Louvain School of Management

The Impact of Economic Policy Uncertainty in Financial Markets: An International Study Analysis

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The economic policy uncertainty (EPU) index provides a benchmark of the economic policy uncertainty level of a given country at a given time. Economic policy uncertainty rises interests among researchers as it can be used as an asset pricing indicator for financial markets. In fact, research found that, generally, the EPU index is negatively related to share and bond markets.

This study aims at assessing the impact of economic policy uncertainty and other determining factors on the financial markets of developed as well as of emerging countries. To achieve the latter, an extensive review of the literature and an empirical analysis based on real-world data are undertaken. In fact, the impact of the EPU index and several key factors of share and bond returns; the Fama-French factors on the share excess returns between 1997 and 2024 as well as on the bond excess returns between 2015 and 2024 for developed as well as for emerging countries will be assessed. Additionally, the share-bond diversification need between 2015 and 2024 for developed and emerging countries will be assessed. In this thesis, simple and multiple linear regression models seeking for statistical significance with their respective assumptions verification along with share and bond excess returns as well as correlation coefficients computations are conducted.

In essence, empirical findings reveal that only the EPU indexes of emerging countries have a significatively positive impact on the share excess returns of emerging countries between 1997 and 2024. Furthermore, most developed and emerging countries present positive share-bond excess returns correlation coefficients between 2015 and 2024 enabling share-bond diversification.

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Declaration Regarding AI Tool Usage in Master's Thesis

We recognize that AI tools might be valuable aids during the master's thesis work, but they are not infallible. Remember that transparency fosters trust, and acknowledging AI's role enhances the credibility of your work.

Therefore, when deciding to use such a tool, you need to adhere to the following principles of responsible use of AI.

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2. **Transparency :**
   - We acknowledge the use of ChatGPT transparently, emphasizing that it contributed to our work but did not replace human judgment.
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   - We actively monitored for biases or unintended consequences introduced by the AI tool.
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During the preparation of this master's thesis, the author(s) utilized ChatGPT for the following purpose:

1. For the empirical part, it helped to know the required R package of some R functions.

2. For the literature review, it was used to rephrase some sentences.

After using ChatGPT, the author(s) diligently reviewed and edited the content produced by the tool. We take full responsibility for the final content presented in this thesis.

By signing this declaration, we affirm that the content of this master's thesis reflects our original work, augmented by the responsible use of AI.

Date: January, 13th 2025.

Signature: HANSE Yann

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1. Introduction

The EPU index is *important and useful to investigate* since it gives insights on the economic policy uncertainty level of a given country at a given time. Moreover, the EPU index can be used as an indicator of the financial climate. In fact, the EPU index reacts (typically increases) to important negative shocks such as the Brexit or the Covid-19 crisis. Since it was found that the EPU index is negatively related to the financial markets (Al-Thaqeb & Algharabali, 2019), rising EPU index values can be an indicator of financial markets disruptions.

The *research question* of the thesis could be formulated as follows: "How does economic policy uncertainty affect financial markets? Is there a difference between emerging and developed countries?". The *research objectives* of the thesis are to investigate the international aspects of economic policy uncertainty based on EPU index measures. Secondly, the assessment of the relationship between the EPU index and other factors on assets (stocks and bonds) returns for developed and emerging countries. Thirdly, to investigate the role of policy uncertainty on diversification by assessing whether policy uncertainty affects stocks and bonds correlations for developed and emerging countries.

Researches carried out by other scholars firstly found that the VIX index is the principal index to which the EPU index must be compared (Baker et al., 2016). The VIX index measures the monthly option-implied volatility of the S&P500 index and is developed by the Chicago Board Options Exchange. The EPU and the VIX indexes have a correlation of 0.58 which shows similar trends. In fact, the EPU index is more reactive to policy-related events impacting stock markets but the VIX index is more reactive to finance-related events impacting stock markets. Secondly, to assess economic uncertainty, the NVIX index was implemented (Manela & Moreira, 2017) for instance. Like the EPU index, it is a newspapers-based index aiming at representing implied volatility based on texts analysis. The index soars during world wars, financial crises as well as during stock market crashes.

The *position of the study in the field* is that - regarding the current state of the study - (Baker et al., 2016) it is acknowledged that high uncertainty levels lead to increased stock price volatility as well as to decreased investment and employment. Moreover, it is acknowledged that high regulatory, monetary and fiscal policy uncertainty has detrimental effects on the economy. Further research regarding the influence of the EPU index on financial markets per country could be undertaken. The thesis research has the aim to fill this gap. The *contribution* of Baker et al. *in the field* is substantial since the EPU index is a largely accepted uncertainty measure. In fact, the EPU index is referred to in many research works such as in "*The effect of economic policy uncertainty on the long-term correlation between U.S. stock and bond markets"* by Fang et al. and in "*Economic Policy Uncertainty: A literature review"* by Al-Thaqeb et al. and in many others.

The *methodology and the data sample* used for the EPU index computations are based on 3 elements. The first is the frequency of economic, policy and uncertainty-related words in 10 leading US-newspapers for the US index. A normalized index is created from the obtained number of articles. The second is a policy uncertainty measure based on the number of dollar-weighted federal tax code provisions expiring in the 10-year horizon. The third is uncertainty indices based on policy-related macroeconomic variables; the Consumer Price Index as well as local, state and federal expenditures.

Concerning the *results preview*, EPU index increases lead to decreased production and economic performance. Moreover, firms face higher stock-price volatility, investment and employment growth rates are reduced.

Concerning the *coming sections*, the **literature review** presents the key findings of the existing literature on the EPU index, on financial markets, on the impact of the EPU index on financial markets, on other explanatory factors of share and bond returns as well as on the role of diversification on share-bond correlations and the formulated hypotheses. Afterwards, the **empirical analysis** aims at testing the hypotheses and at assessing the impacts of significative factors on share and bond excess returns. The **results** section either confirms or rejects hypotheses. The **conclusion** summarises the main findings and tries to give a general answer to the research question. The **appendices** provide graphs, tables, etc. to support the main content and the **bibliography** contains the used references.

2. Literature Review

This section is divided in 3 parts: the *literature overview*, the *theoretical model/framework* and the *hypotheses*.

Regarding the *literature overview*, the **Economic Policy Uncertainty (EPU) Index** aims at assessing the function of policy uncertainty (Baker et al., 2016). It was firstly computed for the United States and secondly, for 11 other countries. The EPU index is built on the frequency of newspapers articles containing the combination of economic, policy and uncertainty-related words. For instance, for the US EPU index, words from articles of 10 leading US-newspapers are scrutinized. The words are the economy-related words "economic" or "economy", the policy-related words "Congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House" and the uncertainty-related words are "uncertain" or "uncertainty". The EPU index responds to notable shocks/events. For instance, the US EPU index responded to the September, 9th attacks, to the various Gulf Wars as well as to the US presidential elections. Furthermore, 11 US category-specific indexes; notably on fiscal policy, taxes, government spending and other, monetary policy, health care, national security, regulation, financial regulation, sovereign debt and currency crises, entitlement programs and trade policy have been created. For instance, the health care policy uncertainty index is created by detecting the words "health care" and "hospital" in addition to the EPU-related words. These categories increase policy uncertainty; in fact, fiscal and health care policies appear to be, respectively, the first and second sources of policy uncertainty in recent years (Baker et al., 2016).

Financial markets (Kumar, 2014) can be defined as marketplaces in which buyers and sellers take part in assets trade. Assets can be equities such as shares or debt instruments such as bonds, derivatives and currencies. Price transparency, basic trading, fees and costs regulations must be applied in financial markets. However, the term *financial markets* is very broad. In this study, the focus is put on capital markets and more specifically on the stock and bond markets. In fact, a *capital market* is a place in which financial securities are exchanged by individuals and institutions. As for the *stock market*, it enables investors to buy and sell shares in publicly-traded companies. As for the *bond*, *debt, credit* or *fixed-income securities market*, it consists of various debt instruments used by corporate state governments, foreign governments as well as by municipalities as financing means. De facto, investors buy and sell bonds on credit markets.

Regarding the **impacts of economic policy uncertainty on financial markets**, it was firstly found that EPU index increases lead to production and economic performance decreases (Al-Thaqeb & Algharabali, 2019). In fact, fiscal, monetary and regulatory policy uncertainty diminishes economic performance (Baker et al., 2016).

Secondly, the EPU index is significantly correlated (Xu et al., 2021); negatively to stock markets (Al-Thaqeb & Algharabali, 2019). In fact, many studies have shown that high EPU index levels lead to economic downturns lowering share returns (Xu et al., 2021) as well as bond prices (Al-Thaqeb & Algharabali, 2019). Consequently, lower share returns should lead to (current) share prices drops considering that initial share prices remain constant and lower (current) bond prices should lead to lower bond returns given that initial bond prices remain constant as stated by the relationship between returns and prices[1]. Moreover, a study on the EPU index-stock markets relationship for China firstly found that the EPU index acts as an asset pricing indicator for the Chinese stock market since the next-month Chinese share returns are significantly and negatively impacted by the monthly EPU indexes. The study also found that the predictive performance of the EPU index for share returns decreases in times of high uncertainty such as during the Great Financial Crisis or the Covid-19 pandemic (Xu et al., 2021). Lastly, EPU index increases make firms more inclined to face greater stock price volatility. For instance, the correlation between the EPU index and the annual frequency of daily policy-triggered market jumps is 0.78 (Baker et al., 2016).

Thirdly, (Fang et al., 2017) found that the EPU index has a significantly negative impact on share-bond returns correlations in the long-term. This means that if the EPU index increases, share-bond returns correlations become negative since the demand for safer assets; bonds increases and the demand for riskier assets; shares decreases. In fact, based on the *supply and demand law*, the bond demand increase generates bond prices increases leading to higher bond returns whereas the share demand decrease generates share prices decreases leading to lower share returns. What happens is that the risk aversion of investors increases in times of high uncertainty which is why the *flight-to-quality phenomenon* takes place; investors substitute riskier assets for safer assets and de facto, share-bond returns correlations become negative (Fang et al., 2017). Moreover, share-bond correlations are weakly negative during times of economic downturns (Fang et al., 2017).

[1] The return-price relationship is the following: $Return = \frac{Current\ Price - Initial\ Price}{Initial\ Price}$.

Fourthly, the EPU index is negatively correlated to investors, households and governments investment (Al-Thaqeb & Algharabali, 2019). In fact, if the EPU index is high, investment rates tend to decrease for largely uncertainty-exposed firms (Baker et al., 2016).

Regarding **the other explanatory factors of the share and bond returns**, the "Fama-French 5 factors" model presents explanatory factors of the share - primarily - returns of developed and emerging markets. Namely, the small minus big (SMB), the high minus low (HML), the robust minus weak (RMW), the conservative minus aggressive (CMA) and the market risk factors. To build these factors, the per-region shares are classified in 2 market cap, 3 book-to-market equity (B/M), 3 operating profitability (OP) and 3 investment (INV) clusters at the end of each month of June. Big shares are those in the per-region top 90% of the June market cap and small ones are those in the 10% bottom. The per-region B/M, OP and INV breakpoints are the 30th and 70th percentiles of each ratio for big shares. In total, 6 value-weighted portfolios built on size and book-to-market equity, 6 value-weighted portfolios built on size and operating profitability and 6 value-weighted portfolios built on size and investment are used[2].

Regarding **the role of diversification on share-bond correlations**, lower share-bond returns correlations lead to more diversification (Fang et al., 2017). Actually, negative share-bond returns correlations enable investors to hedge risk. Let us assume that shares present negative returns whereas bonds present positive returns. A diversified investment portfolio; an invested part in equities; shares and an invested part in fixed income; bonds, enables investors to switch from shares to bonds to benefit from the positive returns of bonds (Coffey, 2024). In this case, diversification is incentivized. Oppositely, if share-bond returns correlations are positive; let us assume that shares and bonds both present positive returns, investors would want to obtain the highest return and compose their portfolios accordingly; with the highest-return asset type whether it be shares or bonds. In this case, diversification is not incentivized.

Regarding the *theoretical model/framework*, newspapers-based index models such as the EPU index model have the advantages to be computable in real-time, to cover large geographies, to cover large time periods on a daily basis. Moreover, for sufficiently large

[2] Appendix 6.2.2 defines the computational details of the Fama-French factors.

countries like the USA, category-specific indexes can be implemented. However, some of the disadvantages of the EPU index model are that it does not capture the causal role of policy uncertainty in macroeconomic performance. To assess it, exogenous policy uncertainty sources such as conflict shifts between North and South Korea or the Brexit should be scrutinized. In fact, it was found that increasing EPU index values lead to the worsening of macroeconomic performance. Moreover, the EPU index may react to large shocks but not sufficiently to small ones (Baker et al., 2016).

Other policy uncertainty measures exist such as the Beige Book (BB) index, computed based on the frequency of the word "uncertain" in Beige Books. Its correlation with the EPU index is of 0.54 showing same-shocks responses. Like the EPU index, it regards fiscal policy as the utmost uncertainty source. Unlike the EPU index, its response to the financial crisis is low. Additionally, the Policy Share of 10-K risk factors is computed based on the frequency of policy-related terms for each 10-k filing of the risk factors section. It shows, after 2009, increased concerns of firms towards policy uncertainty risks (Baker et al., 2016).

Regarding the *hypotheses*, it was found in the literature review that the EPU index is negatively related to stock markets (Al-Thaqeb & Algharabali, 2019); if the EPU index increases, stock prices and returns will be lower. Moreover, based on the following extract of the article "*Economic Policy Uncertainty : A literature review*":

> In addition, there is disagreement on the direction and strength of the relationship between the EPU index and stock markets in emerging markets. Some show that the EPU index has more considerable influence in emerging markets due to credit constraints; however, others argue that the effect is lower in other emerging markets. (Al-Thaqeb & Algharabali, 2019, p.5).

<u>*Hypothesis 1*</u>: For an emerging country, an increase of the EPU index will decrease the country's share returns, and de facto share excess returns to a greater extent as compared to a developed country.

It was found in the literature review that the EPU index is negatively related to bond prices (Al-Thaqeb & Algharabali, 2019). In fact, if the EPU index increases, bond prices will be lower. Moreover, it is assumed that the impact of uncertainty (EPU index) on bond prices and returns in emerging countries should be greater than in developed countries. In fact, emerging countries already face economic and political uncertainty.

Hypothesis 2: For an emerging country, an increase of the EPU index will decrease the country's bond returns, and de facto bond excess returns to a greater extent as compared to a developed country.

It was found in the literature review that the EPU index is negatively related to stock-bond correlations in the long-term allowing for more diversification (Fang et al., 2017). Moreover, it is assumed that the EPU index values should be, on average, higher for emerging countries as they face greater uncertainty.

Hypothesis 3: The share and bond excess returns of an emerging country should exhibit stronger negative correlations as compared to a developed country.

3. Empirical analysis

3.1 Methodology

The **first step** consists in identifying the required theoretical models and apply them for the analyses. The **second step** consists in identifying the per-country share and government bond indexes and classify them into 4 subsets of indexes; the share indexes of developed countries, the share indexes of emerging countries, the bond indexes of developed countries and the bond indexes of emerging countries. To complete that, various databases such as the Federal reserve of Saint-Louis, the S&P agency, Investing.com and Yahoo Finance were searched for financial data. The **third step** consists in computing the excess returns of each subset. The **fourth step** consists in identifying explanatory variables of the share and bond (excess) returns for developed and for emerging countries; the Fama-French factors. The **fifth step** consists in running the various multiple linear regressions to assess the impacts of the EPU index, and the Fama-French factors on share and bond excess returns using RStudio. The **sixth step** consists in computing and assessing the per-country share and bond excess returns correlation coefficients for developed countries as well as for emerging countries. Moreover, simple linear regressions are conducted to assess the influence of the EPU index on share-bond excess returns correlations. The **seventh step** consists in the verification of the models assumptions. The **eighth step** consists in drawing conclusions of the empirical findings.

3.2 Models

3.2.1 Models application[3]

To assess **hypothesis 1**, the following **multiple linear regressions**[4] are conducted:

$$SER_D = \beta_1 + B_2 * \ln(EPU_D) + \beta_3 * SMB_D + \beta_4 * HML_D + \beta_5 * RMW_D + \beta_6 * CMA_D \quad \textbf{(1)}$$

Where:

SER_D[5]: Share excess returns of developed countries (computed based on the share price indexes of developed countries)

EPU_D: EPU indexes of developed countries
SMB_D: SMB Fama-French factor of developed countries
HML_D: HML Fama-French factor of developed countries
RMW_D: RMW Fama-French factor of developed countries
CMA_D: CMA Fama-French factor of developed countries

$$SER_E = \beta_1 + B_2 * \ln(EPU_E) + \beta_3 * SMB_E + \beta_4 * HML_E + \beta_5 * RMW_E + \beta_6 * CMA_E \quad \textbf{(2)}$$

Where:

SER_E[6]: Share excess returns of emerging countries (computed based on the share price indexes of emerging countries)
EPU_E: EPU indexes of emerging countries
SMB_E: Fama-French SMB factor of emerging countries
HML_E: Fama-French HML factor of emerging countries
RMW_E: Fama-French RMW factor of emerging countries
CMA_E: Fama-French CMA factor of emerging countries

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[3] Appendix 6.1.2.4 defines the use of the benchmark model (presented in appendix 6.1.1.3) and lagged variables.
[4] Appendix 6.1.1.2 defines the multiple linear regression model including its underlying assumptions.
[5] Appendix 6.1.1.4 defines the theoretical rate of return and excess return formulas and appendix 6.1.2.1 defines the computational details of the share excess returns of developed countries (SER_D).
[6] Appendix 6.1.2.1 defines the computational details of the share excess returns of emerging countries (SER_E).

To asses **hypothesis 2**, the following **multiple linear regressions** are conducted:

$$BER_D = \beta_1 + \beta_2 * \ln\left(EPU_{D\,(Bond\,Reg)}\right) + \beta_3 * SMB_{D\,(Bond\,Reg)} + \beta_4 * HML_{D\,(Bond\,Reg)} + \beta_5 * RMW_{D\,(Bond\,Reg)} + \beta_6 * CMA_{D\,(Bond\,Reg)} \quad \textbf{(3)}$$

Where:

BER_D[7]: Bond excess returns of developed countries (computed based on the bond price indexes of developed countries)

$EPU_{D\,(Bond\,Reg)}$: EPU indexes of developed countries between 2015 and 2024

$SMB_{D\,(Bond\,Reg)}$: Fama-French SMB factor of developed countries between 2015 and 2024

$HML_{D\,(Bond\,Reg)}$: Fama-French HML factor of developed countries between 2015 and 2024

$RMW_{D\,(Bond\,Reg)}$: Fama-French RMW factor of developed countries between 2015 and 2024

$CMA_{D\,(Bond\,Reg)}$: Fama-French CMA factor of developed countries between 2015 and 2024

$$BER_E = \beta_1 + \beta_2 * \ln\left(EPU_{E\,(Bond\,Reg)}\right) + \beta_3 * SMB_{E\,(Bond\,Reg)} + \beta_4 * HML_{E\,(Bond\,Reg)} + \beta_5 * RMW_{E\,(Bond\,Reg)} + \beta_6 * CMA_{E\,(Bond\,Reg)} \quad \textbf{(4)}$$

Where:

BER_E[8]: Bond excess returns of emerging countries (computed based on the bond price indexes of emerging countries)

$EPU_{E\,(Bond\,Reg)}$: EPU indexes of emerging countries between 2015 and 2024

$SMB_{E\,(Bond\,Reg)}$: Fama-French SMB factor of emerging countries between 2015 and 2024

$HML_{E\,(Bond\,Reg)}$: Fama-French HML factor of emerging countries between 2015 and 2024

$RMW_{E\,(Bond\,Reg)}$: Fama-French RMW factor of emerging countries between 2015 and 2024

$CMA_{E\,(Bond\,Reg)}$: Fama-French CMA factor of emerging countries between 2015 and 2024

It is assumed that the **5 assumptions** of the **multiple linear regression model**[9] are respected for the 4 multiple linear regressions.

To assess **hypothesis 3**, the following **simple linear regressions**[10] are conducted:

[7] Appendix 6.1.1.4 defines the theoretical rate of return and excess return formulas and appendix 6.1.2.2 defines the computational details of the bond excess returns of developed countries (BER_D).
[8] Appendix 6.1.2.2 defines the computational details of the bond excess returns of emerging countries (BER_E).
[9] Appendix 6.1.1.2 defines the assumptions of the multiple linear regression model.
[10] Appendix 6.1.1.1 defines the simple linear regression model including its underlying assumptions.

$$\rho_D = \beta_1 + \beta_2 * \ln(EPU_{D\,(Corr.\ Adj.\ Freq.)}) \quad \textbf{(5)}$$

Where:

ρ_D[11]: Share-bond excess returns correlation coefficients between 2015 and 2024 (yearly basis)

$EPU_{D\,(Adj.Freq.)}$: EPU indexes of developed countries between 2015 and 2024 (yearly basis)

$$\ln(\rho_E) = \beta_1 + \beta_2 * \ln(EPU_{E\,(Corr.\ Adj.\ Freq.)}) \quad \textbf{(6)}$$

Where:

ρ_E [12]: Share-bond excess returns correlation coefficients between 2015 and 2024 (yearly basis)

EPU_E: EPU index of emerging countries between 2015 and 2024 (yearly basis)

It is assumed that the **3 assumptions** of the **simple linear regression model**[13] as well as the **normality assumption** are respected for the 2 simple linear regressions.

3.3 Data

Regarding the *data collection*, the 21 per-country **EPU indexes** are classified in 2 sub-samples. Firstly, the sub-sample of **developed countries** is composed of the following countries: Australia, Canada, Germany, Spain, France, the UK, Greece, Ireland, Italy, Japan, Sweden, Singapore and the USA (Fama & French, 2024). Secondly, the sub-sample of **emerging countries** is composed of the following countries: Brazil, Chile, China (Mainland China), India, Mexico, Pakistan, Russia (Treasurers, 2024), South Korea (Fama & French, 2024).

Regarding the **per-country share and bond indexes**, the exhaustive list of the selected per-country share and government bond indexes is available under appendix 6.2.1. The selected indexes are used as indicators of the stock and bond markets of each country during the various periods of study. For instance, the selected share index for France is the CAC40 index since it tracks the performance of the 40 main shares of the Paris stock exchange. In

[11] Appendix 6.1.1.5 defines the correlation coefficient formula and appendix 6.1.2.3 defines the computational details of the share-bond excess returns correlation coefficients of developed countries (ρ_D).

[12] Appendix 6.1.2.3 defines the computational details of the share-bond excess returns correlation coefficients of emerging countries (ρ_E).

[13] Appendix 6.1.1.1 defines the assumptions of the simple linear regression model.

addition, the selected bond index for Australia is the “Thomson Reuters Australia 10 Years Government Benchmark” index since it tracks the performance of the 10-year maturity government bonds of Australia.

Concerning the **U.S. Treasury-bill rates**, for share excess returns, the one-month US Treasury bill rate is used as the proxy of the risk-free rate of return for developed as well as for emerging countries. The chosen 1-month US T-bill rate is: “4-Week Treasury Bill Secondary Market Rate, Discount Basis”. For bond excess returns, the 10-year US Treasury bill rate is used as the proxy of the risk-free rate of return for developed as well as for emerging countries. In fact, most chosen government bond indexes have a 10-year maturity. The chosen 10-year US T-bill rate is: “United States 10-Year Bond Yield”.

Regarding the **explanatory variables of the regressions on share excess returns (1)** and **(2)**, the first explanatory variable of share returns is the **small minus big** (**SMB**)/**size**[14] factor. Its utility for the research is that it enables to assess the impact of the portfolio size on share and bond excess returns of developed and emerging countries. The second explanatory variable of share returns is the **high minus low (HML)/value**[15] factor. Its utility for the research is that it enables to assess the impact of the portfolio value on share and bond excess returns of developed and emerging countries. The third explanatory variable of share returns is the **robust minus weak (RMW)/operating profitability**[16] factor. Its utility for the research is that it enables to assess the impact of the portfolio operating profitability on share and bond excess returns of developed and emerging countries. The fourth explanatory variable for share returns is the **conservative minus aggressive (CMA)/investment**[17] factor. Its utility for the research is that it enables to assess the impact of the portfolio investment type on the share and bond excess returns of developed and emerging countries. Regarding the **explanatory variables of the regressions on bond excess returns (3)** and **(4)**, the **Fama-French 5 factors model** is applicable to **bonds returns**. In fact, the SMB and HML factors are explanatory factors not only for average stock returns but for bond returns as well. In fact, if markets are integrated,

[14] Appendix 6.2.2.1 defines the computational details of the SMB factor.
[15] Appendix 6.2.2.2 defines the computational details of the HML factor.
[16] Appendix 6.2.2.3 defines the computational details of the RMW factor.
[17] Appendix 6.2.2.4 defines the computational details of the CMA factor.

the model should also apply for bonds returns as there must be overlap between stocks and bonds returns (Fama & French, 1992). The same argument is extended to the RMW and CMA factors.

Regarding the *chosen time periods and frequencies*[18], for the share-related multiple linear regressions **(1)** and **(2)**, the covered time period is from **January 1997** to **August 2024**. For bond-related multiple linear regressions **(3)** and **(4)**, the covered time period is from **January 2015** to **August 2024**. For correlation-related regressions **(5)** and **(6)**, the covered time period is from **January 2015** to **August 2024**. Regarding the *frequencies*, monthly basic data is used for all regressions.

Explanations on *data management*, *data assumptions* and *variables transformations* are provided in the appendices[19].

3.3.1 Descriptive statistics[20]

EPU Indexes - Developed Countries[21]

The **minimum** is 11.29 in August 1999 for France which might be explained by the unemployment rate decrease to 11.3% in August 1999 (IMF, 1999) reducing economic policy uncertainty (Baker et al., 2016). The **maximum** is 1141.8 in July 2016 for the UK caused by the Brexit referendum on June, 23rd 2016 (Electoral Commission, 2024). The **mean** EPU index value of developed countries between 1997 and 2024 is 139.96. The **standard deviation** is 95.28, meaning that EPU index values are fairly around the mean as the standard deviation is lower than the mean. **High EPU index values** can be noticed in 2008-09 peaking at 400 for Canada probably due to the aftermath of the Great Financial Crisis. Peaks in 2019-2020 can be noticed as well; 700 for Canada which caused by the global Covid-19 crisis. In fact, Canada faced a total deficit of $325,540 million in 2020

[18] Appendix 6.2.3 defines further explanations on the chosen time periods and frequencies.
[19] Appendices 6.2.4, 6.2.5 and 6.2.6 define *data management*, *data assumptions*, and *variables transformations* respectively.
[20] All percentages (%) of the share and bond excess returns are expressed in USD terms.
[21] Appendix 6.2.7.1 defines the graphic representation and the key statistics of the EPU indexes of developed countries.

(Statistics Canada, 2021) largely due to government responses to the global pandemic as credit conditions were disrupted (Finances of the Nation, 2020). Lastly, peaks in 2021-2022 can be noticed; 800 for Germany which caused by post Covid-19 crisis effects such as spurred inflation, weakened growth and the Russian invasion in Ukraine (European Commission, 2022) which had significantly increased uncertainty in the euro area including Germany (European Central Bank, 2022). The **general trend** of the EPU indexes of developed countries is slightly increasing between 1997 and 2024.

EPU Indexes - Emerging Countries[22]

The **minimum** is 8.51 in April 2007 for Mexico probably caused by the economic expansion; the growth rate in Mexico in 2007 was about 3% (IMF, 2007). In fact, the relationship between the EPU index and economic conditions is negative (Baker et al., 2016). The **maximum** is 964.14 in April 2022 for Russia can be explained by the Russian invasion in Ukraine on February, 24th 2022 (House of Commons, 2024) since the EPU index responds to large negative shocks (Baker et al., 2016). The **mean** EPU index value of emerging countries between 1997 and 2024 is 128.87. The **standard deviation** is 96.31 meaning that EPU index values are fairly around the mean as the standard deviation is lower than the mean. **High EPU index values** can be noticed in 2016-17; 700 for Brazil certainly caused by the economic and political crises of 2016 with the impeachment of president Dilma Rousseff (Human Rights Watch, 2017). Peaking values in 2019-20 can be noticed; 800 for Russia probably due to the global Covid crisis which led to a 6% GDP growth decrease in Russia in 2020 (World Bank Group, 2020). These values are senseful as EPU index increases lead to economic conditions worsening (Baker et al., 2016). The **general trend** of the EPU index of emerging countries is slightly increasing between 1997 and 2024.

Share Indexes - Developed Countries[23]

The **minimum** is 0 USD for Greece in July 2015. In fact, Greece defaulted on a EUR 1.5 billion debt repayment to the IMF in June 2015 while in government-debt crisis (IMF, 2015).

[22] Appendix 6.2.7.2 defines the graphic representation and the key statistics of the EPU indexes of emerging countries.
[23] Appendix 6.2.7.3 defines the graphic representation and the key statistics of the share indexes of developed countries.

De facto, the ATG index crashed as investors feared default risk. The **maximum** is 59712.45 USD for Italy in April 2007. In fact, the MIB index had increased by 67% from end 2002 to 2007 reaching its best monthly performance in April 2007 (Borsa Italiana, 2007). The **mean** share price index value of developed countries between 1997 and 2024 is 7227.544 USD. The **standard deviation** is 8525.061 USD meaning that share price index values are scattered around the mean as the standard deviation is higher than the mean. Regarding **general trends**, several drops can be observed. The 2002-03 drops are probably due to the aftermath of September, 11th 2001 attacks which caused immediate damage on the US and global financial markets (Cohen & Remolana, 2023). The 2009 drops; from 1000 USD for Singapore to 40000 USD for Italy are explained by the 2007-08 Great Financial Crisis. 2011-2012 drops can be explained by the August, 8th 2011 stock market crash due to the S&P downgrade credit rating for the US on August, 5th 2011 (House Committee on the Budget, 2023) and the strengthening of the European debt crisis (De Grauwe, 2014) which decreased investor confidence. The 2020 drops are caused by the Covid-19 pandemic. The 2022 drops can be caused by the FED interest rates rises of 2022 (Brookings, 2024) since lower interest rates increase borrowing costs which reduces business and consumers spending and lower demand decreases share prices.

Share Indexes - Emerging Countries[24]

The **minimum** is 0.22 USD for Korea in June 1998 due to the 1998 Korean financial crisis (IMF, 2002). The **maximum** is 44629.56 USD for Brazil in May 2008 since Brazil was hit by the Great Financial Crisis end 2008 with a 30% real depreciation (Elcano Royal Institute, 2010). The **mean** share price index value of emerging countries between 1997 and 2024 is 2710.24 USD. The **standard deviation** is 7186.367 USD, indicating that share price index values are largely scattered around the mean as the standard deviation is greater than the mean. Regarding **general trends**, important drops for all indexes; approximately 67% for Brazil, Mexico and Pakistan as well as 62.5% for China can be noticed in 2008-09 obviously caused by the Great Financial Crisis. In 2016, the Brazilian index faced an approximate 75% drop explained by the increased uncertainty level due to political and economic disturbances[25]. Significant drops in 2019-20 for all indexes; approximately 50% for Brazil,

[24] Appendix 6.2.7.4 defines the graphic representations and the key statistics of the share indexes of emerging countries.
[25] As discussed under section 3.3.1 « **EPU Indexes – Emerging Countries** ».

43% for India as well as 33% for Mexico and Pakistan are noticeable, obviously provoked by post Covid-19 effects.

Bond Indexes - Developed Countries[26]

The **minimum** is 0.70 USD in September 2022 for Singapore. In fact, the Singaporean government faced a deficit of SGD 157.4 billion in 2022 (Ministry of Trade & Industry, 2022). The Singaporean government might have issued more bonds to self-finance increasing the bond supply which reduces bond prices. The **maximum** is 1703.37 USD in December 2020 for Spain certainly caused by the Covid crisis leading to a flight-to-quality phenomenon resulting in increasing bond demand and de facto prices. The **mean** bond price index value for developed countries between 2015 and 2024 is 697.08 USD. The **standard deviation** is 458.47 USD, meaning that bond price index values are fairly close to the mean as the standard deviation is lower than the mean. Regarding **general trends**, slight drops for all countries; approximately 7% for Spain and Italy due to Covid-19 can be noticed in 2020 except for Sweden, Japan and Singapore. Moreover, drops are observable in 2022 for all countries; 20% for the UK and 17% for Spain probably caused by the FED interest rates increases in 2022; from nearly 0% in Q1 2022 to 4.5% end 2022 (Forbes Advisor, 2024). In fact, increased interest rates increase borrowing costs for consumers and businesses which decreases the government bonds demand and de facto government bond prices. Moreover, bond price fluctuations are much more limited than share price fluctuations of developed countries[27] since they are less risky than shares.

Bond Indexes - Emerging Countries[28]

The **minimum** is 0.11 USD in February 2016 for South Korea. In fact, the South Korean government issued USD 93.4 billion-worth bonds in 2016 (Qatar News Agency, 2015) explaining bonds prices decreases as bonds supply increased. The **maximum** is 184.82 USD in December 2023 for Brazil which can be explained by the launch of a USD 2 billion

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[26] Appendix 6.2.7.5 defines the graphic representations and the key statistics of the bond indexes of developed countries.
[27] Described under section 3.3.1 "**Share Indexes – Developed Countries**".
[28] Appendix 6.2.7.6 defines the graphic representations and the key statistics of the bond indexes of emerging countries.

sustainable sovereign bond by the Brazilian government in November 2023 (World Bank Group, 2024) probably reducing the "standard" government bond supply increasing its price. The **mean** bond price index value for emerging countries between 2015 and 2024 is 26.05 USD. The **standard deviation** is 48.792 USD, meaning that bond price index values are scattered around the mean. Regarding **general trends**, higher bond price index values for Brazil may come from the self-financing need of the state due to its crisis-reaching indebtedness since 1993 (The World Bank, 2024). Several drops; approximately 25% for Brazil, 20% for Russia, 18% for Mexico in 2020 are observable probably due to the aftermath of the pandemic. A drop of 50% for the Russian index in February 2022 obviously caused by the Russian invasion in Ukraine is noticeable. Moreover, on May 22nd 2022, Russia defaulted on its 4.5% sovereign bonds (Simmons & Simmons, 2022). Unsurprisingly, bond prices dropped as bond demand must have fallen because of the increased default risk. A notable drop of 37.5% for the Chilean index can be noticed around the Chilean presidential elections of November 2021 (Reuters, 2021) increasing political and economic uncertainty.

Share Excess Returns - Developed Countries[29]

The **minimum** is -100.03% for Greece in July 2015 meaning that the Greek share investment underperformed the risk-free investment; the U.S. 1-month Treasury-bill rate by 100.03%. In fact, the return of Greek shares in July 2015 is -100% and the risk-free return is 0.03%; an investment in the Greek shares index maturing in July 2015 would have made a loss of 100% of the initial investment whereas an investment at the risk-free rate would have made a gain of 0.03% of the initial investment. The **maximum** is 38.35% in March 1998 for Greece meaning that the Greek share investment outperformed the risk-free investment by 38.35%; the return of Greek shares in March 1998 is 39.83% whereas the risk-free return is 1.47%. The **mean** share excess return of developed countries between 1997 and 2024 is -1.01% meaning that, generally, share investments underperformed risk-free investments by 1.01%. The **standard deviation** is 6.82%, suggesting that the share excess return values are scattered around the mean as the standard deviation is greater than the mean. However, they are not highly scattered. Regarding **general trends**, most share excess returns are comprised between -20% and 20% with a few extreme excess returns reaching -40% for Ireland in 1997

[29] Appendix 6.2.7.7 defines the graphic representations and the key statistics of the share excess returns of developed countries.

or 40% implying low to moderate volatility. Moreover, it appears that, similar fluctuation trends across developed countries are followed. For instance, the share excess returns all crashed in the wake of the Great Financial Crisis in 2008 with Greece facing -35% or during the pandemic in 2019-2020 with Australia facing -26%. Rising values can be noticed for all countries with Greece peaking at 32% in 2020.

Share Excess Returns - Emerging Countries[30]

The **minimum** is -95.71% for Russia in October 1997 meaning that the Russian share investment underperformed the risk-free investment by 95.71%. In fact, the return of Russian shares in October 1997 is -94.23% and the risk-free return is 1.47%. The minimum is due to the 1998 Russian financial crisis which led to a massive rubble depreciation and to an overall economic downturn (Economics Observatory, 2022). The **maximum** is 66.22% for South Korea in January 1998 meaning that the Korean share investment outperformed the risk-free investment by 66.22%. In fact, the return of Korean shares in January 1998 is 67.69% and the risk-free return is 1.47%. The maximum is explained by the Korean share prices volatility in 1998[31]. The **mean** share index excess return of emerging countries between 1997 and 2024 is -0.65% meaning that, generally, share investments underperformed risk-free investments by 0.65%. The **standard deviation** is 9.35%, suggesting that share excess returns values are scattered around the mean as the standard deviation is greater than the mean. However, they are not highly scattered. Regarding **general trends**, most share excess returns are comprised between -20% and 20% with a few extreme values from -40% to 40% implying low to moderate volatility. However, the share excess returns of emerging countries have less similar fluctuation trends as developed countries except the significant drops of the 2008 Great Financial crisis; -36.8% for Pakistan, -32.7% for Russia, and -27.9% for South Korea and of the Covid-19 in 2020; -40.1% for Brazil, -31.2% for Mexico, -29% for Pakistan which are noticeable for all countries. Nonetheless, negative excess returns for Russia are noticeable; -66.2% in 1998 and -48.9% in 2022 caused by the 1998 Russian financial crisis and the Russian invasion in Ukraine respectively.

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[30] Appendix 6.2.7.8 defines the graphic representations and the key statistics of the share excess returns of emerging countries.
[31] As discussed under section 3.3.1 « **Share Indexes – Emerging Countries** ».

Bond Excess Returns - Developed Countries[32]

The **minimum** is -27.5% for Greece in June 2015 meaning that the Greek bond investment underperformed the risk-free investment; the U.S. 10-year Treasury-bill rate by 27.5%. In fact, the return of the Greek bond in June 2015 is -25.15% and the risk-free return is 2.35%. The minimum can be explained by the Greek government-debt crisis in June 2015[33] meaning that Greece defaulted on its bondholders repayments which obviously caused the Greek bond excess return to fall. The **maximum** is 22.41% for Greece in July 2015 meaning that the Greek bond investment outperformed the risk-free investment by 22.41%. In fact, the Greek bond return in July 2015 is 24.60% and the risk-free return is 2.19%. The maximum might be explained by the July 2015 Greek referendum on bailout proposals (UK Parliament, 2015) which may have increased Greek bond investors' confidence considering it as a solvency mean for Greece. The **mean** bond excess return of developed countries between 2015 and 2024 is -2.32% meaning that, generally, bond investments underperformed the risk-free investments by 2.32%. The **standard deviation** is 3.61% suggesting that values are scattered around the mean. However, they are not highly scattered. Regarding **general trends**, most bond excess returns values are comprised between -10% and 10% with a few extreme values from -20% to 20% implying low to moderate volatility. Similar fluctuation trends across all countries are noticeable except for Greece in 2015 and 2016; plummeting at -18.5% and jumping at 10.8% later in 2015 and plummeting at -9.3% and surging at 18.8% later in 2016 or soaring at 5.4% in 2020 for the U.S. while all indexes were on decline. Notable drops in 2016 are; -11.5% for the UK, -11.4% for Japan probably due to Brexit, in 2018 are; -14.3% for Italy, -10.3% for Greece, due to the declined European bond business because of increased market volatility (BBVA, 2019), in 2022 are; -16.92% for the UK, -12.74% for Australia, and in 2023 are; -11.7% for Italy, -10.8% for Australia.

Bond Excess Returns - Emerging Countries[34]

The **minimum** is -40.33% for Russia in February 2022 meaning that the Russian bond investment underperformed the risk-free investment by -40.33%. In fact, the Russian bond

[32] Appendix 6.2.7.9 defines the graphic representations and the key statistics of the bond excess returns of developed countries.
[33] As discussed under section 3.3.1 "**Share Indexes – Developed Countries**".
[34] Appendix 6.2.7.10 defines the graphic representations and the key statistics of the bond excess returns of emerging countries.

return in February 2022 is -38.50% and the risk-free return is 1.82%. This minimum is explained by the Russian bond price fall in February due to the Russian invasion in Ukraine[35]. The **maximum** is 37.35% for Russia in March 2022 meaning that the Russian bond investment outperformed the risk-free investment by 37.35%. In fact, the Russian bond return in March 2022 is 39.70% and the risk-free return is 2.35%. This maximum value is caused by the Russian bond price re-stabilisation between March 2022 and June 2022[36]. The **mean** bond excess return of emerging countries between 2015 and 2024 is -2.22%, meaning that, generally, bond investments underperformed the risk-free investments. The **standard deviation** is 4.49% suggesting that values are scattered around the mean. However, they are not highly scattered. Regarding **general trends**, most bond excess returns values are comprised between -20% to 20% implying low to moderate volatility. Similar trend fluctuations can be noticed. For instance, soars for all countries except Pakistan can be noticed in 2016; 16% for Brazil and 12.5% for Russia caused by increasing bond prices probably due to favourable economic conditions; the forecasted growth for emerging countries in 2016 was of 4.6% (United Nations, 2016). Surges are observable end 2022; notably 10.5% for Chile as Chilean bond prices increased after the bond price drops caused by the 2021 Chilean election.[37] Drops for all excess returns can be noticed end 2016; -13.4% for Mexico, -9.40% for Brazil, and -6.08% for Korea as Korean bond prices were decreasing.[38] A few major drops are noticeable in 2020; -19.6% for Mexico, -19.4% for Brazil, and -17.25% for Russia due to the aftermath of the Covid-19 pandemic.[39]

Fama-French Factors - Developed Countries[40]

Firstly, for the **SMB factor**, the **minimum** is -8.64 in March 2000 meaning that big outperformed small stock portfolios by the largest value of 8.64. The **maximum** is 8.37 in February 2000 meaning that small outperformed big stock portfolios by the largest value of 8.37. The **mean** factor value is -0.01; meaning that, generally for developed countries, big

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[35] As discussed under section 3.3.1 "**Bond Indexes – Emerging Countries**".
[36] As discussed under section 3.3.1 "**Bond Indexes – Emerging Countries**".
[37] As discussed under section 3.3.1 "**Bond Indexes – Emerging Countries**".
[38] As discussed under section 3.3.1 "**Bond Indexes – Emerging Countries**".
[39] As discussed under section 3.3.1 "**Bond Indexes – Emerging Countries**".
[40] Appendix 6.2.7.11 defines the graphic representation and the key statistics of the Fama-French factors of developed countries.

portfolios outperformed small portfolios by a factor of 0.01. The **standard deviation** is 1.97 implying factor dispersion. Secondly, for the **HML factor**, the **minimum** is -10.15 in February 2000 meaning that growth outperformed value portfolios by the largest value of 10.15. The **maximum** is 12.24 in November 2000 meaning that value outperformed growth portfolios by the largest value of 12.24. The **mean** factor value is 0.22, meaning that, generally for developed countries, value portfolios outperformed growth portfolios by a factor of 0.22. The **standard deviation** is 2.78 implying factor dispersion. Thirdly, for the **RMW factor**, the **minimum** is -5.75 in February 2000 meaning that weak outperformed the robust operating profitability portfolios by the largest value of 5.75. The **maximum** is 6.2 in November 2000 meaning that robust outperformed weak portfolios by the largest value of 6.2. The **mean** factor value is 0.36, meaning that, generally for developed countries, robust portfolios outperformed weak portfolios by a factor of 0.36. The **standard deviation** is 1.55 implying factor dispersion. Fourthly, for the **CMA factor**, the **minimum** is -6.46 in November 1999 meaning that aggressive outperformed conservative investment portfolios by the largest value of 6.46. The **maximum** is 9.58 in November 2000 meaning that conservative outperformed aggressive portfolios by the largest value of 9.58. The **mean** factor value is 0.19, meaning that, generally for developed countries, conservative portfolios outperformed aggressive portfolios by a factor of 0.19. The **standard deviation** is 2.06 implying factor dispersion.

