FINANCIAL CONTAGION AND VOLATILITY SPILLOVER,AN EXPLORATION OF THE UK's ASSET MARKET

Thesis to be submitted in partial fulfillment of the requirements for the degree

of

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by

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CERTIFICATE

This is to certify that we have examined the thesis entitled **FINANCIAL CONTAGION AND VOLATILITY SPILLOVER,AN EXPLORATION OF THE UK's ASSET MARKET**, submitted by **Vidyasagar**(Roll Number: *20MI3FP22*) a undergraduate student of **Department of VINOD GUPTA SCHOOL OF MANAGEMENT** in partial fulfillment for the award of degree of M.Tech Dual. We hereby accord our approval of it as a study carried out and presented in a manner required for its acceptance in partial fulfillment for the undergraduate Degree for which it has been submitted. The thesis has fulfilled all the requirements as per the regulations of the Institute and has reached the standard needed for submission.

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Place: Kharagpur
Date:November 27, 2023

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I, **Vidyasagar** hereby certify that this report titled "**Financial contagion and volatility spillover, An exploration of the UK's asset market**" is an original work and has been done by me under the guidance of my supervisor;I have conformed to ethical norms and guidelines while writing the project;Whenever I have used materials (data, model, figures and text) from other sources, I have given due credit to them by citing them in the text of the report, giving their details in the references, and following 'fair use doctrine' policies of copyrighted materials if any used in this report.

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ABSTRACT

The research aims to assess the degree of financial contagion seen within the asset markets of the United Kingdom. The previously mentioned research demonstrates the transmission of contagion across many financial markets, including bonds, foreign currency, gold, and stocks.The examination of directional volatility spillover among various asset markets has been conducted thereafter.The DCC - MGARCH technique is used to analyze the daily returns of several asset markets in conjunction with other asset markets within the time span of 2006 to 2023. This approach allows for the estimation of time-varying correlations between the different assets.

The findings indicate that the level of financial contagion in the commodities derivative market is highest when compared to the stock market, while it is lowest in the gold market. The findings of a generalized vector autoregressive (VAR) model indicate that bonds exhibit a net inflow of volatility, while gold, foreign currency, and stock markets demonstrate a net outflow of volatility.The transmission of volatility to the commodities market is solely attributed to the stock market.The presence of volatility spillover has been seen to exhibit time-varying characteristics, with a notable increase in volatility spillover observed during the Global Financial Crisis and the period including the Covid crisis (2019-21). The findings of this study have substantial implications for the selection of an optimum portfolio.

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Chapter 1

Introduction

1.1 Introduction to problem

Contagion in the asset markets of the United Kingdom is the subject of this study. In particular, it demonstrates the contagion that has spread across the stock, bond, foreign currency, and gold markets in the United Kingdom. Following this, an investigation on the directional volatility spillover among various asset markets has been carried out.

Asset return co-movements and the transmission of volatility shocks have major consequences for asset pricing and portfolio allocation. This is due to the fact that the presence of a greater degree of co-movement in asset markets decreases the advantages of diversification[1].

Financial contagion may manifest in both internal (cross-market) and global (cross-border) contexts. In the event of a crisis occurring in any market worldwide, the adverse shock is conveyed from the international origin to one or more local asset markets.During the Global Financial Crisis, the impact originally seen in asset markets within advanced countries was subsequently extended to include other asset markets in developing and emerging market economies (EMEs) via the mechanism of financial contagion.

1.2 Research Objective

This research aims to examine the presence and characteristics of financial contagion and volatility spillover in the UK bond market, Gold market, Foreign exchange market, and Stock market, interdependently, from 2006 onwards.

Chapter 2

Literature Review

2.1 Introduction

The literature review for a research paper on financial contagion, volatility spillover, and measuring the degree of financial contagion serves as a critical foundation for understanding the existing body of knowledge in this field. Financial contagion, the transmission of shocks across financial markets, has been a topic of extensive research due to its profound implications for global economic stability. This review explores the key theories and empirical findings related to financial contagion, shedding light on its various dimensions and manifestations.

The examination of volatility spillover mechanisms is integral to comprehending the dynamics of interconnected financial markets. Volatility spillover occurs when the volatility of one market affects and spills over into another, amplifying the potential for contagion. This literature review delves into the diverse channels through which volatility spillover occurs and the methodologies employed to identify measure these spillover effects and measuring the degree of financial contagion

Despite a wealth of literature, financial contagion has no common meaning. In contrast to "inter-dependence", [2]describe contagion as a considerable rise in cross-market links following a shock to one market. Before this definition, research focused on "interdependence" rather than "financial contagion".

2.2 DCC MGARCH method[3]

In a stochastic vector process of returns of N assets $\mathbf{r_t}$ of dimension $N \times 1$, the mean equation can be written as

$$\mathbf{r}_{\boldsymbol{t}} = \boldsymbol{\mu_t} + \boldsymbol{\eta_t} \tag{2.1}$$

where $\boldsymbol{\eta_t} = \mathbf{H}_{\boldsymbol{t}}^{\mathbf{1/2}}\mathbf{z}_{\boldsymbol{t}}$ and $E(\mathbf{n_t}\mathbf{n_t'}) = \mathbf{I}_{\boldsymbol{N}}$.The conditional variance-covariance matrix of $\mathbf{r_t}$ is an $N \times N$ matrix denoted by $\mathbf{H}_t = [h_{ijt}]$. The conditional covariance matrix can be decomposed into conditional standard deviations and a correlation matrix as follows:

