Credit Spread Shocks and the SCR Ratio of a Dutch Life Insurer: an Empirical Analysis

Master Thesis

Wouter Heijs

University of Twente

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Colophon

Student
W.B. Heijs
Industrial Engineering and Management
Financial Engineering and Management
Faculty of behavioral, management and social sciences

University
University of Twente
Drienerlolaan 5
7522 NB Enschede
The Netherlands

External organization

Insurer

Supervision

University of Twente
1st internal supervisor: Prof. Dr. L. Spierdijk
2nd internal supervisor: Dr. B. Roorda

Insurer
External supervisor: Anonymous

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Management Summary

Research setup

This research was done in collaboration with a Dutch life insurer, who wishes to remain anonymous, and shall therefore be called: Insurer. The goal of the research is to provide insight into volatility of the SCR ratio that results from credit spread fluctuations. A novel framework is designed to observe correlations of macroeconomic factors with a portfolio over maturities. The sample data consists of credit spreads from 10/2014 to 10/2021 for Belgian, Danish, Dutch, French, German, and Italian government bonds for maturities 1 to 30. These assets are held by Insurer and as such impact their SCR ratio. Principal component analyses are done on these credit spreads for every maturity. This dimensionality reduction enables the evaluation of Insurer's exposures in a single new variable per maturity. The sample period is split in a pre- and during-corona period. The correlation of each first principal component with macroeconomic factors that, according to literature are significant determinants of credit spreads, is determined. Strong correlations (>0.6) indicate that a macroeconomic factor can function as an early-warning sign. We conclude which macroeconomic factors are relevant for Insurer, or for an organization with similar assets. Furthermore, a sensitivity analysis of credit spread volatility and its impact on the SCR ratio is done. The ultimate forward rate, credit risk adjustment, volatility adjustment, and the credit spread are combined to form negative and positive scenarios.

Results

The principal component analyses yield first principal components with explained variances up to 88%, depending on the countries and sample periods chosen. The macroeconomic factor analysis yielded insight in what macroeconomic factors have strong correlations and which ones do not. Debt as percentage, emerging markets, Euribor 3M, GDP, CLI, M1, and the stock exchanges showed correlations higher than 0.8. Sensitivity analyses showed that an increase in credit spreads and credit risk adjustment have decreasing impacts on the SCR ratio. An increase in the ultimate forward rate and the volatility adjustment showed an increasing effect on the SCR ratio. The negative scenario analyses showed that the light version would already breach the internal policy threshold by 25%, and force Insurer to act.

Recommendations

Insurer is advised to take notice of the "signal indicators" to reduce the possibility of being surprised by sudden credit spread volatility. This enables Insurer to either proactively adjust their portfolio or to manage expectations in and outside their organization. In regular periods, the VIX index and the stock markets are strongly correlated with credit spread volatility in Insurer's portfolio for short maturities. Longer maturities show strong correlations with debt as percentage, emerging markets, unemployment rate, GDP, and M1. During crises, short maturities are strongly correlated with the VIX and the 3-month Euribor rate. Longer maturities are strongly correlated with emerging markets, the VIX index, 3-month Euribor rate, GDP, stock markets, and composite leading indicator. Insurer is also recommended to take note of the negative scenarios and incorporate this in the ORSA. Considering "what if all chips fall the wrong way", provides insight for potential crises, as correlations tend to increase during times of economic turmoil.

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Abbreviations

BEL	= Best estimate of liabilities
CRA	= Credit risk adjustment
DNB	= De Nederlandsche Bank (Dutch supervisory authority)
EIOPA	= European insurance and occupational pensions authority
MA	= Matching adjustment
MCR	= Minimal capital requirement
OAS	= Option adjusted spread
ORSA	= Own risk and solvency assessment
RAS	= Risk appetite statement
SCR	= Solvency capital requirement
UFR	= Ultimate forward rate
VA	= Volatility adjustment

Key concepts

Credit spread = The difference in yield between some debt security and the risk-free rate with the same maturity.

Principal component analysis = A dimension reduction technique that captures as much of the variation in data as possible in a single new variable.

SCR ratio = A solvency measure of insurers calculated according to the methodology of the Solvency II directive

Insurer profile

This research is executed in collaboration with a Dutch insurance company, whose name is disclosed because this research contains sensitive data. We will use “Insurer” to discuss the collaborator from this point onward. To have generalizability Insurer is described in an abstract fashion. Insurer is characterized by the following features:

- Insurer provides life, pension and funeral insurance services.
- Insurer’s asset allocation is focused on Illiquid assets.
- Insurer’s liabilities have longer duration than the average life insurer.
- Insurer is based in the Netherlands.

1 Introduction

The introduction discusses important background knowledge needed to understand this thesis. A description of credit spreads and the Solvency II framework are provided.

1.1 Credit spread

A credit spread refers to the difference in yield between some debt security and the risk-free rate with the same maturity (Ganti, 2021). Corporate credit spreads are based on corporate bond yields, whereas government credit spreads are based on government bonds yields.

A common debt security that is used as the risk-free rate is the 10-year US Treasury bond. This bond is fully backed by the US government, whose probability of default is perceived as very low and thus almost entirely risk-free. Insurer is based in the Netherlands and has no exposure outside of the Euro zone. It is therefore not logical to use a dollar-based risk-free rate proxy. Every month a new risk-free term structure is published by EIOPA, which is used for valuing the liabilities. This rate is also not appropriate as this converges to the ultimate forward rate (UFR) and therefore does not reflect economic reality. It is more sensible to base it upon the German bond yield, which is considered to be the safest European economy. However, in practice, the swap curve is often used. There is a liquid market up to 20 years, after which this becomes a problem. Insurer deals with this by taking the term structure alternative provided by the DNB. DNB uses an approach, where the swap rates are calculated using the forward rates. The forward rates are kept constant where data gaps are observed as result of illiquidity (DNB, 2018). An additional 10 basis points will be added to each data point to compensate for the credit risk adjustment. We will use this swap curve as this makes the thesis compatible with Insurer's calculations.

Credit spreads are expressed in basis points. For example, a 5-year corporate bond with a yield of 5% and the 5-year US treasury bond with a yield 1% is said to have a credit spread of 400 basis points. Corporate credit spreads are important indicators for both monetary policy and financial stability purposes. Credit spreads contribute to the cost of external debt financing for the corporate sector, which forms part of the cost of capital, which in turn affects a firms' investment decisions. Credit spreads can reflect the financial health of a debt security issuer (Churm & Panigirtzoglou, 2005).

Literature decomposes credit spreads into several components. The high-level division is between a credit risk and non-credit risk related compensation. The default probability of a company requires compensation, which is in line with one of the most basic economic principles: risk-reward. The compensation for the uncertainty about the probability of default is also related to credit risk. The non-credit risk components are driven by market factors such as differences between government and corporate bonds, liquidity, regulation and tax (Churm & Panigirtzoglou, 2005).

1.2 Solvency II

This introduction and its figures are based on the paper written by the International Actuarial Association (2016). Insurers that are active on the European market, with gross premium income exceeding €5 million or gross technical provisions in excess of €25 million, have to follow the Solvency II Directive developed by the European Commission in collaboration with the European Insurance and Occupational Pensions Authority (EIOPA). EIOPA is one of the EU's main financial supervisory bodies, which developed from the body previously known as Committee of European Insurance and Occupational Pensions Supervisors. The directive became operative in the beginning of 2016. Insurer has to abide by the Solvency II Directive.

The key objectives of Solvency II are to increase the level of harmonization of solvency regulation across Europe, to protect policyholders, to introduce European-wide capital requirements that are more sensitive to the levels of risk being undertaken, and to provide appropriate incentives for good risk management. The Solvency II framework consists of three pillars. Pillar 1 sets out the capital requirements insurers are should minimally hold. Valuation methodologies are specified for assets and liabilities based on market consistent principals. Pillar 2 sets out requirements for the governance and risk management of insurers, as well as for the effective supervision of insurers. The Own Risk and Solvency Assessment (ORSA) is part of this pillar. Pillar 3 focuses on disclosure and transparency requirements, under which defined reports to regulators and the public are required to be made.

1.2.1 Valuation of assets

Assets should be valued at market value according to Solvency II. Prices can be readily observed in the market. Where these are unavailable, assets can be valued on a mark-to-model basis, provided this valuation is market consistent.

1.2.2 Valuation of technical provisions

Similar to the valuation of the assets, the technical provision should also be valued on an economic basis. The valuation of the technical provisions consists of two parts: the best estimate liability (BEL) and the risk margin. The BEL is the present value of the expected future cashflows, discounted using the risk-free yield curve published by EIOPA. Insurers must consider all relevant available data when making assumptions that best reflect the characteristics of the underlying insurance portfolio.

The risk margin is aimed at increasing the technical provisions up to the amount that another insurance company would be willing to take over the liabilities. It is a theoretical compensation for the risk of the future being worse than the best estimate assumptions. The risk margin is determined using the cost of capital method. To calculate the risk margin, the future capital the insurer is required to hold is projected during the runoff of the existing business. These are then multiplied with the cost of capital rate, which Solvency II has set at 6%. These cashflows are then discounted using EIOPA's risk-free rate to determine the final risk margin.

1.2.3 Solvency capital requirement

The Solvency capital requirement (SCR) is a Value at Risk measure based on a 99.5% confidence interval of the variation over one year of the amount of "basic own funds". The SCR calculation is sub categorized into SCRs for:

- Non-life underwriting risk
- Life underwriting risk
- Health underwriting risk
- Market risk
- Counterparty default risk
- Operational risk
- Intangible risk

The SCRs are calculated using a prescribed approach, after which they are aggregated using prescribed correlation matrices. This approach is known as the standard formula. Internal models can also be used but these must be approved by the supervisory authorities. Insurer uses the standard formula to calculate their SCR. The minimal capital requirement (MCR) is the minimum capital an insurer should hold for it to be allowed to write business. It is calibrated at a confidence level of 85%.

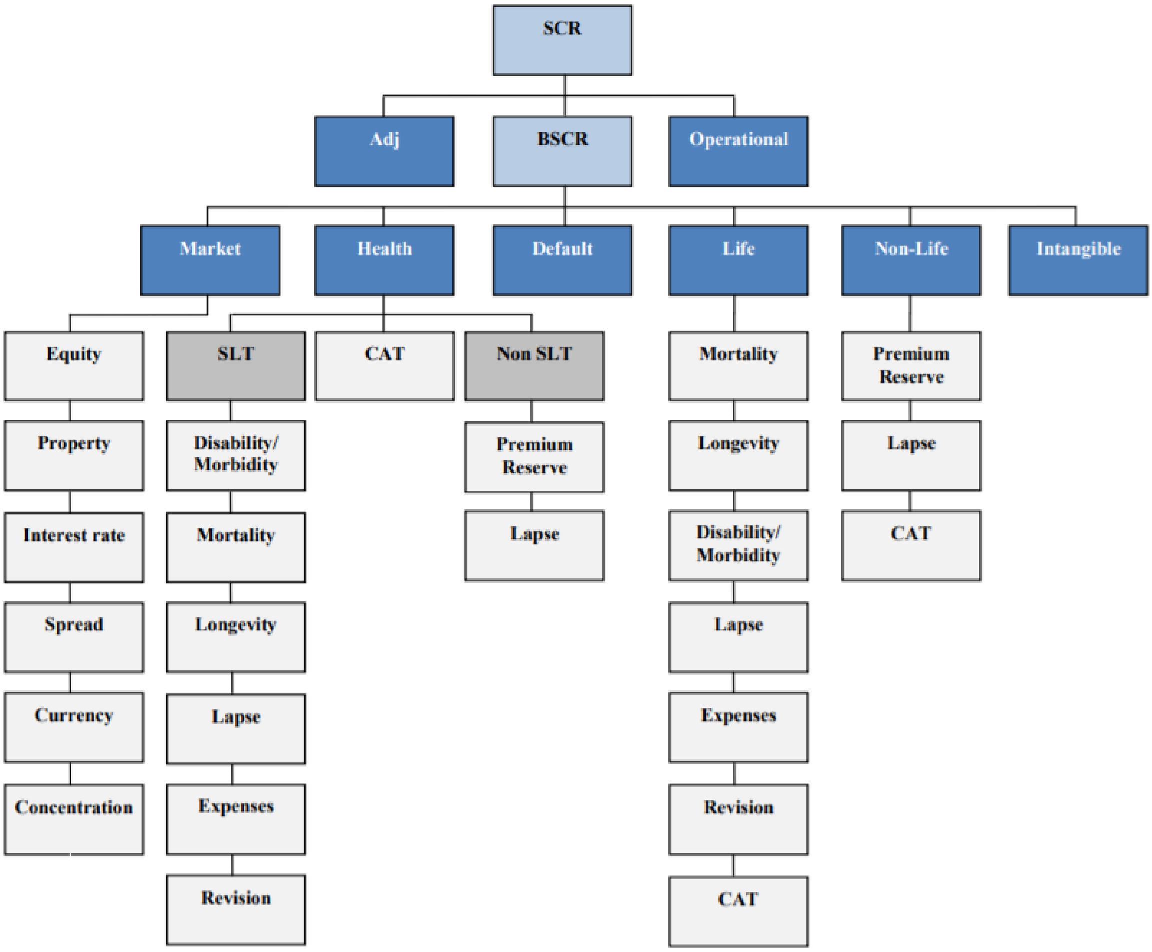

Figure 1: SCR standard formula components

1.2.4 Own funds quantitative requirements

EIOPA has set out basic quality requirements to the equity used to cover the risks. The assets that are eligible for this protection are called 'own funds' in Solvency II. The quality of the own funds is based on the ability of the capital to absorb losses on short term. The own funds are split into tier 1, tier 2, and tier 3 capital with tier 1 being the capital with the highest liquidity.

The eligible amount of own funds must consist for at least one third of tier 1 own funds. The eligible amount of tier 3 capital is at most one third of the total amount of tier 3 capital. The MCR is covered at least for 50% by tier 1 capital. The amount of eligible own funds used to cover the SCR is equal to the sum of tier 1 capital and the eligible amounts of tier 2 and 3 capital. The amount of eligible capital used to cover the MCR is equal to the sum of tier 1 capital and eligible tier 2 capital (EIOPA, 2021). These restrictions are represented in equation 1 and 2. There are more restrictions for tier 2 and 3 capital. At the start of this research (October 2021), Insurer chose to cover all its capital requirements with tier 1 capital. Therefore, these additional restrictions are omitted.

$$Own\ funds = Tier\ 1 + Tier\ 2 + Tier\ 3,\ where \begin{cases} Tier\ 1 & \geq \frac{1}{3} \cdot Own\ funds \\ Tier\ 3 & \leq \frac{1}{3} \cdot Own\ funds \end{cases} \tag{1}$$

$$MCR = Tier\ 1 + Tier\ 2,\ where\ Tier\ 1\ \geq 0.5 \cdot MCR \tag{2}$$

The total of assets and liabilities comprises the balance sheet. Figure 2 shows a graphical representation of a fictional insurer's balance sheet.

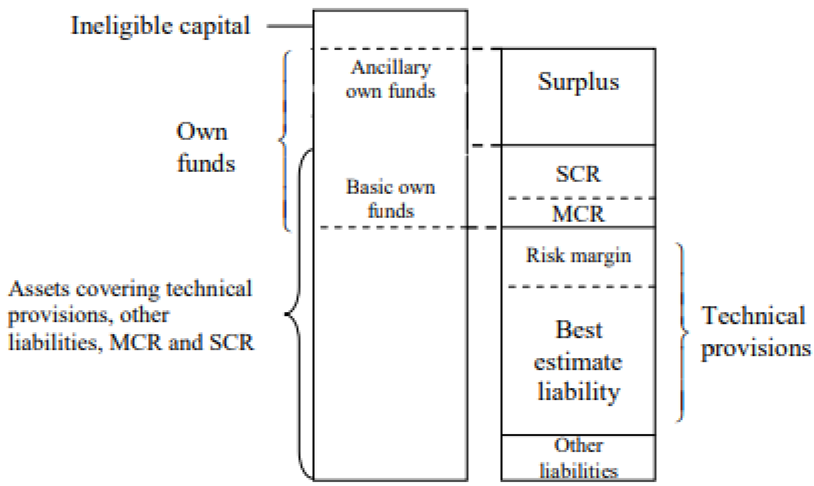

Figure 2: Pilar 1 balance sheet

1.2.5 Risk free term structure and the ultimate forward rate

Solvency II prescribes that the risk-free term structure, which is used to discount the best estimate liabilities, shall be derived from financial instruments for which a deep, liquid and transparent market exists (Akinyemi et al., 2019). The risk-free term structure is published monthly by EIOPA and is essentially based on swap rates (for EUR these are 6-month EURIBOR swap rates) up until the last liquid point (LLP), which is set at 20 years for EUR. Determining the interest rates over more than 20 years becomes difficult as a result of illiquidity in that market. Therefore, Solvency II has created the UFR. After the LLP, the rates are extrapolated between the last liquid rate and the UFR. Extrapolation requires setting a UFR and a conversion horizon from the LLP to the UFR. The Smith-Wilson method uses the available data to exactly fit bond prices where data are available and to extrapolate them by using a weighted average of the last observable data point and the predetermined UFR (Akinyemi et al., 2019).

The UFR is the sum of an expected real rate and an expected inflation rate. The expected real rate is the same for all currencies. It is calculated as a simple average of the past real rates since 1961. The real rate of return is calculated as the nominal interest rate minus the inflation rate. Every year a new real rate enters the sample, and the sample average changes as a consequence. The expected inflation rate is the target inflation for the country (EIOPA, 2021). For the euro area this is set at 2%. The UFR can change a maximum of 15 basis points annually, making sure that long term valuation does not change drastically on short-term. The roll-down of liabilities has an increasing impact on the value of these liabilities and as such produces UFR drag. Moreover, UFR changes can have a significant impact on the valuation, depending on the difference between the interest rate term structure with and without the UFR. The bigger the magnitude of the gap between IRTS with UFR and without, the bigger the UFR drag will be.

UFR creates a trade-off where insurers must choose between hedging their economic balance sheet on the one hand and ensuring a more stable Solvency II position on the other. If an insurer chooses to hedge the Solvency II balance sheet, a more stable Solvency II position will be realized on short-term. If an insurer chooses to hedge their economic balance sheet, a rise in interest rates would cause a fall in Solvency II own funds because the Solvency II value of assets falls faster than that of the liabilities (Insurance Investor, 2019). However, on the long-term the insurer's hedge will reflect economic reality better. This is due to the different yield curves used for discounting, one with and without UFR and volatility adjustment.

This trade-off between economic hedging and Solvency II hedging causes volatility in an Insurer's own funds. Own funds are loosely defined as the net asset value over the liabilities. The UFR is currently well above market rates, but as liabilities move nearer to the present, they will start to become discounted using market rates and not the extrapolated UFR. This shift from extrapolated yields to market yields causes a substantial drop in the discount rates and causes the value of the liabilities to rise. This phenomenon is called UFR drag, and it causes volatility, as well as a sudden drop in the insurer's own funds (Sleijpen, 2019).

In addition to the UFR, a credit risk adjustment is made to risk-free rate term structure. Even rates that are considered to be risk-free are not 100% risk-free. There is a small probability that the US will go bankrupt and therefore an additional credit risk adjustment (CRA) is made. The adjustment is determined on the difference between rates capturing the credit risk reflected in the floating rate of interest rate swaps and overnight indexed swap rates of the same maturity. The CRA is 50 percent of the average of that difference over a time period of one year (EIOPA, 2021). The CRA is always between 10 and 35 basis points. The CRA is applied as a parallel downward shift of the market rates observed for maturities up to the last liquid point (EIOPA, 2019).

1.2.6 Matching adjustment

If insurers have long-term liabilities and they are able to hold matching assets until maturity, they are not exposed to spread fluctuations but only to counterparty default risk. If these conditions are met, insurers are allowed under Solvency II to adjust the risk-free discount rate to match the spread movements of their assets. The matching adjustment is derived by taking the spread on the portfolio of matching assets and deducting the "fundamental spread", an allowance for the credit risks retained by the insurer. The fundamental spread is published by EIOPA.

1.2.7 Volatility adjustment

To value the BEL under Solvency II, the future expected cashflows of long-term guarantee products are discounted using the extrapolated risk-free rates plus a possible volatility adjustment (VA) in case of stressed fixed-income markets as calculated by EIOPA. Under certain circumstances EIOPA allows an addition of the "volatility adjustment" (as a fixed spread) to the risk-free term structure, which is aimed at dampening the own fund "artificial volatility" that is caused by the stressed fixed-income financial markets.

This “artificial volatility” comes from non-default related changes in market values of assets; the market value of a bond can vary due to market movements other than a default risk (most predominantly liquidity changes). However, since insurance companies have long-term guarantees and aim to hold their assets accordingly, Solvency II states that their own funds (and their required capital calculation) should not be affected by those temporary changes. Since their assets in the Solvency II balance sheet are quoted at market value, Solvency II allows for an adjustment to their BEL calculation instead, by applying an additive spread, the VA, to the discount rate (Deloitte, 2018)

EIOPA assumes a reference asset portfolio, which it deems representative for the average European insurer, from which the VA is derived. The VA is calculated using two components, a spread and a risk-correction component. The spread is calculated as the difference between bond market yield and the risk-free rate. The risk-correction component is split for the government and corporate bonds and is aimed at capturing the credit-related risk component of the spread, which an insurer is exposed to. For the government bonds the risk correction amounts to 30% of the long-term average spread. The corporate risk correction is the maximum of 35% of the long-term average corporate bond spread and the sum of probability of default (PoD) and the cost of downgrade (CoD) (Deloitte, 2018).

$$Risk\ correction_{gov} = 0.3 \cdot max\{LTA\ spread_{gov}, 0\} \tag{3}$$

$$Risk\ correction_{corp} = 0.35 \cdot max\{LTA\ spread_{corp}, PD + CoD\} \tag{4}$$

For the government bond portfolio, a spread and risk correction are calculated for each country in the portfolio. For the corporate bond portfolio, a spread and risk correction is calculated for both financials and non-financials and for each rating class (Deloitte, 2018).

All cash flows in the generic bond portfolio are projected using a discount rate. This is done for three different discount rates: market yield, risk-free rate, risk corrected market yield (market yield – risk correction). Three internal effective rates are derived from the projections. Internal effective rates are the discount rate at which the net present value of the future cash flows is equal to the initial investment. An internal effective market yield ($IER_{yield\ market}$), the internal effective risk free rate ($IER_{yield\ RFR}$) and an internal effective risk-corrected market yield are calculated ($IER_{yield\ corrected}$). These rates are then used to determine the portfolio level spread (Deloitte, 2018).

$$Spread_{gov} = IER_{yield\ market-gov} - IER_{yield\ RFR-gov} \tag{5}$$

$$Spread_{corp} = IER_{yield\ market-corp} - IER_{yield\ RFR-corp} \tag{6}$$

Using weights w_{gov} and w_{corp}, which depend on the relative sizes in the reference portfolio, the portfolio spread can be calculated.

$$Spread_{portfolio} = w_{gov} \cdot max\{Spread_{gov}, 0\} + w_{corp} \cdot max\{Spread_{corp}, 0\} \tag{7}$$

Now that the portfolio spread has been calculated, the risk correction for the portfolio needs to be determined. The risk correction is determined by subtracting the $IER_{yield\ corrected}$ from the $IER_{yield\ market}$. This is done for both government and corporate bonds, which are then combined using weights to determine the portfolio risk correction ($Risk\ Corr_{portfolio}$) (Deloitte, 2018).

$$Risk\ Corr_{gov} = IER_{yield\ market-gov} - IER_{yield\ corrected-gov} \tag{8}$$

$$Risk\ Corr_{corp} = IER_{yield\ market-corp} - \ IER_{yield\ corrected-corp} \tag{9}$$

$$Risk\ Corr_{portfolio} = w_{gov}\ \cdot max\{Risk\ Corr_{gov}, 0\} + w_{corp} \cdot max\{Risk\ Corr_{corp}, 0\} \tag{10}$$

Combining both the portfolio spread and risk correction the VA can be determined (see equation 11).

$$VA = 0.65 \cdot (Spread_{portfolio} - Risk\ Corr_{portfolio}) \tag{11}$$

2 Research setup

Chapter two elaborates upon the research setup. It discusses the problem context and deduces the core problem from a problem cluster. The main research question is posed, and its sub questions are crafted. Finally, the scope and the reliability and validity are discussed.

2.1 Problem context

The implementation of Solvency II has increased risk monitoring for a lot of insurers. Insurers have had to produce much documentation on their risks and financials. Insurer already has detailed reports on risks that are relevant to their financial stability. Their risk appetite statements (RAS) explains their desired exposure to these risks. Ranging from risk-acceptance to risk-averse, each risk is linked with measures to hedge these risks. The riskier an asset allocation, the higher the reserves must be. Hence, the RAS, assets, and liabilities are closely related. These risks, and their relation to the solvency capital requirement ratio (SCR ratio) are shown in Figure 3. This figure is centered around the core concept of Solvency II, the SCR ratio. This ratio is defined as the own funds divided by the SCR as represented in equation 12.

$$SCR\ ratio = \frac{Own\ funds}{SCR} \tag{12}$$

Figure 3 can be split in an upper and lower part. The upper part represents the asset side and shows the risks that affect the value of the own funds. The lower part of the figure represents the liability side. The risks affecting this part of the balance sheet are shown as well. The liabilities are prone to considerably more risks. This is partly due to the nature of the life, funeral, and pension insurance business. The asset side is mostly prone to market risks.

2.2 Assignment of the organization

The Solvency II regulation that is applicable to European insurers sets strict requirements to an insurer's capital position to ensure financial stability. This capital position is monitored through ratios, such as the SCR ratio, which needs to be 100% at minimum. This ratio is influenced by a lot of factors and fluctuates drastically over time. Insurer wishes to get a deeper insight into the volatility that is experienced on their balance sheet, and hence the volatility of their SCR ratio.

If the SCR ratio of 100% is breached, meaning that in that point in time Insurer does not have enough buffer given its risk profile, De Nederlandsche Bank (DNB) will intervene, and severe restrictions may be imposed upon Insurer. This is highly undesired and must be prevented at all costs. Therefore, Insurer has set SCR ratio target levels for itself to intervene in order prevent this from happening. The minimal target level to maintain is a SCR ratio of 160%. Insurer's dividend policy is partly based upon this target ratio, meaning that no dividend will be paid out if the SCR ratio is below 160%. A second target level of 135% is set as internal measure. If this ratio is breached, Insurer should intervene to keep from getting low on required capital. Insurer wishes to gain more insight into their SCR ratio's volatility.

Figure 3: Problem context representation

2.3 Core problem

The main problem as perceived by the company is the volatility that is experienced on the balance sheet and thus in the SCR ratio. For most factors[1] influencing this ratio, proper hedging strategies are in place. However, Insurer has difficulties managing the credit spread volatility that is experienced on the asset side. This is a direct consequence of the Solvency II regulation, and the introduction of the VA. This VA is based on a by EIOPA deemed representative portfolio for European insurers and can only be applied for 65% to the discount factor that is used to value the liabilities side. This leads to uncompensated credit spread volatility. To properly manage this risk, better insight in credit spreads is required. An enlarged image of the market factors that affect both sides of the SCR ratio equation is provided in Figure 4. The core problem can be deduced from this and is formulated as the lack of insight in credit spread volatility and its effect on the SCR ratio.

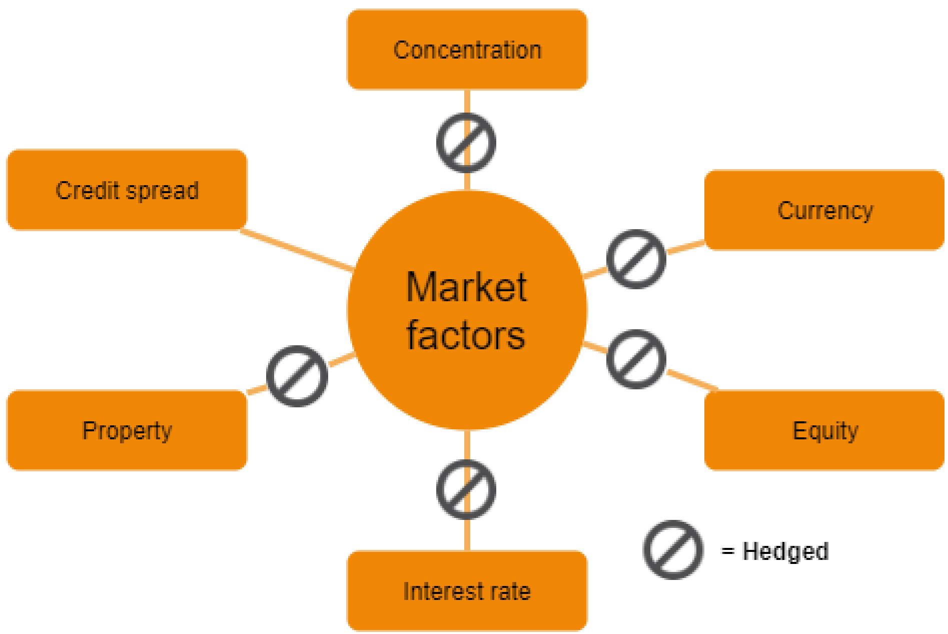

Figure 4: Market factors core problem deduction

2.4 Research problem

To tackle the core problem: the lack of insight in credit spread volatility and its effect on the SCR ratio, the main research question of this thesis is constructed:

What drives credit spreads and how does this influence Insurer's SCR ratio?

An answer to this question should provide insight into credit spreads and the dynamics between the credit spreads and the SCR ratio, and as such should tackle both the core problem and the problem as perceived by Insurer.

[1] Concentration risk is the risk relating to accumulation of exposures with the same counterparty (Bank and Insurance Capital Management (n.d.)).

2.5 Research questions

To answer the main research question, several sub questions are answered. These sub questions make up the chapters of this thesis. The sub questions are answered based on different methods, depending on the type of question.

1. What are determinants for credit spreads according to literature?
2. How does Insurer determine its SCR ratio?
3. What determinants have impacted the credit spread volatility for Insurer?
4. How do credit spread shocks influence the SCR ratio and its determinants?
5. What combination of SCR ratio determinants shocks constitutes a negative scenario for Insurer?

2.6 Scope

Taking into account the large number of factors influencing the SCR ratio, only those that are affected by credit spread volatility will be taken into account, with the addition of the UFR and credit risk adjustment (CRA) in the basic risk-free rate of the liabilities. Moreover, this research is confined to the exposures of Insurer, meaning that we will not consider assets outside the portfolio of Insurer. The sample period selected ranges from October 2014 up to October 2021. Furthermore, the matching adjustment will not be taken into account as a serious possibility, because Insurer has made clear that the conditions for its use cannot be met.

2.7 Reliability and validity

Reliability means performing consistently. A framework is built in Python for a PCA and correlation analysis. This ensures reproducibility, consistency and it reduces errors. Minitab is used to validate the Python analysis by verifying randomly selected outputs from the PCA in python with the outputs of a PCA on the same data in Minitab. Minitab is a software that has many statistical analysis functionalities, including principal component analysis. In all test samples, the same results were achieved. Moreover, the correlation analysis was done with twice the same variables, which should yield a perfect correlation, which was indeed the case. This confirms that this analysis functions properly.

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3 Theoretical framework

Chapter three discusses the theoretical framework. An extensive literature research is provided to answer two sub questions. The section Determinants for credit spreads handles the sub question: "What are determinants for credit spreads according to literature?". The section SCR ratio discusses the sub question: "How does Insurer determine its SCR ratio?". The answer is based upon the standard formula as prescribed by the Solvency II directive.

3.1 Literature study

For this literature research both the Netspar and Scopus databases have been utilized. Because the Netspar database is not that extensive the search query: "spread" has been used. This resulted in 28 results, which titles were scanned manually for their relevance to the topic. A total of 3 articles were selected. The Scopus database is much more extensive and requires a more scoped search query[2], which yielded 55 results. These were then manually scanned for their relevance to this research, after which 24 articles were selected.

3.1.1 Determinants for credit spreads

Gonzalez-Rozada (2008) finds that credit ratings represent a summary measure of the relevant country-specific factors. Longstaff et al. (2011) research drivers of sovereign credit spreads, especially CDS spreads. They find that sovereign spreads are driven primarily by US equity and high-yield factors. Also, sovereign spreads are significantly related to the volatility risk premium embedded in the VIX index. They decompose the CDS spread into a risk-premium and default risk component using a credit risk valuation model. One-third of the CDS spread is due to the risk premium. They conclude that global macroeconomic factors are strongly correlated with CDS spreads. They note that global financial markets have the tendency to be more correlated in times of crisis.

Cenesizoglu & Essid (2012) find that unexpected monetary policy tightening (easing) has a widening (narrowing) effect on credit spreads during periods of economic slowdown. Monetary policy could therefore also be a determinant for credit spreads.

Eichler & Maltriz (2013) analyze which determinants drive sovereign default risk for different maturities and whether default risk for different maturities is driven by different variables. A fixed effects panel regression approach on annual data is used. The studies' results indicate that that economic growth and a countries' openness, measured by the sum of exports and imports to gross domestic products (GDP), are significant drivers of default risk for all maturities, where higher economic growth reduces default risk. A higher degree of openness increases default risk. A country's debt level (to GDP) influences only short-term risk, but not long-term risk. The growth of debt plays a decisive role in the long-run equilibrium and thus for the long-run default risk. The trade balance has a long-term influence on default risk. An overview of the determinants and their effectiveness on both long -and-short-term is provided in Table 1.

Table 1: Long- and short-term explanatory power of determinants on sovereign spreads, Eichler and Maltriz (2013)

Factor	**Short-term**	**Long-term**
Economic growth	X	X
Country openness	X	X

[2] The query used is: "TITLE-ABS-KEY("default spread" OR "credit spread" OR "bond spread" AND "predict" OR "future" OR "forecast" OR "project") AND (LIMIT-TO (OA,"all")) AND (LIMIT-TO (SUBJAREA,"ECON"))"

Country debt level	X	
Growth of debt		X
Trade level balance		X

Saygun (2014) researches CDS spreads and uses multiple statistical models to explain CDS spreads. He concludes that VIX is effective to predict change in CDS spreads in countries which are close to jump to the well-developed markets class. Bond spread and global and local stock returns have the most effective forecast power and stronger contemporaneous relation. TED (liquidity) is found to have no significant forecasting power.

Clark and Kassimatis (2015) perform a literature research on determinants of sovereign credit spreads. They distinguish between local and global macroeconomic determinants. Their findings are added to the results of this literature research, which can be seen in Table 2 and Table 3. They find the variables RT (return to the economy), CO (the correlation coefficient between returns to the economy and the exchange rate) and FP (the financial risk premium) to be significant determinants of the sovereign risk spread.

Cimadomo, Claeys & Poplawski-Ribeiro (2016) assess the influence of a countries' fiscal balance, defined as general government primary balance plus interest payments, GDP growth, a global risk factor, and CPI inflation on expert sovereign bonds spread forecasts and realized spreads. It is found that expected growth in GDP, CPI inflation, and the global risk factor (10-year US government bond) is positively correlated with sovereign bond spread growth. An expected improvement in the economic outlook is likely to be associated with expectations of tighter monetary policy in the medium-term and an upward shift in the term structure. This effect seems to outweigh the fall in spreads triggered by fading concerns over the sustainability of public finances on the back of better growth prospects. Conversely, it is found that a higher fiscal surplus has a negative correlation with the sovereign bond spreads (Cimadomo, Claeys, & Poplawski-Ribeiro, 2016). Global risk factors often used in literature are corporate risk premia in the US, the VIX index or a bond rate of a reference country (Cimadomo, Claeys, & Poplawski-Ribeiro, 2016).

Cabbalero, Fernández, and Park (2019) research corporate credit spreads in emerging economies. They design an external financial indicator using option adjusted spreads (OAS). Four models are developed and tested for parameter significance. A panel structural vector autoregressive method was used to estimate regression parameters. They use VIX and US corporate Baa Spread as proxies for global financial risk and find that both are statistically significant covariates in forecasting regression of economic activity. The EMBI index is used as proxy for sovereign spreads but is found insignificant.

Kobayashi (2021) analyzes firm-based credit spreads of major Japanese corporate bonds. Principal component analysis in combination with the dynamic Nelson-Siegel model is used to develop a model that predicts Japanese corporate credit spreads based on data ranging from 1997 up to 2012. They regress their results against macroeconomic factors (GDP, CPI, unemployment rate) to test predictability of future economic activity. They find that GDP is strongly correlated, whereas CPI and unemployment are only loosely correlated.

To answer the sub question: "What are determinants for credit spreads according to literature?" an overview of the findings from the literature research is given in Table 2 and Table 3.