Fama-French Factors - Emerging Countries[41]

Firstly, for the **SMB factor**, the **minimum** is -7.89 in December 1999 meaning that big outperformed small stock portfolios by the largest value of 7.89. The **maximum** is 6.52 in February 2001 meaning that small outperformed big stock portfolios by the largest value of 6.52. The **mean** factor value is -0.0083, meaning that, generally for emerging countries, big stock portfolios outperformed small stock portfolios by a factor of 0.0083. The **standard deviation** is 1.93 implying factor dispersion. Secondly, for the **HML factor**, the **minimum** is -11.54 in February 2000 meaning that growth outperformed value portfolios by the largest value of 11.54. The **maximum** is 6.2 in July 2000 meaning that value outperformed growth portfolios by the largest value of 6.2. The **mean** is 0.77, meaning that, generally for emerging

[41] Appendix 6.2.7.12 defines the graphic representation and the key statistics of the Fama-French factors of emerging countries.

countries, value portfolios outperformed growth portfolios by a factor of 0.77. The **standard deviation** is 2.25 implying factor dispersion. Thirdly, for the **RMW factor**, the **minimum** is -4.44 in April 1999 meaning that weak outperformed robust operating profitability portfolios by the largest value of 4.44. The **maximum** is 8.05 in February 2000 meaning that robust outperformed weak operating profitability portfolios by the largest value of 8.05. The **mean** is 0.21, meaning that, generally for emerging countries, robust portfolios outperform weak portfolios by a factor of 0.21. The **standard deviation** is 1.42 implying factor dispersion. Fourthly, for the **CMA factor**, the **minimum** is -6.22 in April 2009 meaning that aggressive outperformed conservative investment portfolios by the largest value of 6.22. The **maximum** is 6.53 in July 1999 meaning that conservative outperformed aggressive investment portfolios by the largest value of 6.53. The **mean** is 0.32, meaning that, generally for emerging countries, conservative portfolios outperformed aggressive portfolios by a factor of 0.32. The **standard deviation** is 1.8 implying factor dispersion.

3.4 Findings

3.4.1 Share excess returns of developed countries (1) – Results interpretation[42]

Firstly, the **intercept $\boldsymbol{\beta_1}$** is the constant term of the linear regression (Van Bellegem, 2021-2022). The coefficient value is -0.654471. However, β_1 is not statistically significative meaning that the coefficient value cannot be the average share excess return of developed countries.

Secondly, the **coefficient $\boldsymbol{\beta_2}$** represents the marginal effect (Van Bellegem, 2021-2022) of the **EPU Indexes of developed countries** on the share excess returns of developed countries between January 1997 and August 2024. The coefficient value is 0.182206. However, β_2 is not statistically significative meaning that the **EPU indexes of developed countries** do not explain the share excess returns of developed countries.

Thirdly, the **coefficient $\boldsymbol{\beta_3}$** represents the marginal effect of the **SMB/size factor** of developed countries on the share excess returns of developed countries between January 1997 and August

[42] Appendix 6.3.1.1 defines the R output of the linear regression on the share excess returns of developed countries.

2024. The coefficient value is -0.008997. However, β_3 is not statistically significative meaning that the **SMB factor of developed countries** does not explain the share excess returns of developed countries.

Fourthly, the **coefficient $\boldsymbol{\beta_4}$** represents the marginal effect of the **HML/value factor** of developed countries on the share excess returns of developed countries between January 1997 and August 2024. The coefficient value is 0.120246, meaning that a 1-unit increase of the HML factor generates an increase of 12.02% of the share excess returns of developed countries. As the HML factor is the difference of the average return of 2 *value* portfolios and 2 *growth* portfolios, this means that a 1-unit increase of the HML factor corresponds to either a 1% increase of the average return of the *value* portfolios or to a 1% diminution of the average return of the *growth* portfolios (while keeping the other average return constant). In fact, β_4 is statistically significative at a 0.1% level meaning that the share excess returns of developed countries tend to **increase** as the ***value* stock portfolios average return increases** (assuming portfolio average return maximization).

Fifthly, the **coefficient $\boldsymbol{\beta_5}$** represents the marginal effect of the **RMW/ operating profitability factor** of developed countries on the share excess returns of developed countries between January 1997 and August 2024. The coefficient value is -0.123981, meaning that a 1-unit increase of the RMW factor generates a decrease of 12.4% of the share excess returns of developed countries. As the RMW factor is the difference of the average return of 2 *robust* and 2 *weak operating profitability* portfolios, this means that a 1-unit increase of the RMW factor corresponds to either a 1% increase of the average return of the *robust* portfolios or to a 1% diminution of the average return of the *weak* portfolios (while keeping the other average return constant). In fact, β_5 is statistically significative at a 0.1% level, meaning that the share excess returns of developed countries tend to **decrease** as the ***robust* stock portfolios average return increases** (assuming portfolio average return maximization).

Sixthly, the **coefficient $\boldsymbol{\beta_6}$** represents the marginal effect of the **CMA/investment factor** of developed countries on the share excess returns of developed countries between January 1997 and August 2024. The coefficient value is -0.223656, meaning that a 1-unit increase of the

CMA factor generates a decrease of 22.37% of the share excess returns of developed countries. As the CMA factor is the difference of the average return of 2 *conservative* and 2 *aggressive investment* portfolios, this means that a 1-unit increase of the CMA factor corresponds to either a 1% increase of the average return of the *conservative* portfolios or to a 1% diminution of the average return of the *aggressive* portfolios (while keeping the other average return constant). In fact, β_6 is statistically significative at a 0.1% level meaning that the share excess returns of developed countries tend to **decrease** as the ***conservative*** **stock portfolios average return increases** (assuming portfolio average return maximization).

3.4.2 Share excess returns of emerging countries (2) – Results interpretation[43]

Firstly, the **intercept $\boldsymbol{\beta_1}$**, the constant term, has a value is 0.74724, meaning that the average share excess return of emerging countries between January 1997 and August 2024, when all other explanatory variables of the model are held constant at 0, is 74.72%. In fact, β_1 is statistically significative at a 10% significance level. Nevertheless, this figure must be interpreted carefully since the explanatory variables; ln (EPU_E), SMB_E, HML_E, RMW_E, and CMA_E are unlikely to be equal to 0.

Secondly, the **coefficient $\boldsymbol{\beta_2}$** represents the marginal effect of the **EPU Indexes of emerging countries** on the share excess returns of emerging countries between January 1997 and August 2024. The coefficient value is -0.26183, meaning that a 1-unit increase of the EPU_E would generate a 77%[44] increase of the share excess returns of emerging countries. In fact, B_2 is statistically significative at a 10% level meaning that the share excess returns of emerging countries tend to **increase** as the **EPU indexes of emerging countries increase**.

Thirdly, the **coefficient $\boldsymbol{\beta_3}$** represents the marginal effect of the **SMB/size factor** of emerging countries on the share excess returns of emerging countries between January 1997 and August 2024. The coefficient value is -0.08017, meaning that a 1-unit increase of the SMB factor generates a decrease of 8.02% of the share excess returns of developed countries. As the SMB

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[43] Appendix 6.3.1.2 defines the R output of the linear regression on the share excess returns of emerging countries.

[44] In fact, as a natural logarithmic (ln) function is applied on the EPU_E, a 1-unit increase of the EPU_E generates a $e^{-0.26183} = 0.7696 = 77\%$ increase.

factor is the difference of the average return of 9 *small* and 9 *big* stock portfolios, this means that a 1-unit increase of the SMB factor corresponds to either a 1% increase of the average return of the *small* stock portfolios or to a 1% diminution of the average return of the *big* stock portfolios (while keeping the other average return constant). In fact, β_3 is statistically significative at a 0.1% level meaning that the share excess returns of emerging countries tend to **decrease** as the ***small* stock portfolios average return increases** (assuming portfolio average return maximization).

Fourthly, the **coefficient $\boldsymbol{\beta_4}$** represents the marginal effect of the **HML/value** factor of emerging countries on the share excess returns of emerging countries between January 1997 and August 2024. The coefficient value is 0.03511, meaning that a 1-unit increase of the HML factor generates an increase of 3.51% of the share excess returns of emerging countries. In fact, β_4 is statistically significative at a 1% level meaning that the, based on the factor's construction, the share excess returns of emerging countries tend to **increase** as the ***value* stock portfolios average return increases** (assuming portfolio average return maximization).

Fifthly, the **coefficient $\boldsymbol{\beta_5}$** represents the marginal effect of the **RMW/operating profitability** factor of emerging countries on the share excess returns of emerging countries between January 1997 and August 2024. The coefficient value is -0.07326, meaning that a 1-unit increase of the RMW factor generates a decrease of 7.33% of the share excess returns of emerging countries. In fact, β_5 is statistically significative at a 0.1% level meaning that, based on the factor's construction, the share excess returns of emerging countries tend to **decrease** as ***robust* stock portfolios average return increases** (assuming portfolio average return maximization).

Sixthly, the **coefficient $\boldsymbol{\beta_6}$** represents the marginal effect of the **CMA/investment** factor of emerging countries on the share excess returns of emerging countries between January 1997 and August 2024. The coefficient value is -0.09585, meaning that a 1-unit increase of the CMA factor generates a decrease of 9.59% of the share excess returns of emerging countries. In fact, β_6 is statistically significative at a 0.1% level, meaning that, based on the factor's construction, the share excess returns of emerging countries tend to **decrease** as ***conservative* stock portfolios average return increases** (assuming portfolio average return maximization).

3.4.3 Bond excess returns of developed countries (3) – Results interpretation[45]

Firstly, the **intercept $\boldsymbol{\beta_1}$**, the constant term, has a value of -1.219564. However, β_1 is not statistically significative meaning that the coefficient value cannot be the average bond excess return of developed countries.

Secondly, the **coefficient $\boldsymbol{\beta_2}$** represents the marginal effect of the **EPU Indexes of developed countries** on the bond excess returns of developed countries between January 2015 and August 2024. The coefficient value is 0.267415. However, $\boldsymbol{\beta_2}$ is not statistically significative meaning that the **EPU Indexes of developed countries** do not explain the bond excess returns of developed countries.

Thirdly, the **coefficient $\boldsymbol{\beta_3}$** represents the marginal effect of the **SMB/size factor** of developed countries on the bond excess returns of developed countries between January 2015 and August 2024. The coefficient value is 0.057904, meaning that a 1-unit increase of the SMB factor generates an increase of 5.8% of the bond excess returns of developed countries. In fact, β_3 is statistically significative at a 5% level, meaning that, based on the factor's construction, the bond excess returns of developed countries tend to **increase** as ***small*** **bond portfolios average return increases** (assuming portfolio average return maximization).

Fourthly, the **coefficient $\boldsymbol{\beta_4}$** represents the marginal effect of the **HML/value factor** of developed countries on the bond excess returns of developed countries between January 2015 and August 2024. The coefficient value is -0.003322. However, β_4 is not statistically significative, meaning that the **HML factor of developed countries** does not explain the bond excess returns of developed countries.

Fifthly, the **coefficient $\boldsymbol{\beta_5}$** represents the marginal effect of the **RMW/ operating profitability factor** of developed countries on the bond excess returns of developed countries between January 2015 and August 2024. The coefficient value is 0.067555, meaning that a 1-unit

[45] Appendix 6.3.1.3 defines the R output of the linear regression on the bond excess returns of developed countries.

increase of the RMW factor generates an increase of 6.76% of the bond excess returns of developed countries. In fact, β_5 is statistically significative at a 5% level, meaning that, based on the factor's construction, the bond excess returns of developed countries tend to **increase** as the ***robust*** **bond portfolios average return** increases (assuming portfolio average return maximization).

Sixthly, the **coefficient $\boldsymbol{\beta_6}$** represents the marginal effect of the **CMA/investment factor** of developed countries on the bond excess returns of developed countries between January 2015 and August 2024. The coefficient value is -0.041344. However, β_6 is not statistically significative, meaning that the **CMA factor** does not explain the bond excess returns of developed countries.

3.4.4 Bond excess returns of emerging countries (4) – Results interpretation[46]

Firstly, the **intercept $\boldsymbol{\beta_1}$**, the constant term, has a value of -0.54851. However, β_1 is not statistically significative, meaning that the coefficient value cannot be the average bond excess return of emerging countries.

Secondly, the **coefficient $\boldsymbol{\beta_2}$** represents the marginal effect of the **EPU indexes of emerging countries** on the bond excess returns of emerging countries between January 2015 and August 2024. The coefficient value is 0.11902. However, B_2 is not statistically significative, meaning that the **EPU indexes of emerging countries** do not explain the bond excess returns of emerging countries.

Thirdly, the **coefficient $\boldsymbol{\beta_3}$** represents the marginal effect of the **SMB/size factor** of emerging countries on the bond excess returns of emerging countries between January 2015 and August 2024. The coefficient value is -0.02557 meaning that a 1-unit increase of the SMB factor generates a decrease of 2.56% of the bond excess returns of emerging countries. In fact, β_3 is statistically significative at a 10% level, meaning that, based on the factor's construction, the

[46] Appendix 6.3.1.4 defines the R output of the linear regression on the bond excess returns of emerging countries.

bond excess returns of emerging countries tend to **decrease** as ***small* bond portfolios average return increases** (assuming portfolio average return maximization).

Fourthly, the **coefficient $\boldsymbol{\beta_4}$** represents the marginal effect of the **HML/value factor** of emerging countries on the bond excess returns of emerging countries between January 2015 and August 2024. The coefficient value is 0.01186. However, β_4 is not statistically significative, meaning that the **HML factor** does not explain the bond excess returns of emerging countries.

Fifthly, the **coefficient $\boldsymbol{\beta_5}$** represents the marginal effect of the **RMW/operating profitability factor** of emerging countries on the bond excess returns of emerging countries between January 2015 and August 2024. The coefficient value is -0.04499, meaning that a 1-unit increase of the RMW factor generates a decrease of 4.5% of the bond excess returns of emerging countries. In fact, β_5 is statistically significative at a 1% level, meaning that, based on the factor's construction, the bond excess returns of emerging countries tend to **decrease** as ***robust* bond portfolios average return increases** (assuming portfolio average return maximization).

Sixthly, the **coefficient $\boldsymbol{\beta_6}$** represents the marginal effect of the **CMA/investment factor** of emerging countries on the bond excess returns of emerging countries between January 2015 and August 2024. The coefficient value is -0.02516. However, β_6 is not statistically significative, meaning that the **CMA factor** does not explain the bond excess returns of emerging countries.

3.4.5 Share-bond excess returns correlations of developed countries

To gauge the need for assets; shares and bonds diversification of developed countries, the **per-country share-bond excess returns correlation coefficients** are computed on a 24-month basis between 2015 and 2024[47]. Afterwards, the **co-movements** between correlation coefficients and the EPU indexes are assessed.

[47] Appendix 6.3.2.1 defines the 2-year share-bond excess returns correlation coefficients of developed countries.

Regarding **Australia**[48], share-bond excess returns are **positively** correlated. In fact, the correlations are moderate; 0.56 in 2015-16 and strong; 0.79, 0.91 in 2019-20 and in 2023-24 respectively. The moving average trendline depicts upward correlations from 2017-18 onwards indicating that share-bond excess returns evolve in the **same direction**, at an increasing intensity between 2015 and 2024. As for the **EPU index**, the trend is upward between 2017-18 and 2021-22 and downward afterwards implying that the EPU index and the correlations evolve in the **same direction**; as the EPU index rises, correlations increase between 2017 and 2022. Concerning **Canada**[49], share-bond excess returns are **positively** correlated. In fact, the correlations are strong; 0.72 in 2015-16 and 0.85 in 2023-24 and moderate; 0.48 in 2017-18. The moving average trendline depicts downward correlations between 2017-18 and 2019-20 and upward afterwards indicating that the share-bond excess returns move in the **same direction** at a varying intensity between 2015 and 2024. As for the **EPU index**, the trend is upward from 2017-18 to 2019-20 and downward afterwards implying that the EPU index and the correlations evolve in **opposite directions**; as the EPU index increases, correlations decrease and vice-versa between 2017 and 2024.

Regarding **Germany**[50], share-bond excess returns are **positively** correlated except in 2015-16 for which the correlation is weakly **negative**; -0.01. The correlations are weak; 0.29 in 2019-20, moderate; 0.34 in 2017-18 and strong; 0.78 in 2023-24. The moving average trendline clearly depicts upward correlations from 2017 to 2024 implying that share-bond excess returns evolve in the **same direction** at an increasing intensity over the years except in 2015-2016 where they moved in **opposite directions**. As for the **EPU index**, the trend is upward from 2017-18 onwards indicating that the EPU index and the correlations evolve in the **same direction**; as the EPU index increases, correlations increase between 2017 and 2024. For **Spain**[51], share-bond excess returns are **positively** correlated. In fact, correlations are weak; 0.31 in 2015-16, moderate; 0.58 in 2017-18 and strong; 0.65 in 2023-24. The moving average trendline depicts upward trends between 2017-18 and 2019-20 as well as between 2021-22 and 2023-24 and a downward trend between 2019-20 and 2021-22 implying that the share-bond excess returns evolve in the **same direction** at a varying intensity between 2015 and 2024. As

[48] Appendix 6.3.2.2.1 defines the Australian 2-year correlation coefficients and EPU index.
[49] Appendix 6.3.2.2.2 defines the Canadian 2-year correlation coefficients and EPU index.
[50] Appendix 6.3.2.2.3 defines the German 2-year correlation coefficients and EPU index.
[51] Appendix 6.3.2.2.4 defines the Spanish 2-year correlation coefficients and EPU index.

for the **EPU index**, an upward trend from 2017-18 to 2021-22 and a downward trend from 2021-22 to 2023-24 are depicted indicating that the EPU index and the correlations evolve in the **same** and **opposite directions** between 2017 and 2024.

Concerning **France**[52], share-bond excess returns are **positively** correlated. The correlations are weak; 0.19 in 2015-16, moderate; 0.38 in 2019-2020 and strong; 0.78 in 2021-2022. The moving average trendline depicts upward correlations from 2017-2018 onwards implying that the share-bond excess returns move in the **same direction** at an increasing intensity between 2015 and 2024. As for the **EPU index**, an upward trend from 2017 to 2024 is depicted indicating that the EPU index and the correlations evolve in the **same direction**; as the EPU index increases, the correlations increase between 2017 and 2024. Regarding the **UK**[53], share-bond excess returns are **positively** correlated. The correlations are moderate; 0.44, 0.51 in 2017-18 and 2019-20 respectively and strong; 0.83 in 2021-22. The moving average trendline depicts upward correlations from 2017-18 onwards implying that the share-bond excess returns evolve in the **same direction** at an increasing intensity between 2017 and 2024. As for the **EPU index**, constant between 2017-18 and 2019-20 and downward trends between 2019-20 and 2023-24 are depicted indicating that the EPU index and the correlations evolve in **opposite directions**; as the EPU index decreases, correlations increase between 2019 and 2024.

For **Greece**[54], share-bond excess returns are **positively** correlated except in 2015-16 since the correlation was weakly **negative**; -0.16. The correlations are weak; 0.31 in 2019-20, moderate; 0.53 in 2023-24 and strong; 0.86 in 2017-18. The moving average trendline depicts upward between 2017 and 2020 as well as between 2021 and 2024 and downward between 2019 and 2022 correlations implying that the share-bond excess returns mostly evolve in the **same direction** at a varying intensity between 2017 and 2024 except in 2015-2016 where they moved in **opposite directions**. As for the **EPU index**, a downward trend from 2017 to 2022 and an upward trend from 2021 to 2024 are depicted indicating that the EPU index and the correlations evolve in the **same** and **opposite directions** between 2017 and 2024. Regarding **Ireland**[55], share-bond excess returns are **positively** correlated. The correlations are weak; 0.07 in 2015-

[52] Appendix 6.3.2.2.5 defines the French 2-year correlation coefficients and EPU index.
[53] Appendix 6.3.2.2.6 defines the British 2-year correlation coefficients and EPU index.
[54] Appendix 6.3.2.2.7 defines the Greek 2-year correlation coefficients and EPU index.
[55] Appendix 6.3.2.2.8 defines the Irish 2-year correlation coefficients and EPU index.

16, moderate; 0.46, 0.56 in 2019-20 and 2021-22 respectively and strong; 0.71 in 2023-24. The moving average trendline depicts upward correlations between 2017 and 2024 implying that the share-bond excess returns move in the **same direction** at an increasing intensity between 2015 and 2024. As for the **EPU index**, an upward trend from 2017 to 2024 is depicted indicating that the EPU index and the correlations evolve in the **same direction**; as the EPU index increases, correlations increase between 2017 and 2024.

Regarding **Italy**[56], share-bond excess returns are **positively** correlated. The correlations are weak; 0.24 in 2015-16, moderate; 0.50 in 2019-20 and strong; 0.71 in 2021-22 and 2023-24. The moving average trendline depicts upward correlations between 2017 and 2024 implying that the share-bond excess returns move in the **same direction** at an increasing intensity between 2015 and 2024. As for the **EPU index**, an upward trend from 2017-18 to 2021-22 and a downward trend from 2021-22 to 2023-24 are depicted indicating that the EPU index and the correlations evolve in the **same** and **opposite directions** between 2017 and 2024. As for **Japan**[57], share-bond excess returns are **negatively** and **positively** correlated. The correlations are weakly negative; -0.11, -0.16 in 2015-16 and 2017-18 respectively, moderately positive; 0.59 in 2021-22 and strongly positive; 0.72 in 2023-24. The moving average trendline depicts upward correlations between 2017 and 2024 implying that the share-bond excess returns evolve in **opposite directions** between 2015 and 2020 and in the **same direction** between 2021 and 2024 at varying intensities. As for the **EPU index**, an upward trend from 2017-18 to 2021-22 and a downward trend from 2021-22 to 2023-24 are depicted indicating that the EPU index and the correlations evolve in the **same** and **opposite directions** between 2017 and 2024.

Regarding **Sweden**[58], share-bond excess returns are **positively** correlated. The correlations are weak; 0.04 in 2015-16, moderate; 0.48 in 2017-18 and 2019-20 and strong; 0.82 in 2023-24. The moving average trendline depicts upward correlations between 2017 and 2024 implying that the share-bond excess returns evolve in the **same direction** at an increasing intensity between 2015 and 2024 . As for the **EPU index**, an upward trend from 2017-18 to 2021-22 and a downward trend from 2021-22 to 2023-24 are depicted indicating that the EPU index and the

[56] Appendix 6.3.2.2.9 defines the Italian 2-year correlation coefficients and EPU index.
[57] Appendix 6.3.2.2.10 defines the Japanese 2-year correlation coefficients and EPU index.
[58] Appendix 6.3.2.2.11 defines the Swedish 2-year correlation coefficients and EPU index.

correlations evolve in the **same** and **opposite directions** between 2017 and 2024. Regarding **Singapore**[59], share-bond excess returns are **positively** correlated. The correlations are moderate; 0.42, 0.38 in 2017-18 and in 2021-22 respectively and strong; 0.73 in 2015-16 and in 2023-24. The moving average trendline depicts downward between 2017-18 and 2021-22 and upward between 2021-22 and 2023-24 correlations implying that the share-bond excess returns evolve in the **same direction** at a varying intensity between 2015 and 2024. As for the **EPU index**, an upward trend from 2017-18 to 2021-22 and a downward trend from 2021-22 to 2023-24 are depicted indicating that the EPU index and the correlations evolve in **opposite directions**; as the EPU index increases, the correlations decrease and vice-versa between 2017 and 2024.

Regarding the **US**[60], share-bond excess returns are **negatively** and **positively** correlated. The correlations are weakly; -0.26 in 2017-18 and moderately; -0.53 in 2019-20 negative and strongly; 0.74 in 2023-24 positive. The moving average trendline depicts downward between 2017-18 and 2019-20 and upward between 2019-20 and 2023-24 correlations implying that the share-bond excess returns evolve in **opposite directions** between 2015 and 2020 and in the **same direction** between 2021 and 2024 at varying intensities. As for the **EPU index**, an upward trend from 2017-18 to 2021-22 and a downward trend from 2021-22 to 2023-24 are depicted indicating that the EPU index and the correlations evolve in the **same** and **opposite directions** between 2017 and 2024.

To sum up, most developed countries possess **positive ($\boldsymbol{\rho > 0}$)** share-bond excess returns **correlation coefficients** between 2015 and 2024 except the USA and Japan between 2015 and 2020 as well as Greece in 2015-16 which show **negative ($\boldsymbol{\rho < 0}$) correlation coefficients**. Therefore, between 2015 and 2024, the **share** and **bond excess returns** of **developed countries** tend to move in the **same direction**; if share excess returns increase, bond excess returns tend to increase and vice-versa (Wackerly et al., 2008). Regarding the *share-bond diversification need of developed countries*, given that (Fang et al., 2017) found that low/negative share-bond returns correlations increase the need for diversification, and that

[59] Appendix 6.3.2.2.12 defines the Singaporean 2-year correlation coefficients and EPU index.
[60] Appendix 6.3.2.2.13 defines the American 2-year correlation coefficients and EPU index.

most developed countries possess positive correlation coefficients, then the **share-bond diversification need** of **developed countries** is **low** between **2015** and **2024**.

Regression on $\rho_{Developed}$ (5) - Results interpretations[61]

Firstly, the **intercept β_1**, the constant term, has a value of -2.020. However, β_1 is not statistically significative, meaning that the coefficient value cannot be the **average share-bond excess returns correlation coefficient of developed countries** between 2015 and 2024.

Secondly, the **coefficient β_2** represents the marginal effect of the **EPU indexes of developed countries** on the share-bond excess returns correlation coefficients of developed countries between 2015 and 2024. The coefficient value is 2.295. However, B_2 is not statistically significative, meaning that the **EPU indexes of developed countries** do not explain the correlation coefficients of developed countries.

3.4.6 Share-bond excess returns correlations of emerging countries

To gauge the need for assets; shares and bonds **diversification** of emerging countries, the **per-country share-bond excess returns correlation coefficients** are computed on a 24-month basis between 2015 and 2024[62]. Afterwards, the **co-movements** between correlation coefficients and the EPU indexes are described.

Regarding **Brazil**[63], share-bond excess returns are **positively** correlated. The correlations are strong; 0.88, 0.93 and 0.92 in 2015-16, 2017-18 and in 2019-20 respectively. The moving average trendline depicts upward between 2017-18 and 2019-20 and downward between 2019-20 and 2023-24 correlations implying that the share-bond excess returns evolve in the **same direction** at a strong intensity between 2015 and 2024. As for the **EPU index**, a downward trend from 2017 to 2024 is depicted indicating that the EPU index and the correlations evolve

[61] Appendix 6.3.1.5 defines the R output of the linear regression on the share-bond excess returns correlation coefficients of developed countries.
[62] Appendix 6.3.2.3 defines the 2-year share-bond excess returns correlation coefficients of emerging countries.
[63] Appendix 6.3.2.4.1 defines the Brazilian 2-year correlation coefficients and EPU index.

in the **same** and **opposite directions** between 2017 and 2024. As for **Chile**[64], share-bond excess returns are **positively** correlated. The correlations are moderate; 0.64 in 2019-20 and strong; 0.86, 0.70 in 2015-16 and 2017-18. The moving average trendline depicts downward between 2017-18 and 2019-20 and upward between 2019-20 and 2023-24 correlations implying that the share-bond excess returns evolve in the **same direction** at a varying intensity between 2015 and 2024. As for the **EPU index**, an upward trend from 2017-18 to 2021-22 and a downward trend from 2021-22 to 2023-24 are depicted indicating that the EPU index and the correlations evolve in the **same** and **opposite directions** between 2017 and 2024.

Regarding **China**[65], share-bond excess returns are **positively** correlated. The correlations are moderate; 0.37, 0.62 in 2015-16 and in 2023-24 respectively and strong; 0.70 in 2021-22. The moving average trendline depicts upward between 2017-18 and 2019-20 as well as between 2021-22 and 2023-24 and constant between 2019-20 and 2021-22 correlations implying that the share-bond excess returns evolve in the **same direction** at an increasing intensity between 2015 and 2024. As for the **EPU index**, an upward trend from 2017-18 to 2021-22 and a downward trend from 2021-22 to 2023-24 are depicted indicating that the EPU index and the correlations evolve in the **same** and **opposite directions** between 2017 and 2024.

Regarding **India**[66], share-bond excess returns are **positively** correlated except in 2023-2024 for which the correlation is weakly **negative**; -0.09. The correlations are moderate; 0.60, 0.46 in 2017-18 and in 2019-20 respectively and strong; 0.75 in 2021-22. The moving average trendline depicts downward between 2017-18 and 2019-20 as well as between 2021-22 and 2023-24 and upward between 2019-20 and 2021-22 correlations implying that the share-bond excess returns evolve in the **same direction** between 2015 and 2022 at varying intensities and evolve in **opposite directions** in 2023-2024. As for the **EPU index**, an upward trend from 2017 to 2024 is depicted indicating that the EPU index and the correlations evolve in the **same** and **opposite directions** between 2017 and 2024. Regarding **Mexico**[67], share-bond excess returns are **positively** correlated. The correlations are strong; 0.90 in 2015-16, 0.66 in 2021-22 and 0.88 in 2023-24. The moving average trendline depicts downward between 2017-18 and 2021-

[64] Appendix 6.3.2.4.2 defines the Chilean 2-year correlation coefficients and EPU index.
[65] Appendix 6.3.2.4.3 defines the Chinese 2-year correlation coefficients and EPU index.
[66] Appendix 6.3.2.4.4 defines the Indian 2-year correlation coefficients and EPU index.
[67] Appendix 6.3.2.4.5 defines the Mexican 2-year correlation coefficients and EPU index.

22 and upward between 2021-22 and 2023-24 correlations implying that the share-bond excess returns evolve in the **same direction** at a strong intensity between 2015 and 2024. As for the **EPU index**, an upward trend from 2017-18 to 2021-22 and a downward trend from 2021-22 to 2023-24 are depicted indicating that the EPU index and the correlations evolve in **opposite directions**; as the EPU index increases, the correlations decrease and vice versa between 2017 and 2024.

Regarding **Pakistan**[68], share-bond excess returns are **negatively** and **positively** correlated. The correlations are weakly; -0.10 in 2015-16 and moderately negative; -0.57 in 2023-24 as well as weakly positive; 0.25 in 2021-22. The moving average trendline outlines upward between 2017-18 and 2021-22 and downward between 2021-22 and 2023-24 correlations implying that the share-bond excess returns evolve in the **same direction** between 2017 and 2022 at an increasing intensity and in the **opposite direction** in 2015-2016 and 2023-2024 at varying intensities. As for the **EPU index**, the trend is upward from 2017 to 2024 indicating that the EPU index and the correlations evolve in the **same** and **opposite directions** between 2017 and 2024. Regarding **Russia**[69], share-bond excess returns are **positively** correlated. The correlations are moderate; 0.55 in 2023-24 and strong; 0.84, 0.90 in 2015-16, and in 2021-22 respectively. The moving average trendline presents upward between 2017-18 and 2021-22 and downward between 2021-22 and 2023-24 correlations implying that the share-bond excess returns evolve in the **same direction** at a varying intensity between 2015 and 2024. As for the **EPU index**, an upward trend from 2017-18 to 2021-22 and a downward trend between 2021-22 and 2023-24 are depicted indicating that the EPU index and the correlations evolve in the **same direction**; as the EPU index increases, the share-bond excess returns correlations increase and vice versa between 2017 and 2024.

Regarding **South Korea**[70], share-bond excess returns are **positively** correlated. The correlations are strong; 0.90 in 2015-16, 0.69 in 2019-20 and 0.85 in 2023-24. The moving average trendline depicts downward between 2017-18, constant between 2019-20 and 2021-22 and upward between 2021-22 and 2023-24 correlations implying that the share-bond excess

[68] Appendix 6.3.2.4.6 defines the Pakistani 2-year correlation coefficients and EPU index.
[69] Appendix 6.3.2.4.7 defines the Russian 2-year correlation coefficients and EPU index.
[70] Appendix 6.3.2.4.8 defines the South Korean 2-year correlation coefficients and EPU index.

returns evolve in the **same direction** at a strong intensity between 2015 and 2024. As for the **EPU index**, an upward trend from 2017 to 2024 is depicted indicating that the EPU index and the correlations evolve in the **same** and **opposite directions** between 2017 and 2024.

To sum up, most emerging countries possess **positive ($\rho > 0$) share-bond excess returns correlation coefficients** between 2015 and 2024 except Pakistan in 2015-16 and in 2023-24 as well as India in 2023-24 which show **negative ($\rho < 0$) correlation coefficients**. Therefore, between 2015 and 2024, the **share** and **bond excess returns** of **emerging countries** tend to move in the **same direction**; if share excess returns increase, bond excess returns tend to increase and vice-versa (Wackerly et al., 2008). Regarding the *share-bond diversification need of emerging countries*, given that (Fang et al., 2017) found that low/negative share-bond returns correlations increase the need for diversification, and that most emerging countries possess positive correlation coefficients, then the **share-bond diversification need** of **emerging countries** is **low** between **2015** and **2024**.

Regression on $\rho_{Emerging}$ (6) - Results interpretations[71]

Firstly, the **intercept β_1**, the constant term, has a value is 24.172. However, β_1 is not statistically significative, meaning that the coefficient value cannot be the **average share-bond excess returns correlation coefficient of emerging countries** between 2015 and 2024.

Secondly, the **coefficient β_2** represents the marginal effect of the **EPU indexes of emerging countries** on the share-bond excess returns correlation coefficients of emerging countries between 2015 and 2024. The coefficient value is -10.773. However, β_2 is not statistically significative, meaning that the **EPU indexes of emerging countries** do not explain the correlation coefficients of emerging countries between 2015 and 2024.

[71] Appendix 6.3.1.6 defines the R output of the linear regression on the share-bond excess returns correlation coefficients of emerging countries.

3.5 Assumptions testing[72] [73]

3.5.1 Regression on SER_D (1); the share excess returns of developed countries[74]

Regarding the **absence of multicollinearity assumption**, the Farrar-Glauber test detects the presence of collinearity. However, the correlation matrix of the independent variables indicates that most correlation coefficients do not reach (–) 0.1 with a few exceptions which do not reach extreme values (-1 or 1) indicating that collinearity remains low and is not a significant concern. Regarding the **homoscedastic variance assumption**, the Goldfeld-Quandt test indicates that it is respected. Regarding the **normal distribution of the residuals assumption**, the Jarque-Bera test indicates that it is respected. Regarding the **absence of autocorrelation of the residuals assumption**, the Durbin-Watson test detects an empirical autocovariance: $\rho = 0.12$[75], meaning that there is very weakly positive and negligeable autocorrelation.

3.5.2 Regression on SER_E (2); the share excess returns of emerging countries[76]

Regarding the **absence of multicollinearity assumption**, the Farrar-Glauber test detects the presence of collinearity. However, the correlation matrix of the independent variables shows that most correlation coefficients do not reach (-) 0.1 with a few exceptions which do not reach extreme values (-1 or 1) indicating that collinearity remains low and is not a significant concern. Regarding the **homoscedastic variance assumption**, the Goldfeld-Quandt test indicates that it is respected. Regarding the **normal distribution of the residuals,** the Jarque-Bera test indicates that it is not respected. However, as the residuals frequency histogram and QQ-plot denote, the residuals are close to being normally distributed. The assumption rejection probably comes from the presence of a few outliers. Regarding the **absence of autocorrelation of the residuals assumption**, the Durbin-Watson test detects an empirical autocovariance: $\rho = 0.23$[77], meaning that there is weakly positive and negligeable autocorrelation.

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[72] Appendices 6.1.1.1, 6.1.1.2 define the assumptions of the simple and multiple linear regression models respectively and appendix 6.2.5 defines the *data assumptions*.

[73] The conducted tests and empirical autocovariance formula are from *LINGE1221 – Econométrie* (Van Bellegem, 2021-2022).

[74] Appendix 6.4.1 defines the conducted tests (6.4.1.1 to 6.4.1.4) and the correlation matrix (6.4.1.1.1) of linear regression (1).

[75] The empirical autocovariance is computed as follows: $\rho = -\left(\frac{DW}{2} - 1\right) = 0.12$ as $DW = 1.7501$.

[76] Appendix 6.4.2 defines the conducted tests (6.4.2.1 to 6.4.2.4), the correlation matrix (6.4.2.1.1), the residuals frequency histogram (6.4.2.3.1) and QQ-plot (6.4.2.3.2) of linear regression (2).

[77] The empirical autocovariance is computed as follows: $\rho = -\left(\frac{DW}{2} - 1\right) = 0.23$ as $DW = 1.54$.

3.5.3 Regression on BER_D (3); the bond excess returns of developed countries[78]

Regarding the **absence of multicollinearity assumption**, the Farrar-Glauber test detects the presence of collinearity. However, the correlation matrix of the independent variables shows that most correlation coefficients do not reach (-) 0.1 with a few exceptions which do not reach extreme values (-1 or 1) meaning that collinearity remains low and is not a significant concern. Regarding the **homoscedastic variance assumption**, the White test indicates that the homoscedasticity of the residuals assumption is respected. Regarding the **normal distribution of the residuals assumption**, the Jarque-Bera test indicates that it is respected. Regarding the **absence of autocorrelation of the residuals assumption**, the Durbin-Watson test detects an empirical autocovariance: $\rho = 0.14$[79]; there is very weakly positive and negligeable autocorrelation.

3.5.4 Regression on BER_E (4); the bond excess returns of emerging countries[80]

Regarding the **absence of multicollinearity assumption**, the Farrar-Glauber test detects the presence of collinearity. However, the correlation matrix of the independent variables shows that correlation coefficients do not reach extreme values (-1 or 1) indicating that collinearity remains low and is not a significant concern. Regarding the **homoscedastic variance assumption**, the White test indicates that the homoscedasticity of the residuals assumption is respected. Regarding the **normal distribution of the residuals assumption**, the Jarque-Bera test indicates that it is respected. Regarding the **absence of autocorrelation of the residuals assumption**, the Durbin-Watson test detects an empirical autocovariance; $\rho = 0.16$[81]; there is very weakly positive and negligeable autocorrelation.

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[78] Appendix 6.4.3 defines the conducted tests (6.4.3.1 to 6.4.3.4) and the correlation matrix (6.4.3.1.1) of linear regression (3).

[79] The empirical autocovariance is computed as follows: $\rho = -\left(\frac{DW}{2} - 1\right) = 0.14$ as $DW = 1.73$.

[80] Appendix 6.4.4 defines the conducted tests (6.4.4.1 to 6.4.4.4) and the correlation matrix (6.4.4.1.1) of linear regression (4).

[81] The empirical autocovariance is computed as follows: $\rho = -\left(\frac{DW}{2} - 1\right) = 0.16$ as $DW = 1.68$.

3.5.5 Regression on ρ_D (5); the share-bond excess returns correlation coefficients of developed countries[82]

Regarding the **linearity between ρ_D and EPU_D assumption**, the scatterplot of both variables and its corresponding regression line confirms that it is respected. Regarding the **homoscedastic variance assumption**, the White test indicates that it is respected. Regarding the **normal distribution of the residuals assumption**, the Jarque-Bera test indicates that it is respected. Regarding the **absence of autocorrelation of the residuals assumption**, the Durbin-Watson test detects an empirical autocovariance; $\rho = 0.54$[83]; there is moderately positive autocorrelation most likely coming from the non-independence of the share-bond excess returns correlation coefficients through time.

3.5.6 Regression on ρ_E (6); the share-bond excess returns correlation coefficients of emerging countries[84]

Regarding the **linearity between $\rho_{Emerging}$ and $EPU_{Emerging}$ assumption**, the scatterplot of both variables and its corresponding regression line confirms that it is respected. Concerning the **homoscedastic variance assumption**, the White test indicates that it is respected. Concerning the **normal distribution of the residuals assumption**, the Jarque-Bera test indicates that it is respected. Concerning the **absence of autocorrelation of the residuals assumption**, the Durbin-Watson test detects an empirical autocovariance; $\rho = -0.3$[85]; there is weakly negative autocorrelation most likely coming from the non-independence of the share-bond excess returns correlation coefficients through time.

4. Results

Hypothesis 1 is **rejected** since the findings of linear regression **(2)** indicate that an increase of the EPU indexes of emerging countries significatively decreases the share excess returns of

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[82] Appendix 6.4.5 defines the scatterplot (6.4.5.1) and the conducted tests (6.4.5.2 to 6.4.5.4) of linear regression (5).

[83] The empirical autocovariance is computed as follows: $\rho = -\left(\frac{DW}{2} - 1\right) = 0.54$ as $DW = 0.92$.

[84] Appendix 6.4.6 defines the scatterplot (6.4.6.1) and the conducted tests (6.4.6.2 to 6.4.6.4) of linear regression (6).

[85] The empirical autocovariance is computed as follows: $\rho = -\left(\frac{DW}{2} - 1\right) = -0.3$ as $DW = 2.59$.

emerging countries. However, the findings of linear regression **(1)** indicate that the EPU indexes of developed countries do not statistically explain the share excess returns of developed countries. For the latter reasons, it cannot be confirmed that "for an emerging country, an increase of the EPU index will *decrease* the country's share returns, and de facto share excess returns *to a greater extent* as compared to a developed country". **Hypothesis 2** is **rejected** since the findings of linear regressions **(3)** and **(4)** respectively indicate that the EPU indexes of developed countries do not statistically explain the bond excess returns of developed countries and that the EPU indexes of emerging countries do not statistically explain the bond excess returns of emerging countries. For the latter reasons, it cannot be confirmed that "for an emerging country, an increase of the EPU index will decrease the country's bond returns, and de facto bond excess returns to a greater extent as compared to a developed country". **Hypothesis 3** is **confirmed** since the average *negative* correlation coefficient of developed countries is **-0.21**[86] and of emerging countries is **-0.25**[87] meaning that **emerging countries** present (slightly) **stronger negative share-bond excess returns correlation coefficients** as compared to developed countries.

5. Conclusion

To sum up, an extensive literature review along with the empirical analysis composed of simple and multiple linear regressions with their corresponding assumptions tests were conducted to analyse the influence of the EPU indexes and the Fama-French factors on the share and bond excess returns of developed as well as of emerging countries. Moreover, the share-bond excess returns correlation coefficients were computed to analyse the share-bond diversification need and whether the EPU indexes influence the share-bond excess returns correlations of developed and emerging countries.

The findings reveal that only the **EPU indexes** of emerging countries have a significatively **positive** effect on the share excess returns of emerging countries between 1997 and 2024[88]. In

[86] Computed as follows: $\frac{(-0.01)+(-0.16)+(-0.11)+(-0.16)+(-0.06)+(-0.35)+(-0.26)+(-0.53)}{8} = -0.21$ (appendix 6.3.2.1 defines the 2-year share-bond excess returns correlation coefficients of developed countries).

[87] Computed as follows: $\frac{(-0.09)+(-0.10)+(-0.57)}{3} = -0.25$ (appendix 6.3.2.3 defines the 2-year share-bond excess returns correlation coefficients of emerging countries).

[88] All subsequent findings for the share excess returns are from 1997 to 2024.

fact, the relationships between the EPU indexes and the share excess returns of developed countries, the bond excess returns of developed countries between 2015 and 2024[89] and the bond excess returns of emerging countries, respectively, are found to be statistically non-significative. The **size (SMB)** factor denotes a significatively **negative** effect on the share and bond excess returns, respectively, of emerging countries and a **positive** effect on the bond excess returns of developed countries. Nevertheless, the factor is not statistically significative for the share excess returns of developed countries. The **value (HML)** factor denotes a significatively **positive** effect on the share excess returns of developed and emerging countries. Nonetheless, the factor is not statistically significative for the bond excess returns of developed and emerging countries. The **operating profitability (RMW)** factor denotes a significatively **negative** effect on the share excess returns of developed and emerging countries as well as on the bond excess returns of emerging countries. However, its effect is significatively **positive** on the bond excess returns of developed countries. The **investment type (CMA)** factor denotes a significatively **negative** impact on the share excess returns of developed and emerging countries. Nonetheless, the factor is not statistically significative for the bond excess returns of developed and emerging countries. Moreover, the **share-bond excess returns correlations** of most developed and emerging countries are positive, lowering the share-bond diversification need between 2015 and 2024. Regarding the influence of the EPU index on the correlations, the EPU indexes turn out to be statistically non-significative meaning that the EPU indexes do not directly impact the share-bond excess returns correlations of developed and emerging countries.

The main limitation of the research is the short time period of analysis for bonds caused by the bond index data scarcity and consequently, for the computed share-bond excess returns correlations. This research gives modest insights on the impact of the EPU index and the Fama-French factors on the share and bond excess returns of developed and emerging countries. Further research could perhaps explore the impact of other economic policy uncertainty indexes and other determinants of the share and bond returns qualitatively and empirically to see if they more prominently drive share and bond (excess) returns. Personally, I believe that economic policy uncertainty affects financial markets in several ways; directly or indirectly, largely depending on geographies, time as well as on the economic conditions.

[89] All subsequent findings for the bond excess returns are from 2015 to 2024.