$$\mathbf{H_t} = \mathbf{D_t R_t D_t}, \tag{2.2}$$

where $\mathbf{D_t} = \text{diag}(\sqrt{h_{1t}}, \sqrt{h_{2t}}, \ldots, \sqrt{h_{nt}})$ is the conditional standard deviation, and $\mathbf{R}_t$ is the correlation matrix. To guarantee that $\mathbf{R}_t$ is positive definite and all the elements of $\mathbf{R}_t$ are equal or less than one, $\mathbf{R}_1$ is decomposed into

$$\mathbf{R}_t = \mathbf{Q_t^{*-1} Q_t Q_t^{*-1}}, \tag{2.3}$$

where $\mathbf{Q}_t$ is a positive definite matrix defining the structure of the dynamics and $\mathbf{Q}_t^{*-1}$ rescales the elements in $\mathbf{Q}_t$ to ensure $|q_{ij}| \leq 1$. Then $\mathbf{Q}_t^*$ is the diagonal matrix consisting of square root of diagonal elements of $\mathbf{Q}_t$. Thus, $\mathbf{Q}^* = \text{diag}(\sqrt{q_{11t}}, \sqrt{q_{22t}}, \ldots, \sqrt{q_{nnt}})$.Now, $\mathbf{Q_t}$ follows the dynamics in the form of

$$\mathbf{Q}_t = (1 - \theta_1 - \theta_2)\bar{\mathbf{Q}} + \theta_1 \epsilon_{\mathbf{t-1}} \epsilon_{\mathbf{t-1}}^{\mathbf{T}} + \theta_2 \mathbf{Q}_t - 1). \tag{2.4}$$

where $\bar{\mathbf{Q}}_t = \text{Cov}(\varepsilon_t \varepsilon_t^T) = E(\varepsilon_t^T \varepsilon_t')$ is the unconditional covariance matrix of standardized errors, and $\theta_{\mathbf{1}}$ and $\theta_{\mathbf{2}}$ are DCC parameters.In Eq(5) $\theta_{\mathbf{1}}$ and $\theta_{\mathbf{2}}$ are scalars and must satisfy the following conditions: $\theta_1 \geq 0$, $\theta_2 \geq 0$ and $\theta_1 + \theta_2 < 1$

The log-likelihood using Normal distribution to estimative the aboce model is :

$$\ln(\mathbf{L}(\mathbf{\Phi})) = -\frac{1}{2} \sum_{t=1}^{T} (n \ln(2\pi) + 2\ln(|D_t|) + \ln(|R_t|) + \eta_t \mathbf{D_t^{-1} R_t^1 D_t^{-1}} \eta_{\mathbf{t}}^{\mathbf{T}}) \tag{2.5}$$

where $\mathbf{\Phi}$ denotes parameters of the method

2.3 Financial contagion: A regression[4]

From the DCC-MGARCH(1,1) method, pairwise time-varying conditional correlations can be obtained, and from the univariate GARCH methods, a series of conditional standard deviations or volatility can be obtained for each asset. Following[5], conditional correlation is regressed on conditional volatilities:

$$\boldsymbol{\rho_{ijt}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1 h_{it}} + \boldsymbol{\beta_2 h_{jt}} + \boldsymbol{\epsilon_t} \tag{2.6}$$

where $\boldsymbol{\rho_{ijt}}$ is the estimated pairwise conditional correlation coefficient between the returns of one asset with other the returns from the other three assets, such that $\boldsymbol{i} =$ asset 1 and $\boldsymbol{j} =$ other three assets. $\boldsymbol{h_{it}}$ is the conditional volatility of the asset 1, and $\boldsymbol{h_{jt}}$ is that of other three asset returns. A positive $\boldsymbol{\beta_i}$ $(i = 1, 2)$ obtained by estimating the above method with the least square technique would suggest that conditional correlation increases at the time of high volatility and hence evidence in favor of financial contagion[4].

In the case of multiple regressions, R^2 measures the goodness of fit. Here, the same can be interpreted as the degree of financial contagion. Since the degree of financial contagion is not expected to remain constant over time, rolling regression and measuring the degree of financial contagion become important and carried out[4]

2.4 Diebold-Yilmaz VAR based volatility spillover index[6]

The Diebold-Yilmaz (DY) spillover index is used, which measures the directional spillovers in a generalized VAR framework that excludes the possible dependence of the results on ordering driven by Cholesky factor orthogonalization.Let the covariance stationary N-variable VAR(p) process be specified as

$$\mathbf{X}_t = \sum_{i=1}^{p} \phi_i \mathbf{X}_{t-i} + \boldsymbol{\varepsilon}_t \tag{2.7}$$

where ε is a vector that follows iid$(0, \mathbf{\Sigma})$, and $\mathbf{\Sigma}$ is the variance matrix of the error. Then the above VAR process can be represented as a moving average process as follows:

$$\mathbf{X}_t = \sum_{i=0}^{\infty} \boldsymbol{A}_i \boldsymbol{\varepsilon}_{t-i} \tag{2.8}$$

where A_i is the $N \times N$ coefficient matrix obeying the recursion process $A_i = \sum_{k=1}^{p} \phi_k A_{i-k}$ with A_0 being an $N \times N$ identity matrix and with $A_i = 0$ for $i < 0$.Variance decomposition allows us to parse the forecast error variances of each variable into parts which are ascribed to various system shocks. When this system of VAR produces contemporaneously correlated innovations, orthogonal innovations for variance decomposition is required. Orthogonality can be achieved by Cholesky factorization. However, in that case, variance decomposition becomes highly sensitive to variables ordering. The generalized VAR approach introduced by [7] solves this problem.

