0.167	-0.508	0.797
<b>IYR</b>	5,736	0.101	0.211	-0.592	1.250
<b>PCOPPUSDM</b>	8,373	0.081	0.312	-0.581	1.486
<b>platinum</b>	8,147	0.047	0.219	-0.543	0.978
<b>silver</b>	10,438	0.045	0.303	-0.700	1.712
<b>SPY</b>	10,932	0.103	0.163	-0.486	0.750
<b>TIP</b>	4,877	0.034	0.057	-0.134	0.206
<b>TLT</b>	5,218	0.045	0.130	-0.358	0.434
<b>URA</b>	3,122	-0.035	0.381	-0.600	1.776
<b>VCIT</b>	3,373	0.037	0.062	-0.182	0.211
<b>VEA</b>	3,951	0.049	0.191	-0.525	0.787
<b>WILL5000PR</b>	11,282	0.101	0.168	-0.488	0.817
<b>XLB</b>	6,111	0.093	0.191	-0.545	1.017
<b>XLE</b>	6,111	0.108	0.264	-0.595	1.166
<b>XLF</b>	6,111	0.073	0.235	-0.721	1.507
<b>XLI</b>	6,111	0.095	0.191	-0.555	0.995
<b>XLK</b>	6,111	0.111	0.253	-0.638	0.878
<b>XLP</b>	6,111	0.074	0.112	-0.299	0.452
<b>XLU</b>	6,111	0.081	0.153	-0.463	0.504
<b>XLV</b>	6,111	0.090	0.129	-0.337	0.557
<b>XLY</b>	6,111	0.106	0.193	-0.495	1.003
<b>^SP500-50</b>	7,532	0.052	0.228	-0.58	0.755

Note: series named 'gold' are referring to returns of LBMA Gold Price PM (\$/ozt), PCOPPUSDM – FRED Global price of copper (\$/ton), platinum – Platinum London PM Fix (\$/ozt), silver – LBMA Silver Price (\$/ozt), WILL5000PR – Wilshire 5000 Total Market Index, and ^SP500-50 – S&P 500 Communication Services (Sector).



January 3, 2009 – January 3, 2010, will not include these dividends. These two components – return from price change and return from dividends – were summed to get the return over the corresponding period: that is, if price changed by 20% and dividends are 5%, then total return is 25%. Such calculations were done for each data entry, excluding the first data entries that fall into the range of the corresponding period (simply, we cannot look back for nonexistent data entries before the sample period). As an example, the summary statistics of calculated yearly rolling returns are provided in Table 2 below. The descriptive statistics reveal several notable patterns among selected asset classes. Generally, the mean returns of the assets indicate a diverse performance landscape, with some instruments showing significantly higher average returns compared to others. The standard deviations reflect varying levels of volatility, suggesting that while some assets exhibit stable returns, others are characterised by considerable fluctuations. Furthermore, the minimum and maximum return values illustrate the risk associated with each asset class, highlighting the potential for both substantial gains and losses. In particular, certain assets display high mean returns alongside elevated standard deviations, indicating a risk-return trade-off that investors may need to consider. Conversely, assets with lower mean returns typically exhibit less volatility, suggesting a more conservative investment profile.

For calculating the correlation, we choose Pearson's correlation coefficient as it is widely used for asset correlation analysis. This measure quantifies the strength and direction of linear relationships between pairs of variables (W. Liu, 2021). Pearson's correlation coefficient is calculated using the formula:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \quad (1)$$

where  $cov(X,Y)$  is the covariance between the returns of assets X and Y, and  $\sigma_X$  and  $\sigma_Y$  are the standard deviations of the returns of assets X and Y, respectively.

The Pearson's correlation coefficient provides insight into the relationships between variables, indicating whether they tend to move together (positive correlation), move in opposite directions (negative correlation), or show no obvious patterns of relationship (zero or near-zero correlation). For interpretation purposes, we use methodology suggested by Witz et al. (1990), shown in Table 3 below.

**Table 3.** Rule of thumb for interpreting the size of a correlation coefficient

Size of correlation	Interpretation
.90 to 1.00 (-.90 to -1.00)	Very high positive (negative) correlation
.70 to .90 (-.70 to -.90)	High positive (negative) correlation
.50 to .70 (-.50 to -.70)	Moderate positive (negative) correlation
.30 to .50 (-.30 to -.50)	Low positive (negative) correlation
.00 to .30 (.00 to -.30)	Negligible correlation

If we simply select all the data for two assets that cover the entire period of observation and will calculate the correlation, it will reflect the average, 'generalised' picture regarding the correlation between assets. However, as already concluded in numerous studies, the correlation is not static over time and can deviate significantly from the average value throughout the observation period, which means that a method for computing a dynamic correlation should be used, if we want to assess these deviations. As pointed out by McMillan (2019), there is no single approach to calculate dynamic asset correlation, and the existing literature considers a various approaches. The author provides an examples of whether more complex models such as the Multivariate-GARCH model (Baur & Lucey, 2010), or the simpler – and more widespread – sliding window method (rolling window) can be used to calculate correlation.

Furthermore, we can further add that not only do the methods of correlation calculation depend on the approach chosen by the authors, but also how the input data is prepared and calculated depends on the authors' approach.

For example, McMillan (2019) calculated the monthly return correlation using a 1-year rolling window, which means that each point in the resulting dataset represents the monthly returns correlation of 12 observations from the original data set (since one year covers 12 monthly returns). In this case, the results of the analysis will help us to understand which correlation of the monthly returns can be expected over the next year.

However, when using annual returns, it's important to note that this creates a limitation when calculating rolling correlations. Specifically, if the return period is the same length as the rolling



window (e.g., both are 1 year), it becomes impossible to calculate a rolling correlation because the annual return in this case is represented by a single data point for each year. A rolling correlation requires multiple data points within the window to make comparisons, so the return period must be shorter than the rolling window to allow for sufficient data.

In other words, the length of the rolling window must always be longer than the return period to perform rolling correlations. However, this restriction does not apply when using rolling returns as the basis for the rolling correlation. Since rolling returns provide a continuous series of data points (even with longer return periods), it remains possible to calculate rolling correlations without this limitation. For example, we have calculated the rolling return on assets over 5 different periods, representing short-term (3 months, 6 months), medium-term (1 year, 2 years) and long-term (5 years) horizons. These rolling returns serve as the inputs for our correlation calculations. In this context, it is not necessary for the rolling window size to be greater than the return period. This is because rolling returns themselves consist of a set of observations with daily granularity for each of the periods analysed.

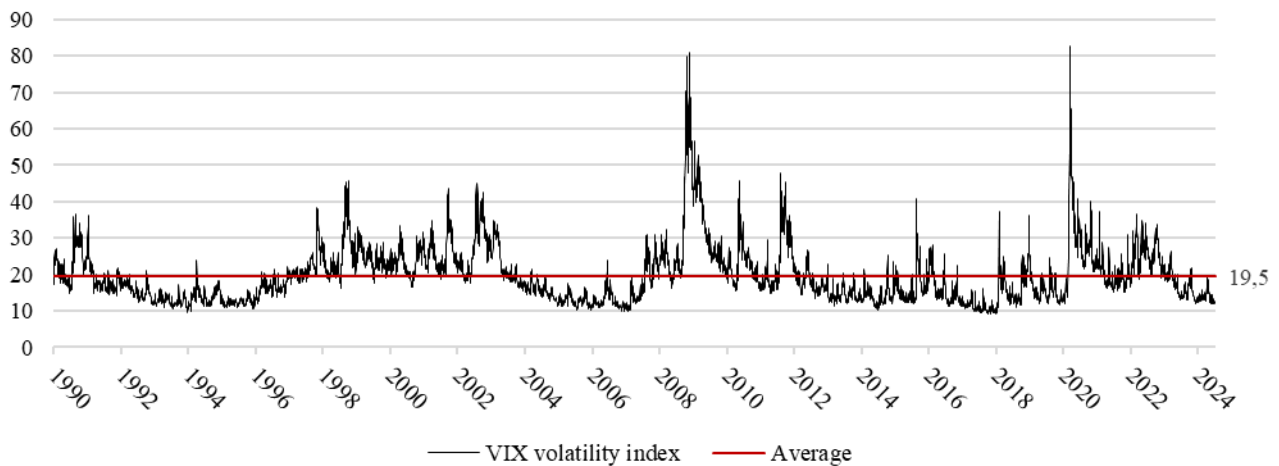
For our research, we chose to apply a rolling correlation with a window size that matches the rolling return period. For instance, for 3-month rolling returns, we utilised a 3-month rolling correlation window. This approach not only ensures consistency between the investment period for both the returns and the correlation calculation but also allows for a more accurate assessment of the relationships between asset returns over the same timeframe. This alignment should enable us to derive insights that are directly applicable to investment strategies, as it reflects how the expected returns and their relationships evolve over the same periods of interest.