6. Appendices

6.1 Models

6.1.1 Theoretical models

6.1.1.1 Simple linear regression model

The independent and identically distributed sample (Y_i, X_i) , $\forall\ i = 1, \dots, n$ follows a **simple linear regression model** if the following conditions are respected for all i:

1. There exists 2 real coefficients $\beta_1$and β_2 such that:
$$Y_i = \beta_1 + \beta_2 X_i + \epsilon_i,$$
This condition ensures the **linearity assumption** of the **conditional expectation** $E(Y_i|X_i)$.

2. Variables ϵ_i are such that $E(\epsilon_i|X_i) = 0$.
This condition is the **strict exogeneity assumption**.

3. This model has an **homoscedastic conditional variance** if there exists a strictly positive real number σ such that $Var(\epsilon_i|X_i = x_i) = \sigma^2$ ∀ i.

6.1.1.2 Multiple linear regression model

The equation of the model for the conditional expectation is the following (Van Bellegem, 2021-2022):

$$E(Y|X_1, X_2, \dots, X_k) = \beta_1 X_1 + \dots + \beta_K X_K$$

Where:

X_1, X_2, X_K : K independent variables

Y : dependent variable

Including the error term**,** the previous regression equation becomes:

$$Y = \beta_1 X_1 + \dots + \beta_K X_K + \boldsymbol{\epsilon}$$

The general definition of a **multiple linear regression model** is (Van Bellegem, 2021-2022):

The independent and identically distributed sample $(Y_i, \underline{X_i})$ $\forall\ i = 1, \dots, n$ follows a multiple linear regression model if the following conditions are respected for all i:

1. There exists K real coefficients $\beta_1, \dots, \beta_K$ such that:

   $\underline{Y} = \boldsymbol{X}\underline{\beta} \ + \underline{\epsilon}$

   Where:

   $\underline{Y}$ represents the observations vector $n\ x\ 1$

   $\boldsymbol{X}$ represents a random matrix $n\ x\ K$ of the observations of explanatory variables

   $\underline{\beta}$ represents the parameters vector $K\ x\ 1$

   $\underline{\epsilon}$ represents the errors vector $n\ x\ 1$

   This condition ensures the **linearity assumption** of the **conditional expectation** $E(Y_i|X_i)$.

2. Variables $\underline{\epsilon}$ are such that $E\left(\underline{\epsilon}\middle|\boldsymbol{X}\right) = \underline{0}$.

   Where:

   $\underline{0}$ represents a vector $n\ x\ 1$ of zero numbers.

   $E\left(\underline{\epsilon}\middle|\boldsymbol{X}\right)$ represents the conditional expectation of the error term.

   This condition is the **strict exogeneity assumption**.

3. The rank of matrix **X** is K with a probability of 1.

   This condition imposes the conditional variance $Var\ (Y_i|X_i)$ to be homogenous; identical for all values of X_i. The general notation is: $Var(\epsilon_i|X_i = x) = \ \sigma^2(x)$, a conditional variance depending on X which is called the heteroscedastic variance.

   This condition is the **absence of collinearity assumption**.

4. This model has an homoscedastic conditional variance if there exists a strictly positive real number σ such that $Var\left(\underline{\epsilon}\middle|\boldsymbol{X}\right) = \ \sigma^2\mathbf{I}_n$.

   Where:

   $\mathbf{I}_n$ represents the identity matrix $n\ x\ n$.

   This condition summarises the concept of **homoscedastic error**.

5. The **multiple linear regression model** is **normal** if the following condition is respected:
   $\underline{\epsilon}|\boldsymbol{X} \sim N(\underline{0}, \sigma^2\mathbf{I})$: the error term follows a normal distribution with homoscedastic variance

6.1.1.3 Benchmark model

The **benchmark model** of interest (Xu et al., 2021) is the following:

$$R^m_{t\rightarrow\, t+h} = \alpha + \beta EPU_t + \Psi Z^K_t + \varepsilon_{t\rightarrow\, t+h}, k = \text{explanatory variables}$$

Where:

$R^m_{t\rightarrow\, t+h}$: h-month cumulative stock market return from month *t* to month *t* + *h*

EPU_t : EPU index at month t

Z^K_t : explanatory variables at month t

6.1.1.4 Excess returns

Rates of returns are computed according to the following formula :

$$\boldsymbol{Rate\ of\ return} = \left[\frac{Current\ value - Initial\ value}{Initial\ value}\right] * 100$$

Excess returns are computed according to the following formula (Xu et al., 2021):

$$\boldsymbol{Excess\ return} = Rate\ of\ return - Risk\ free\ rate$$

6.1.1.5 Correlation coefficient (Uyttendaele, 2021-2022) between variables $\boldsymbol{x^j}$ and $\boldsymbol{x^k}$:

$$\boldsymbol{r_{jk}} = \frac{s_{jk}}{\sqrt{s_{jj}s_{kk}}}$$

Where:

$\boldsymbol{s_{jk}}$: covariance, $\boldsymbol{s_{jj}}$: variance of variable $\boldsymbol{x^j}$, $\boldsymbol{s_{kk}}$: variance of variable $\boldsymbol{x^k}$

6.1.2 Models application

6.1.2.1 Share Excess Returns Computations

SER_D and SER_E; the share excess returns of developed and emerging countries, respectively, will be computed as follows[90]. In fact, the **rate of return formula** can be applied to compute stock returns for developed and emerging countries; SR_D and SR_E based on the per-country share price indexes. The formula becomes :

$$\boldsymbol{Return\ rate\ of\ stock\ price\ index\ i} : R_{Stock\ price\ index\ i} = \left[\frac{V_{Stock\ price\ index\ i}(t)}{V_{Stock\ price\ index\ i}(t-1)} - 1\right] * 100$$

$$SR_D = R_{Stock\ price\ index\ i} \quad \forall\, i \in Developed\ countries$$

$$SR_E = R_{Stock\ price\ index\ i} \quad \forall\, i \in Emerging\ countries$$

Where:

$\mathrm{R}_{\mathrm{Stock\ price\ index\ i}}$: return rate of stock price index i

$\mathrm{V}_{\mathrm{Stock\ price\ index\ i}}(\mathrm{t})$: value of stock price index i at time (t)

$\mathrm{V}_{\mathrm{Stock\ price\ index\ i}}(\mathrm{t}-1)$: value of stock price index i at time $(\mathrm{t}-1)$

In fact, the **excess return formula** can be applied to compute the share excess returns of developed and emerging countries; SER_D and SER_E based on the $\mathrm{SR_D}$ and $\mathrm{SR_E}$. The formula becomes :

$$\textbf{\textit{Excess return of stock index i:}}\ ER_{Stock\ price\ index\ i} = R_{Stock\ price\ index\ i} - R_f$$

$$SER_D = ER_{Stock\ price\ index\ i} \quad \forall\, i \in Developed\ countries$$

$$SER_E = ER_{Stock\ price\ index\ i} \quad \forall\, i \in Emerging\ countries$$

Where:

[90] Appendix 6.1.1.4 defines the theoretical rate of return and excess return models.

$ER_{\text{Stock price index I}}$: excess return of stock price index i

$R_{\text{Stock price index I}}$: return rate of stock price index i

R_f : risk-free rate : U.S. one-month Treasury-bill rate

The used risk-free rate in the computations of share excess returns is the **U.S. 1-month Treasury-bill rate** (according to the CAPM).

6.1.2.2 Bond Excess Returns Computations

BER_D and BER_E; the bond excess returns of developed and emerging countries, respectively, will be computed as follows[91]. In fact, the **rate of return formula** can be applied to compute bond returns of developed and emerging countries; BR_D and BR_E based on the per-country bond price indexes. The formula becomes :

$$\boldsymbol{Return\ rate\ of\ bond\ index\ i} : R_{Bond\ price\ index\ i} = \left[\frac{V_{Bond\ price\ index\ i}(t)}{V_{Bond\ price\ index\ i}(t-1)} - 1\right] * 100$$

$$BR_D = R_{Bond\ price\ index\ i} \quad \forall\, i \in Developed\ countries$$

$$BR_E = R_{Bond\ price\ index\ i} \quad \forall\, i \in Emerging\ countries$$

Where:

$R_{\text{Bond price index i}}$: return rate of bond price index i

$V_{\text{Bond price index i}}(t)$: value of bond price index i at time (t)

$V_{\text{Bond price index i}}(t-1)$: value of bond price index i at time $(t-1)$

[91] Appendix 6.1.1.4 defines the theoretical rate of return and excess return models.

In fact, the **excess return formula** can be applied to compute bond excess returns for emerging and developed countries; BER_D and BER_E based on the $\mathrm{BR_D}$ and $\mathrm{BR_E}$. The formula becomes :

$$\textbf{\textit{Excess return of bond index i :}}\ ER_{Bond\ price\ index\ i} = R_{Bond\ price\ index\ i} - R_f$$

$$BER_D = ER_{Bond\ price\ index\ i} \quad \forall\, i\ \in Developed\ countries$$

$$BER_E = ER_{Bond\ price\ index\ i} \quad \forall\, i \in Emerging\ countries$$

Where:

$\mathrm{ER_{Bond\ price\ index\ I}}$: excess return of bond price index i

$\mathrm{R_{Bond\ price\ index\ I}}$: return rate of bond price index i

$\mathrm{R_f}$: risk-free rate : U.S. one-month Treasury-bill rate

The used risk-free rate in the computations of bonds excess returns is the **U.S. 10-Year Treasury-bill rate** (according to the CAPM).

6.1.2.3 Correlation Coefficients Computations

The share-bond excess returns correlation coefficients are computed for each country firstly for the sub-sample of developed countries; ρ_D and secondly for the sub-sample of emerging countries; ρ_E[92]:

$$\boldsymbol{r_{jk}} = \frac{\boldsymbol{s_{jk}}}{\sqrt{\boldsymbol{s_{jj}s_{kk}}}}$$

Where:

$\boldsymbol{s_{jk}}$: covariance between variables $\boldsymbol{x^j}$ and $\boldsymbol{x^k}$

[92] Appendix 6.1.1.5 defines the formula of the correlation coefficient.

$\boldsymbol{s_{jj}}$: variance of variable $\boldsymbol{x^j}$; per-country and time frame-specific share excess returns

$\boldsymbol{s_{kk}}$: variance of variable $\boldsymbol{x^k}$; per-country and time frame-specific bond excess returns

The share-bond excess returns correlation coefficients of each country are computed for each **2-year period** between **January 2015** and **August 2024**[93] for sections 3.4.5 and 3.4.6. In fact, as correlation coefficients must be computed based on the largest number of observation points for each variable, it was chosen to work on 2-year periods; 24 observation points instead of on 1-year periods; 12 observation points for each coefficient. Proceeding as such enables to improve correlation coefficients statistical quality leading to more accurate results even though year-to-year temporality of correlation variations had to be given up. However, the correlation coefficients of each country are computed for **each 1 year period** between **January 2015** and **August 2024**[94] for the simple linear regressions on ρ_D **(5)** and ρ_E **(6)**.

6.1.2.4 Benchmark model and lagged variables

The benchmark model will be applied for $\boldsymbol{SER_D}$, $\boldsymbol{SER_E}$, $\boldsymbol{BER_D}$ and $\boldsymbol{BER_E}$. In fact, no lagged variables are used in the model since it aims at assessing the impact of the EPU index as well as of other explanatory variables on share and bond excess returns. It does not aim at forecasting them. As the regressions are conducted for determined time periods without lagged variables, the h-month cumulative market returns from month t to month $t + h$ are no longer relevant, but $\boldsymbol{SER_D}$, $\boldsymbol{SER_E}$, $\boldsymbol{BER_D}$ and $\boldsymbol{BER_E}$ sets at the determined time periods are.

6.2 Data

6.2.1 Selected per-country stock and government bond indexes

Australia: “S&P/ASX 200”, “Thomson Reuters Australia 10 Years Government Benchmark”.

[93] Appendices 6.3.2.1 and 6.3.2.3 define the 2-year share-bond excess returns correlations of developed and emerging countries respectively.
[94] Appendices 6.3.2.5 and 6.3.2.6 define the 1-year share-bond excess returns correlations of developed and emerging countries respectively.

Brazil: “Bovespa (IBOV) Live”, “S&P/B3 Brazil Sovereign Inflation-Linked Bond Index”.

Canada: “S&P/TSX Composite (GSPTSE) Live”, “Thomson Reuters Canada 10 Years Government Benchmark“.

Chile: “S&P CLX IPSA (SPIPSA) Live”, “S&P Chile Sovereign Inflation-Linked Bond Index”.

China: “Shanghai Composite (SSEC)”, “S&P China Sovereign Bond Index“.

France: “CAC 40 (FCHI)”, “Thomson Reuters France 10 Years Government Benchmark“.

Germany: “DAX (GDAXI)”, “Thomson Reuters Germany 10 Years Government Benchmark”.

Greece: “Athens General Composite (ATG)”, “Thomson Reuters Greece 10 Years Government Benchmark”.

India: “Nifty 50 (NSEI)”, “S&P India Sovereign Inflation-Linked Bond Index”.

Ireland: “ISEQ Overall (ISEQ)”, “Thomson Reuters Ireland 10 Years Government Benchmark”.

Italy: “FTSE MIB (FTMIB)”, “Thomson Reuters Italy 10 Years Government Benchmark“.

Japan: “Nikkei 225 (N225)”, “Thomson Reuters Japan 10 Years Government Benchmark”.

Korea (South): “KOSPI (KS11)”, “S&P South Korea Sovereign Inflation-Linked Bond Index”.

Mexico: “S&P/BMV IPC (MXX) Live”, “S&P/BMV Mexico Sovereign Bond Index”.

Pakistan: “Karachi 100 (KSE)”, “Pakistan 10-Year Bond Yield”.

Russia: “MOEX Russia Index (IMOEX)”, “Russian Government Bond RGBI”.

Singapore: “FTSE Straits Times Singapore (STI)”, “ABF Singapore Bond (ABFB)”.

Spain: “IBEX 35 (IBEX)”, “Thomson Reuters Spain 10 Years Government Benchmark”.

Sweden: “OMX Stockholm 30 (OMXS30) Live”, “Thomson Reuters Sweden 10 Years Government Benchmark”.

UK: “FTSE 100 (FTSE) Live”, “Thomson Reuters UK 10 Years Government Benchmark”.

US: “S&P 500 (SPX)”, “Thomson Reuters US 10 Year Government Benchmark”.

6.2.2 Explanatory variables – Computations details (Fama & French, 2024)

6.2.2.1 SMB Factor

The **SMB** factor is the difference between the average return of 9 small stock portfolios and the average return of 9 big stock portfolios:

$$\boldsymbol{SMB} = \frac{1}{3} * \left(SMB_{\left(\frac{B}{M}\right)} + SMB_{(OP)} + SMB_{(INV)} \right)$$

Where:

$$SMB_{\left(\frac{B}{M}\right)} = \frac{1}{3} * (Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3} * (Big\ Value + \quad Big\ Neutral + Big\ Growth)$$

$$SMB_{(OP)} = \frac{1}{3} * (Small\ Robust + Small\ Neutral + Small\ Weak) - \frac{1}{3} * (Big\ Robust + Big\ Neutral + Big\ Weak)$$

$$SMB_{(INV)} = \frac{1}{3} * (Small\ Conservative + Small\ Neutral + Small\ Aggressive) - \frac{1}{3} * (Big\ Conservative + Big\ Neutral + Big\ Aggressive)$$

6.2.2.2 HML Factor

The **HML** factor is the difference between the average return of the 2 value portfolios and the average return of the 2 growth portfolios:

$$HML = \frac{1}{2} * (Small\ Value + Big\ Value) - \frac{1}{2} * (Small\ Growth + Big\ Growth)$$

6.2.2.3 RMW Factor

The **RMW** factor is the difference between the average return of 2 robust operating profitability portfolios and the average return of 2 weak operating profitability portfolios:

$$RMW = \frac{1}{2} * (Small\ Robust + Big\ Robust) - \frac{1}{2} * (Small\ Weak + Big\ Weak)$$

6.2.2.4 CMA Factor

The **CMA** factor is the difference between the average return of 2 the conservative investment portfolios and the average return of the 2 aggressive investment portfolios and is de facto computed as follows:

$$CMA = \frac{1}{2} * (Small\ Conservative + Big\ Conservative) - \frac{1}{2} * (Small\ Aggressive + Big\ Aggressive)$$

6.2.3 Chosen time periods and frequencies

EPU index values are provided on a monthly basis from **1985** to **August 2024** except Sweden for which a few values are missing. However, most values are only available from **January 1997** onwards except for Singapore.

Regarding the *share-related multiple linear regressions* **(1)** and **(2)**, the selected data time period starts in **January 1997**. In fact, most stock index values are available from January 1997 onwards except for Greece, Ireland, Italy and Russia. The selected data time period ends in **August 2024** in order to capture latest trends. In fact, stock index values are all available until August 2024. These regressions are conducted over a **27-year horizon** to capture long-term trends. Moreover, they include data of this year; 2024 till the last available month; August 2024 to capture latest trends. The chosen frequency is **monthly** data values since EPU index measures are provided on a monthly basis.

Regarding *bond-related multiple linear regressions* **(3)** and **(4)**, the selected data time period starts in **January 2015**. In fact, S&P bond index values are only available from September 2014 onwards. That is why January of the following year was chosen as start date of the analysis. The selected data time period ends in **August 2024** in order to capture latest trends. In fact, bond index values are all available until August 2024 except for the Indian bond index whose last value dates from May 2023. These regressions are de facto conducted over an almost **10-year horizon** to capture long-term trends. Moreover, they include data of this year; 2024 till the last available month; August 2024 to capture latest trends. The chosen frequency is **monthly** data values since EPU index measures are provided on a monthly basis.

Regarding *correlation coefficients-related simple linear regressions* **(5)** and **(6)**, the selected time period starts in **January 2015** and the selected time period ends in **August 2024** to align with share and bond excess returns computations.

6.2.4 Data Management

Concerning *data transformations*, as far as the **EPU Indexes** and the **Fama-French factors values** are concerned, no data transformation were applied to these datasets. As **for stock and bond indexes**, as expressed in their per-country currencies, USD exchange rates were applied to express them in USD. In fact, this enables returns and risk-free rates; the US T-bill rates, expressed in USD terms, comparisons in excess returns computations. As for **Pakistan**, no government bond index was available but only the Pakistan 10-year bond yield expressed in PKR terms. To express it into USD terms, returns in PKR terms were multiplied by PKR-USD exchange rate values to obtain Pakistan bond returns in USD terms.

Concerning *missing values*, which reduce the quality of linear regressions, mean values of the available per-country data were computed and used to fill missing data cells afterwards. This rule is applied to missing EPU, stock and bond indexes as well as to the U.S. 1-month Treasury-bill rates. With regard to the **EPU indexes**, missing values were firstly sought trough in the country-specific EPU index values available on the Economic Policy Uncertainty website. Afterwards, country-specific EPU index means were computed and used to fill empty cells. For instance, EPU index values for Sweden were missing from April 2024 to August 2024. Missing values from April 2024 to June 2024 could be found in Swedish EPU index values. Missing values from June 2024 to August

2024 were then filled with the mean of all Swedish EPU index values. Moreover, values were missing for Singapore from January 1997 to December 2002. The previously-explained mechanism was applied. With regard to the **share indexes**, missing values were firstly sought through in various databases for Greece, Ireland, Italy, Russia, Singapore and the UK. Some missing values were found for all countries except for Italy and Russia. Afterwards, for the remaining missing values; for Greece and Ireland from January 1997 to July 1997, for Italy from January 1997 to December 1997, for Russia from January 1997 to September 1997, mean values of the available share price index values were computed and used to fill empty cells for each of the 4 countries. With regard to the **bond indexes**, missing values were detected for India from June 2023 to August 2024. The previously-explained mechanism was applied. With regard to the **U.S. 1-month Treasury-bill rates**, missing values were detected from January 1997 to June 2001. The previously-explained mechanism was applied. With regard to the **U.S. 10-year Treasury-bill rates,** no missing values were detected.

Concerning the *frequency*, it is important to note that **S&P Brazil**, **Chile**, **China**, **India**, **South Korea** and **Mexico daily bond index** values were converted into monthly bond index values by computing the mean of the daily values of the specific month and consider it as the monthly bond index value.

Regarding the *format*, the decimal separator is set to dots "(.)". In fact, dots were set as decimal separators for all data whose decimal separators were commas.

6.2.5 Data Assumptions

This section concerns all variables sets of the 4 multiple linear regressions; **(1)**, **(2)**, **(3)** and **(4)** as well as of the 2 simple linear regressions **(5)** and **(6)**; namely SER_D, SER_E, BER_D, BER_E, EPU_D, $EPU_{D(Bond\ Reg)}$, EPU_E, $EPU_{E\ (Bond\ Reg)}$, SMB_D, $SMB_{D\ (Bond\ Reg)}$, HML_D, $HML_{D\ (Bond\ Reg)}$, RMW_D, $RMW_{D\ (Bond\ Reg)}$, CMA_D, $CMA_{D\ (Bond\ Reg)}$, SMB_E, $SMB_{E\ (Bond\ Reg)}$, HML_E, $HML_{E\ (Bond\ Reg)}$, RMW_E, $RMW_{E\ (Bond\ Reg)}$, CMA_E, $CMA_{E\ (Bond\ Reg)}$, ρ_D, ρ_E, $EPU_{D\ (Corr.\ Reg.\ Adj.)}$, and $EPU_{E\ (Corr.\ Reg.\ Adj.)}$.

As for *stationarity*, it is assumed that all the above-mentioned variable sets are **stationary**; the mean, variance and auto-correlation structures remain constant even though their values fluctuate over time (National Institute of Standards and Technology, 2024). To assess the stationarity assumption, **augmented Dickey-Fuller tests** (R-Project, 2024) are applied to all above-mentioned variable sets. The tests results[95] confirm the stationarity assumption, all tests p-values are lower than the significance level; $\alpha = 0.05$, meaning that the null hypothesis: H_0 of non-stationarity can be rejected which implies stationarity for these variable sets at the significance level; $\alpha = 0.05$. However, for $\boldsymbol{\rho_E}$[96], $\boldsymbol{EPU_{D\,(Corr.\ Adj.\ Freq.)}}$[97], and $\boldsymbol{EPU_{E\,(Corr.\ Adj.\ Freq.)}}$[98] non-stationarity is detected.

As for *auto-correlation*, there should be no auto-correlation in any of the 6 models as it is assumed that variables in a linear regression model are independent. However, for instance, SER_D in a given year may influence SER_D in another year of the set which would contradict the independence hypothesis. Consequently, the presence of auto-correlation in the 6 models must be tested (Van Bellegem, 2021-2022).

6.2.6 Variables Transformations

As for the *functional form*, to assess whether variables transformations are required for the multiple linear regressions **(1), (2), (3), (4)** and the simple linear regressions **(5)**, **(6)**, frequency histograms (see below) of each variable set and of the logarithm of the treated variable set are presented to see which is the most symmetric. In fact, if the distribution of a variable is symmetric, this means that the distribution is "similar to" a normal distribution which will improve the estimation of the parameters (Van Bellegem, 2021-2022).

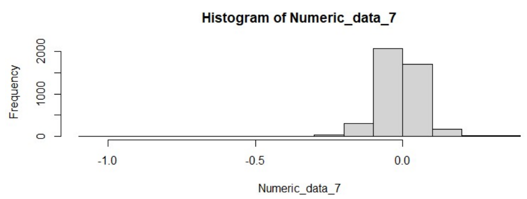
Frequency histograms of variables sets; SER_D **(1)**, SER_E **(2)**, BER_D **(3)**, BER_E **(4)**, SMB_D **(9)**, $SMB_{D\,(Bond\ Reg)}$ **(10)**, HML_D **(11)**, $HML_{D\,(Bond\ Reg)}$ **(12)**, RMW_D **(13)**,

[95] Appendix 6.2.6 "**Augmented Dickey-Fuller tests**" defines the R outputs of the conducted tests.
[96] Appendix 6.2.6 "**Augmented Dickey-Fuller tests**" (**30**) defines the R output of the test for $\boldsymbol{\rho_E}$.
[97] Appendix 6.2.6 "**Augmented Dickey-Fuller tests**" (**3**) defines the R output of the test for $\boldsymbol{EPU_{D\,(Corr.\ Adj.\ Freq.)}}$.
[98] Appendix 6.2.6 "**Augmented Dickey-Fuller tests**" (**7**) defines the R output of the test for $\boldsymbol{EPU_{E\,(Corr.\ Adj.\ Freq.)}}$.

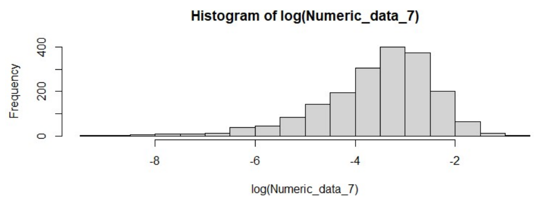
$RMW_{D\ (Bond\ Reg)}$ **(14)**, CMA_D **(15)**, $CMA_{D\ (Bond\ Reg)}$ **(16)**, SMB_E **(17)**, $SMB_{E\ (Bond\ Reg)}$ **(18)**, HML_E **(19)**, $HML_{E\ (Bond\ Reg)}$ **(20)**, RMW_E **(21)**, $RMW_{E\ (Bond\ Reg)}$ **(22)**, CMA_E **(23)** and $CMA_{E\ (Bond\ Reg)}$ **(24)**, ρ_D **(25)** show symmetric distributions as compared to their logarithms. Therefore, no transformation for these variables sets is applied. *Frequency histograms of the logarithms of the variables sets*; EPU_D **(5)** and $EPU_{D\ (Bond\ Reg)}$ **(6)**, EPU_E **(7)**, and $EPU_{E\ (Bond\ Reg)}$ **(8)** show symmetric distributions as compared to frequency histograms of the variables sets. Therefore, logarithmic (ln) transformations are applied to these variables sets. Based on these results, ln functions were applied on the differentiated $EPU_{D\ (Corr.\ Adj.\ Freq.)}$ and $EPU_{E\ (Corr.\ Adj.\ Freq.)}$ as well.

Frequency Histograms

1. Share Excess Returns of Developed Countries: SER_D (Regression (1))

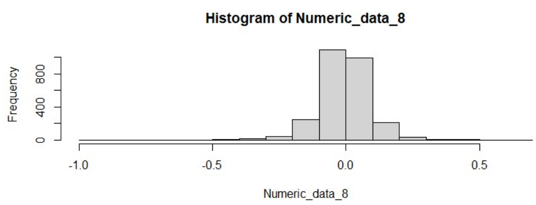


Frequency Histogram of Share Excess Returns of Developed Countries

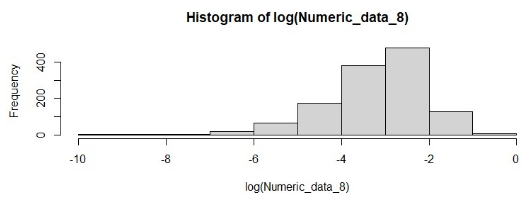


Frequency Histogram of the logarithm of Share Excess Returns of Developed Countries

2. Share Excess Returns of Emerging Countries: SER_E (Regression (2))

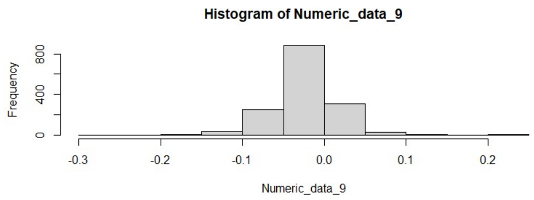


Frequency Histogram of Share Excess Returns of Emerging Countries

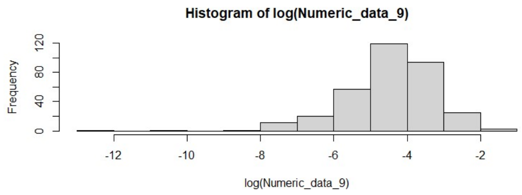


Frequency Histogram of the logarithm of Share Excess Returns of Emerging Countries

3. Bond Excess Returns of Developed Countries: BER_D (Regression (3))

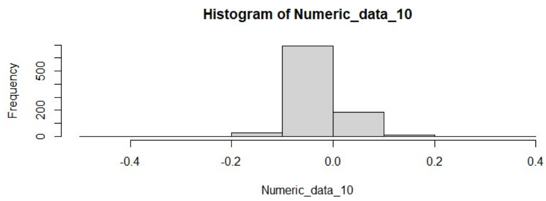


Frequency Histogram of Bond Excess Returns of Developed Countries

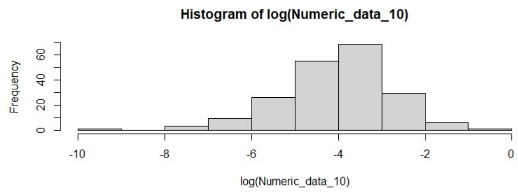


Frequency Histogram of the logarithm of Bond Excess Returns of Developed Countries

4. Bond Excess Returns of Emerging Countries: BER_E (Regression (4))



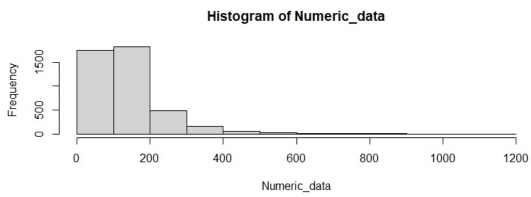
Frequency Histogram of Bond Excess Returns of Emerging Countries



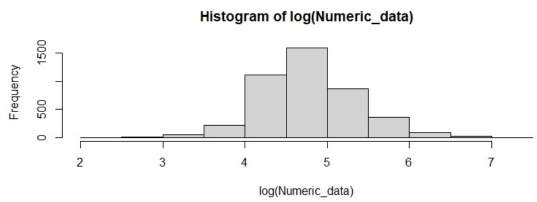
Frequency Histogram of the logarithm of Bond Excess Returns of Emerging Countries

EPU Indexes of Developed Countries

5. $EPU_{Developed}$: Regression on SER_D (1)

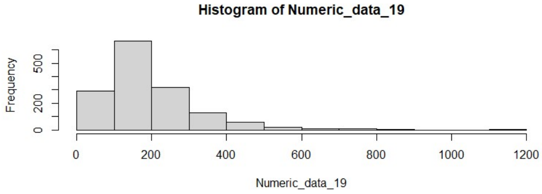


Frequency Histogram of EPU Indexes of Developed Countries

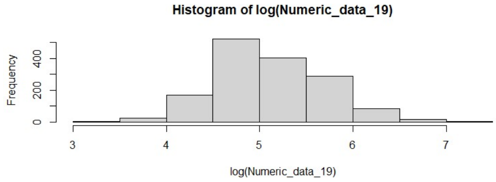


Frequency Histogram of the logarithm of EPU Indexes of Developed Countries

6. $EPU_{Developed\ (Bond\ Reg)}$: Regression on BER_D (3)



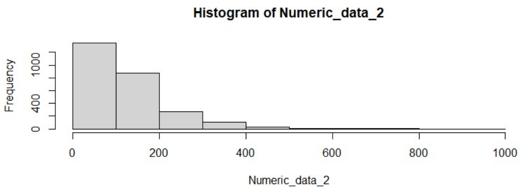
Frequency Histogram of EPU Indexes of Developed Countries (Bond Regression)



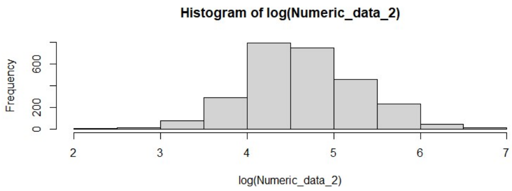
Frequency Histogram of the logarithm of EPU Indexes of Developed Countries (Bond Regression)

EPU Indexes of Emerging Countries

7. EPU_E: Regression on SER_E (2)

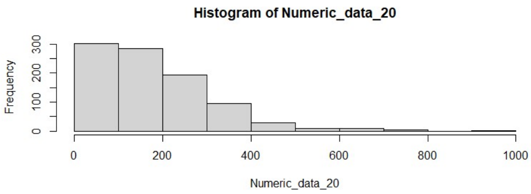


Frequency Histogram of EPU Indexes of Emerging Countries

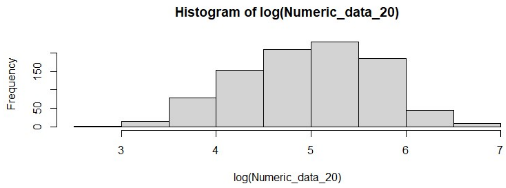


Frequency Histogram of the logarithm of EPU Indexes of Emerging Countries

8. $EPU_{E\ (Bond\ Reg)}$: Regression on BER_E (4)



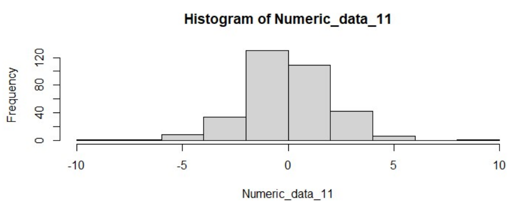
Frequency Histogram of EPU Indexes of Emerging Countries (Bond Regression)



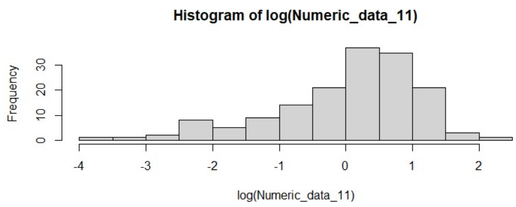
Frequency Histogram of the logarithm of EPU Indexes of Emerging Countries (Bond Regression)

Fama-French SMB Factor of Developed Countries

9. SMB_D: Regression on SER_D (1)

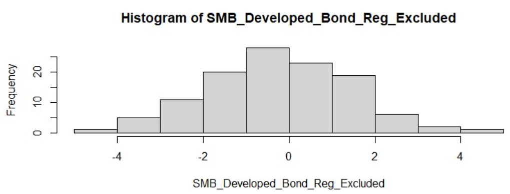


Frequency Histogram of the SMB Factor of Developed Countries

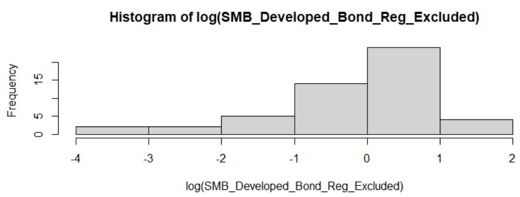


Frequency Histogram of the logarithm of the SMB Factor of Developed Countries

10. $SMB_{D\ (Bond\ Reg)}$: Regressions on BER_D (3)



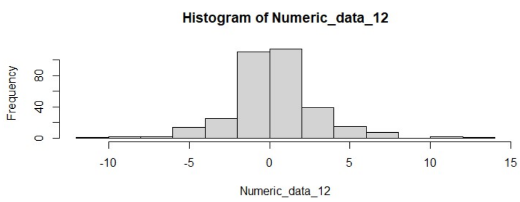
Frequency Histogram of the SMB Factor of Developed Countries (Bond Regression)



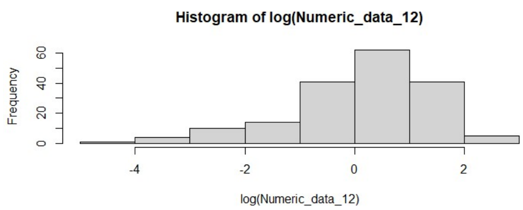
Frequency Histogram of the logarithm of the SMB Factor of Developed Countries (Bond Regression)

Fama-French HML Factor of Developed Countries

11. HML_D: Regressions on SER_D (1)

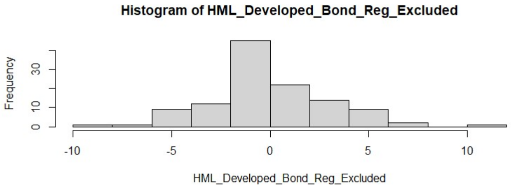


Frequency Histogram of the HML Factor of Developed Countries

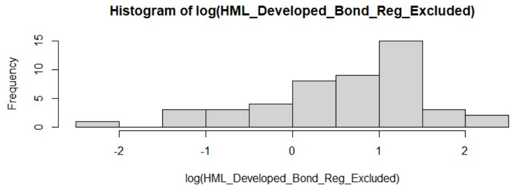


Frequency Histogram of the logarithm of the HML Factor of Developed Countries

12. $HML_{D\,(Bond\,Reg)}$: Regressions on BER_D (3)



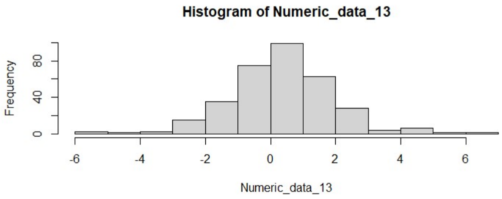
Frequency Histogram of the HML Factor of Developed Countries (Bond Regression)



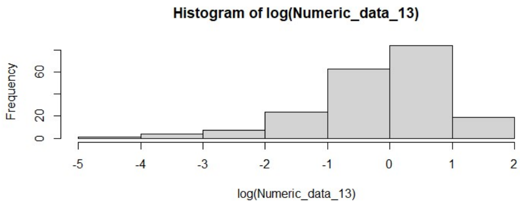
Frequency Histogram of the logarithm of the HML Factor of Developed Countries (Bond Regression)

Fama-French RMW Factor of Developed Countries

13. RMW_D: Regression on SER_D (1)

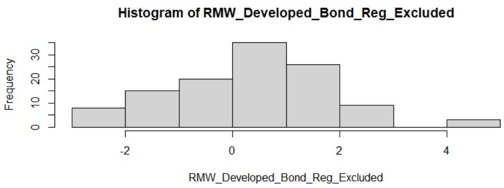


Frequency Histogram of the RMW Factor of Developed Countries

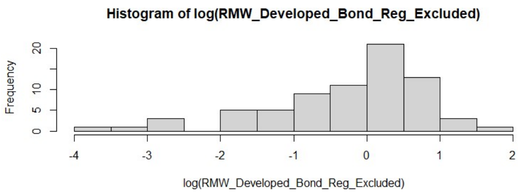


Frequency Histogram of the logarithm of the RMW Factor of Developed Countries

14. $RMW_{D\,(Bond\,Reg)}$: Regression on BER_D (3)



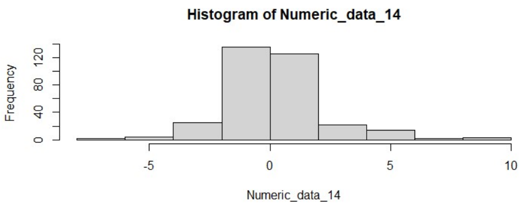
Frequency Histogram of the RMW Factor of Developed Countries (Bond Regression)



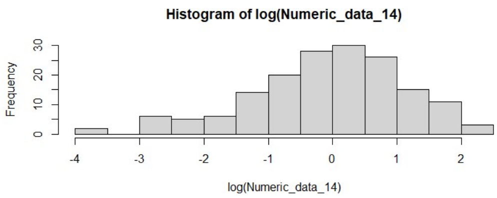
Frequency Histogram of the logarithm of the RMW Factor of Developed Countries (Bond Regression)

Fama-French CMA Factor of Developed Countries: CMA_D

15. CMA_D: Regression on SER_D (1)

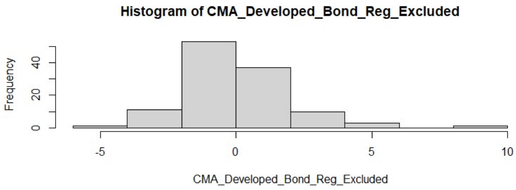


Frequency Histogram of the CMA Factor of Developed Countries

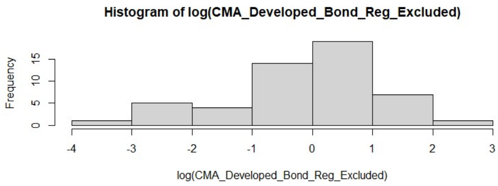


Frequency Histogram of the logarithm of the CMA Factor of Developed Countries

16. $CMA_{D\,(Bond\ Reg)}$: Regression on BER_D (3)



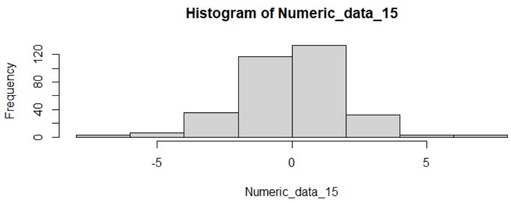
Frequency Histogram of the CMA Factor of Developed Countries (Bond Regression)



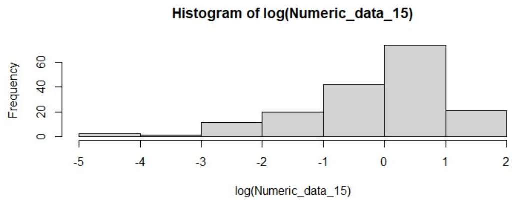
Frequency Histogram of the logarithm of the CMA Factor of Developed Countries (Bond Regression)

Fama-French SMB Factor of Emerging Countries: SMB_E

17. SMB_E: Regression on SER_E (2)

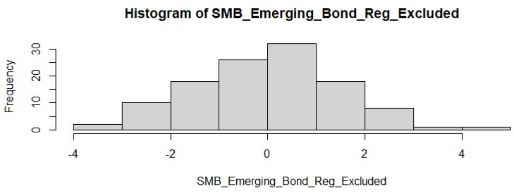


Frequency Histogram of the SMB Factor of Emerging Countries

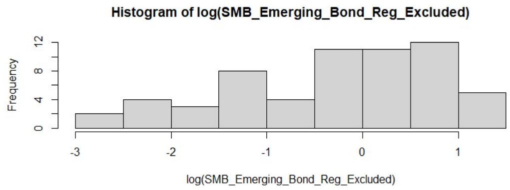


Frequency Histogram of the logarithm of the SMB Factor of Emerging Countries

18. $SMB_{E\,(Bond\ Reg)}$: Regression on BER_E (4)



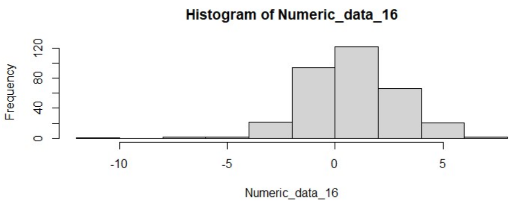
Frequency Histogram of the SMB Factor of Emerging Countries (Bond Regression)



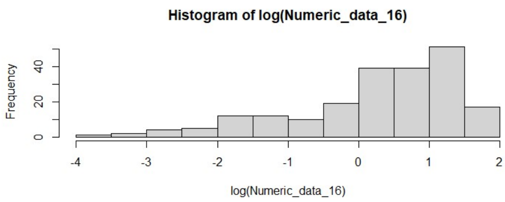
Frequency Histogram of the logarithm of the SMB Factor of Emerging Countries (Bond Regression)

Fama-French HML Factor of Emerging Countries: HML_E

19. HML_E: Regression on SER_E (2)

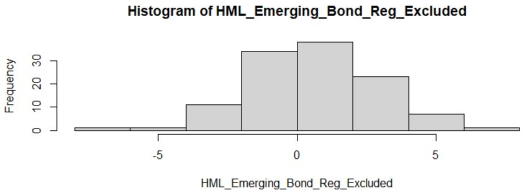


Frequency Histogram of the HML Factor of Emerging Countries

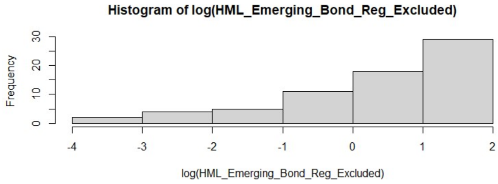


Frequency Histogram of the logarithm of the HML Factor of Emerging Countries

20. $HML_{E\ (Bond\ Reg)}$: Regression on BER_E (4)



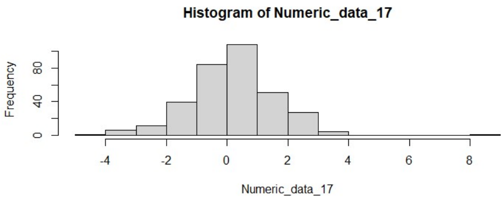
Frequency Histogram of the HML Factor of Emerging Countries (Bond Regression)



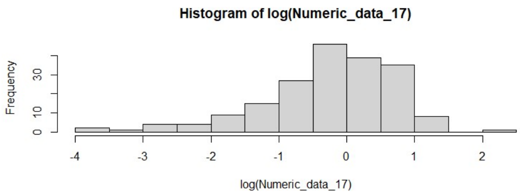
Frequency Histogram of the logarithm of the HML Factor of Emerging Countries (Bond Regression)

Fama-French RMW Factor of Emerging Countries: RMW_E

21. RMW_E: Regression on SER_E (2)

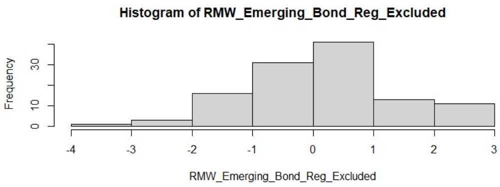


Frequency Histogram of the RMW Factor of Emerging Countries

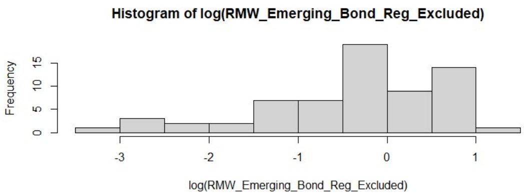


Frequency Histogram of the logarithm of the RMW Factor of Emerging Countries

22. $RMW_{E\ (Bond\ Reg)}$: Regression on BER_E (4)



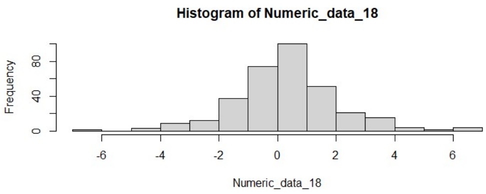
Frequency Histogram of the RMW Factor of Emerging Countries (Bond Regression)



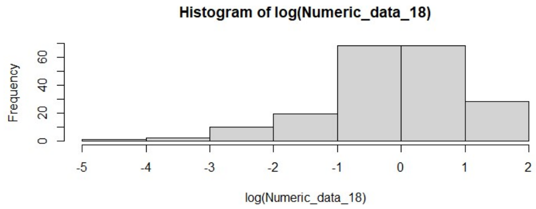
Frequency Histogram of the logarithm of the RMW Factor of Emerging Countries (Bond Regression)

Fama-French CMA Factor of Emerging Countries: CMA_E

23. CMA_E: Regression on SER_E (2)

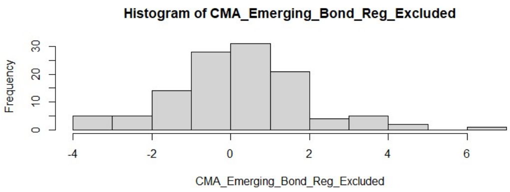


Frequency Histogram of the CMA Factor of Emerging Countries

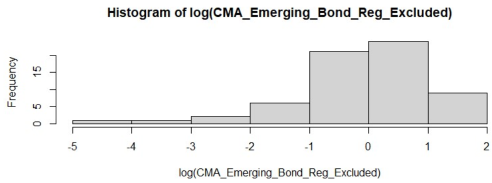


Frequency Histogram of the logarithm of the CMA Factor of Emerging Countries

24. $CMA_{E\ (Bond\ Reg)}$: Regression on BER_E (4)

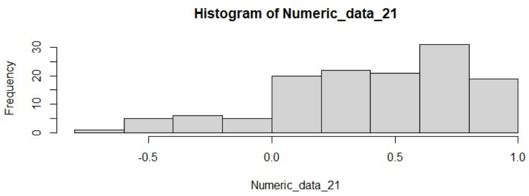


Frequency Histogram of the CMA Factor of Emerging Countries (Bond Regression)

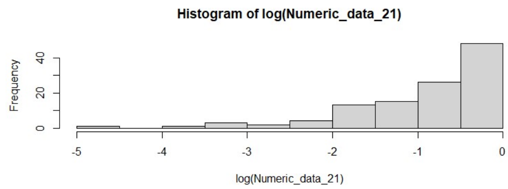


Frequency Histogram of the logarithm of the CMA Factor of Emerging Countries (Bond Regression)

25. Share-Bond Excess Returns Correlation Coefficients of Developed Countries: ρ_D (Regression(5))



Frequency Histogram of the Share-Bond Excess Returns Correlations of Developed Countries



Frequency Histogram of the logarithm of the Share-Bond Excess Returns Correlations of Developed Countries

As for the *variables stationarity*, based on the conducted **augmented Dickey-Fuller tests** (see below), it was found that variable sets are stationary at the significance level $\alpha = 0.05$ except ρ_E (**30**), $EPU_{D\ (Corr.\ Adj.\ Freq.)}$ (**3**) and $EPU_{E\ (Corr.\ Adj.\ Freq.)}$ (**7**). A **logarithmic (ln)** transformation is applied to ρ_E (**31**), **differencing** transformations are applied to $EPU_{D\ (Corr.\ Adj.\ Freq.)}$ (**4**), and $EPU_{E\ (Corr.\ Adj.\ Freq.)}$ (**8**) to remove non-stationarity.