Now, the H-step-ahead forecast error variance decomposition is as follows:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_i^{'} A_h \sum e_j^{'})^2}{\sum_{h=0}^{H-1} (e_i^{'} A_h \sum e_j^{'})} \tag{2.9}$$

where σ_{jj} is the standard deviation of the error term for the j-th equation, and e_i is the selection error with value one as the i-th element and zero otherwise. The sum of elements in each row of the variance decomposition matrix is not equal to one, that is $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$. Then each element of the variance decomposition matrix is normalized by dividing them by respective row sums. Then the new H-step-ahead variance decomposition is:

$$\tilde{\Theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{2.10}$$

Then automatically, $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$.

Now, from Equation (6.10), the total spillover index, denoted by $S^g(H)$, is:

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)}.100 = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N}.100 \tag{2.11}$$

The advantage of VAR based volatility spillover index is that it enables us to calculate directional spillover indices. Directional volatility spillovers received by market i from all other markets j is measured as:

$$S_{i.}^{g} = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)}.100 = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N}.100 \tag{2.12}$$

and similarly, directional volatility spillovers transmitted by market i to all other markets j as:

$$S_{.i}^{g} = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)}.100 = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N}.100 \tag{2.13}$$

After calculating directional volatility spillover from other markets and to other markets, it is certainly possible to calculate net volatility spillover from market i to all other markets as follows:

$$S_{i}^{g} = S_{.i}^{g} - S_{i.}^{g} \tag{2.14}$$

As the net spillover index provides only summary information that shows how much each market contributes to volatility in other markets, one may also calculate net pairwise volatility spillovers as follows:

$$S_{ij}^{g} = \left\{ \frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{jk}^{g}(H)} \right\}.100 = \left\{ \frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N} \right\}.100 \tag{2.15}$$

It captures the difference between the gross volatility shocks transmitted from market i to market j and those transmitted from market j to market i.

Chapter 3

Data used

3.1 Data and certain stylized facts

The data included in this study consists of daily observations of real asset prices or asset price indices for each market, spanning from April 4, 2006 to March 31, 2023.

The valuation of UK 10-year bonds is seen as significant within the bond market. The analysis takes into account the exchange rates between USD and GBP in the exchange market, the daily price of gold per troy ounce as reported by the World Gold Council is considered , and the performance of the Financial Times Stock Exchange (FTSE100) Index in the stock market.

The selected time period for the empirical research enables the examination of the responsiveness of asset returns to significant events such as the subprime crisis of 2008–09, the Eurozone crisis of 2010–12, the substantial devaluation of the rupee in 2013–14, and the Covid Crisis spanning from 2019 to 2021.

The conventional practice is to compute the return of an asset by taking the logarithmic value of the ratio between two subsequent prices. The logarithmic filter is used to calculate the constantly compounded daily returns.

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

Table 3.1 shows descriptive statistics of different assets that have been considered, namely bond price (BOND), exchange rate (ER), gold price (GP), and equity (FTSE). Investment in the gold market, as evident from Table 3.1, offers the highest average daily returns (0.036%), and that in the bond market offers the least returns (−0.005%). However, the bond market is the most risky, as approximated by a standard deviation of (4.69%), followed by equity (1.17%), followed by gold (1.12%). This