However, it is important to note that the annual return effectively captures the price changes over the preceding year as of that date. Because of this, the rolling correlation is calculated for the preceding corresponding period at the date, not the previous one. For instance, let's look at one example of calculating the annual rolling correlation for annual rolling return for one specific observation day: let's say, July 15, 2007. At this date, rolling return value shows return for the period July 15, 2006-July 15, 2007. We are applying rolling correlation for values of returns, which are falling into the range between July 15, 2007, and July 15, 2008. In this case, the correlation value

calculated on July 15, 2007, encompasses a series of annual returns: first from July 15, 2006, to July 15, 2007; second, from July 16, 2006, to July 16, 2007; and so on, extending through the following year until the latest annual return from July 15, 2007, to July 15, 2008. As a result, the correlation captures the full impact of any event that falls into this range and caused changes in volatility, allowing us to examine its impact on the correlation, which will smoothly be changing while more dates after an event will fall into the correlation range calculated.

An important aspect of computing correlations is the handling of missing values. In this study, pairs of variables with missing data were excluded from the calculation of correlations: if on a given day the return of asset X is absent and asset Y is present, then that day was excluded from the correlation dataset. This practice ensures that correlations are calculated only from complete data pairs, which preserves the integrity and accuracy of the correlation analysis.

Volatility indexes are designed to quantify the level of risk or uncertainty in the markets. They provide insights into market sentiment, expectations of future price movements, and potential risk premiums. These indexes are usually tied to specific markets, measuring the volatility of the selected broad stock index. There is also the St. Louis Fed Financial Stress Index (FSI), a broad-based measure designed to capture financial stress across multiple regions, including not only the U.S. but emerging markets and the Eurozone. When we took this index into consideration for representing the volatility data, we found a limitation in the granularity of this index, which is limited to weekly data. Another well-known volatility index is VIX, the CBOE Volatility Index, which is based on the S&P 500 index options and represents the 30-day expected volatility of the S&P 500 index. It reflects investor concerns about investing in securities (Vuong et al., 2022) and is commonly referred to as the world's premier barometer of investor sentiment (Z. Liu et al., 2022). We found that, according to Mbanga et al. (2019), the correlation between FSI and VIX is 0.81. Considering that the VIX volatility index is available on a daily basis, and its high correlation with FSI, we decided to use the VIX as a reference measure of financial market stress. Correlation was not the only reason to use it; the rationale for choosing VIX is supported by several other considerations. For example, H. Wang (2019) found that VIX has strong explanation ability not only for the U.S. but for the international stock markets' volatility as well,



**Figure 1.** VIX – volatility index, 1990-2024

providing background for us for further investigation the impact of VIX on non-U.S. assets. Another study by Huang & Wang (2017) concluded that change in VIX affects investors' behaviour. In this matter, VIX may affect not only stocks but other asset classes due to the changes in asset allocation of the investors' portfolios in response to these changes. The impact of VIX on non-U.S. equity asset classes can be further supported with existing research which shows that U.S. inflation levels strongly correlate with global inflation (Guirguis et al., 2022), and inflation itself is linked to cyclical movements in real economic activity and unemployment (Bianchi et al., 2023), which, in turn, is connected to changes in business cycles and associated crises. Considering the current level of financial globalisation, the significant share of U.S. stock market capitalisation in the world (nearly 45%), and the strong role of the U.S. dollar in international transactions (nearly 54%), we can assume that most financial assets are, to some extent, affected by U.S. economic stresses, therefore can be affected by VIX fluctuations in this regard as well. VIX data was obtained from Yahoo Finance, which has been provided on a daily basis from 1990, as shown in Figure 1. The sample size is relatively large, consisting of 8,639 observations, providing a robust dataset for analysis. The sample period mean is 19.5, while median and mode is 17.6 and 12.4, respectively, with standard deviation of 7.9 and sample variance 62.1. The relatively high standard deviation and variance indicates that there is significant dispersion in the data, meaning the values fluctuate quite a bit around the mean. The distribution is not normal, exhibiting heavy tails and high kurtosis of 8.4, indicating the presence of extreme values, which occur during major crises.

To determine the impact of high volatility on asset correlations, we will use two approaches. First is the regression analysis, one of the most common methods for assessing relationships between a dependent variable and one or more independent variables, as well as for modeling future connections between them (Skiera et al., 2021). In this paper, we will not delve into the detailed principles of regression analysis. In our case, the dependent variable will be the precomputed rolling correlation between asset pairs, and the independent variable will be the value of the VIX volatility index over the maximum period of available correlation or volatility data, whichever is shorter – the rest of data will be cut so the variable's observation length will match. To check the robustness of the results, several tests will be performed, such as the Shapiro-Wilk test, which checks for normality of residuals, as proposed by Shapiro & Wilk (1965), the Breusch-Pagan test, which checks for heteroscedasticity, proposed by Breusch & Pagan (1979), and the Durbin-Watson test, which checks for autocorrelation in the residuals, proposed by Durbin & Watson (1971). Performing these tests will enable us to assess the underlying assumptions of our regression model, specifically the distribution of residuals, the consistency of variance across observations, and the independence of error terms over time. By identifying any violations of these assumptions, we can better understand the reliability of our model's estimates and predictions. However, it is crucial to properly interpret the results of these tests, as violations or nonviolations may be influenced by the market nature of the returns, reflecting the complexities and dynamics inherent in financial data. This understanding will contribute to the overall validity of our conclusions regarding asset correlations in different market environments. We

will consider an acceptable level of  $R^2$  that confirms persisting impact of volatility as 0.1. Recent studies argue that in social sciences, an acceptable level of  $R^2$  can be as low as 0.10, when some or most independent variables are statistically significant (Ozili, 2023). In an earlier study that reviewed the literature on acceptable levels of the coefficient of determination (Purwanto & Sudargini, 2021), the authors state: 'Acceptable  $R^2$  values depend on the context, and in some disciplines,  $R^2$  values as low as 0.10 are considered satisfactory, for instance, when predicting stock returns.' Since the analysis focuses on asset returns, we will consider a minimum acceptable  $R^2$  level of 0.10 to be appropriate.

Our second approach will be comparing the average correlation during the periods divided by some VIX threshold, which will indicate the periods of high volatility and uncertainty for financial markets. İskenderoglu & Akdag (2020) noted, (and this is also commonly accepted), that a VIX value below 20 suggests that market volatility has decreased, investors' risk appetite has grown, and there is optimism about future prospects. Conversely, a VIX value above 30 signals heightened uncertainty and volatility, indicating that market conditions are less favorable for investment. These levels are supported by other studies, such as Merlo (2024), where VIX was studied as a predictor for future volatility and a level above 20 was considered as 'unstable' and above 30 as 'turbulent'. It is also seen from Figure 1 that the sample average VIX value is 19.5 over the observed period, which further reinforces the selection of 20 as a meaningful threshold. Since 19.5 represents the typical volatility level during the sample period, setting the threshold at 20 allows for a clear distinction between periods of lower-than-average volatility below 20 and periods of heightened volatility above 20. Merlo (2024) followed same logic of using a historical mean close to 20 as the turning threshold between a stable and unstable level. Since the level of 30 is also considered significant, we will calculate the average correlations for periods above this level as well, allowing us to see how much correlations differ in extreme volatility periods.