Augmented Dickey-Fuller tests

EPU Indexes of Developed Countries

1. EPU_D: Regressions on SER_D (1) and SER_E (2)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data
Dickey-Fuller = -6.4292, Lag order = 16, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data) : p-value smaller than printed p-value
```

2. $EPU_{D\ (Bond\ Reg)}$: Regressions on BER_D (3) and BER_E (4)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_19
Dickey-Fuller = -5.1046, Lag order = 11, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_19) : p-value smaller than printed p-value
```

3. $EPU_{D\ (Corr.\ Adj.\ Freq.)}$: Regression on ρ_D (5)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_23
Dickey-Fuller = -3.3613, Lag order = 5, p-value = 0.06414
alternative hypothesis: stationary
```

4. Differencing of $EPU_{D\ (Corr.\ Adj.\ Freq.)}$: Regression on ρ_D (5)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_27
Dickey-Fuller = -6.0192, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_27) : p-value smaller than printed p-value
```

EPU Indexes of Emerging Countries: EPU_E

5. EPU_E: Regressions on SER_D (1) and SER_E (2)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_2
Dickey-Fuller = -5.0825, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_2) : p-value smaller than printed p-value
```

6. $EPU_{E\,(Bond\,reg)}$: Regressions on BER_D (3) and BER_E (4)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_20
Dickey-Fuller = -3.7029, Lag order = 9, p-value = 0.02385
alternative hypothesis: stationary
```

7. $EPU_{E\,(Corr.\ Adj.\ Freq.)}$: Regression on ρ_E (6)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_24
Dickey-Fuller = -2.634, Lag order = 4, p-value = 0.3163
alternative hypothesis: stationary
```

8. Differencing of $EPU_{E\,(Corr.\ Adj.\ Freq.)}$: Regression on ρ_E (6)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_27
Dickey-Fuller = -6.0192, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_27) : p-value smaller than printed p-value
```

9. Share Excess Returns of Developed Countries: SER_D (Regression (1))

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_7_clean
Dickey-Fuller = -14.875, Lag order = 16, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_7_clean) : p-value smaller than printed p-value
```

10. Share Excess Returns of Emerging Countries: SER_E (Regression (2))

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_8
Dickey-Fuller = -13.739, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_8) : p-value smaller than printed p-value
```

11. Bond Excess Returns of Developed Countries: BER_D (Regression (3))

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_9
Dickey-Fuller = -8.2629, Lag order = 11, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_9) : p-value smaller than printed p-value
```

12. Bond Excess Returns of Emerging Countries: BER_E (Regression (4))

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_10
Dickey-Fuller = -9.323, Lag order = 9, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_10) : p-value smaller than printed p-value
```

Fama-French SMB Factor of Developed Countries

13. SMB_D: Regressions on SER_D (1) and SER_E (2)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_11
Dickey-Fuller = -5.9821, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_11) : p-value smaller than printed p-value
```

14. $SMB_{D\,(Bond\ Reg)}$: Regressions on BER_D (3) and BER_E (4)

```
        Augmented Dickey-Fuller Test

data:  SMB_Developed_Bond_Reg_Excluded
Dickey-Fuller = -4.0373, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(SMB_Developed_Bond_Reg_Excluded) :
  p-value smaller than printed p-value
```

Fama-French HML Factor of Developed Countries

15. HML_D: Regression on SER_D (1) and SER_E (2)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_12
Dickey-Fuller = -6.1929, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_12) : p-value smaller than printed p-value
```

16. $HML_{D\,(Bond\ Reg)}$: Regression on BER_D (3) and BER_E (4)

```
        Augmented Dickey-Fuller Test

data:  HML_Developed_Bond_Reg_Excluded
Dickey-Fuller = -4.1512, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(HML_Developed_Bond_Reg_Excluded) :
  p-value smaller than printed p-value
```

Fama-French RMW Factor of Developed Countries

17. RMW_D: Regressions on SER_D (1) and SER_E (2)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_13
Dickey-Fuller = -6.4787, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_13) : p-value smaller than printed p-value
```

18. $RMW_{D\,(Bond\ Reg)}$: Regressions on BER_D (3) and BER_E (4)

```
        Augmented Dickey-Fuller Test

data:  RMW_Developed_Bond_Reg_Excluded
Dickey-Fuller = -5.1434, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(RMW_Developed_Bond_Reg_Excluded) :
  p-value smaller than printed p-value
```

Fama-French CMA Factor of Developed Countries

19. CMA_D: Regressions on SER_D (1) and SER_E (2)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_14
Dickey-Fuller = -6.0324, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_14) : p-value smaller than printed p-value
```

20. $CMA_{D\,(Bond\,Reg)}$: Regressions on BER_D (3) and BER_E (4)

```
        Augmented Dickey-Fuller Test

data:  CMA_Developed_Bond_Reg_Excluded
Dickey-Fuller = -4.3864, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(CMA_Developed_Bond_Reg_Excluded) :
  p-value smaller than printed p-value
```

Fama-French SMB Factor of Emerging Countries

21. SMB_E: Regressions on SER_D (1) and SER_E (2)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_15
Dickey-Fuller = -7.8665, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_15) : p-value smaller than printed p-value
```

22. $SMB_{E\,(Bond\,Reg)}$: Regressions on BER_D (3) and BER_E (4)

```
        Augmented Dickey-Fuller Test

data:  SMB_Emerging_Bond_Reg_Excluded
Dickey-Fuller = -4.3636, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(SMB_Emerging_Bond_Reg_Excluded) :
  p-value smaller than printed p-value
```

Fama-French HML Factor of Emerging Countries

23. HML_E: Regressions on SER_D (1) and SER_E (2)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_16
Dickey-Fuller = -5.5082, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_16) : p-value smaller than printed p-value
```

24. $HML_{E\,(Bond\,Reg)}$: Regressions on BER_D (3) and BER_E (4)

```
        Augmented Dickey-Fuller Test

data:  HML_Emerging_Bond_Reg_Excluded
Dickey-Fuller = -3.6693, Lag order = 4, p-value = 0.03009
alternative hypothesis: stationary
```

Fama-French RMW Factor of Emerging Countries

25. RMW_E: Regressions on SER_D (1) and SER_E (2)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_17
Dickey-Fuller = -6.4983, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_17) : p-value smaller than printed p-value
```

26. $RMW_{E\ (Bond\ Reg)}$: Regressions on BER_D (3) and BER_E (4)

```
        Augmented Dickey-Fuller Test

data:  RMW_Emerging_Bond_Reg_Excluded
Dickey-Fuller = -5.7866, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(RMW_Emerging_Bond_Reg_Excluded) :
  p-value smaller than printed p-value
```

Fama-French CMA Factor of Emerging Countries

27. CMA_E: Regressions on SER_D (1) and SER_E (2)

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_18
Dickey-Fuller = -6.4064, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_18) : p-value smaller than printed p-value
```

28. $CMA_{E\ (Bond\ Reg)}$: Regressions on BER_D (3) and BER_E (4)

```
        Augmented Dickey-Fuller Test

data:  CMA_Emerging_Bond_Reg_Excluded
Dickey-Fuller = -3.9131, Lag order = 4, p-value = 0.01592
alternative hypothesis: stationary
```

Correlation coefficients between share-bond excess returns

29. ρ_D: Share-bond excess returns correlation coefficients of developed countries (Regression (5))

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_21
Dickey-Fuller = -5.1089, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Numeric_data_21) : p-value smaller than printed p-value
```

30. ρ_E: Share-bond excess returns correlation coefficients of emerging countries (Regression (6))

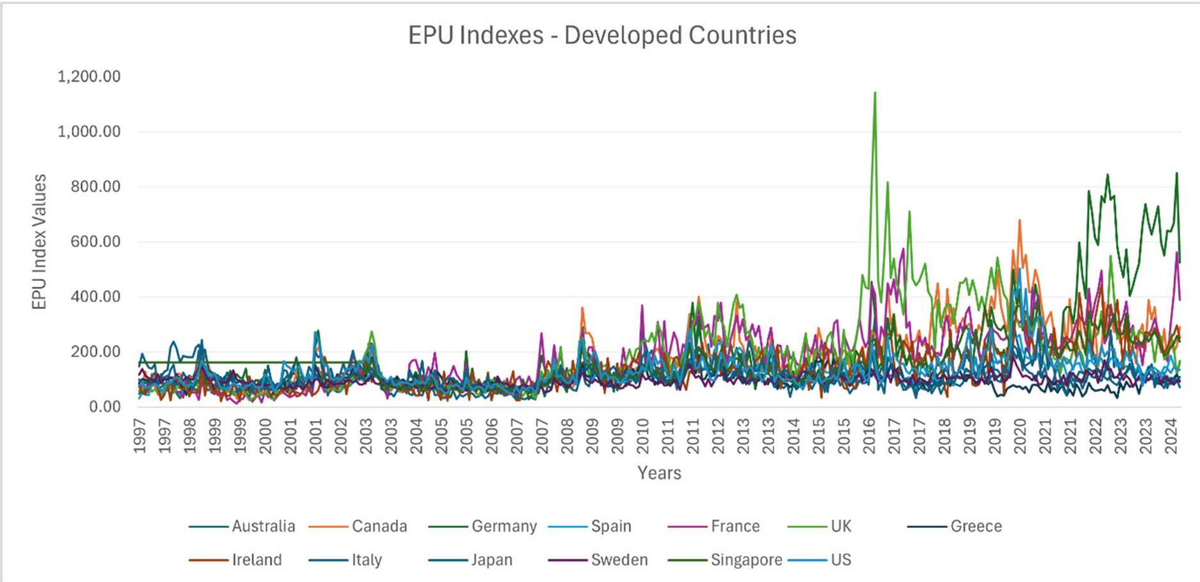
```
        Augmented Dickey-Fuller Test

data:  Numeric_data_22
Dickey-Fuller = -2.7624, Lag order = 4, p-value = 0.2637
alternative hypothesis: stationary
```

31. ρ_E: Logarithmic (ln) transformation of share-bond excess returns correlation coefficients of emerging countries (Regression (6))

```
        Augmented Dickey-Fuller Test

data:  Numeric_data_25_clean
Dickey-Fuller = -3.6841, Lag order = 4, p-value = 0.03219
alternative hypothesis: stationary
```

6.2.7 Descriptive Statistics

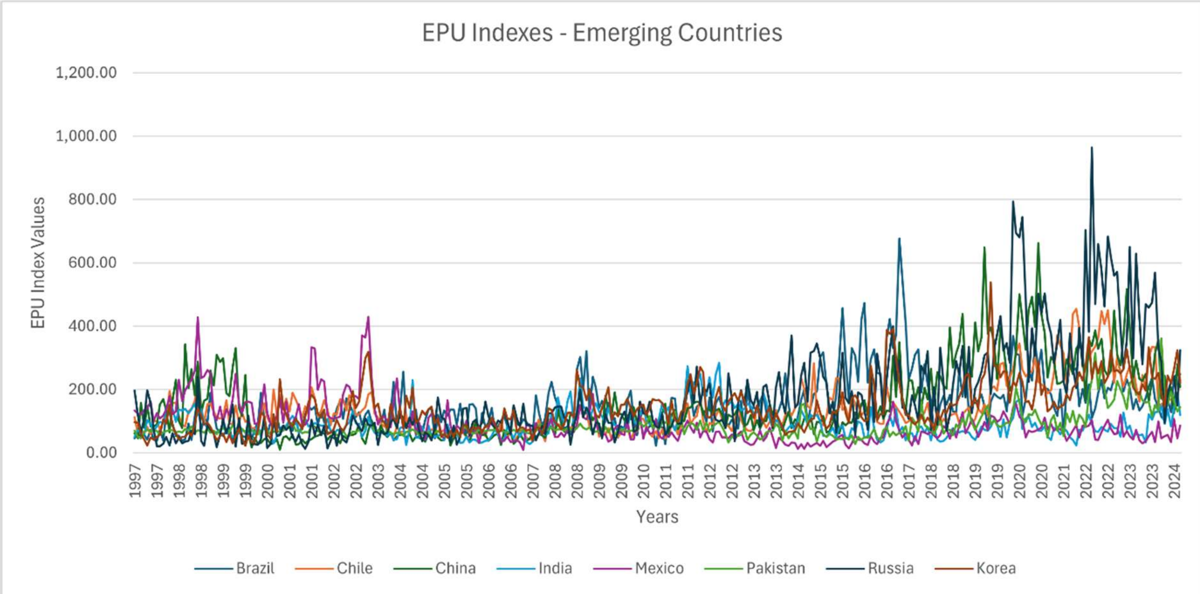
6.2.7.1 EPU Indexes of Developed Countries - Graphic representation



6.2.7.1.1 Key statistics

```
> print(min_value)
[1] 11.28731
> print(max_value)
[1] 1141.796
> print(mean_value)
[1] 139.9593
> print(sd_value)
[1] 95.28399
```

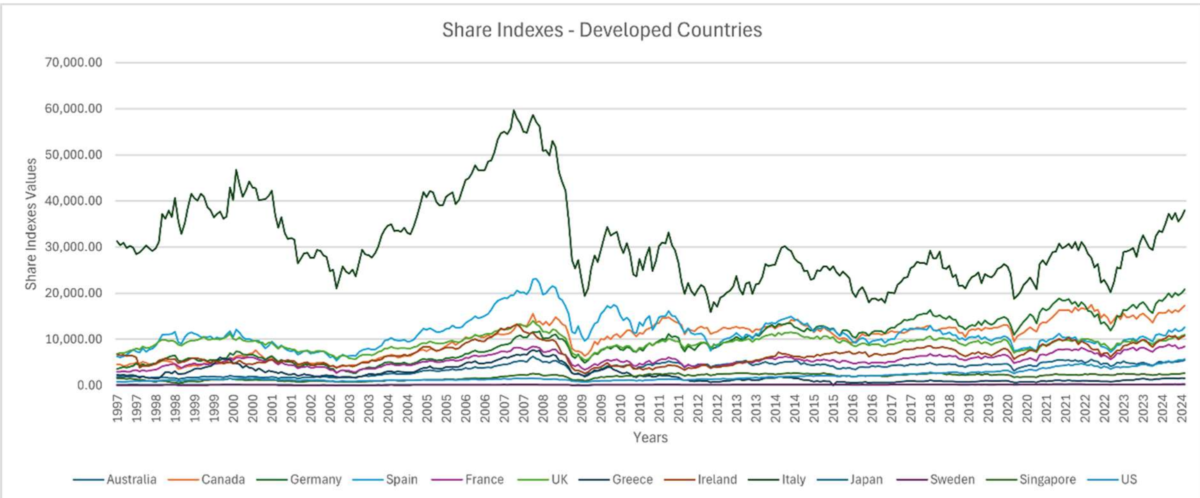
6.2.7.2 EPU Indexes of Emerging Countries - Graphic representation



6.2.7.2.1 Key statistics

```
> print(min_value)
[1] 8.508975
> print(max_value)
[1] 964.1407
> print(mean_value)
[1] 128.8677
> print(sd_value)
[1] 96.31138
```

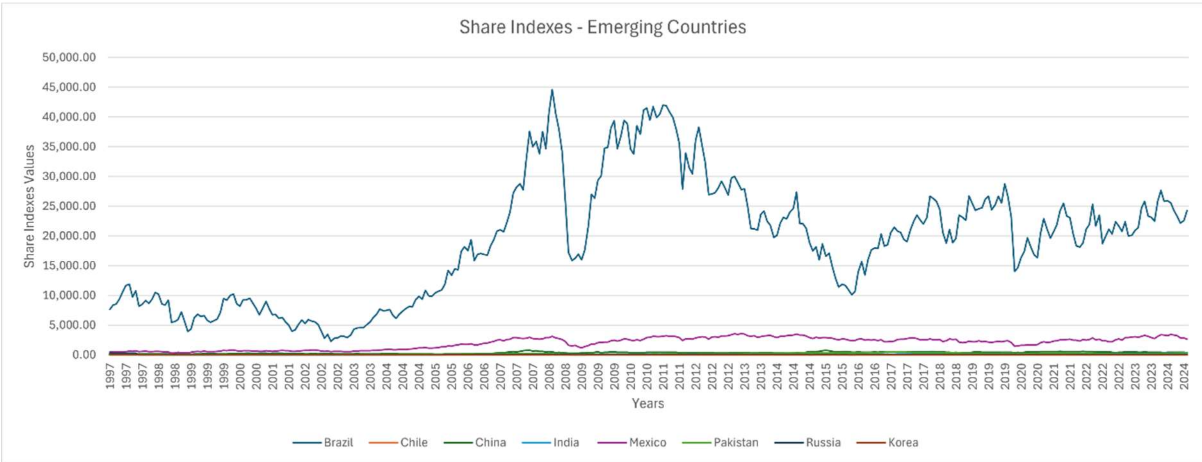
6.2.7.3 Share Indexes of Developed Countries - Graphic representation



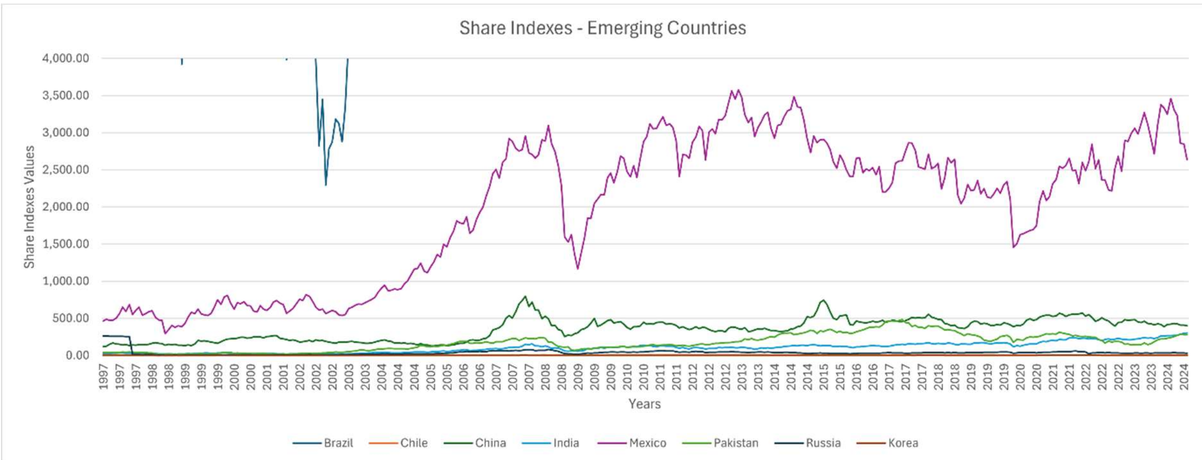
6.2.7.3.1 Key statistics

```
> print(min_value)
[1] 0
> print(max_value)
[1] 59712.45
> print(mean_value)
[1] 7227.544
> print(sd_value)
[1] 8525.061
```

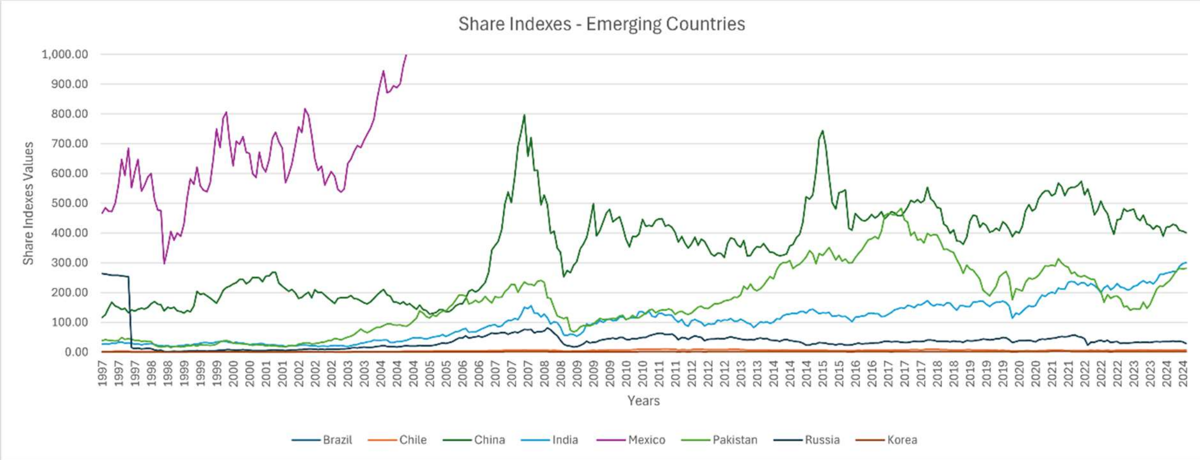
6.2.7.4 Share Indexes of Emerging Countries - Graphic representations



N.B.: Scale: 0-50,000 (Share Indexes Values)



N.B.: Scale: 0-4000 (Share Indexes Values)

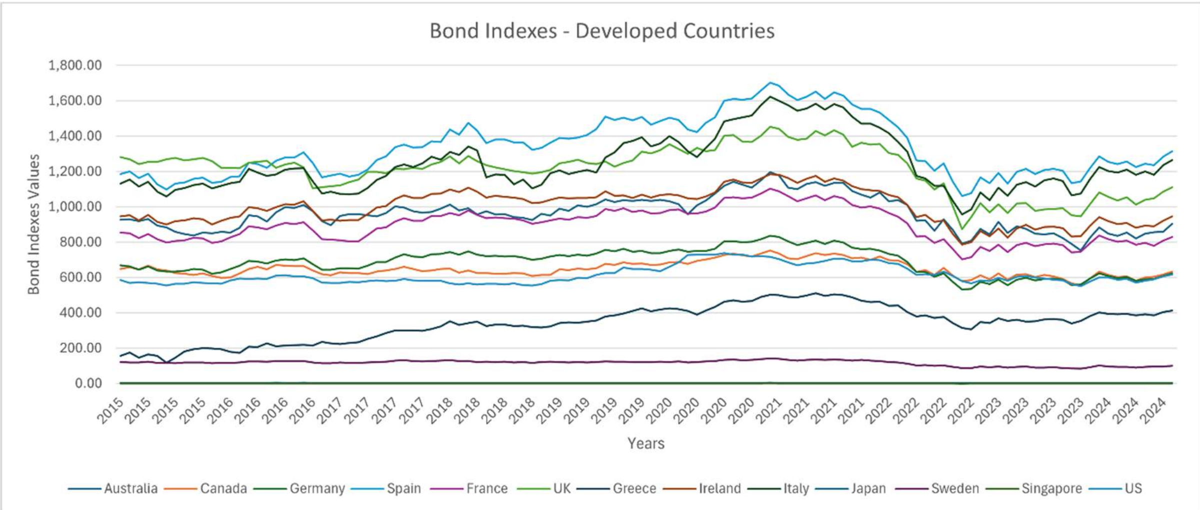


N.B.: Scale: 0-1,000 (Share Indexes Values)

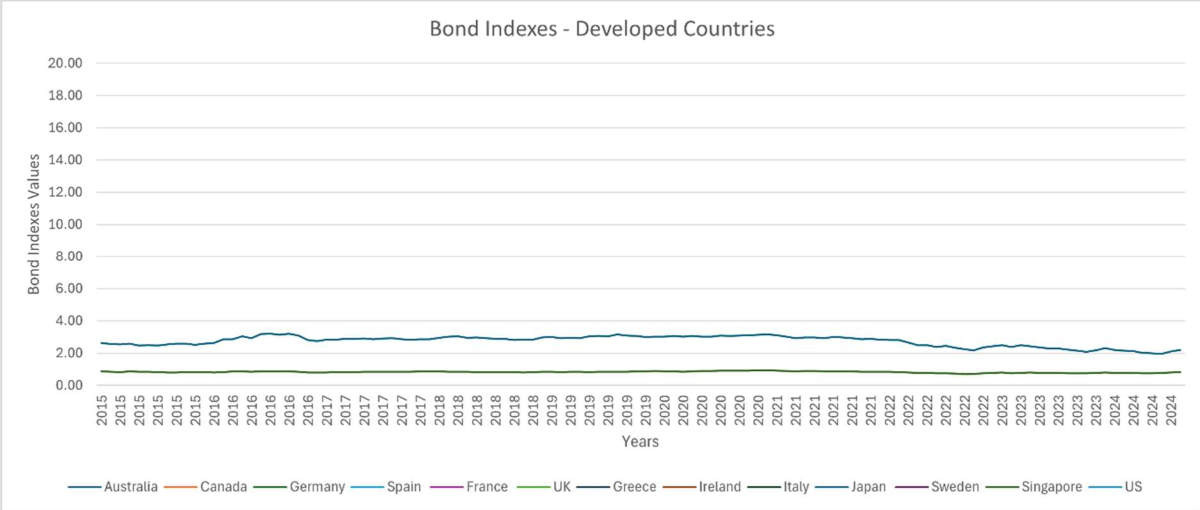
6.2.7.4.1 Key statistics

```
> print(min_value)
[1] 0.2169556
> print(max_value)
[1] 44629.56
> print(mean_value)
[1] 2710.235
> print(sd_value)
[1] 7186.367
```

6.2.7.5 Bond Indexes of Developed Countries - Graphic representations



N.B.: Scale: 0-1,800 (Bond Indexes Values)

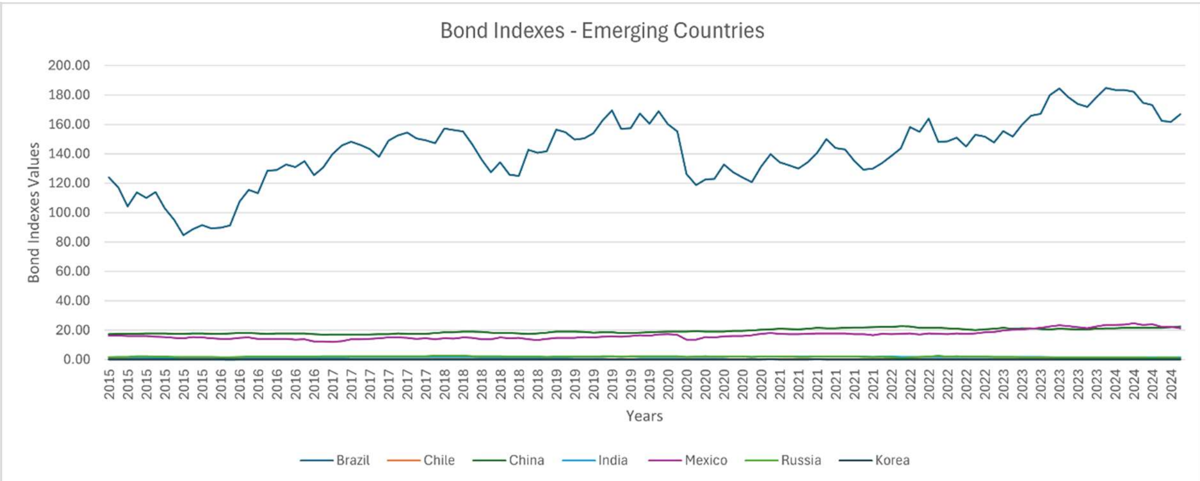


N.B.: Scale: 0-20 (Bond Indexes Values)

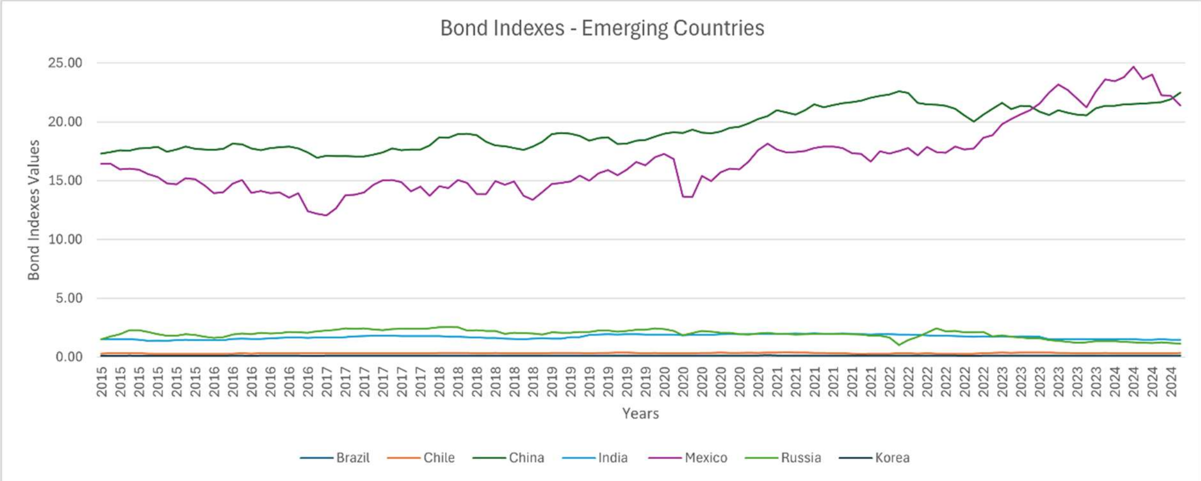
6.2.7.5.1 Key statistics

```
> print(min_value)
[1] 0.7027685
> print(max_value)
[1] 1703.372
> print(mean_value)
[1] 697.0787
> print(sd_value)
[1] 458.4711
```

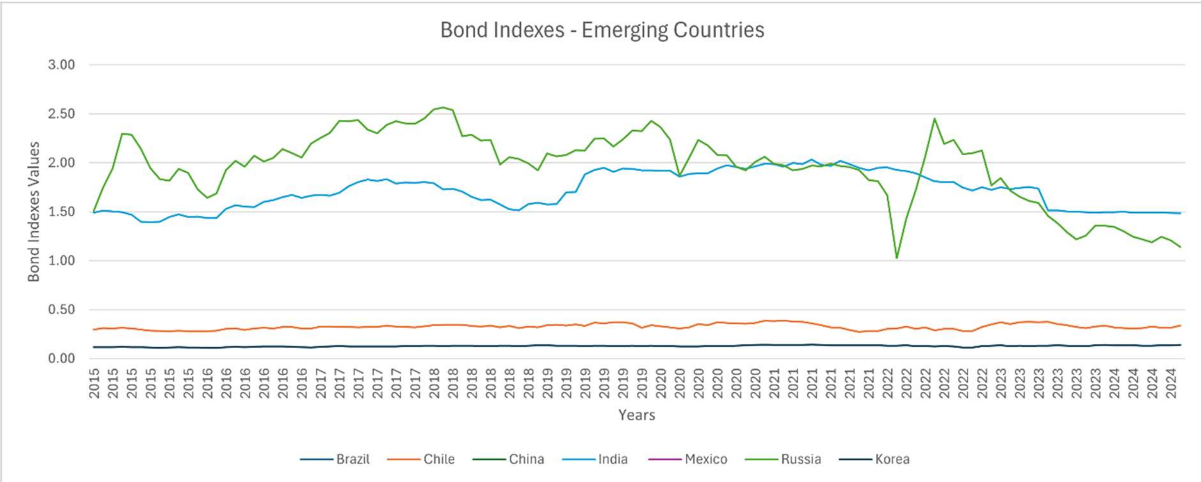
6.2.7.6 Bond Indexes of Emerging Countries - Graphic representations



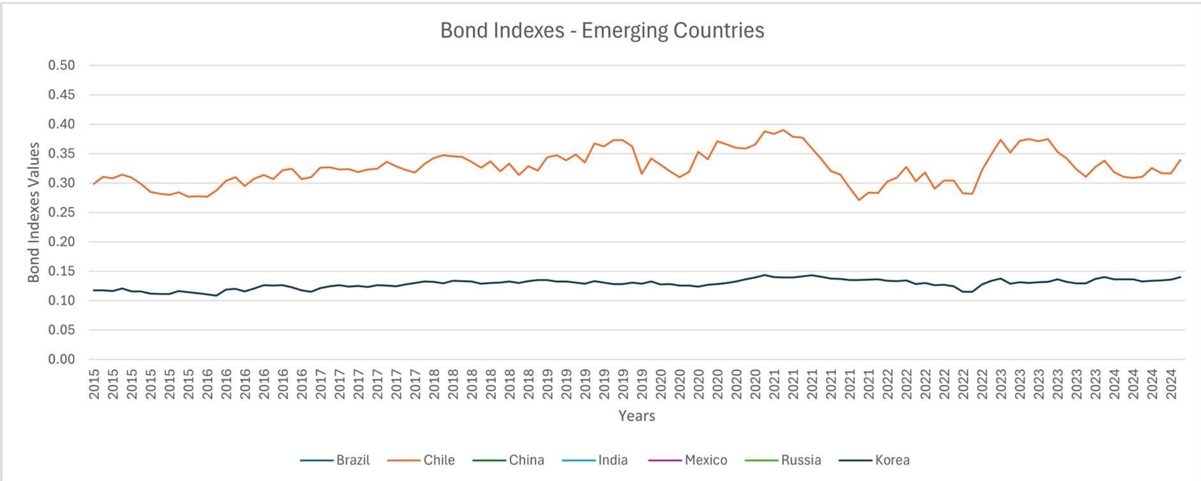
N.B.: Scale: 0-200 (Bond Indexes Values)



N.B: Scale: 0-25 (Bond Indexes Values)



N.B.: Scale: 0-3 (Bond Indexes Values)

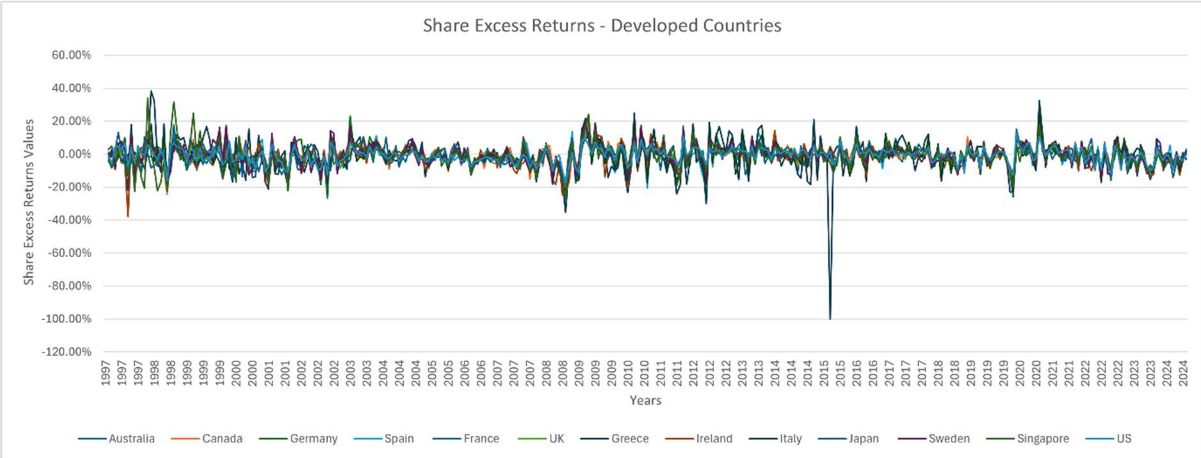


N.B.: Scale: 0-0.5 (Bond Indexes Values)

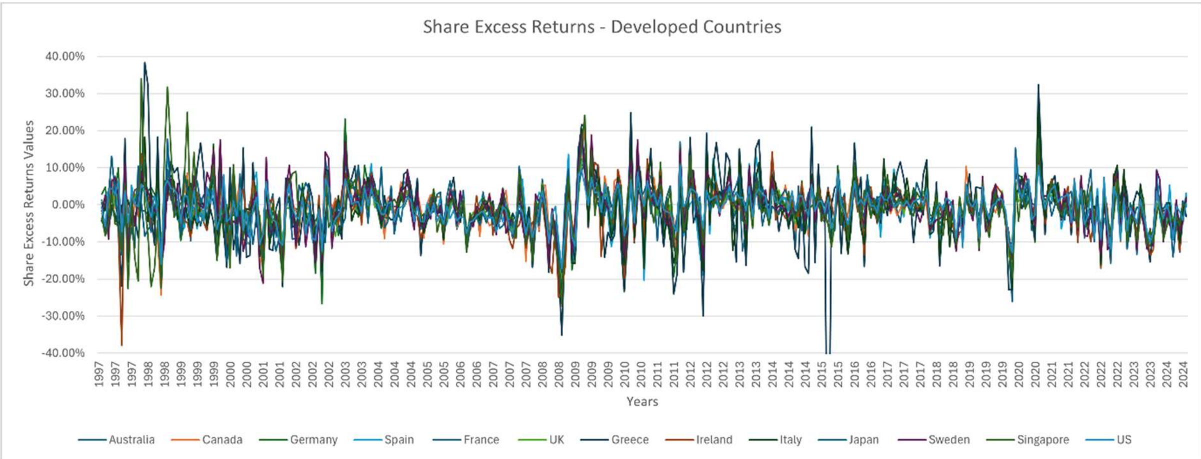
6.2.7.6.1 Key statistics

```
> print(min_value)
[1] 0.108856
> print(max_value)
[1] 184.8153
> print(mean_value)
[1] 26.05405
> print(sd_value)
[1] 48.79224
```

6.2.7.7 Share Excess Returns of Developed Countries - Graphic representations



N.B.: Scale: -120% to 60% (Share Excess Returns Values)

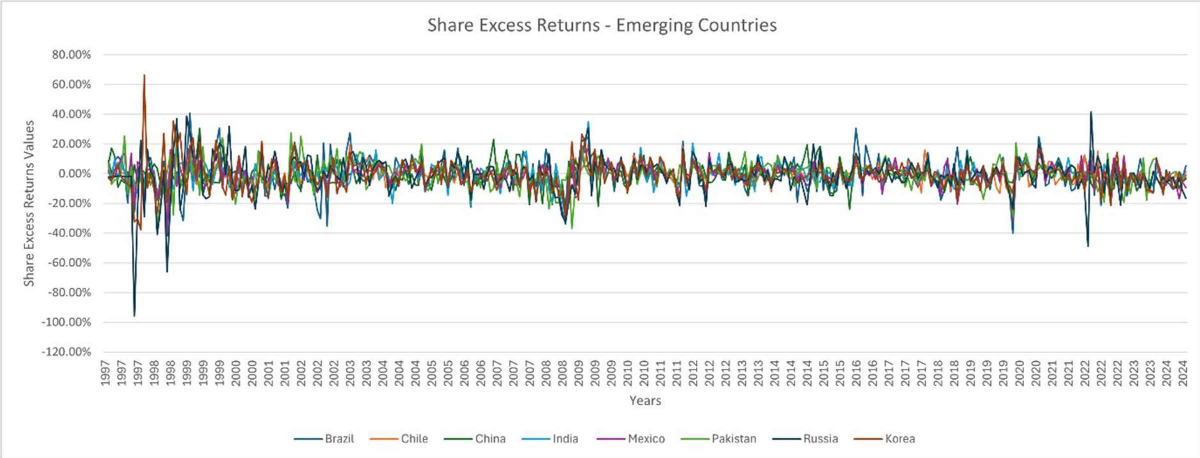


N.B.: Scale: -40% to 40% (Share Excess Returns Values)

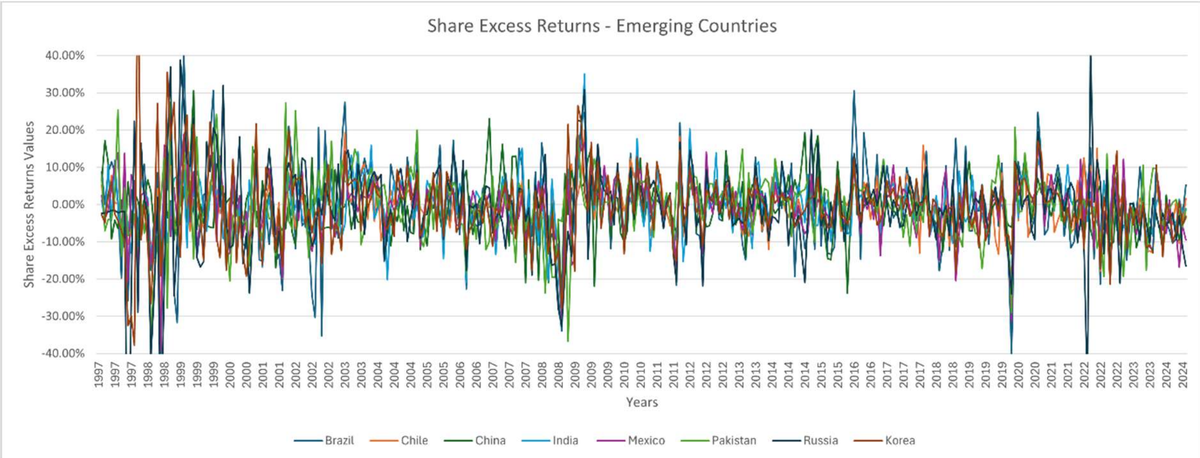
6.2.7.7.1 Key statistics