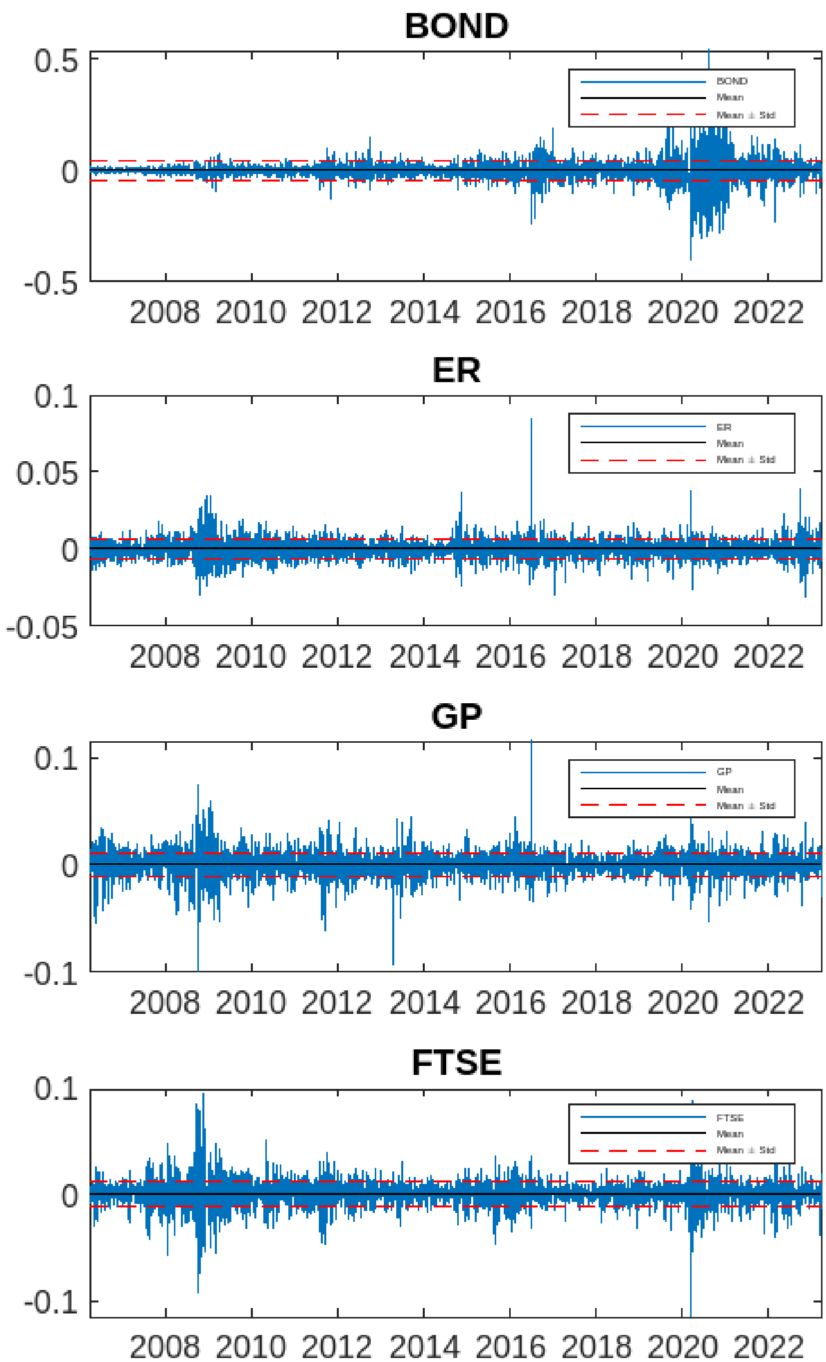

Figure 3.1: Asset return series in UK

Table 3.1: Descriptive statistics.

	BOND	ER	GP	FTSE
Mean	−0.000055	0.000078	0.000360	0.000056
Maximum	0.538997	0.083970	0.115146	0.093843
Minimum	−0.399156	−0.031027	−0.098993	−0.115124
Std. Dev.	0.046812	0.006157	0.011232	0.011695
ADF Test Stat	−10.926673	−63.976427	−18.216550	−25.555589

certainly indicates low uncertainty or risk is associated with high potential returns for the gold market in the UK.

Asset prices and exchange rates often exhibit trending behavior or non-stationarity in mean. Econometrically, these series are checked for (non) stationarity using Augmented Dicky Fuller (ADF) unit root test.From Figure 3.1 also, volatility clustering is observed which points to the existence of ARCH effect.

Studying financial contagion requires thorough analysis of cross market dynamic correlations to avoid heteroskedasticity caused by increased volatility during crises,[2]argue that there is no contagion, merely interdependence, if asset returns show no significant connection after accounting for heteroskedasticity.

Multiple studies[3] employ Dynamic Conditional Correlation–Multivariate GARCH (DCC-MGARCH) to quantify heteroskedastiscty adjusted time changing correlation across assets and evaluate financial contagion.

Chapter 4

Estimated results and discussions

4.1 Static unconditional correlation analysis

For portfolio selection, static and dynamic correlation analysis are crucial. Correlation is when one asset's returns move in sync with others. Combining uncorrelated assets may reduce portfolio volatility by minimizing the impact of one item on another.

Table 4.1: Static unconditional correlation.

	BOND	ER	GP	FTSE
BOND	1.0000000			
ER	−0.1141719	1.0000000		
GP	−0.1657955	0.2784274	1.00000000	
FTSE	0.2139561	−0.1429253	−0.04748961	1.00000000

From Table 4.1, the unconditional static correlation matrix indicates a strong link between exchange returns and gold and stock returns. Stock returns are negatively correlated with gold and exchange.

A "hedge" asset is uncorrelated or negatively associated with another asset or portfolio. A "diversifier" refers to an asset that is favorably connected but not completely associated with another asset. Based on the static unconditional correlation, stock may be considered a "hedge" against foreign currency and gold, and a "diversifier" against bonds.

This correlation study is unconditional and static, thus it cannot account for unexpected occurrences. Our unconditional static correlation may be understood as a long-term average. Measured correlations may be variable, and shorter observation windows increase the likelihood of deviations from the long-term average.More crucially, financial contagion research benefits from dynamic correlation over static correlation.

4.2 Dynamic conditional correlation analysis

Table 4.2: Univariate GARCH estimates.

	BOND	ER	GP	FTSE
$\boldsymbol{\mu}$	−0.000003	−0.000003	0.000277	0.000367
$\boldsymbol{\omega}$	0.000001	0.000001	0.000002	0.000003
$\boldsymbol{\alpha}$	0.073609	0.076515	0.075866	0.127772
$\boldsymbol{\beta}$	0.925391	0.910225	0.911803	0.847506
$\boldsymbol{\alpha+\beta}$	0.999000	0.986740	0.987669	0.975278

Results of univariate GARCH estimate and correlations from DCC-MGARCH techniques are shown in Tables 4.2 and 4.3. Table 4.2 reveals substantial α and β coefficients in univariate GARCH approaches for each asset class.Stability is guaranteed when α and β are positive and $(\alpha+\beta)$ is smaller than unity for daily return series. The sum of α and β indicates series persistence. A substantial and near-unity value of $(\alpha+\beta)$ suggests shock or volatility persistence.

Table 4.3: Average conditional correlation between univariate volatilities of each asset.

	BOND	ER	GP	FTSE
BOND	1.0000000			
ER	0.16476164	1.0000000		
GP	0.07921671	0.5874496	1.00000000	
FTSE	0.20722214	0.5065548	0.64736593	1.00000000

Average conditional correlations involves the determination of the correlation between pairs of assets returns,it can be seen that none of the correlation is found to be significantly equal to zero and thus DCC - MGARCH is the appropriate method here to analyse the dynamic behaviour[8]