Table 2: Local determinants of credit spreads

Local determinants of credit spreads	**Author**
GDP growth or some similar activity-based indicator	Baek & Bandopadhyaya (2005), Beck (2001), Gibson et al. (2012), Eichler & Maltriz (2013), Cimadomo, Claeys & Poplawski-Ribeiro (2016), Kobayashi (2021)
The terms of trade (i.e. price of exports relative to the price of imports), which have an inverse relationship with spreads	Bulow & Rogoff (1989), Hilscher & Nosbusch (2010), Min (1998), Baldacci et al. (2011), Gibson et al. (2012)
Volatility of terms of trade	Hilscher & Nosbusch (2010)
Trade balance and the current account balance, ambiguous results	Eichler & Maltriz (2013), Beck (2001)
Inflation	Significant effect: Min (1998), Beck (2001), Cimadomo, Claeys & Poplawski-Ribeiro (2016), Kobayashi (2021) Insignificant effect: Diaz Gemmill (2006)
Solvency: debt to GDP	Hilscher & Nosbusch (2010), Min (1998), Eichler & Maltriz (2013), Edwards (1986), Eichengreen & Mody (1998)
Liquidity: reserves to GDP	Hilscher & Nosbusch (2010), Min (1998), Diaz & Gemmill (2006), Baldacci et al. (2011), Cline & Barnes (1997)
Time to maturity	Bandiera et al. (2010), Bernoth et al. (2012), Min (1998)
Political risk	Credit rating (Standard & Poor's or Institutional Investor Magazine): Kamin & Von Kleist (1999), Gonzalez-Rozada & Levy-Yeyati (2008) Heritage Foundation economic freedom index and the World Bank governance index: Baldacci et al. (2011)
Size of shadow economy	Elgin & Uras (2013)
Default history	Reinhart et al. (2004)
Currency mismatch	Caballero & Krishnamurthy (2005), Catao & Sutton (2002), Duffie et al. (2003), Gibson & Sundaresan (2001), Gray et al. (2007), Havrylyshyn & Beddies (2003), Hilscher & Nosbusch (2010), Longstaff et al. (2011), Diaz & Gemmill (2006)
Fiscal balance	Cimadomo, Claeys & Poplawski-Ribeiro (2016)
Unemployment rate	Kobayashi (2021)
Return to economy	Clark and Kassimatis (2015)
Correlation coefficient between returns to the economy and the exchange rate	Clark and Kassimatis (2015)
Financial risk premium	Clark and Kassimatis (2015)

Table 3: Global determinants of credit spreads

Global determinants of credit spread	**Author**
Volatility: VIX index	Longstaff et al. (2011), Pan & Singleton (2008), Gonzalez-Rozada & Levy-Yeyati (2008), Hilscher & Nosbusch (2010), Baldacci et al. (2011), Beck (2001), Cimadomo, Claeys & Poplawski-Ribeiro (2016)
Global economic condition and business cycle: U.S. stock and high-yield markets	Longstaff et al. (2011), Gonzalez-Rozada & Levy-Yeyati (2008)
U.S. economy: long-term treasury yield	Longstaff et al. (2011)
Default yield spread (spread between corporate bonds with low and high credit rating)	Gonzalez-Rozada & Levy-Yeyati (2008), Hilscher & Nosbusch (2010), Baldacci et al. (2011)
Global liquidity	10-year U.S. treasury: Gonzalez-Rozada & Levy-Yeyati (2008), Hilscher & Nosbusch (2010) TED spread: Hilscher & Nosbusch (2010)
International interest rate: 10-year U.S. treasury	Hilscher & Nosbusch (2010), Beck (2001)
Monetary policy	Cenesizoglu & Essid (2012)
Business cycle	Cenesizoglu & Essid (2012)

3.1.2 SCR ratio

In the introduction to Solvency II the SCR ratio is already briefly mentioned. Equation 12 shows the formula for calculating the SCR ratio as the ratio between the own funds and the SCR, which should at least be above 100%. The own funds and the SCR itself are already discussed in the chapter on Solvency II introduction as well. Different detailed approaches are specified for the determination of the SCR for each type of exposure, which are then combined using a given formula. Having obtained the SCR for each module, a specified correlation matrix is used to combine each sub module to determine the Basic SCR (BSCR). Aggregation is therefore performed at different levels (International Actuarial Association, 2016). However, insurer does not have exposure to all SCR sub modules. In this section, a deeper look at Insurer's SCR calculation is taken.

The SCR is comprised of three components: the BSCR, an adjustment for the loss absorbing capacity of technical provisions and deferred taxes, and the operational SCR, which is shown in Figure 1 (European Union, 2021).

The loss-absorbing capacity of technical provisions and deferred taxes reflects potential compensation of unexpected losses through a simultaneous decrease in technical provisions or deferred taxes or a combination of the two. That adjustment takes account of the risk mitigating effect provided by future discretionary benefits of insurance contracts, to the extent that a reduction in such benefits may be used to cover unexpected losses when they arise (European Union, 2021).

The operational risk is calculated to correspond to a 99.5% VaR of the basic own funds over a one-year period. Operational risk includes legal risks, and excludes risks arising from strategic decisions, as well as reputation risks. The capital requirement for operational risks must not exceed 30 % of the BSCR relating to those insurance and reinsurance operations (European Union, 2021). The resultant operational capital amount is added to the BSCR, with no recognition of any partial correlation or diversification effects with other risks (International Actuarial Association, 2016).

3.1.2.1 Basic solvency capital requirement

As a result of Insurer's risk exposures, not all by Solvency II specified SCR sub modules are applicable to Insurer. In the standard formula each insurer has to calculate its SCR_{life}, $SCR_{non\text{-}life}$, SCR_{health}, SCR_{market}, and $SCR_{default}$, which are then combined to form the BSCR through correlation according to equation 13.

$$Basic\ SCR = \sqrt{\sum_{i,j} Corr_{i,j} \cdot SCR_i \cdot SCR_j} \tag{13}$$

For the market and insurance risk modules, each individual stress is performed separately according to detailed rules, which can be found in Delegated Regulation (EU) 2015/35. The calibration and application of each stress is specified within the standard formula. The SCR for each individual risk is determined as the difference between the net asset in the unstressed balance sheet and the net asset value in the stressed balance sheet (International Actuarial Association, 2016).

The correlation inputs are defined in solvency II and are depicted in Table 12, which can be found in Appendix A. Insurer has only exposures to SCR_{life}, SCR_{market}, and $SCR_{default}$. $SCR_{non\text{-}life}$ and SCR_{health} are therefore ignored in the elaboration on the BSCR calculation.

The SCR_{life} consists of the sub modules: $SCR_{mortality}$, $SCR_{longevity}$, $SCR_{disability}$, $SCR_{life\ expense}$, $SCR_{revision}$, SCR_{lapse}, and $SCR_{life\ catastrophe}$. Insurer does not have exposure to each of these sub modules. $SCR_{revision}$ and $SCR_{disability}$ do not have to be taken into account. The SCR_{life} can be calculated following equation 14. The correlations are depicted in Table 13.

$$SCR_{life} = \sqrt{\sum_{i,j} Corr_{i,j} \cdot SCR_i \cdot SCR_j} \tag{14}$$

SCR_{market} consists of the sub modules $SCR_{interest\ rate}$, SCR_{equity}, $SCR_{property}$, SCR_{spread}, $SCR_{concentration}$, and $SCR_{currency}$. Again, Insurer does not have exposure to all these sub modules, as explained in the problem introduction phase. Insurer only has exposure to $SCR_{interest\ rate}$ and SCR_{spread}. These SCR modules are added together following equation 15. The correlations are depicted in Table 14.

$$SCR_{market} = \sqrt{\sum_{i,j} Corr_{i,j} \cdot SCR_i \cdot SCR_j} \tag{15}$$

$SCR_{default}$ reflects possible losses as a result of unexpected defaults or downgrades of the counterparty's credit rating over the next year. The module covers risk-mitigating contracts, such as reinsurance arrangements, securitizations and derivatives, and receivables from intermediaries, as well as any other credit exposures which are not covered in the spread risk sub-module. For the counterparty risk module, the calculation approach is similar to market risk modules (International Actuarial Association, 2016). For each counterparty, the counterparty default risk module takes account of the overall counterparty risk exposure of the insurance undertaking concerned to that counterparty (International Actuarial Association, 2016).

4 Research design

This chapter describes the approach that is taken to answer the main research question, the sample data that is used, and the analyses that are done, such as the PCAs and correlation analyses.

4.1 Approach

In a broad sense, the aim of this research is to gain insight into credit spread volatility. Research with similar aims is analyzed. The approach taken by Longstaff et al. (2011) is followed because their approach is appropriate, as they have similar goals. They study the commonality in the sovereign credit spreads by conducting a principal component analysis (PCA). The principal components are then plotted on the original plane and their correlations with macroeconomic variables are calculated. This approach is followed, but repeated for every maturity, enabling us to evaluate how this is impacted over the maturities.

The PCA provides insight into commonalities amongst the credit spreads in the data set. We differentiate and extend the approach taken by Longstaff et al. with the period and the sample data and by repeating over maturities respectively. The period that is analyzed ranges from 12/2014 to 10/2021 (including corona crisis), and the government bond spreads selected are deducted from insurer's exposures and as such will not be confined to emerging markets, which is the case for the Longstaff analysis. Furthermore, we opt not to choose CDSs but actual bond spreads, as these are of direct impact on Insurer's balance sheet, which we aim to investigate. Additionally, the variables chosen to analyze in the correlation analysis are based on our own literature research. Finally, this research evaluates the impacts on the SCR of insurers with similar characteristics as Insurer and as such can be considered a case study.

Bu et al. (2018) follow the methodology proposed by Feldhütter and Stephen. An analysis is done on sample periods, separating input data based on volatility. The period of March 1992 up to March 2001 is defined as a stable period and the period from 2001 – 2009 is defined as volatile. The latter period exhibits large volatility due to the dotcom bubble and the global financial crisis of 2008. Due to a tendency for correlations in financial markets to increase during crisis periods (Ang & Bekaert, 2002), the data is split in post and during crisis data and the PCA is conducted for different sample periods also.

Using the existing tools of Insurer, credit spread shocks of different magnitude are simulated to analyze their effect on the Insurer's assets. A simple intuitive tool is made to approximate the response of the VA to the credit spread shock. Using this estimated VA, EIOPA's curve is adjusted to match the new situation, which is then used to value the liabilities and the new SCR. This is done for every credit spread shock. These newly valued assets and liabilities are then combined to come to the gross assets over liabilities value, after which taxes are calculated and the net assets over liabilities is determined. Finally, dividing the net assets over liabilities value by the SCR yields the SCR ratio, which we find for every shock scenario, and this allows us the observe its sensitivity to these changes.

After all individual scenarios are evaluated, combinations of these scenarios are tested and evaluated with the purpose of extracting a negative and positive scenario. Especially the negative scenario could be adopted in the regular risk analyses and potentially included in the ORSA) In this part, the UFR and CRA are included. The research is both empirical as diagnostic in nature.

4.2 Data description

The description of the data set is split into two sections. The first section will elaborate on the credit spread data that is used for the PCA. The second section elaborates upon the macroeconomic variables that are subjected to the correlation analysis.

4.2.1 Government bond credit spreads

The sample data has partly been made accessible through Insurer's partners (Cadence and Bloomberg). The remainder of the data was publicly available. The credit spread data is collected on government bonds from Belgium, Denmark, The Netherlands, France, Germany, and Italy. These countries are chosen because Insurer has exposure in government bonds from most of these countries. Preferably Norway and Austria were included in this analysis also, but this data was inaccessible. Denmark was accessible and is added as replacement of Norway. Norwegian and Denmark are both Scandinavian countries and as such share many similarities. They both have a non-euro currency, but the exposure Insurer has in Norway is in euros. The spreads that were collected are option adjusted spreads (OAS) and are the spreads of the government bonds over the Eur Swap Curve. This is suitable for our purpose because it provides a way to homogenize spreads across a variety of bonds of different characteristic (Cabbalero, Fernández & Park, 2019). Therefore, no further subdivisions are needed into for example callability, floating and fixed features. Credit spreads are collected for maturities of 1 to 30 years over the period 12/2014 – 10/2021. Analyses are done on three sets of this data:

- The entire data set
- Pre-corona period: 10/2014 – 12/2019
- During corona period: 1/2020 – 10/2021

To present an overview of the credit spread data, the mean and standard deviation per maturity are calculated after which they are averaged and plotted in Figure 5. This representation clearly shows that Italy deviates from the sample.

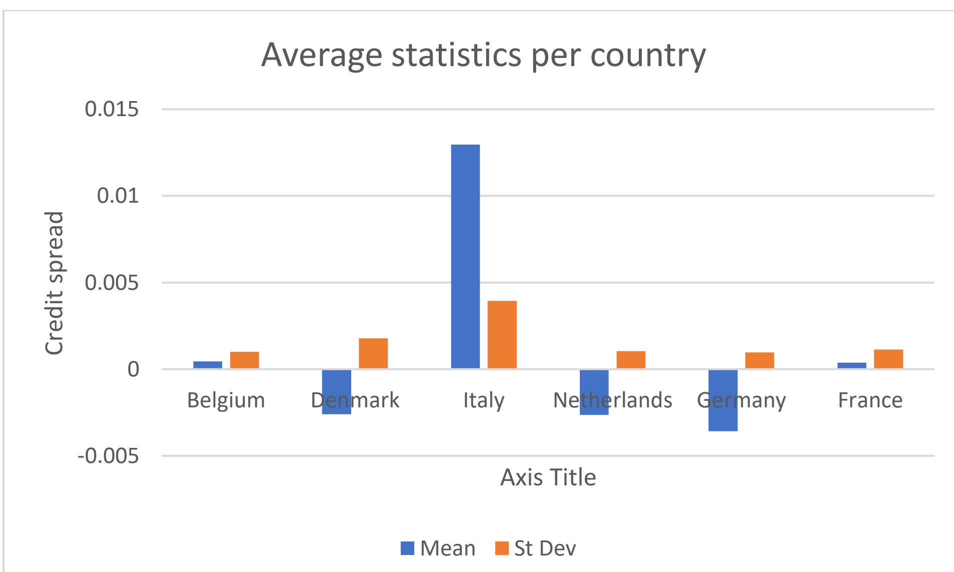

Figure 5: Average statistics per country

The correlation of the spread data to macroeconomic variables of which some of them represent a statistic for the entire euro area is calculated. Considering the limited number of countries in our sample this may lead to misleading results. However, Table 4 shows that our sample represents 77% of the GDP of the euro area and as such can be considered a proper representative. Finland is taken as proxy for Denmark because these countries have many similarities and Denmark is not part of the euro area. Denmark has a higher GDP than Finland, meaning that the percentage of the sample should even be slightly higher than 77%.

Table 4: GDP euro area (The World Bank, 2022)

Country	**2020 EUR millions**	**% of total GDP**	**% of sample**
Austria	€ 433,258	3.3%	
Belgium	€ 521,861	4.0%	4.0%
Cyprus	€ 24,613	0.2%	
Estonia	€ 30,650	0.2%	
Finland	€ 269,751	2.1%	2.1%
France	€ 2,630,318	20.2%	20.2%
Germany	€ 3,846,414	29.5%	29.5%
Greece	€ 188,835	1.5%	
Ireland	€ 425,889	3.3%	
Italy	€ 1,888,709	14.5%	14.5%
Latvia	€ 33,707	0.3%	
Lithuania	€ 56,547	0.4%	
Luxembourg	€ 73,353	0.6%	
Malta	€ 14,647	0.1%	
Netherlands	€ 913,865	7.0%	7.0%
Portugal	€ 228,539	1.8%	
Slovakia	€ 105,173	0.8%	
Slovenia	€ 53,590	0.4%	
Spain	€ 1,281,485	9.8%	
Total	€ 13,021,206	100.0%	77.3%

4.2.2 Macroeconomic variables

The literature research on credit spread determinants showed which factors must be collected. On top of that, factors are included that are easily accessible and tested for their correlation. In this section, every variable is explained, and their source is provided.

4.2.2.1 Current account and Debt as % of GDP

The current account balance as percentage of GDP is calculated as a three-year moving average. The current account balance of the euro area is used. The data was received from Cadence, partner of Insurer. The current account balance is made up of three parts:

- The trade balance: value of exports of goods and services minus value of imports of goods and services.

- Balance on income: primary income received from the rest of the world minus primary income paid to the rest of the world. Primary income consists of compensation of employees, taxes and subsidies on production and imports, and property income.
- Net current transfers: current transfers received from the rest of the world minus current transfers paid to the rest of the world. Current transfers are dividend tax, social security premiums and benefits and other current transfers (CBS, 2021).

The consolidated debt of the general government (valued at the nominal value) excluding other accounts payable and the debt on financial derivatives, expressed as a percentage of GDP. For the general government the public debt is consolidated. This means that transactions between government-units are eliminated (CBS, 2021). The debt and the GDP are calculated for the entire euro area. The data was received from Cadence.

4.2.2.2 Inflation, Eurozone HICP, and German inflation

The inflation data that is used is the Eurozone HICP Ex Tobacco published by Eurostat. The Harmonized Indices of Consumer Prices (HICP) are designed for international comparison of consumer price inflation. The data was gathered by Cadence through Bloomberg using the CPTFEMU Index. The German HICP represents the inflation in Germany and is published by DESTATIS (DESTATIS, 2022). The HICP of the euro area as published is also evaluated (European Central Bank, 2022). These variables are chosen to see if there is a difference in correlation between the different inflation variables.

4.2.2.3 EUR swaps 5, 10, 30, and 50 years

An interest rate swap is an agreement to exchange a stream of cash flows by applying a fixed and floating interest rate to a specified notional over a term to maturity. The “swap rate” is the fixed interest rate that the receiver demands in exchange for the uncertainty of having to pay the short-term floating rate over time. The 5-, 10-, 30-, and 50-year EUR swaps are interest rate swaps that express the fixed rate that must be paid to swap for the floating EURIBOR 6-month. The data is provided by Cadence through Bloomberg with indexes EUSA5 Index, EUSA10 Index, EUSA30 Index, and EUSA50 Index.

4.2.2.4 Emerging markets, Italian government bonds, European government bonds AA-rated, and European corporate bond

The performance of the emerging market government bonds is summarized in the ICE BofA Diversified Emerging Markets External Debt Sovereign Bond Index. The Italian government bonds index represents the performance of the Italian government bonds. The European AA-rated government bonds are of 15+ years maturity. The European corporate index is a proxy for the entire corporate market. The option adjusted spread is calculated with respect to the Libor. These indices are pulled from ICE.

4.2.2.5 VIX-index, TED spread, and Composite leading indicator

The VIX Index is based on the S&P 500 Index, the core index for U.S. equities, and estimates expected volatility by aggregating the weighted prices of SPX puts and calls over a wide range of strike prices (Cboe, 2022). The VIX-index is a proxy for the volatility in the US equity market. The TED spread is a proxy for liquidity in the market. The TED Spread (3 Month LIBOR / 3 Month Treasury Bill) is a measure of the perceived credit risk in the U.S. economy. LIBOR measures the interbank lending rate so as the spread between LIBOR and the T-bill rate increases, it shows an accelerating lack of trust between banks and a corresponding tightening of credit for all other counterparties (Macrotrends, 2022). The Composite Leading Indicator (CLI) is designed to provide early signals of turning points in business cycles showing fluctuation of the economic activity around its long-term potential level. CLIs show short-term economic movements in qualitative rather than quantitative terms (OECD, 2022).

4.2.2.6 Unemployment rate and the GDP of the euro area

The unemployment rate of the euro area is published by Eurostat. It reflects percentage of population in the labor force that is not gainfully employed (Eurostat, 2022). The GDP is a monetary measure of the market value of all the final goods and services produced in a specific time period. The Federal Reserve Economic Data (FRED) publishes the GDP of the euro area (FRED, 2022).

4.2.2.7 3-month Euribor rate and European euro bonds 10 years

The Euro Interbank Offered Rate (Euribor) is a daily reference rate, published by the European Money Markets Institute, based on the averaged interest rates at which Eurozone banks offer to lend unsecured funds to other banks in the euro wholesale money market (European Central Bank, 2022). The ECB publishes its euro bond yield in its statistical data warehouse also (European Central Bank, 2022).

4.2.2.8 Dow Jones Industrial Average, Nasdaq, and Euronext 100 index

The Dow Jones Industrial Average is a price-weighted measurement stock market index of 30 prominent companies listed on stock exchanges in the United States (Yahoo Finance, 2022). Nasdaq is both a stock exchange and an index (Yahoo Finance, 2022). NASDAQ mainly comprises companies in the technology sector or the companies in the growth stages while Dow Jones is more about the stock price and is hence dependent on the earnings. The Euronext 100 Index is the blue chip index of the pan-European exchange, Euronext NV (Yahoo Finance, 2022). It comprises the largest and most liquid stocks traded on Euronext.

4.2.2.9 M1

Monetary policy is found to be of significant influence on credit spreads in literature (see literature review). The monetary policy of the ECB is not a value that can be observed; therefore, a proxy is needed. M1 is defined as sum of currency in circulation and overnight deposits (European Central Bank, 2022). We find this a suitable proxy for the, as it measures the amount of money in circulation. The data is available through the data warehouse of the ECB (European Central Bank, 2022).

4.3 Principal component analysis

This section describes principal component analysis (PCA). PCA is used to identify a smaller number of uncorrelated variables (PCs) from a large data set with many highly correlated variables. Principal components are linear combinations of the observed variables. Principal components have two interpretations. The first is to interpret PCs as directions of the data that explain the maximal amount of variance of the lines that capture most information of the data (Jaadi, 2021). The second is to interpret the PCs as low-dimensional linear surfaces that are closest to the observations. It is the line in p-dimensional space that is closest to the n observations using average squared Euclidean distance as a measure of closeness (James et al., 2013).

The goal of PCA is to explain the maximum amount of variance with the fewest number of principal components. For example, 10-dimensional data gives you 10 principal components, but PCA tries to put the maximum amount of possible information in the first component, then the maximum remaining information in the second and so on (Jaadi, 2021). This results in dimensionality reduction with very limited loss of information.

4.3.1 Principal component setup

The first principal component of a set of features, in this case the features are the countries, is the normalized linear combination of the features in equation 16 (James et al., 2013). The features are represented by X_i. This is the result that is needed to be able to calculate the loading, percentage of explained variance, and to plot the PCs on the original plane.

$$Z_1 = \varphi_{11}X_1 + \varphi_{21}X_2 + \cdots + \varphi_{p1}X_p \tag{16}$$

By normalized the following is meant: $\sum_{j=1}^{p} \varphi_{j1}^2 = 1$. Without normalization the variance in a single feature can become arbitrarily large. The number of countries is represented by *p* and the number of observations by *n*, yielding a $n \times p$ matrix. The elements $\varphi_{11}, \dots, \varphi_{p1}$ are referred to as the loadings of the first principal component, Z. The elements together make up the loadings vector $\varphi_1 = (\varphi_{11}, \varphi_{21}, \dots, \varphi_{p1})^T$.

The raw dataset contains credit spreads from 6 (*p*) countries over many days (*n*). This data is standardized by removing the mean and scaling to unit variance. For all the spread data, per country the mean (μ) of the spreads is subtracted from the observation and divided by the standard deviation (σ). Standardization is necessary for performing classical PCA to ensure that the first principal component describes the direction of maximum variance (Miranda, Borgne & Bontempi, 2008).

PCA looks for the linear combination of the sample feature values in the form of equation 17 that has the maximum variance, subject to the constraint $\sum_{j=1}^{p} \varphi_{j1}^2 = 1$ (James et al., 2013).

$$z_{i1} = \varphi_{11}x_{i1} + \varphi_{21}x_{i2} + \cdots + \varphi_{p1}x_{ip} \tag{17}$$

This can be formulated as an optimization problem as written in equation 18, which is subject to $\sum_{j=1}^{p} \varphi_{j1}^2 = 1$. The first principal component solves this equation (James et al., 2013).

$$\max_{\varphi_{11},\dots,\varphi_{p1}} \left\{ \frac{1}{n} \sum_{i=1}^{n} \left(\sum_{j=1}^{p} \varphi_{j1} x_{ij} \right)^2 \right\} \tag{18}$$

4.3.2 Eigenanalysis

This optimization problem can be solved using an eigen decomposition or a singular value decomposition. Both approaches are suitable for this analysis. Eigen decomposition is often more efficient and can therefore reduce computational time (Mueller, 2018). We choose to use eigen decomposition for this research, which is also the approach taken by Longstaff et al. (2011).

To perform the eigen decomposition, the covariance matrix is needed first. Suppose the $n \times p$ data matrix is called **A**. Starting with the raw data matrix **A**, the scores are transformed into deviation scores for matrix **a** following equation 19, where **1** is $n \times 1$ column vector of ones and $\mathbf{1}^\mathbf{T}$ is the transpose of vector **1** (Abraham & Inouye, 2014).

$$\boldsymbol{a} = \boldsymbol{A} - \mathbf{1}\mathbf{1}^{\boldsymbol{T}}\boldsymbol{A}\left(\frac{1}{n}\right) \tag{19}$$

Next, we calculate $\mathbf{a}^{\mathbf{T}}\mathbf{a}$, the $p \times p$ deviation scores, and the cross products matrix for **a**. Consequently, each term in the deviation sums of squares and cross product matrix is divided by *n* to the create covariance matrix **V** (see equation 20).

$$\boldsymbol{V} = \boldsymbol{a}^{\boldsymbol{T}}\boldsymbol{a}\left(\frac{1}{n}\right) \tag{20}$$

According to the definition, a nonzero vector **d** of dimension *P* is an eigenvector of a square $p \times p$ matrix **V** if it satisfies linear equation (see equation 21) for some scalar λ. Then λ is called the eigenvalue corresponding to **x** (Abraham & Inouye, 2014).

$$\boldsymbol{Vd} = \lambda\boldsymbol{d} \tag{21}$$

Rewriting this eigenvalue problem to the characteristic polynomial, equation 22, and solving this equation accordingly yields the eigenvalues, λ_i. **I** is the identity matrix. There are *P* distinct solutions to this problem.

$$\boldsymbol{det}(\boldsymbol{V} - \lambda\boldsymbol{I}) = \boldsymbol{0} \tag{22}$$

Plugging the eigenvalues λ_i back into equation 21 enables us to solve for the eigenvector, **d**. The eigenvectors are usually normalized but they need not be. At this point we have a $p \times p$ covariance matrix **V**, a matrix **Q,** which is the square $p \times p$ matrix with eigenvectors ($\boldsymbol{d}_i$) of **V**, and $\boldsymbol{\Lambda}$, which is the diagonal matrix whose diagonal elements are the corresponding eigenvalues λ_i. Similar to equation 21, this can be written as equation 23 (Abraham & Inouye, 2014).

$$\boldsymbol{VQ} = \boldsymbol{Q\Lambda} \tag{23}$$

This is rewritten to resemble equation 24, which is the eigen decomposition of the matrix (Abraham & Inouye, 2014).

$$\boldsymbol{V} = \boldsymbol{Q\Lambda Q^T} \tag{24}$$

The eigenvector with the highest eigenvalue represents the loadings for the first principal component. The eigenvector with the second highest eigenvalue forms the basis for the second PC, and so on.

4.3.3 Proportion of explained variance

PCA is a dimension reduction method and as such tries to capture as much information of the original dataset as possible with as little PCs as possible. Hence the loss of some data is therefore a given. Which makes the metric: proportion of variance explained (PVE) an interesting metric. First the total variance present in the data is determined by following equation 25 (James et al., 2013).

$$\sum_{j=1}^{P} Var(X_j) = \sum_{j=1}^{p} \frac{1}{n} \sum_{i=1}^{n} x_{ij}^2 \tag{25}$$

The variance explained by the *m*th PC is calculated with equation 26 (James et al., 2013).

$$\frac{1}{n}\sum_{i=1}^{n} z_{im}^2 = \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{p} \varphi_{jm} x_{ij}\right)^2 \tag{26}$$

Taking the ratio of the variance explained by the *m*th component to the total variance explained, the PVE can be found, see equation 27 (James et al., 2013).

$$\frac{\sum_{i=1}^{n}\left(\sum_{j=1}^{p}\varphi_{jm}x_{ij}\right)^{2}}{\sum_{j=1}^{p}\sum_{i=1}^{n}x_{ij}^{2}} \tag{27}$$

The PVE of each principal component is always a positive quantity. We repeat this analysis for every maturity. We then plot the PVE for each PC for all maturities. This enables us to review how the PVE behaves over the different maturities.

4.4 Correlation analysis

The principal components and the macroeconomic variables are subjected to a correlation analysis. The term correlation is used to denote association between two quantitative variables. The degree of association is measured by Pearson's correlation coefficient. The correlation coefficient is measured on a scale that varies from + 1 to – 1. Complete correlation between two variables is expressed by either + 1 or -1. When one variable increases as the other increases the correlation is positive; when one decreases as the other increases it is negative. Complete absence of correlation is represented by 0 (Swinscow, 1997). Following the approach taken by Longstaff et al., the principal components are correlated with macroeconomic variables to find commonalities between the principal components and these variables.

Both the PCA and correlation analysis are done in Python[3]. The PCA yields new variables in the form of principal components, which are plotted on the original plane using the eigenvectors and the original data.

This yields 6 principal components per maturity which are plotted over the sample period for all 30 maturities. These PCs are then subjected to the correlation analysis. This yields one correlation for each PC and each maturity. Consequently, these are plotted over the maturities. To interpret the graphs created in Python the correlation strength is defined as shown in Table 5 (Swinscow, 1997).

Table 5: Correlation strength definition

Type of correlation	Value
Very weak	0 – 0.19
Weak	0.2 – 0.39
Moderate	0.4 – 0.59
Strong	0.6 – 0.79
Very strong	0.8 - 1

4.5 Sensitivity analysis SCR ratio to credit spread shocks

Using existing tools from Insurer, that operate according to the Solvency II standard formula, the effect of credit spread shocks on the SCR ratio are evaluated. A tool that approximates the VA shocks for Insurer for a given credit spread shock is developed. This tool takes a VA of 5 basis points as basis (situation June 2021). Using indexation, and the weights in the formula for the VA, an estimate of what the effect on the VA will be is made. Insurer's exposures are used to determine the weights. Insurer has had a separate research into the same VA response as this research does. Comparison between the results showed that they do not deviate a lot. The UFR and CRA are not directly influenced by credit spreads, but they are incorporated in the analysis because these are factors that have major influence on the SCR ratio, and

[3] Python code is available on request: wouter_heijs@hotmail.com

they are subject to change. Including these factors produces negative and positive scenarios that are more comprehensive and therefore more suitable for the ORSA.

The credit spread shock is simulated as a shock to the yield curve that is used to value the assets. To determine the effect of this shock, several steps are taken for each scenario. First, the new value of the assets is calculated using a shocked curve. These assets are then used to determine SCR for the market risks. On the other side of the Solvency II balance sheet, the liabilities are valued using a new shocked curve. This is the EIOPA curve, adjusted for the new VA, UFR, and CRA, depending on the scenario that is simulated. Having produced this new curve, the cashflows are discounted which produces the liabilities under the chosen scenario. Combining the new value of assets and liabilities enables the calculation of the new SCR and the SCR ratio.

4.6 Negative and positive scenarios

Shock scenarios for credit spreads and the VA, the UFR, and the CRA are simulated separately. These individual scenarios are then combined to form a negative and positive scenario. For the negative scenarios, these factors are shocked in the direction from the base case that resulted in a declining SCR ratio. The opposite is true for the positive scenarios. For both the negative and positive scenario a light, medium, and heavy scenario are simulated.

4.7 Realistic negative and positive scenarios

Since the start of this research a lot of developments have happened in the world and at Insurer. The data that was collected at the start of this research (October 2021) needs to be updated. Given the drop in UFR to 3.45%, the negative and positive scenarios are determined given a fixed UFR of 3.45%, providing more relevant and up-to-date data. The UFR can only change once a year and will therefore not change again this year (2022). The CRA is a long-term average and is not likely to change. Hence, to have the most realistic negative and positive scenarios only the credit spread shock and the VA are factored in as variables. The CRA and UFR are fixed at 10 basis points and 3,45% respectively.

5 Results

In this chapter the results of the analyses are presented. The principal component, correlation, and sensitivity analyses are depicted in that order.

5.1 Principal component analysis

As described in 4.3, the principal components that summarize the credit spreads for the six countries are calculated for every maturity separately. For each PCA the proportion of explained variance is determined per principal component. Because the PCA is performed on all 30 thirty maturities, the behavior of the explained variance over the maturity can be plotted. The blue line represents the first principal component, as indicated by the legend. The designed analysis framework enables to easily repeat the calculations with different settings. Features such as the ability to exclude a country, the ability to choose the sample period, i.e., include or exclude or exclusively the corona period, and the ability to choose the frequency of the data, i.e., monthly or quarterly are included. Combining these different settings based on our preferences yields insight into the effect of these changes.

Figure 6 shows that the first principal component is responsible for roughly 70 percent of the total variance in the data set, with a decrease in the maturities between 5 and 10 years. The feature of excluding a country provides the ability to uncover the effect of a specific country on the PCA. Italy deviates significantly from the other 5 countries in the sample data, which is shown clearly in Figure 5. To increase the proportion of explained variance for the first PC the same graph is constructed for the sample data excluding Italy.

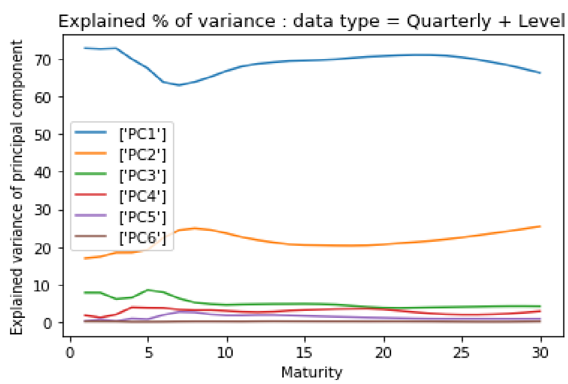

Figure 6: Explained variance of principal components

Figure 7 shows that the first principal component is responsible for roughly 80 percent of the total variance in the data set and with peaks up to 88% but with a decrease in the period between 5 and 10 years. This is a significant increase compared to the PCA on the data set including Italy. In appendix B, similar graphs are presented for all the other countries in the data set. Excluding Italy from the data set results in the largest explained variance for the first principal component. Because this strengthens the conclusions that can be drawn from the correlation analysis, every result will be generated with and without Italy in the data set.

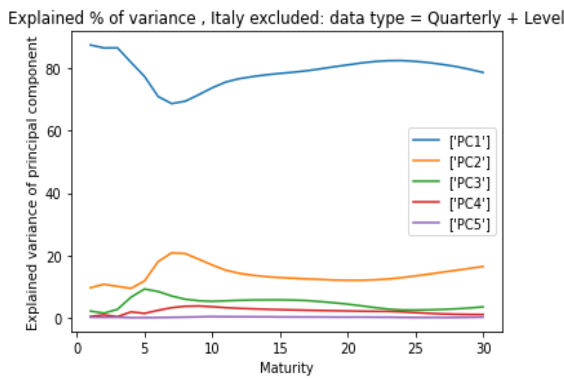

Figure 7: Explained variance of principal components, excluding Italy

In the first comparison is differentiated between the frequency of the data points, as shown in Figure 8. On the left side of the illustration the data that is used is represented quarterly. On the right side the frequency is monthly. Little difference can be found from this comparison.

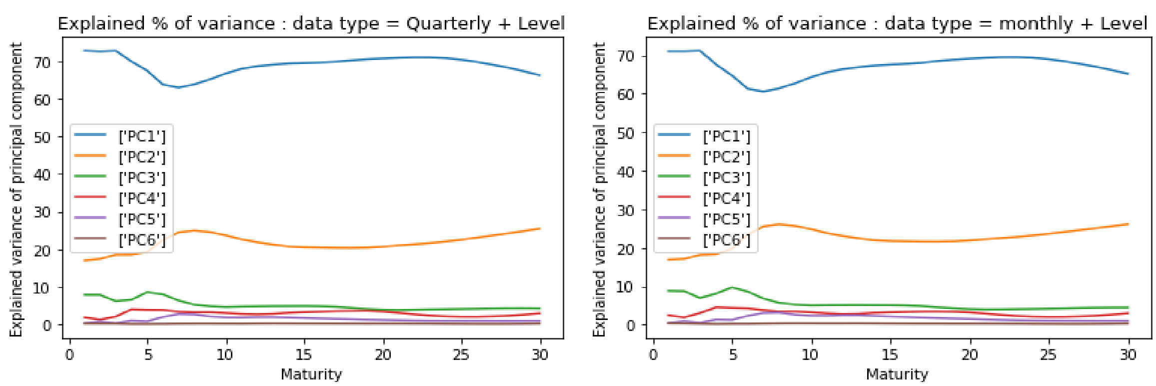

Figure 8: Comparison explained variance: quarterly vs. monthly

The second comparison is depicted in Figure 9. The graph that is based on the data set excluding Italy shows a slightly higher explained variance than the graph that is based on the data set including Italy.

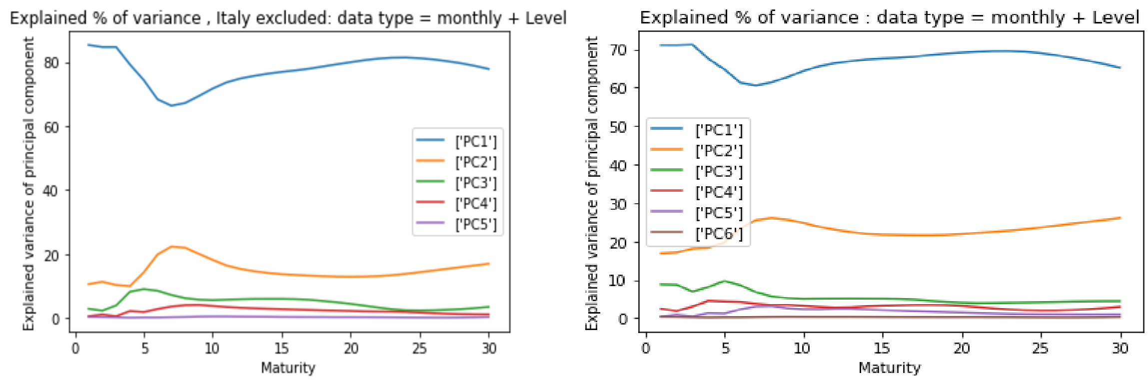

Figure 9: Comparison explained monthly variance: incl vs excl Italy

The third comparison shown in Figure 10 compares the data set during the corona period. The initial explained variance is higher for both graphs but the explained variance between maturities 5 to 10 is lower compared to full data set case. The Italian case does not differ signifanctly.

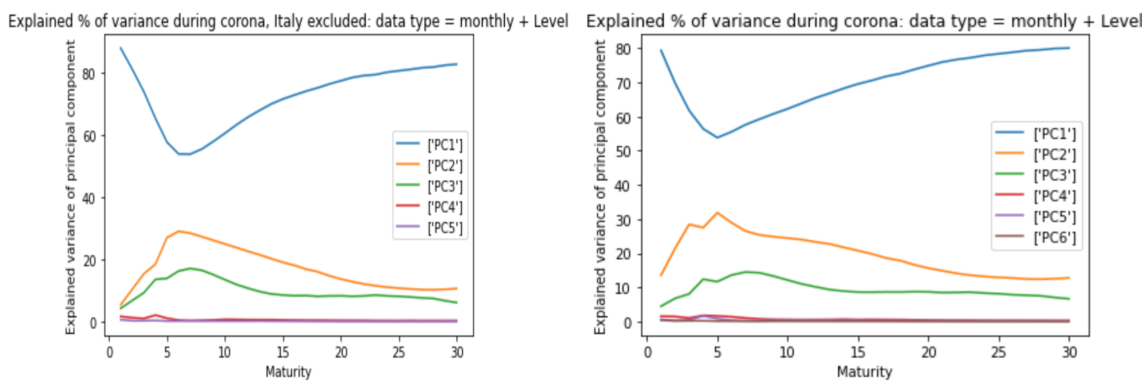

Figure 10: Comparison explained monthly variance during corona: incl vs excl Italy

The comparison represented in Figure 11 shows very similar results for the graphs. Notable is that the period between maturities 5 to 10 does not seem significantly different from the other maturities, whereas this was the case in the previous comparions. A single PC represents the spreads from the 6 countries in a single new variable, and thus reduces the dimension from 6 to 1. A principal component with a high explained variance can be considered a proxy for or a summary of the original data. The PCA analyses yield 30 first prinicpal components, one for each maturity. This enables us to examine the effects over the maturities.