```
> print(min_value)
[1] -1.0003
> print(max_value)
[1] 0.3835151
> print(mean_value)
[1] -0.01008604
> print(sd_value)
[1] 0.06819636
```

6.2.7.8 Share Excess Returns of Emerging Countries - Graphic representations



N.B.: Scale: -120% to 80% (Share Excess Returns Values)

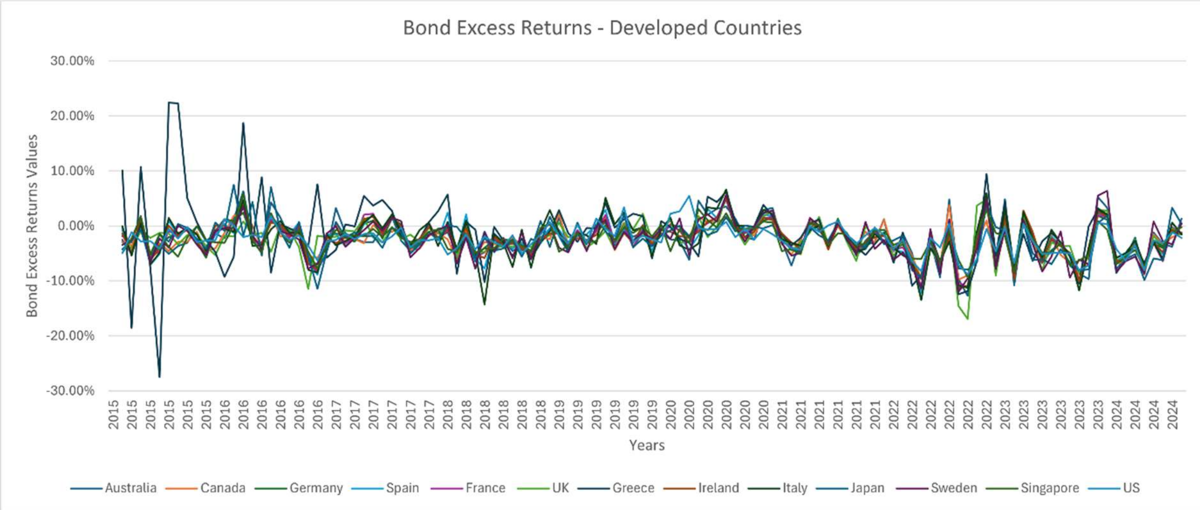


N.B.: Scale: -40% to 40% (Share Excess Returns Values)

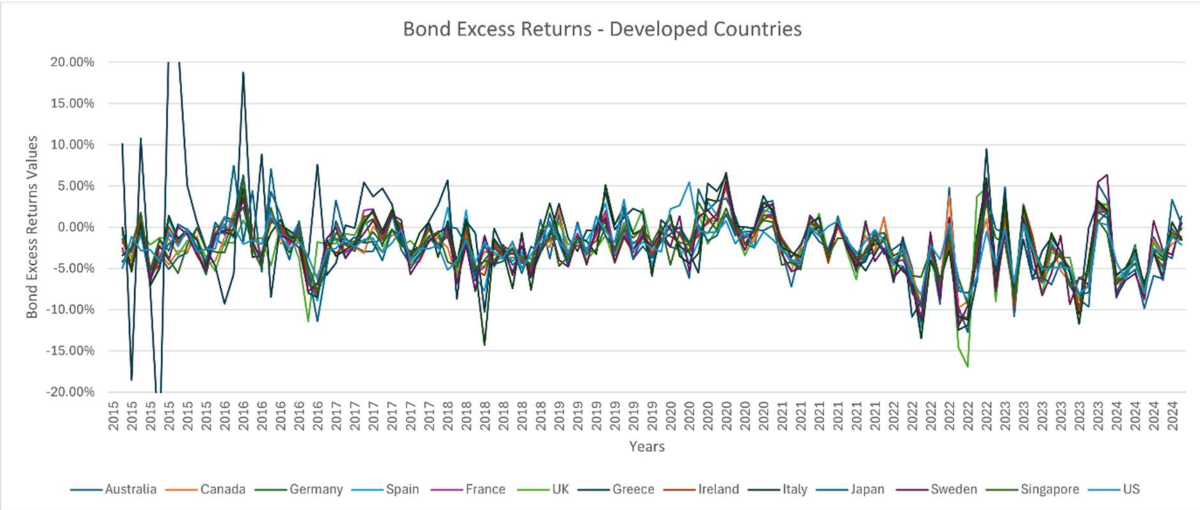
6.2.7.8.1 Key statistics

```
> print(min_value)
[1] -0.9570924
> print(max_value)
[1] 0.662175
> print(mean_value)
[1] -0.006481555
> print(sd_value)
[1] 0.09354489
```

6.2.7.9 Bond Excess Returns of Developed Countries - Graphic representations



N.B.: Scale: -30% to 30% (Bond Excess Returns Values)

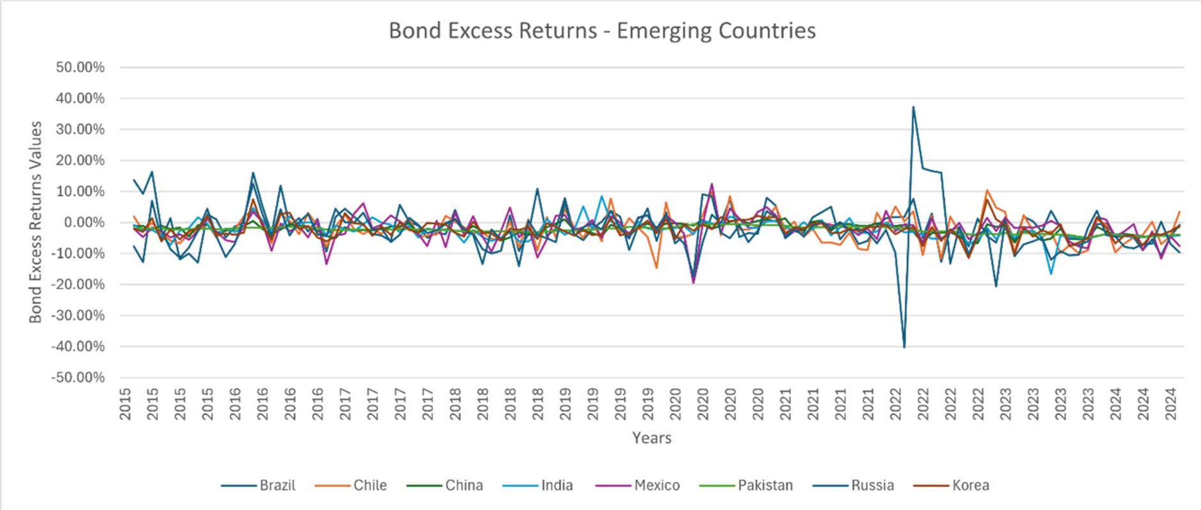


N.B.: Scale: -20% to 20% (Bond Excess Returns Values)

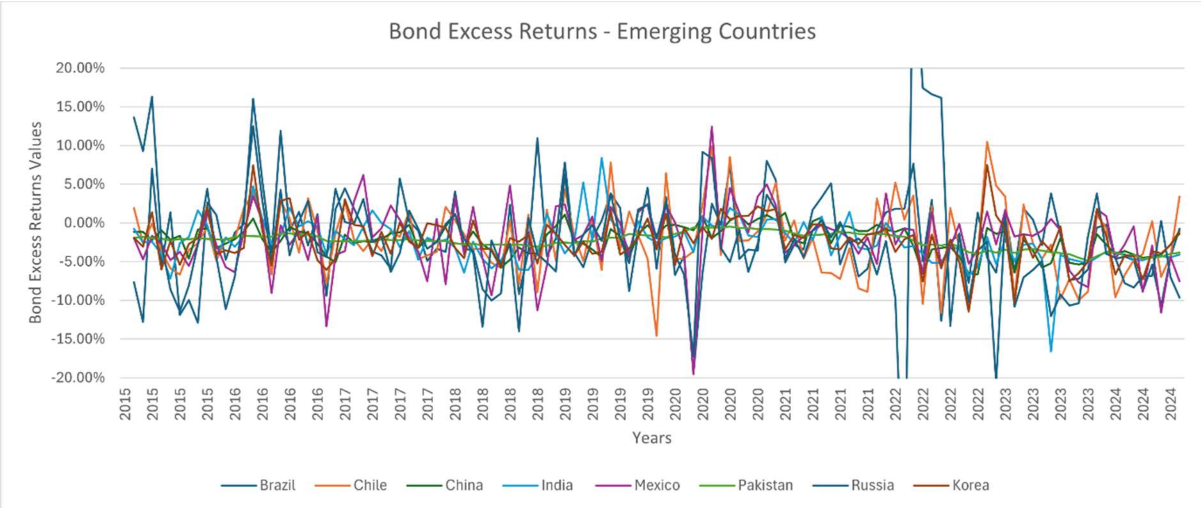
6.2.7.9.1 Key statistics

```
> print(min_value)
[1] -0.2750267
> print(max_value)
[1] 0.2241469
> print(mean_value)
[1] -0.02323011
> print(sd_value)
[1] 0.03610588
```

6.2.7.10 Bond Excess Returns of Emerging Countries - Graphic representations



N.B.: Scale: -50% to 50% (Bond Excess Returns Values)

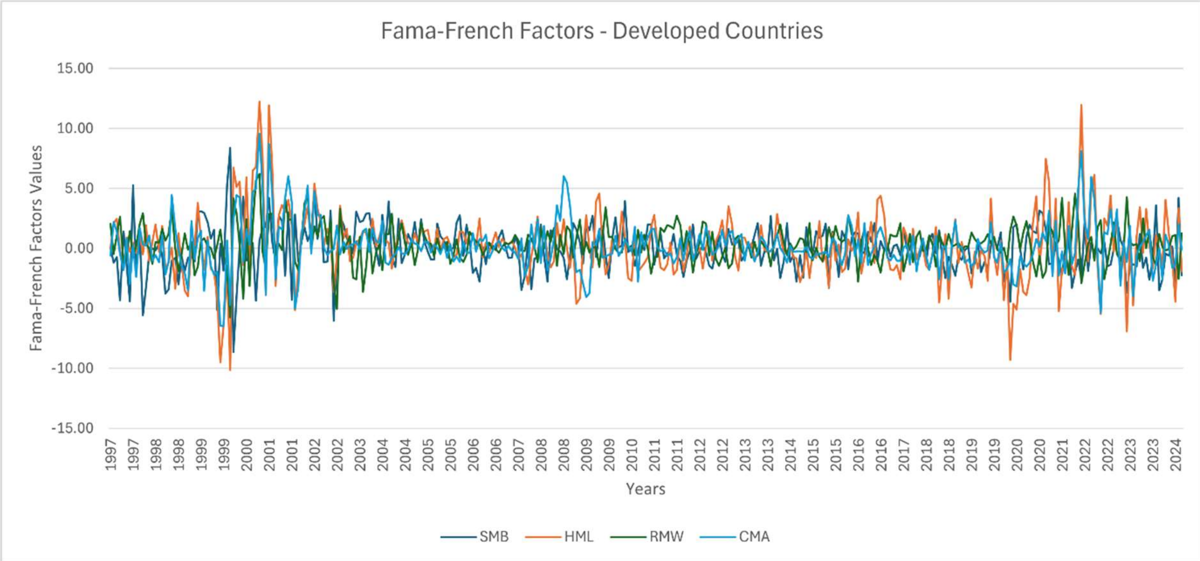


N.B.: Scale: -20% to 20% (Bond Excess Returns Values)

6.2.7.10.1 Key statistics

```
> print(min_value)
[1] -0.4032657
> print(max_value)
[1] 0.373544
> print(mean_value)
[1] -0.02221537
> print(sd_value)
[1] 0.04493817
```

6.2.7.11 Fama-French Factors of Developed Countries - Graphic representation



N.B.: Scale: -15% to 15% (Fama-French Factors Values)

6.2.7.11.1 Key statistics

6.2.7.11.1.1 SMB Factor

```
> print(min_value)
[1] -8.64
> print(max_value)
[1] 8.37
> print(mean_value)
[1] -0.01262048
> print(sd_value)
[1] 1.966949
```

6.2.7.11.1.2 HML Factor

```
> print(min_value)
[1] -10.15
> print(max_value)
[1] 12.24
> print(mean_value)
[1] 0.2152108
> print(sd_value)
[1] 2.784517
```

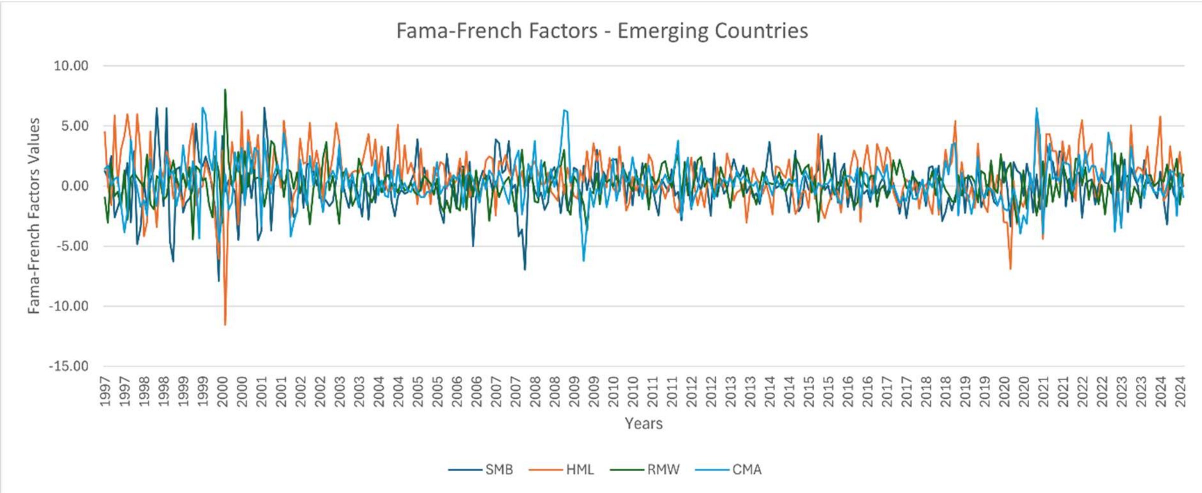
6.2.7.11.1.3 RMW Factor

```
> print(min_value)
[1] -5.75
> print(max_value)
[1] 6.2
> print(mean_value)
[1] 0.3631928
> print(sd_value)
[1] 1.547761
```

6.2.7.11.1.4 CMA Factor

```
> print(min_value)
[1] -6.46
> print(max_value)
[1] 9.58
> print(mean_value)
[1] 0.194488
> print(sd_value)
[1] 2.055384
```

6.2.7.12 Fama-French Factors of Emerging Countries - Graphic representation



N.B.: Scale: -15 to 10 (Fama-French Factors Values)

6.2.7.12.1 Key statistics

6.2.7.12.1.1 SMB Factor

```
> print(min_value)
[1] -7.89
> print(max_value)
[1] 6.52
> print(mean_value)
[1] -0.008283133
> print(sd_value)
[1] 1.934778
```

6.2.7.12.1.2 HML Factor

```
> print(min_value)
[1] -11.54
> print(max_value)
[1] 6.2
> print(mean_value)
[1] 0.7662048
> print(sd_value)
[1] 2.251002
```

6.2.7.12.1.3 RMW Factor

```
> print(min_value)
[1] -4.44
> print(max_value)
[1] 8.05
> print(mean_value)
[1] 0.2110241
> print(sd_value)
[1] 1.41767
```

6.2.7.12.1.4 CMA Factor

```
[1] -6.22
> print(max_value)
[1] 6.53
> print(mean_value)
[1] 0.3242771
> print(sd_value)
[1] 1.797746
```

6.3 Findings

6.3.1 Linear regressions results

6.3.1.1 Multiple linear regression on SER_D (1)

```
Call:
lm(formula = Australia_SER + Canada_SER + Germany_SER + Spain_SER +
    France_SER + UK_SER + Greece_SER + Ireland_SER + Italy_SER +
    Japan_SER + Sweden_SER + Singapore_SER + US_SER ~ log10(Australia_EPU +
    Canada_EPU + Germany_EPU + Spain_EPU + France_EPU + UK_EPU +
    Greece_EPU + Ireland_EPU + Italy_EPU + Japan_EPU + Sweden_EPU +
    Singapore_EPU + US_EPU) + SMB_Developed + HML_Developed +
    RMW_Developed + CMA_Developed, data = Regression_SER_DEV_Data,
    na.action = na.omit)

Residuals:
     Min       1Q   Median       3Q      Max
-1.79672 -0.37188  0.03316  0.37117  1.82860

Coefficients:

Estimate
(Intercept)
-0.654471
log10(Australia_EPU + Canada_EPU + Germany_EPU + Spain_EPU + France_EPU + UK_EPU + Greece_EPU
+ Ireland_EPU + Italy_EPU + Japan_EPU + Sweden_EPU + Singapore_EPU + US_EPU)  0.182206
SMB_Developed
-0.008997
HML_Developed
0.120246
RMW_Developed
-0.123981
CMA_Developed
-0.223656
```

```
Std. Error
(Intercept)
0.633095
log10(Australia_EPU + Canada_EPU + Germany_EPU + Spain_EPU + France_EPU + UK_EPU + Greece_EPU
+ Ireland_EPU + Italy_EPU + Japan_EPU + Sweden_EPU + Singapore_EPU + US_EPU)   0.195873
SMB_Developed
0.018298
HML_Developed
0.019303
RMW_Developed
0.023538
CMA_Developed
0.026153

t value
(Intercept)
-1.034
log10(Australia_EPU + Canada_EPU + Germany_EPU + Spain_EPU + France_EPU + UK_EPU + Greece_EPU
+ Ireland_EPU + Italy_EPU + Japan_EPU + Sweden_EPU + Singapore_EPU + US_EPU)   0.930
SMB_Developed
-0.492
HML_Developed
6.229
RMW_Developed
-5.267
CMA_Developed
-8.552

Pr(>|t|)
(Intercept)
0.302
log10(Australia_EPU + Canada_EPU + Germany_EPU + Spain_EPU + France_EPU + UK_EPU + Greece_EPU
+ Ireland_EPU + Italy_EPU + Japan_EPU + Sweden_EPU + Singapore_EPU + US_EPU)    0.353
SMB_Developed
0.623
HML_Developed
1.45e-09
RMW_Developed
2.53e-07
CMA_Developed
4.88e-16

(Intercept)
log10(Australia_EPU + Canada_EPU + Germany_EPU + Spain_EPU + France_EPU + UK_EPU + Greece_EPU
+ Ireland_EPU + Italy_EPU + Japan_EPU + Sweden_EPU + Singapore_EPU + US_EPU)
SMB_Developed
HML_Developed
***
RMW_Developed
***
CMA_Developed
***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6174 on 324 degrees of freedom
  (2 observations deleted due to missingness)
Multiple R-squared:  0.284,     Adjusted R-squared:  0.2729
F-statistic:  25.7 on 5 and 324 DF,  p-value: < 2.2e-16
```

6.3.1.2 Multiple linear regression on SER_E (2)

```
Call:
lm(formula = Brazil_SER + Chile_SER + China_SER + India_SER +
    Mexico_SER + Pakistan_SER + Russia_SER + Korea_SER ~ log10(Brazil_EPU +
    Chile_EPU + China_EPU + India_EPU + Mexico_EPU + Pakistan_EPU +
    Russia_EPU + Korea_EPU) + SMB_Emerging + HML_Emerging + RMW_Emerging +
    CMA_Emerging, data = Regression_SER_EMR_Data, na.action = na.omit)

Residuals:
     Min       1Q   Median       3Q      Max
-1.79329 -0.22639  0.03808  0.26198  1.61487

Coefficients:

Estimate
(Intercept)
0.74724
log10(Brazil_EPU + Chile_EPU + China_EPU + India_EPU + Mexico_EPU + Pakistan_EPU + Russia_EPU
+ Korea_EPU) -0.26183
SMB_Emerging
-0.08017
HML_Emerging
0.03511
RMW_Emerging
-0.07326
CMA_Emerging
-0.09585

Std. Error
(Intercept)
0.43745
log10(Brazil_EPU + Chile_EPU + China_EPU + India_EPU + Mexico_EPU + Pakistan_EPU + Russia_EPU
+ Korea_EPU)    0.14635
SMB_Emerging
0.01292
HML_Emerging
0.01330
RMW_Emerging
0.01983
CMA_Emerging
0.01485

t value
(Intercept)
1.708
log10(Brazil_EPU + Chile_EPU + China_EPU + India_EPU + Mexico_EPU + Pakistan_EPU + Russia_EPU
+ Korea_EPU)  -1.789
SMB_Emerging
-6.207
HML_Emerging
2.640
RMW_Emerging
-3.694
CMA_Emerging
-6.454

Pr(>|t|)
(Intercept)
0.088562
log10(Brazil_EPU + Chile_EPU + China_EPU + India_EPU + Mexico_EPU + Pakistan_EPU + Russia_EPU
+ Korea_EPU) 0.074530
SMB_Emerging
1.65e-09
HML_Emerging
0.008680
RMW_Emerging
0.000258
CMA_Emerging
3.95e-10
```

```
(Intercept)
.
log10(Brazil_EPU + Chile_EPU + China_EPU + India_EPU + Mexico_EPU + Pakistan_EPU + Russia_EPU
+ Korea_EPU) .
SMB_Emerging
***
HML_Emerging
**
RMW_Emerging
***
CMA_Emerging
***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.446 on 325 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.2514,    Adjusted R-squared:  0.2399
F-statistic: 21.83 on 5 and 325 DF,  p-value: < 2.2e-16
```

6.3.1.3 Multiple linear regression on BER_D (3)

```
Call:
lm(formula = Australia_BER + Canada_BER + Germany_BER + Spain_BER +
    France_BER + UK_BER + Greece_BER + Ireland_BER + Italy_BER +
    Japan_BER + Sweden_BER + Singapore_BER + US_BER ~ log10(Australia_EPU +
    Canada_EPU + Germany_EPU + Spain_EPU + France_EPU + UK_EPU +
    Greece_EPU + Ireland_EPU + Italy_EPU + Japan_EPU + Sweden_EPU +
    Singapore_EPU + US_EPU) + SMB_Developed + HML_Developed +
    RMW_Developed + CMA_Developed, data = Regression_BER_DVP_Data,
    na.action = na.omit)

Residuals:
     Min       1Q   Median       3Q      Max
-0.91513 -0.15457  0.03105  0.21770  0.76689

Coefficients:

Estimate
(Intercept)
-1.219564
log10(Australia_EPU + Canada_EPU + Germany_EPU + Spain_EPU + France_EPU + UK_EPU + Greece_EPU
+ Ireland_EPU + Italy_EPU + Japan_EPU + Sweden_EPU + Singapore_EPU + US_EPU)  0.267415
SMB_Developed
0.057904
HML_Developed
-0.003322
RMW_Developed
0.067555
CMA_Developed
-0.041344
```

```
Std. Error
(Intercept)
1.236431
log10(Australia_EPU + Canada_EPU + Germany_EPU + Spain_EPU + France_EPU + UK_EPU + Greece_EPU
+ Ireland_EPU + Italy_EPU + Japan_EPU + Sweden_EPU + Singapore_EPU + US_EPU)   0.364116
SMB_Developed
0.023241
HML_Developed
0.022665
RMW_Developed
0.032690
CMA_Developed
0.031254

t value
(Intercept)
-0.986
log10(Australia_EPU + Canada_EPU + Germany_EPU + Spain_EPU + France_EPU + UK_EPU + Greece_EPU
+ Ireland_EPU + Italy_EPU + Japan_EPU + Sweden_EPU + Singapore_EPU + US_EPU)   0.734
SMB_Developed
2.491
HML_Developed
-0.147
RMW_Developed
2.067
CMA_Developed
-1.323

Pr(>|t|)
(Intercept)
0.3261
log10(Australia_EPU + Canada_EPU + Germany_EPU + Spain_EPU + France_EPU + UK_EPU + Greece_EPU
+ Ireland_EPU + Italy_EPU + Japan_EPU + Sweden_EPU + Singapore_EPU + US_EPU)   0.4643
SMB_Developed
0.0142
HML_Developed
0.8837
RMW_Developed
0.0411
CMA_Developed
0.1887

(Intercept)
log10(Australia_EPU + Canada_EPU + Germany_EPU + Spain_EPU + France_EPU + UK_EPU + Greece_EPU
+ Ireland_EPU + Italy_EPU + Japan_EPU + Sweden_EPU + Singapore_EPU + US_EPU)
SMB_Developed
*
HML_Developed
RMW_Developed
*
CMA_Developed
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3611 on 109 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.1539,    Adjusted R-squared:  0.115
F-statistic: 3.964 on 5 and 109 DF,  p-value: 0.002426
```

6.3.1.4 Multiple linear regression on BER_E (4)

```
Call:
lm(formula = Brazil_BER + Chile_BER + China_BER + India_BER +
    Mexico_BER + Pakistan_BER + Russia_BER + Korea_BER ~ log10(Brazil_EPU +
    Chile_EPU + China_EPU + India_EPU + Mexico_EPU + Pakistan_EPU +
    Russia_EPU + Korea_EPU) + SMB_Emerging + HML_Emerging + RMW_Emerging +
    CMA_Emerging, data = Regression_BER_EMR_Data, na.action = na.omit)

Residuals:
    Min      1Q  Median      3Q     Max
-0.4834 -0.1272  0.0061  0.1138  0.4984

Coefficients:

Estimate
(Intercept)
-0.54851
log10(Brazil_EPU + Chile_EPU + China_EPU + India_EPU + Mexico_EPU + Pakistan_EPU + Russia_EPU
+ Korea_EPU)  0.11902
SMB_Emerging
-0.02557
HML_Emerging
0.01186
RMW_Emerging
-0.04499
CMA_Emerging
-0.02516

Std. Error
(Intercept)
0.45508
log10(Brazil_EPU + Chile_EPU + China_EPU + India_EPU + Mexico_EPU + Pakistan_EPU + Russia_EPU
+ Korea_EPU)    0.14466
SMB_Emerging
0.01290
HML_Emerging
0.01169
RMW_Emerging
0.01705
CMA_Emerging
0.01533

t value
(Intercept)
-1.205
log10(Brazil_EPU + Chile_EPU + China_EPU + India_EPU + Mexico_EPU + Pakistan_EPU + Russia_EPU
+ Korea_EPU)   0.823
SMB_Emerging
-1.982
HML_Emerging
1.014
RMW_Emerging
-2.639
CMA_Emerging
-1.642

Pr(>|t|)
(Intercept)
0.23069
log10(Brazil_EPU + Chile_EPU + China_EPU + India_EPU + Mexico_EPU + Pakistan_EPU + Russia_EPU
+ Korea_EPU)  0.41244
SMB_Emerging
0.05004
HML_Emerging
0.31266
RMW_Emerging
0.00953
CMA_Emerging
0.10355
```

```
(Intercept)
log10(Brazil_EPU + Chile_EPU + China_EPU + India_EPU + Mexico_EPU + Pakistan_EPU + Russia_EPU
+ Korea_EPU)
SMB_Emerging
.
HML_Emerging
RMW_Emerging
**
CMA_Emerging
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2011 on 109 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.1072,    Adjusted R-squared:  0.0662
F-statistic: 2.616 on 5 and 109 DF,  p-value: 0.02829
```

6.3.1.5 Regression on ρ_D (5)

```
Call:
lm(formula = Australia_CORR + Canada_CORR + Germany_CORR + Spain_CORR +
    France_CORR + UK_CORR + Greece_CORR + Ireland_CORR + Italy_CORR +
    Japan_CORR + Sweden_CORR + Singapore_CORR + US_CORR ~ log10(Australia_EPU_Diff +
    Canada_EPU_Diff + Germany_EPU_Diff + Spain_EPU_Diff + France_EPU_Diff +
    UK_EPU_Diff + Greece_EPU_Diff + Ireland_EPU_Diff + Italy_EPU_Diff +
    Japan_EPU_Diff + Sweden_EPU_Diff + Singapore_EPU_Diff + US_EPU_Diff),
    data = Regression_COR_DVP_Data, na.action = na.omit)

Residuals:
      1       2       5       6       8
-3.0440 -0.7165 -2.8417  1.8429  4.7594

Coefficients:

Estimate
(Intercept)
-2.020
log10(Australia_EPU_Diff + Canada_EPU_Diff + Germany_EPU_Diff + Spain_EPU_Diff + France_EPU_D
iff + UK_EPU_Diff + Greece_EPU_Diff + Ireland_EPU_Diff + Italy_EPU_Diff + Japan_EPU_Diff + Sw
eden_EPU_Diff + Singapore_EPU_Diff + US_EPU_Diff)    2.295

Std. Error
(Intercept)
20.090
log10(Australia_EPU_Diff + Canada_EPU_Diff + Germany_EPU_Diff + Spain_EPU_Diff + France_EPU_D
iff + UK_EPU_Diff + Greece_EPU_Diff + Ireland_EPU_Diff + Italy_EPU_Diff + Japan_EPU_Diff + Sw
eden_EPU_Diff + Singapore_EPU_Diff + US_EPU_Diff)      6.969

t value
(Intercept)
-0.101
log10(Australia_EPU_Diff + Canada_EPU_Diff + Germany_EPU_Diff + Spain_EPU_Diff + France_EPU_D
iff + UK_EPU_Diff + Greece_EPU_Diff + Ireland_EPU_Diff + Italy_EPU_Diff + Japan_EPU_Diff + Sw
eden_EPU_Diff + Singapore_EPU_Diff + US_EPU_Diff)   0.329
Pr(>|t|)
(Intercept)
0.926
log10(Australia_EPU_Diff + Canada_EPU_Diff + Germany_EPU_Diff + Spain_EPU_Diff + France_EPU_D
iff + UK_EPU_Diff + Greece_EPU_Diff + Ireland_EPU_Diff + Italy_EPU_Diff + Japan_EPU_Diff + Sw
eden_EPU_Diff + Singapore_EPU_Diff + US_EPU_Diff)    0.764

Residual standard error: 3.825 on 3 degrees of freedom
  (5 observations deleted due to missingness)
Multiple R-squared:  0.03488,   Adjusted R-squared:  -0.2868
F-statistic: 0.1084 on 1 and 3 DF,  p-value: 0.7636
```

6.3.1.6 Regression on ρ_E (6)

```
Call:
lm(formula = Brazil_CORR + Chile_CORR + China_CORR + India_CORR +
    Mexico_CORR + Pakistan_CORR + Russia_CORR + Korea_CORR ~
    log10(Brazil_EPU_DIFF + Chile_EPU_DIFF + China_EPU_DIFF +
        India_EPU_DIFF + Mexico_EPU_DIFF + Pakistan_EPU_DIFF +
        Russia_EPU_DIFF + Korea_EPU_DIFF), data = Regression_CORR_EMR_Data,
    na.action = na.omit)

Residuals:
       5        6        8
 0.29265 -0.31095  0.01829

Coefficients:

Estimate
(Intercept)
24.172
log10(Brazil_EPU_DIFF + Chile_EPU_DIFF + China_EPU_DIFF + India_EPU_DIFF + Mexico_EPU_DIFF +
Pakistan_EPU_DIFF + Russia_EPU_DIFF + Korea_EPU_DIFF)  -10.773

Std. Error
(Intercept)
12.342
log10(Brazil_EPU_DIFF + Chile_EPU_DIFF + China_EPU_DIFF + India_EPU_DIFF + Mexico_EPU_DIFF +
Pakistan_EPU_DIFF + Russia_EPU_DIFF + Korea_EPU_DIFF)      4.656

t value
(Intercept)
1.958
log10(Brazil_EPU_DIFF + Chile_EPU_DIFF + China_EPU_DIFF + India_EPU_DIFF + Mexico_EPU_DIFF +
Pakistan_EPU_DIFF + Russia_EPU_DIFF + Korea_EPU_DIFF)  -2.314