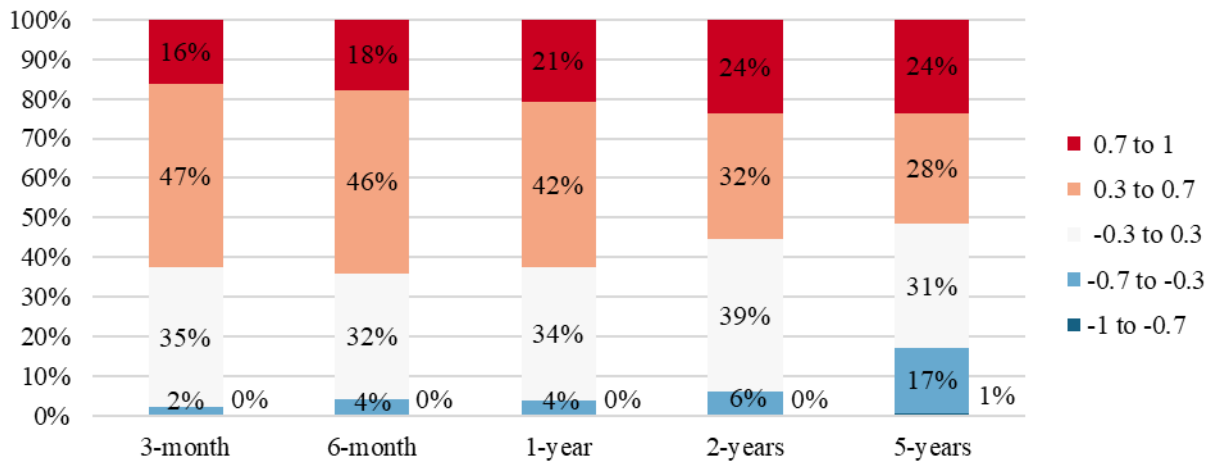
According to our asset classification, we have a total of 35 assets, resulting in approximately 1,225 pairs. Out of these, the number of unique pairs is 595. Correlation and regression analysis will be calculated for this number of pairs. Further, when we calculate average calculations among the major asset classes, we will exclude pairs where the asset tickers belong to the same asset class, as indicated in Table 1. This allows us to avoid the impact of 'duplicated' asset class

pairs in the subsequent calculation of generalised results for individual asset classes. After filtering out pairs that belong to the same asset class, we obtain 467 unique pairs. Our primary dataset will be the rolling 1-year correlation of annual returns for the asset pairs, which we have previously computed. However, for a comparative analysis, we will also examine datasets for 3-month, 6-month, 2-year, and 5-year returns.

### 3. Results and discussion

The summarised results of calculating the Pearson correlation coefficient of the returns of 595 unique pairs between 35 assets for each of 5 periods (3-month returns, 6-month, 1-year, 2-year, 5-year) are shown in Figure 2, revealing several important findings. First, a significant number of asset pairs – from 30% to 40% in different periods – do not show significant correlation. Regardless of the period analysed, a certain sector of the asset pairs does not show a significant correlation. However, as the time interval increases, the distribution of periods becomes more balanced. Notably, only over the 5-year returns do a certain number of asset pairs show a strong negative correlation, while the percentage of moderate positive correlations decreases to 28%, significantly lower than the 47% observed for 3-month returns. These findings indicate that, in the short term, many assets tend to exhibit co-directional dynamics. For the 3-month return period, 64% of the assets show moderate to strong positive correlation, whereas this figure drops to 52% for the 5-year return period. While the difference might seem small, the negative correlation increases from 2% for 3-month returns to 18% for 5-year returns. This underscores the importance of long-term planning when diversifying a portfolio across different asset classes, as short-term diversification may be less effective due to the moderate to significant correlation among most assets in the short and medium term.

One plausible explanation for the observed shift in correlations across different time horizons is that shorter holding periods capture more immediate market reactions to short-term events, such as macroeconomic data releases, geopolitical events, or corporate earnings announcements. In terms of equities, existing studies suggests that significant abnormal returns following the publication of corporate governance news depend on the kind of information (Carlini et al., 2020). Macroeconomic announcements impact both equity and bond markets



**Figure 2.** Distribution of correlation intervals by asset return periods

(Paiardini, 2014), and notably, these affect overall allocation of the investors' portfolio, therefore affecting the rest of assets. As a result, during these periods, asset returns are more likely to move in tandem due to synchronised responses to such events, which to some extent explains the higher proportion of positive correlations over 3- and 6-month windows.

As the holding period extends to one year, two years, and beyond, the impact of these short-term drivers diminishes, and asset-specific factors, such as changes in industry fundamentals, sector-specific risks, or divergent economic cycles, become more pronounced. This leads to a more balanced correlation distribution, where fewer asset pairs exhibit strong positive correlation. For example, in longer periods, commodities, bonds, and equities can respond differently to shifts in interest rates or inflation, which could explain the increase in negative correlations, as seen in the two- and five-year holding periods.

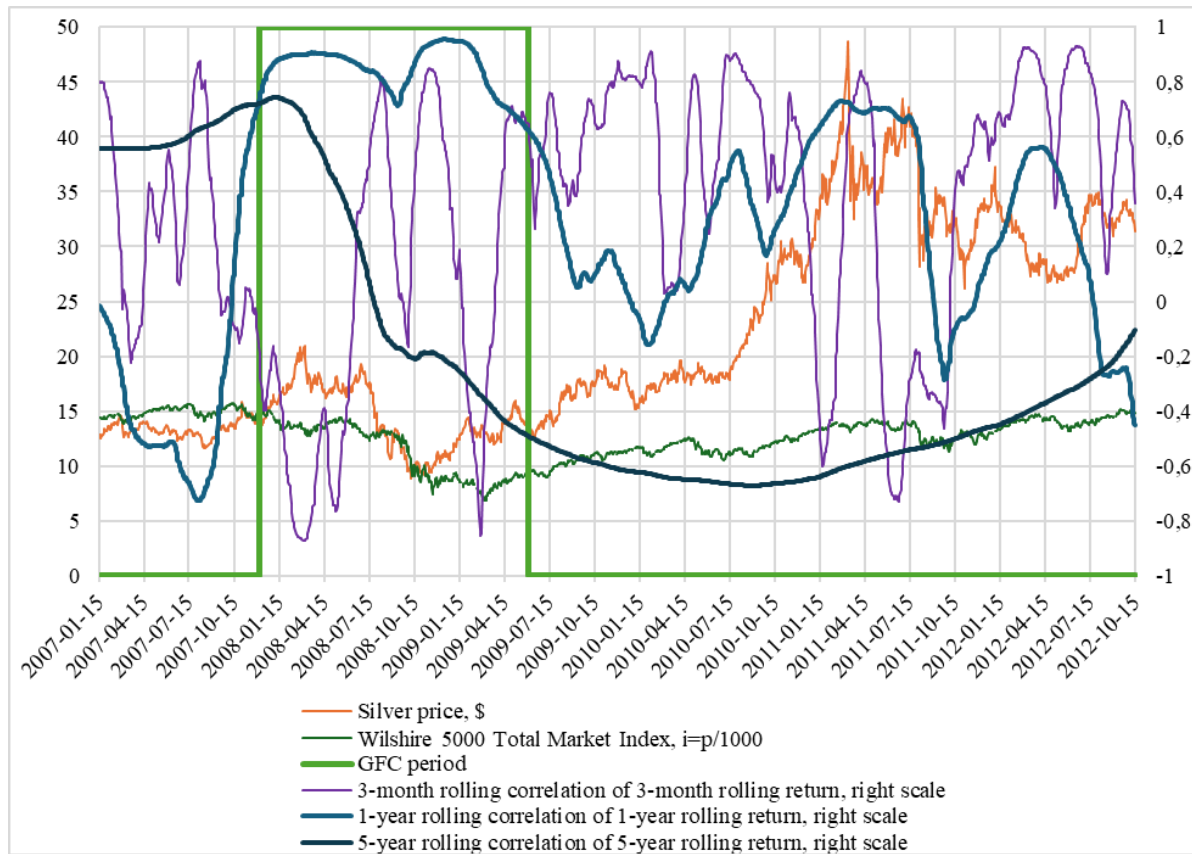
These factors suggest that while short-term correlations tend to reflect immediate market conditions and sentiment, longer-term correlations are shaped by more fundamental, asset-specific factors and structural economic changes, which can influence asset prices in divergent directions. In this regard, investigating factors that drive asset prices and assessing their impact can shed light on the causality of these differences in correlations distribution among different holding periods.

To better understand how investment horizons impact correlation, let's examine the 2008 global financial crisis and its impact on correlation of silver and the broad U.S. stock market index (Willshire 5000), shown in Figure 3.