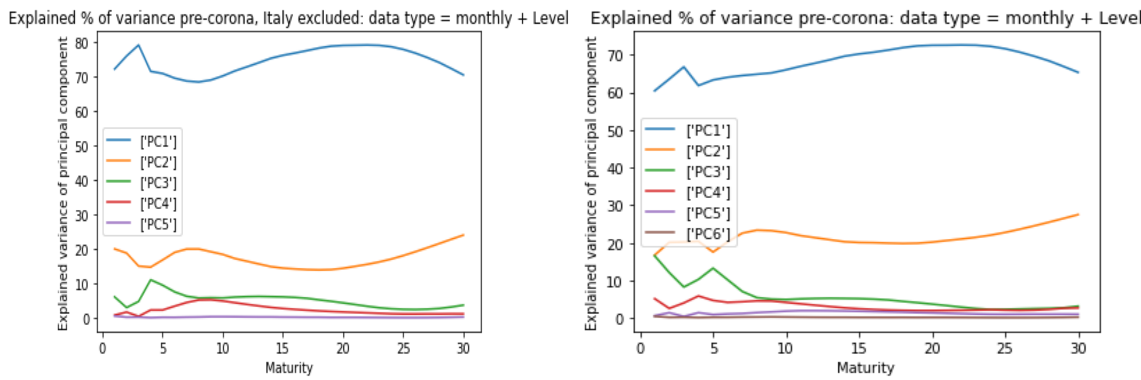

Figure 11: Comparison explained monthly variance pre-corona: incl vs excl Italy

5.2 Correlation analysis

The Correlation analysis determines the correlation for every maturity's PCs with a macroeconomic factor, and then plots these correlations over the maturities. This analysis is done for many macroeconomic factors. The composite leading indicator, current account eurozone, debt as percentage eurozone, Dow Jones index, emerging markets, EU 10-year treasury, EU corporate bond index, EUR swap 5, 10, 30 and 50 year, Euribor 3 month, GDP eurozone, Germany HICP, EU government bonds AA rated, Italian Government bond, Eurozone HICP, inflation, Nasdaq, Euronext 100 index, TED spread, unemployment rate eurozone, M1, and the VIX index are to the correlation analysis. The macroeconomic factors that scored the highest correlations over the maturities are presented below. The bulk of the correlation analysis can be found in Appendix C. For readability purposes, only the most interesting macroeconomic factors are presented in this section. In the graphs, the correlation of the first two principal components with each macroeconomic factor is plotted over the maturities. The blue lines represent the first principal component, and the orange lines represent the second one. The first PC is the most relevant because this PC represents the most variation in the sample data.

It needs to be noted that, as a result of our analysis, the sign for the correlation between the PCs and the macroeconomic variables flips sometimes, which causes strange figures. This abnormality is caused by the code underlying the skicit.learn package in Python, which is used for the PCA. The eigenvalue of the vector remains the same, but all loadings of the eigenvector have their positive or negative signs flipped. When looking for correlations over maturities, 30 separate PCAs are done, which leads to 30 possibilities of a sign flip. For PC1 this behavior was not encountered because it turns out that PC1 act as a weighted average of the credit spreads. For PC2 this is not the case, and the correlation can therefore only be evaluated on its absolute value. By including an if-statement in the code that “flips” the PCs if the sum of the eigenvalues of a PC is negative, this behavior is countered effectively, which yields insightful figures. The interpretation of the results in chapter 6 therefore is limited to the interpretation of PC1.

5.2.1 Debt as percentage

This factor refers to the debt as percentage of the GDP the Eurozone has. The Eurozone, officially called euro area, are all the EU member states that have adopted the euro as their primary currency. The debt as percentage statistic is published quarterly. In Figure 12, the effect Italy has on the correlation of the principal components is evaluated. Excluding Italy has no significant impact on the first principal component, but the second PC becomes less stable and moves directly to the opposite of the first one. Debt as percentage has a strong correlation with PC1 for all maturities.

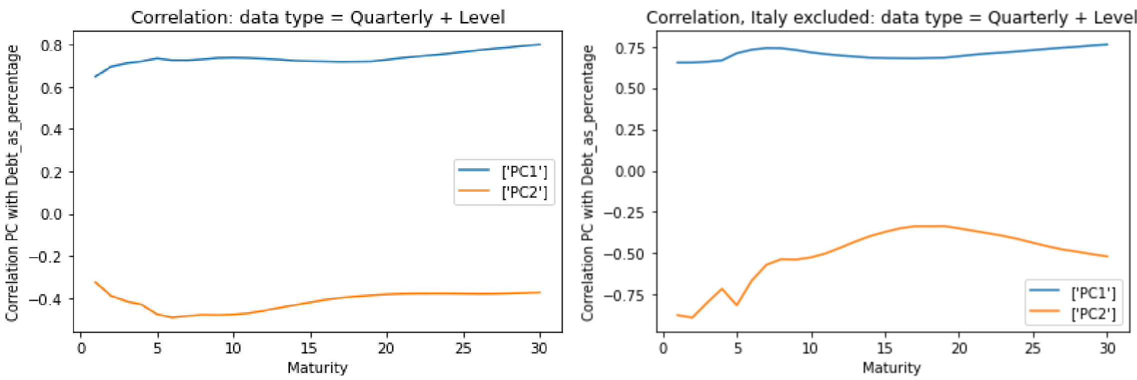

Figure 12: Debt as percentage: incl vs excl Italy

Figure 13 depicts the division of the sample period the data set includes. The graphs show that PC1 and debt as percentage have a strong positive correlation in the pre-corona situation for maturities higher than 5 years, whereas they have a weak negative correlation during the corona period for maturities higher than 5 years. PC2 moves opposite to PC1 in all cases.

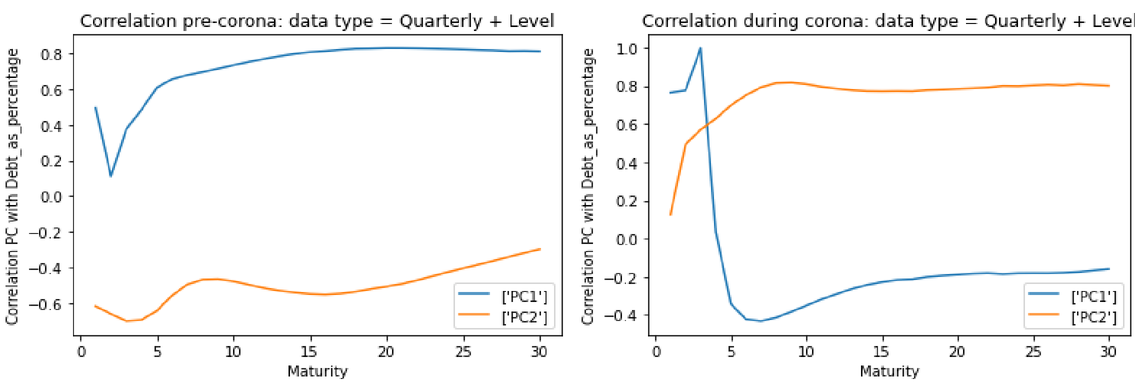

Figure 13: Debt as percentage: pre vs. during corona

5.2.2 Inflation

The inflation is represented by the CPTFEMU Index as can be downloaded from Eurostat. It represents the HICP of the euro area excluding tobacco. The analysis on inflation uses monthly data. Figure 14 shows that inflation has a very weak negative correlation with PC1 without Italy for middle-long maturities. Including Italy strengthens this correlation to weak/moderate for middle-long maturities.

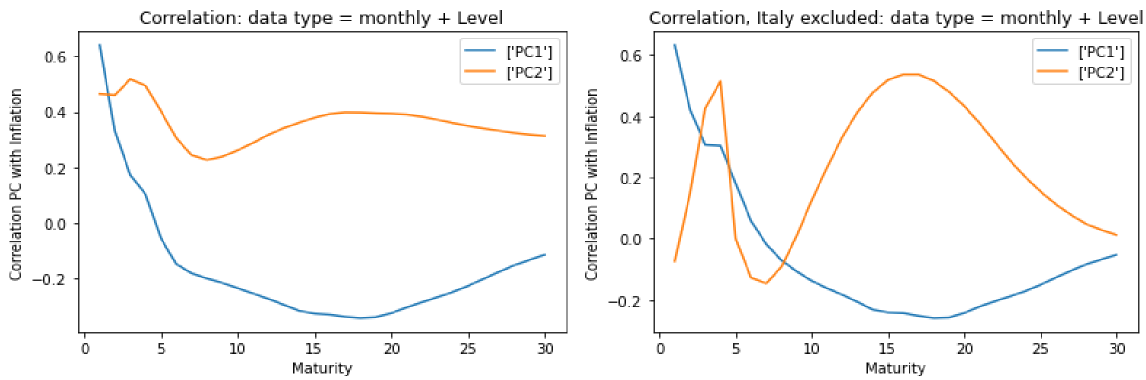

Figure 14: Inflation: incl vs. excl Italy

When we further dissect the anaylsis into a pre-corona and during corona period, it becomes clear that in the pre-corona period inflation has a very strong negative correlation to PC1, whereas this correlation is very weak during corona.

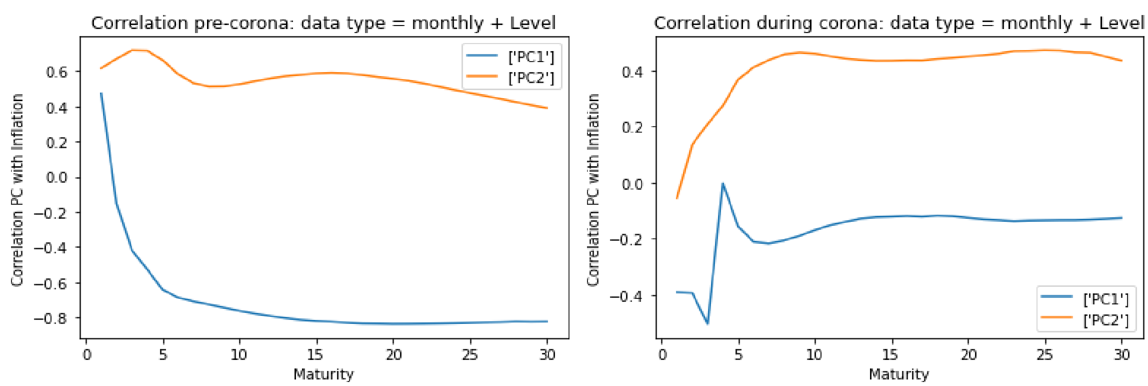

Figure 15: Inflation: pre vs. during corona

These results are similar to those of the correlation analysis for the German HICP and the HICP euro area, which can be found in appendix C.

5.2.3 Emerging markets

The ICE BofA Diversified Emerging Markets External Debt Sovereign Bond Index represents the performance of emerging markets government bonds. The analysis uses monthly data. Figure 16 shows that PC1 has a moderate positive correlation with emerging markets. Excluding Italy from the data set strengthens this correlation to strongly positive.

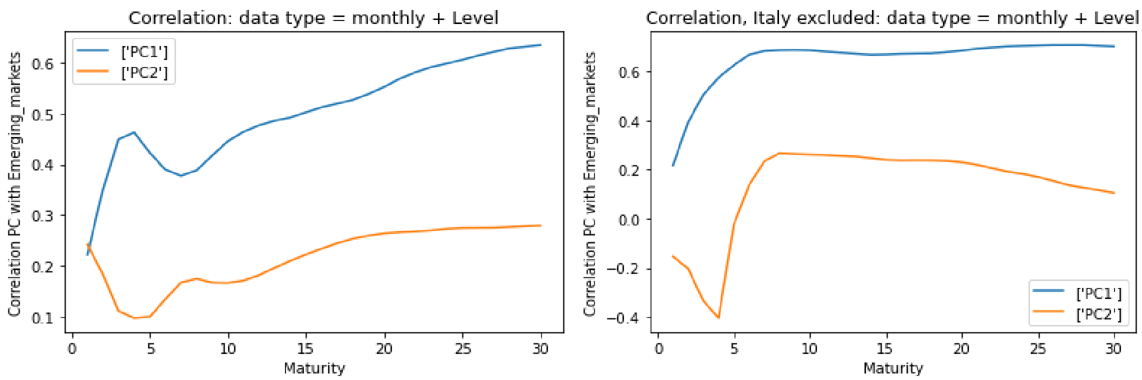

Figure 16: Emerging markets: incl vs. excl Italy

Figure 17 shows that the correlation is strongly positive in both the pre- and during corona period. This applies to the case including and excluding Italy.

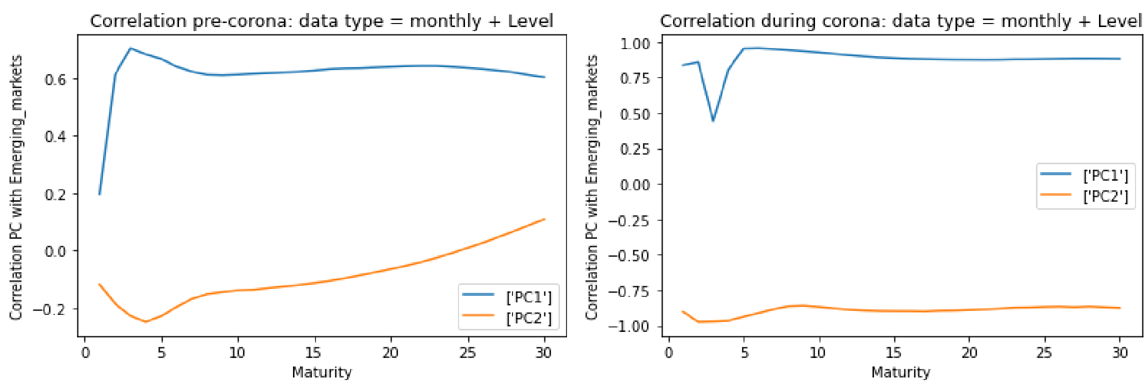

Figure 17: Emerging markets: pre vs. during corona

5.2.4 VIX-index

The VIX-index is a proxy for global market volatility. The analysis is based on monthly data. Figure 18 shows that the correlation between PC1 and the VIX-index is moderately positive for short and long maturities but weak for middle-long maturities (5-20 years). Excluding Italy creates a stable moderately positive correlation.

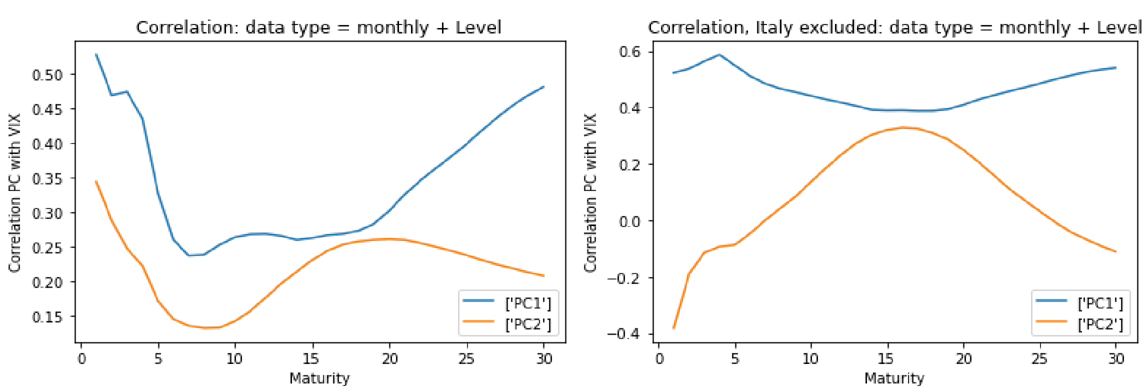

Figure 18: VIX-index: incl vs. excl Italy

Figure 19 shows that the VIX-index only has a weak positive correlation with PC1 for short maturities in pre-corona period. During corona PC1 has a strong positive correlation with PC1.

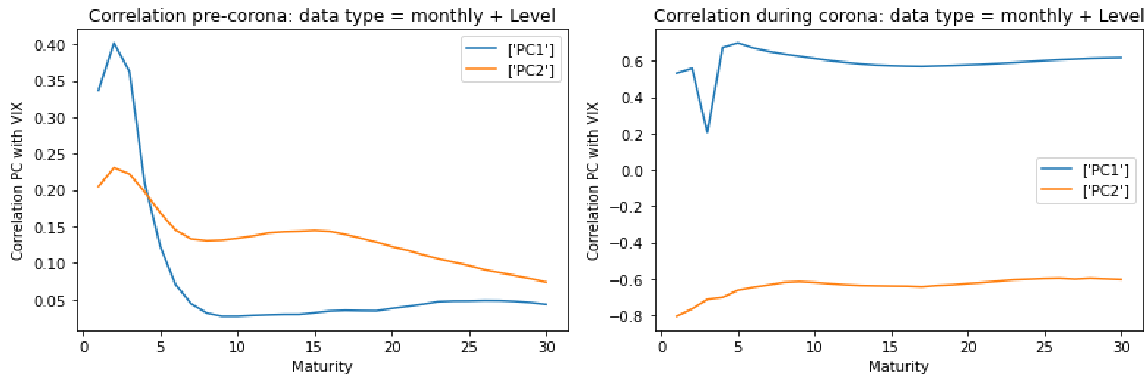

Figure 19: VIX-index: pre vs. during corona

5.2.5 Unemployment rate

The unemployment rate of the euro area is used in this analysis. The analysis is based on monthly data. Figure 20 shows that including Italy in the data set results in a stronger correlation between PC1 and the unemployment rate. Short maturities have little correlation with unemployment rate.

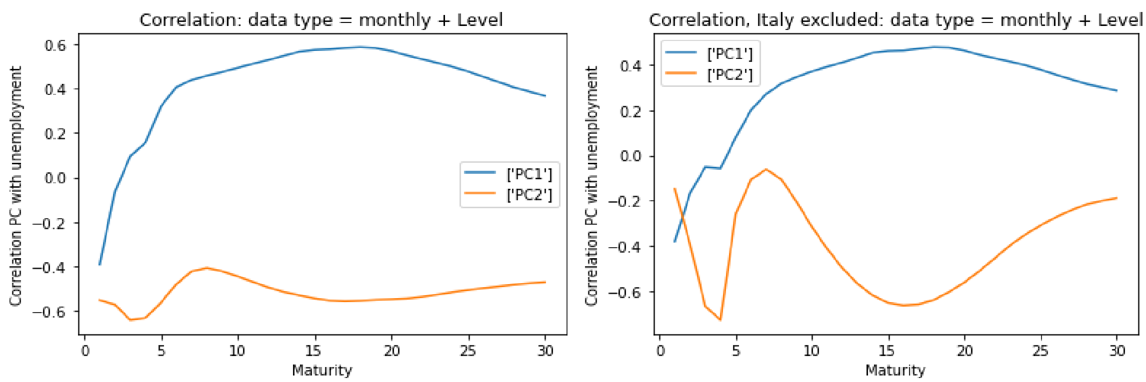

Figure 20: Unemployment rate: incl vs. excl. Italy

Figure 21 displays a clear difference between the pre- and during corona period. Whereas in the period leading up to the corona pandemic there is a strong positive correlation between PC1 and the unemployment rate, there is a moderately negative correlation during the corona period.

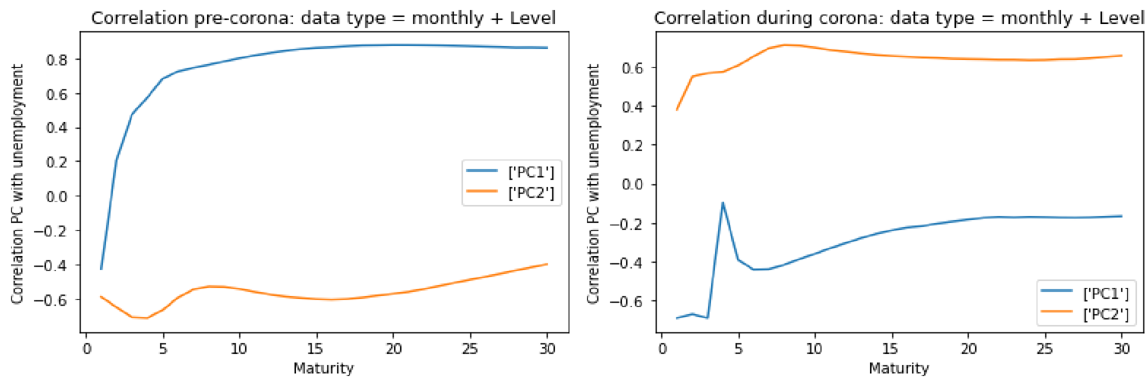

Figure 21: Unemployment rate: pre vs. during corona

5.2.6 Euribor 3-month

The Euribor is a daily reference rate, published by the European Money Markets Institute, based on the average interest rates at which Eurozone banks offer to lend unsecured funds to other banks in the euro wholesale money market. Figure 22 shows that there is little difference in the correlation between PC1 and the 3-month Euribor rate for the case with and without Italy in the sample data.

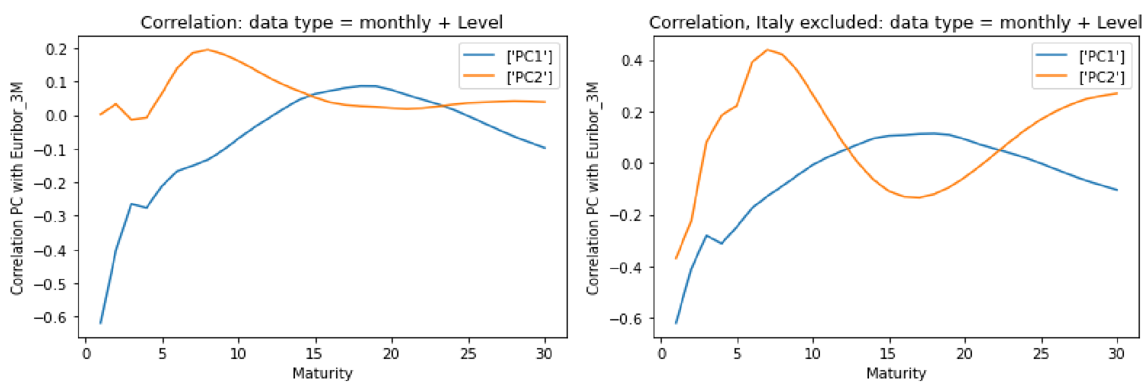

Figure 22: Euribor 3 month: incl vs. excl Italy

Figure 23 shows that there is a very strong positive correlation between PC1 and the 3-month Euribor rate during the corona period, whereas this is only a moderately positive correlation in pre-corona period.

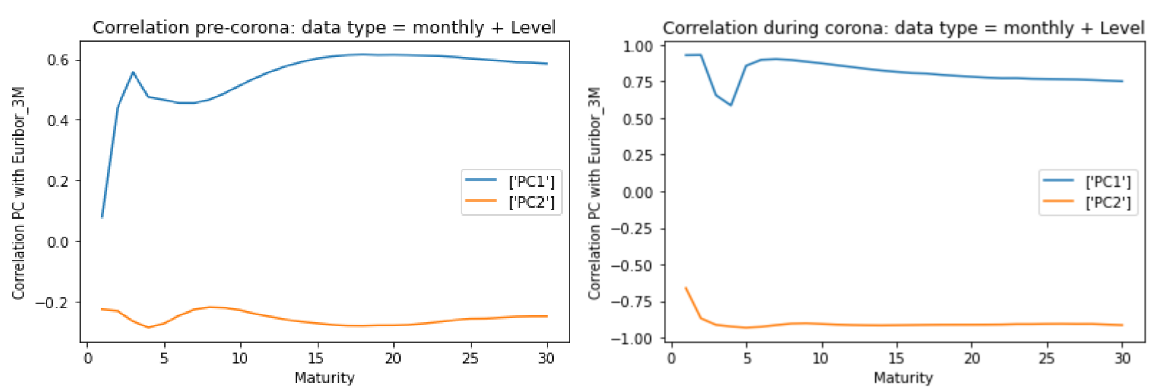

Figure 23: Euribor 3 month: pre vs. during corona

5.2.7 GDP euro area

The GDP of the euro area is indexed at 2015. The analysis is based on monthly data. Figure 24 depicts the correlation of the first and second PCs with GDP of the euro area. Both graphs in the figure show a correlation that starts weakly negative for low maturities and ends with a correlation that is very strongly negative. Excluding Italy has the effect that the correlation is very strongly negative from maturity 10, instead of 25.

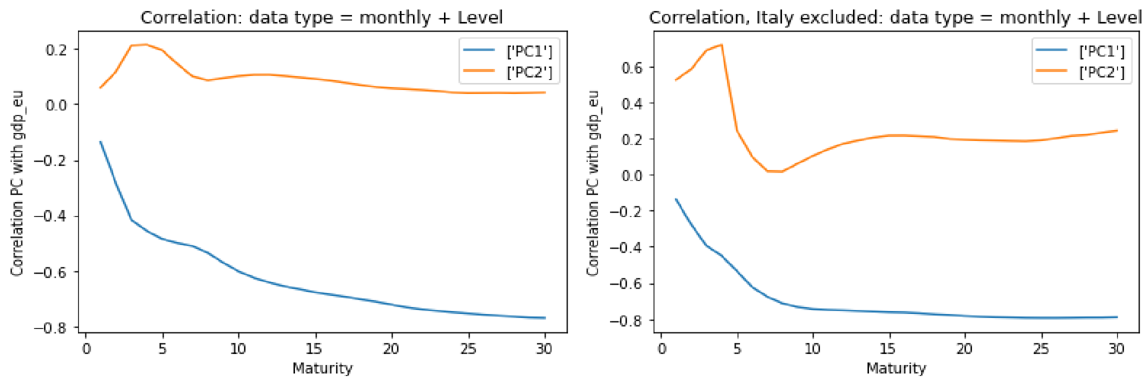

Figure 24: European GDP: incl vs. excl Italy

Figure 25 shows the correlation of the first and second PC with the European GDP. The graphs move similar to each other.

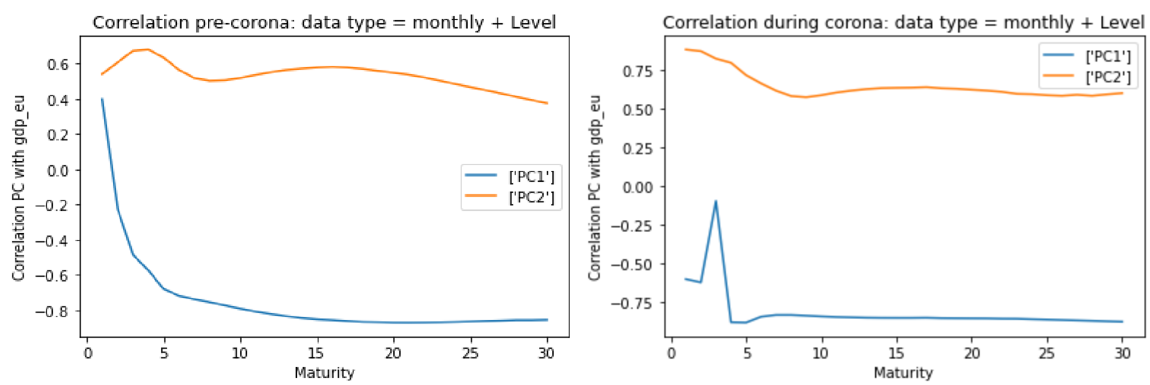

Figure 25: European GDP: pre vs. during corona

5.2.8 Euronext

The Euronext 100 index is a European stock market. The data that is used for the analysis is on a monthly frequency. Figure 26 shows similar correlations for both graphs in the figure. PC1 has a weak positive correlation on short-term with the Euronext but on the long-term a weak negative correlation.

Euronext

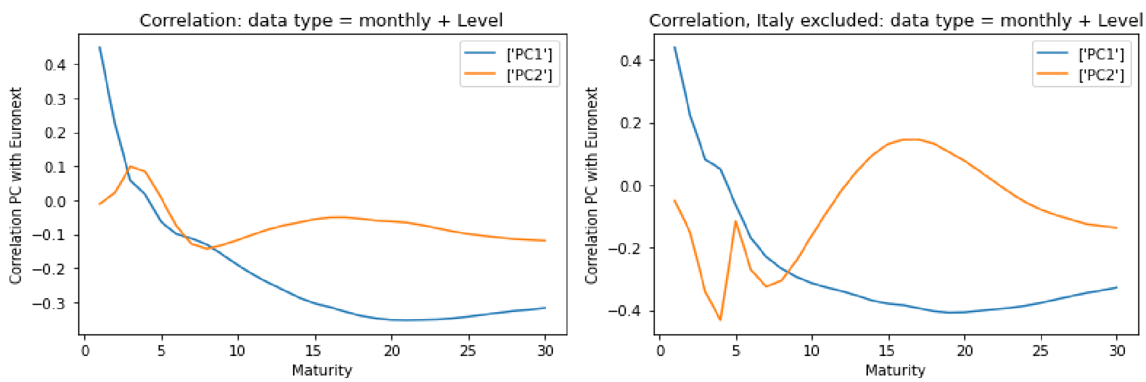

Figure 26: Euronext: incl vs. excl Italy

Figure 27 shows that during the corona period the correlation is very strongly negative. Whereas in the period leading up to the corona pandemic there is a moderately negative correlation.

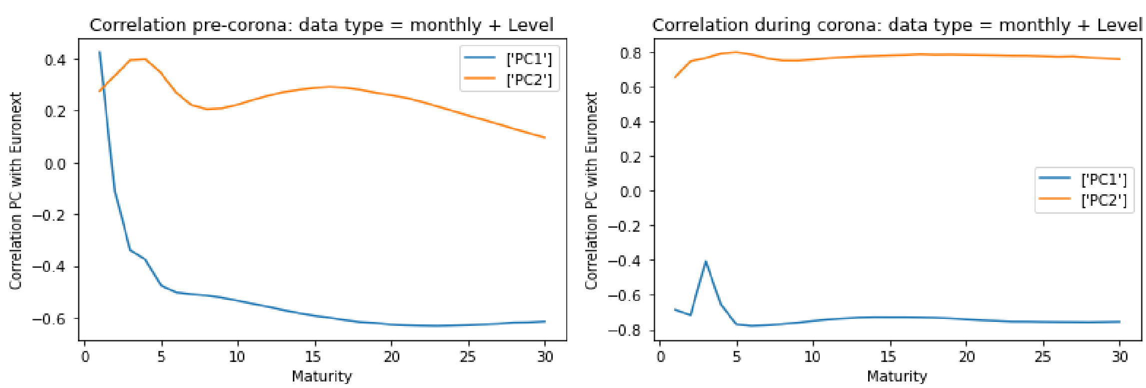

Figure 27: Euronext: pre vs. during corona

5.2.9 Composite leading indicator

The composite leading indicator is designed to provide early signals of turning points in business cycles showing fluctuation of the economic activity around its long-term potential level. The OECD publishes the CLI on a monthly basis. Figure 28 shows the correlation of the first and second PC with the CLI. A moderately negative correlation is observed in both graphs but excluding Italy from the data set decreases the correlation further and creates a more stable correlation over the maturities.

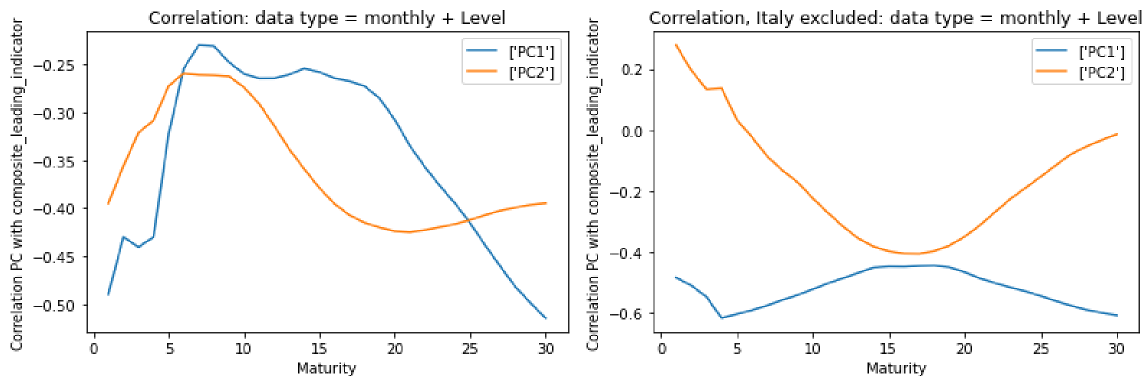

Figure 28: Composite leading indicator: incl vs. excl Italy

Figure 29 depicts the correlation of the PCs in both sample periods. In the pre-corona period there is a weakly negative correlation for short maturities and this is uncorrelated for maturities from 10 years and larger. During the corona period there is very strong negative correlation with the CLI and PC1.

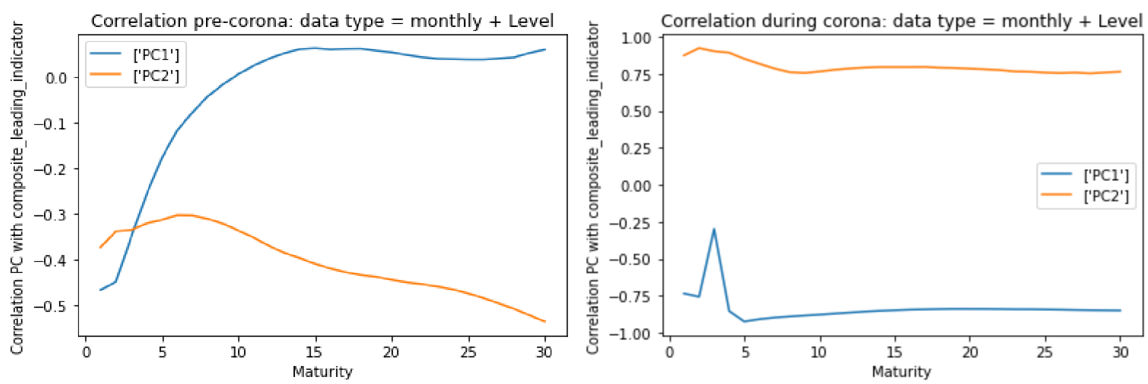

Figure 29: Composite leading indicator: pre vs. during corona

5.2.10 M1

M1 is a proxy for the monetary policy of the ECB as it measures the amount of money in the euro area. The ECB published this data monthly. Figure 30 depicts the correlation of both principal components with M1. Except for maturities lower than 5 years, a strong positive correlation is found in the pre-pandemic sample period. On the contrary, during the pandemic a weakly negative correlation is observed between PC1 and M1 for maturities over 5 years.

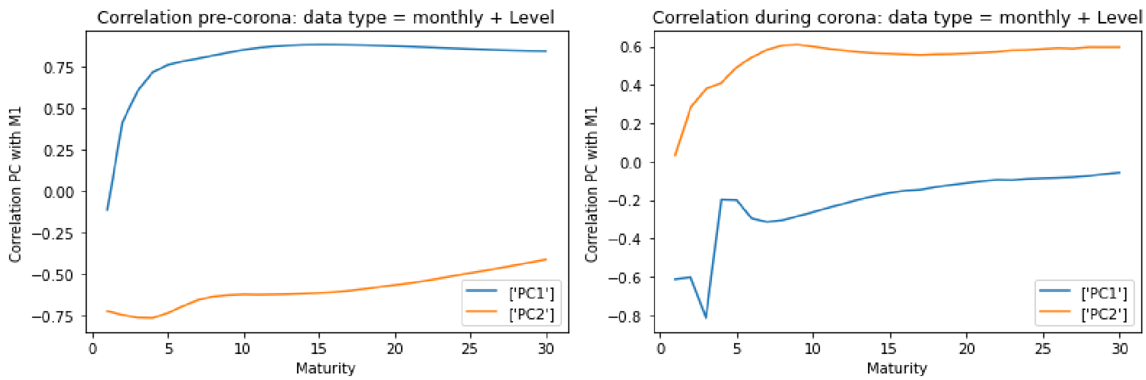

Figure 30: M1: pre vs. during corona

5.2.11 Low correlation factors

In the section on correlation analysis the factors that have strong correlations are discussed. In this section the macroeconomic factors that have either a weak correlation or that are uncorrelated are mentioned. Current account, EUR swap 5, 10, 30, and 50 years, and the TED spread are not deemed appropriate as early signal factors because of their low correlations. Italian government bonds, European corporate bonds, and European AA government bonds have strong correlations with the PCs but are not recommended as early-warning signal. This is because these are credit spreads and as such serve as validation, not as warning.

5.3 Sensitivity analysis SCR ratio to credit spread shocks

The results of the sensitivity analysis are presented in this section. First, the sensitivity of the SCR ratio to the credit spread and VA are discussed. The VA is influenced by credit spreads, which is why these are simulated simultaneously. Consequently, the effect of the UFR and the CRA are presented after which these are combined to establish negative and positive scenarios.

5.3.1 Credit spread and VA

Table 6 shows the effect of the credit spread shock and its corresponding VA, which is determined using the VA estimation tool, have on the SCR ratio. A negative shock proves to be beneficial for the SCR ratio. An increase in credit spreads has a decreasing effect on the SCR ratio, even though it is dampened by the VA.