Pr(>|t|)
(Intercept)
0.301
log10(Brazil_EPU_DIFF + Chile_EPU_DIFF + China_EPU_DIFF + India_EPU_DIFF + Mexico_EPU_DIFF +
Pakistan_EPU_DIFF + Russia_EPU_DIFF + Korea_EPU_DIFF)    0.260
Residual standard error: 0.4274 on 1 degrees of freedom
  (7 observations deleted due to missingness)
Multiple R-squared:  0.8426,    Adjusted R-squared:  0.6852
F-statistic: 5.353 on 1 and 1 DF,  p-value: 0.2597
```

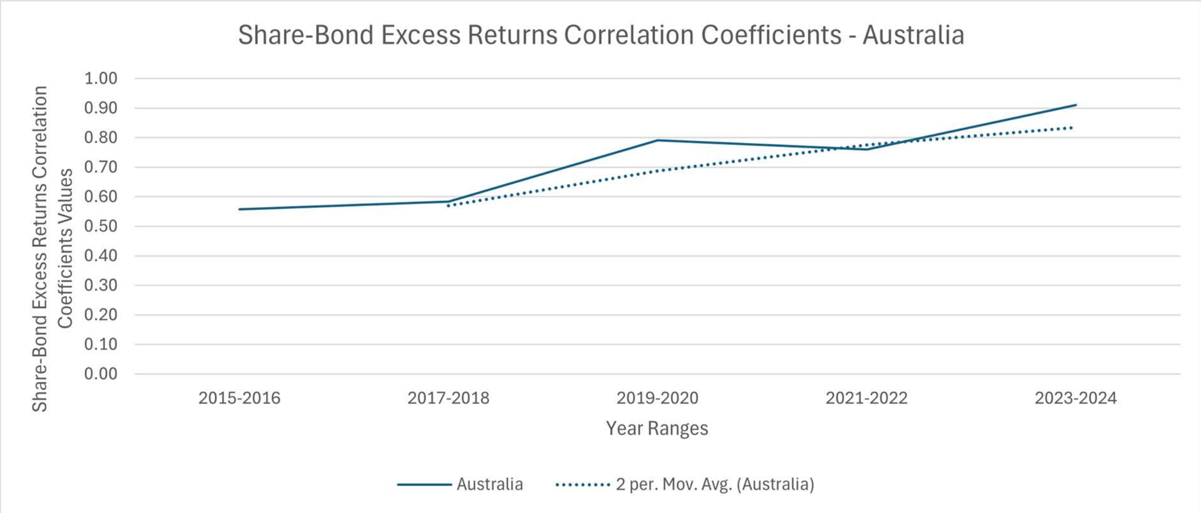
6.3.2 Per-country share-bond excess returns correlation coefficients and the 2-year EPU indexes

6.3.2.1 Developed countries – 2-year correlation coefficients

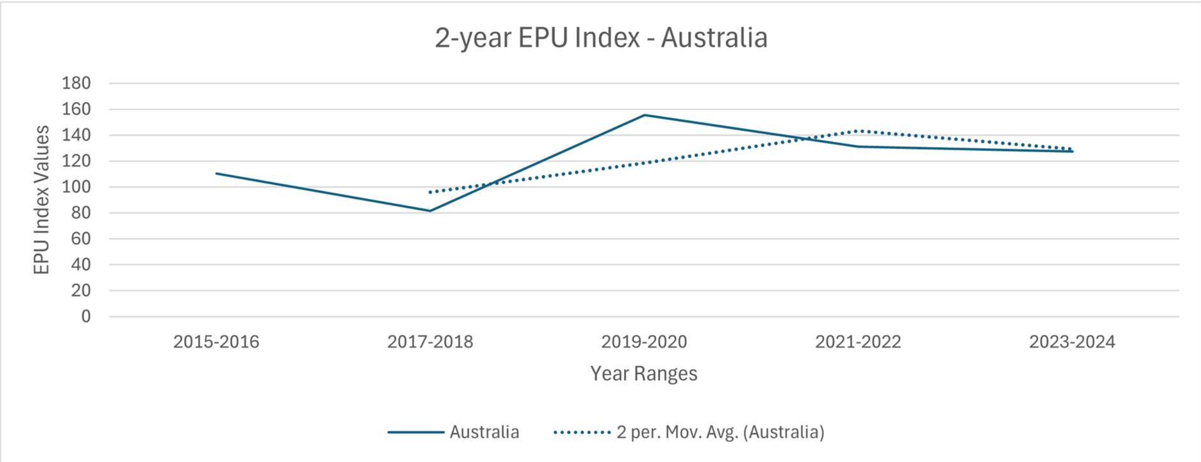
Year Ranges	AU	CA	GER	ES	FR	UK	GR	IRL	IT	JPN	SE	SG	US
2015-2016	0.56	0.72	- 0.01	0.31	0.19	0.48	-0.16	0.07	0.24	-0.11	0.04	0.73	-0.35
2017-2018	0.58	0.48	0.34	0.58	0.39	0.44	0.86	0.48	0.66	-0.16	0.48	0.42	-0.26
2019-2020	0.79	0.57	0.29	0.47	0.38	0.51	0.31	0.46	0.50	-0.06	0.48	0.40	-0.53
2021-2022	0.76	0.74	0.69	0.54	0.78	0.83	0.39	0.56	0.71	0.59	0.78	0.38	0.60
2023-2024	0.91	0.85	0.78	0.65	0.74	0.64	0.53	0.71	0.71	0.72	0.82	0.73	0.74

6.3.2.2 Graphic representations – Each developed country

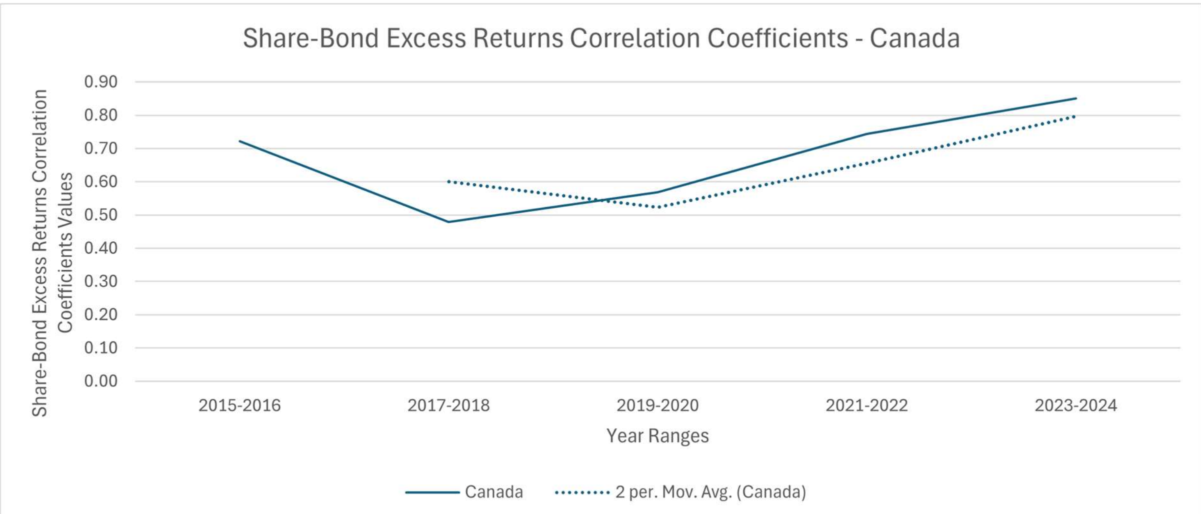
6.3.2.2.1 Share-Bond Excess Returns Correlation Coefficients – Australia



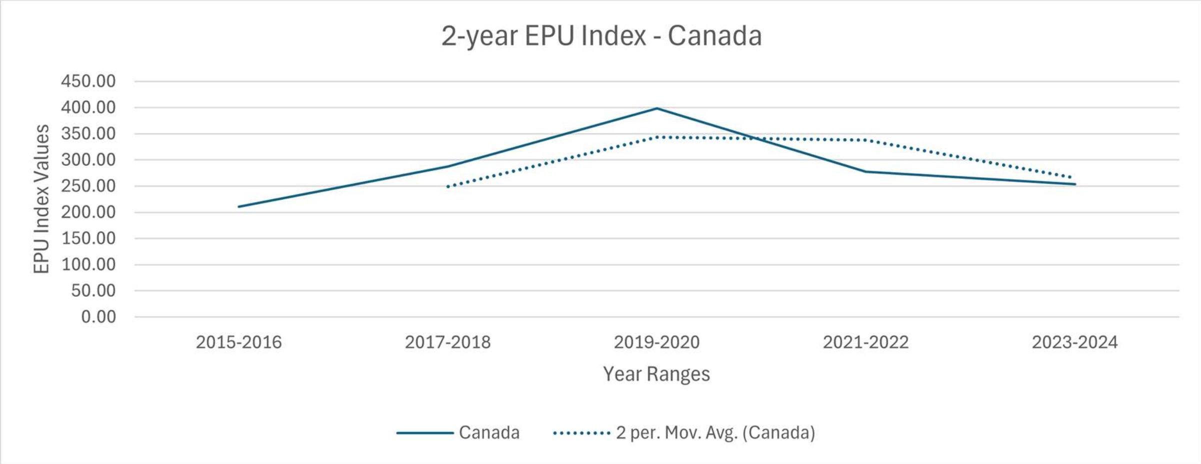
6.3.2.2.1.1 2-year EPU Index – Australia



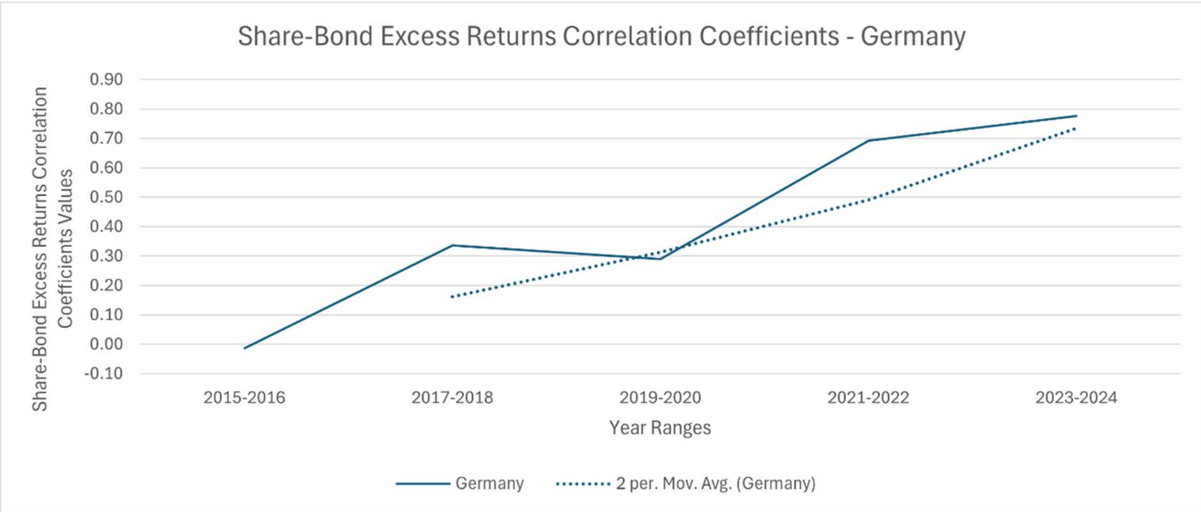
6.3.2.2.2 Share-Bond Excess Returns Correlation Coefficients – Canada



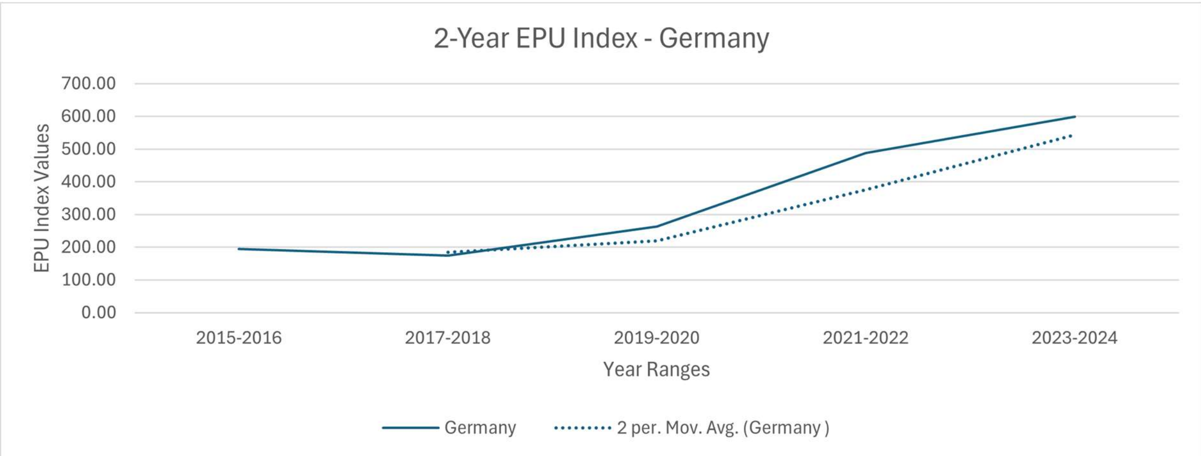
6.3.2.2.2.1 2-year EPU Index – Canada



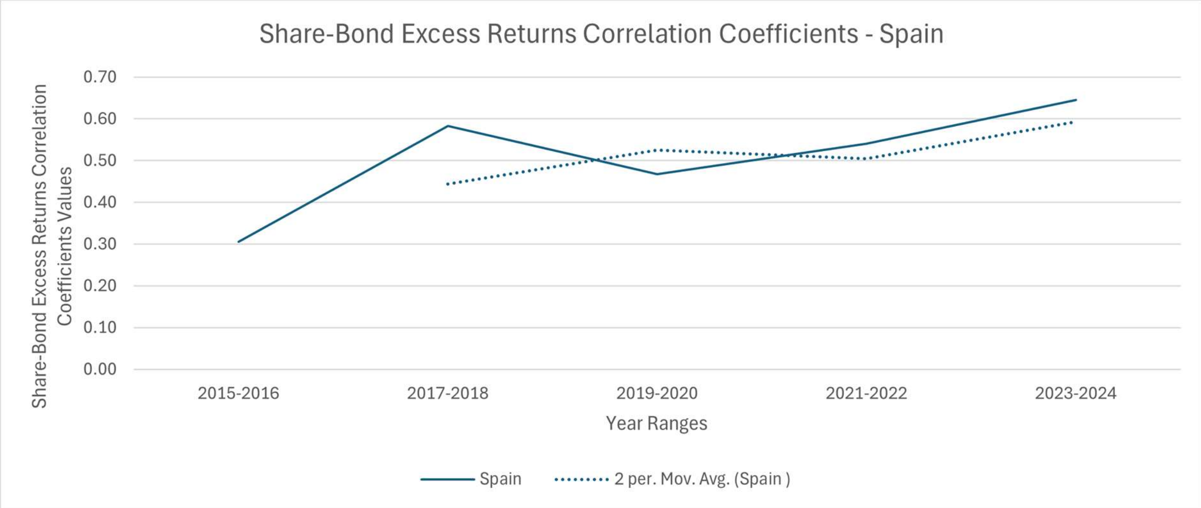
6.3.2.2.3 Share-Bond Excess Returns Correlation Coefficients – Germany



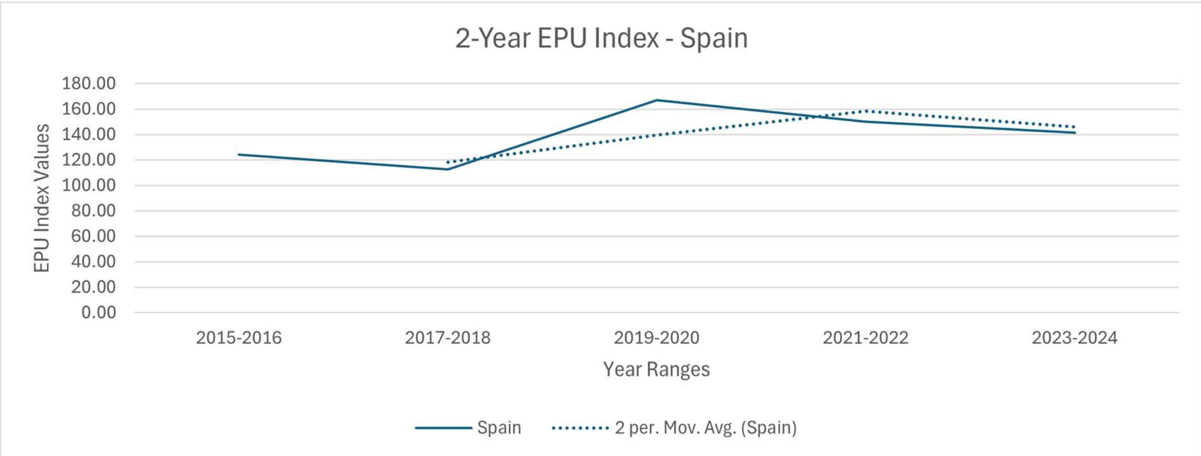
6.3.2.2.3.1 2-Year EPU Index – Germany



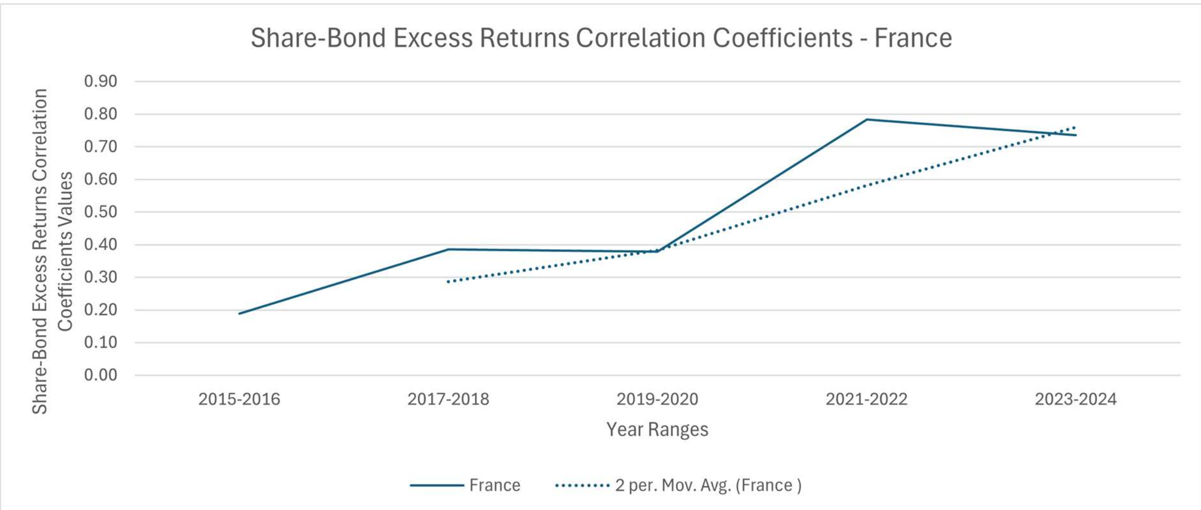
6.3.2.2.4 Share-Bond Excess Returns Correlation Coefficients – Spain



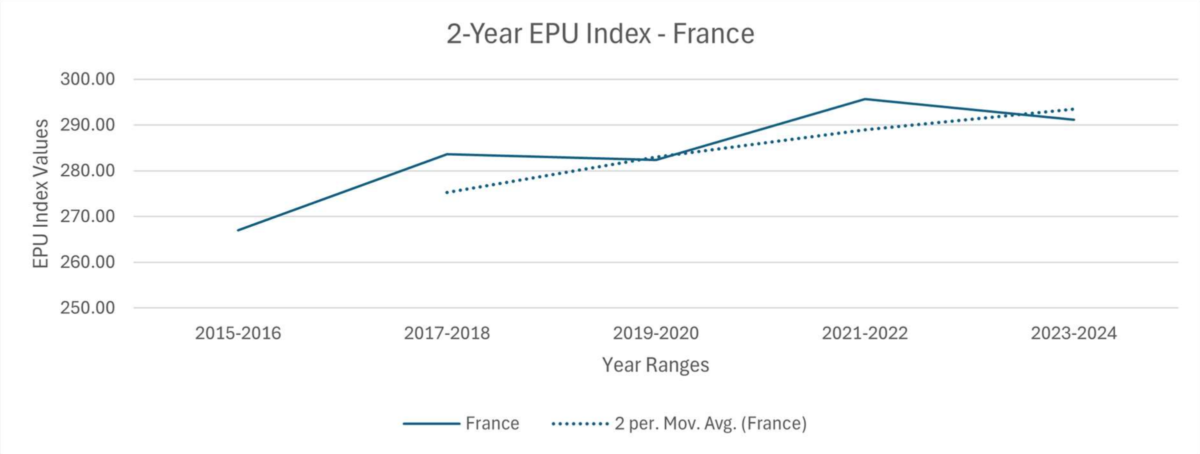
6.3.2.2.4.1 2-Year EPU Index – Spain



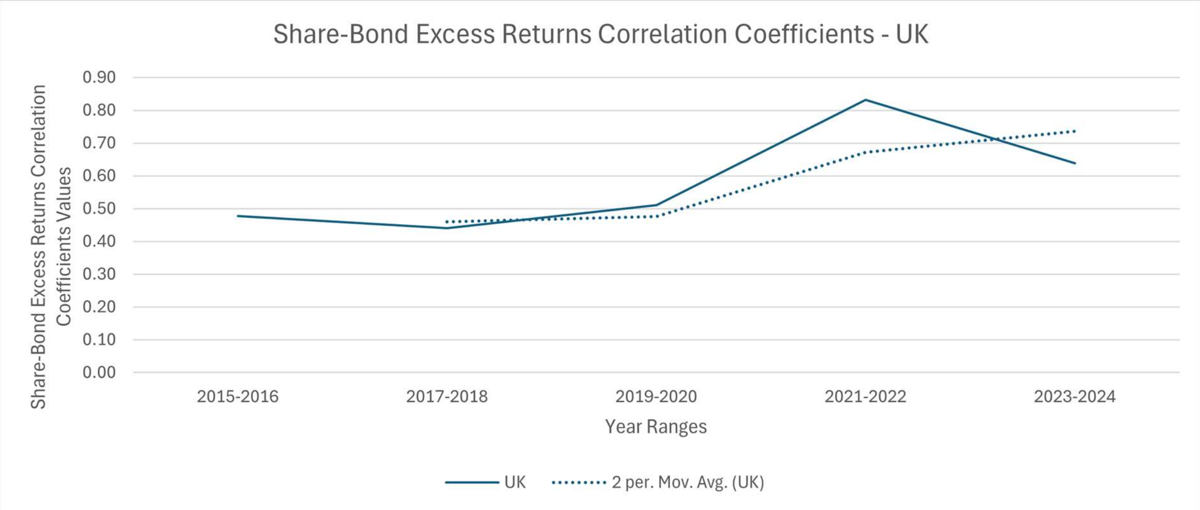
6.3.2.2.5 Share-Bond Excess Returns Correlation Coefficients – France



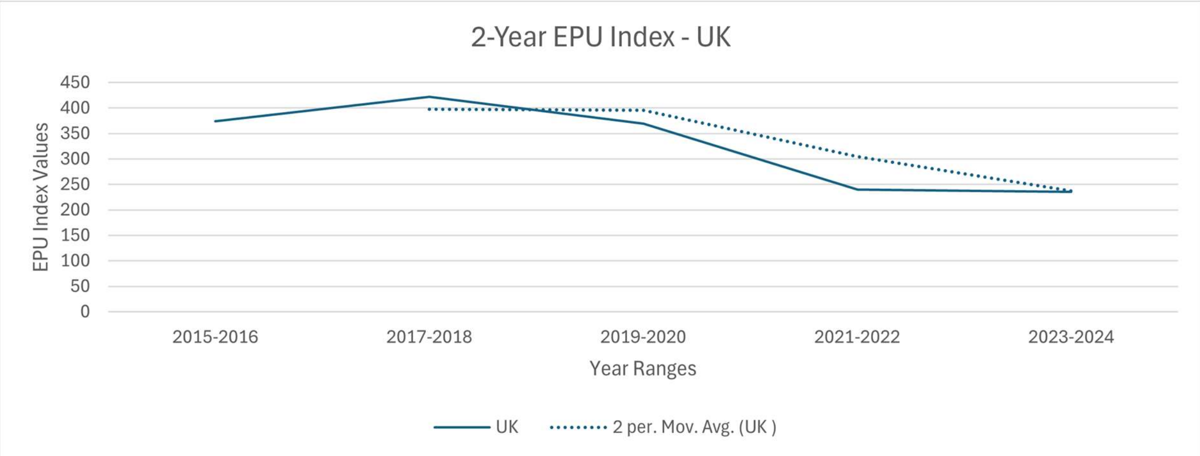
6.3.2.2.5.1 2-Year EPU Index – France



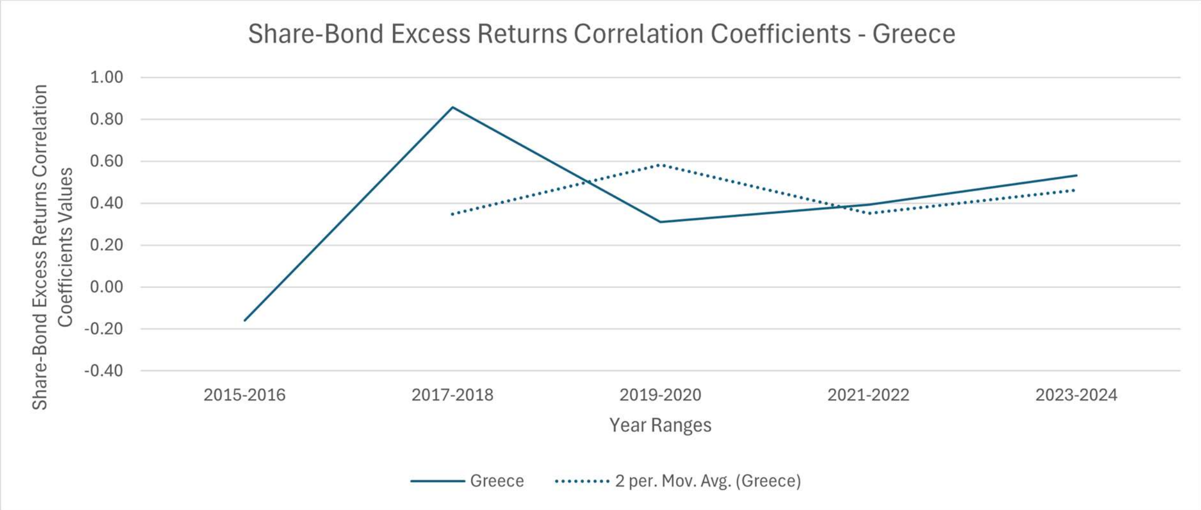
6.3.2.2.6 Share-Bond Excess Returns Correlation Coefficients – UK



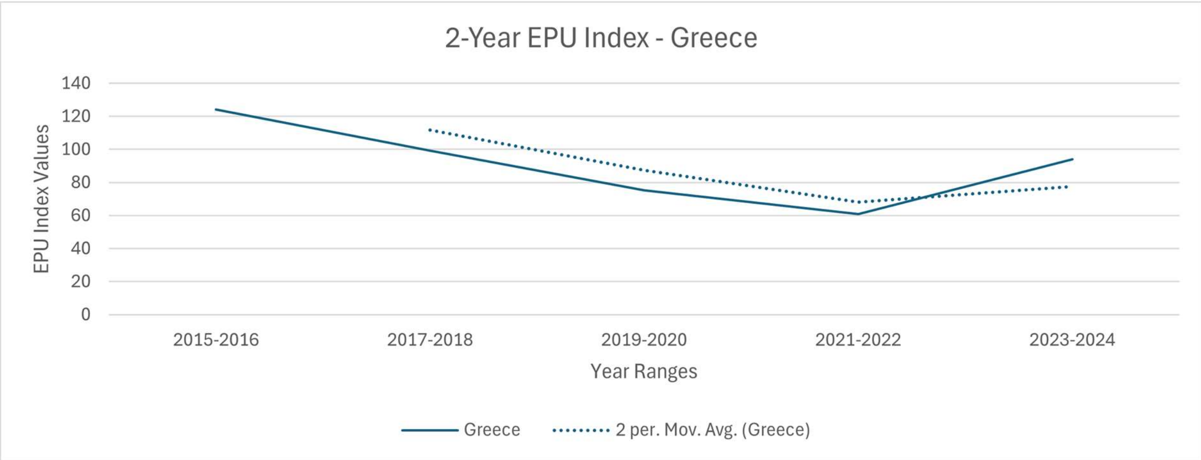
6.3.2.2.6.1 2-Year EPU Index – UK



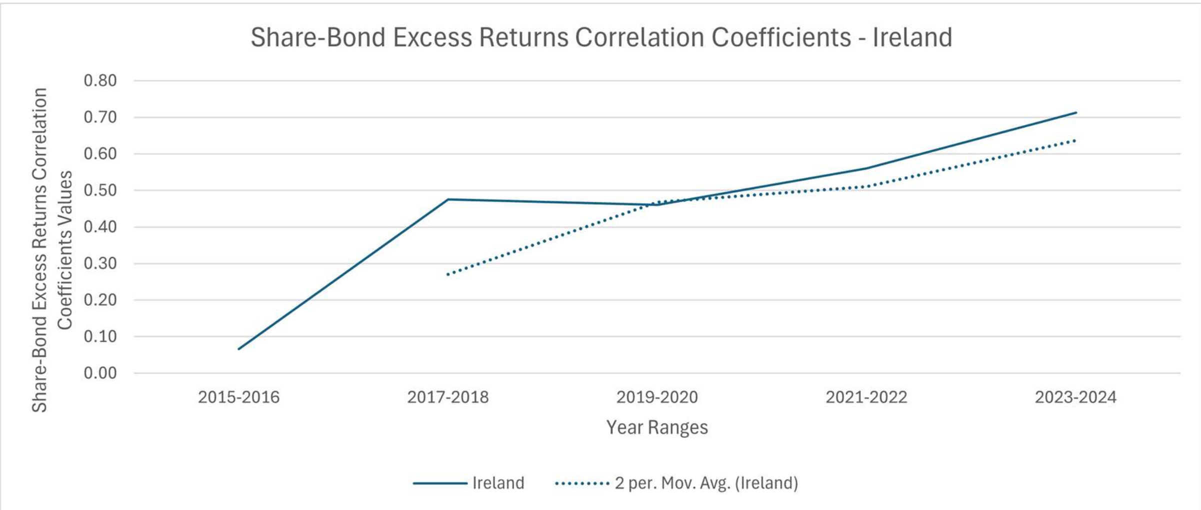
6.3.2.2.7 Share-Bond Excess Returns Correlation Coefficients – Greece



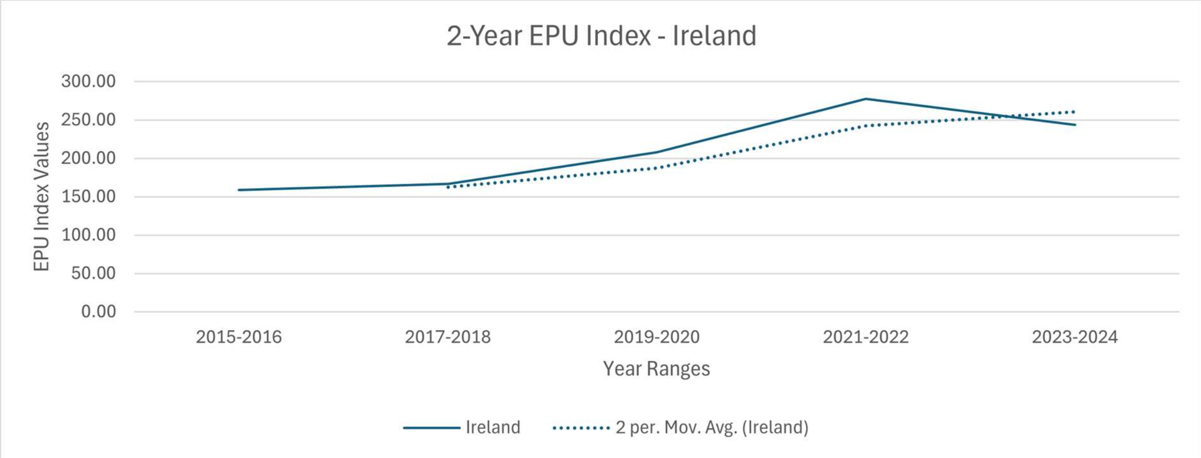
6.3.2.2.7.1 2-Year EPU Index – Greece



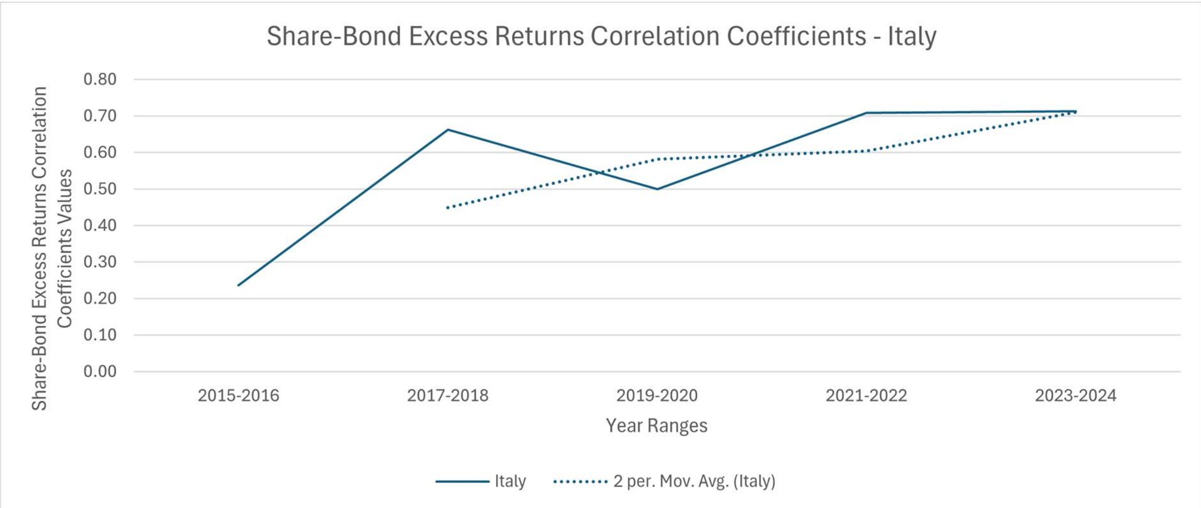
6.3.2.2.8 Share-Bond Excess Returns Correlation Coefficients – Ireland



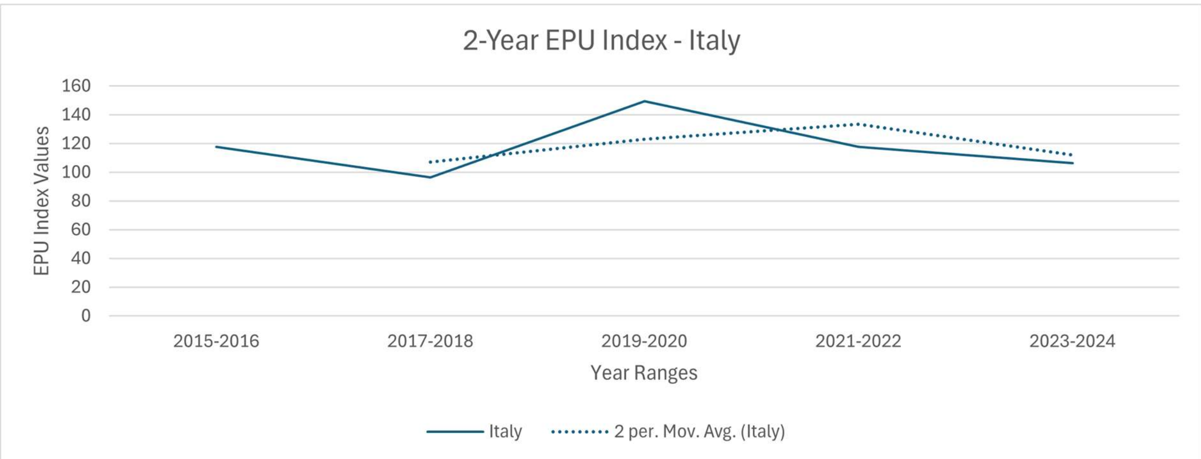
6.3.2.2.8.1 2-Year EPU Index – Ireland



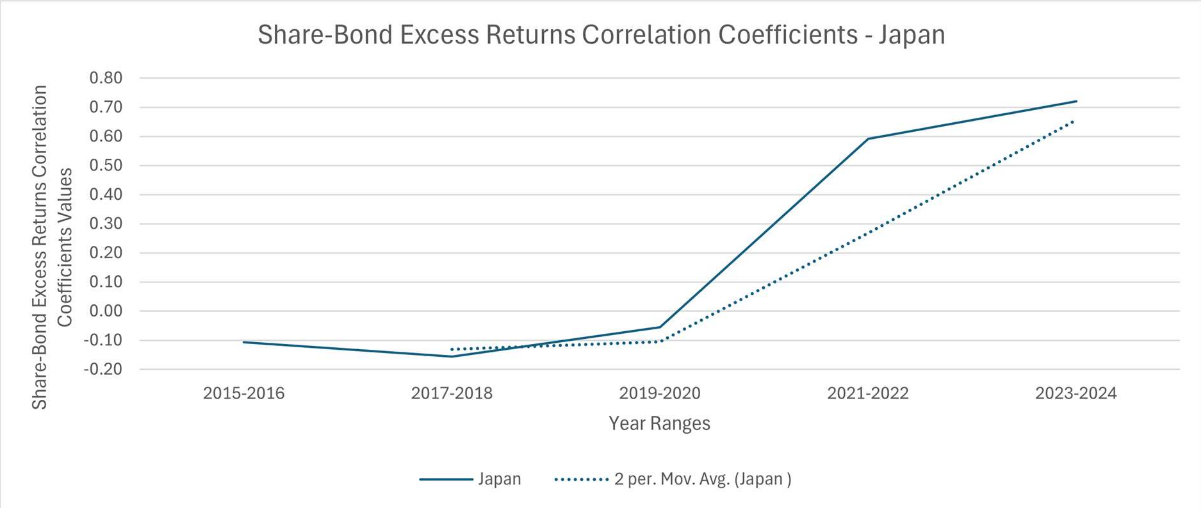
6.3.2.2.9 Share-Bond Excess Returns Correlation Coefficients – Italy



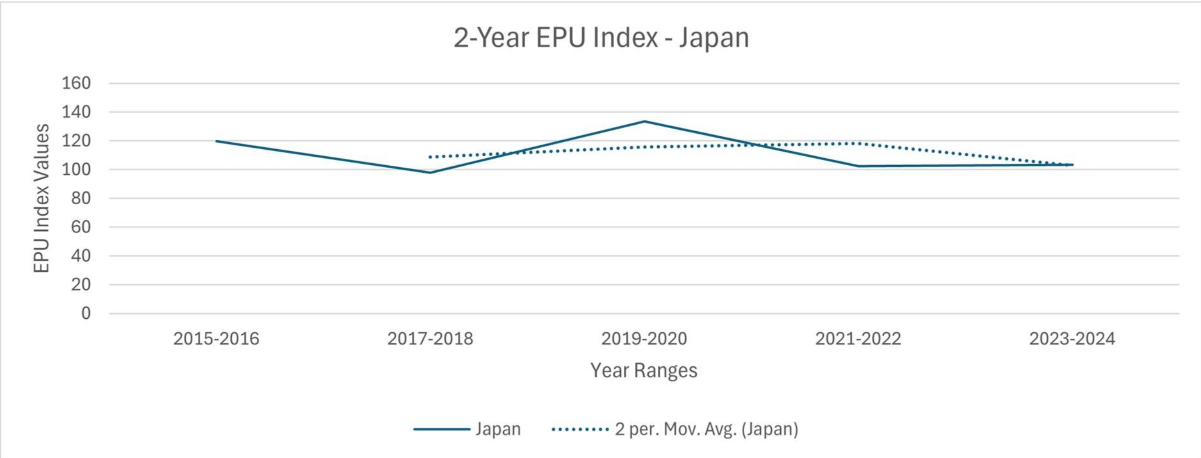
6.3.2.2.9.1 2-Year EPU Index – Italy



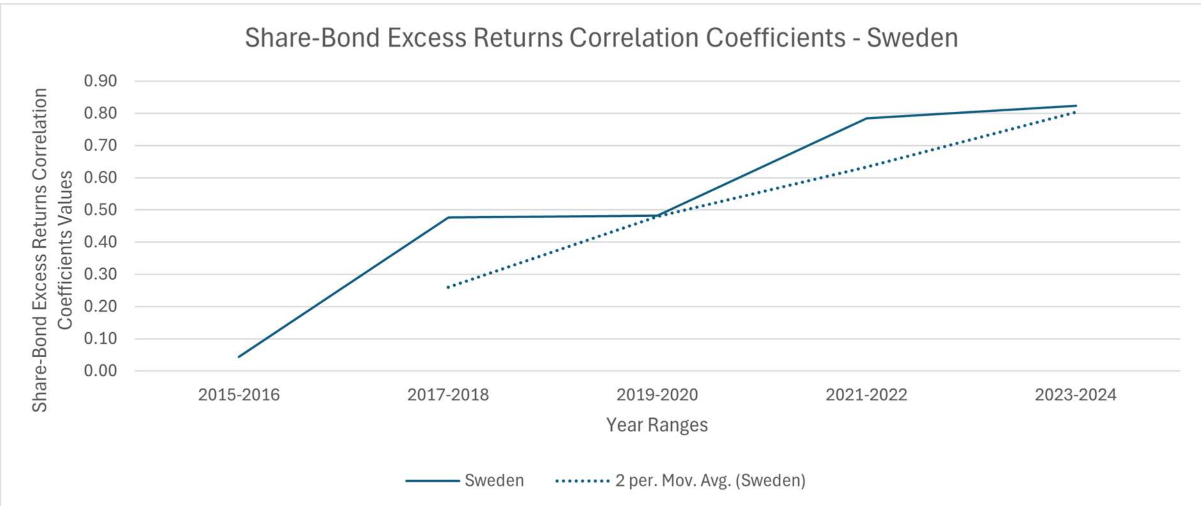
6.3.2.2.10 Share-Bond Excess Returns Correlation Coefficients – Japan



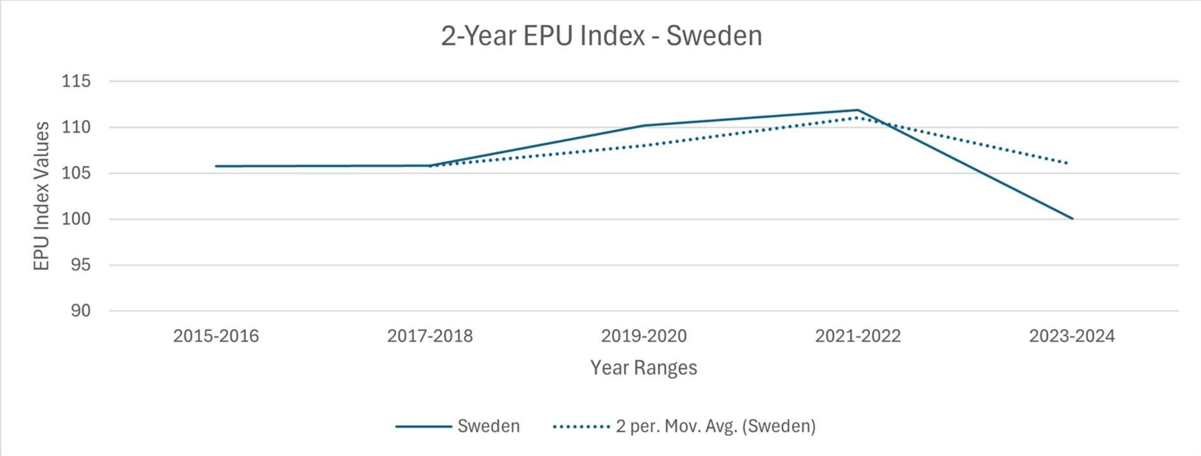
6.3.2.2.10.1 2-Year EPU Index – Japan



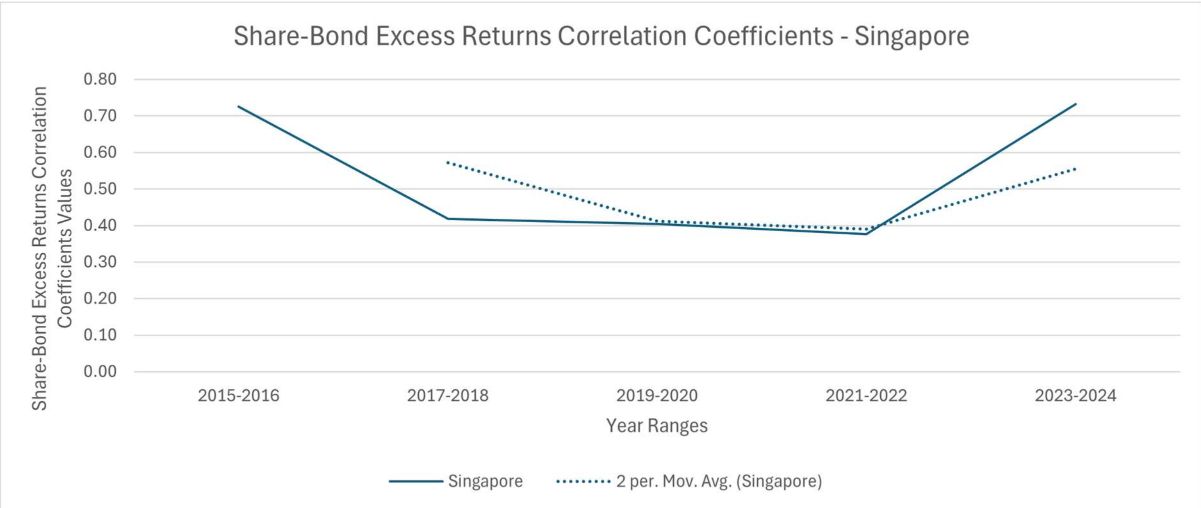
6.3.2.2.11 Share-Bond Excess Returns Correlation Coefficients – Sweden



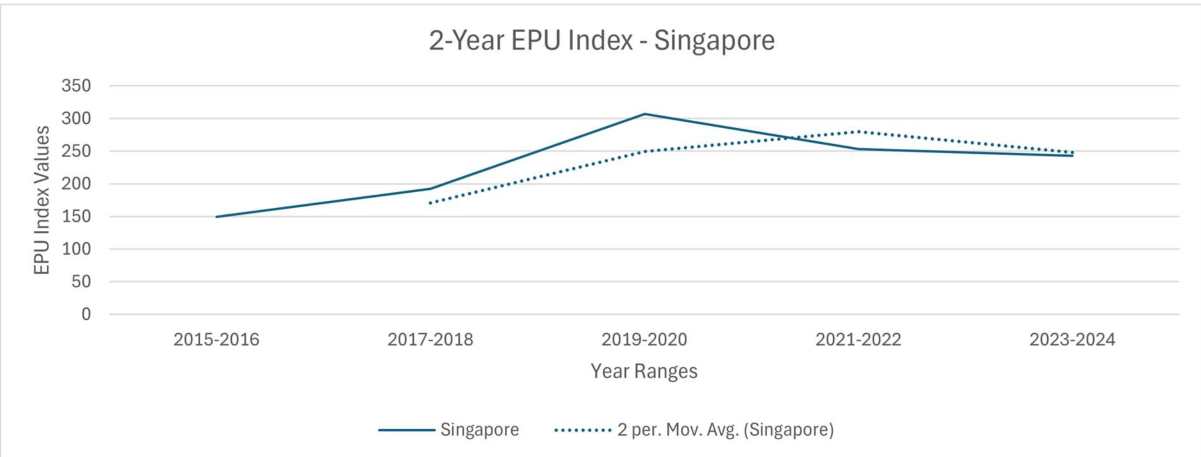
6.3.2.2.11.1 2-Year EPU Index – Sweden



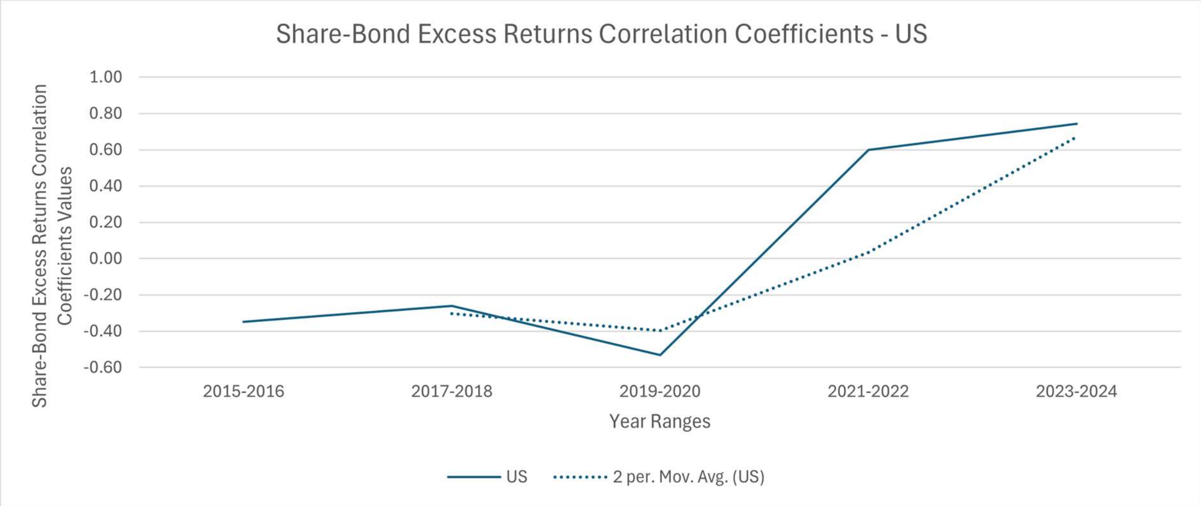
6.3.2.2.12 Share-Bond Excess Returns Correlation Coefficients – Singapore



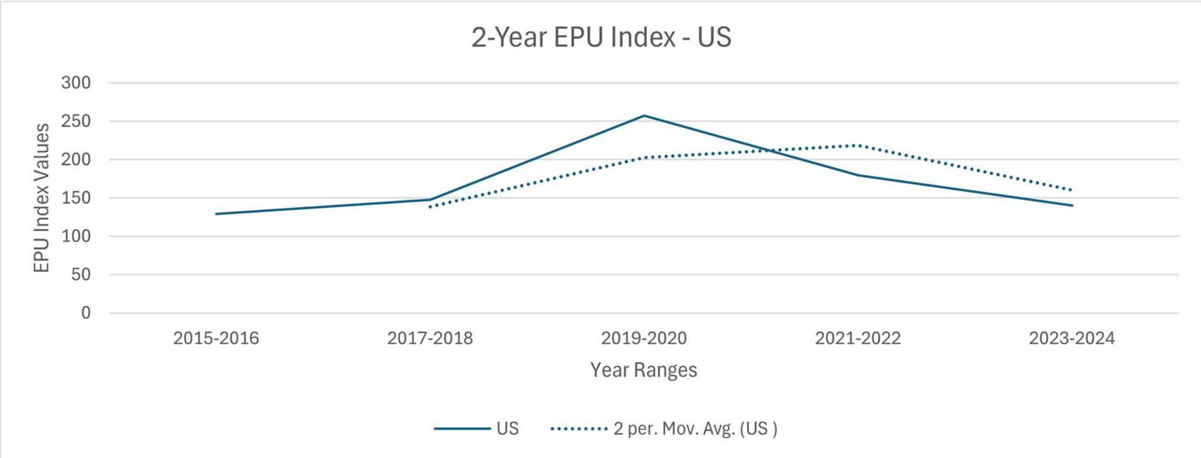
6.3.2.2.12.1 2-Year EPU Index – Singapore



6.3.2.2.13 Share-Bond Excess Returns Correlation Coefficients – US



6.3.2.2.13.1 2-Year EPU Index – USA

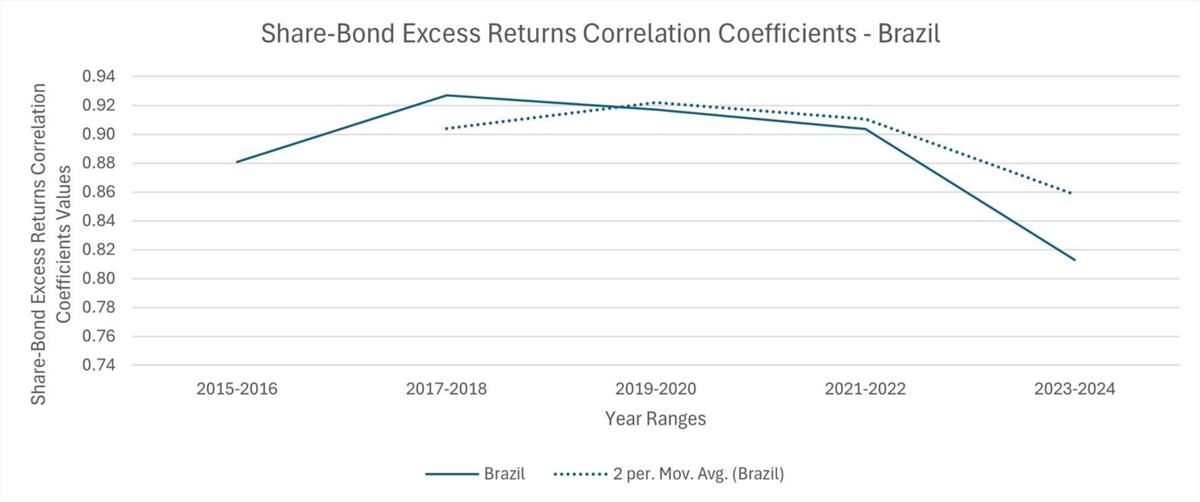


6.3.2.3 Emerging countries – 2-year correlation coefficients

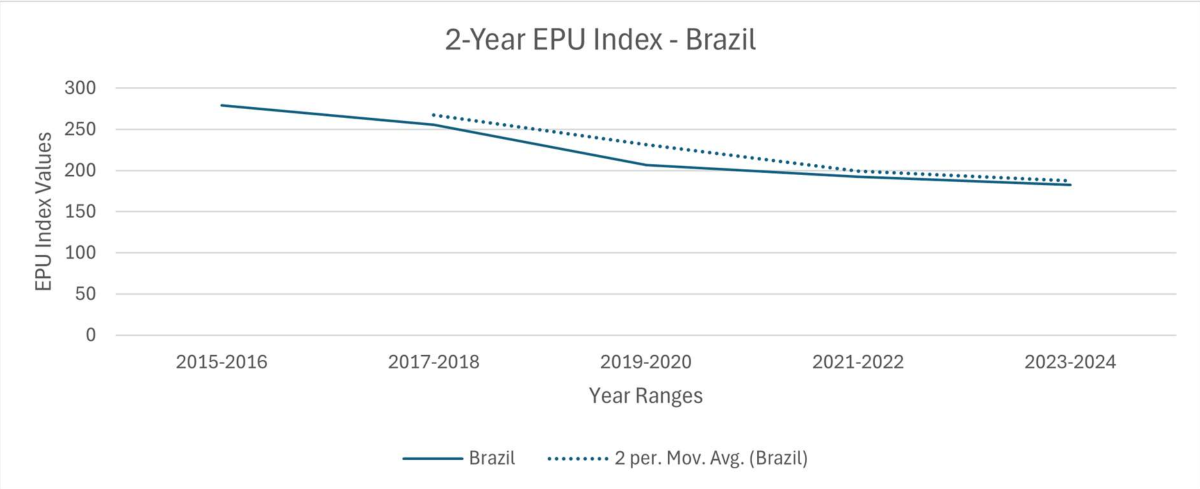
Year Ranges	Brazil	Chile	China	India	Mexico	Pakistan	Russia	Korea
2015-2016	0.88	0.86	0.37	0.56	0.90	-0.10	0.84	0.90
2017-2018	0.93	0.70	0.69	0.60	0.86	0.18	0.74	0.73
2019-2020	0.92	0.64	0.52	0.46	0.86	0.18	0.89	0.69
2021-2022	0.90	0.77	0.70	0.75	0.66	0.25	0.90	0.74
2023-2024	0.81	0.75	0.62	-0.09	0.88	-0.57	0.55	0.85

6.3.2.4 Graphic representations – Each emerging country

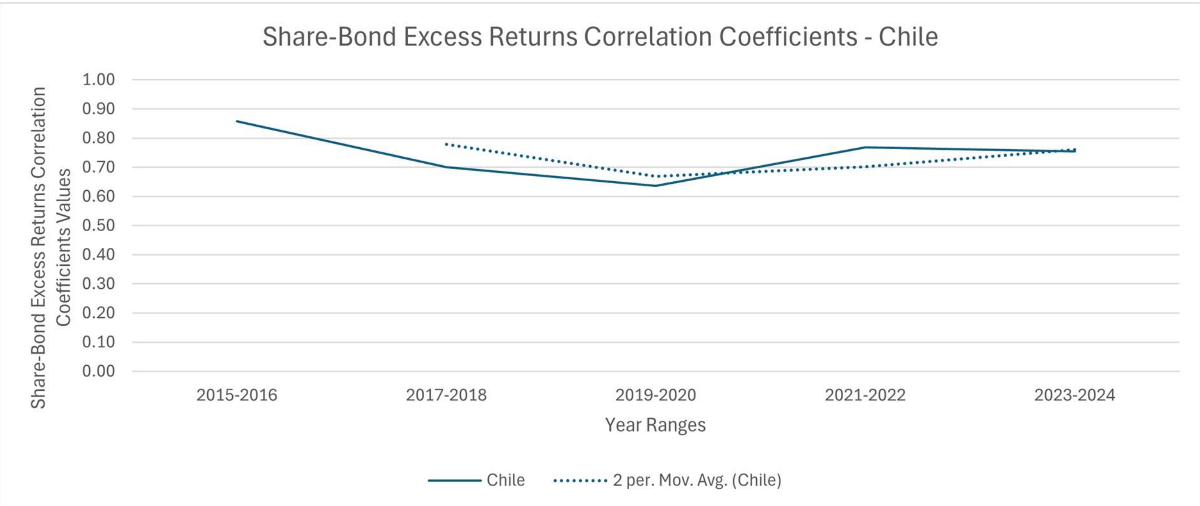
6.3.2.4.1 Share-Bond Excess Returns Correlation Coefficients – Brazil



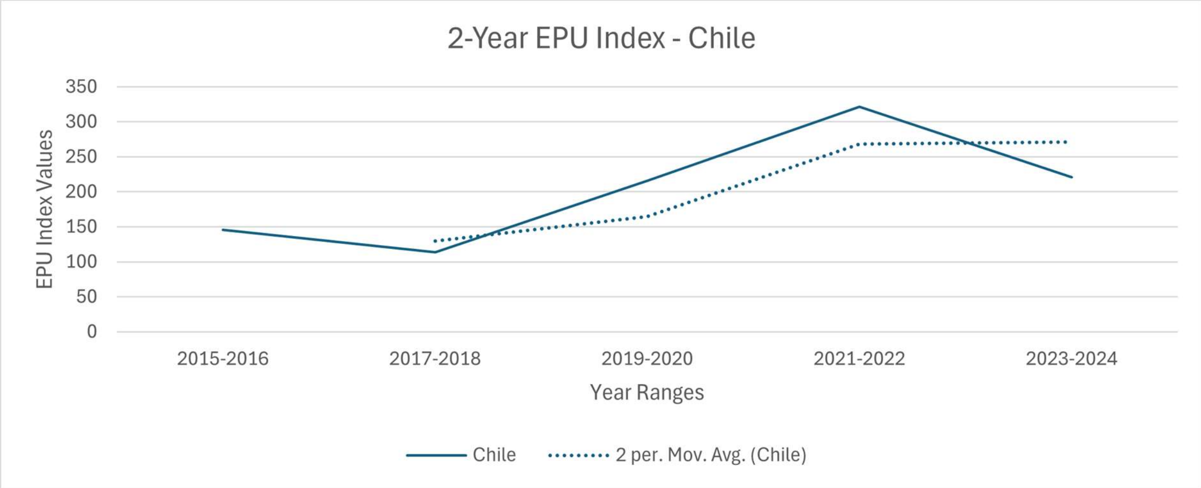
6.3.2.4.1.1 2-Year EPU Index – Brazil



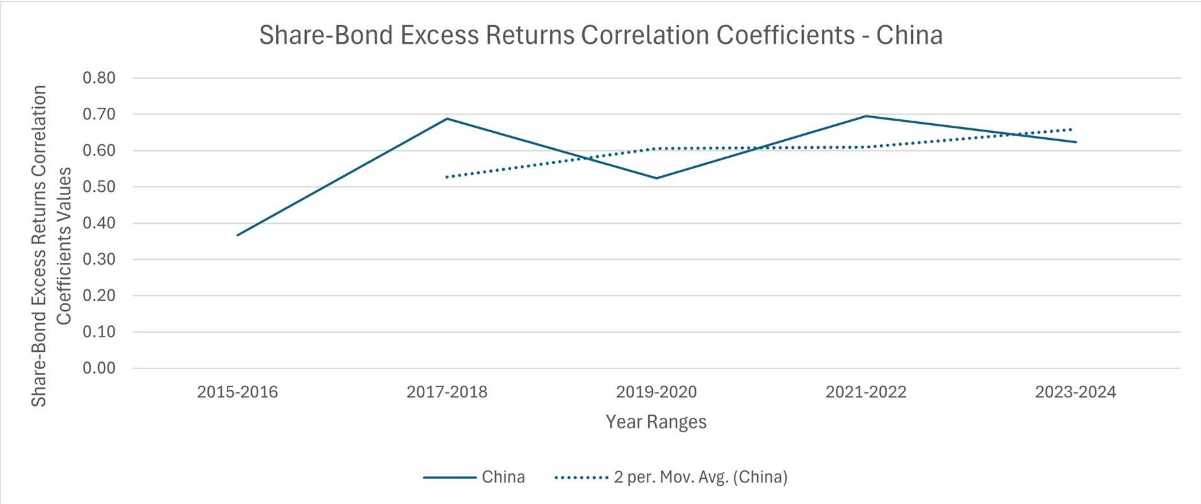
6.3.2.4.2 Share-Bond Excess Returns Correlation Coefficients – Chile



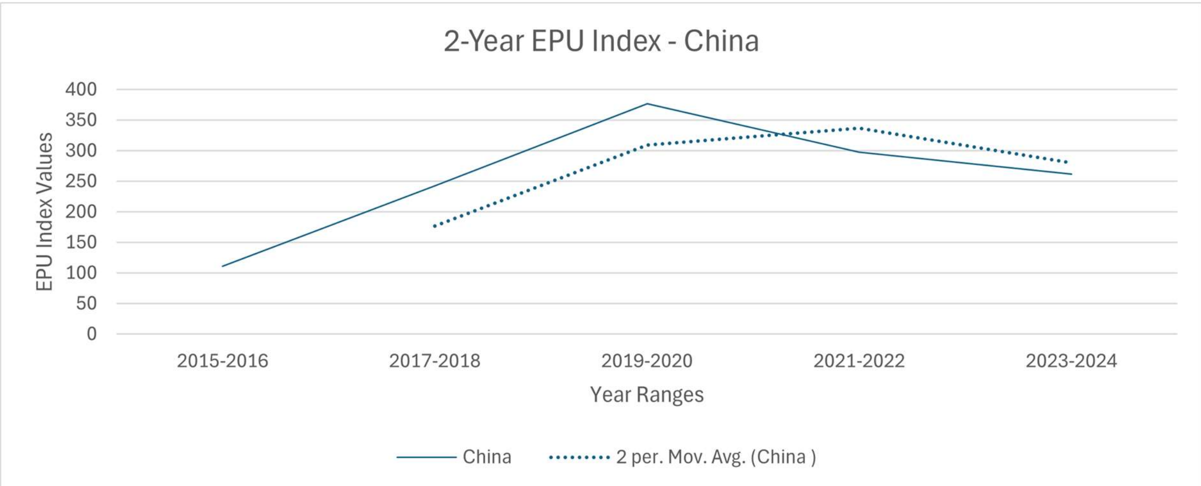
6.3.2.4.2.1 2-Year EPU Index – Chile



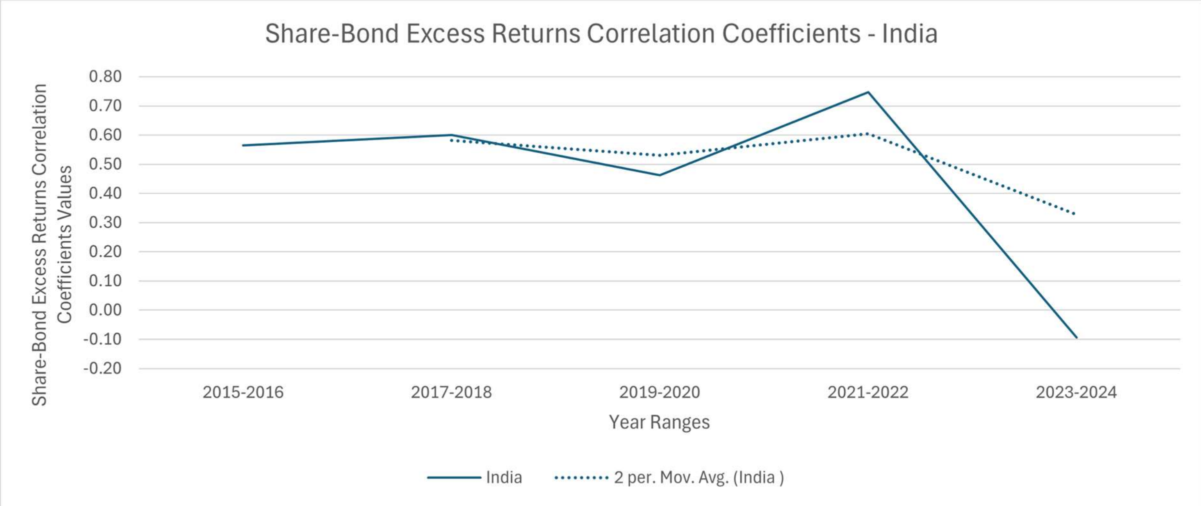
6.3.2.4.3 Share-Bond Excess Returns Correlation Coefficients – China



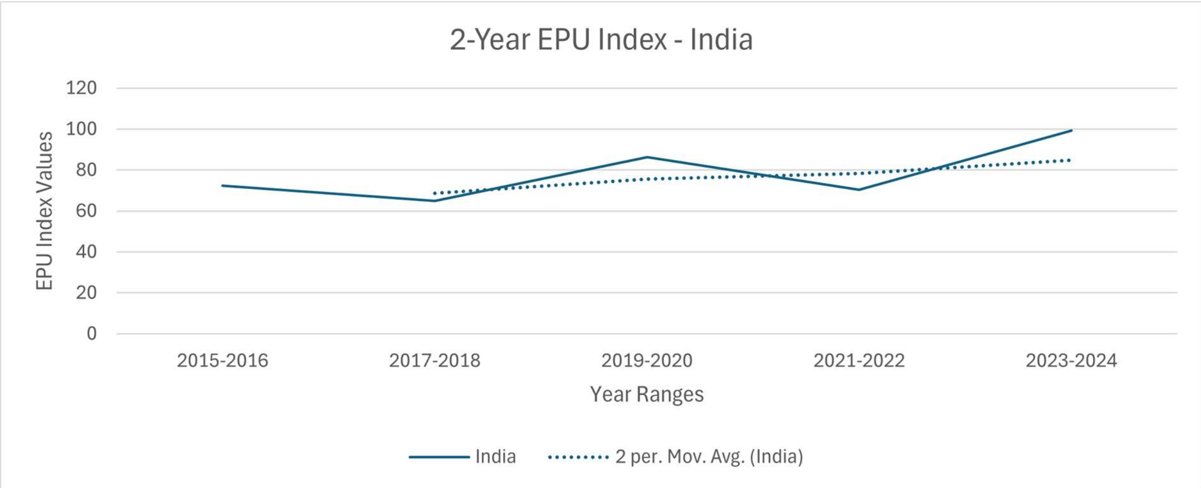
6.3.2.4.3.1 2-Year EPU Index – China



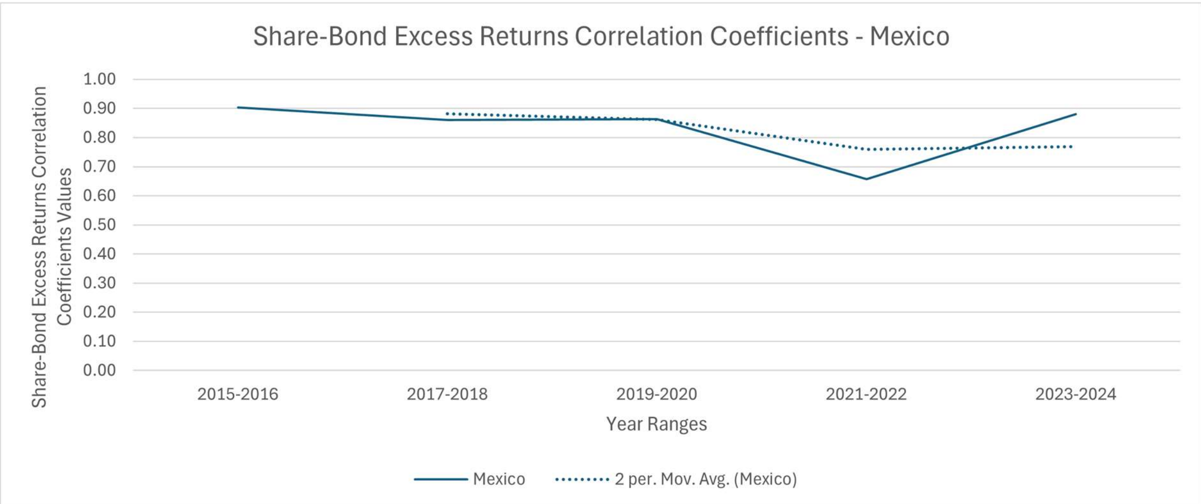
6.3.2.4.4 Share-Bond Excess Returns Correlation Coefficients – India



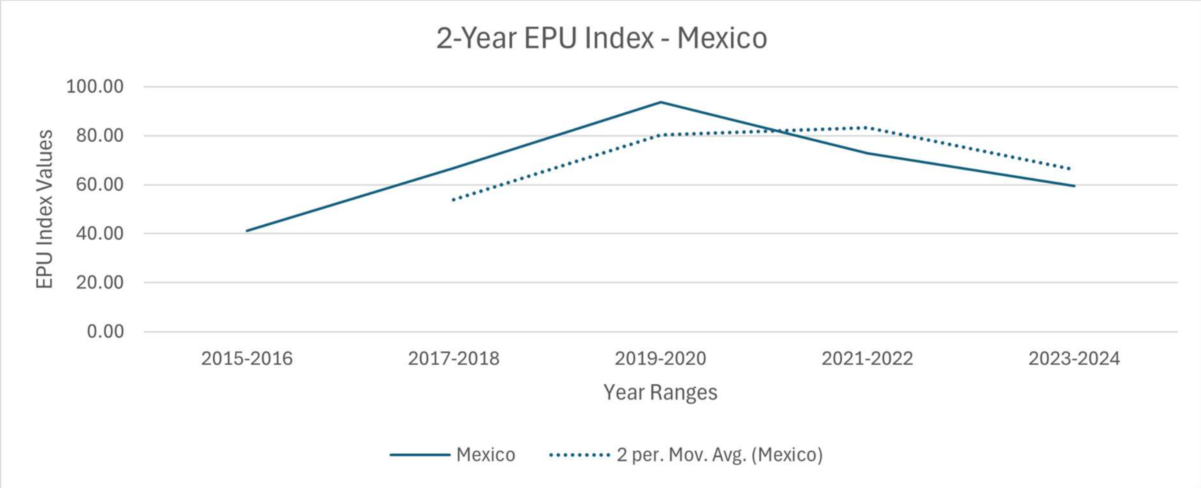
6.3.2.4.4.1 2-Year EPU Index – India



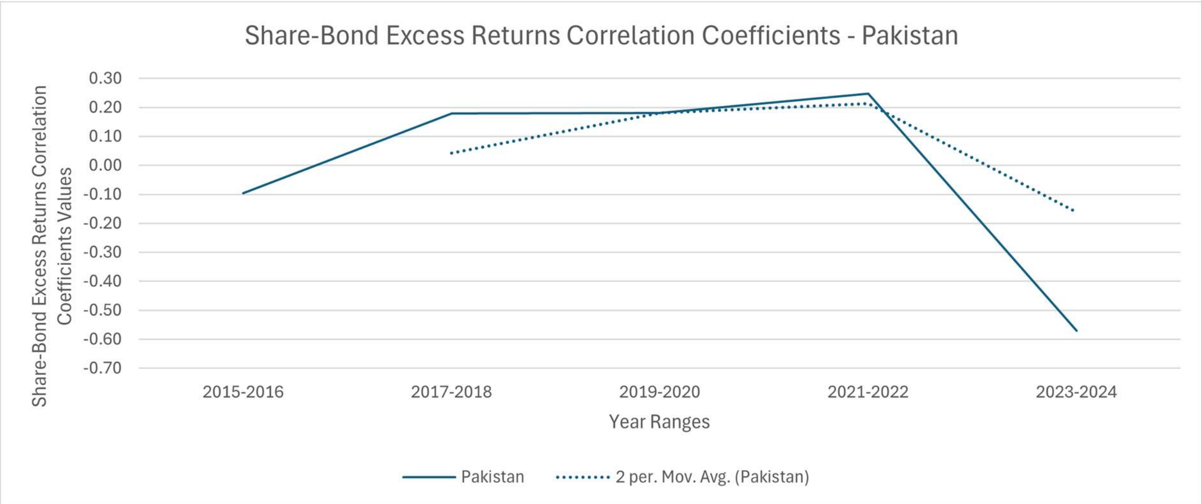
6.3.2.4.5 Share-Bond Excess Returns Correlation Coefficients – Mexico



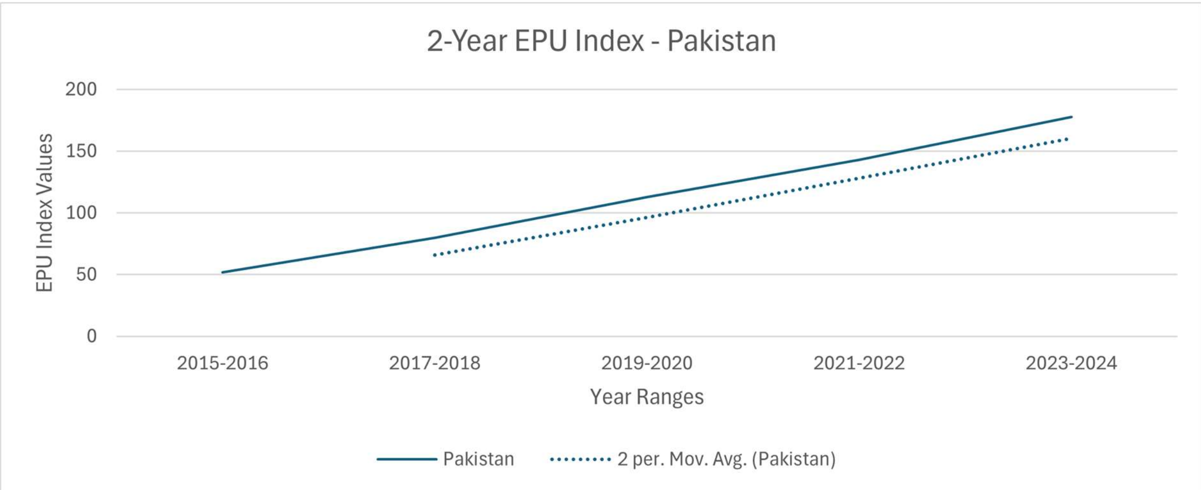
6.3.2.4.5.1 2-Year EPU Index – Mexico



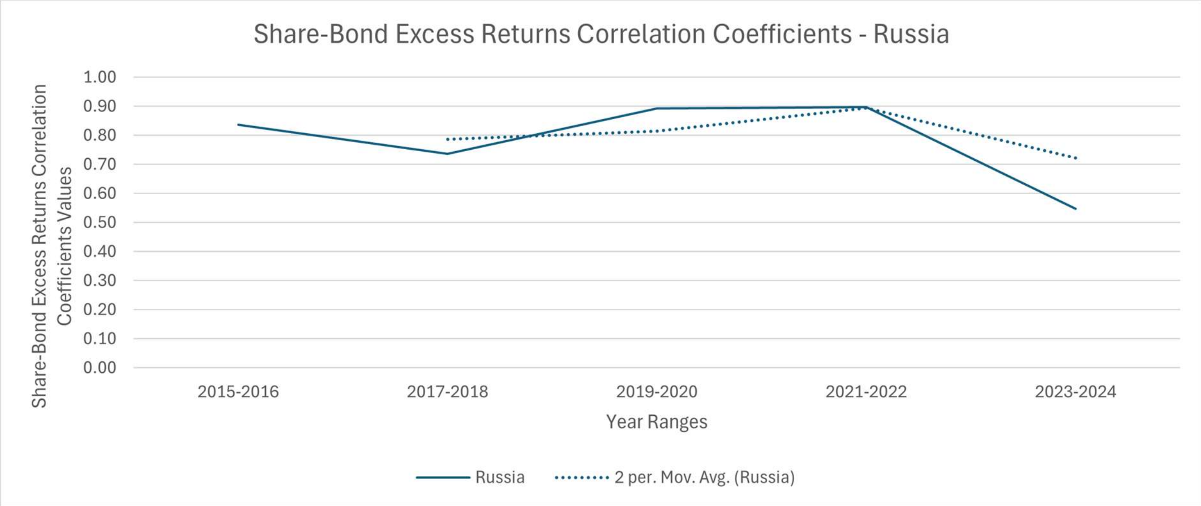
6.3.2.4.6 Share-Bond Excess Returns Correlation Coefficients – Pakistan



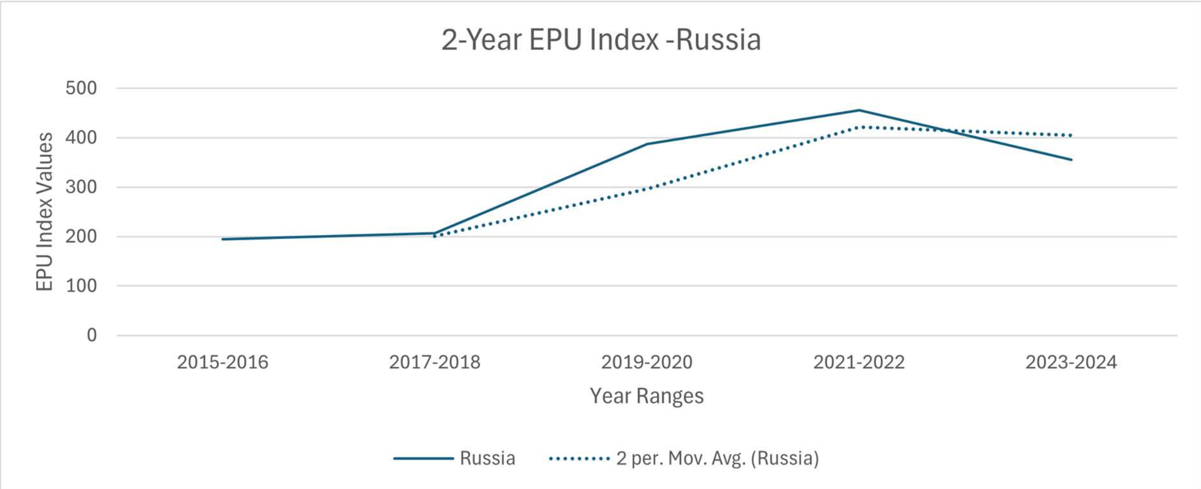
6.3.2.4.6.1 2-Year EPU Index – Pakistan



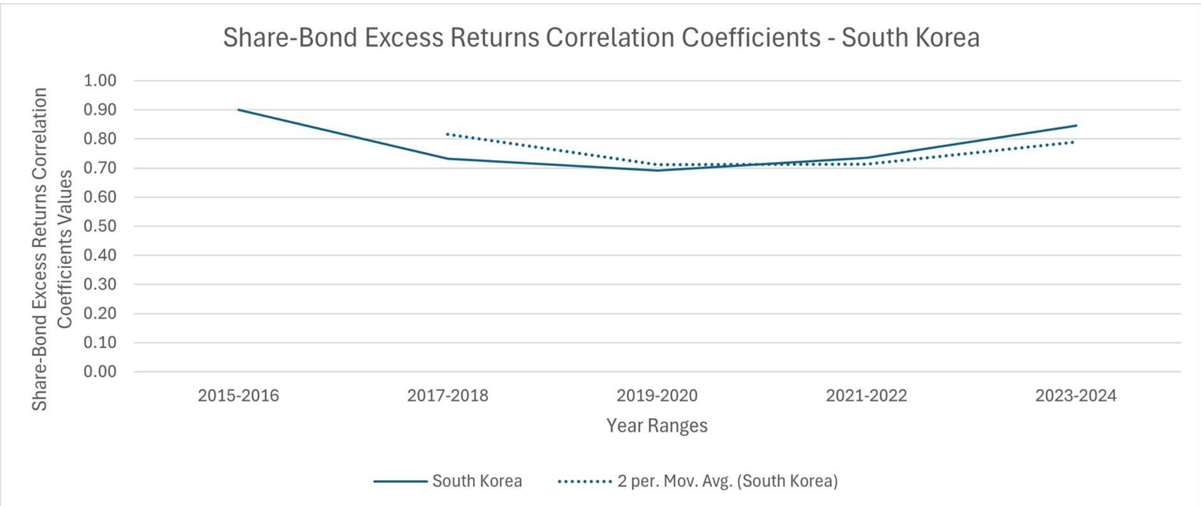
6.3.2.4.7 Share-Bond Excess Returns Correlation Coefficients – Russia



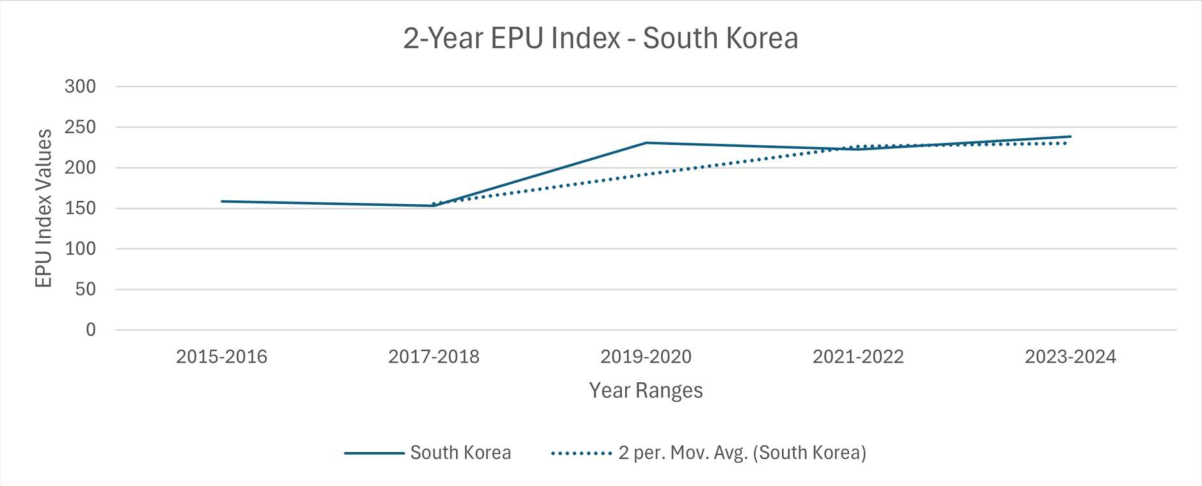
6.3.2.4.7.1 2-Year EPU Index – Russia



6.3.2.4.8 Share-Bond Excess Returns Correlation Coefficients - South Korea



6.3.2.4.8.1 2-Year EPU Index – South Korea



6.3.2.5 Developed countries – 1-year correlation coefficients

Year Ranges	AU	CA	GER	ES	FR	UK	GR	IRL	IT	JPN	SE	SG	US
2015	0.64	0.89	-0.24	0.33	0.27	0.53	-0.36	0.35	0.41	-0.50	-0.3	0.73	-0.35
2016	0.57	0.60	0.11	0.29	0.14	0.60	0.85	-0.02	0.18	0.03	0.25	0.76	-0.42
2017	0.77	0.39	-0.11	0.31	0.23	0.25	0.82	0.28	0.37	0.02	0.20	0.47	-0.14
2018	0.28	0.34	0.18	0.60	0.22	0.21	0.83	0.19	0.67	-0.38	0.46	0.18	-0.48
2019	0.23	0.44	-0.05	0.17	0.11	0.37	0.04	0.14	0.34	-0.52	0.01	0.13	-0.57
2020	0.90	0.85	0.45	0.59	0.57	0.61	0.40	0.64	0.61	0.05	0.69	0.56	-0.65
2021	0.42	0.45	0.10	0.05	0.21	0.43	0.24	0.17	0.05	-0.20	0.43	-0.3	0.15
2022	0.80	0.77	0.79	0.70	0.89	0.91	0.44	0.63	0.80	0.69	0.84	0.63	0.56
2023	0.90	0.87	0.82	0.65	0.75	0.66	0.52	0.77	0.73	0.80	0.84	0.73	0.82
2024	0.99	0.83	0.65	0.70	0.66	0.66	0.53	0.51	0.67	0.61	0.75	0.81	0.54

6.3.2.6 Emerging countries – 1-year correlation coefficients

Years	Brazil	Chile	China	India	Mexico	Pakistan	Russia	Korea
2015	0.85	0.92	0.43	0.10	0.81	-0.33	0.84	0.87
2016	0.88	0.82	0.33	0.84	0.97	-0.46	0.86	0.94
2017	0.85	0.47	0.67	0.14	0.83	-0.37	0.56	0.66
2018	0.95	0.91	0.65	0.67	0.89	0.25	0.82	0.74
2019	0.92	0.84	0.58	0.51	0.80	0.21	0.96	0.70
2020	0.94	0.52	0.51	0.83	0.87	0.13	0.88	0.65
2021	0.87	0.60	0.53	0.74	0.85	0.03	0.56	0.52
2022	0.93	0.82	0.67	0.68	0.52	0.05	0.93	0.75
2023	0.82	0.72	0.80	-0.12	0.87	-0.60	0.60	0.91
2024	0.74	0.83	0.21	0.07	0.89	-0.74	0.55	0.60

6.4 Assumptions testing

6.4.1 Regression on SER_D (1)

6.4.1.1 Multicollinearity – Farrar-Glauber Test