The period of the global financial crisis is marked in between two vertical green lines on the graph. This crisis is considered to span from December 2007 to June 2009. We can see that the 1-year rolling correlation of annual returns was around 0.7 at the beginning of the global financial crisis. We observe a sharp increase in correlation from approximately -0.7 in August 2007 to 0.7 in December of the same year. Meanwhile, the 5-year rolling correlation declined significantly from 0.73 at its peak to near -0.67. After the crisis ended, the correlation of 5-year returns still remained negative for several years while 1-year correlation mostly remained positive. Consequently, this contributes to the overall average correlation of 5-year rolling returns, lowering it to negative values. Based on results from Figure 2, we can suggest that some other asset pairs of 5-year rolling returns exhibit the same correlation dynamics and contribute to overall distribution of correlation ranges among asset pairs. It also confirms the point of longer horizons 'smoothing' impact of the events. We can see that the 3-month rolling correlation of 3-month rolling returns deviates significantly thorough the sample period, suggesting strong momentum responses of the price.

Moving forward to investigating the impact of volatility on assets correlation, the regression analysis and related tests, described earlier in the Data and Methods section, was conducted using the statistical package of Python programming language. Considering the total amount of results data, which represents regression results for each unique pair for five periods, it is impossible to display raw results in the paper. However, the pairs that have most change of average correlation in a 1-year rolling return during





**Figure 3.** Different responses to crisis of the range of holding/correlation periods of the price of silver and the broad US stock index during the period of the global financial crisis, 2007-2012

**Table 4.** 1-year rolling volatility implications on annual rolling asset returns correlation, sample table of regression results.

Ticker Pair	TLT-XLU	IEF-XLU	DBO-XLU	CEMB-XLY	EMB-XLY	GBTC- ^SP500-50	IEF-IYR	IYR-TLT	VEA- ^SP500-50
R <sup>2</sup>	0.26	0.25	0.20	0.22	0.22	0.25	0.15	0.15	0.19
Intercept	0.81	0.79	-0.31	-0.29	-0.23	-0.10	0.69	0.66	-0.05
Slope	-0.03	-0.03	0.02	0.03	0.03	0.03	-0.03	-0.03	0.02
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Standard Error	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Avg Corr VIX ≤ 20	0.42	0.41	0.00	0.15	0.15	0.28	0.33	0.30	0.27
Avg Corr VIX > 20	-0.19	-0.16	0.51	0.65	0.63	0.75	-0.14	-0.16	0.72
Avg Corr VIX > 30	-0.32	-0.33	0.59	0.72	0.73	0.78	-0.39	-0.38	0.84
Absolute difference at VIX > 20 and VIX ≤ 20	0.61	0.57	0.52	0.50	0.48	0.48	0.47	0.46	0.46
T-value	-41.56	-40.35	31.46	26.74	32.36	24.52	-29.62	-29.76	29.73
Conf Int Lower	-0.032	-0.031	0.023	0.030	0.026	0.026	-0.028	-0.028	0.023
Conf Int Upper	-0.029	-0.028	0.027	0.035	0.030	0.031	-0.025	-0.025	0.026
Shapiro-Wilk Stat	0.960	0.961	0.953	0.966	0.962	0.899	0.923	0.942	0.942
Shapiro-Wilk P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Pagan Stat	364	189	15	41	78	36	5	39	149
Breusch-Pagan P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.027	0.000	0.000
Durbin-Watson Stat	0.0158	0.0150	0.0124	0.0185	0.0146	0.0209	0.0082	0.0083	0.0112

VIX $\leq$ 20 and VIX $>$ 20, are presented in Table 4 and can be further discussed. The full data on results is available on request.

First, we can observe that for selected asset pairs,  $R^2$  is greater than specified threshold of 0.10, meaning that volatility may have significant impact on their correlation. Specifically, out of the overall sample of 595 pairs, 27% of asset pairs in the 1-year period exhibit  $R^2$  values greater than 0.10. For shorter periods, such as the 3-month and 6-month horizons, the percentages are notably lower, at 6% and 11%, respectively. Similarly, for longer periods, such as 2-year and 5-year horizons, the percentages are 15% and 8%, respectively. What stands out here is that the mid-term horizon, such as 1-year, seems to exhibit a stronger influence of volatility on asset correlations compared to both short- and long-term horizons. This pattern could be attributed to the nature of the drivers affecting asset prices across different time frames.

As we noted earlier, in shorter periods, correlations tend to be influenced by immediate market reactions to events and these short-term fluctuations may reduce the impact of volatility on correlations, as the market is more driven by sentiment and short-lived shocks rather than fundamental asset performance. On the other hand, longer-term horizons are often shaped by more structural economic factors, such as shifts in monetary policy, changes in economic growth patterns, or industry transformations. These long-term forces could also diminish the influence of volatility on correlations, as asset prices begin to reflect fundamental value adjustments and gradual economic shifts. In this matter, these results are in line on what we observed from Figure 3, where 3-month correlations exhibited profound fluctuations, and 5-year correlations exhibited structural change in trend, most probably due to structural shifts in economy after 2008 financial crisis.

Based on residual and specification tests, we can say that  $R^2$  results can be relied upon to some extent, but with caution, since tests reveal potential issues that suggest  $R^2$  alone does not provide a complete picture of the relationship between asset returns and volatility.

Durbin-Watson Stat for all the ticket pairs are  $<1.5$ , which indicates the presence of strong positive autocorrelation in the residuals. In terms of asset correlation, it may reveal several important insights. First, strong positive autocorrelation suggests that if an asset's return is positive today, it's likely to be positive tomorrow, and similarly for negative

returns. It is well-known fact concerning momentum persistence on the asset returns (Lewellen, 2002), so that the correlation between asset returns highly likely exhibits momentum as well. Whether strong or weak, correlation today most likely will not deviate much from correlation yesterday. This may indicate that, if the trend of correlation is changed, it is likely that correlation will follow this trend for some time in the future. We can evidence this from Figure 3, where the correlation between silver and stocks over longer periods exhibits clear trends over the sample period. Positive autocorrelation is also persistent for all analysed investment horizons. Even the 3-month correlation exhibits strong trends, even if for short periods only, as we see from Figure 3.

Second, investors often exhibit herding behaviour or trend-following strategies, which can lead to similar movements in asset prices over time (Galariotis et al., 2016). Positive autocorrelation could reflect these behaviours in the market: for example, during periods of high volatility, investors might flock to TLT as a defensive strategy. If this behaviour continues, it can create a trend where TLT's returns are positively correlated over time.

Finally, autocorrelation in the residuals implies that there may be missing variables or omitted factors in the model (Huitema & Laraway, 2009). It is only obvious that correlation is driven by variety of factors and not only volatility; however, the regression analysis still can show on correlation which assets volatility impacts most. Further, these results can be applied, for instance, in asset allocation models, where the implications of volatility on specific asset pairs can be considered when optimising allocation during periods of high volatility.

The Shapiro-Wilk test for all asset pairs shows p-value  $<0.05$ , so the null hypothesis of normality is rejected. This suggests that the residuals are not normally distributed, which may imply some non-linear relationships or heteroscedasticity in the data. Moreover, the fact that residuals are not normally distributed suggests that the correlation is not constant over time. We may observe from Table 4 that assets have different correlations over different inflation regimes. For the rest of the assets, even with low absolute difference at VIX  $> 20$  and VIX  $\leq 20$ , correlation is also not static over time.

The Breusch-Pagan test also shows p-value  $<0.05$  for all asset pairs, further confirming that the correlation between assets changes depending on the market's volatility regime. This finding is in line with



other studies' findings regarding correlation changes between calm and turbulent market periods (Bernhart et al., 2011).

The combination of these tests confirms that relying solely on the R-squared value to assess the relationship between asset returns can be misleading, as it only explains a portion of the variability. The presence of heteroscedasticity (as indicated by the Breusch-Pagan test) and non-normality of residuals (as shown by the Shapiro-Wilk test) suggests that there are multiple factors influencing correlation beyond what is captured by the model. This indicates that while volatility plays a significant role, it is not the only driver of changes in asset correlations.

However, despite these results, we can still confirm that volatility has a meaningful impact on the correlation between assets. This is evidenced by the changing correlations in different volatility regimes (e.g.,  $VIX \leq 20$  vs.  $VIX > 20$ ), which provides valuable insight into how asset pairs behave under varying market conditions. Therefore, while R-squared alone cannot be fully trusted to describe the relationship, the statistical tests support the idea that volatility is a significant factor.