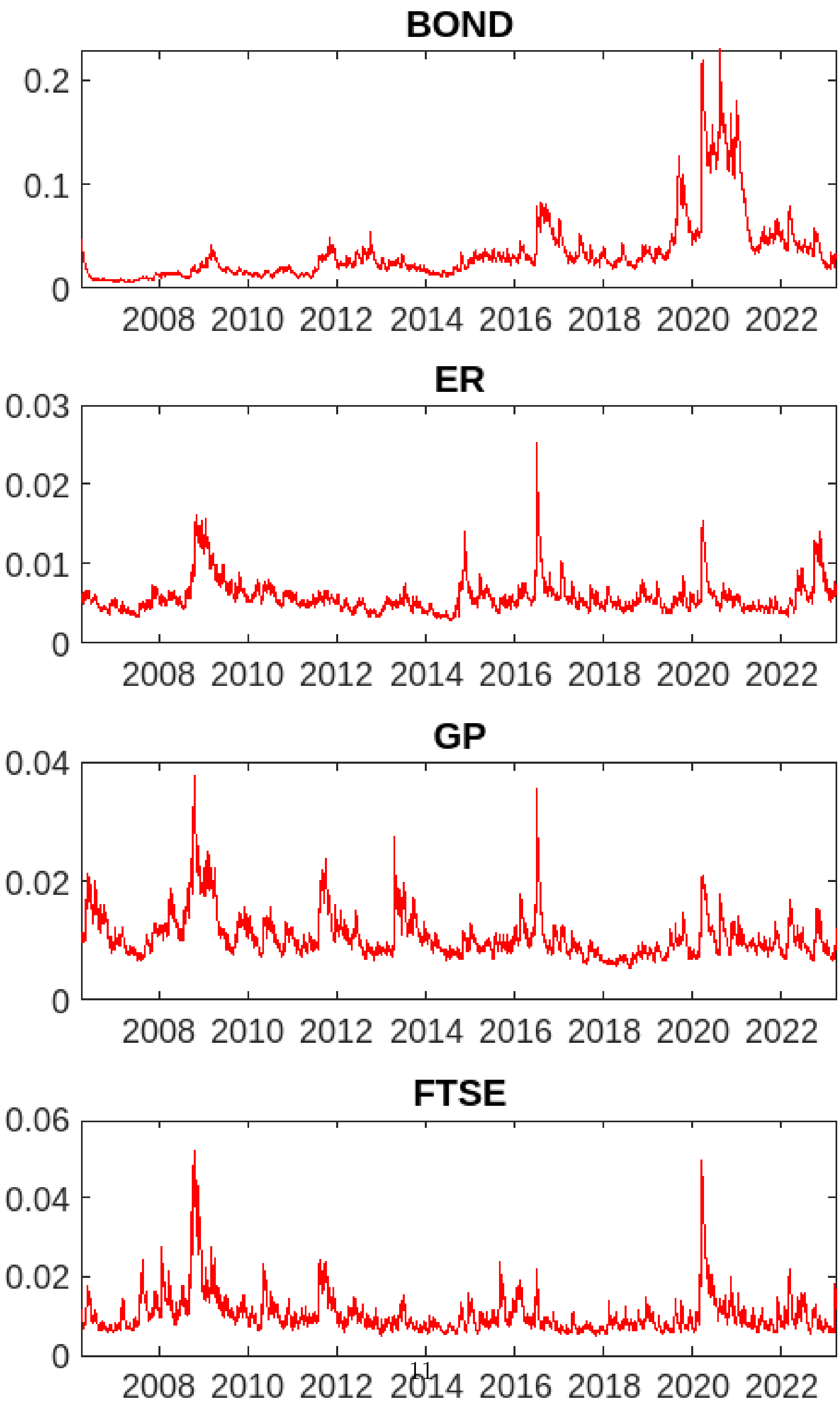

Figure 4.1: Estimated volatility using Univariate GARCH method for the assets returns