Table 6: Sensitivity of SCR ratio to credit spread and volatility adjustment shock

Shock	**VA**	**SCR ratio**
-50	-15	233%
-45	-13	223%
-40	-11	213%
-35	-9	204%
-30	-7	194%
-25	-5	185%
-20	-3	177%
-15	-1	168%
-10	1	159%
-5	3	147%

0	5	136%
5	7	126%
10	9	116%
15	12	110%
20	14	102%
25	16	93%
30	18	88%
35	20	81%
40	22	75%
45	24	69%
50	26	61%

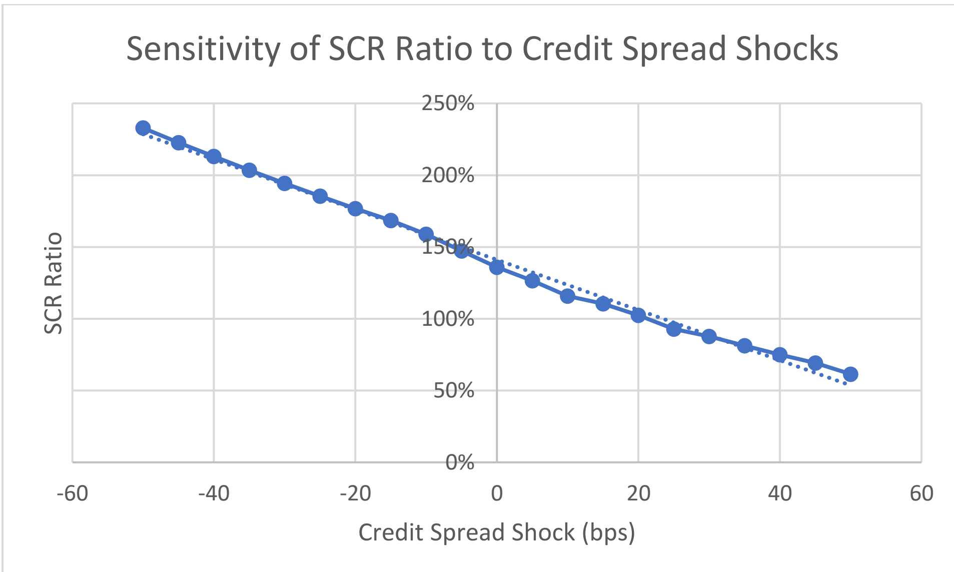

Figure 31: Sensitivity of SCR ratio to credit spread and VA shock

5.3.2 UFR

Table 7 shows the effect of a UFR shock on the SCR ratio. A lower UFR, in this case a higher downwards shock, leads to a lower SCR ratio. Whereas a higher UFR, in this case a higher upwards shock, has an increasing effect on the SCR ratio. The UFR can only change by 15 basis points at once. Hence, shocks are in steps of 15 basis points. The upwards shocks are very unlikely given current conditions. For the UFR to rise, the real rate must rise significantly, which means the risk-free interest rate has probably risen, and the liabilities are valued on a new curve. This new curve will differ on both the UFR and the risk-free rate. That this is not taken into account must be considered when looking at these sensitivities. These sensitivities are presented to show the effect of purely the UFR. The downwards shocks are realistic, given that current market conditions will cause the UFR to drop, but the height of the RFR does not change as a result of changing interest, merely the UFR.

Table 7: Sensitivity of SCR ratio to UFR

UFR Shock	**SCR ratio**
-45	87%

-30	103%
-15	119%
0	136%
15	154%
30	169%
45	180%

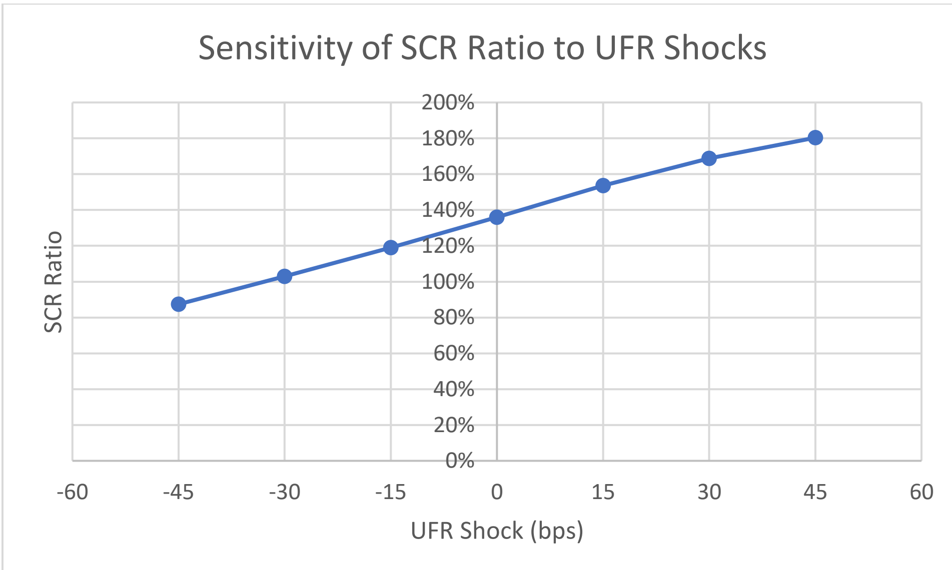

Figure 32: Sensitivity of SCR ratio to UFR

5.3.3 CRA

Table 8 shows a clear linear relationship. The current situation, a CRA of 10 basis points, results in a SCR ratio 136%. Because the CRA cannot go lower than 10 basis points by regulation, the CRA is only shocked upwards. This has a decreasing effect on the SCR ratio.

Table 8: Sensitivity of SCR ratio to CRA

CRA Shock	SCR ratio
0	136%
1	134%
2	132%
3	130%
4	128%
5	126%
6	124%

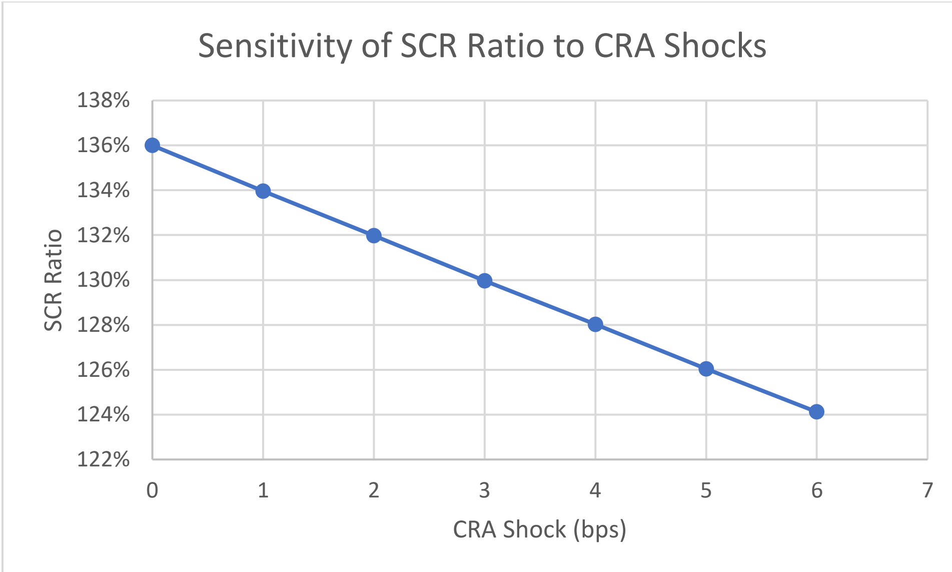

Figure 33: Sensitivity of SCR ratio to CRA

5.3.4 Negative and positive scenarios

Table 9 shows combinations of the factors that are known to have a significant effect on the SCR ratio. The previous analysis showed which directions had a decreasing effect on the SCR ratio. In the negative scenarios the directions that have a decreasing impact on the SCR ratio are combined and shocked in the SCR ratio-decreasing direction. Vice versa, in the positive scenarios the factors of impact are shocked in a SCR ratio-increasing direction.

Table 9: Effect of negative and positive scenario on SCR ratio

Scenario	Credit spread	VA	UFR	CRA	SCR ratio
Negative scenario heavy	50	26	3,15%	13	28%
Negative scenario medium	25	16	3,3%	12	65%
Negative scenario light	5	7	3,45%	11	109%
Base scenario	0	5	3,6%	10	136%
Positive scenario light	-5	3	3,75%	10	165%
Positive scenario medium	-25	-5	3,9%	10	210%
Positive scenario heavy	-50	-15	4,05%	10	271%

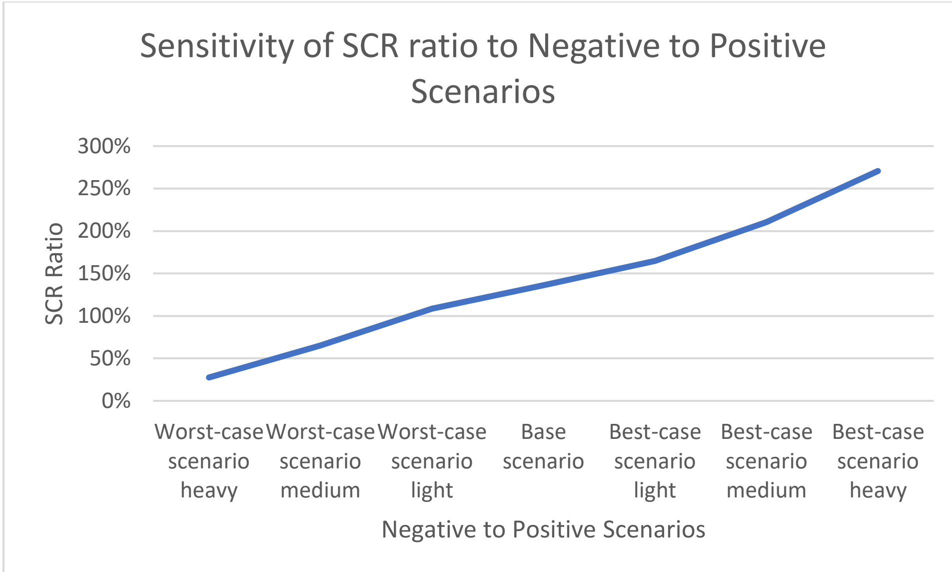

Figure 34: Effect of negative and positive scenarios on SCR ratio

5.3.5 Realistic negative and positive scenarios

Table 10 shows the sensitivity of the SCR ratio to the scenarios. In all cases, the UFR is kept at 3,45%, which is the current UFR (April 2022). A method similar to the one in the previous section is used to determine the direction of the shocks.

Table 10: UFR 3,45% - Effect of negative and positive scenarios on SCR ratio

Scenario	Credit spread	VA	UFR	CRA	SCR ratio
Negative scenario heavy	50	26	3,45%	10	53%
Negative scenario medium	25	16	3,45%	10	81%
Negative scenario light	5	7	3,45%	10	110%
Base scenario	0	5	3,45%	10	119%
Positive scenario light	-5	3	3,45%	10	129%
Positive scenario medium	-25	-5	3,45%	10	172%
Positive scenario heavy	-50	-15	3,45%	10	219%

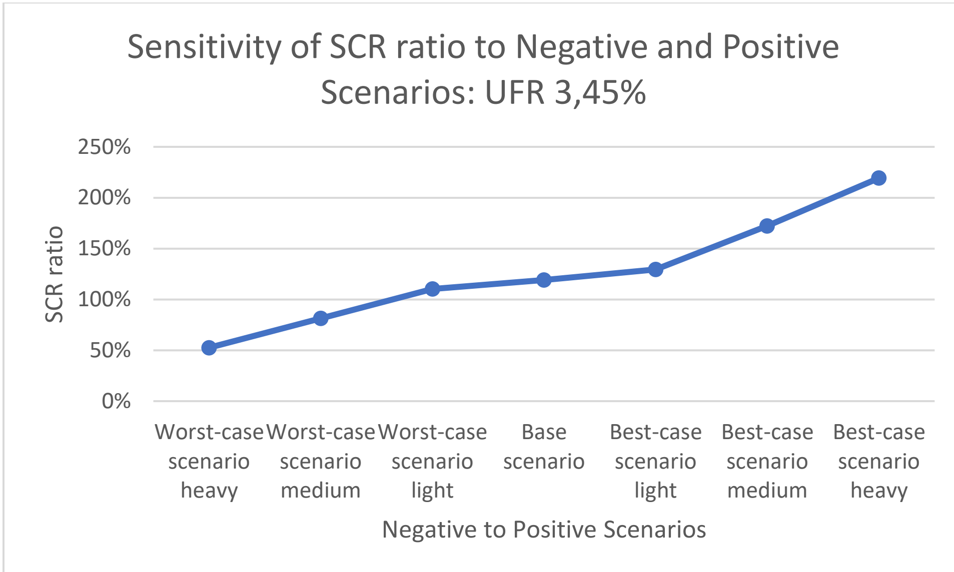

Figure 35: UFR 3,45% - effect of negative and positive scenarios on SCR ratio

6 Conclusion

This research evaluates credit spread shocks and their influence on the SCR ratio of a Dutch life insurer. A comprehensive literature research on credit spread determinants is provided. A novel framework is created which summarizes the credit spreads of Insurer's assets into a new variable using principal component analysis. After which the correlation against macroeconomic factors that are considered to be of significant influence on credit spreads according to literature is determined. This provided insight into the behavior of these correlations over the maturities. The effect of credit spreads shocks on Insurer's SCR ratio was evaluated using a sensitivity analysis, which provided insight into negative and positive scenarios of the determinants. In this chapter, the results of the analyses are discussed. A recommendation on which macroeconomic factors can function as early-warning signs is given. Consequently, an evaluation of the research is done, and the limitations are discussed. Finally, the contribution to theory and practice, as well as the possibilities for future research are presented.

6.1 Discussion

In this section, the results of the previous chapter are discussed. The principal component, correlation, and sensitivity analysis are evaluated.

6.1.1 Principal component analysis

Excluding Italy from the dataset increases the percentage of explained variance for the first PC. Excluding Belgium and France creates a more stable graph. The pre-corona period provides a more stable first principal component over the maturities also, whereas during the corona period a drop in the explained percentage of variance in observed around the 5 years-maturities. Figure 36 shows Belgian government bonds credit spreads for 30 maturities for randomly picked dates from the sample. The figure shows indeed that the spreads for maturities 3, 4, and 5 behave differently. Similar patterns are discovered for the other countries except Italy. The maturities surrounding the 5-year maturity are generally the most liquid and have the largest market size. Therefore, the liquidity premium that is paid for this higher liquidity could be the cause for this observed behavior.

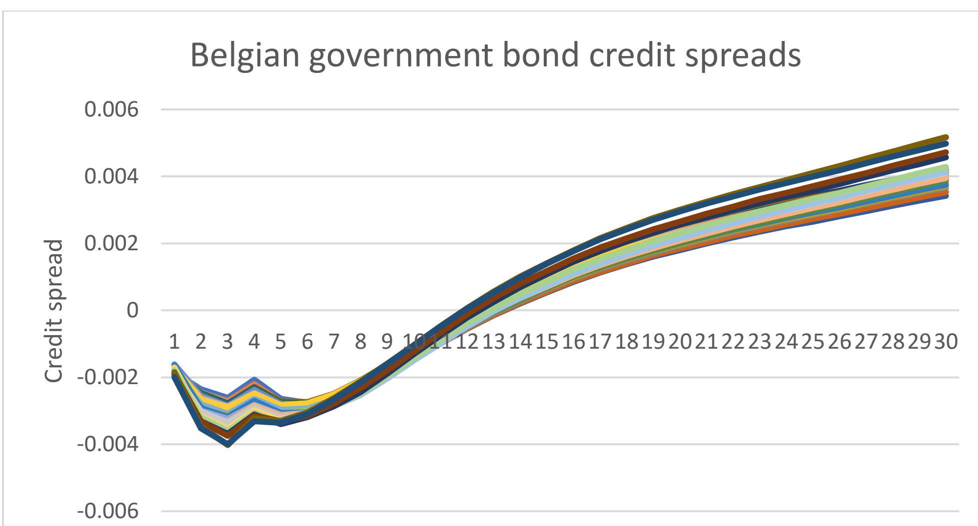

Figure 36: Belgian government bonds credit spreads

6.1.2 Correlation analysis

In this section, the results presented in chapter 5 are evaluated and discussed. Many of these interpretations are possible explanations for the observed data. This is based on correlation and not on causality and should therefore not be interpreted as such. It is therefore possible to have contradicting explanations.

6.1.2.1 Debt as percentage

The graphs show that there is a strong positive correlation for the debt as percentage. This indicates that a higher debt is associated with higher spreads, which confirms the ideas from the literature research. This can be explained by the concept of risk. A higher debt as percentage of the GDP results in a bigger probability of default. Therefore, investors want to be compensated with higher spreads. The pre-corona period shows an even stronger correlation with PC1 and debt as percentage. However, during the corona pandemic there is even a slight negative correlation. A possible explanation for this is that in times of financial crisis, this metric becomes less important. Another explanation may be that in crisis times, government bonds are considered safer than most investments. Even though debt as percentage increases, investors relatively invest more in government bonds causing the spreads to decrease, resulting in a negative correlation. Monetary policy also plays a major role during the covid crisis.

6.1.2.2 Inflation

The results section on inflation discusses that inflation has a weak negative correlation with PC1 during corona and a strong negative correlation in the pre-corona period. In the pre-corona period, inflation was low but stable for several years, even deflation was observed.

Nominal rates of return generally move with inflation as investors demand higher nominal returns to offset the impact of expected inflation (Berkovich, Dinerstein & Ricco, 2021). The credit spreads in the data set are determined based on the EUR swap curve, which is a proxy for the risk-free interest and as such is influenced by inflation. The spreads in the data set may therefore not, or partially, include the impact of inflation and as such can be regarded as an approximation of the real return. Hence, it is concluded that other market conditions cause credit spreads to move in the opposite direction of inflation in the pre-corona period and to move more or less uncorrelated during the corona crisis.

6.1.2.3 Emerging markets

The emerging markets show a strong positive correlation with PC1, both in the pre- and during corona period. This can be explained by one of the drivers of the credit spreads: credit risk. If market risk were to increase, the probability of default increases as well, which results in higher spreads. As global markets are strongly intertwined the effect should be similar for developed bond markets, yielding a positive correlation.

6.1.2.4 VIX-index

The VIX-index is a proxy for market volatility. Volatility creates risk, which has stimulating effect on credit spreads. However, in the pre-corona period, this variable is approximately uncorrelated with the sample spreads, except for short maturities. During the pandemic, a very strong correlation is observed. This implies that the volatility factor is only relevant in times of crisis and for short maturities in regular periods.

6.1.2.5 Unemployment rate

The unemployment rate of the euro area is very strongly positively correlated with the sample spreads, except during the corona period. A high unemployment rate often comes hand in hand with slow economic conditions. Vice versa, a low unemployment rate tends to coincide with a booming economy. Both scenarios imply a positive correlation, which is not the case. The unemployment rate did not rise with the credit spreads during the pandemic. This can be explained by the government support offered to companies, preventing massive layoffs as a result of declining turnovers and even lowering unemployment rates to record lows.

6.1.2.6 Euribor 3-month

The Euribor is the reference rate at which banks lend money to one another. Again, a higher rate could be caused by higher market risk or a slowdown in the monetary policy of central banks. This leads to increased credit spreads as well, yielding a positive correlation. During the corona pandemic this correlation is stronger, suggesting that risk is more important during the corona period.

6.1.2.7 GDP euro area

The GDP the in the euro area is strongly negatively correlated with the sample credit spreads. GDP measures the turnover of an economy and as such functions as a measure an economy's performance. A higher GDP reflects a better performing economy and vice versa. On the other side, the performance of an economy has the opposite effect on credit spreads, because a strong economy has less risk than a weak economy and thus has tighter credit spreads. This dynamic yields a negative correlation. No significant deviation can be found between both periods.

6.1.2.8 Nasdaq, Dow Jones Industrial Average, and Euronext

All three market indexes exhibit very similar behavior, which is why these three are addressed simultaneously. The indexes show a negative correlation, which increases during the pandemic. Market indexes are proxies for the state of an economy. In this case the indexes reflect the American and European markets. Growing indexes imply a better state of the economy, which reduces risk and thus decreases credit spreads, yielding a negative correlation.

6.1.2.9 Composite leading indicator

The composite leading indicator is designed to provide early signals of turning points in business cycles showing fluctuation of the economic activity around its long-term potential level. The CLI provides insight into whether an economy can restore to its long-term potential. The pandemic causes credit spreads to widen whereas the CLI indicates that the economy is likely to restore. The CLI is a "leading" indicator which means it predicts ahead of time. It is the opposite of a "lagged" indicator. This explains the negative correlation during the pandemic.

6.1.2.10 M1

In the period leading up to the pandemic a positive correlation between M1 and PC1 is found. During this period M1 fluctuates. If the amount of money in circulation is increased, investors become reluctant to stick with bonds with longer maturities, where they would earn a low interest for a long time. Hence, demand for these bonds decreases, resulting in higher yields, which constitutes to a positive correlation. Vice versa, the same reasoning can be done.

During the pandemic a strong negative correlation is observed. M1 showed a strong increase in March 2020. In this period of uncertainty, where you would expect that credit spreads rise, they dropped. The amount of money in circulation increased as a result of change in the monetary policy. This increase in ECB spending is likely to have caused the credit spreads to drop as a result of increased liquidity in the market (more supply than demand). However, our analysis is a correlational one, meaning that we can only conclude that these events were highly correlated.

6.1.3 Sensitivity analysis SCR ratio to credit spread shocks

This sub section discusses the sensitivity analyses in order. The credit spread and VA analysis shows a declining, almost linear trend. This small deviation from linearity is caused by the VA. The VA is estimated and rounded to a full percentage. Hence, the line deviates marginally from linearity. Considering the base scenario has a SCR ratio of 136% (June 2021), and internal policy of Insurer has marked an SCR ratio of 135% as crucial point, even the smallest positive credit spread shock of 5 basis points causes the policy threshold to be crossed, forcing Insurer to act. A credit spread shock of 25 basis points causes Insurer to cross the 100% DNB threshold, allowing the DNB to intervene and force action on Insurer. On the other hand, were credit spreads to decrease, meaning that the yield curve against which assets are valued would decrease, the value of Insurer's assets would increase, and the SCR ratio would increase.

The UFR of 3,6% in the base case yielded a SCR ratio of 136%. A decrease of 15 basis points would decrease the ratio to 119%. During this research, the UFR did move from 3,6% to 3,45%, drastically pushing the SCR ratio, and crossing the internal policy threshold causing Insurer to take action. These effects have been excluded from this research. An increase in UFR would increase the SCR ratio, as the value of the liabilities would decrease. However, current market conditions suggest that the UFR would sooner drop another 15 basis points than that it would increase. The possibility of an increase has been included for the positive scenario analysis, but it should be noted that given current market conditions (April 2022) this would be wishful thinking.

The CRA is a downwards shift to the curve against which the liabilities are valued, and as such has an increasing effect on the value of the liabilities. The CRA is regulated to be between the 10 and 35 basis points but has been at 10 basis points for years now. To have realistic scenarios the shocks are of 1 basis point. Increasing the CRA by 1 basis point, decreases the SCR ratio by 2% linearly. The smallest increase in CRA would cause Insurer to cross the internal policy threshold and stimulate Insurer to act.

Combining these three scenarios analyses into negative and positive scenarios provides insight into possible high-risk situations. The "light" negative scenario pushes the SCR ratio 109%, far past the internal threshold. Unfortunately, current market conditions (April 2022) resemble this negative scenario, possibly with even higher spreads. Current market conditions include a drop in UFR to 3,45%, high inflation, increasing credit spreads as results of Russian-Ukrainian war, and a near-end-pandemic world. Middle and heavy negative scenarios yield SCR ratios of 65% and 28% respectively. The positive scenarios paint a much brighter picture, with SCR ratios of 165%, 218%, and 292% for the light, medium, and heavy scenarios. However, it should be noted that these more unlikely in the near future than the negative scenarios. On the long-run, market conditions are expected to revert back to normal, and resemble positive scenarios were the credit spreads and CRA are concerned.

The realistic negative and positive scenarios showed that even the base case drops to 119%. In both the light negative and positive scenarios, the next event levels are not breached, 100% and 135%. The scenarios are less sensitive than the negative and positive scenarios from previous section, which makes sense as more factors are shocked in those scenarios. The heavy negative realistic scenario results in a SCR ratio of 53%, which is alarmingly low.

6.2 Recommendations

Insurer is recommended to take notice of the discovered correlations between the credit spread and macroeconomic variable movements. In Table 11 an overview of the variables that show strong correlations with PC1 is provided. We recommend that Insurer keeps an eye on the behavior of the VIX index and the stock market performances when no global financial crisis is happening so that they won't be surprised by sudden credit spread movements in short maturities. For longer maturities, we recommend tracking the movements of the following factors: debt as percentage, emerging markets performance, unemployment rate and GDP of the euro area, and the M1.

The covid pandemic can be considered both a demand and supply driven crisis, but the demand shocks play a more significant role in this crisis (DNB, 2020). We consider the covid pandemic to be a demand driven financial crises. We generalize our recommendation to crises that are similar to the corona crisis, which means the recommendation is applicable to demand driven crises. In periods similar to the corona crisis, Insurer should take notice of the VIX and the Euribor 3-month rate to not be surprised by sudden movements in credit spreads for short maturities. For movements in credit spreads for longer maturities Insurer should keep an eye on the factors: emerging markets, VIX, Euribor 3 month, GDP, stock markets, and the composite leading indicator. This enables Insurer to either proactively adjust their portfolio or to manage expectations in and outside their organization.

Table 11: Early-warning signs

Factor		**Regular**		**Crisis**	
Maturity	**Value**	**Short**	**Long**	**Short**	**Long**
Debt as percentage	High		X		
Emerging markets	High		X		X
VIX	High	X		X	X
Unemployment rate	High		X		
Euribor 3M	High			X	X
GDP euro area	Low		X		X
Stock markets	Low	X			X
CLI	Low				X
M1	High (regular)/ low (crisis)		X		

Given the nature of a correlational analyses, none of these factors are proven to be causal, but combined they may make up for a strong indicator.

Both the negative scenario analyses paint a bleak picture for Insurer in the near future. It is therefore recommended that Insurer takes swift action to increase their SCR ratio making sure their capital position is future proof. A possible capital injection would strengthen their eligible capital and increase their SCR ratio, enabling Insurer to remain financially healthy during these volatile conditions.

6.3 Limitations

Loss of information is a feature of the chosen research methodology. By doing principal component analysis and focusing only on the first principal component, you lose variation in the data, and thus lose information. The correlation results may therefore be weaker/stronger than they seem, although still strong (and it is not sure if they would be stronger or weaker if the full variation were in there), because they correlate with the first principal component that entails about 80% of the information on spread movements. Furthermore, the correlational analysis by nature does not prove causalities. We find results and can only reason what could be the cause of these results. This phenomenon occurs often in economic studies as this is not an experimental science, where causalities can be proven using double blind trials. The sample data is limited to a single cycle, containing one period of financial stability and one of crisis. This causes the generalizability to be less robust.

6.4 Contributions to theory and practice

The literature review on credit spread volatility provides insight for future researchers and as such contributes to scientific body of knowledge. The case study of the Dutch life insurer can be generalized to insurers with similar characteristics and therefore is also a contribution to theory. The framework that is made to analyze the correlation of macroeconomic factors with credit spreads over maturities is, to the extent of our knowledge, a novel approach which makes it an important contribution to literature.

Because the analyses are adjusted to match Insurer's assets and liabilities, the insights gained are directly applicable to their operation. The correlation analysis with macroeconomic factors provides Insurer with insight in what macroeconomic factors can function as early-warning signs, provided the assets are not changed to drastically. The sensitivity analysis provides insight into the effect of SCR ratio determinants on their SCR ratio and is tailored to their specific situation. The negative scenarios could be incorporated in the ORSA.

6.5 Future research

It was briefly mentioned that this research focusses on correlations and not on causality. Proving causalities where they exist could provide stronger insight into what will happen in the future. This research focused on a sample period that ended in 10-2021. Shocking events have happened since then that have a great impact on the world, such as the war between Russia and Ukraine. It would be interesting to see what happened to the spreads and the macroeconomic factors, and consequently the effect this would have had on the SCR ratio. It could be that what is happening now (April 2022), resembles the light version of the negative scenario. This research would be specific to Insurer. Moreover, extending the sample period would enable the researcher to analyze several business cycles and discover similarities and differences between crises. Furthermore, this research has chosen to do a PCA over the countries for 30 maturities separately. It would be interesting to see what the result would be of a PCA on the PCs. This would enable the researcher to come up with a single PC that would represent the entire sample data for all countries and all maturities. Provided that the proportion of the explained variance does not drop too low the correlations with macroeconomic factors can be examined for all maturities at once. Moreover, the behavior of credit spreads around the maturities 3, 4, and 5 years differs from the other maturities. Future research into why this is the case could provide new insights.

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Appendix A: SCR sub module correlation matrices

This appendix contains the correlations matrices for the SCR modules.

Table 12: SCR sub module correlation matrix

i/j	Market	Default	Life	Health	Non-life
Market	1	0.25	0.25	0.25	0.25
Default	0.25	1	0.25	0.25	0.5
Life	0.25	0.25	1	0.25	0
Health	0.25	0.25	0.25	1	0
Non-life	0.25	0.5	0	0	1

Table 13: SCR life correlation matrix (Commission Delegated Regulation, 2015)

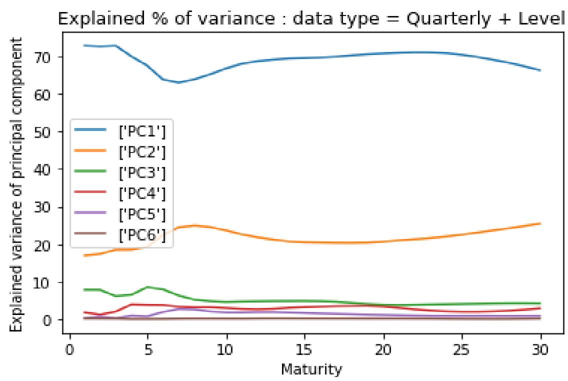
i/j	Mortality	Longevity	Disability	Life expense	Revision	Lapse	Life catastrophe
Mortality	1	-0.25	0.25	0.25	0	0	0.25
Longevity	-0.25	1	0	0.25	0.25	0.25	0
Disability	0.25	0	1	0.5	0	0	0.25
Life expense	0.25	0.25	0.5	1	0.5	0.5	0.25
Revision	0	0.25	0	0.5	1	0	0
Lapse	0	0.25	0	0.5	0	1	0.25
Life catastrophe	0.25	0	0.25	0.25	0	0.25	1

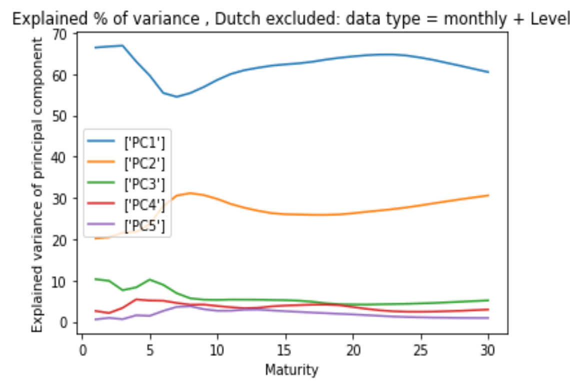
Table 14: SCR market correlation matrix (Commission Delegated Regulation, 2015)

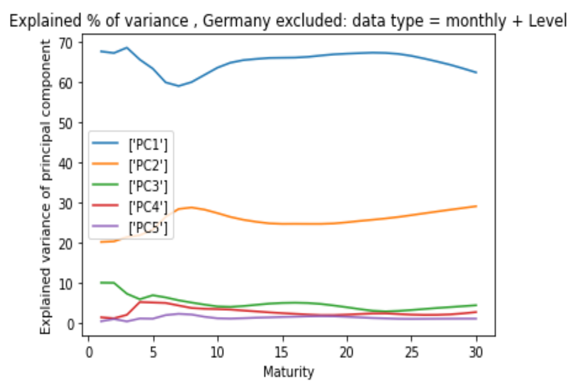
i/j	Interest rate	Equity	Property	Spread	Concentration	Currency
Interest rate	1	A	A	A	0	0.25
Equity	A	1	0.75	0.75	0	0.25
Property	A	0.75	1	0.5	0	0.25
Spread	A	0.75	0.5	1	0	0.25
Concentration	0	0	0	0	1	0
Currency	0.25	0.25	0.25	0.25	0	1

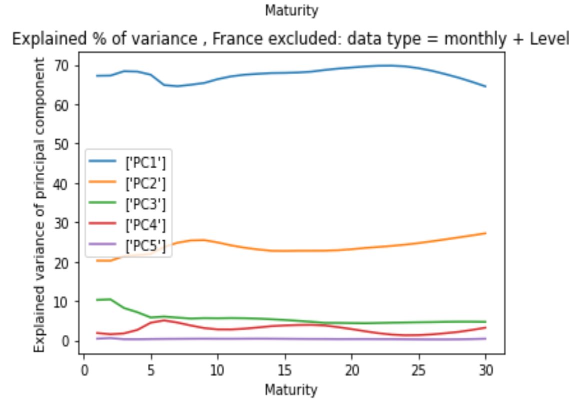
Appendix B: Principal component analysis and the explained proportion of variance in different settings

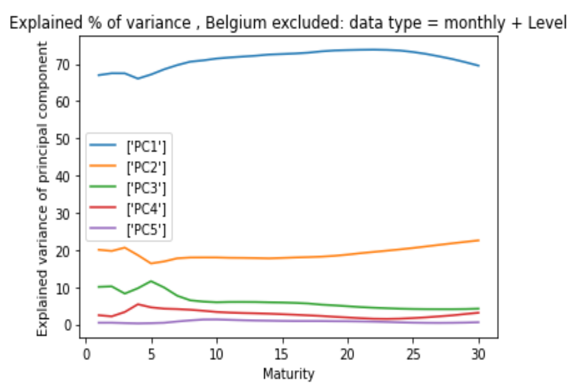
This appendix contains the graphs that show the explained variance of the principal components over the maturities. The graphs show the explained variance for different samples. Each sample has one country excluded from the sample. Table 15 shows the percentage of explained variance for the sample with Italy excluded for every PC and every maturity.











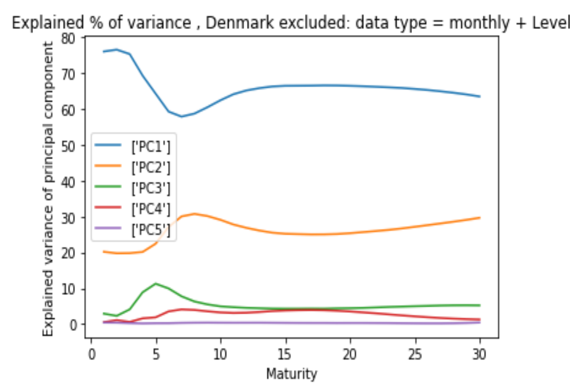


Table 15: Explained variance of principal components; Italy excluded, monthly, level

Maturity	PC1	PC2	PC3	PC4	PC5
1	0.852842	0.106623	0.029668	0.006439	0.004428
2	0.8464	0.114059	0.023846	0.011832	0.003862
3	0.846357	0.103896	0.040122	0.006465	0.00316
4	0.79185	0.100486	0.082884	0.022722	0.002058
5	0.743238	0.143465	0.091058	0.019595	0.002644
6	0.683237	0.199367	0.085883	0.028919	0.002594
7	0.663335	0.223832	0.072751	0.036684	0.003398
8	0.671819	0.220194	0.062784	0.040988	0.004214
9	0.693748	0.201018	0.058177	0.04173	0.005327
10	0.716926	0.182117	0.056589	0.038506	0.005862
11	0.736127	0.164819	0.058129	0.03519	0.005734
12	0.748227	0.154158	0.059434	0.032886	0.005295
13	0.756381	0.146803	0.0605	0.031278	0.005038
14	0.763276	0.141509	0.060626	0.029772	0.004817
15	0.768851	0.137718	0.06063	0.028482	0.00432
16	0.773483	0.135403	0.059807	0.027243	0.004065
17	0.778852	0.133254	0.057796	0.026145	0.003953
18	0.78581	0.131493	0.053939	0.024872	0.003886
19	0.792667	0.129982	0.049881	0.023946	0.003525
20	0.799085	0.129519	0.044943	0.022901	0.003551
21	0.805361	0.130084	0.039344	0.021742	0.003469
22	0.810253	0.131722	0.033524	0.02123	0.003271
23	0.813122	0.134625	0.028312	0.020865	0.003076
24	0.813751	0.138756	0.025092	0.01974	0.002661
25	0.811483	0.143849	0.024516	0.017732	0.002419
26	0.807684	0.149146	0.025135	0.015769	0.002266
27	0.802214	0.154546	0.026701	0.014267	0.002271
28	0.795813	0.159801	0.028627	0.01318	0.002579
29	0.787582	0.164994	0.03169	0.012574	0.00316
30	0.777954	0.170219	0.035529	0.012278	0.00402

Appendix C: Correlation Analysis extras

Current account results

The factor current account refers to current balance account as percentage of GDP of the euro area. The current account is published quarterly. Figure 37 shows effect Italy has on the correlation of PC1 with the current balance account. Excluding Italy from the data set results in a more stable correlation to the first PC.

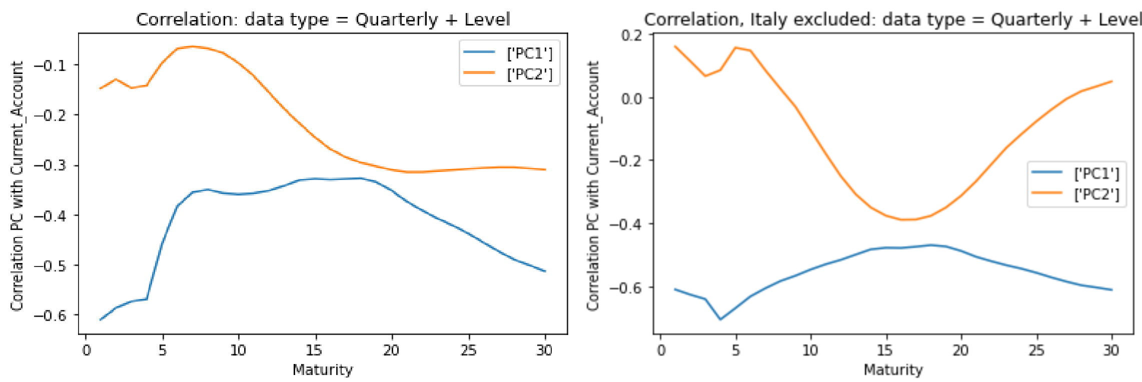


Figure 37: Current account: incl vs. excl Italy

Figure 38 shows that current account has a negatively weak correlation with PC1 for maturities larger than 10 in the pre-corona period. For maturities 0 – 10 there is negatively moderate correlation. During corona the correlation is negatively strong for maturities up to 5 years. Maturities larger than 5 years have a negatively moderate correlation to PC1.

