Market sentiment and financial variables as drivers of sovereign spreads mispricing

Bocconi University, MSc in Finance Thesis

Market sentiment as driver of euro area sovereign bonds 10-Year term premium

Stockholm School of Economics, MSc in Finance Thesis

MATTEO MONTANI - 42693

Bocconi University Tutor: Paolo Colla, Associate Professor, Department of Finance, Bocconi University

Stockholm School of Economics Tutor: Gualtiero Azzalini, Assistant Professor, Department of Finance, Stockholm School of Economics

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MATTEO MONTANI

Advisor: Paolo Colla, Associate Professor, Department of Finance, Bocconi University

Author: Matteo Montani (Bocconi ID: 3108735)

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Abstract

This paper examines the impact of financial variables and market sentiment proxies on the mispricing of the Euro Area's sovereign bond spreads, where mispricing is defined as the difference between the market spreads and the spreads estimated with the sole use of economic fundamentals, current and expected. Both previous research and the findings of this paper suggest that proxies of market sentiment are drivers of mispricing. However, this investigation found that in a linear model setting market sentiment and financial variables only account for a small portion of the mispricing variation.

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1. Introduction

The sovereign bond spreads of Euro Area countries are a highly debated topic in the financial industry. After all, the Euro Area has undergone a serious sovereign debt crisis, with peripherical economies being influenced by the deterioration of the fiscal sustainability of Greece and countries pertaining to the PIIGS groups seeing their bonds' yields diverge from those of the German Bund. Since then, the field of fair value models for the sovereign spreads has been gaining and losing popularity in a periodical manner. The introduction of the Transmission Protection Instrument by the ECB in July 2022 represents the most recent episode of a sudden spark in popularity of the latter field.

In the light of this recent flare in the relevance of fair value models, this paper investigates the theoretical mispricing, quantified by the difference between the market spreads and theoretical fair value spreads, which are obtained through the Ceci and Pericoli (2022) methodology. More specifically, the investigation focuses on identifying whether market sentiment proxies and financial variables can be identified as drivers of spread mispricings. The variables used to proxy market sentiment and to capture trends present of financial markets were mostly inspired by previous research on sovereign CDS spreads, with some fine tuning from adjacent publications. The market sentiment proxies included measures of equity market implied volatility, economic policy uncertainty and systemic stress of Euro Area financial markets, whereas the financial variables were related to the equity performance of a country's banking as well as broader equity market performance. Moreover, all the variables included were either country specific[1] or measurements of the Euro Area as whole. Though, unlike most literature, no global variables were included.

To assess the relevance of these variables in driving mispricings mainly two approaches were followed. Initially, a multivariate panel regression model, inspired by Ceci and Pericoli (2022) was used. Then, simpler time series regressions at country level were employed. A more advanced autoregressive model was tried as well, however due to the lack of autocorrelation of the

[1] The countries analyzed were Italy, France, Spain, Ireland and Portugal.

mispricings observations, the results from the model did not add any further findings to the investigation.

The findings of the two main approaches suggest that the variables used to represent market sentiment can be deemed as drivers of the mispricing, while the financial variables could not be deemed statistically relevant in influencing the variations of the mispricing. The time series model highlighted some country heterogeneity regarding which of the variables affect the mispricings relevantly in statistical terms, though VSTOXX (implied equity volatility) turned out to be a driver of mispricing in four out of the five countries present in the sample as well as in the panel model. Nevertheless, within our linear framework, sentiment proxies and financial variables were able to explain a small fraction in the observed variability of the mispricing, as indicated by the low R-squared values in all the regressions carried out.

The findings of this research add to the already well-established field of Euro Area sovereign spreads estimation by providing an updated assessment of the period between 01/01/2014 and 01/07/2024 on the effects of market sentiment and financial variables on deviations from spreads estimated determined by economic fundamentals, for Italy, France, Spain, Ireland and Portugal.

With regards to the structure, this paper is organized as follows: Section 2 explains the findings of existent research; Section 3 deals with the data considered and its financial rationale, as well as the information carried out on the time series to make them fit for the use; Section 4 explains the multivariate panel approach; Section 5 explains the time series model approach; Section 6 discusses the findings of the previous sections and Section 7 provides possibilities of further research.

2. Literature Review

2.1 Definition of yield spreads, fair-value measure and mispricing

In the financial industry, the word "spread" refers to the differences in returns of numerous securities. Hence, it is important to specify that this paper investigates the spreads of Euro Area's government bonds, defined as the difference between a country's 10-year government bond yield and a benchmark yield. In this research the difference is taken with respect to the 10-year German government bond (Bund), which is the benchmark suggested by Dunne et al. (2007) thanks to Germany's government debt risk free status and the absence of a true risk-free asset. Therefore, using Italy as an example, the spread between the 10Y Bund's yield and the 10Y BTP's yield represents the additional risk-premium required by investors to hold the riskier BTP. Similarly, the concept of "fair value" is often ambiguous too. Hence, "spreads' fair value" refers to the theoretical spread estimated on the basis of the country's observable economic fundamentals as suggested by Ceci and Pericoli (2022) "Sovereign Spreads and Economic Fundamentals: An Econometric Analysis" research. The economic fundamentals are debt-to-GDP, medium-term inflation expectations, short and medium-term real growth expectations, and unemployment. The fair value measure of spreads therefore differs from the observed market spreads as it should grant a measure that is not influenced by investor sentiment and fear but rather represents the risk-premium required when jointly considering the five aforementioned economic variables.

Consequently, the difference between observed and fundamental (theoretical) spread represents a bifurcation in values. Thanks to divergence there is a theoretical 'mispricing' of the risk-premium in question. As a result, mispricing refers to the difference between the spread estimated by a fair-value model (based on economic fundamentals) and the observed spread determined by the market (supply and demand forces).