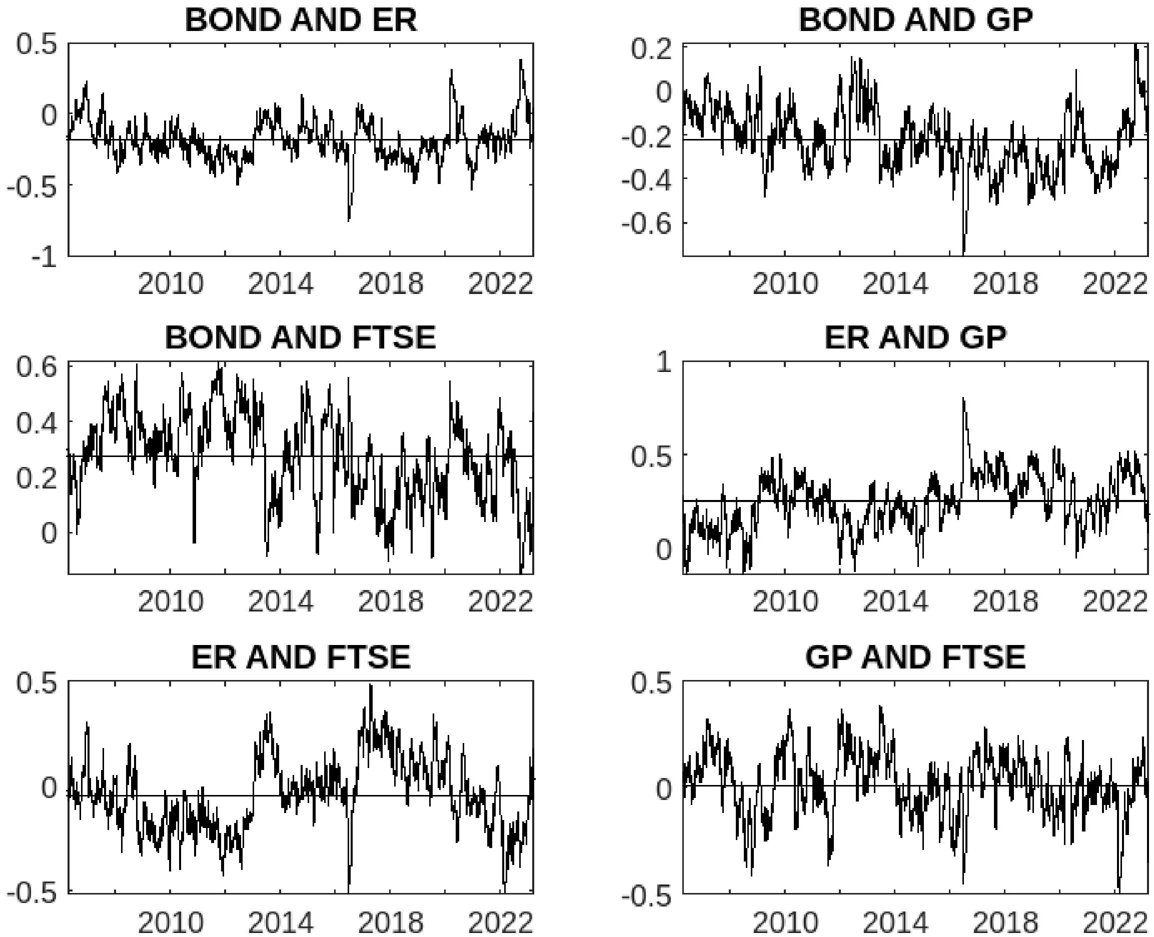

Figure 4.2: Dynamic conditional coorelation

4.3 Analysis of financial contagion

Figure 4.2 shows the dynamic conditional correlation of the volatilities of different assets. The bond market and stock market are mostly positively correlated,on the other hand, bond and gold markets are most of the time negatively correlated. Bond and foreign exchange market more are less zero correlation and the correlation of risks is also less .During the period of Indian rupee depreciation ,the foreign exchange market is negatively coorelated with gold market.

Using Equation (2.6), A multiple linear regression is performed, and the R^2 is used to measure the financial contagion. Table 3.4 shows the high degree of financial contagion in the exchange market and gold market.

Financial contagion is dynamic in nature, the results of Table 4.4 are averaged results of the time period 2006 to 2023. To understand the dynamic nature of financial

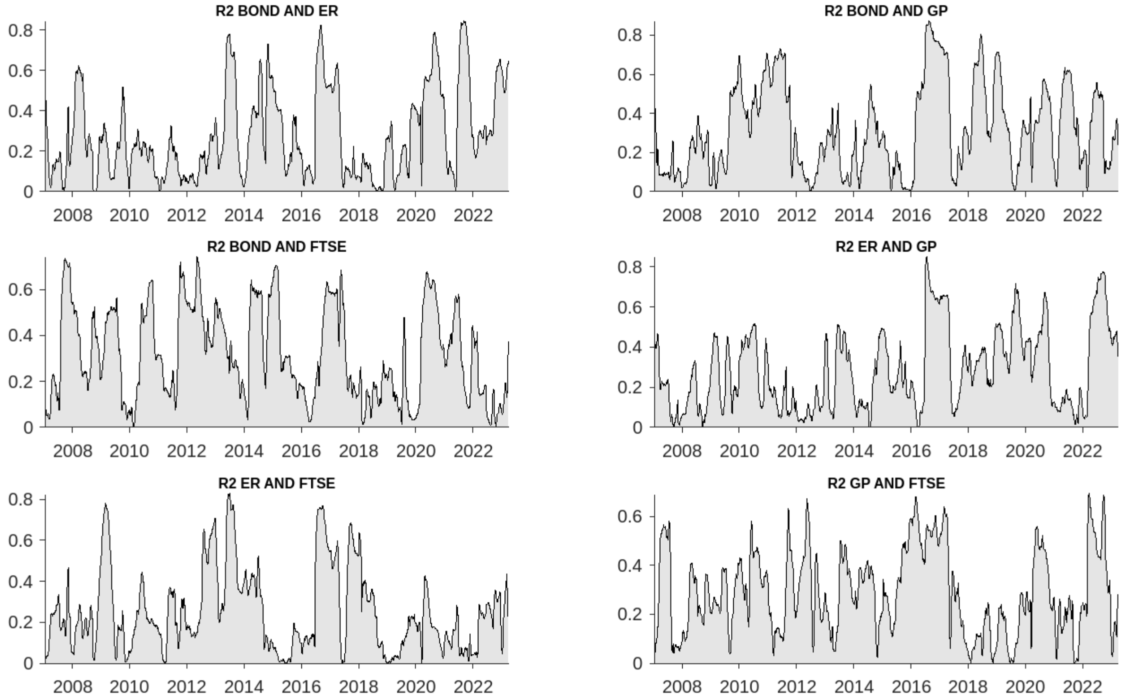

Figure 4.3: Degree of financial contagion between assets

contagion, a 200 day rolling regression is carried out.

Table 4.4: Averaged Degree of financial contagion

	Degree of financial contagion(R^2)
BOND AND ER	0.002973
BOND AND GP	0.021566
BOND AND FTSE	0.189950
ER AND GP	0.205110
ER AND FTSE	0.098736
GP AND FTSE	0.096106

Figure 4.3 depicts the variation of financial contagion over a time period. From 2016 to 2023, It is observed a high degree of financial contagion in major markets during the Eurozone crisis from 2009-2010 further gold market, foreign exchange market, and the stock market had a longer time of financial contagion from 2016 to 2017 because of exit of UK from European union on 2016 and several new foreign policies by US govt. It is also observed degree of financial contagion peaked during the Covid crisis on bond and stock markets.

4.4 Analysis of volatility spillover

An analysis of volatility spillover is being presented here,the table 4.5 demonstrates the transmission of volatility across various asset markets. The calculation of forecast error variance and subsequent determination of volatility spillover indices is conducted using a first-order vector autoregressive (VAR) model using a generalized variance decomposition approach for forecasting mistakes in volatility over a 10-day horizon.