Looking at Table 4, the top 10 asset pairs by difference in average correlation during  $VIX \leq 20$  and  $> 20$  create interesting points for discussion. For example, consider the correlation difference for the tickers TLT-XLU, where TLT belongs to the Government Bonds class, and XLU belongs to U.S. equities. When  $VIX$  is  $\leq 20$ , the average correlation is 0.42, whereas when  $VIX$  is  $> 20$ , it is -0.19, resulting in an absolute difference of 0.61. This indicates that during less stressful periods in financial markets, these tickers have a moderate positive correlation, but during crises, they have a weak negative correlation. Thus, including these tickers in a portfolio during crisis periods would promote portfolio diversification. Importantly, the  $R^2$  coefficient for the regression analysis of this pair is 0.257, confirming a certain degree of correlation dependence on financial market volatility levels.

However, the difference in correlations alone does not allow for definitive conclusions. For example, in the case of the fourth asset pair, CEMB-XLY (Corporate Bonds-U.S. Stocks), the average correlation when  $VIX$  is  $\leq 20$  is 0.152, while it is 0.65 when  $VIX$  is  $> 20$ . This pair does not show significant correlation during calm periods but demonstrates a strong correlation during crisis periods. This can be attributed to the fact that both stocks and corporate bonds are issued

by companies that benefit during periods of economic growth and low market volatility, and conversely, suffer during crisis times.

There is also the case with DBO-XLU, which is Invesco DB Oil Fund, consisting of WTI Crude futures, and Utilities Select Sector SPDR Fund. No significant correlation is observed while  $VIX \leq 20$ , however it reaches 0.51 when  $VIX > 20$  and even 0.59 at higher stress periods when  $VIX > 30$ . Although it aligns with the results of Bašta & Molnár (2018), which found a strong correlation between implied volatilities ( $VIX$  and  $OVX$ ) of the equity and oil markets, it is also considered by another researcher that the XLU is defensive or 'antirecessionary' ETF, which is relatively less aligned with changes in the market as a whole (Valadkhani, 2023). From this perspective, it is rather surprising to see moderate positive correlation during periods of high volatility of these assets, as oil is not considered to be a defensive asset.

Results for each asset pair may be interesting to discuss; however, considering the total amount of unique asset pairs, it is impossible to shed a light on each of these pairs, and this can be a point for future research. Instead, we will examine the average results across asset class pairs in terms of average absolute difference of average correlation during  $VIX > 20$  and  $VIX < 20$  across different periods to define whether there is a persistent trend among these periods. The results are displayed in Table 5.

Examining trends among periods, no evidence of persisting trends across asset class pairs were found: some pairs demonstrated an increase in average absolute difference of correlation with increases in the period, which means that these pairs exhibited increased volatility implication on correlation, while others shown decrease or no significant trend. For example, U.S. equities – Metals such as gold, silver, platinum and copper, – two asset classes widely used for diversification purposes – are showing persistent trend, having 0.071 of average absolute difference in correlation per 3-month period and 0.323 per 5-year period, respectively. If one were to pick one specific ticker pair – for example, SPY-gold – the results show that difference for the 1-year period is 0.11, while for the 5-year period it is 0.22, so the trend is in line with the trend over the asset class pair. However, for the rest of the asset class pairs, we can see that some of them have no trend, and some have declining trends. It suggests that for different assets, time has a different impact on the difference of correlation. It can be advised that the investors consider each ticker

**Table 5.** Average absolute difference of average correlation during VIX>20 and VIX<20 per different periods

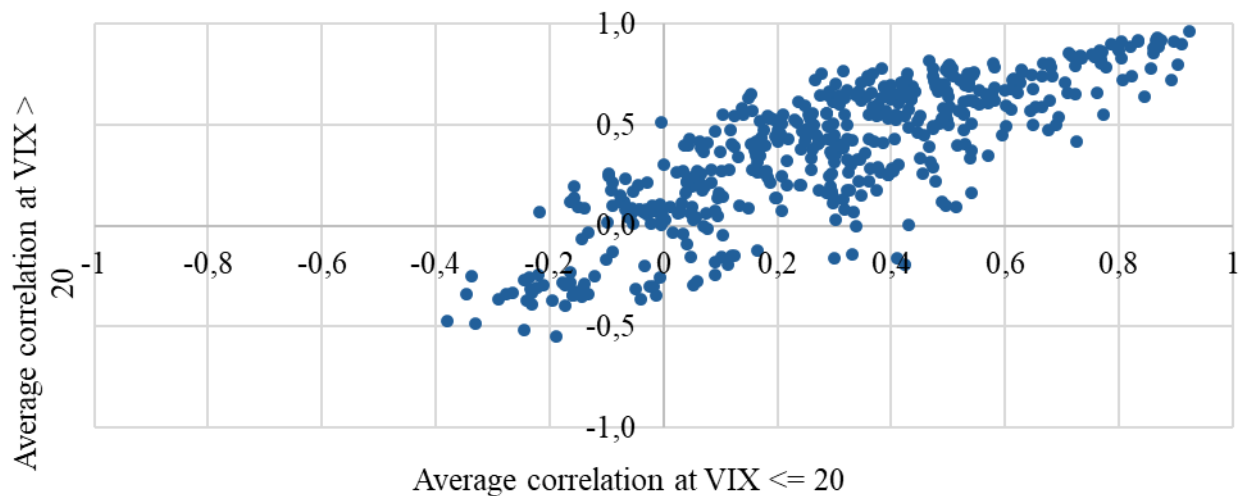
Asset class pair	3-month	6-month	1-year	2-year	5-year
International equities-Alternative investment	0.301	0.269	0.125	0.160	n/a
International equities-Government bonds	0.140	0.109	0.168	0.202	0.125
International equities-Mixed bonds	0.243	0.058	0.147	0.247	0.066
International equities-Corporate bonds	0.268	0.155	0.265	0.213	0.096
International equities-Metals such as gold, silver, platinum and copper	0.119	0.094	0.220	0.167	0.105
U.S. equities-International equities	0.112	0.150	0.123	0.120	0.078
U.S. equities-Oil. Energy. and Agriculture commodities	0.157	0.137	0.215	0.112	0.181
U.S. equities-Alternative investment	0.229	0.186	0.229	0.165	n/a
U.S. equities-Government bonds	0.143	0.153	0.216	0.169	0.195
U.S. equities-Mixed bonds	0.173	0.119	0.144	0.203	0.138
U.S. equities-Corporate bonds	0.203	0.198	0.218	0.169	0.075
U.S. equities-Metals such as gold, silver, platinum and copper	0.071	0.111	0.177	0.203	0.323
Oil, Energy, and Agriculture commodities -International equities	0.110	0.137	0.207	0.118	0.103
Oil, Energy, and Agriculture commodities -Alternative investment	0.257	0.35	0.224	0.374	n/a
Oil, Energy, and Agriculture commodities -Government bonds	0.149	0.086	0.123	0.123	0.110
Oil, Energy, and Agriculture commodities -Mixed bonds	0.135	0.04	0.130	0.087	0.164
Oil, Energy, and Agriculture commodities -Corporate bonds	0.167	0.059	0.129	0.193	0.168
Oil, Energy, and Agriculture commodities -Metals such as gold, silver, platinum and copper	0.129	0.146	0.122	0.164	0.057
Alternative investment -Government bonds	0.181	0.227	0.149	0.227	n/a
Alternative investment -Mixed bonds	0.042	0.272	0.062	0.353	n/a
Alternative investment -Corporate bonds	0.158	0.087	0.167	0.168	n/a
Alternative investment - Metals such as gold, silver, platinum and copper	0.183	0.180	0.234	0.174	n/a
Government bonds-Mixed bonds	0.072	0.058	0.128	0.125	0.034
Government bonds-Corporate bonds	0.084	0.066	0.113	0.119	0.043
Government bonds- Metals such as gold, silver, platinum and copper	0.095	0.116	0.16	0.093	0.261
Mixed bonds-Corporate bonds	0.084	0.051	0.072	0.154	0.030
Mixed bonds- Metals such as gold, silver, platinum and copper	0.084	0.067	0.095	0.173	0.050
Corporate bonds- Metals such as gold, silver, platinum and copper	0.170	0.085	0.106	0.090	0.187
The absolute value of the correlation difference at VIX >20 and at VIX ≤ 20, the average value of the difference across all asset pairs	0.139	0.132	0.173	0.160	0.160

pair individually within their specified timeframe to be aware of how these ticker pairs behave in terms of correlation during heightened volatility.