```
Overall Multicollinearity Diagnostics

                       MC Results detection
Determinant |X'X|:         0.3489         0
Farrar Chi-Square:       343.7645         1
Red Indicator:             0.2691         0
Sum of Lambda Inverse:     8.3363         0
Theil's Method:            0.3527         0
Condition Number:         38.9414         1

1 --> COLLINEARITY is detected by the test
0 --> COLLINEARITY is not detected by the test
```

6.4.1.1.1 Correlation Matrix – Independent Variables

	Numeric_data	Numeric_data_11	Numeric_data_12	Numeric_data_13	Numeric_data_14
Numeric_data	1.000000000	-0.070890705	-0.08112404	0.006152337	-0.010918603
Numeric_data_11	-0.070890705	1.000000000	0.08037767	-0.299161803	-0.003504685
Numeric_data_12	-0.081124037	0.080377670	1.00000000	-0.001088530	0.757388823
Numeric_data_13	0.006152337	-0.299161803	-0.00108853	1.000000000	0.140595342
Numeric_data_14	-0.010918603	-0.003504685	0.75738882	0.140595342	1.000000000

N.B.: Numeric_data: $EPU_{Developed}$, *Numeric_data_11:* $SMB_{Developed}$, *Numeric_data_12:* $HML_{Developed}$, *Numeric_data_13:* $RMW_{Developed}$, *Numeric_data_14:* $CMA_{Developed}$.

6.4.1.2 Homoscedastic variance – Goldfeld-Quandt Test

```
        Goldfeld-Quandt test

data:  Regression_1
GQ = 1.1531, df1 = 159, df2 = 159, p-value = 0.185
alternative hypothesis: variance increases from segment 1 to 2
```

6.4.1.3 Normality distribution of the residuals - Jarque-Bera Test

```
Jarque-Bera test for normality
-------------------------------

Hypotheses:
                           H0:                                  H1:
  skew = 0 and kur = 3 (norm.)  skew <> 0 or kur <> 3 (non-norm.)

Test results:
      JB  crit.value  p.value  sig.level           H0
  4.1144      5.9915   0.1278       0.05  not rejected
```

6.4.1.4 Autocorrelation of the residuals – Durbin-Watson Test

```
> durbinWatsonTest(Resid_Reg_1)
[1] 1.7501
```

6.4.2 Regression on SER_E (2)

6.4.2.1 Multicollinearity – Farrar-Glauber Test

```
Overall Multicollinearity Diagnostics

                       MC Results detection
Determinant |X'X|:         0.6429         0
Farrar Chi-Square:       144.6558         1
Red Indicator:             0.2026         0
Sum of Lambda Inverse:     6.0272         0
Theil's Method:           -0.2383         0
Condition Number:         38.1231         1

1 --> COLLINEARITY is detected by the test
0 --> COLLINEARITY is not detected by the test
```

6.4.2.1.1 Correlation Matrix – Independent Variables

	Numeric_data_2	Numeric_data_15	Numeric_data_16	Numeric_data_17	Numeric_data_18
Numeric_data_2	1.000000000	-0.01696548	-0.02739253	-0.003735608	0.02878948
Numeric_data_15	-0.016965475	1.00000000	0.05821549	-0.160736375	0.09842964
Numeric_data_16	-0.027392527	0.05821549	1.00000000	-0.464330217	0.37197508
Numeric_data_17	-0.003735608	-0.16073638	-0.46433022	1.000000000	-0.11502572
Numeric_data_18	0.028789477	0.09842964	0.37197508	-0.115025724	1.00000000

N.B.: Numeric_data_2: EPU_E, Numeric_data_15: SMB_E , Numeric_data_16: HML_E, Numeric_data_17: RMW_E, Numeric_data_18: CMA_E.

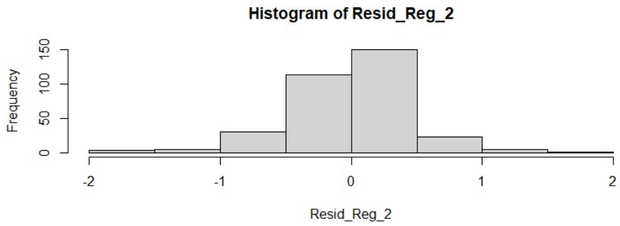
6.4.2.2 Homoscedastic variance – Goldfeld-Quandt Test

```
        Goldfeld-Quandt test

data:  Regression_2
GQ = 0.62575, df1 = 160, df2 = 159, p-value = 0.9984
alternative hypothesis: variance increases from segment 1 to 2
```

6.4.2.3 Normal distribution of the residuals - Jarque-Bera Test

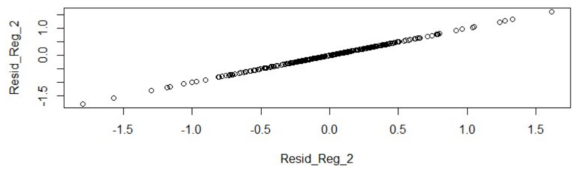
```
Jarque-Bera test for normality
-------------------------------

Hypotheses:
                           H0:                                H1:
  skew = 0 and kur = 3 (norm.)  skew <> 0 or kur <> 3 (non-norm.)

Test results:
       JB  crit.value  p.value  sig.level        H0
  62.8888      5.9915  < 1e-04       0.05  rejected
```

6.4.2.3.1 Frequency Histogram of the residuals



N.B.: Frequency Histogram of the residuals of Regression 2; on $SER_{Emerging}$

6.4.2.3.2 QQ-plot of the residuals



N.B.: QQ-plot of the residuals of Regression 2; on $SER_{Emerging}$

6.4.2.4 Autocorrelation of the residuals – Durbin-Watson Test

```
> durbinWatsonTest(Resid_Reg_2)
[1] 1.544148
```

6.4.3 Regression on BER_D (3)

6.4.3.1 Multicollinearity – Farrar-Glauber Test

```
Overall Multicollinearity Diagnostics

                       MC Results detection
Determinant |X'X|:         0.1764         0
Farrar Chi-Square:       193.4722         1
Red Indicator:             0.3553         0
Sum of Lambda Inverse:    11.4352         0
Theil's Method:            1.5233         1
Condition Number:         80.7332         1

1 --> COLLINEARITY is detected by the test
0 --> COLLINEARITY is not detected by the test
```

6.4.3.1.1 Correlation Matrix – Independent Variables

	Numeric_data_19	SMB_Developed	HML_Developed	RMW_Developed	CMA_Developed
Numeric_data_19	1.00000000	-0.01455660	-0.02064844	0.0179469	0.01723867
SMB_Developed	-0.01455660	1.00000000	0.22128768	-0.4301929	0.01922944
HML_Developed	-0.02064844	0.22128768	1.00000000	-0.5725299	0.78450167
RMW_Developed	0.01794690	-0.43019289	-0.57252991	1.0000000	-0.27084932
CMA_Developed	0.01723867	0.01922944	0.78450167	-0.2708493	1.00000000

N.B.: Numeric_data_19: $EPU_{D\ (Bond\ Reg.)}$, *SMB_Developed:* $SMB_{D\ (Bond\ Reg.)}$, *HML_Developed:* $HML_{D\ (Bond\ Reg.)}$, *RMW_Developed:* $RMW_{D\ (Bond\ Reg.)}$, *CMA_Developed:* $CMA_{D\ (Bond\ Reg.)}$.

6.4.3.2 Homoscedastic variance – White Test

```
> white_test(Regression_3)
White's test results

Null hypothesis: Homoskedasticity of the residuals
Alternative hypothesis: Heteroskedasticity of the residuals
Test Statistic: 5.04
P-value: 0.080397
```

6.4.3.3 Normality distribution of the residuals - Jarque-Bera Test

```
Jarque-Bera test for normality
------------------------------

Hypotheses:
                          H0:                                  H1:
  skew = 0 and kur = 3 (norm.)  skew <> 0 or kur <> 3 (non-norm.)

Test results:
      JB  crit.value  p.value  sig.level           H0
  4.7953      5.9915   0.0909       0.05  not rejected
```

6.4.3.4 Autocorrelation of the residuals – Durbin-Watson Test

```
> durbinWatsonTest(Resid_Reg_3)
n the residuals
[1] 1.729143
```

6.4.4 Regression on BER_E (4)

6.4.4.1 Multicollinearity – Farrar-Glauber Test

```
Overall Multicollinearity Diagnostics

                         MC Results detection
Determinant |X'X|:          0.3818         0
Farrar Chi-Square:        107.3705         1
Red Indicator:              0.3024         0
Sum of Lambda Inverse:      7.5075         0
Theil's Method:             0.8879         1
Condition Number:          51.9776         1

1 --> COLLINEARITY is detected by the test
0 --> COLLINEARITY is not detected by the test
```

6.4.4.1.1 Correlation Matrix – Independent Variables

	Numeric_data_20	SMB_Emerging	HML_Emerging	RMW_Emerging	CMA_Emerging
Numeric_data_20	1.000000000	0.003864547	0.03655804	-0.0420458	0.04009265
SMB_Emerging	0.003864547	1.000000000	0.17234077	-0.2298573	0.14759348
HML_Emerging	0.036558040	0.172340767	1.00000000	-0.4151547	0.70265320
RMW_Emerging	-0.042045805	-0.229857290	-0.41515469	1.0000000	-0.33249967
CMA_Emerging	0.040092647	0.147593485	0.70265320	-0.3324997	1.00000000

6.4.4.2 Homoscedastic variance – White Test

```
> white_test(Regression_4)
White's test results

Null hypothesis: Homoskedasticity of the residuals
Alternative hypothesis: Heteroskedasticity of the residuals
Test Statistic: 3.11
P-value: 0.211352
```

6.4.4.3 Normality distribution of the residuals - Jarque-Bera Test

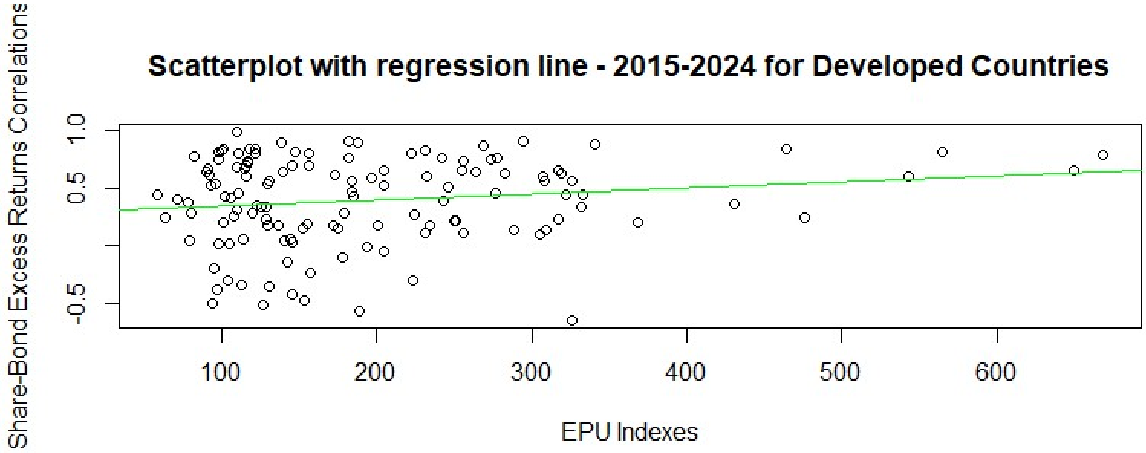
```
Jarque-Bera test for normality
------------------------------

Hypotheses:
                          H0:                            H1:
  skew = 0 and kur = 3 (norm.)  skew <> 0 or kur <> 3 (non-norm.)

Test results:
      JB  crit.value  p.value  sig.level           H0
  0.2994      5.9915    0.861       0.05  not rejected
```

6.4.4.4 Autocorrelation of the residuals – Durbin-Watson test

```
> durbinWatsonTest(Resid_Reg_4)
the residuals
[1] 1.676111
```

6.4.5 Regression on ρ_D (5)

6.4.5.1 Linearity – Scatterplot of the dependent and independent variables with regression line



6.4.5.2 Homoscedastic variance – White Test

```
> white_test(Regression_5)
White's test results

Null hypothesis: Homoskedasticity of the residuals
Alternative hypothesis: Heteroskedasticity of the residuals
Test Statistic: 0.07
P-value: 0.967661
```

6.4.5.3 Normality of the residuals – Jarque-Bera Test

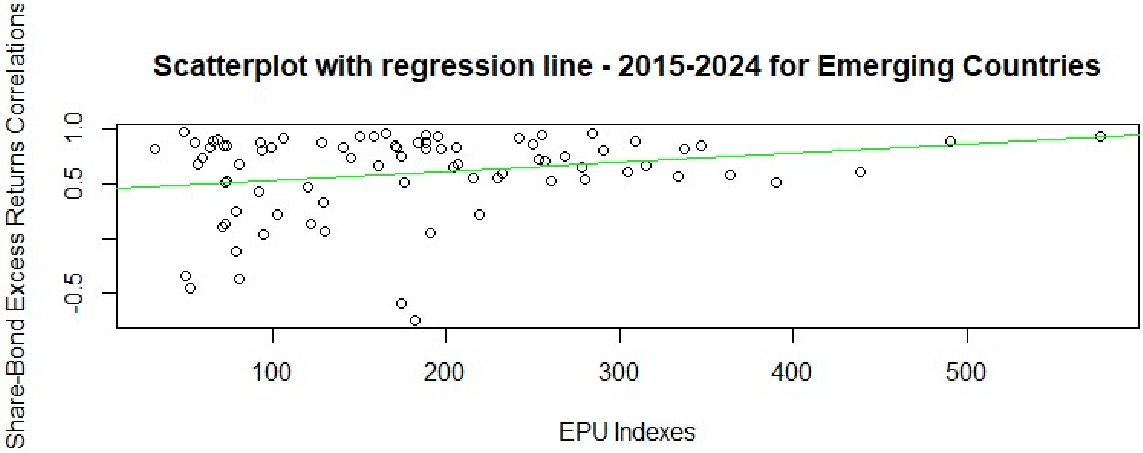
```
Jarque-Bera test for normality
-------------------------------

Hypotheses:
                           H0:                                H1:
  skew = 0 and kur = 3 (norm.)  skew <> 0 or kur <> 3 (non-norm.)