The jth item in Table 3.5 represents the expected contributions to the forecast error variance of market i that arise from innovations in market j. The off-diagonal column sums, referred to as contributions TO others, and row sums, referred to as contributions FROM others, represent the overall spillover of volatility from the ith market to all other markets and the overall spillover of volatility from all other markets to the ith market, respectively.

The calculation of net volatility spillovers involves the subtraction of "FROM spillover" from "TO spillover". The metric quantifies the aggregate impact of the ith market on the overall transmission of volatility spillovers.

The "TO others" row displays gross directional volatility spillovers from the four asset markets to other markets. The column, "FROM others", indicates how much each asset gains volatility from other markets. The "total non-directional volatility spillover index" combines several directional volatility spillovers into one index.

Although the spillover table 4.5 and index summarize the average volatility spillover behavior of four markets, it overlooks significant secular and cyclical shifts in spillovers. We estimate volatility spillovers using 200-day rolling samples and analyze the variance across time using spillover indices.

Table 4.5: Volatility spillover (unconditional).

	BOND	ER	GP	FTSE	FROM others
BOND	0.995173	−0.031084	−0.051607	0.047541	−0.035150
ER	−0.000082	0.968959	−0.000821	0.009219	0.008317
GP	−0.000480	0.004458	0.958203	0.020292	0.024270
FTSE	0.000167	−0.006131	0.017212	0.968036	0.011248
TO others	−0.000395	0.967285	0.974594	0.997548	
Contribution Including Own	0.994778	0.936201	0.936201	1.045088	
Net Volatility Spillover	0.034755	0.958969	0.950325	0.986300	
Total Volatality Index (Percent)	75.380000				