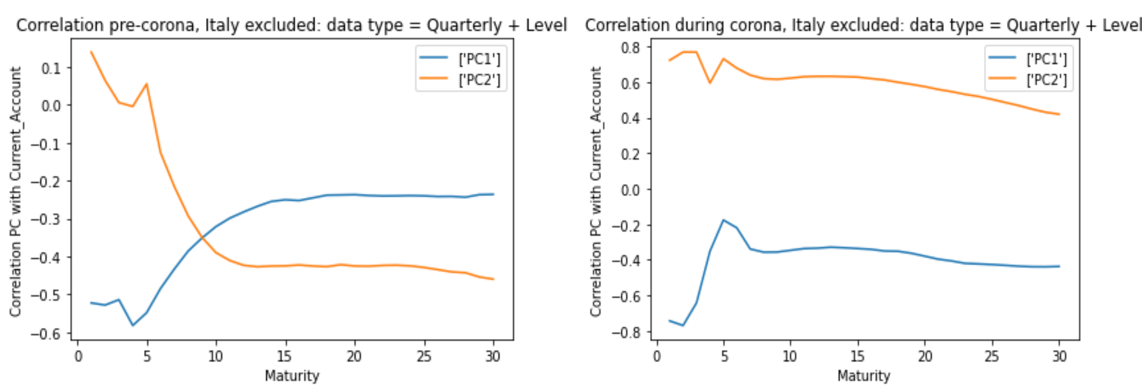


Figure 38: Current account: pre vs. during corona

Current account discussion

The graphs show a strong negative correlation. Excluding Italy makes this strong correlation more stable over the maturities. Current account represents how well a country is able to trade with foreign countries. A positive current account means that there is more money coming in than that there is going out, which is a sign of a strong economy. An increase in current account means a stronger economy and thus less risk. This reduces credit spreads and hence yields a negative correlation.

EUR swaps 5, 10, 30, and 50 years results

An interest rate swap is an agreement to exchange a stream of cash flows by applying a fixed and floating interest rate to a specified notional over a term to maturity. The "swap rate" is the fixed interest rate that the receiver demands in exchange for the uncertainty of having to pay the short-term floating rate over time. The 5-, 10-, 30-, and 50-year EUR swaps are interest rate swaps that express the fixed rate that must be paid to swap for the floating EURIBOR 6-month. In this section, the EUR swaps are examined and presented. The analysis is based on monthly data. Figure 39 shows that there is little difference between the EUR swaps and their correlation to PC1. Excluding Italy has no significant impact on the correlations either.

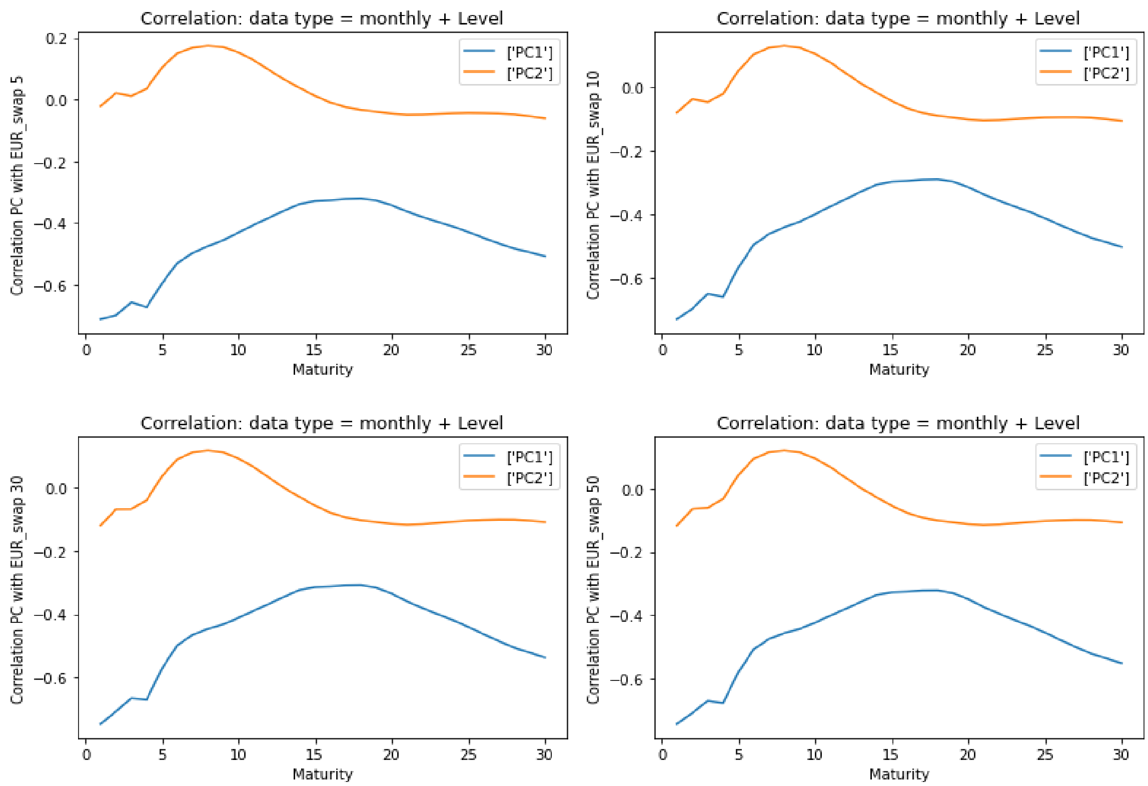


Figure 39: EUR swaps 5-, 10-, 30-, 50-years

This similarity does not stay intact if the analysis period is split into a pre- and during corona period. Figure 40, Figure 41, Figure 42, and Figure 43 show EUR swaps and their correlation to the principal components. The first figure shows that PC1 has a declining weakly negative correlation with the 5-, 10-, 30-, and 50-year EUR swap. During corona this correlation weakly/moderately positive for the 5-year EUR swap. This is however not true for the EUR swaps of greater maturity. The 10-year EUR swap has a very weak negative correlation to PC1 during corona, whereas the 30- and 50-years EUR swaps have strong negative correlation to PC1.

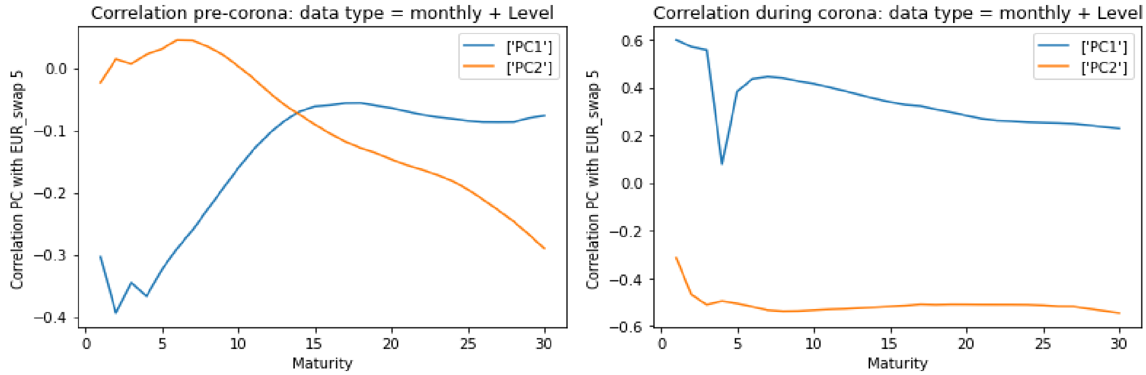


Figure 40: EUR swap 5 year: pre vs. during corona

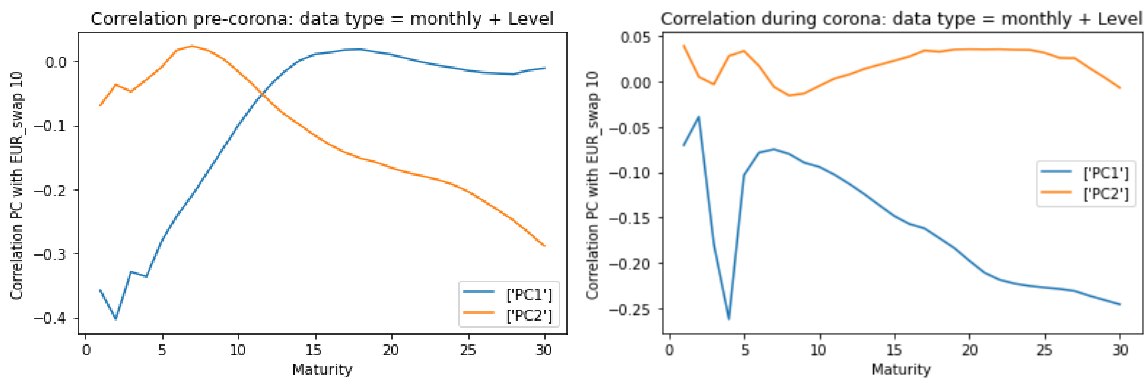


Figure 41: EUR swap 10 years: pre vs. during corona

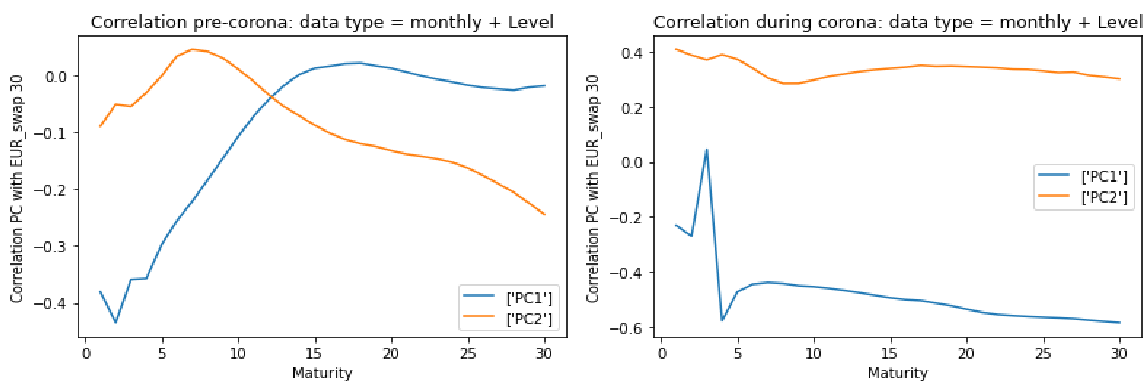


Figure 42: EUR swap 30 years: pre vs. during corona

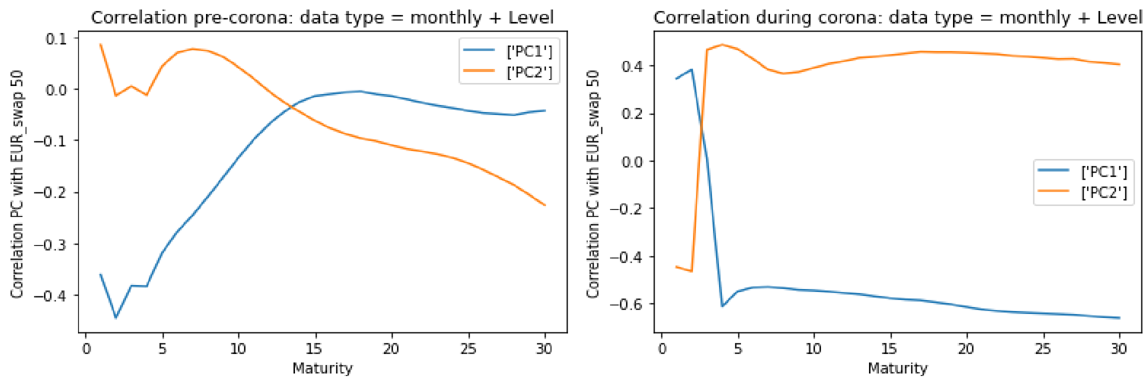


Figure 43: EUR swap 50 years: pre vs. during corona

EUR swaps 5, 10, 30, and 50-year discussion

A negative correlation is observed for all EUR swap maturities. The EUR swap rates are proxies for the risk-free rate. Except during corona, the 5-year EUR swap has a positive correlation. Literature does not agree on whether the risk-free interest rate positively or negatively impacts credit spreads. For the government spreads in our data, a negative correlation is observed for maturities up to 15 years, whereas higher maturities are uncorrelated. A possible explanation can be found in differentiating between government and corporate credit spreads. If overall risk in the market rises, central banks may choose to stimulate the economy by adjusting their monetary policy to prevent a slowdown. The increase in liquidity in the market will press the risk-free rate. On the other side, this risk will cause credit spreads to increase, which constitutes to a negative correlation.

The 5-year EUR swap during corona deviates from the longer maturity EUR swaps. The short-term deviation can be explained as a result of the crisis. Risk increases in the entire market and thus both the risk-free rate and the credit spreads increase, yielding a positive correlation. On the long-term other factors may play a more dominant role.

Italian government bonds results

The Italian government bond index represent the returns on Italian government bonds. Italy is part of our sample and therefore it is interesting to examine the effect of including vs. excluding Italy on the analysis. The analysis is based on monthly data. Figure 44 shows a moderate/strong negative correlation between PC1 and the Italian government index. PC2 shows a very strong positive correlation. Excluding Italy from the data set results in a weak negative correlation for PC1.

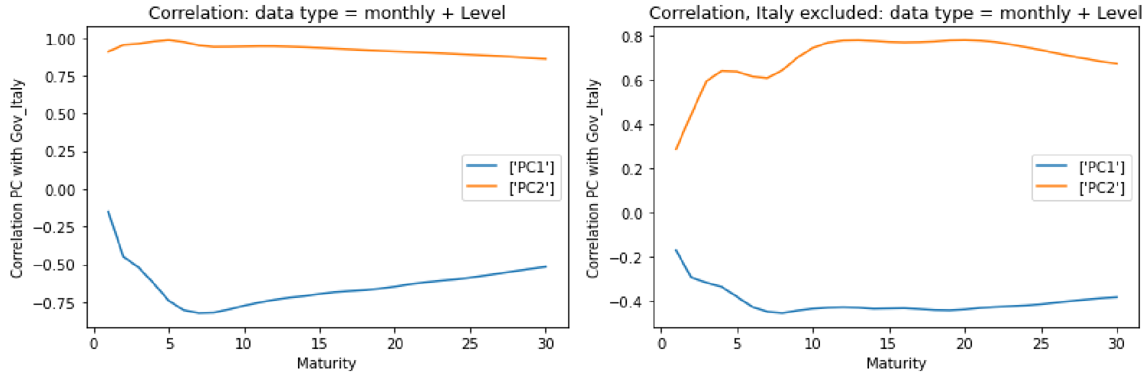


Figure 44: Italian government bond: incl vs. excl Italy

Figure 45 shows that in the pre-corona period PC1 has a very strong negative correlation with the Italian government bond index, whereas PC2 has a very strong positive correlation with this index. During the corona period this correlation is exactly opposite to the pre-corona period.

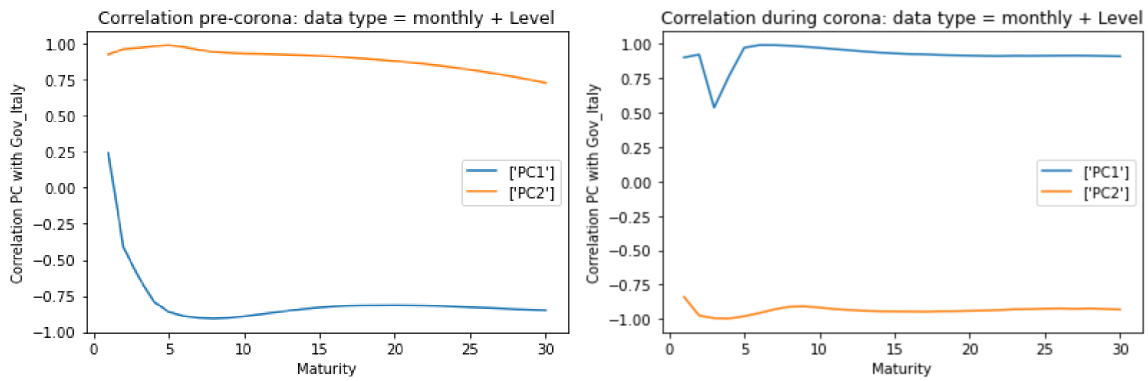


Figure 45: Italian government bond: pre vs. during corona

Figure 46 is notably different from the previous figure in the pre-corona period. The correlation of PC1 is moderately negative with the Italian government bond index, whereas PC2 shows a different pattern altogether.

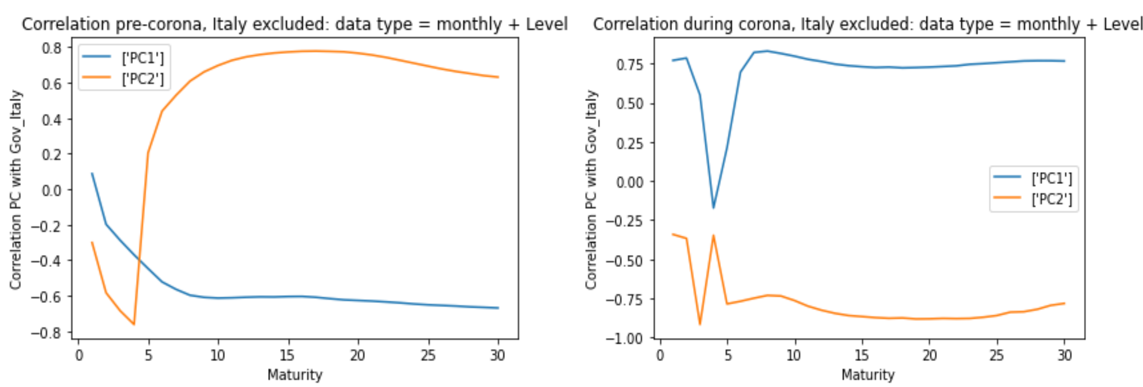


Figure 46: Italian government bond: pre vs. during corona, excluding Italy

Italian government bonds discussion

Italian government bonds show a negative correlation in pre-corona period and very strong positive correlation during corona. Compared to the bonds in the sample, Italy is the only southern European country. These countries are generally considered to be riskier than northern European countries. This could explain the movements in opposite direction that is observed during the pre-corona period. During corona, the sample and Italy strongly move in the same direction. This makes sense because risk in the entire world increased which leads to an increase in all government spreads. Hence, a very strong positive correlation is observed. Furthermore, correlating Italian spreads with PC1 both with and without Italy should show that with Italy is stronger correlated than without. This is indeed the case hence serves as some form of validation. Furthermore, the Italian case is a special case because Italy is part of the sample data. Excluding Italy should therefore result in less correlation and including Italy should result in a stronger correlation. This is indeed the case, which contributes to the validation of this research.

European AA government bonds results

The European AA government bonds index represents an average of the performance of all European AA rated government bonds. The analysis is based on monthly data. Figure 47 shows that the correlation between PC1 and the AA-rated European government bonds significantly increases from moderately/strongly to strongly/very strongly positive.

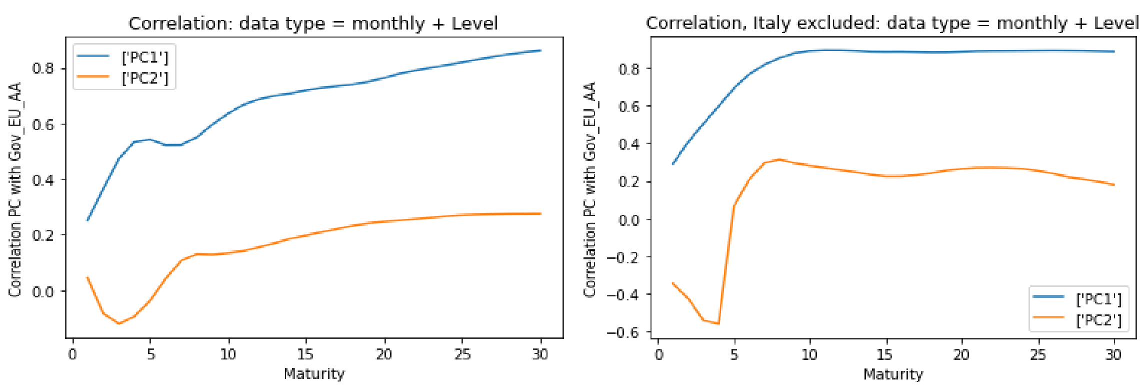


Figure 47: European AA-rated government bonds: incl vs. excl Italy

Figure 48 shows that there is a (very) strong positive correlation between the AA-rated European government bonds and PC1 for both periods with a dip around maturities 3 and 4.

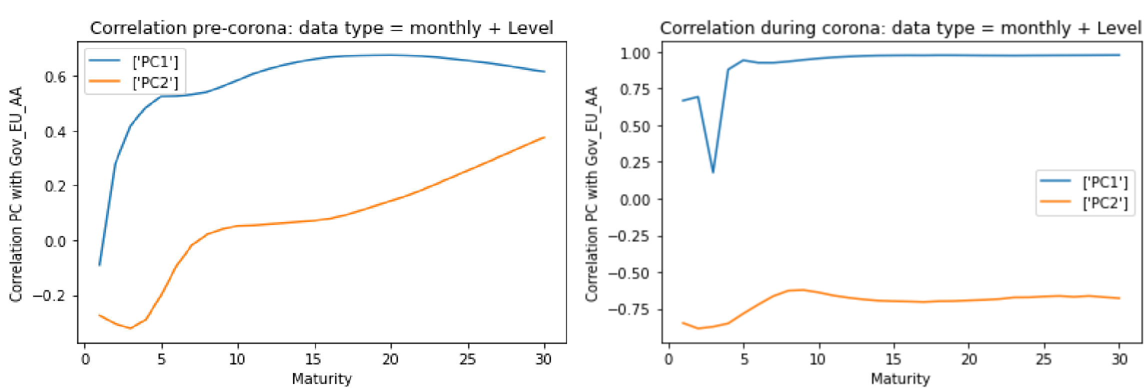


Figure 48: European AA-rated government bonds: pre vs. during corona

European AA-rated government bonds discussion

European AA-rated bonds show a positive correlation with the spreads in the sample, in both periods. Excluding Italy from the sample increases the correlation even further. This confirms the theory that Italian spreads move opposite to the sample spreads (PC1). During the corona crisis the correlation increase even further, which is in line with the theory that correlations tend to increase in times of crisis.

European corporate bond index results

The European corporate bond index represents the performance returns of corporate European bonds. The analysis is based on monthly data. Figure 49 shows that there is a positive correlation between PC1 and the European corporate bonds. Excluding Italy from the data set increases the correlation from weakly to moderately positive.

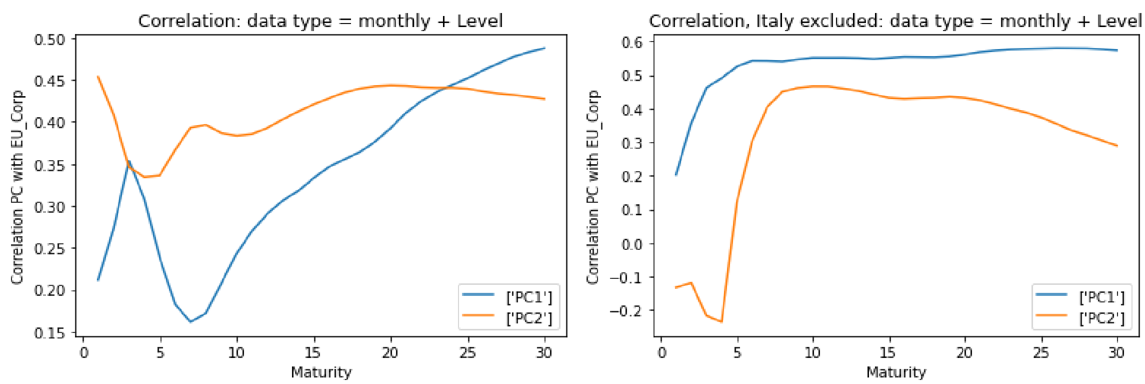


Figure 49: European corporate bonds: incl vs. excl Italy

Figure 50 depicts the correlation between European corporate bonds and PC1. In the pre-corona period, there is a weakly/moderately positive correlation, whereas during the corona period this correlation becomes very strongly positive.

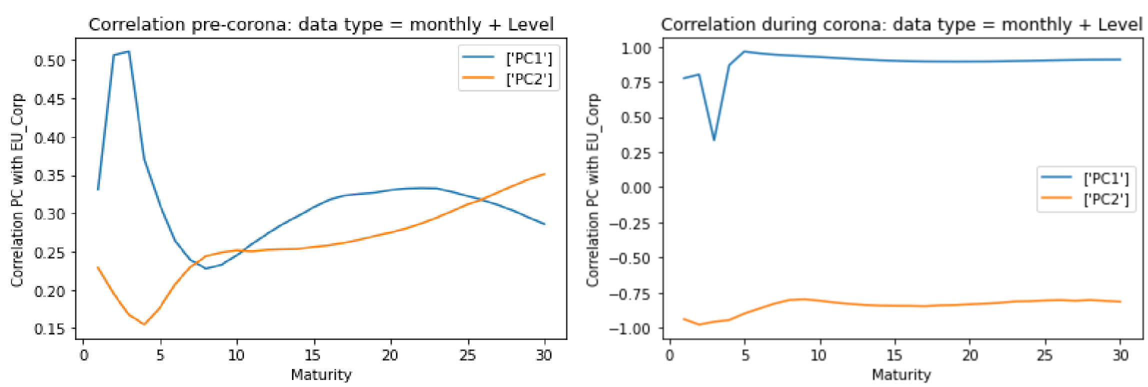


Figure 50: European corporate bonds: pre vs. during corona

European corporate bond index discussion

European corporate bonds have a weak positive correlation with the spreads in our sample. Excluding Italy from the sample increases the correlation, implying that the corporate bond index represents high quality bonds. During the corona period, correlation becomes very strong, which can be explained by increase in market risk, leading both corporate and government bonds to widen their spreads.

TED spread results

The TED spread is a proxy for market liquidity. The analysis is based on monthly data. Figure 51 shows that PC1 is uncorrelated to the TED spread on maturities over 10 years. On short-term maturities there is a weakly negative correlation. There is no significant difference between the case with and without Italy in the data set.

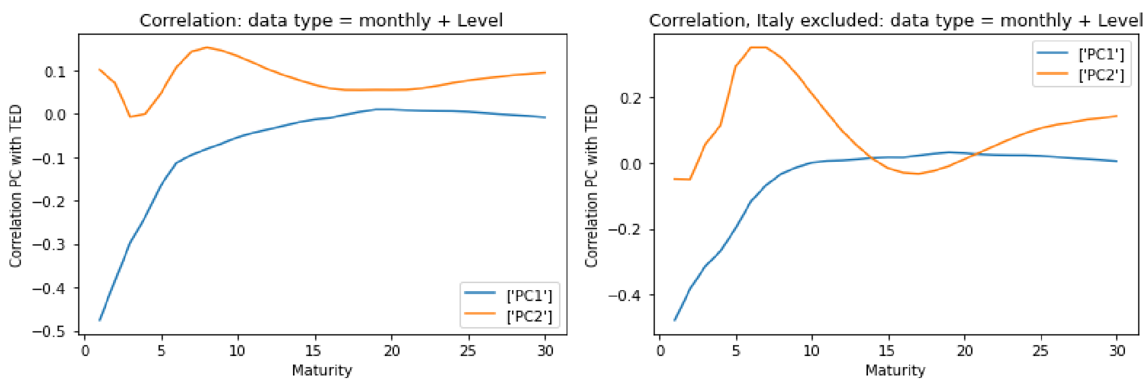


Figure 51: TED spread: incl vs. excl Italy

Figure 52 shows that there is an increase in correlation during the corona period. Whereas in the pre-corona period there is a weakly positive correlation, there is moderate to strong positive correlation during the corona period.

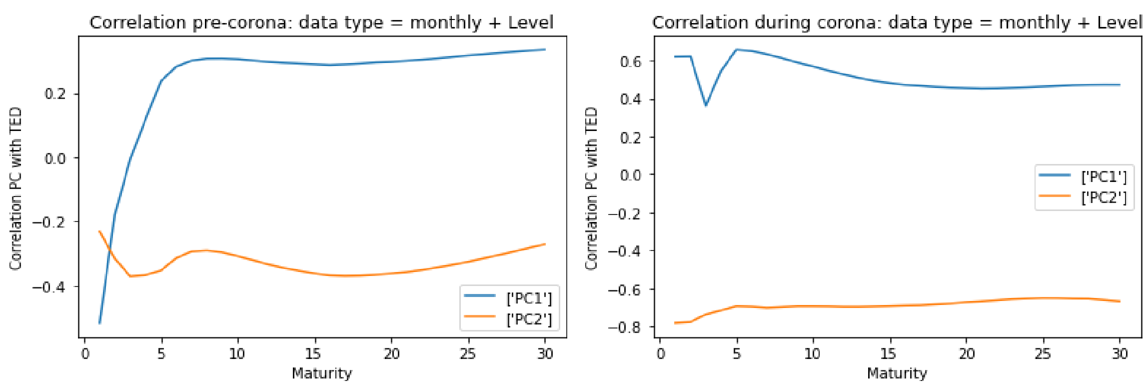


Figure 52: TED spread: pre vs. during corona

TED spread discussion

The TED spread is a proxy for liquidity in the market. The correlation analysis shows that this is uncorrelated in "normal" times for larger maturities, which makes sense because liquidity is a short-term issue by definition. During the corona pandemic a strong correlation is observed. The widening of the spreads as a result of increased risk and the monetary policies of the central banks aimed at countering an economic crisis happen simultaneously, which explains the positive correlation in during the pandemic.

Nasdaq results

The Nasdaq is an American stock market. Their index is tracked continuously, but in this analysis monthly data is used. Figure 53 shows the correlation of the first and second PC with the Nasdaq index. On short-term there is a descending positive correlation from very strong to uncorrelated after which the correlation becomes weakly positive. Excluding Italy does not notably change the correlation.

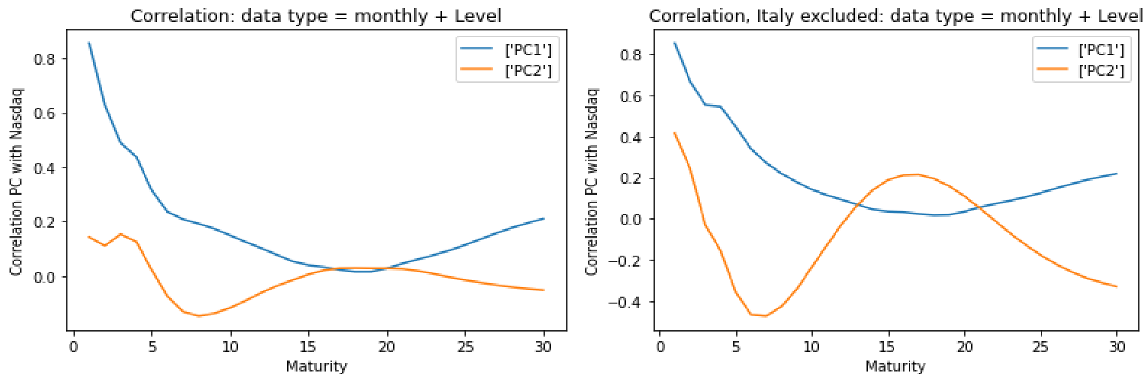


Figure 53: Nasdaq: incl vs. excl Italy

Figure 54 depicts the correlation of the PCs before and during the corona period. In the pre-corona period, the first PC is positively correlated on maturity one and two, after which the correlation gradually becomes very strongly negative. PC2 shows the opposite behavior. A similar pattern can be seen during the corona period.

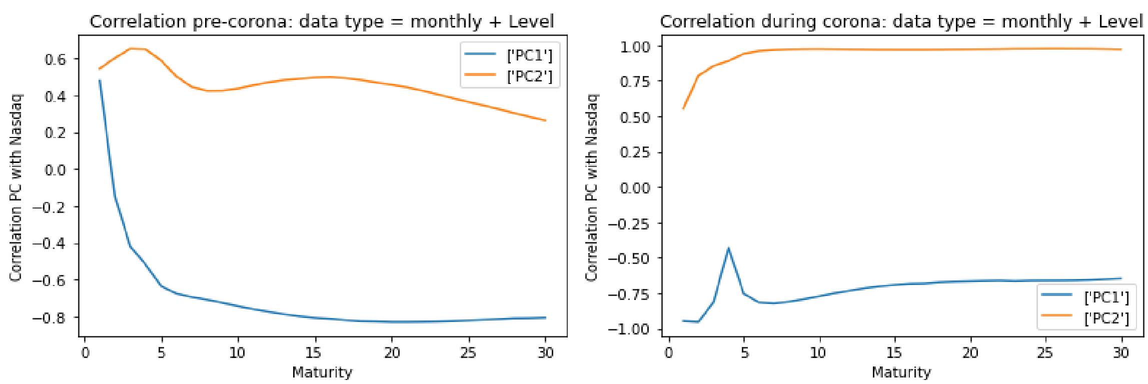


Figure 54: Nasdaq: pre vs. during corona

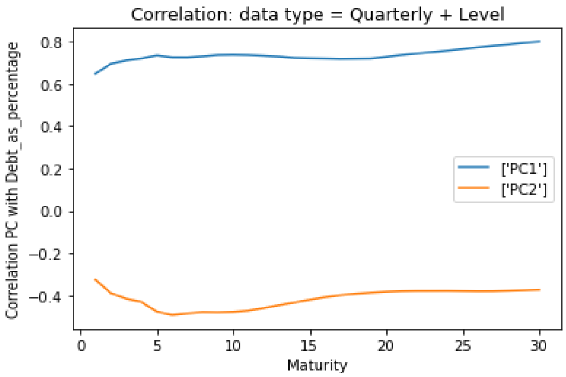
This analysis is also done for the Dow Jones Industrial Average index.

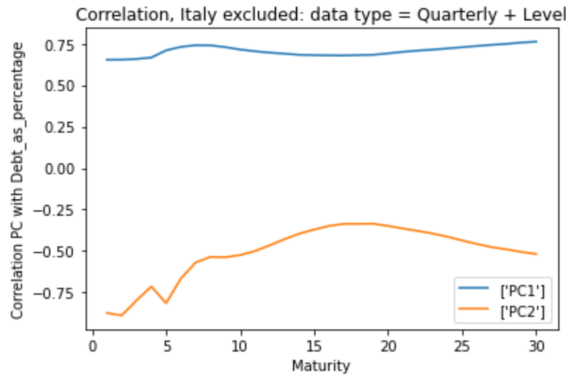
Nasdaq, Dow Jones Industrial Average, and Euronext

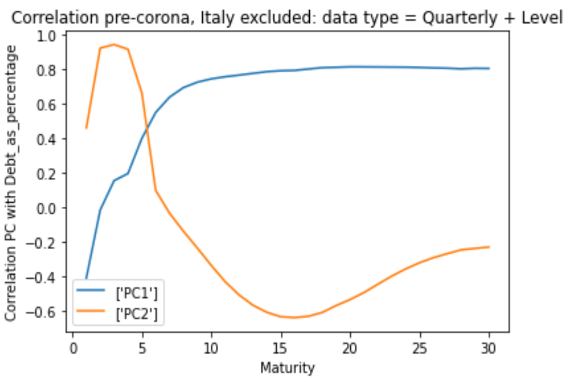
All three market indexes exhibit very similar behavior, which is why these three are addressed simultaneously. The indexes show a negative correlation in both periods. Market indexes are proxies for the state of an economy. In this case this reflects the American and European market. Growing indexes imply a better state of the economy, which reduces risk and thus decreases credit spreads, yielding a negative correlation.