Another key indicator of the impact of volatility on correlation is the change in the sign of the correlation (e.g., from negative to positive or vice versa) and the shift in the degree of correlation (from weak, within +/-0.3, to strong, and vice versa). To calculate this, we

can say that X axis is the average correlation during  $VIX \leq 20$ , and the Y axis is average correlation during  $VIX > 20$ , as in an example showed in Figure 4.

In this way, the first (+; +) and third (-; -) quadrants contain asset pairs whose correlations remain positive or negative before and during periods of volatility, respectively. Conversely, quadrants 2 (-; +) and 4 (+; -) reflect assets whose returns tend to change the sign of



**Figure 4.** Average correlation of the rolling annual return of individual pairs of assets with a volatility index greater than 20 and less than 20

**Table 6.** The number of transition pairs with a change in the sign of correlation and the strength of correlation for each rolling period

	3-month	6-month	1 year	2 years	5 years
x=pos, y=pos	341	356	364	308	242
x=pos, y=neg	11	15	21	17	67
x=neg, y=pos	64	33	39	53	2
x=neg, y=neg	51	63	43	89	92
Share of asset pairs which do not change the sign of the correlation	16%	10%	13%	15%	17%
x<0.3; x>-0.3; y>-0.3; y<0.3 – weak correlation during both periods	238	196	126	114	140
x<0.3; x>-0.3; y<-0.3; y>0.3 – weak correlation during VIX<20, stronger correlation during VIX>20	82	90	104	75	42
x>0.3; x<-0.3; y>-0.3; y<0.3 – stronger correlation during VIX<20, weak correlation during VIX>20	12	19	31	40	56
x>0.3; x<-0.3; y<-0.3; y>0.3 – stronger correlation during both periods	135	162	206	238	165
Share of asset pairs which changed correlation both from weak to stronger and from stronger to weak	20%	23%	29%	25%	24%

their correlation when VIX exceeds 20. Summarised results are shown in Table 6, where for each period we calculated the number of results that changed sign of correlation, and that changed the strength of correlation, during periods of higher volatility. For the strength of correlation, we simply put number of instances that meet the conditions, as specified in the table.

There is a clear tendency for most asset pairs to maintain the same correlation sign during periods of market volatility. Most asset pairs that do change their correlation sign, however, fall within the range of  $\pm 0.3$ , indicating that their correlation remains

relatively weak during both crisis periods and stable times. Nevertheless, it is clearly seen that the number of pairs with low correlation during both periods is almost twice as low for the 5-year period in comparison with the 3-month period. However, for assets with data starting only from 2010 or later, the 5-year rolling correlation covers a significantly shorter historical period compared to the other periods. This reduced data availability for longer periods may lead to less reliable calculations for the 5-year correlations, making it more difficult to capture long-term trends or structural changes. This constraint should be considered when interpreting the findings, as it could affect the generalisability of the results.

Additionally, it is evident that the overall number of asset pairs with negative correlations increases both during periods of increased volatility and during calmer times in the financial markets. This aligns with the earlier conclusion from the correlation analysis, where the number of negatively correlated pairs increased with the lengthening of the investment period.

When analysing the strength of the correlation, there is also no clear trend regarding the proportion of 'transitional pairs', whose correlation strength was influenced by the period of volatility. The only noticeable trend is a decrease in the share of pairs with weak correlations and an increase in the share of pairs with strong correlations as the return period (and the moving correlation window) increases.

The observed dynamics in correlation behaviour highlight the importance of incorporating a multi-horizon perspective in investment strategies. By recognising that short-term volatility can lead to temporary correlations that do not necessarily reflect underlying fundamentals, investors can avoid overreacting to fleeting market movements.

## 4. Summary and conclusions

This paper investigates the impact of volatility on asset return correlations across a selected broad range of 35 asset classes. Using rolling returns for 3-month, 6-month, 1-year, 2-year, and 5-year periods, we calculated rolling correlations by applying a window size equal to the corresponding return period. Using correlation data, we employed regression analysis to assess the relationship between the VIX volatility index and asset return correlations, and did series of analyses to investigate how much correlation between assets is changing during periods of high volatility.

Our analysis reveals that while volatility does impact correlation, the effects are not uniform across all asset pairs. Some asset pairs exhibit significant shifts in correlation during periods of heightened market volatility, while others remain largely unaffected. Specifically, 27% of asset pairs demonstrate  $R^2$  values exceeding 0.10 in the one-year period, compared to just 6% and 11% in the 3-month and 6-month periods, respectively. This trend suggests that correlations are more stable and influenced by volatility over longer time frames, while short-term correlations are swayed by market sentiment and transient shocks.

Key findings also highlight the presence of strong positive autocorrelation in residuals, indicating that current correlations tend to persist, which could be driven by investor behaviour such as herding. Furthermore, tests indicate non-normality and heteroscedasticity in the residuals, suggesting that multiple factors beyond volatility influence correlations, and these relationships are not static.

The correlation patterns are complex and asset-specific. The impact of volatility on correlation varies greatly across different asset pairs. Some asset classes, such as U.S. equities and metals such as gold, silver, platinum and copper, demonstrate a stronger correlation during periods of high volatility. This highlights the importance of analysing individual asset pairs and their specific behaviour during periods of market stress.

Longer investment horizons tend to show greater volatility impact. While the number of asset pairs exhibiting a change in correlation sign due to increased volatility remains relatively constant across different periods, a greater proportion of asset pairs with significant negative correlations are observed during the 5-year rolling return period. This suggests that longer-term diversification strategies need to account for the increased potential for negative correlations during periods of market stress.

Correlation stability increases with longer horizons. While the average absolute difference in correlation between periods of high and low VIX can be variable, the overall share of asset pairs displaying stable correlation signs, especially for longer investment horizons, indicates a more predictable relationship over time. This finding suggests that diversification strategies designed for longer-term investments may be more resilient to the fluctuating effects of market volatility.

These findings have significant implications for portfolio management. While multiple studies have already revealed that investors should be aware that asset correlations are not constant and can shift significantly during periods of market stress, our study goes beyond this conclusion by providing empirical evidence of how volatility influences correlation across different time horizons. Specifically, we highlight the importance of mid-term horizons where correlations are most affected, offering a nuanced understanding that can inform investment strategies. Our research underscores the necessity for investors to regularly reassess their



portfolio compositions, particularly during periods of heightened volatility. By acknowledging the dynamic nature of asset correlations and incorporating this knowledge into asset allocation models, investors can enhance diversification and mitigate risks associated with potential negative correlations. Diversification strategies should account for the specific time horizon of investment and the unique behaviour of individual asset pairs. Long-term investors can benefit from the greater stability of asset correlations observed over longer periods. However, they should still remain vigilant regarding potential shifts in correlation during periods of market stress. Investors can use this information to anticipate correlation trends and adjust their portfolios accordingly, especially when the market exhibits significant shifts in volatility. Investors can use this knowledge in asset allocation models by incorporating volatility as a factor when optimising portfolios, particularly in periods of market stress. Recognising how correlations behave during highly volatile periods can help investors better manage risk and enhance diversification, providing more robust strategies during turbulent market conditions.

This research faces several limitations that should be considered when interpreting the findings. The availability of historical data varies across assets, with some having data only from 2017. This limited time period might not capture the full range of historical volatility and its impact on correlation, particularly for assets with shorter data histories. This could affect the generalisability of the findings. The grouping of assets into asset classes, as done in this research, is a simplification that might miss nuanced relationships between specific assets within a class. Exploring individual asset pairs, rather than just relying on class-level analysis, could offer a more detailed understanding of the impact of volatility on correlation. Using the same rolling window for return calculation and rolling correlation may not be the optimal approach. Applying different correlation windows to the same rolling return period and comparing the resulting correlations could provide valuable insights into how correlation changes within a given return period. The analysis relies on historical data and is therefore an ex-post assessment. This approach might not perfectly predict future correlation behaviour, as market dynamics can change over time. These limitations highlight areas for future research. Exploring alternative asset classification methodologies, expanding the time period, incorporating multiple volatility indicators, or

investigating non-linear models to better capture the relationship between volatility and correlation would be valuable avenues for further investigation.

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## Annexes

All data used in this research, both raw data and the results, are available upon request. Contact authors as per specified e-mail address.