Test results:
      JB  crit.value  p.value  sig.level           H0
  0.5163      5.9915   0.7725       0.05  not rejected
```

6.4.5.4 Auto-correlation of the residuals – Durbin-Watson Test

```
> durbinWatsonTest(Resid_Reg_5)
n the residuals
[1] 0.9198794
```

6.4.6 Regression on ρ_E (6)

6.4.6.1 Linearity – Scatterplot of the dependent and independent variables with regression line



6.4.6.2 Homoscedastic variance – White Test

```
> white_test(Regression_6)
White's test results

Null hypothesis: Homoskedasticity of the residuals
Alternative hypothesis: Heteroskedasticity of the residuals
Test Statistic: 3
P-value: 0.22313
```

6.4.6.3 Normality of the residuals – Jarque-Bera Test

```
Jarque-Bera test for normality
-------------------------------

Hypotheses:
                           H0:                                 H1:
  skew = 0 and kur = 3 (norm.)  skew <> 0 or kur <> 3 (non-norm.)

Test results:
      JB  crit.value  p.value  sig.level          H0
  0.2874      5.9915   0.8662       0.05  not rejected
```

6.4.6.4 Autocorrelation of the residuals – Durbin-Watson Test

```
> durbinWatsonTest(Resid_Reg_6)
n the residuals
[1] 2.587928
```

6.5 R Code

```
#Install & update necessary packages and libraries
install.packages("readxl")
library("readxl")
update.packages("readxl")

#DESCRIPTIVE STATISTICS
##EPU_Index_Developed
#Load the Excel data
EPU_Index <- read_xlsx("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "EPU Index")
#Select the subset of developed countries
EPU_Index_Developed <- EPU_Index[341:672, 3:15]
View(EPU_Index_Developed)
#Convert list in vector data                    #as.numeric requires a vector of values
Vector_data <- unlist(EPU_Index_Developed)
#Numeric data conversion                        #to convert the vector in numeric data
Numeric_data <- as.numeric(Vector_data)
is.numeric(Numeric_data)                        #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data, na.rm = TRUE)    #min function requires numeric data
max_value <- max(Numeric_data, na.rm = TRUE)
mean_value <- mean(Numeric_data, na.rm = TRUE)
sd_value <- sd(Numeric_data, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)
```

```
##EPU_Index_Emerging
#Select the subset of emerging countries
EPU_Index_Emerging <- EPU_Index[679:1010, 3:10]
View(EPU_Index_Emerging)
#Convert list in vector data                              #as.numeric requires a vector of values
Vector_data_2 <- unlist(EPU_Index_Emerging)
#Numeric data conversion                                  #to convert the vector in numeric data
Numeric_data_2 <- as.numeric(Vector_data_2)
is.numeric(Numeric_data_2)                                #check if Numeric_data is numeric
#Computation of key statistics
min_value <- min(Numeric_data_2, na.rm = TRUE)  #min function requires numeric data
max_value <- max(Numeric_data_2, na.rm = TRUE)
mean_value <- mean(Numeric_data_2, na.rm = TRUE)
sd_value <- sd(Numeric_data_2, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)

##Share_Price_Index_Developed
#Load the Excel data
Stocks <- read_xlsx("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "Stocks")
#Select the subset of developed countries
Share_Price_Index_Developed <- Stocks[1355:1686, 3:15]
View(Share_Price_Index_Developed)
#Convert list in vector data                    #as.numeric requires a vector of values
Vector_data_3 <- unlist(Share_Price_Index_Developed)
#Numeric data conversion                        #to convert the vector in numeric data
Numeric_data_3 <- as.numeric(Vector_data_3)
```

```
is.numeric(Numeric_data_3)                    #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_3, na.rm = TRUE)     #min function requires numeric data
max_value <- max(Numeric_data_3, na.rm = TRUE)
mean_value <- mean(Numeric_data_3, na.rm = TRUE)
sd_value <- sd(Numeric_data_3, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)

##Share_Price_Index_Emerging
#Select the subset of emerging countries
Share_Price_Index_Emerging <- Stocks[1693:2024, 3:10]
View(Share_Price_Index_Emerging)
#Convert list in vector data                   #as.numeric requires a vector of values
Vector_data_4 <- unlist(Share_Price_Index_Emerging)
#Numeric data conversion                       #to convert the vector in numeric data
Numeric_data_4 <- as.numeric(Vector_data_4)
is.numeric(Numeric_data_4)                    #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_4, na.rm = TRUE)   #min function requires numeric data
max_value <- max(Numeric_data_4, na.rm = TRUE)
mean_value <- mean(Numeric_data_4, na.rm = TRUE)
sd_value <- sd(Numeric_data_4, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
```

```
print(sd_value)

##Bond_Price_Index_Developed
#Load the Excel data
Bonds <- read_xlsx("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "Bonds")
#Select the subset of developed countries
Bond_Price_Index_Developed <- Bonds[491:606, 3:15]
View(Bond_Price_Index_Developed)
#Convert list in vector data                    #as.numeric requires a vector of values
Vector_data_5 <- unlist(Bond_Price_Index_Developed)
#Numeric data conversion                        #to convert the vector in numeric data
Numeric_data_5 <- as.numeric(Vector_data_5)
is.numeric(Numeric_data_5)                      #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_5, na.rm = TRUE)   #min function requires numeric data
max_value <- max(Numeric_data_5, na.rm = TRUE)
mean_value <- mean(Numeric_data_5, na.rm = TRUE)
sd_value <- sd(Numeric_data_5, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)

##Bond_Price_Index_Emerging
#Select the subset of emerging countries
Bond_Price_Index_Emerging <- Bonds[613:728, 3:10]
View(Bond_Price_Index_Emerging)
#Convert list in vector data                    #as.numeric requires a vector of values
Vector_data_6 <- unlist(Bond_Price_Index_Emerging)
```

```
#Numeric data conversion                              #to convert the vector in numeric data
Numeric_data_6 <- as.numeric(Vector_data_6)
is.numeric(Numeric_data_6)                           #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_6, na.rm = TRUE)  #min function requires numeric data
max_value <- max(Numeric_data_6, na.rm = TRUE)
mean_value <- mean(Numeric_data_6, na.rm = TRUE)
sd_value <- sd(Numeric_data_6, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)

##Share_Index_Excess_Returns_Developed
#Select the subset of developed countries
Share_Index_Excess_Returns_Developed <- Stocks[2708:3038, 3:15]
View(Share_Index_Excess_Returns_Developed)
#Convert list in vector data                           #as.numeric requires a vector of values
Vector_data_7 <- unlist(Share_Index_Excess_Returns_Developed)
#Numeric data conversion                               #to convert the vector in numeric data
Numeric_data_7 <- as.numeric(Vector_data_7)
is.numeric(Numeric_data_7)                 #check if Numeric_data is numeric : YES
Numeric_data_7_clean <- na.omit(Numeric_data_7)    #to omit NA values
is.numeric(Numeric_data_7_clean)
#Computation of key statistics
min_value <- min(Numeric_data_7, na.rm = TRUE)    #min function requires numeric data
max_value <- max(Numeric_data_7, na.rm = TRUE)
mean_value <- mean(Numeric_data_7, na.rm = TRUE)
sd_value <- sd(Numeric_data_7, na.rm = TRUE)
```

```
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)

##Share_Index_Excess_Returns_Emerging
#Select the subset of emerging countries
Share_Index_Excess_Returns_Emerging <- Stocks[3046:3376, 3:10]
View(Share_Index_Excess_Returns_Emerging)
#Convert list in vector data                    #as.numeric requires a vector of values
Vector_data_8 <- unlist(Share_Index_Excess_Returns_Emerging)
#Numeric data conversion                        #to convert the vector in numeric data
Numeric_data_8 <- as.numeric(Vector_data_8)
is.numeric(Numeric_data_8)                      #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_8, na.rm = TRUE)   #min function requires numeric data
max_value <- max(Numeric_data_8, na.rm = TRUE)
mean_value <- mean(Numeric_data_8, na.rm = TRUE)
sd_value <- sd(Numeric_data_8, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)

##Bond_Index_Excess_Returns_Developed
#Select the subset of developed countries
Bond_Index_Excess_Returns_Developed <- Bonds[980:1094, 3:15]
View(Bond_Index_Excess_Returns_Developed)
```

```
#Convert list in vector data                    #as.numeric requires a vector of values
Vector_data_9 <- unlist(Bond_Index_Excess_Returns_Developed)
#Numeric data conversion                        #to convert the vector in numeric data
Numeric_data_9 <- as.numeric(Vector_data_9)
is.numeric(Numeric_data_9)                      #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_9, na.rm = TRUE)   #min function requires numeric data
max_value <- max(Numeric_data_9, na.rm = TRUE)
mean_value <- mean(Numeric_data_9, na.rm = TRUE)
sd_value <- sd(Numeric_data_9, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)

##Bond_Index_Excess_Returns_Emerging
#Select the subset of emerging countries
Bond_Index_Excess_Returns_Emerging <- Bonds[1102:1216, 3:10]
View(Bond_Index_Excess_Returns_Emerging)
#Convert list in vector data                    #as.numeric requires a vector of values
Vector_data_10 <- unlist(Bond_Index_Excess_Returns_Emerging)
#Numeric data conversion                        #to convert the vector in numeric data
Numeric_data_10 <- as.numeric(Vector_data_10)
is.numeric(Numeric_data_10)                     #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_10, na.rm = TRUE)   #min function requires numeric data
max_value <- max(Numeric_data_10, na.rm = TRUE)
mean_value <- mean(Numeric_data_10, na.rm = TRUE)
sd_value <- sd(Numeric_data_10, na.rm = TRUE)
```

```
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)


##Fama_French_Factors_Developed
##SMB
#Load the Excel data
Fama_French_Factors <- read_xlsx("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "Fama-French Factors")
#Select the SMB factor for the subset of developed countries
Fama_French_factors_Developed_SMB <- Fama_French_Factors[342:673, 3:3]
View(Fama_French_factors_Developed_SMB)
#Convert list in vector data                          #as.numeric requires a vector of values
Vector_data_11 <- unlist(Fama_French_factors_Developed_SMB)
#Numeric data conversion                              #to convert the vector in numeric data
Numeric_data_11 <- as.numeric(Vector_data_11)
is.numeric(Numeric_data_11)                           #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_11, na.rm = TRUE)  #min function requires numeric data
max_value <- max(Numeric_data_11, na.rm = TRUE)
mean_value <- mean(Numeric_data_11, na.rm = TRUE)
sd_value <- sd(Numeric_data_11, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)
```

```
#HML
#Select the HML factor for the subset of developed countries
Fama_French_factors_Developed_HML <- Fama_French_Factors[342:673, 4:4]
View(Fama_French_factors_Developed_HML)
#Convert list in vector data                      #as.numeric requires a vector of values
Vector_data_12 <- unlist(Fama_French_factors_Developed_HML)
#Numeric data conversion                          #to convert the vector in numeric data
Numeric_data_12 <- as.numeric(Vector_data_12)
is.numeric(Numeric_data_12)                       #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_12, na.rm = TRUE)  #min function requires numeric data
max_value <- max(Numeric_data_12, na.rm = TRUE)
mean_value <- mean(Numeric_data_12, na.rm = TRUE)
sd_value <- sd(Numeric_data_12, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)

##RMW
#Select the RMW factor for the subset of developed countries
Fama_French_factors_Developed_RMW <- Fama_French_Factors[342:673, 5:5]
View(Fama_French_factors_Developed_RMW)
#Convert list in vector data                      #as.numeric requires a vector of values
Vector_data_13 <- unlist(Fama_French_factors_Developed_RMW)
#Numeric data conversion                          #to convert the vector in numeric data
Numeric_data_13 <- as.numeric(Vector_data_13)
is.numeric(Numeric_data_13)                       #check if Numeric_data is numeric : YES
```

```
#Computation of key statistics
min_value <- min(Numeric_data_13, na.rm = TRUE)        #min function requires numeric data
max_value <- max(Numeric_data_13, na.rm = TRUE)
mean_value <- mean(Numeric_data_13, na.rm = TRUE)
sd_value <- sd(Numeric_data_13, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)

##CMA
#Select the RMW factor for the subset of developed countries
Fama_French_factors_Developed_CMA <- Fama_French_Factors[342:673, 6:6]
View(Fama_French_factors_Developed_CMA)
#Convert list in vector data                               #as.numeric requires a vector of values
Vector_data_14 <- unlist(Fama_French_factors_Developed_CMA)
#Numeric data conversion                                   #to convert the vector in numeric data
Numeric_data_14 <- as.numeric(Vector_data_14)
is.numeric(Numeric_data_14)                                #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_14, na.rm = TRUE) #min function requires numeric data
max_value <- max(Numeric_data_14, na.rm = TRUE)
mean_value <- mean(Numeric_data_14, na.rm = TRUE)
sd_value <- sd(Numeric_data_14, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)
```

```
##Emerging Countries
##SMB
#Select the SMB factor for the subset of emerging countries
Fama_French_factors_Emerging_SMB <- Fama_French_Factors[342:673, 12:12]
View(Fama_French_factors_Emerging_SMB)
#Convert list in vector data                    #as.numeric requires a vector of values
Vector_data_15 <- unlist(Fama_French_factors_Emerging_SMB)
#Numeric data conversion                        #to convert the vector in numeric data
Numeric_data_15 <- as.numeric(Vector_data_15)
is.numeric(Numeric_data_15)                     #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_15, na.rm = TRUE)  #min function requires numeric data
max_value <- max(Numeric_data_15, na.rm = TRUE)
mean_value <- mean(Numeric_data_15, na.rm = TRUE)
sd_value <- sd(Numeric_data_15, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)

##HML
#Select the HML factor for the subset of emerging countries
Fama_French_factors_Emerging_HML <- Fama_French_Factors[342:673, 13:13]
View(Fama_French_factors_Emerging_HML)
#Convert list in vector data                    #as.numeric requires a vector of values
Vector_data_16 <- unlist(Fama_French_factors_Emerging_HML)
#Numeric data conversion                        #to convert the vector in numeric data
Numeric_data_16 <- as.numeric(Vector_data_16)
is.numeric(Numeric_data_16)                     #check if Numeric_data is numeric : YES
```

```
#Computation of key statistics
min_value <- min(Numeric_data_16, na.rm = TRUE)        #min function requires numeric data
max_value <- max(Numeric_data_16, na.rm = TRUE)
mean_value <- mean(Numeric_data_16, na.rm = TRUE)
sd_value <- sd(Numeric_data_16, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)

##RMW
#Select the RMW factor for the subset of emerging countries
Fama_French_factors_Emerging_RMW <- Fama_French_Factors[342:673, 14:14]
View(Fama_French_factors_Emerging_RMW)
#Convert list in vector data                                #as.numeric requires a vector of values
Vector_data_17 <- unlist(Fama_French_factors_Emerging_RMW)
#Numeric data conversion                                    #to convert the vector in numeric data
Numeric_data_17 <- as.numeric(Vector_data_17)
is.numeric(Numeric_data_17)                                 #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_17, na.rm = TRUE)  #min function requires numeric data
max_value <- max(Numeric_data_17, na.rm = TRUE)
mean_value <- mean(Numeric_data_17, na.rm = TRUE)
sd_value <- sd(Numeric_data_17, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)
```

```
##CMA
#Select the CMA factor for the subset of emerging countries
Fama_French_factors_Emerging_CMA <- Fama_French_Factors[342:673, 15:15]
View(Fama_French_factors_Emerging_CMA)
#Convert list in vector data                    #as.numeric requires a vector of values
Vector_data_18 <- unlist(Fama_French_factors_Emerging_CMA)
#Numeric data conversion                        #to convert the vector in numeric data
Numeric_data_18 <- as.numeric(Vector_data_18)
is.numeric(Numeric_data_18)                     #check if Numeric_data is numeric : YES
#Computation of key statistics
min_value <- min(Numeric_data_18, na.rm = TRUE) #min function requires numeric data
max_value <- max(Numeric_data_18, na.rm = TRUE)
mean_value <- mean(Numeric_data_18, na.rm = TRUE)
sd_value <- sd(Numeric_data_18, na.rm = TRUE)
#Print key statistics
print(min_value)
print(max_value)
print(mean_value)
print(sd_value)

##VARIABLES TRANSFORMATIONS?
#FREQUENCY HISTOGRAMS
#Share_Index_Excess_Returns_Developed
Numeric_data_7                    #Numeric set of share_index_excess_returns_developed
Share_Index_Excess_Returns_Developed_Histogram <- hist(Numeric_data_7)
#Share_Index_Excess_Returns_Emerging
Numeric_data_8                    #Numeric set of share_index_excess_returns_emerging
Share_Index_Excess_Returns_Emerging_Histogram <- hist(Numeric_data_8)
```

```
#Bond_Index_Excess_Returns_Developed
Numeric_data_9                #Numeric set of bond_index_excess_returns_developed
Bond_Index_Excess_Returns_Developed_Histogram <- hist(Numeric_data_9)
#BER_Emerging
Numeric_data_10               #Numeric set of bond_index_excess_returns_emerging
Bond_Index_Excess_Returns_Emerging_Histogram <- hist(Numeric_data_10)
#EPU_Index_Developed
Numeric_data
EPU_Index_Developed_Histogram <- hist(Numeric_data)
#EPU_Index_Emerging
Numeric_data_2
EPU_Index_Emerging_Histogram <- hist(Numeric_data_2)
#SMB_Developed
Numeric_data_11
SMB_Developed_Histogram <- hist(Numeric_data_11)
#HML_Developed
Numeric_data_12
HML_Developed_Histogram <- hist(Numeric_data_12)
#RMW_Developed
Numeric_data_13
RMW_Developed_Histogram <- hist(Numeric_data_13)
#CMA_Developed
Numeric_data_14
CMA_Developed_Histogram <- hist(Numeric_data_14)
#SMB_Emerging
Numeric_data_15
SMB_Emerging_Histogram <- hist(Numeric_data_15)
#HML_Emerging
Numeric_data_16
HML_Emerging_Histogram <- hist(Numeric_data_16)
```

```
#RMW_Emerging
Numeric_data_17
RMW_Emerging_Histogram <- hist(Numeric_data_17)
#CMA_Emerging
Numeric_data_18
CMA_Emerging_Histogram <- hist(Numeric_data_18)

#DATA STATIONARITY TESTS
install.packages("tseries")          #Install & update necessary package for ADF test
library("tseries")
update.packages("tseries")

#EPU_Index_Developed
adf.test(Numeric_data)
#EPU_Index_Emerging
adf.test(Numeric_data_2)
#Share_Index_Excess_Returns_Developed
adf.test(Numeric_data_7_clean)
#Share_Index_Excess_Returns_Emerging
adf.test(Numeric_data_8)
#Bond_Index_Excess_Returns_Developed
adf.test(Numeric_data_9)
#Bond_Index_Excess_Returns_Emerging
adf.test(Numeric_data_10)

##Developed countries
#SMB
adf.test(Numeric_data_11)
#HML
adf.test(Numeric_data_12)
```

```
#RMW
adf.test(Numeric_data_13)
#CMA
adf.test(Numeric_data_14)
##Emerging countries
#SMB
adf.test(Numeric_data_15)
#HML
adf.test(Numeric_data_16)
#RMW
adf.test(Numeric_data_17)
#CMA
adf.test(Numeric_data_18)


##MULTIVARIATE LINEAR REGRESSIONS
#LOAD DATA FOR REGRESSION ANALYSIS (numeric)
SER_Developed <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "Share_Excess_Returns_Developed")
SER_Emerging <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "Share_Excess_Returns_Emerging")
BER_Developed <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet ="Bond_Excess_Returns_Developed")
BER_Emerging <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "Bond_Excess_Returns_Emerging")
EPU_Developed <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "EPU_Index_Developed")
EPU_Emerging <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "EPU_Index_Emerging")
SMB_Developed <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "SMB_Developed")
HML_Developed <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "HML_Developed")
```

RMW_Developed <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "RMW_Developed")

CMA_Developed <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "CMA_Developed")

SMB_Emerging <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "SMB_Emerging")

HML_Emerging <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "HML_Emerging")

RMW_Emerging <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "RMW_Emerging")

CMA_Emerging <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "CMA_Emerging")

##Share_Index_Excess_Returns_Developed

Regression_SER_DEV_Data <- cbind(SER_Developed, EPU_Developed, SMB_Developed, HML_Developed, RMW_Developed, CMA_Developed) #create a single data frame for regression 1

Regression_1 <- lm(Australia_SER+Canada_SER+Germany_SER+Spain_SER+France_SER+UK_SER+Greece_SER+Ireland_SER+Italy_SER+Japan_SER+Sweden_SER+Singapore_SER+US_SER #Run regression 1 on SER of developed countries

~

log10(Australia_EPU+Canada_EPU+Germany_EPU+Spain_EPU+France_EPU+UK_EPU+Greece_EPU+Ireland_EPU+Italy_EPU+Japan_EPU+Sweden_EPU+Singapore_EPU+US_EPU)

+ SMB_Developed

+ HML_Developed

+ RMW_Developed

+ CMA_Developed, data = Regression_SER_DEV_Data, na.action = na.omit)

summary(Regression_1) #to have the summary of Regression_1

#CORRELATION MATRIX (EXPLANATORY VARIABLES) - REGRESSION 1

Corr_Mat_Regression_1_Data <- cbind(Numeric_data, Numeric_data_11, Numeric_data_12, Numeric_data_13, Numeric_data_14) #1 single data frame of Regression_1_Explanatory variables

Corr_Matrix_Regression_1 <- cor(Corr_Mat_Regression_1_Data) #compute the correlation matrix

View(Corr_Matrix_Regression_1)

View(EPU_Index_Developed)

##Share_Index_Excess_Returns_Emerging

Regression_SER_EMR_Data <- cbind(SER_Emerging, EPU_Emerging, SMB_Emerging, HML_Emerging, RMW_Emerging, CMA_Emerging) #create a single data frame for regression 2

Regression_2 <- lm(Brazil_SER+Chile_SER+China_SER+India_SER+Mexico_SER+Pakistan_SER+Russia_SER+Korea_SER #Run regression 2

~

log10(Brazil_EPU+Chile_EPU+China_EPU+India_EPU+Mexico_EPU+Pakistan_EPU+Russia_EPU+Korea_EPU)

+ SMB_Emerging

+ HML_Emerging

+ RMW_Emerging

+ CMA_Emerging, data = Regression_SER_EMR_Data, na.action = na.omit)

summary(Regression_2) #to have the summary of Regression_2

#CORRELATION MATRIX (EXPLANATORY VARIABLES) - REGRESSION 2

Corr_Mat_Regression_2_Data <- cbind(Numeric_data_2, Numeric_data_15, Numeric_data_16, Numeric_data_17, Numeric_data_18) #1 single data frame of Regression_1_Explanatory variables

Corr_Matrix_Regression_2 <- cor(Corr_Mat_Regression_2_Data) #compute the correlation matrix

View(Corr_Matrix_Regression_2)

#Load the date-adjusted data for bond_excess_returns regressions

EPU_Developed_Bond_Reg <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "EPU_Index_Developed_Short")

EPU_Emerging_Bond_Reg <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "EPU_Index_Emerging_Short")

SMB_Developed_Bond_Reg <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "SMB_Developed_Short")

SMB_Emerging_Bond_Reg <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "SMB_Emerging_Short")

HML_Developed_Bond_Reg <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "HML_Developed_Short")

HML_Emerging_Bond_Reg <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "HML_Emerging_Short")

RMW_Developed_Bond_Reg <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "RMW_Developed_Short")

RMW_Emerging_Bond_Reg <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "RMW_Emerging_Short")

CMA_Developed_Bond_Reg <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "CMA_Developed_Short")

CMA_Emerging_Bond_Reg <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "CMA_Emerging_Short")

##Numeric conversion of date-adjusted data for bond_excess_returns

##EPU_Developed_Bond_Reg

#Exclude columns "Year" & "Month"

EPU_Developed_Bond_Reg_Excluded <- EPU_Developed_Bond_Reg[,!names(EPU_Developed_Bond_Reg) %in% c("Year", "Month")]

#Convert list in vector data #as.numeric requires a vector of values

Vector_data_19 <- unlist(EPU_Developed_Bond_Reg_Excluded)

```
#Numeric data conversion #to convert the vector in numeric data
Numeric_data_19 <- as.numeric(Vector_data_19)
is.numeric(Numeric_data_19)
##EPU_Emerging_Bond_Reg
#Exclude columns "Year" & "Month"
EPU_Emerging_Bond_Reg_Excluded <- EPU_Emerging_Bond_Reg[,!names(EPU_Emerging_Bond_Reg) %in% c("Year", "Month")]
#Convert list in vector data #as.numeric requires a vector of values
Vector_data_20 <- unlist(EPU_Emerging_Bond_Reg_Excluded)
#Numeric data conversion #to convert the vector in numeric data
Numeric_data_20 <- as.numeric(Vector_data_20)
is.numeric(Numeric_data_20)
##SMB_Developed_Bond_Reg
#Exclude columns "Year" & "Month"
SMB_Developed_Bond_Reg_Excluded <- SMB_Developed_Bond_Reg[,!names(SMB_Developed_Bond_Reg) %in% c("Year", "Month")]
is.numeric(SMB_Developed_Bond_Reg_Excluded)
##SMB_Emerging_Bond_Reg
#Exclude columns "Year" and "Month"
SMB_Emerging_Bond_Reg_Excluded <- SMB_Emerging_Bond_Reg[,!names(SMB_Emerging_Bond_Reg) %in% c("Year", "Month")]
is.numeric(SMB_Emerging_Bond_Reg_Excluded)
##HML_Developed_Bond_Reg
#Exclude columns "Year" and "Month"
HML_Developed_Bond_Reg_Excluded <- HML_Developed_Bond_Reg[,!names(HML_Developed_Bond_Reg) %in% c("Year", "Month")]
is.numeric(HML_Developed_Bond_Reg_Excluded)
##HML_Emerging_Bond_Reg
#Exclude columns "Year" and "Month"
```

```
HML_Emerging_Bond_Reg_Excluded <- HML_Emerging_Bond_Reg[,!names(HML_Emerging_Bond_Reg) %in% c("Year", "Month")]

is.numeric(HML_Emerging_Bond_Reg_Excluded)

##RMW_Developed_Bond_Reg

#Exclude columns "Year" & "Month"

RMW_Developed_Bond_Reg_Excluded <- RMW_Developed_Bond_Reg[,!names(RMW_Developed_Bond_Reg) %in% c("Year", "Month")]

is.numeric(RMW_Developed_Bond_Reg_Excluded)

##RMW_Emerging_Bond_Reg

#Exclude columns "Year" & "Month"

RMW_Emerging_Bond_Reg_Excluded <- RMW_Emerging_Bond_Reg[,!names(RMW_Emerging_Bond_Reg) %in% c("Year", "Month")]

is.numeric(RMW_Emerging_Bond_Reg_Excluded)

##CMA_Developed_Bond_Reg

#Exclude columns "Year" & "Month"

CMA_Developed_Bond_Reg_Excluded <- CMA_Developed_Bond_Reg[,!names(CMA_Developed_Bond_Reg) %in% c("Year", "Month")]

is.numeric(CMA_Developed_Bond_Reg_Excluded)

##CMA_Emerging_Bond_Reg

#Exclude columns "Year" & "Month"

CMA_Emerging_Bond_Reg_Excluded <- CMA_Emerging_Bond_Reg[,!names(CMA_Emerging_Bond_Reg) %in% c("Year", "Month")]

is.numeric(CMA_Emerging_Bond_Reg_Excluded)


##DATA STATIONARITY TESTS

install.packages("tseries")        #Install & update necessary package for ADF test

library("tseries")

update.packages("tseries")
```

```
#EPU_Developed_Bond_Reg
adf.test(Numeric_data_19)
#EPU_Emerging_Bond_Reg
adf.test(Numeric_data_20)
#SMB_Developed_Bond_Reg
adf.test(SMB_Developed_Bond_Reg_Excluded)
#SMB_Emerging_Bond_Reg
adf.test(SMB_Emerging_Bond_Reg_Excluded)
#HML_Developed_Bond_Reg
adf.test(HML_Developed_Bond_Reg_Excluded)
#HML_Emerging_Bond_Reg
adf.test(HML_Emerging_Bond_Reg_Excluded)
#RMW_Developed_Bond_Reg
adf.test(RMW_Developed_Bond_Reg_Excluded)
#RMW_Emerging_Bond_Reg
adf.test(RMW_Emerging_Bond_Reg_Excluded)
#CMA_Developed_Bond_Reg
adf.test(CMA_Developed_Bond_Reg_Excluded)
#CMA_Emerging_Bond_Reg
adf.test(CMA_Emerging_Bond_Reg_Excluded)

##FREQUENCY HISTOGRAMMS
#EPU_Developed_Bond_Reg
hist(Numeric_data_19)
#EPU_Emerging_Bond_Reg
hist(Numeric_data_20)
#SMB_Developed_Bond_Reg
hist(SMB_Developed_Bond_Reg_Excluded)
#HML_Developed_Bond_Reg
hist(HML_Developed_Bond_Reg_Excluded)
```

```
#RMW_Developed_Bond_Reg
hist(RMW_Developed_Bond_Reg_Excluded)
#CMA_Developed_Bond_Reg
hist(log(CMA_Developed_Bond_Reg_Excluded))
#SMB_Emerging_Bond_Reg
hist(SMB_Emerging_Bond_Reg_Excluded)
#HML_Emerging_Bond_Reg
hist(HML_Emerging_Bond_Reg_Excluded)
#RMW_Emerging_Bond_Reg
hist(RMW_Emerging_Bond_Reg_Excluded)
#CMA_Emerging_Bond_Reg
hist(CMA_Emerging_Bond_Reg_Excluded)


##Bond_Index_Excess_Returns_Developed
Regression_BER_DVP_Data <-
cbind(BER_Developed,EPU_Developed_Bond_Reg,SMB_Developed_Bond_Reg,HML_Developed_Bond_Reg,RMW_Developed_Bond_Reg,CMA_Developed_Bond_Reg)
#create a single data frame for regression 3


Regression_3 <-
lm(Australia_BER+Canada_BER+Germany_BER+Spain_BER+France_BER+UK_BER+Greece_BER+Ireland_BER+Italy_BER+Japan_BER+Sweden_BER+Singapore_BER+US_BER #run regression 3

            ~
log10(Australia_EPU+Canada_EPU+Germany_EPU+Spain_EPU+France_EPU+UK_EPU+Greece_EPU+Ireland_EPU+Italy_EPU+Japan_EPU+Sweden_EPU+Singapore_EPU+US_EPU)
            + SMB_Developed
            + HML_Developed
            + RMW_Developed
            + CMA_Developed, data = Regression_BER_DVP_Data, na.action = na.omit)
summary(Regression_3)                    #to have the summary of Regression_3
```

#CORRELATION MATRIX (EXPLANATORY VARIABLES) - REGRESSION 3

Corr_Mat_Regression_3_Data <- cbind(Numeric_data_19, SMB_Developed_Bond_Reg_Excluded, HML_Developed_Bond_Reg_Excluded, RMW_Developed_Bond_Reg_Excluded, CMA_Developed_Bond_Reg_Excluded) #1 single data frame of Regression_1_Explanatory variables

Corr_Matrix_Regression_3 <- cor(Corr_Mat_Regression_3_Data) #compute the correlation matrix

View(Corr_Matrix_Regression_3)

##Bond_Index_Excess_Returns_Emerging

Regression_BER_EMR_Data <- cbind(BER_Emerging,EPU_Emerging_Bond_Reg,SMB_Emerging_Bond_Reg,HML_Emerging_Bond_Reg,RMW_Emerging_Bond_Reg,CMA_Emerging_Bond_Reg) #create a single data frame for regression 4

Regression_4 <- lm(Brazil_BER+Chile_BER+China_BER+India_BER+Mexico_BER+Pakistan_BER+Russia_BER+Korea_BER #run regression 4

~

log10(Brazil_EPU+Chile_EPU+China_EPU+India_EPU+Mexico_EPU+Pakistan_EPU+Russia_EPU+Korea_EPU)

+ SMB_Emerging

+ HML_Emerging

+ RMW_Emerging

+ CMA_Emerging, data = Regression_BER_EMR_Data, na.action = na.omit)

summary(Regression_4) #to have the summary of Regression_4

#CORRELATION MATRIX (EXPLANATORY VARIABLES) - REGRESSION 4

Corr_Mat_Regression_4_Data <- cbind(Numeric_data_20, SMB_Emerging_Bond_Reg_Excluded, HML_Emerging_Bond_Reg_Excluded, RMW_Emerging_Bond_Reg_Excluded, CMA_Emerging_Bond_Reg_Excluded) #1 single data frame of Regression_1_Explanatory variables

Corr_Matrix_Regression_4 <- cor(Corr_Mat_Regression_4_Data) #compute the correlation matrix

View(Corr_Matrix_Regression_4)

##CORRELATION REGRESSIONS

#Load Share-Bond Excess Returns Correlations for developed & emerging countries + EPU_DEV_FREQ_ADJ_CORR + EPU_EME_FREQ_ADJ_CORR

Correlations_DVP <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "Correlations_DEV_2")

Correlations_EME <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "Correlations_EME_2")

Correlations_EME_LN <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "Correlations_EME_2_LN")

EPU_Developed_FREQ_CORR <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "EPU_Index_Dev_Short_CORR_2")

EPU_Developed_FREQ_CORR_DIFF <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "EPU_Dev_Short_CORR_2_DIF")

EPU_Emerging_FREQ_CORR <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "EPU_Index_Eme_Short_CORR_2")

EPU_Emerging_FREQ_CORR_DIFF <- read_excel("C:\\Users\\Yann Hanse\\Documents\\Master's thesis\\Working Directory\\Master's thesis - Spreadsheet.xlsx", sheet = "EPU_Index_Eme_Short_CORR_2_DIFF")

#Exclude column "Year Ranges"

Correlations_DVP_Excluded <- Correlations_DVP[,!names(Correlations_DVP) %in% c("Year Ranges")]

Correlations_EME_Excluded <- Correlations_EME[,!names(Correlations_EME) %in% c("Years")]

Correlations_EME_LN_Excluded <- Correlations_EME_LN[,!names(Correlations_EME_LN) %in% c("Years")]

EPU_Developed_FREQ_CORR_Excluded <- EPU_Developed_FREQ_CORR[,!names(EPU_Developed_FREQ_CORR) %in% c("Year")]

EPU_Developed_FREQ_CORR_DIFF_Excluded <- EPU_Developed_FREQ_CORR_DIFF[,!names(EPU_Developed_FREQ_CORR_DIFF) %in% c("Year")]

EPU_Emerging_FREQ_CORR_Excluded <- EPU_Emerging_FREQ_CORR[,!names(EPU_Emerging_FREQ_CORR) %in% c("Years")]

```
EPU_Emerging_FREQ_CORR_DIFF_Excluded <- EPU_Emerging_FREQ_CORR_DIFF[,!names(EPU_Emerging_FREQ_CORR_DIFF) %in% c("Years")]

#Convert to numeric data

#Convert list in vector data                    #as.numeric requires a vector of values

Vector_data_21 <- unlist(Correlations_DVP_Excluded)

Vector_data_22 <- unlist(Correlations_EME_Excluded)

Vector_data_23 <- unlist(EPU_Developed_FREQ_CORR_Excluded)

Vector_data_24 <- unlist(EPU_Emerging_FREQ_CORR_Excluded)

Vector_data_25 <- unlist(Correlations_EME_LN_Excluded)

Vector_data_27 <- unlist(EPU_Developed_FREQ_CORR_DIFF_Excluded)

Vector_data_28 <- unlist(EPU_Emerging_FREQ_CORR_DIFF_Excluded)

#Numeric data conversion                    #to convert the vector in numeric data

Numeric_data_21 <- as.numeric(Vector_data_21)

is.numeric(Numeric_data_21)

Numeric_data_22 <- as.numeric(Vector_data_22)

is.numeric(Numeric_data_22)

Numeric_data_23 <- as.numeric(Vector_data_23)

is.numeric(Numeric_data_23)

Numeric_data_24 <- as.numeric(Vector_data_24)

is.numeric(Numeric_data_24)

Numeric_data_25 <- as.numeric(Vector_data_25)

is.numeric(Numeric_data_25)

Numeric_data_27 <- as.numeric(Vector_data_27)

is.numeric(Numeric_data_27)

Numeric_data_28 <- as.numeric(Vector_data_28)

is.numeric(Numeric_data_28)

#Remove "N/A values"

Numeric_data_25_clean <- na.omit(Numeric_data_25)
```

```
#DATA STATIONARITY TESTS
#Correlations_DVP
adf.test(Numeric_data_21)
#Correlations_EMR
adf.test(Numeric_data_22)
adf.test(Numeric_data_25_clean)                    #LN transformation for stationarity
#EPU_Developed_FREQ_CORR
adf.test(Numeric_data_23)
adf.test(Numeric_data_27)                          #differencing transformation for stationarity
#EPU_Emerging_FREQ_CORR
adf.test(Numeric_data_24)
adf.test(Numeric_data_28)                          #differencing transformation for stationarity

#FREQUENCY HISTOGRAMS
#Correlations_DVP
hist(Numeric_data_21)
#Correlations_EMR
hist(Numeric_data_22)                              #normal
hist(Numeric_data_25_clean)                        #ln

##Regression_Correlations_DEV
Regression_COR_DVP_Data <- cbind(Correlations_DVP, EPU_Developed_FREQ_CORR_DIFF)

Regression_5 <-
lm(Australia_CORR+Canada_CORR+Germany_CORR+Spain_CORR+France_CORR+UK_CORR+Greece_CORR+Ireland_CORR+Italy_CORR+Japan_CORR+Sweden_CORR+Singapore_CORR+US_CORR                                #run regression 5
           ~
log10(Australia_EPU_Diff+Canada_EPU_Diff+Germany_EPU_Diff+Spain_EPU_Diff+France_EPU_Diff+UK_EPU_Diff+Greece_EPU_Diff+Ireland_EPU_Diff+Italy_EPU_Diff+Japan_EPU_Diff+Sweden_EPU_Diff+Singapore_EPU_Diff+US_EPU_Diff)
           , data = Regression_COR_DVP_Data, na.action = na.omit)
```

```
summary(Regression_5)                    #to have the summary of Regression_5


##Regression_Correlations_EMR

Regression_CORR_EMR_Data <- cbind(Correlations_EME_LN,
EPU_Emerging_FREQ_CORR_DIFF)          #create a single data frame for regression 6

Regression_6 <-
lm(Brazil_CORR+Chile_CORR+China_CORR+India_CORR+Mexico_CORR+Pakistan_C
ORR+Russia_CORR+Korea_CORR            #run regression 6

        ~
log10(Brazil_EPU_DIFF+Chile_EPU_DIFF+China_EPU_DIFF+India_EPU_DIFF+Mexico
_EPU_DIFF+Pakistan_EPU_DIFF+Russia_EPU_DIFF+Korea_EPU_DIFF)

        , data = Regression_CORR_EMR_Data, na.action = na.omit)

summary(Regression_6)                    #to have the summary of Regression_6


##ASSUMPTIONS TESTS

##Regression_1: SER_Developed

#MULTICOLLINEARITY - FARRAR-GLAUBER TEST

install.packages("mctest")               #Install and load necessary packages

library("mctest")

mctest(Regression_1)

#HOMOSCEDASTIC VARIANCE - GOLDFELD-QUANDT TEST

install.packages("lmtest")               #Install and load necessary packages

library("lmtest")

gqtest(Regression_1)

#NORMALITY OF THE RESIDUALS - JARQUE-BERA TEST

install.packages("desk")                 #Install & load necessary packages

library("desk")

Resid_Reg_1 <- residuals(Regression_1)   #Extract the residuals of Regression_1

jb.test(Resid_Reg_1)                     #Jarque-Bera test on residuals of Regression_1

#AUTO-CORRELATION OF THE RESIDUALS - DURBIN-WATSON TEST

#install & load necessary packages

install.packages("car")
```

```
library(car)
durbinWatsonTest(Resid_Reg_1)                    #Durbin-Watson test on residuals

##Regression_2: SER_Emerging
#MULTICOLLINEARITY - FARRAR-GLAUBER TEST
install.packages("mctest")                       #Install and load necessary packages
library("mctest")
mctest(Regression_2)
#HOMOSCEDASTIC VARIANCE - GOLDFELD-QUANDT TEST
install.packages("lmtest")                       #Install and load necessary packages
library("lmtest")
gqtest(Regression_2)
#NORMALITY OF THE RESIDUALS - JARQUE-BERA TEST
install.packages("desk")                         #Install & load necessary packages
library("desk")
Resid_Reg_2 <- residuals(Regression_2)           #Extract the residuals of Regression 2
jb.test(Resid_Reg_2)             #Jarque-Bera test on the residuals of Regression 2
#NON-NORMALITY DETECTED - TROUBLESHOOTING
hist(Resid_Reg_2)                                #histogram of residuals
qqplot(Resid_Reg_2, Resid_Reg_2)                 #qqplot
#AUTO-CORRELATION OF THE RESIDUALS - DURBIN-WATSON TEST
install.packages("car")
library(car)
durbinWatsonTest(Resid_Reg_2)                    #Durbin-Watson test on residuals

##Regression_3: BER_Developed
#MULTICOLLINEARITY - FARRAR-GLAUBER TEST
mctest(Regression_3)
#HOMOSCEDASTIC VARIANCE - WHITE TEST
install.packages("whitestrap")                   #Install & load necessary packages
```

```
library("whitestrap")
white_test(Regression_3)
#NORMALITY OF THE RESIDUALS - JARQUE-BERA TEST
Resid_Reg_3 <- residuals(Regression_3)          #Extract the residuals of Regression 3
jb.test(Resid_Reg_3)          #Jarque-Bera test on the residuals of Regression 3
#AUTO-CORRELATION OF THE RESIDUALS - DURBIN-WATSON TEST
durbinWatsonTest(Resid_Reg_3)          #Durbin-Watson test on the residuals
##Regression_4: BER_Emerging
#MULTICOLLINEARITY - FARRAR-GLAUBER TEST
mctest(Regression_4)
#HOMOSCEDASTIC VARIANCE - WHITE TEST
install.packages("whitestrap")          #Install & load necessary packages
library("whitestrap")
white_test(Regression_4)
#NORMALITY OF THE RESIDUALS - JARQUE-BERA TEST
Resid_Reg_4 <- residuals(Regression_4)          #Extract the residuals of Regression 4
jb.test(Resid_Reg_4)          #Jarque-Bera test on the residuals of Regression 4
#AUTO-CORRELATION OF THE RESIDUALS - DURBIN-WATSON TEST
durbinWatsonTest(Resid_Reg_4)          #Durbin-Watson test on the residuals

##Regression 5: Correlations_Developed: Simple linear regression
#LINEARITY - SCATTERPLOT WITH REGRESSION LINE
plot(Numeric_data_23, Numeric_data_21, main = "Scatterplot with regression line - 2015-2024 for Developed Countries", xlab= "EPU Indexes", ylab="Share-Bond Excess Returns Correlations")          #creation of the scatter plot with plot() function
regression_line <- lm(Numeric_data_21 ~ Numeric_data_23)
#creation of the regression line
abline(regression_line, col = "green")
#add the regression line on the scatter plot (add a straight line to the plot)
#HOMOSCEDASTIC VARIANCE - WHITE TEST
white_test(Regression_5)
```

```
#NORMALITY OF THE RESIDUALS - JARQUE-BERA TEST
install.packages("desk")                                    #Install & load necessary packages
library("desk")
Resid_Reg_5 <- residuals(Regression_5)                      #Extract the residuals of Regression
5
jb.test(Resid_Reg_5)                    #Jarque-Bera test on the residuals of Regression 5
#AUTO-CORRELATION OF THE RESIDUALS - DURBIN-WATSON TEST
install.packages("car")
library(car)
durbinWatsonTest(Resid_Reg_5)                               #Durbin-Watson test on the residuals


##Regression 6: Correlations_Emerging
#LINEARITY - SCATTERPLOT WITH REGRESSION LINE
plot(Numeric_data_24, Numeric_data_22, main = "Scatterplot with regression line - 2015-
2024 for Emerging Countries", xlab= "EPU Indexes", ylab="Share-Bond Excess Returns
Correlations")                          #creation of the scatter plot with plot() function
regression_line <- lm(Numeric_data_22 ~ Numeric_data_24)
#creation of the regression line
abline(regression_line, col = "green")
#HOMOSCEDASTIC VARIANCE - WHITE TEST
library(whitestrap)
white_test(Regression_6)
#NORMALITY OF THE RESIDUALS - JARQUE-BERA TEST
install.packages("desk")                                    #Install & load necessary packages
library("desk")
Resid_Reg_6 <- residuals(Regression_6)                      #Extract the residuals of Regression 6
jb.test(Resid_Reg_6)                    #Jarque-Bera test on the residuals of Regression 6
#AUTO-CORRELATION OF THE RESIDUALS - DURBIN-WATSON TEST
install.packages("car")
library(car)
durbinWatsonTest(Resid_Reg_6)                               #Durbin-Watson test on the residuals
```

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