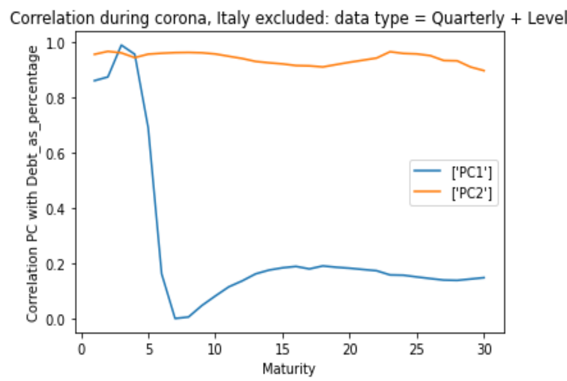
Appendix D: Correlation PCs with macroeconomic factors

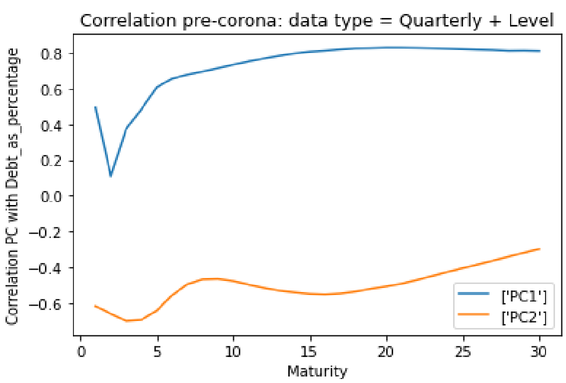
Debt as percentage

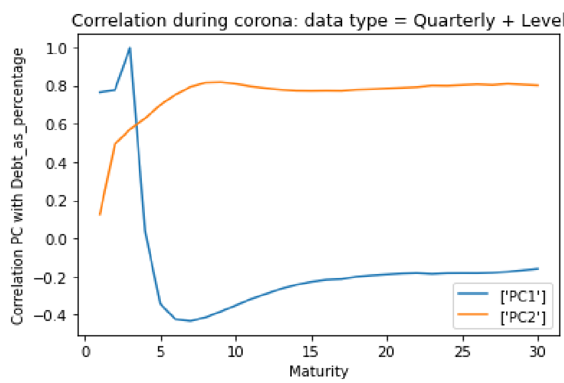




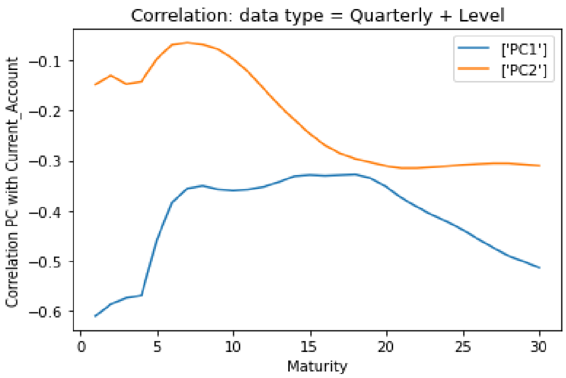


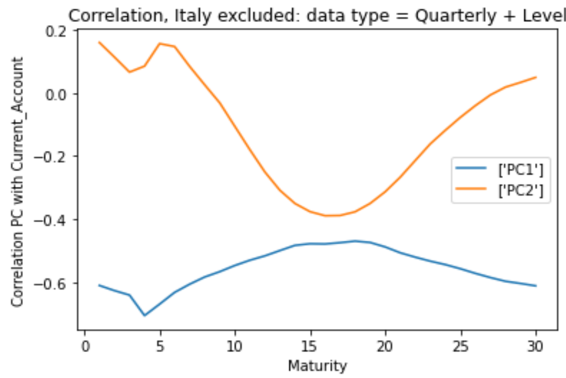


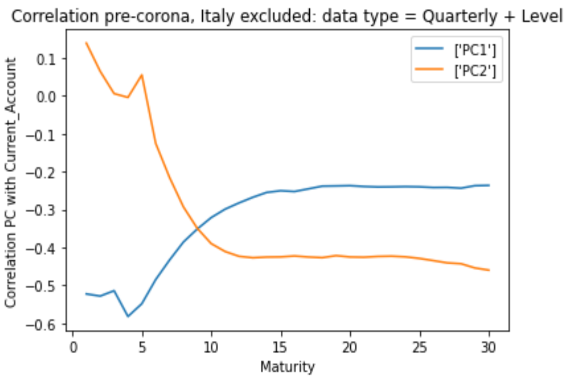


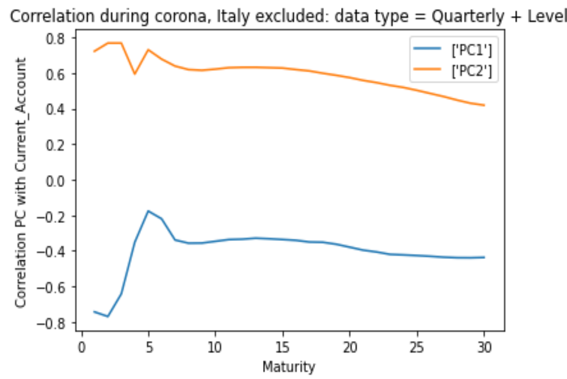


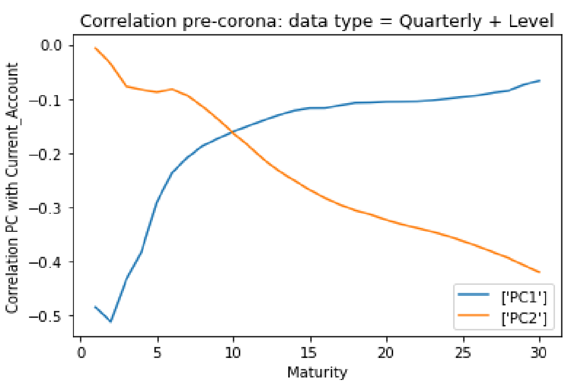
Current account eurozone

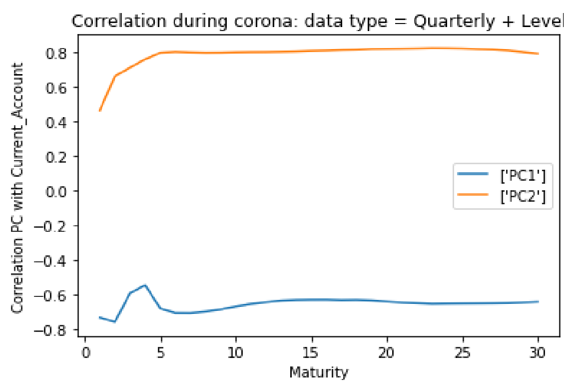




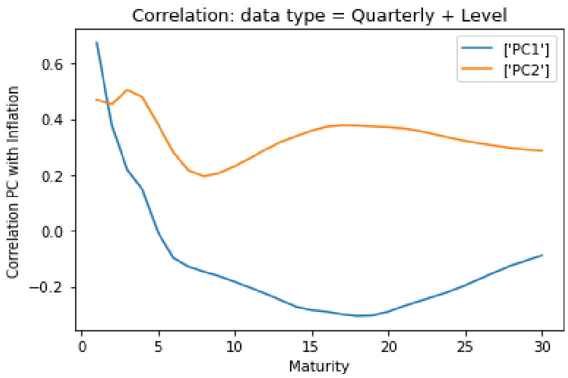


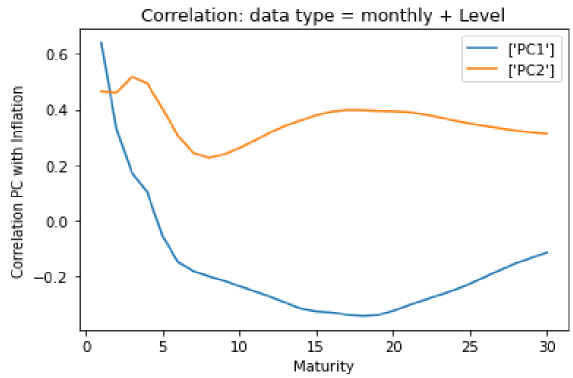






Inflation


Correlation: data type = Quarterly + Level
Correlation PC with Inflation
Maturity
['PC1']
['PC2']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Correlation PC with Inflation
Maturity
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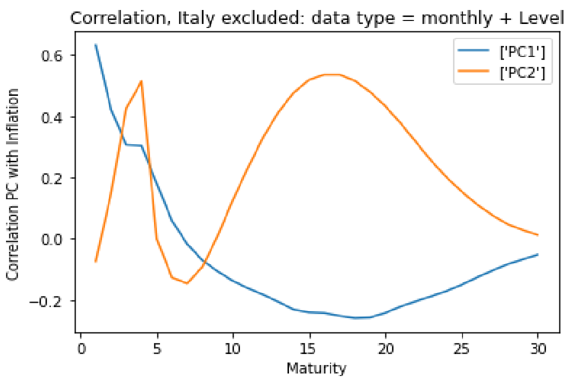
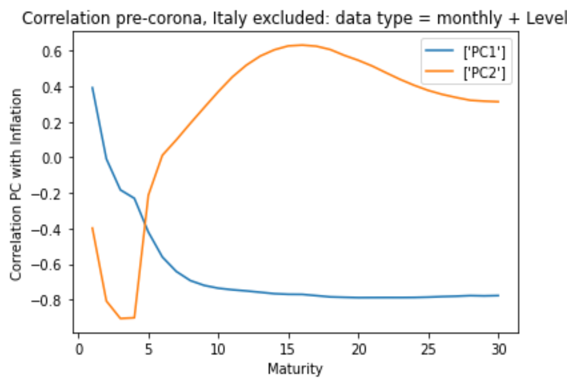
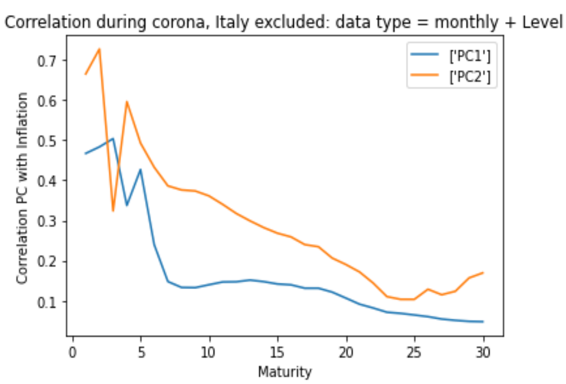
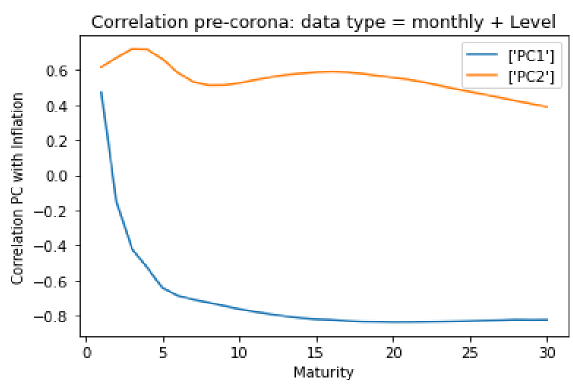
['PC2']


Correlation, Italy excluded: data type = monthly + Level
Correlation PC with Inflation
Maturity
['PC1']
['PC2']


Correlation pre-corona, Italy excluded: data type = monthly + Level
Correlation PC with Inflation
Maturity
['PC1']
['PC2']


Correlation during corona, Italy excluded: data type = monthly + Level
Correlation PC with Inflation
Maturity
['PC1']
['PC2']


Correlation pre-corona: data type = monthly + Level
Correlation PC with Inflation
Maturity
['PC1']
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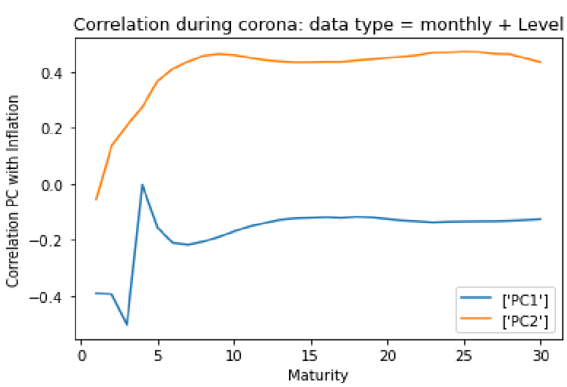
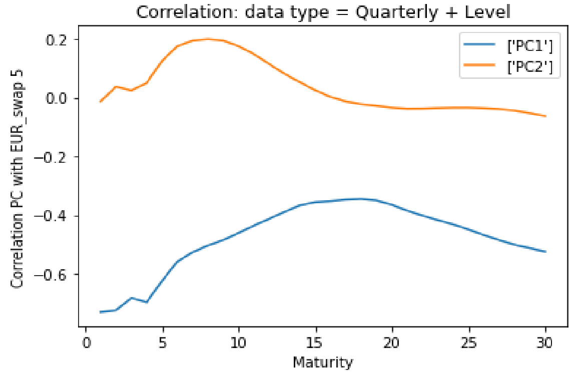
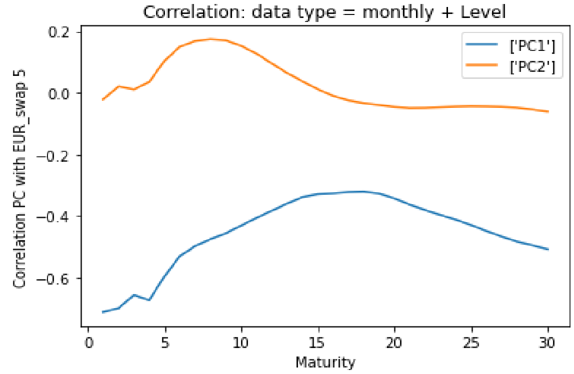
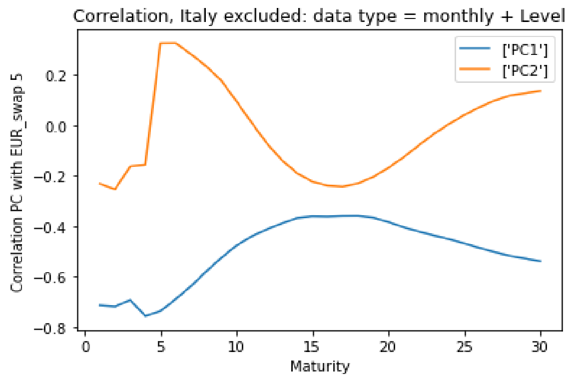
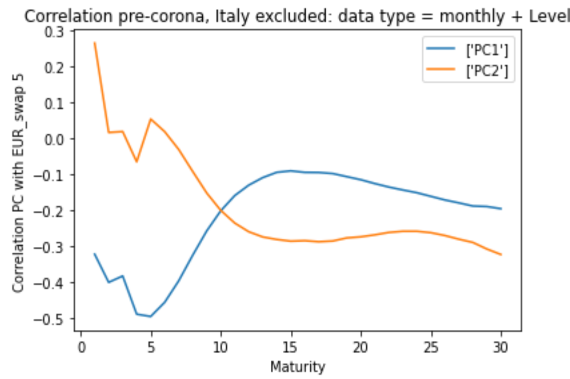

Correlation during corona: data type = monthly + Level
Correlation PC with Inflation
Maturity
['PC1']
['PC2']