**Table 7.** Regression results for 1-year rolling correlation of 1-year rolling returns, asset pairs with difference >0.30 of average correlation between different volatility regimes

No.	Ticker Pair	R <sup>2</sup>	Intcpt.	Slope	P-value	Stand. Err.	Avg Corr VIX ≤ 20	Avg Corr VIX > 20	Avg Corr VIX > 30	Abs. difference at VIX > 20 and VIX ≤ 20	T-val.	Conf Int Lower	Conf Int Upper	Shapiro-Wilk Stat	Shapiro-Wilk P-value	Breusch-Pagan Stat	Breusch-Pagan P-value	Durbin-Watson Stat
1	TLT-XLU	0.26	0.81	-0.03	0.00	0.001	0.42	-0.19	-0.32	0.61	-41.56	-0.032	-0.029	0.960	0.000	364	0.000	0.0158
2	IEF-XLU	0.25	0.79	-0.03	0.00	0.001	0.41	-0.16	-0.33	0.57	-40.35	-0.031	-0.028	0.961	0.000	189	0.000	0.0150
3	DBO-XLU	0.20	-0.31	0.02	0.00	0.001	0.00	0.51	0.59	0.52	31.46	0.023	0.027	0.953	0.000	15	0.000	0.0124
4	CEMB-XLY	0.22	-0.29	0.03	0.00	0.001	0.15	0.65	0.72	0.50	26.74	0.030	0.035	0.966	0.000	41	0.000	0.0185
5	EMB-XLY	0.22	-0.23	0.03	0.00	0.001	0.15	0.63	0.73	0.48	32.36	0.026	0.030	0.962	0.000	78	0.000	0.0146
6	GBTC- ^SP500-50	0.25	-0.10	0.03	0.00	0.001	0.28	0.75	0.78	0.48	24.52	0.026	0.031	0.899	0.000	36	0.000	0.0209
7	IEF-IYR	0.15	0.69	-0.03	0.00	0.001	0.33	-0.14	-0.39	0.47	-29.62	-0.028	-0.025	0.923	0.000	5	0.027	0.0082
8	IYR-TLT	0.15	0.66	-0.03	0.00	0.001	0.30	-0.16	-0.38	0.46	-29.76	-0.028	-0.025	0.942	0.000	39	0.000	0.0083
9	VEA-^SP500- 50	0.19	-0.05	0.02	0.00	0.001	0.27	0.72	0.84	0.46	29.73	0.023	0.026	0.942	0.000	149	0.000	0.0112
10	CEMB-EWJ	0.15	-0.02	0.03	0.00	0.001	0.32	0.77	0.80	0.45	21.54	0.024	0.028	0.927	0.000	2	0.201	0.0121
11	DBO-XLP	0.21	-0.21	0.02	0.00	0.001	0.10	0.55	0.65	0.45	32.37	0.023	0.026	0.961	0.000	19	0.000	0.0130
12	GBTC-URA	0.27	-0.24	0.03	0.00	0.001	0.14	0.58	0.73	0.44	25.62	0.026	0.031	0.980	0.000	46	0.000	0.0232
13	BSV-XLU	0.10	0.57	-0.02	0.00	0.001	0.43	0.00	0.04	0.43	-21.10	-0.017	-0.014	0.976	0.000	709	0.000	0.0058
14	VCIT-XLU	0.16	0.82	-0.02	0.00	0.001	0.51	0.09	0.14	0.42	-24.45	-0.025	-0.021	0.963	0.000	976	0.000	0.0129
15	PCOPPUS- DM-XLV	0.23	-0.22	0.03	0.00	0.001	0.12	0.54	0.66	0.42	42.07	0.025	0.027	0.955	0.000	176	0.000	0.0136
16	GBTC-silver	0.14	-0.03	0.02	0.00	0.001	0.16	0.57	0.61	0.41	14.61	0.014	0.019	0.911	0.000	4	0.048	0.0104
17	PCOPPUSDM- WILL5000PR	0.18	-0.26	0.03	0.00	0.001	0.14	0.55	0.70	0.41	41.07	0.027	0.030	0.930	0.000	232	0.000	0.0092
18	GBTC-PCOP- PUSDM	0.18	0.01	0.02	0.00	0.001	0.30	0.70	0.76	0.40	19.53	0.021	0.025	0.919	0.000	31	0.000	0.0139
19	BND-XLU	0.07	0.58	-0.01	0.00	0.001	0.50	0.10	0.22	0.40	-16.83	-0.013	-0.011	0.971	0.000	852	0.000	0.0039
20	CEMB-EZU	0.10	0.10	0.02	0.00	0.001	0.38	0.78	0.86	0.40	17.27	0.020	0.025	0.912	0.000	126	0.000	0.0079
21	GBTC-XLY	0.28	0.08	0.02	0.00	0.001	0.37	0.75	0.79	0.39	26.36	0.021	0.024	0.917	0.000	44	0.000	0.0245
22	DBA-XLV	0.20	-0.23	0.02	0.00	0.001	0.04	0.43	0.53	0.38	30.87	0.019	0.022	0.982	0.000	39	0.000	0.0119
23	CEMB-IUSG	0.16	0.05	0.02	0.00	0.001	0.36	0.74	0.77	0.38	21.92	0.021	0.025	0.899	0.000	10	0.002	0.0125
24	DBA-XLP	0.18	-0.19	0.02	0.00	0.001	0.09	0.47	0.58	0.38	29.48	0.020	0.023	0.966	0.000	14	0.000	0.0109
25	URA-^SP500- 50	0.22	-0.06	0.03	0.00	0.001	0.29	0.67	0.77	0.38	28.82	0.024	0.027	0.962	0.000	8	0.004	0.0190
26	EMB-EWJ	0.10	-0.01	0.02	0.00	0.001	0.24	0.61	0.64	0.38	20.57	0.017	0.021	0.931	0.000	65	0.000	0.0061
27	BND-IYR	0.07	0.68	-0.01	0.00	0.001	0.54	0.17	0.15	0.37	-16.58	-0.016	-0.012	0.913	0.000	361	0.000	0.0037

Continued **Table 7.** Regression results for 1-year rolling correlation of 1-year rolling returns, asset pairs with difference >0.30 of average correlation between different volatility regimes