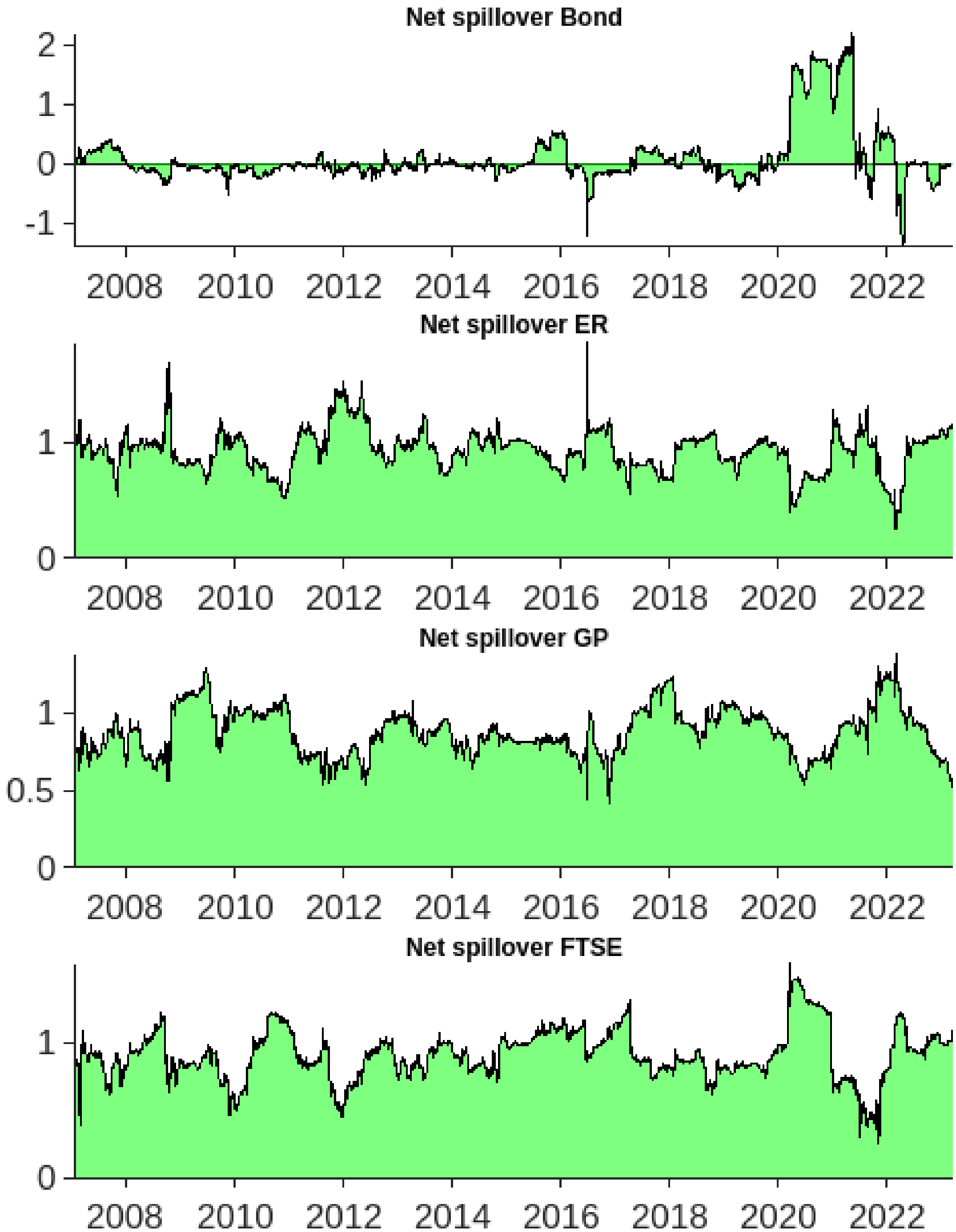

Figure 4.4: Net directional volatility spillover

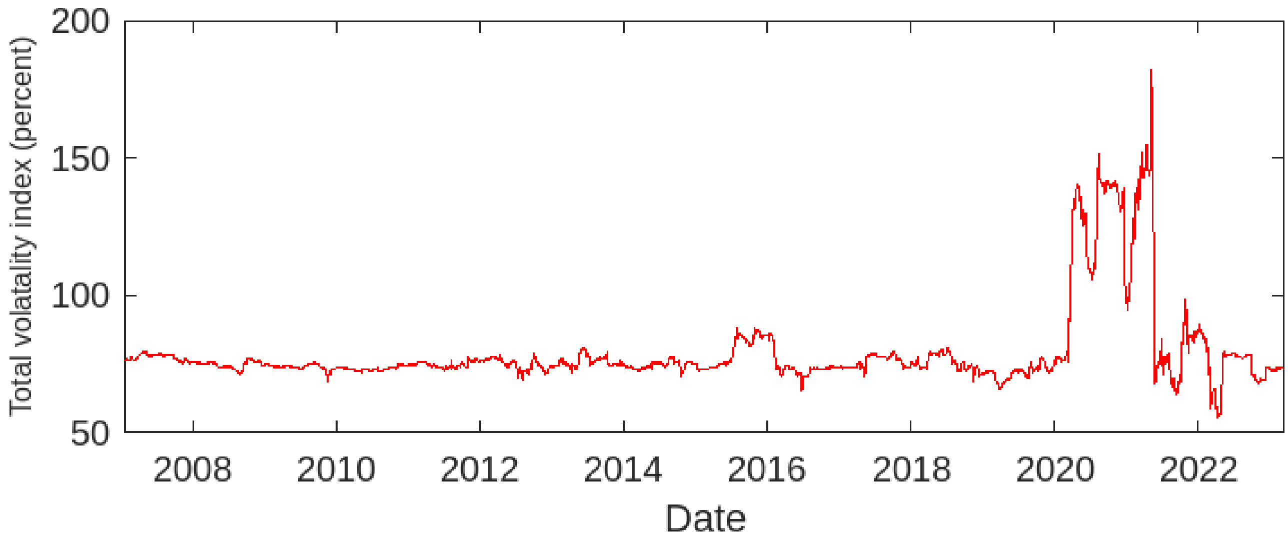

Figure 4.5: Total volatality Index

From the figure 4.4, For an Environment (Excluding Commodity market) where Bond, Gold,Exchange, Stock Markets are only involved, the major interpretations are, the exchange rate , Gold market, Stock Market (FTSE 100) are major transmitters of the volatility.The bond Market receives and transmits the volatility.Bond Market transmitted Highest spillover during the Covid Crisis (2019 to 2021) period

Figure 3.5 shows the net volatility spillover index of an environment where the commodity market is not considered, it shows the total volatility index peaked during the Covid crisis which in turn supports the reason for a high degree of financial contagion in all markets during Covid crisis

Chapter 5

Managerial implication, limitations and future extensions

5.1 Managerial implications

This research evaluates financial contagion and volatility spillover in key UK bond, gold, stock, and foreign currency markets. Potential managerial implications are,

Strategic Risk Management,The study shows financial market interdependence. This knowledge may help managers create comprehensive risk management strategies that account for asset class contagion. To reduce financial shocks, portfolio allocations and hedging methods are adjusted.

Asset allocation choices and diversification of portfolio,Managers may improve diversification strategies by understanding spillover effects' direction and size. The project's findings may help investors choose the best asset mix to diversify and decrease contagion risk. The study may help managers allocate assets. Managers may modify asset allocations to reduce risk if the analysis shows strong market contagion during certain periods.

Crisis Preparedness and policy changes, This research improves crisis readiness. Managers may use volatility spillover data to detect financial crisis causes and create contingency strategies. This involves setting up mechanisms for speedy decision-making and communication under market stress and the study may recommend organizational policy changes. Investment policies, liquidity management methods, and financial planning frameworks may be adjusted to reflect contagion and spillover patterns.

5.2 Limitations

The current limitation of this study involves not considering the commodity market, since it played a very active role during the crisis movement. Another drawback of this study is the model assumptions and lack of market dynamics. In reality, assumptions such as linear relationships or stationarity assumptions, may not fully capture the complexities of financial markets, and financial markets are dynamic and subject to rapid changes. The research may not capture sudden and unexpected events that can significantly influence contagion and spillover effects, such as major geopolitical events, natural disasters, or unexpected policy changes.

5.3 Future extensions

This research can be extended to include the commodity market, and it can even be expanded to include the analysis of each segment of the market. For instance, it might be extended to include the analysis of how the energy commodity market reacts to the metal commodity market, as well as how these markets interact with all other asset markets during times of crisis.The ability to examine each section of a variety of markets and the behaviors of those segments in a dynamic manner will be further enabled by this.

Chapter 6

Conclusion

Figure 4.2 .We can say,the bond market and stock market are mostly positively correlated, which indicates we cant use bonds to hedge[9] against the stock market in the UK, on the other hand, bond and gold markets are most of the time negatively correlated which implies, bond and gold assets portfolio will be much diversified. Bond and foreign exchange market more are less zero correlation and the correlation of risks is also less volatile indicates neural portfolio to invest but not the best,

If we consider the commodity market, it acts as good transmitter and reciever of volatility The study shows how global market dynamics affect UK financial markets, which is relevant to worldwide businesses. Managers may use this knowledge to plan international business based on global financial events' contagion impacts.

The static correlation study may be misleading due to its inability to capture various market movements and the underlying dynamics of changes in correlation in response to diverse shocks and financial stress. In light of these conditions, it is essential to conduct an examination of the dynamic connection between commodities and other asset classes.

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