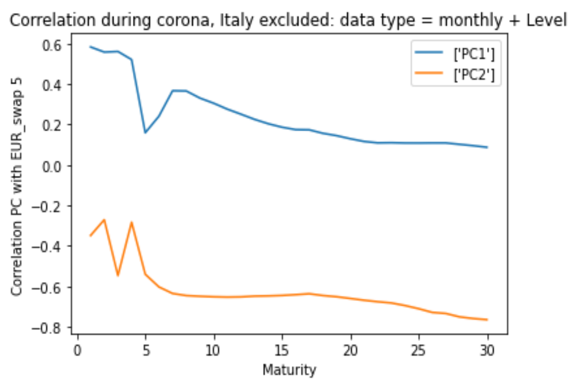
EUR swap 5 year

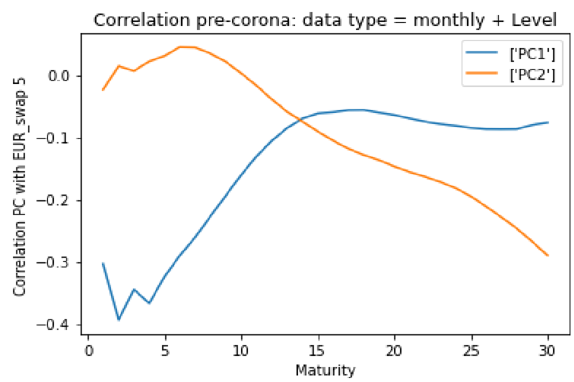


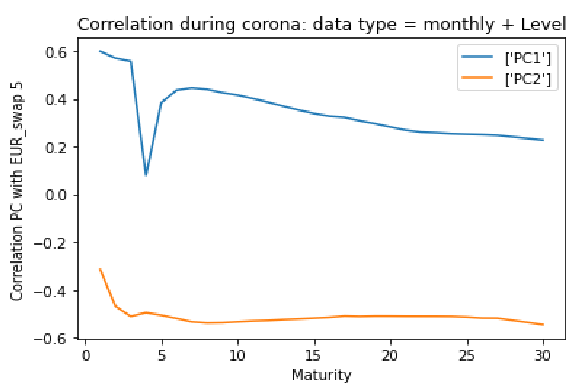




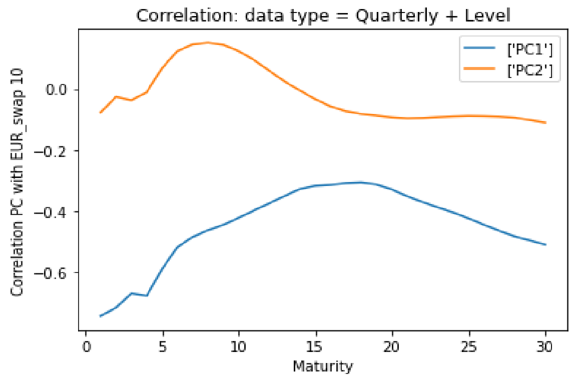


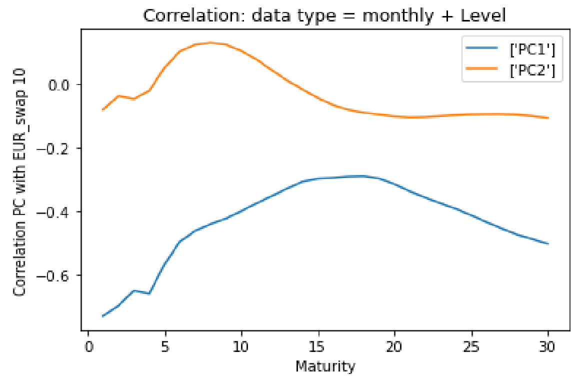


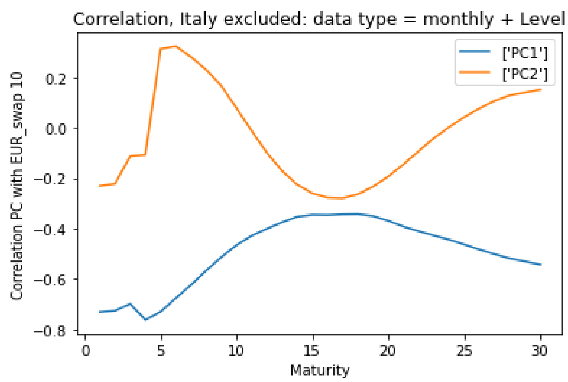


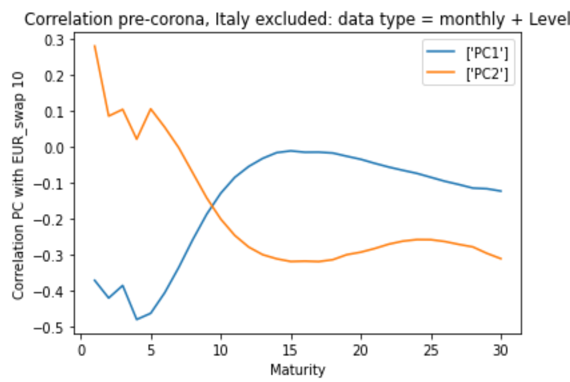


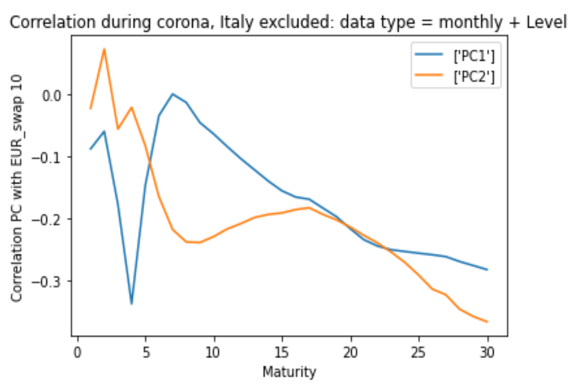
EUR swap 10 year

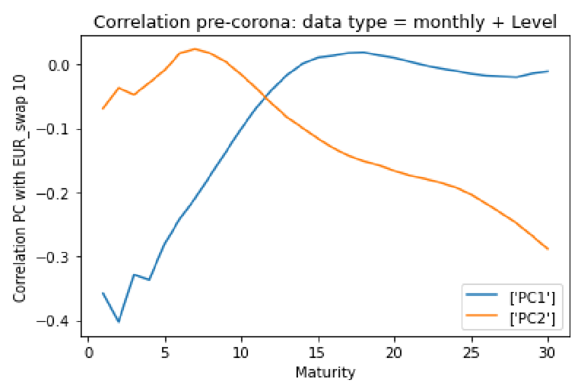


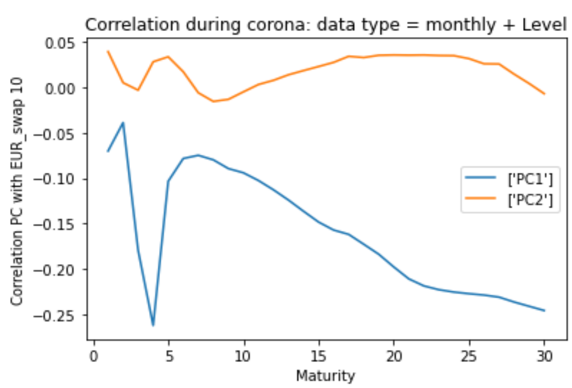




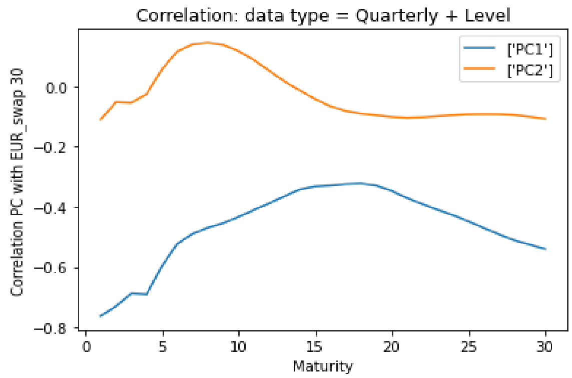


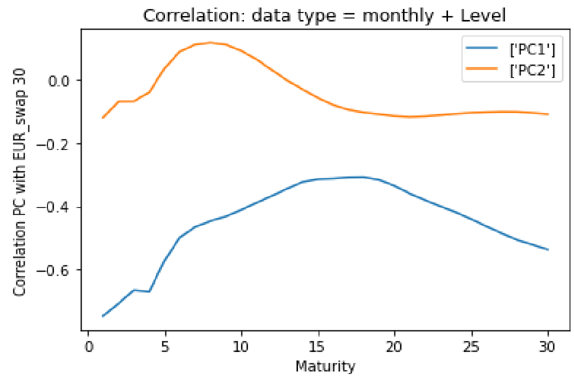


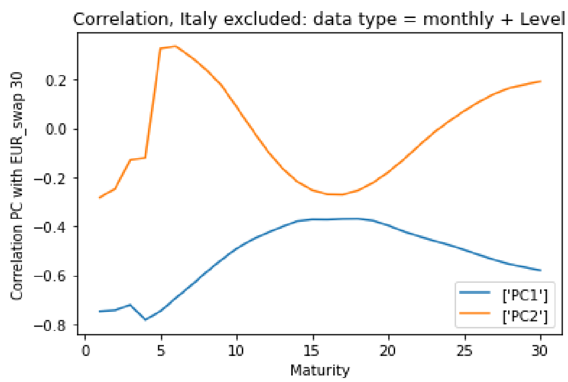


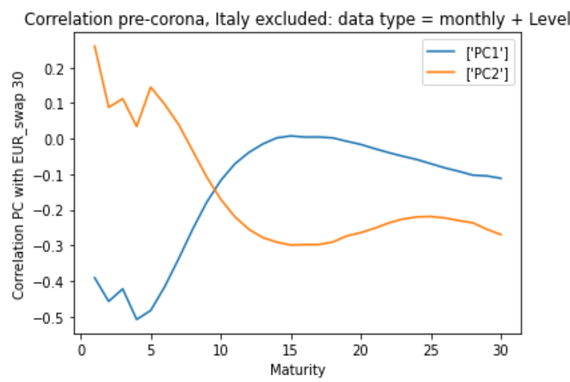


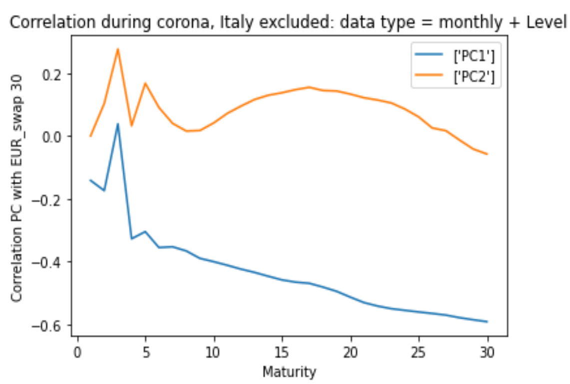
EUR swap 30 year

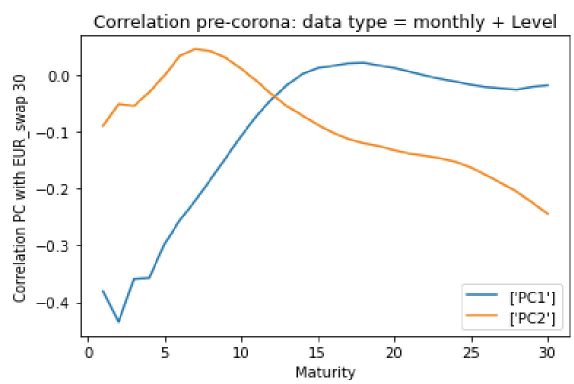


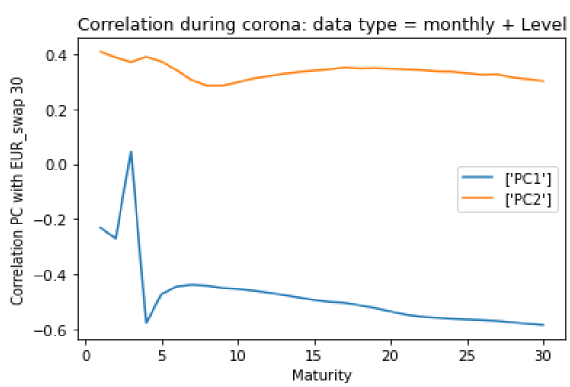




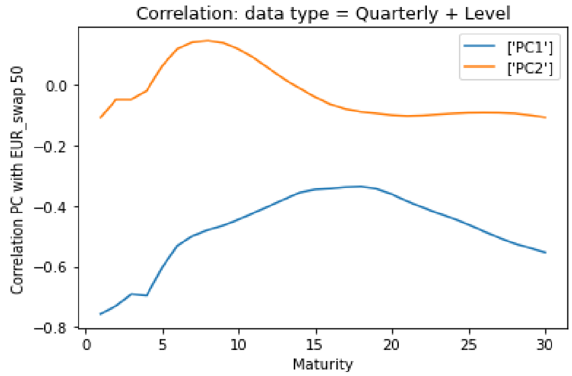


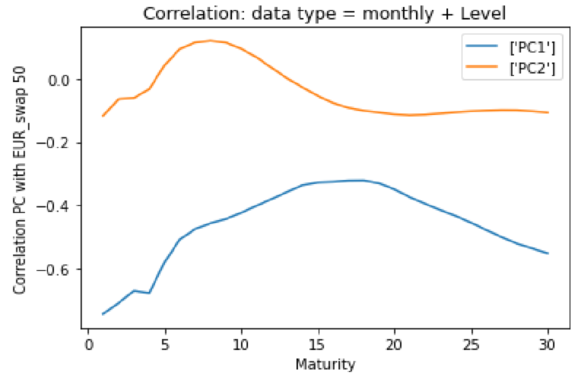


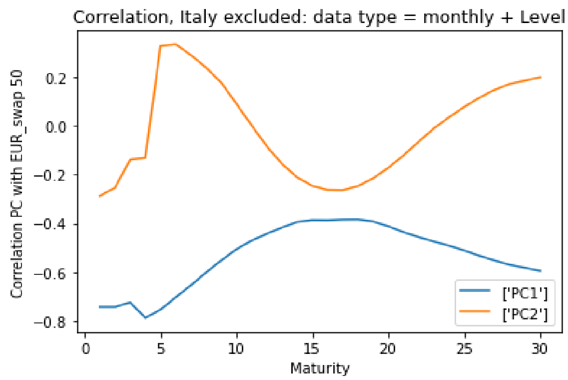


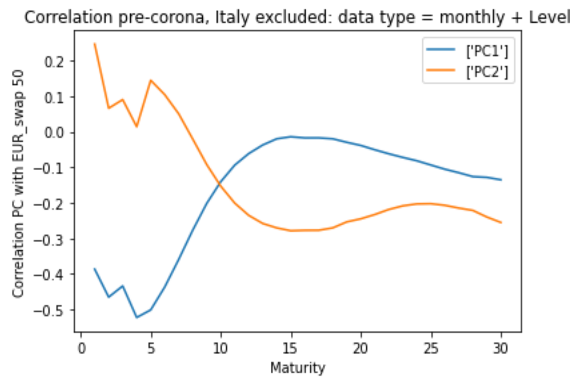


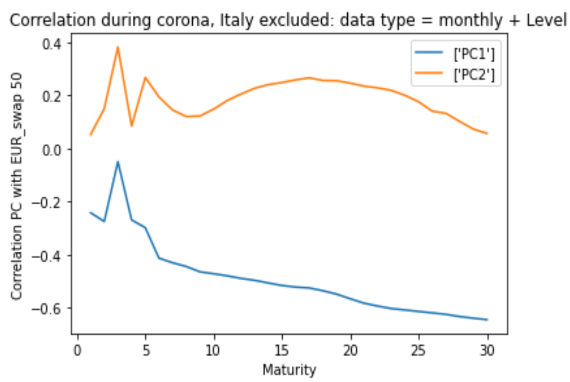
EUR swap 50 year

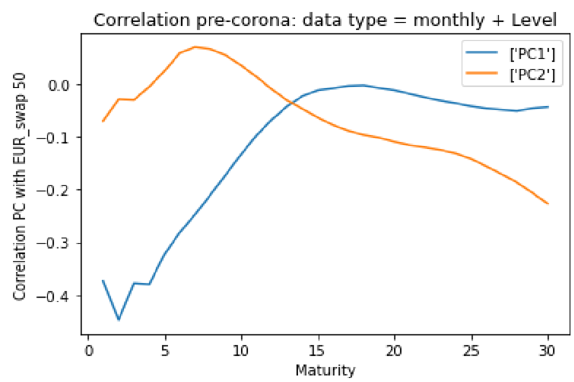


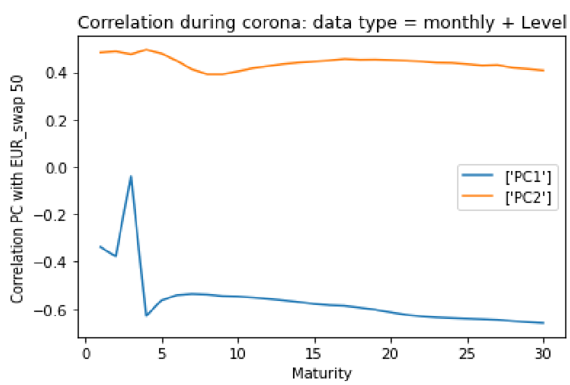




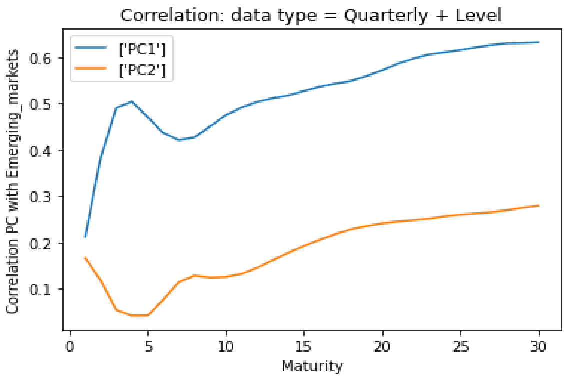


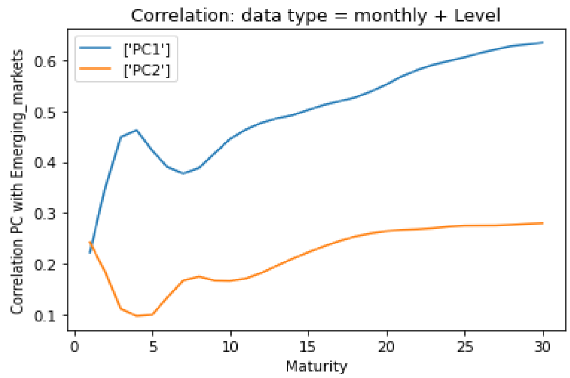


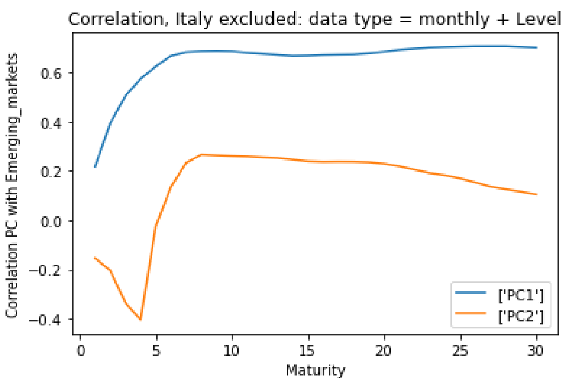


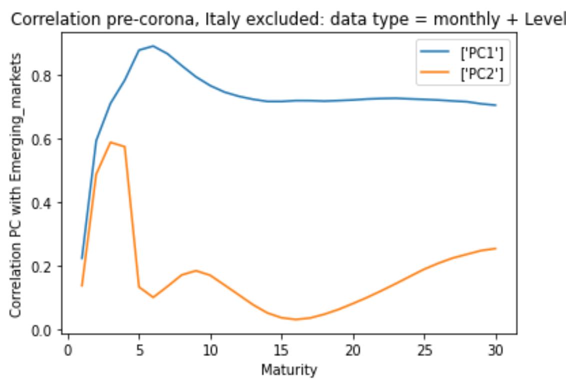


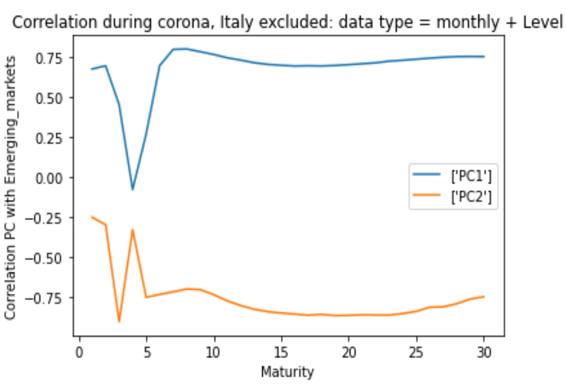
Emerging markets

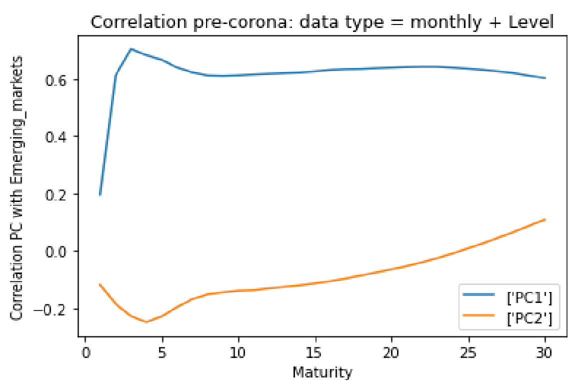


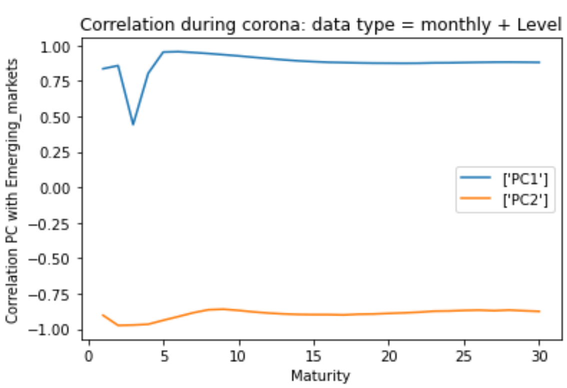




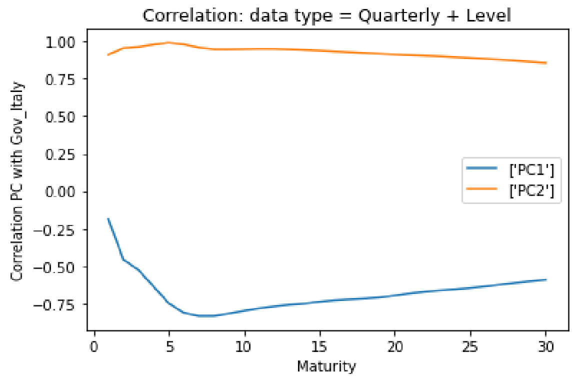


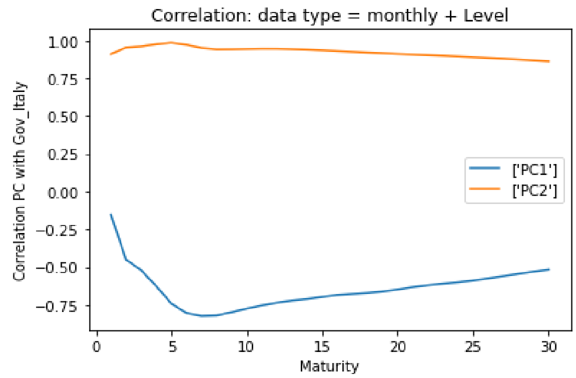


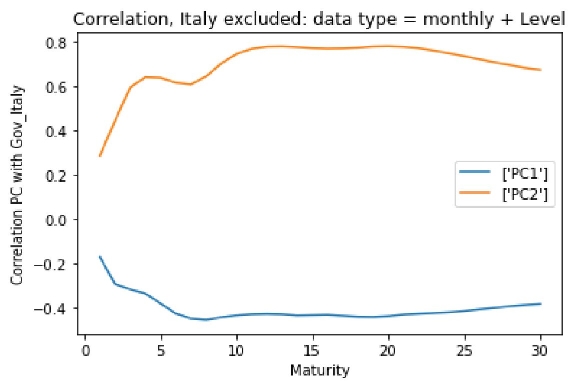


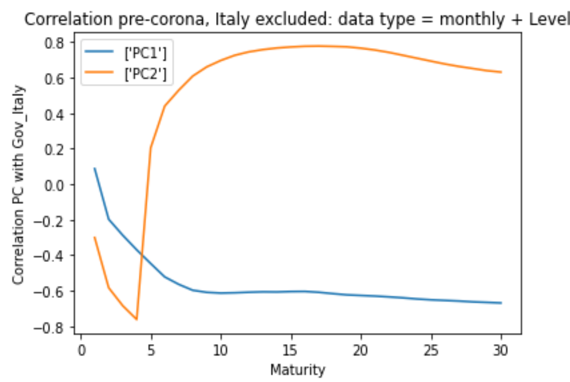


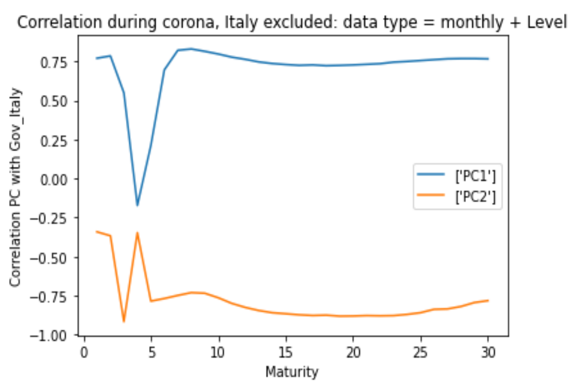
Italian government bonds

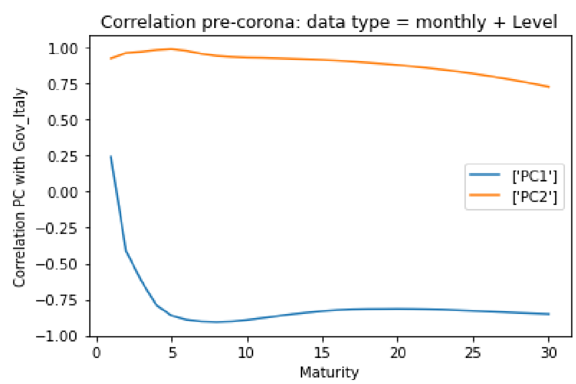


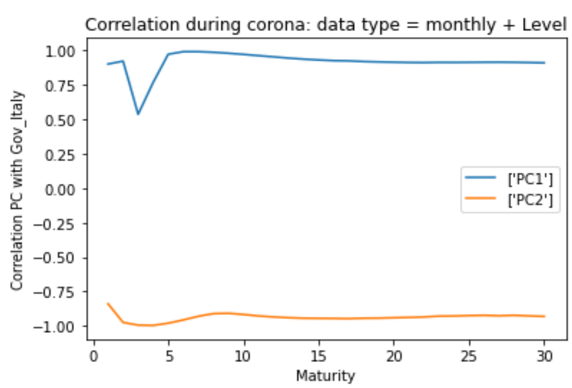




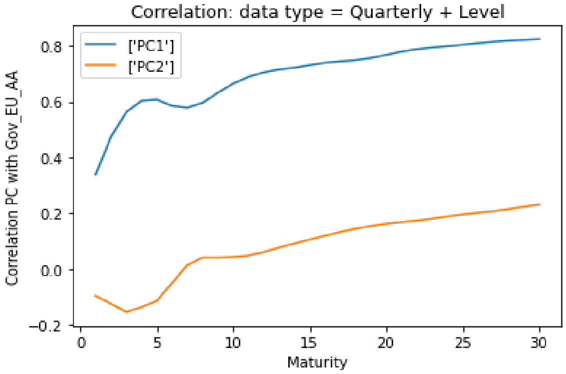


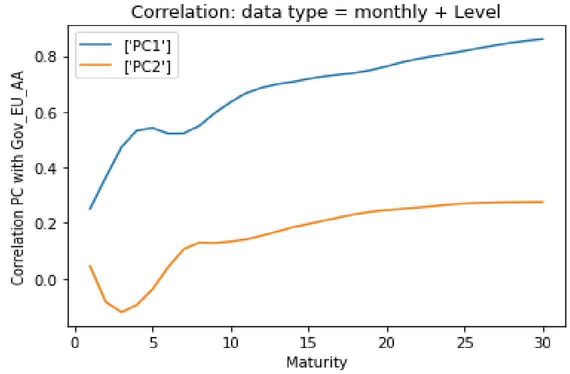


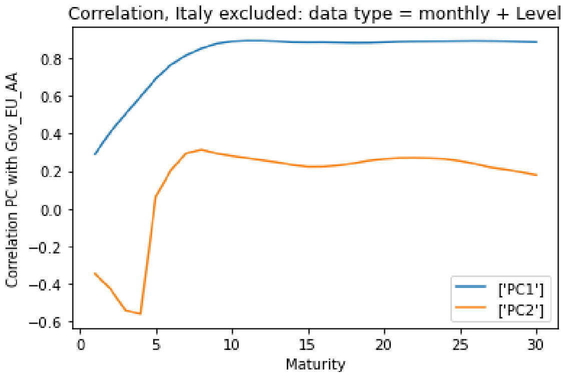


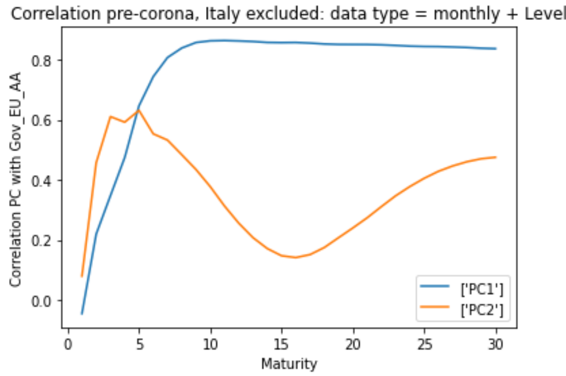


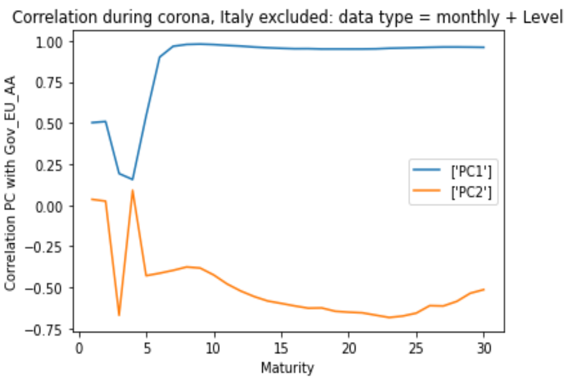
EU government AA bonds

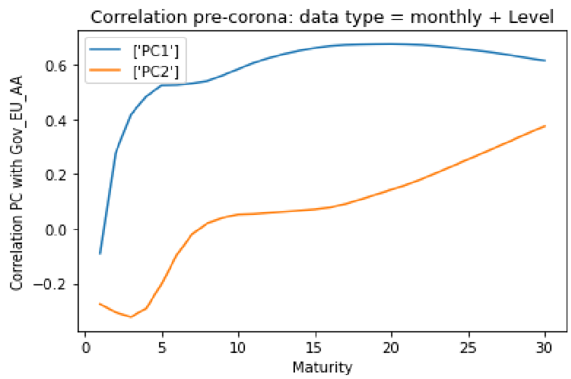


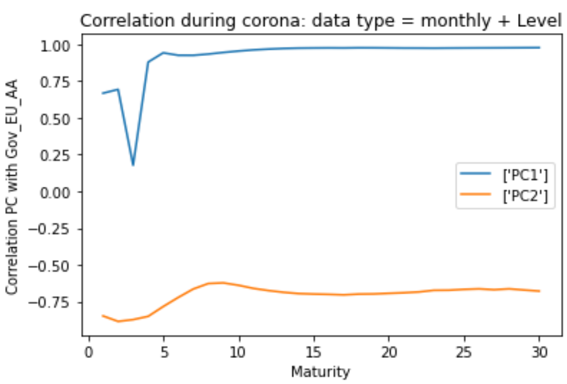




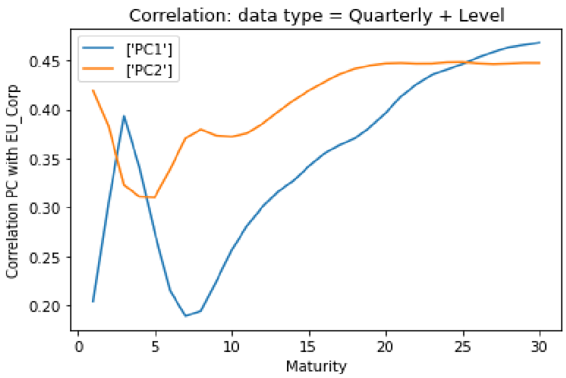


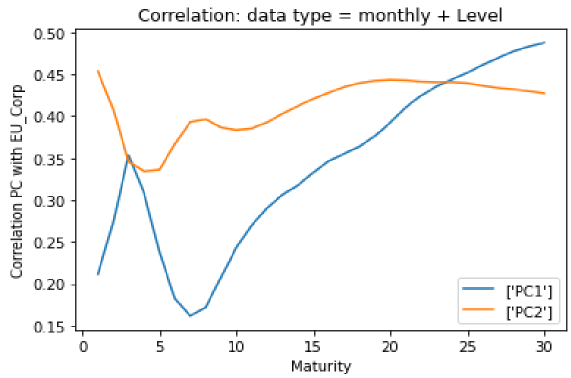


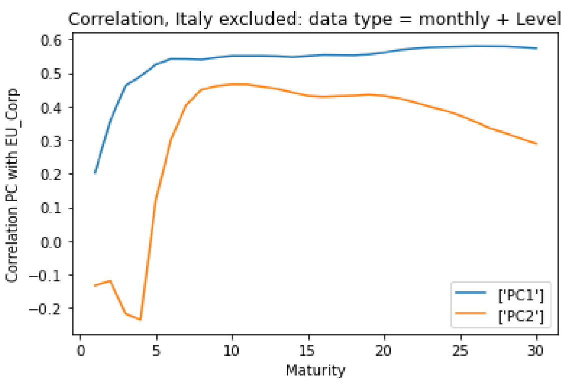


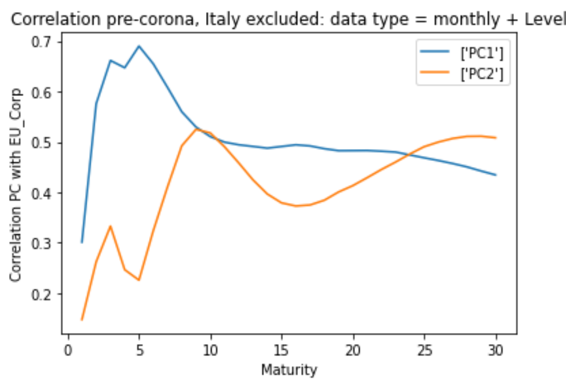


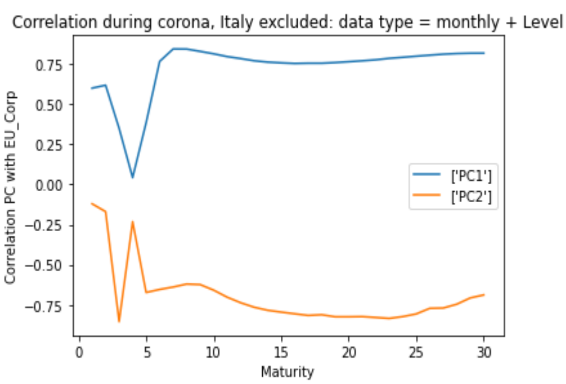
EU corporate bonds

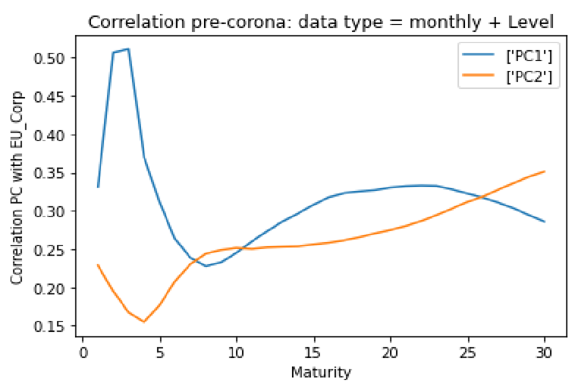


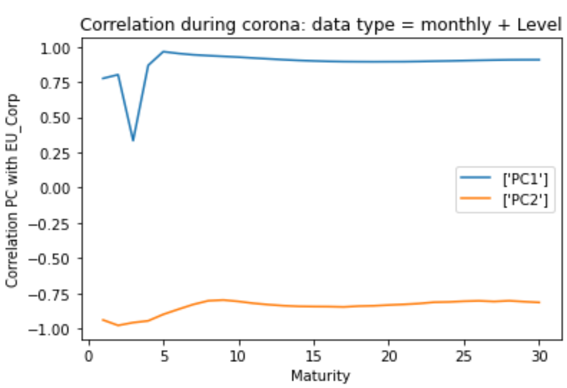




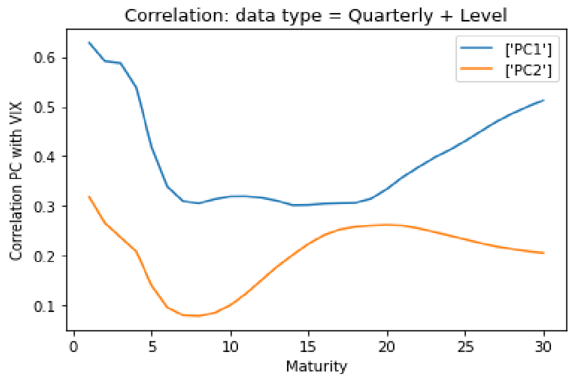


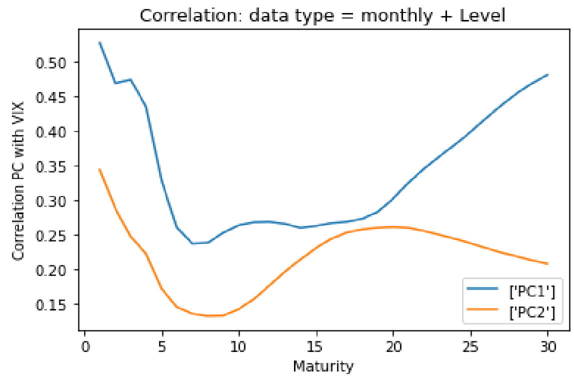


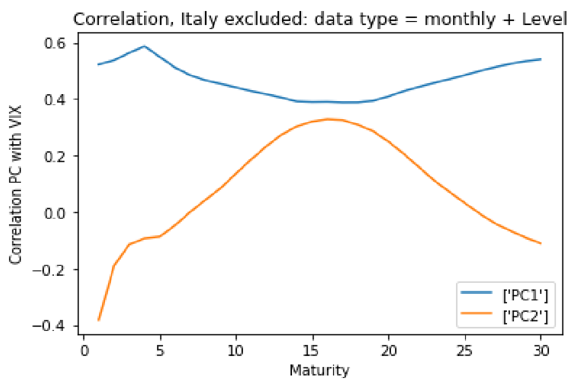


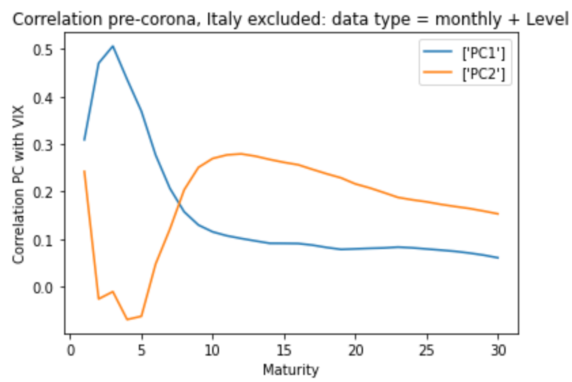


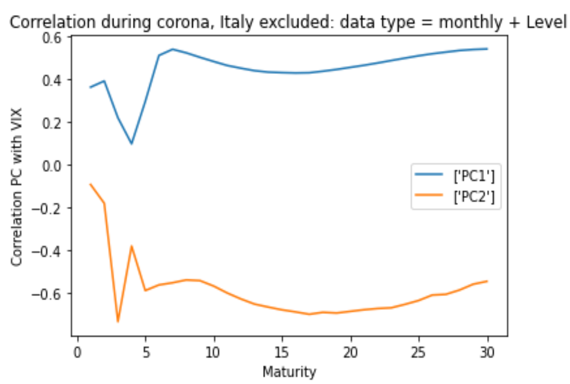
VIX index

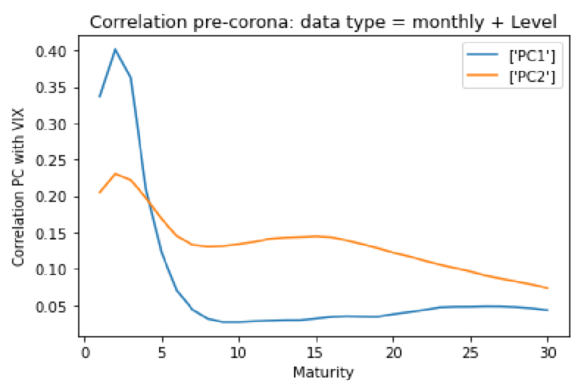

Correlation: data type = Quarterly + Level
Correlation PC with VIX
Maturity
['PC1']
['PC2']

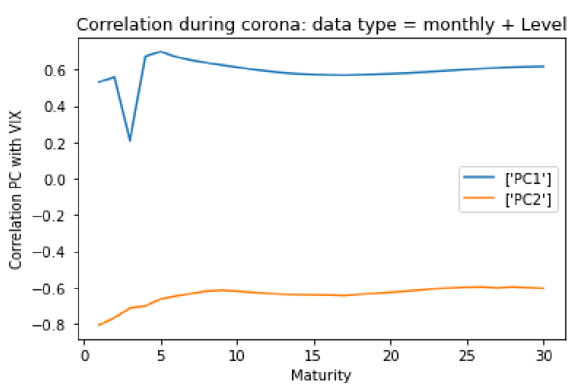

Correlation: data type = monthly + Level
Correlation PC with VIX
Maturity
['PC1']
['PC2']


Correlation, Italy excluded: data type = monthly + Level
Correlation PC with VIX
Maturity
['PC1']
['PC2']

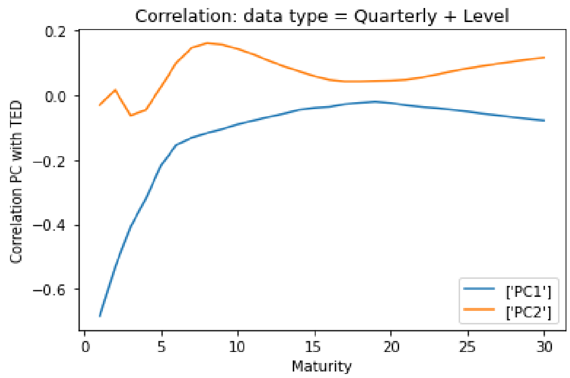

Correlation pre-corona, Italy excluded: data type = monthly + Level
Correlation PC with VIX
Maturity
['PC1']
['PC2']


Correlation during corona, Italy excluded: data type = monthly + Level
Correlation PC with VIX
Maturity
['PC1']
['PC2']


Correlation pre-corona: data type = monthly + Level
Correlation PC with VIX
Maturity
['PC1']
['PC2']


Correlation during corona: data type = monthly + Level
Correlation PC with VIX
Maturity
['PC1']
['PC2']

TED spread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Correlation PC with TED
Maturity
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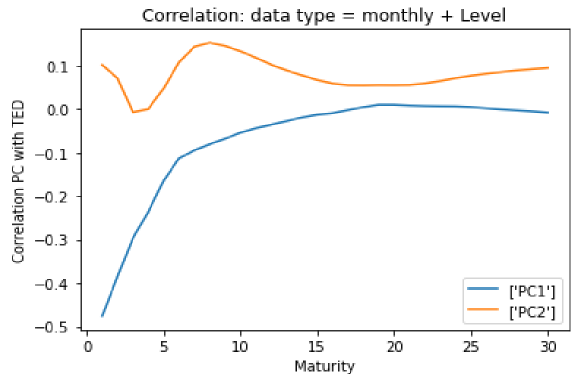
['PC2']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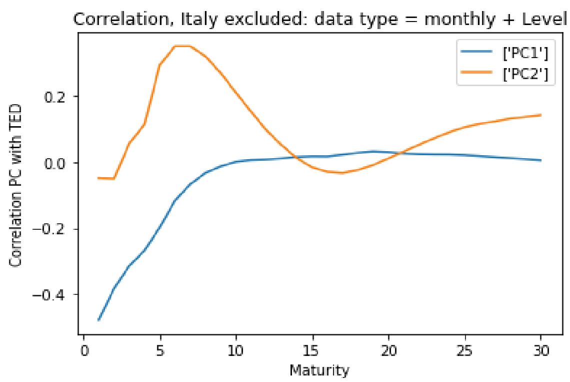
Correlation PC with TED
Maturity
['PC1']
['PC2']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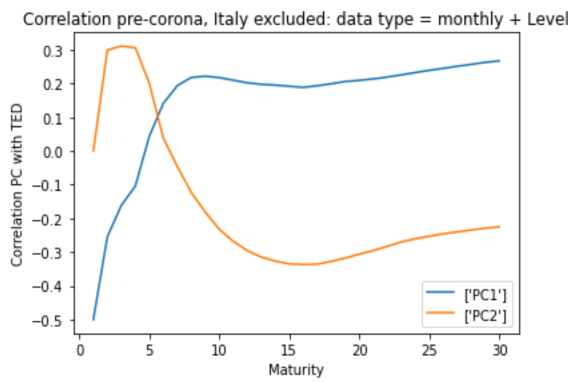
Correlation PC with TED
Maturity
['PC1']
['PC2']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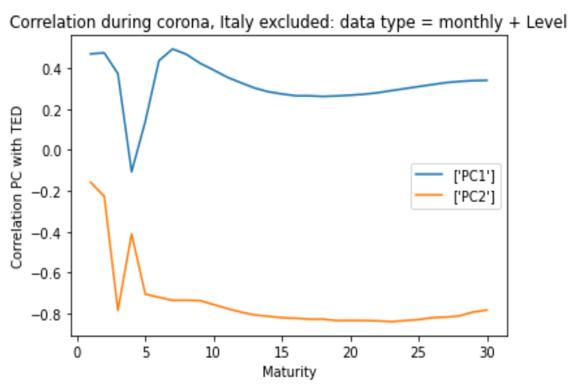
Correlation PC with TED
Maturity
['PC1']
['PC2']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Correlation PC with TED
Maturity
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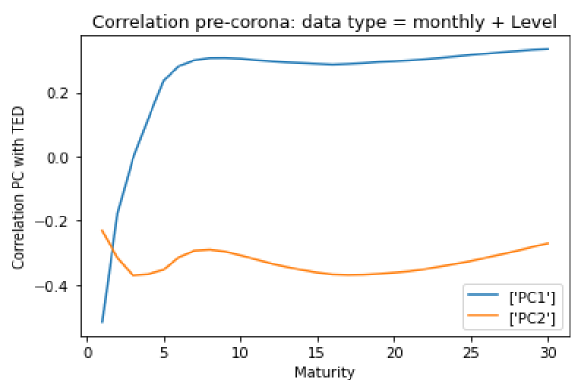
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Correlation PC with TED
Maturity
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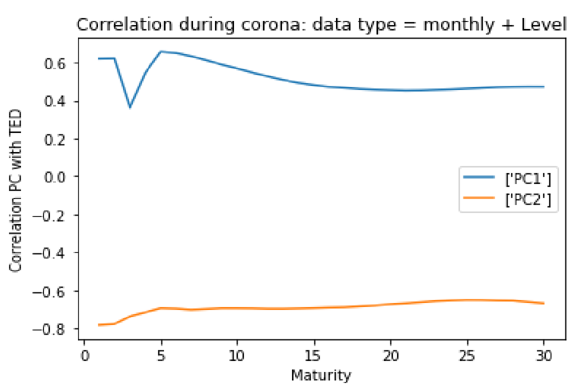
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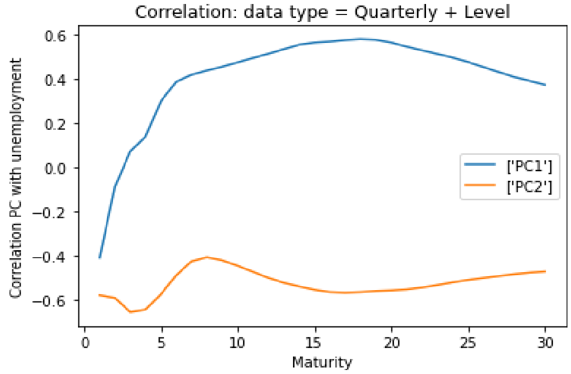
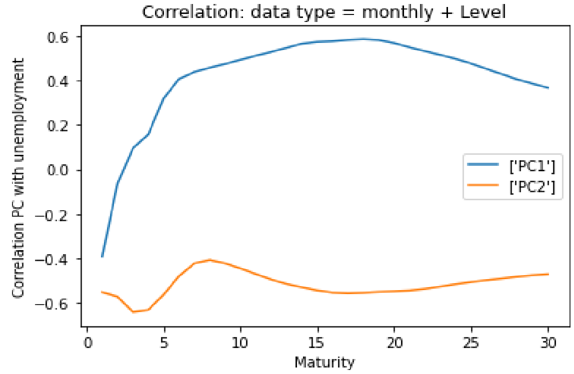
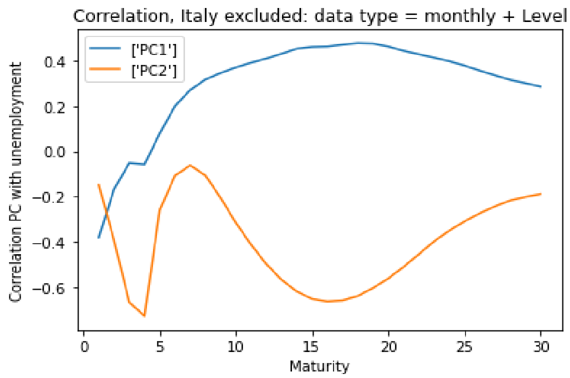
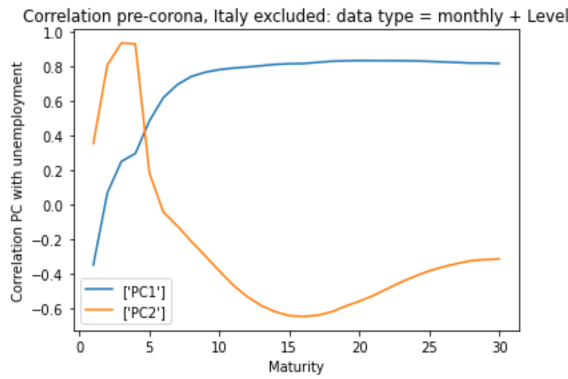
Correlation PC with TED
Maturity
['PC1']
['PC2']

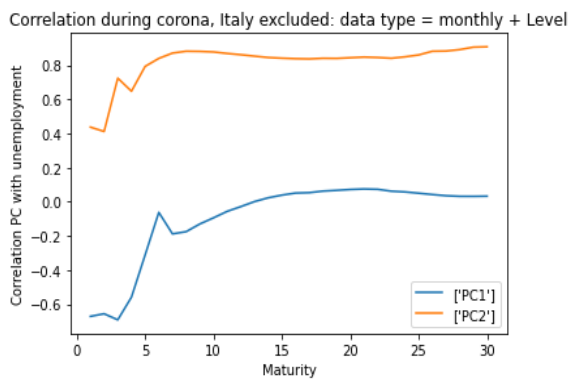
Unemployment rate

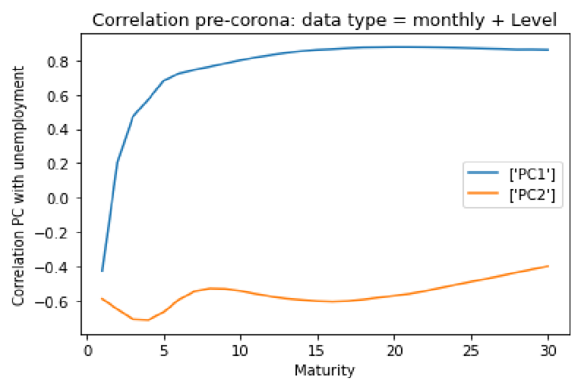


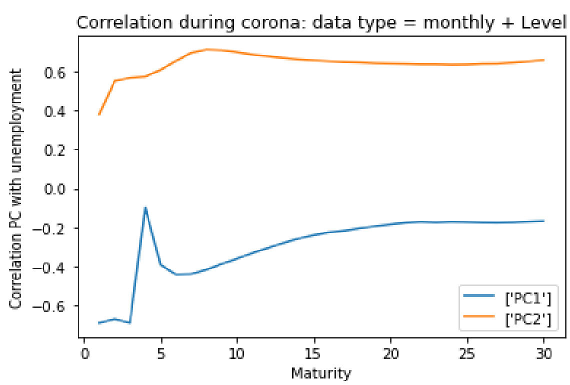




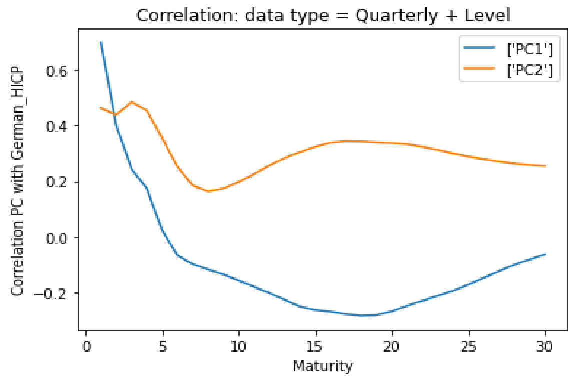


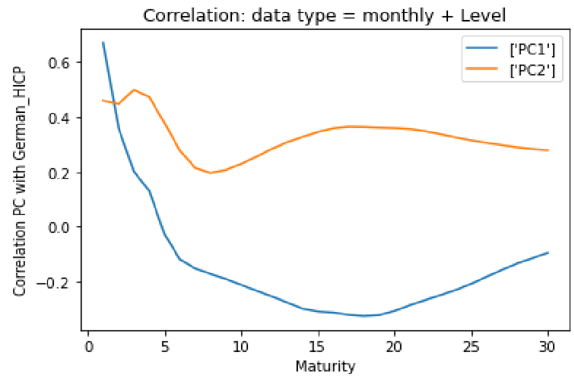


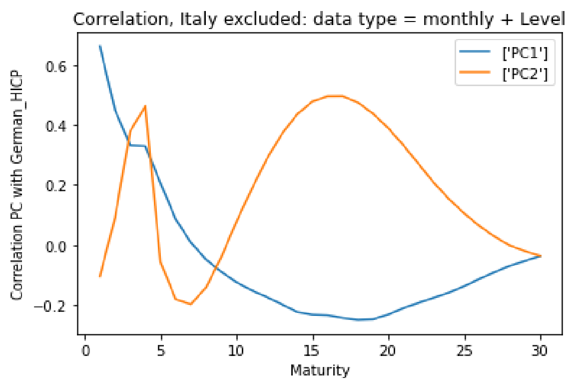


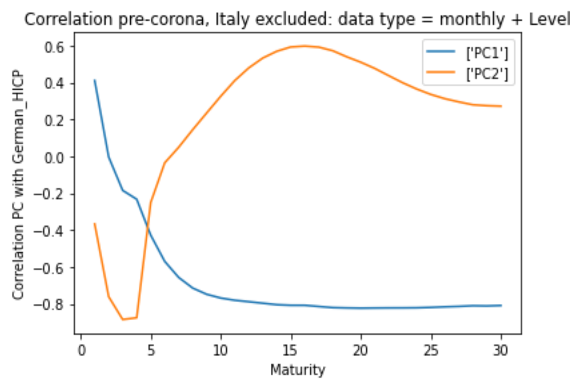


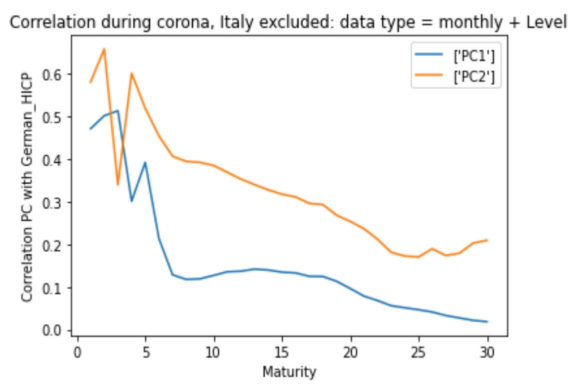
German HICP

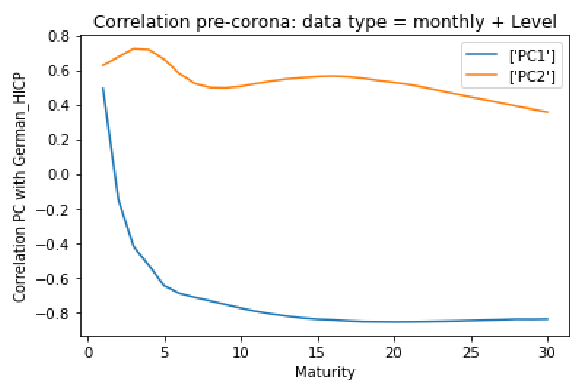

Correlation: data type = Quarterly + Level
['PC1']
['PC2']
Correlation PC with German_HICP
Maturity


Correlation: data type = monthly + Level
['PC1']
['PC2']
Correlation PC with German_HICP
Maturity


Correlation, Italy excluded: data type = monthly + Level
['PC1']
['PC2']
Correlation PC with German_HICP
Maturity


Correlation pre-corona, Italy excluded: data type = monthly + Level
['PC1']
['PC2']
Correlation PC with German_HICP
Maturity


Correlation during corona, Italy excluded: data type = monthly + Level
['PC1']
['PC2']
Correlation PC with German_HICP
Maturity


Correlation pre-corona: data type = monthly + Level
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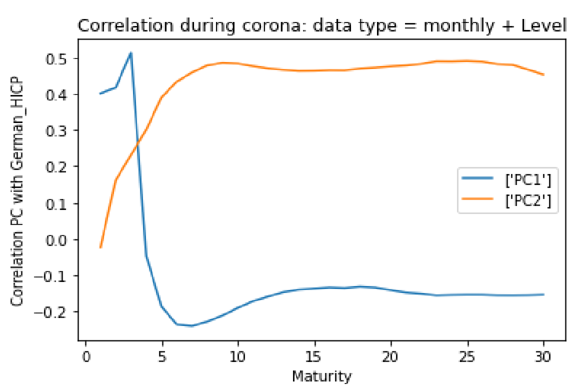
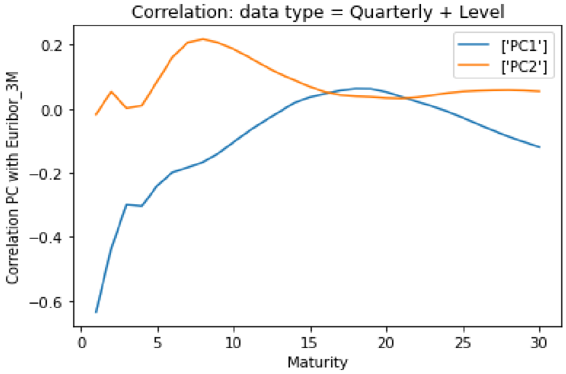
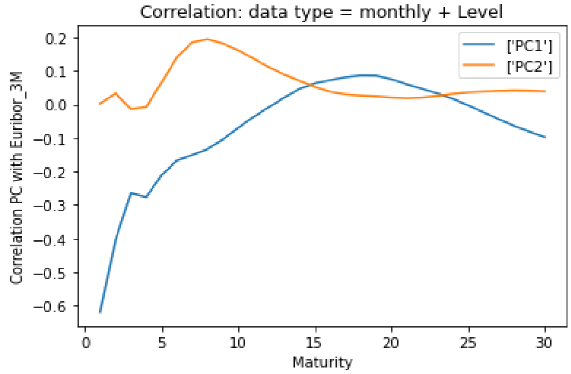
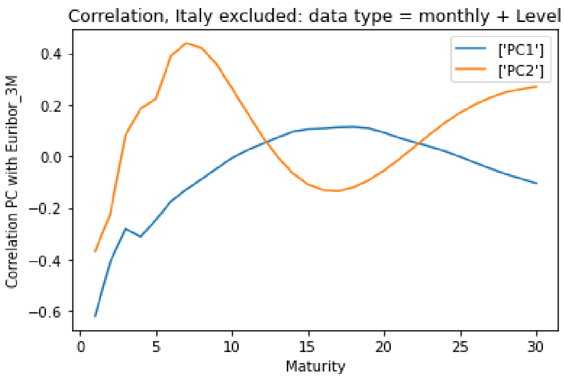
['PC2']
Correlation PC with German_HICP
Maturity

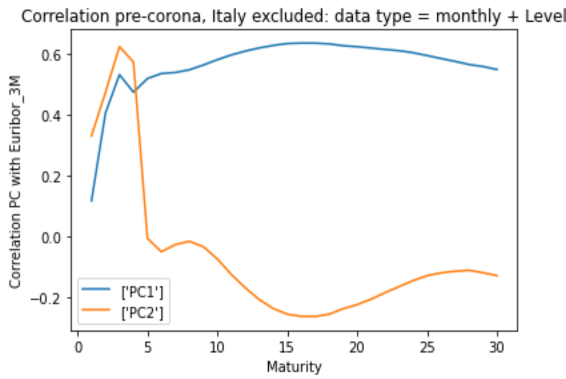

Correlation during corona: data type = monthly + Level
['PC1']
['PC2']
Correlation PC with German_HICP
Maturity