No.	Ticker Pair	R <sup>2</sup>	Intcpt.	Slope	P-value	Stand. Err.	Avg Corr VIX ≤ 20	Avg Corr VIX > 20	Avg Corr VIX > 30	Abs. difference at VIX > 20 and VIX ≤ 20	T-val.	Conf Int Lower	Conf Int Upper	Shapiro-Wilk Stat	Shapiro-Wilk P-value	Breusch-Pagan Stat	Breusch-Pagan P-value	Durbin-Watson Stat
28	BSV-IYR	0.10	0.65	-0.02	0.00	0.001	0.49	0.12	0.00	0.37	-20.49	-0.017	-0.014	0.946	0.000	479	0.000	0.0055
29	IUSG-PCOP-PUSDM	0.18	-0.04	0.02	0.00	0.001	0.28	0.65	0.75	0.37	34.90	0.022	0.024	0.912	0.000	140	0.000	0.0100
30	IYR-URA	0.18	0.08	0.02	0.00	0.001	0.36	0.72	0.79	0.36	25.31	0.020	0.023	0.948	0.000	0	0.892	0.0144
31	VCIT-XLY	0.08	-0.22	0.02	0.00	0.001	0.04	0.40	0.30	0.36	16.52	0.017	0.022	0.962	0.000	0	0.521	0.0061
32	EZU-PCOP-PUSDM	0.16	0.08	0.02	0.00	0.001	0.35	0.71	0.80	0.36	31.80	0.019	0.022	0.909	0.000	154	0.000	0.0084
33	DBO-IYR	0.14	-0.09	0.02	0.00	0.001	0.18	0.54	0.63	0.36	25.49	0.019	0.022	0.930	0.000	35	0.000	0.0083
34	EZU-^SP500-50	0.13	0.00	0.02	0.00	0.001	0.29	0.65	0.77	0.36	29.13	0.020	0.023	0.937	0.000	251	0.000	0.0069
35	TLT-XLE	0.12	0.04	-0.02	0.00	0.001	-0.19	-0.55	-0.65	0.36	-26.26	-0.019	-0.016	0.956	0.000	1	0.299	0.0065
36	DBA-EWJ	0.13	-0.23	0.02	0.00	0.001	0.06	0.42	0.55	0.36	24.49	0.020	0.023	0.930	0.000	110	0.000	0.0075
37	PCOPPUS-DM-XLY	0.17	-0.25	0.03	0.00	0.001	0.12	0.47	0.67	0.35	35.23	0.024	0.027	0.938	0.000	33	0.000	0.0096
38	EWJ-TIP	0.09	-0.40	0.02	0.00	0.001	-0.16	0.20	0.25	0.35	21.03	0.017	0.021	0.937	0.000	67	0.000	0.0045
39	silver-XLV	0.20	-0.40	0.02	0.00	0.001	-0.10	0.26	0.41	0.35	36.31	0.021	0.023	0.967	0.000	43	0.000	0.0107
40	DBA-XLY	0.16	-0.27	0.02	0.00	0.001	0.04	0.40	0.53	0.35	27.12	0.020	0.024	0.949	0.000	47	0.000	0.0092
41	PCOPPUS-DM-SPY	0.15	-0.20	0.03	0.00	0.001	0.17	0.52	0.66	0.35	37.52	0.024	0.027	0.922	0.000	168	0.000	0.0077
42	CEMB-VEA	0.11	0.22	0.02	0.00	0.001	0.47	0.82	0.86	0.35	17.80	0.017	0.022	0.888	0.000	97	0.000	0.0084
43	EWJ-URA	0.19	-0.13	0.03	0.00	0.001	0.25	0.59	0.73	0.35	26.14	0.025	0.029	0.950	0.000	4	0.047	0.0157
44	EMB-EZU	0.09	0.09	0.02	0.00	0.001	0.32	0.67	0.70	0.35	19.36	0.016	0.020	0.914	0.000	122	0.000	0.0054
45	TLT-XLP	0.12	0.35	-0.02	0.00	0.001	0.05	-0.29	-0.45	0.35	-26.44	-0.023	-0.020	0.926	0.000	9	0.003	0.0065
46	EZU-silver	0.17	-0.07	0.02	0.00	0.001	0.19	0.53	0.61	0.34	31.46	0.018	0.020	0.949	0.000	38	0.000	0.0088
47	DBA-VCIT	0.10	0.62	-0.02	0.00	0.001	0.34	0.00	-0.27	0.34	-18.95	-0.023	-0.018	0.938	0.000	57	0.000	0.0081
48	EWJ-IYR	0.17	-0.10	0.02	0.00	0.001	0.19	0.53	0.62	0.34	33.59	0.020	0.022	0.955	0.000	8	0.004	0.0091
49	silver-VEA	0.20	-0.03	0.02	0.00	0.001	0.21	0.55	0.69	0.34	28.22	0.017	0.019	0.952	0.000	146	0.000	0.0114
50	EMB-IUSG	0.13	0.06	0.02	0.00	0.001	0.31	0.65	0.70	0.34	23.00	0.017	0.020	0.908	0.000	54	0.000	0.0075
51	TIP-XLY	0.09	-0.33	0.02	0.00	0.001	-0.10	0.24	0.32	0.34	21.67	0.017	0.020	0.964	0.000	65	0.000	0.0048
52	silver-TLT	0.11	0.32	-0.02	0.00	0.001	0.06	-0.28	-0.52	0.33	-23.31	-0.021	-0.018	0.971	0.000	195	0.000	0.0055
53	IEF-XLP	0.13	0.39	-0.02	0.00	0.001	0.09	-0.24	-0.44	0.33	-26.77	-0.023	-0.020	0.948	0.000	18	0.000	0.0067
54	IUSG-silver	0.15	-0.18	0.02	0.00	0.001	0.08	0.41	0.50	0.33	29.90	0.018	0.021	0.971	0.000	2	0.169	0.0078
55	DBA-TLT	0.10	0.23	-0.02	0.00	0.001	-0.01	-0.34	-0.53	0.33	-20.89	-0.020	-0.017	0.967	0.000	0	0.784	0.0056
56	DBA-IUSG	0.17	-0.07	0.02	0.00	0.001	0.19	0.52	0.62	0.33	28.49	0.018	0.020	0.957	0.000	1	0.351	0.0102
57	TLT-XLV	0.12	0.25	-0.02	0.00	0.001	-0.04	-0.36	-0.49	0.33	-26.59	-0.022	-0.019	0.929	0.000	39	0.000	0.0067
58	URA-XLY	0.18	-0.03	0.03	0.00	0.001	0.34	0.67	0.78	0.32	25.42	0.024	0.028	0.923	0.000	22	0.000	0.0149
59	GBTC-WILL5000PR	0.23	0.18	0.02	0.00	0.001	0.43	0.75	0.80	0.32	23.25	0.018	0.021	0.890	0.000	5	0.021	0.0189

**Table 7.** Regression results for 1-year rolling correlation of 1-year rolling returns, asset pairs with difference >0.30 of average correlation between different volatility regimes

No.	Ticker Pair	R <sup>2</sup>	Intcpt.	Slope	P-value	Stand. Err.	Avg Corr VIX ≤ 20	Avg Corr VIX > 20	Avg Corr VIX > 30	Abs. difference at VIX > 20 and VIX ≤ 20	T-val.	Conf Int Lower	Conf Int Upper	Shapiro-Wilk Stat	Shapiro-Wilk P-value	Breusch-Pagan Stat	Breusch-Pagan P-value	Durbin-Watson Stat
60	platinum-XLV	0.15	-0.22	0.02	0.00	0.001	0.07	0.39	0.46	0.32	32.13	0.019	0.022	0.951	0.000	272	0.000	0.0082
61	EMB-XLF	0.12	0.04	0.02	0.00	0.001	0.30	0.62	0.70	0.32	22.75	0.017	0.021	0.944	0.000	234	0.000	0.0075
62	IUSV-PCOP-PUSDM	0.14	0.04	0.02	0.00	0.001	0.32	0.63	0.72	0.31	30.19	0.019	0.021	0.906	0.000	18	0.000	0.0077
63	IYR-VCIT	0.14	0.94	-0.02	0.00	0.001	0.73	0.42	0.37	0.31	-22.93	-0.018	-0.015	0.897	0.000	289	0.000	0.0114
64	GBTC-IUSV	0.17	0.06	0.02	0.00	0.001	0.34	0.65	0.71	0.31	19.18	0.019	0.023	0.862	0.000	46	0.000	0.0128
65	TLT-^SP500-50	0.09	0.40	-0.02	0.00	0.001	0.11	-0.19	-0.46	0.31	-22.15	-0.022	-0.018	0.960	0.000	14	0.000	0.0047
66	EWJ-XLU	0.13	-0.40	0.02	0.00	0.001	-0.09	0.22	0.41	0.30	29.87	0.020	0.023	0.978	0.000	192	0.000	0.0069
67	EMB-XLI	0.08	0.18	0.02	0.00	0.001	0.39	0.69	0.73	0.30	18.23	0.014	0.018	0.882	0.000	196	0.000	0.0048
68	CEMB-WILL5000PR	0.11	0.24	0.02	0.00	0.001	0.47	0.78	0.81	0.30	18.15	0.016	0.020	0.889	0.000	46	0.000	0.0087
69	EMB-VEA	0.08	0.20	0.02	0.00	0.001	0.40	0.70	0.72	0.30	18.21	0.014	0.017	0.905	0.000	79	0.000	0.0049
70	EMB-XLV	0.14	-0.05	0.02	0.00	0.001	0.21	0.51	0.67	0.30	24.53	0.017	0.020	0.962	0.000	198	0.000	0.0086
71	EZU-TIP	0.08	-0.28	0.02	0.00	0.001	-0.07	0.23	0.31	0.30	19.54	0.015	0.018	0.958	0.000	60	0.000	0.0040
72	IUSG-TIP	0.06	-0.19	0.02	0.00	0.001	0.00	0.30	0.33	0.30	17.90	0.014	0.017	0.953	0.000	97	0.000	0.0034
73	DBA-SPY	0.14	0.03	0.02	0.00	0.001	0.26	0.56	0.63	0.30	24.94	0.016	0.018	0.928	0.000	31	0.000	0.0080
74	IYR-PCOP-PUSDM	0.16	-0.14	0.02	0.00	0.001	0.18	0.47	0.64	0.30	32.04	0.020	0.023	0.955	0.000	4	0.058	0.0085
75	CEMB-XLI	0.09	0.28	0.02	0.00	0.001	0.50	0.80	0.84	0.30	16.33	0.015	0.019	0.845	0.000	64	0.000	0.0071
76	URA-XLF	0.19	0.12	0.02	0.00	0.001	0.43	0.72	0.82	0.30	26.02	0.020	0.024	0.936	0.000	3	0.070	0.0156