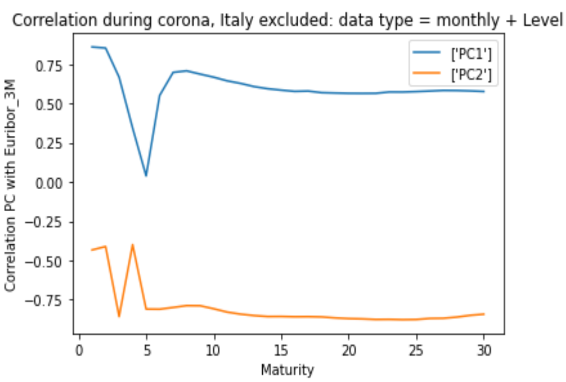
Euribor 3 months

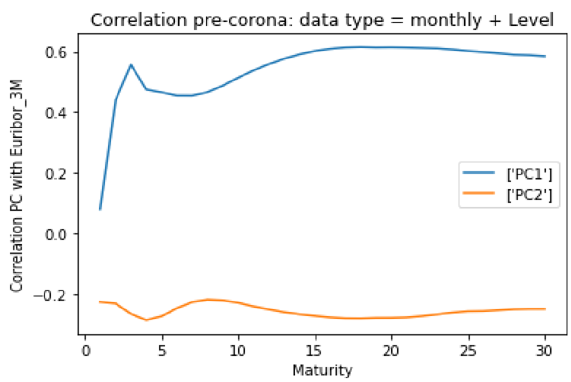


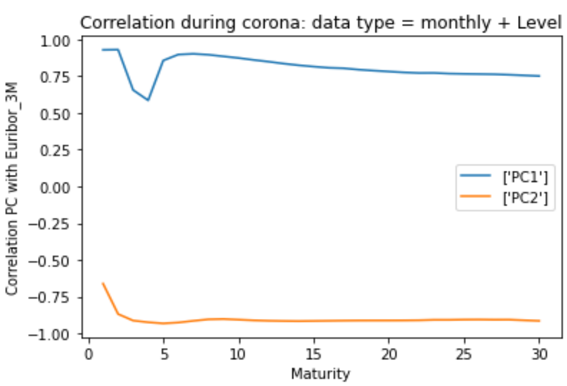




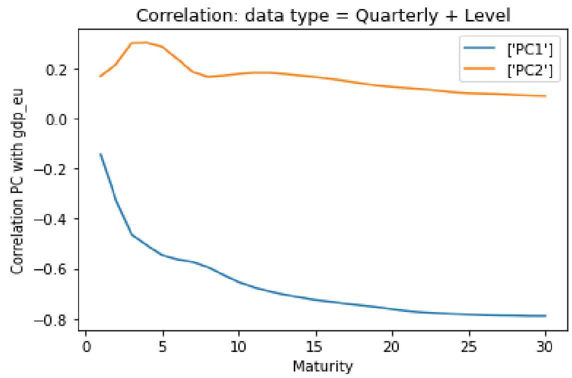


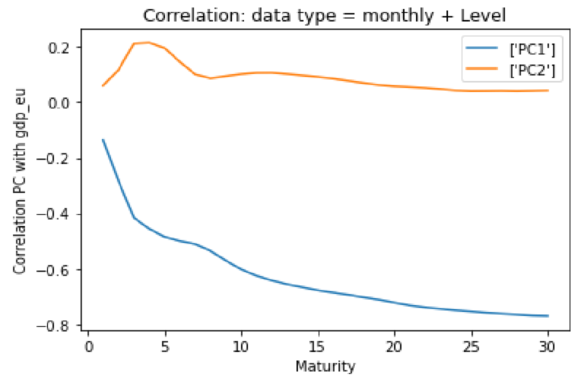


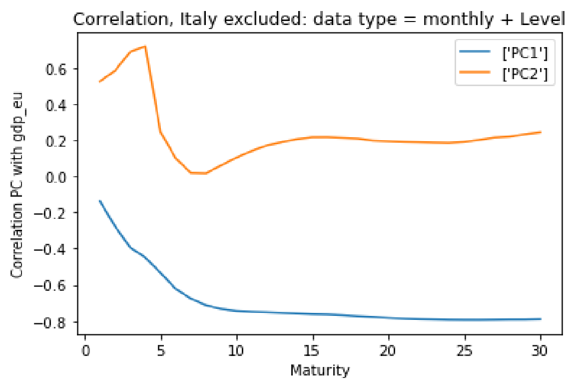


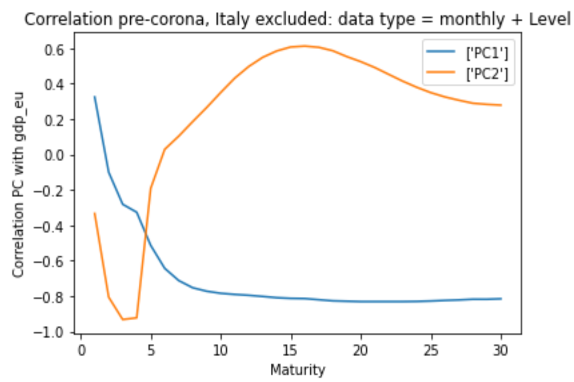


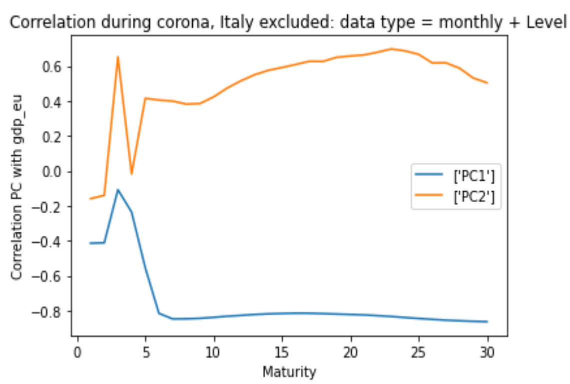
GDP Eurozone

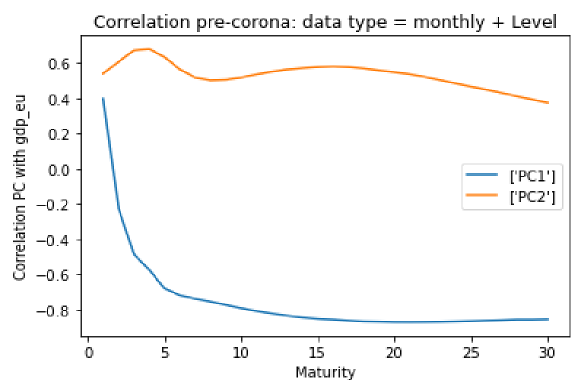


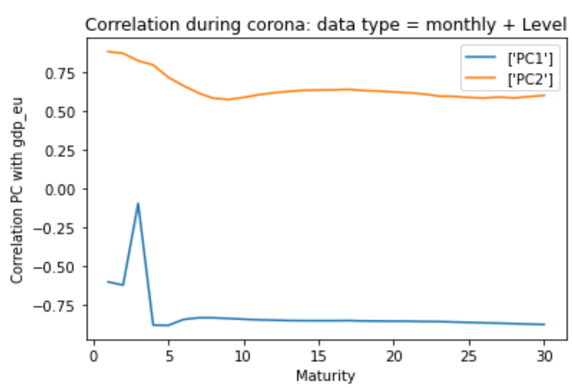




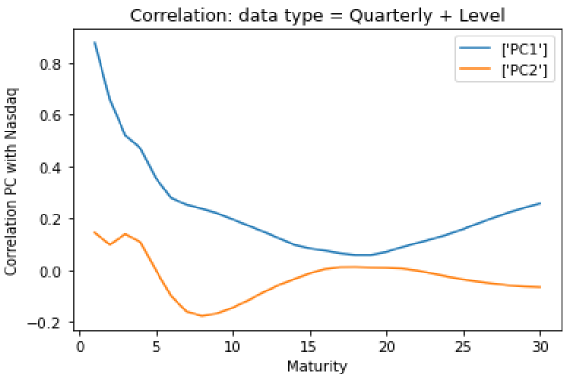


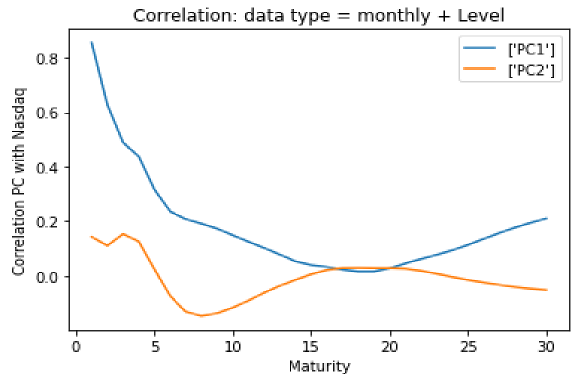






Nasdaq


Correlation: data type = Quarterly + Level
Correlation PC with Nasdaq
Maturity
['PC1']
['PC2']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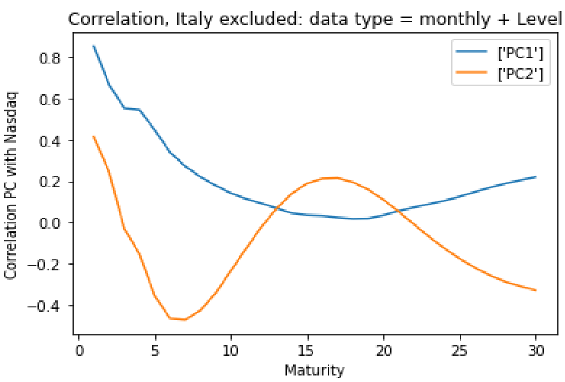
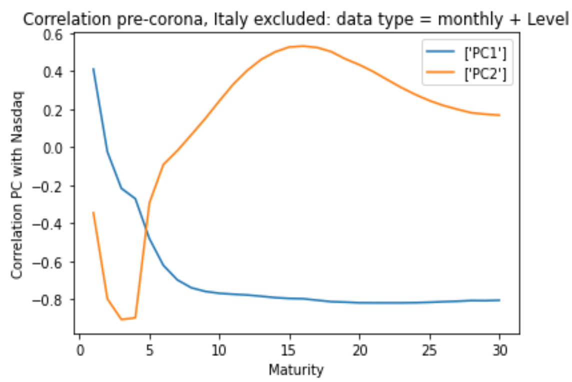
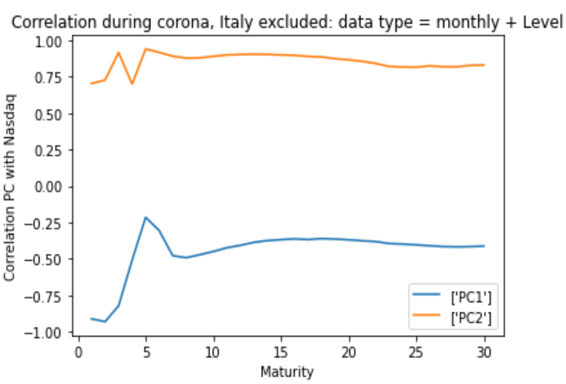
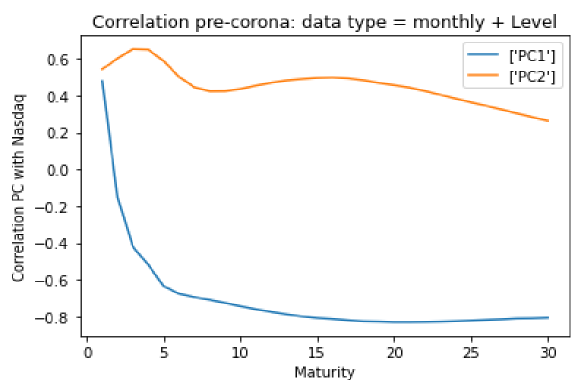
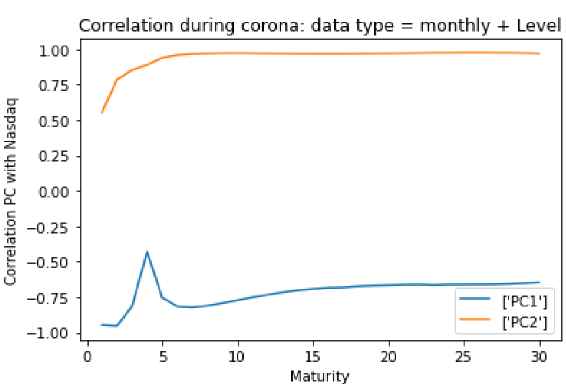
Correlation PC with Nasdaq
Maturity
['PC1']
['PC2']


Correlation, Italy excluded: data type = monthly + Level
Correlation PC with Nasdaq
Maturity
['PC1']
['PC2']

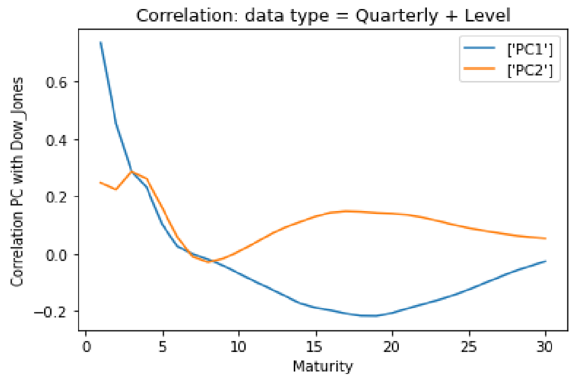

Correlation pre-corona, Italy excluded: data type = monthly + Level
Correlation PC with Nasdaq
Maturity
['PC1']
['PC2']


Correlation during corona, Italy excluded: data type = monthly + Level
Correlation PC with Nasdaq
Maturity
['PC1']
['PC2']


Correlation pre-corona: data type = monthly + Level
Correlation PC with Nasdaq
Maturity
['PC1']
['PC2']


Correlation during corona: data type = monthly + Level
Correlation PC with Nasdaq
Maturity
['PC1']
['PC2']

Dow Jones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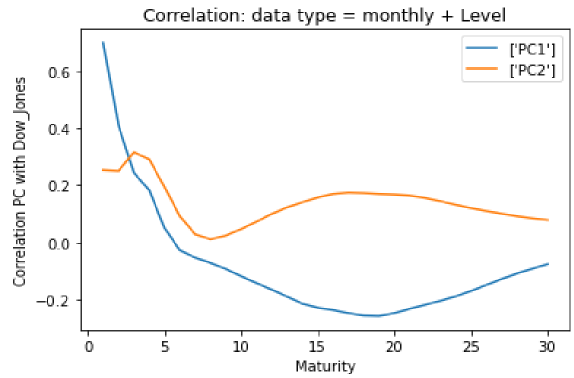
['PC2']
Correlation PC with Dow_Jones
Maturity


Correlation: data type = monthly + Level
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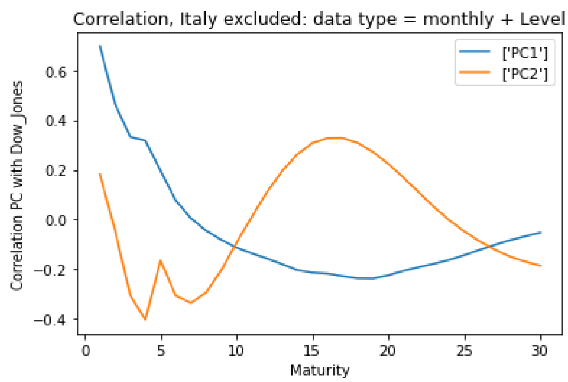
Correlation PC with Dow_Jones
Maturity


Correlation, Italy excluded: data type = monthly + Level
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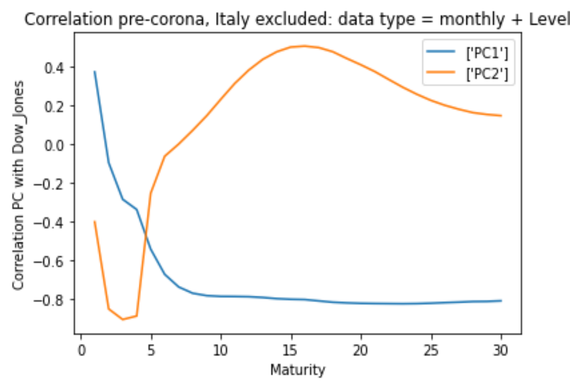
Correlation PC with Dow_Jones
Maturity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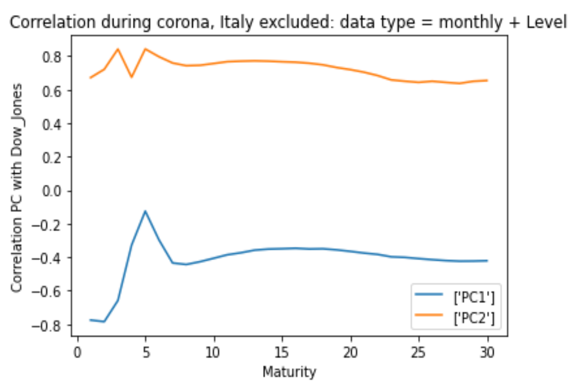
Correlation PC with Dow_Jones
Maturity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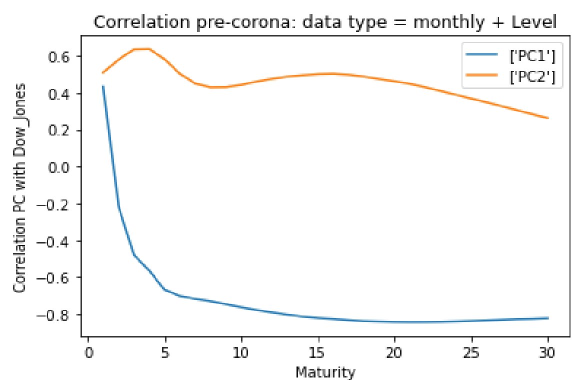
Correlation PC with Dow_Jones
Maturity


Correlation pre-corona: data type = monthly + Level
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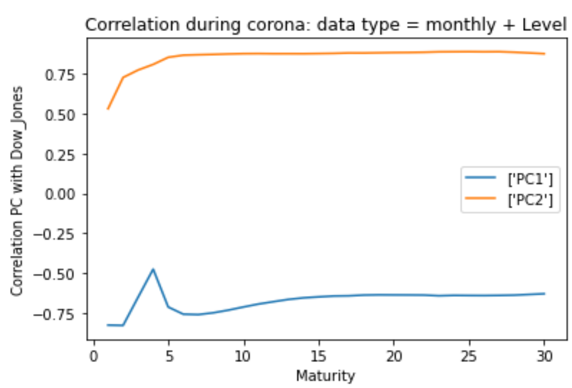
Correlation PC with Dow_Jones
Maturity


Correlation during corona: data type = monthly + Level
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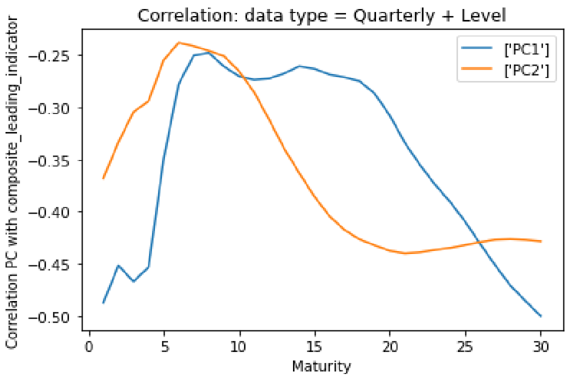
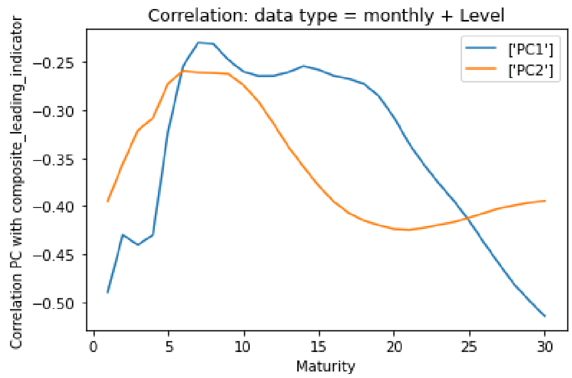
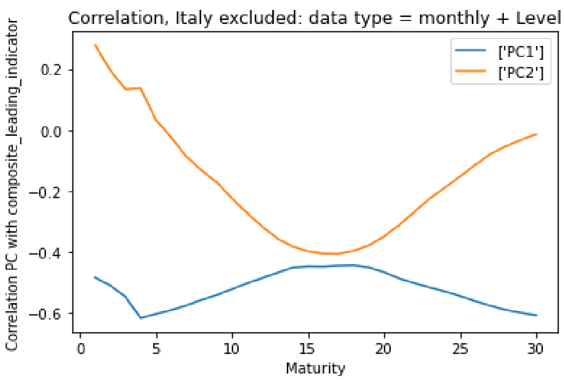
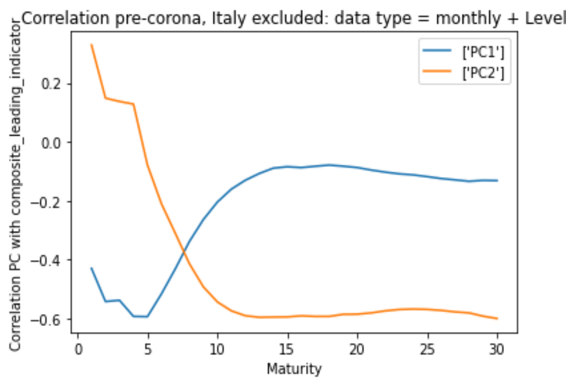
['PC2']
Correlation PC with Dow_Jones
Maturity

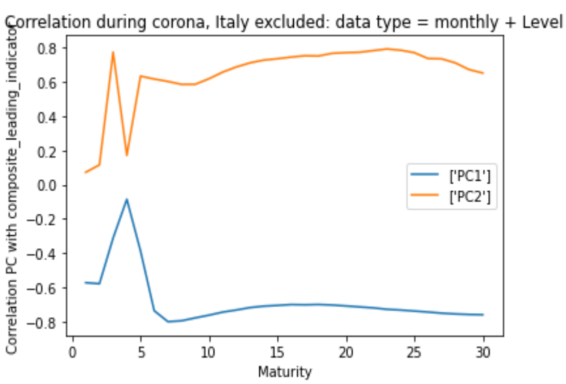
Composite leading indicator

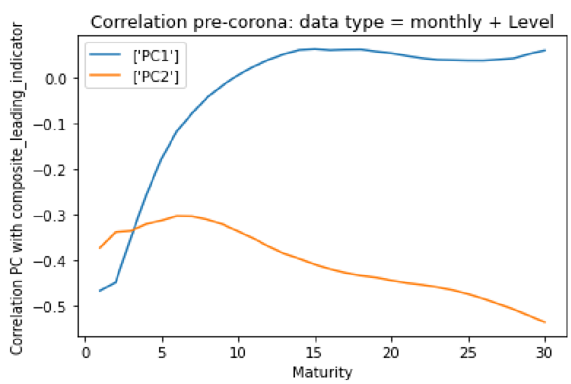


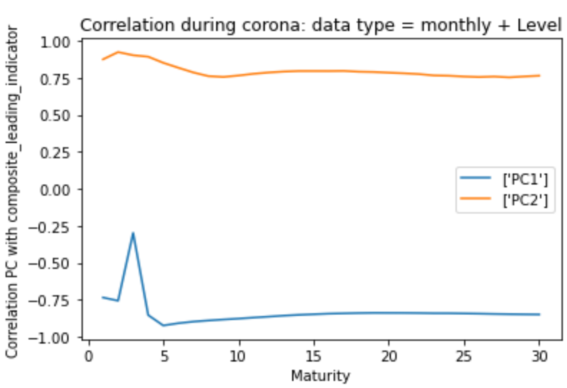




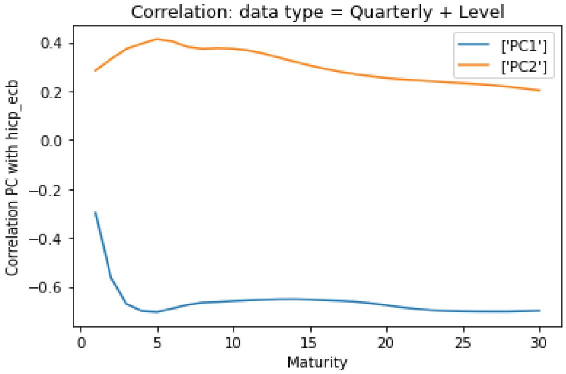


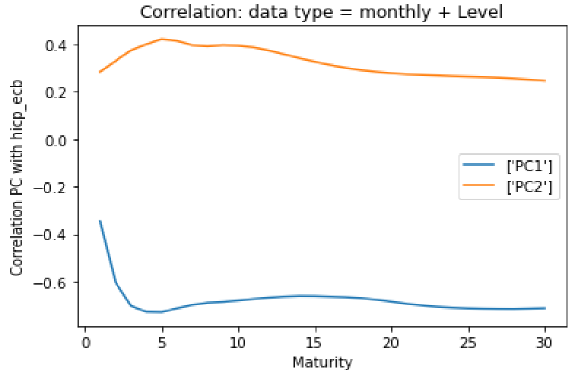


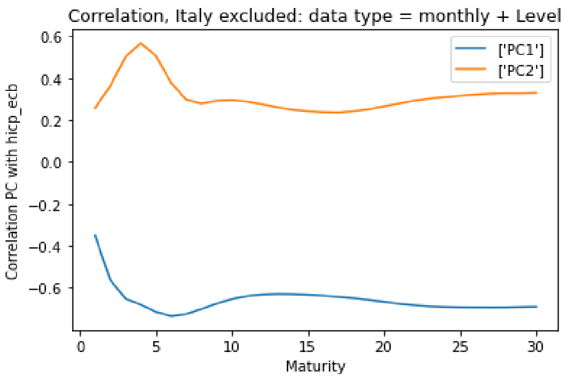


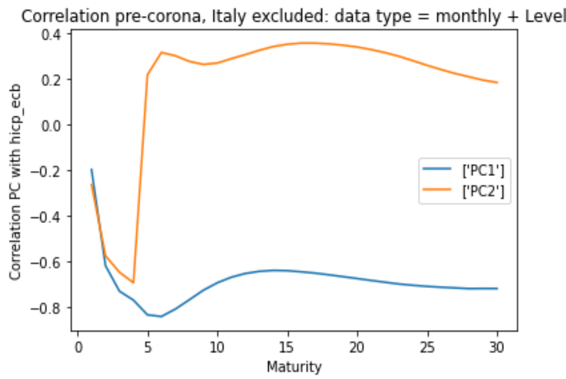


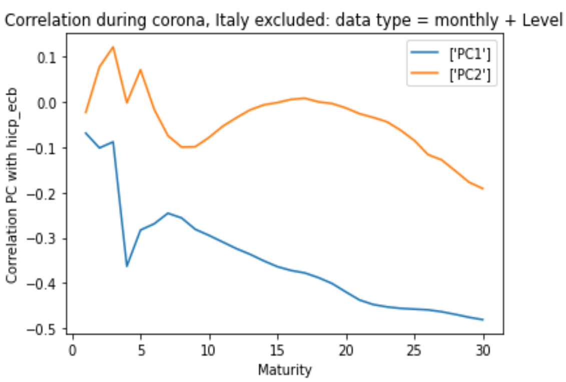
HICP eurozone

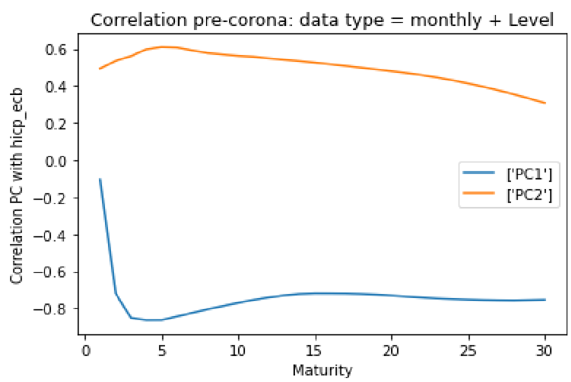


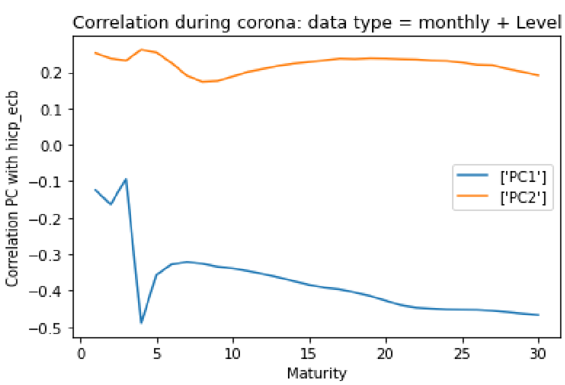




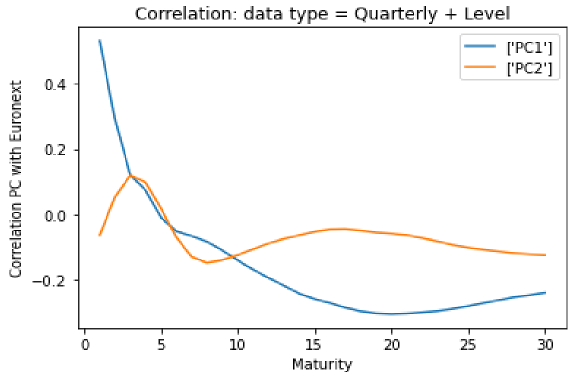


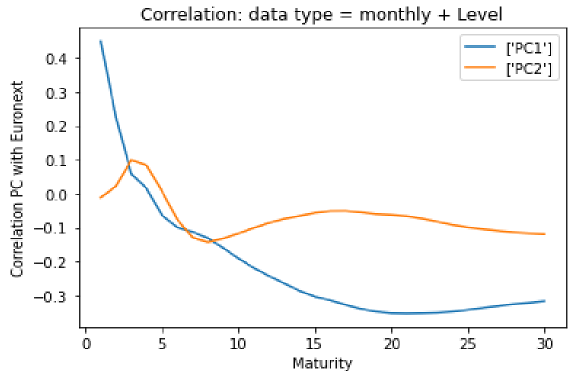


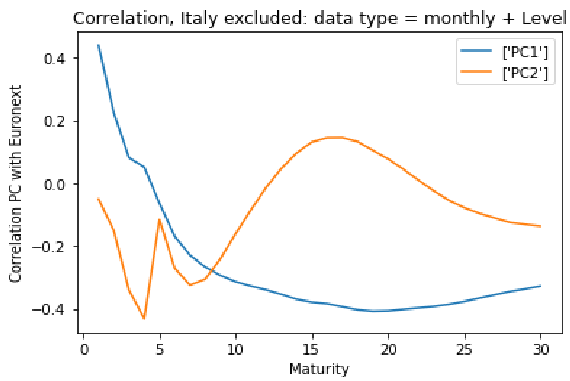


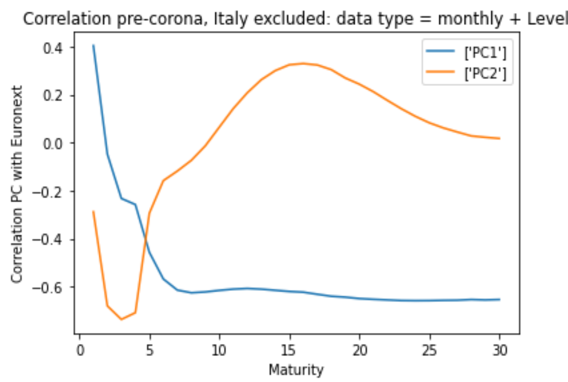


Euronext


Correlation: data type = Quarterly + Level
['PC1']
['PC2']
Correlation PC with Euronext
Maturity


Correlation: data type = monthly + Level
['PC1']
['PC2']
Correlation PC with Euronext
Maturity


Correlation, Italy excluded: data type = monthly + Level
['PC1']
['PC2']
Correlation PC with Euronext
Maturity


Correlation pre-corona, Italy excluded: data type = monthly + Level
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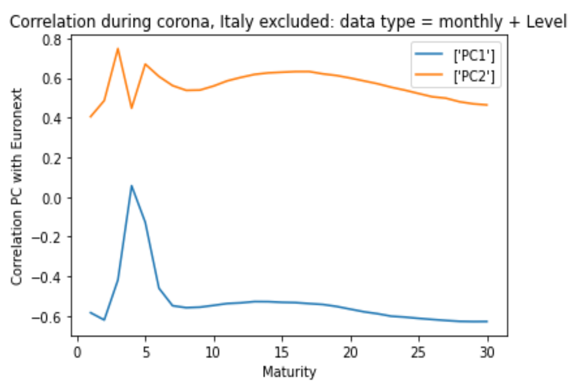
['PC2']
Correlation PC with Euronext
Maturity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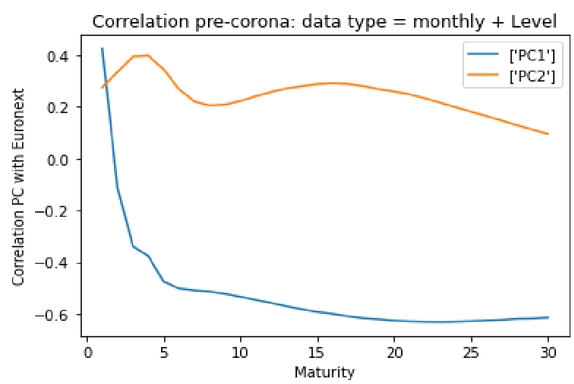
['PC2']
Correlation PC with Euronext
Maturity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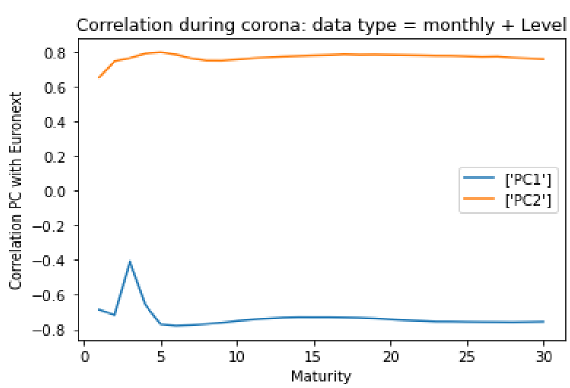
Correlation PC with Euronext
Maturity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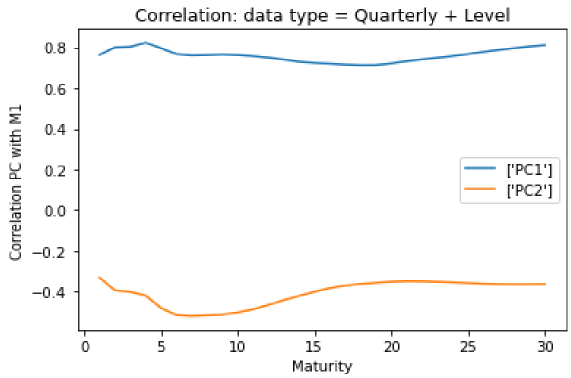
Correlation PC with Euronext
Maturity

M1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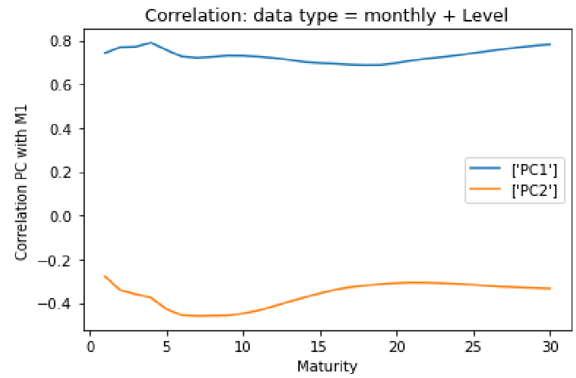
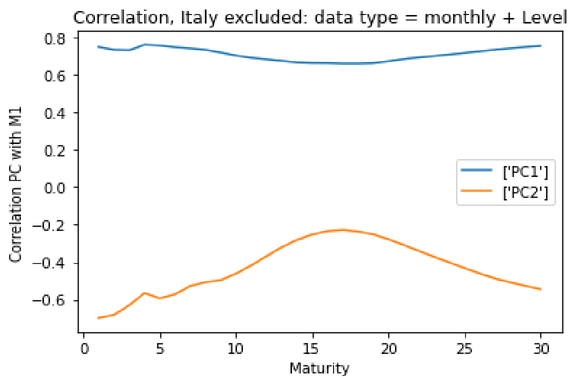
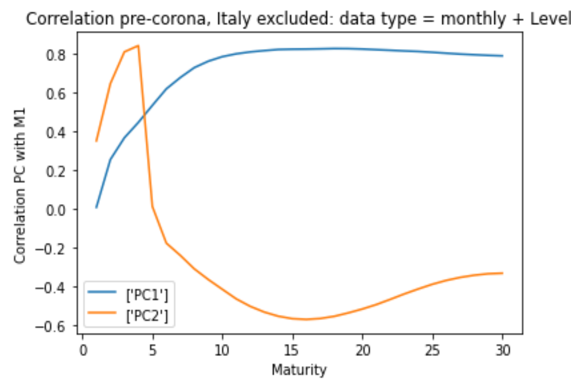
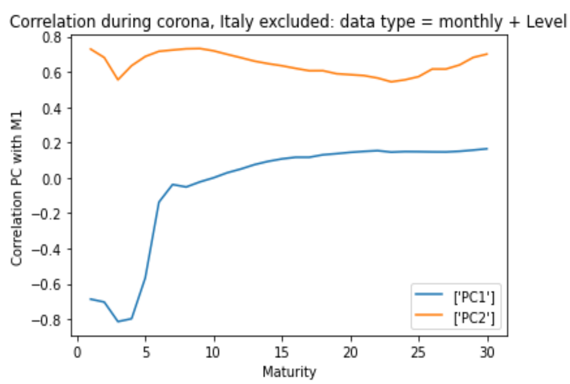
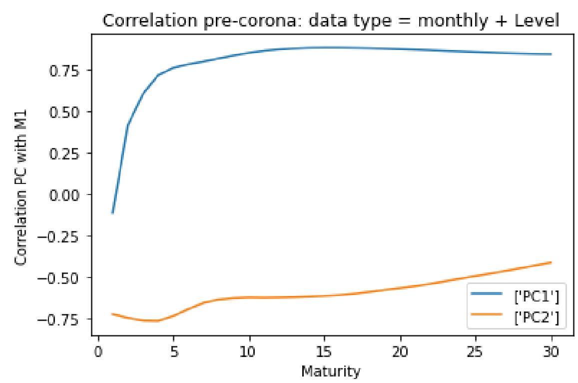
Correlation PC with M1
Maturity
['PC1']
['PC2']

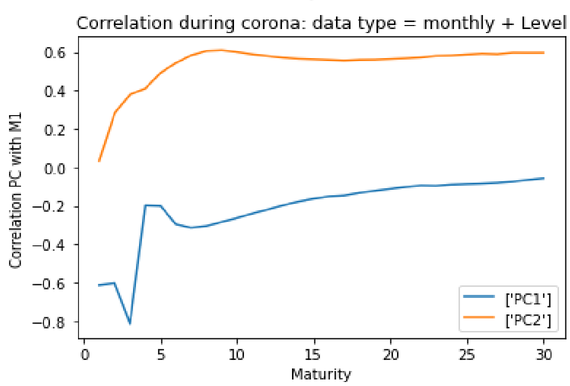

Correlation: data type = monthly + Level
Correlation PC with M1
Maturity
['PC1']
['PC2']


Correlation, Italy excluded: data type = monthly + Level
Correlation PC with M1
Maturity
['PC1']
['PC2']


Correlation pre-corona, Italy excluded: data type = monthly + Level
Correlation PC with M1
Maturity
['PC1']
['PC2']


Correlation during corona, Italy excluded: data type = monthly + Level
Correlation PC with M1
Maturity
['PC1']
['PC2']


Correlation pre-corona: data type = monthly + Level
Correlation PC with M1
Maturity
['PC1']
['PC2']


Correlation during corona: data type = monthly + Level
Correlation PC with M1
Maturity
['PC1']
['PC2']