2.2 Present literature

Fair-value models have been researched for some time now, in fact some of the research covered dates back to the 80s. However, in the Euro Area, research on models regarding the sovereign yields in the Euro Area has gained quite a lot of interest with the most recent times, first following the 2007-2009 financial crisis, then as result of 2012 European sovereign debt crisis, and lastly with the introduction of Transmission Protection Instrument (TPI)[2] in 2022, bringing about extensive research of both academic and financial institution nature.

An early example of the link between government financing conditions and economic fundamentals comes from Edwards (1984), who studied the role that various macroeconomic variables (such as debt-to-GNP and debt service-to-exports ratio) have in driving the interest rates charged to a specific, less economically developed country above LIBOR[3]. Similarly, Laubach (2003) investigated the influence of government debt and deficit on the future long-term interest rates, using the Congressional Budget Office (CBO) and the Office of Management and Budget (OMB) 5-year-ahead projections of fiscal variables. The latter study concluded that effects on government debt and deficits on interest rates are statistically significant, such that a one percentage point increase in deficit-to-GDP results to an estimated 25 basis points increase in the expected long-term interest rates for USA. This behavior is also displayed across the Atlantic, as studies focusing on the European Union suggest that deficit-to-GDP of member states have similar effects as those found by Laubach (2003) for US sovereign debt. Faini (2006) not only concludes that increases in deficit-to-GDP increase an EMU member state's spread, but also that expansionary fiscal policy by one member state results in a general increase in the levels of interest rates for all members. Though, Faini (2006) also emphasized that according to the majority of pre-2006 literature, the market fiscal discipline imposed on EMU members, judged by the sensitivity of investors to an increase in debt-to-GDP, was lower than that in USA. Nevertheless, after October

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[2] The European Central Bank (ECB) introduced the TPI in July 2022, to ensure the smooth transmission of monetary policy across all Euro countries. Through this tool, the Euro system can make secondary market purchases of securities from jurisdictions who are experiencing a deterioration in the financing conditions, which cannot be justified by economic fundamentals. Decision:
https://www.ecb.europa.eu/press/pr/date/2022/html/ecb.pr220721~973e6e7273.en.html

[3] LIBOR: London Inter-Bank Offered Rates

2009 and the events of the Greek crisis, financial market participants became more attuned to country-specific fundamentals, as discovered by Giordano et al. (2012).

Related to responsiveness of financial markets to country-specific economic fundamentals, Di Cesare et al. (2013) investigated the relationship between the current debt-to-GDP and the spreads on 2, 5 and 10 years maturities. They initially employed a very simple fair-value model with regressions at country level: $s_t = \beta_1 + \beta_2(\frac{debt}{GDP})_t + \varepsilon_t$, where s_t is the spread of country sovereign debt with respect to the German Bund, and the countries used were Belgium, France, Ireland, Italy, Portugal and Spain. The spreads fair-values are the fitted $\hat{s}_t$. Then, they moved on to a more complex fair-value model, which accounted for nonlinear relationships between debt-to-GDP and spreads, and estimated it using a panel regression with the data of the latter six countries[4]. Their discovery was that the relationship between spreads and debt-to-GDP is non-linear and convex in every country except for Belgium.

Spread fair-values models are also developed in investment banks. Barclays (2022) developed a framework for European Government Bonds (EGB) in which estimates are obtained by taking the differences with respect to Germany of debt-to-GDP, unemployment, inflation expectations, and short and medium-term growth expectations; regressing the market spreads on those differences while controlling for the VIX index; and using the fitted coefficients of the economic variables to obtain the fair-values. A further example comes from Ardagna et al. (2012) from Goldman Sachs, who estimated the 10-year CDS spreads (with respect to Germany) of Italy, France and Spain by using public debt, primary deficit, expected nominal GDP growth and expected 3-month rates.

Going back to sovereign bond spreads, on top of the research on the effects that economic fundamentals have on sovereign spreads, there is quite a lot of evidence that in times of high financial and economic uncertainty market spreads tend to diverge from values estimated by models based on economic fundamentals. As the next sub-section will display, this behavior is displayed in the model of Ceci and Pericoli (2022) as well. Though, other researchers evidenced the tendency as well. For example, Giordano et al. (2012) tried capturing these mispricing's widenings by including time dummies and interaction terms between time dummies and economic

[4] Di Cesare et al (2013) second model:
$s_{i,t} = \beta_1 + \beta_2(\frac{debt}{GDP})_{i,t} + \beta_3[(\frac{debt}{GDP})_{i,t}]^2 + \beta_4 D_i + \beta_5 D_i(\frac{debt}{GDP})_{i,t} + \beta_6 D_i[(\frac{debt}{GDP})_{i,t}]^2 + \varepsilon_{i,t}$

fundamentals for the 2009 Greek crisis. Though their specifications were still unable to fully capture the widenings in the latter period. Present literature offers numerous examples of variables and phenomena these divergences can be linked to. Accordingly, Metiu (2012) suggested that in the time span between January 2008 and February 2012, a possible cause of these market vs. fundamentals spread difference widenings was the contagion risk. According to the author, Italy's spread suffered contagion from Spain and Portugal, who were themselves importers of risk from Greece. Another phenomenon is the "flight-to-safety" or "to safe havens", whereby investors sell the riskier PIIGS[5] bonds to purchase securities pertaining to the risk-free category – Bunds – causing both a decrease in price (increase in yield) of bonds from the former geographical areas and an increase in price (decrease in yield) of bonds from Germany. In fact, De Santis (2012) discovered that the increase in PIIGS spreads, as well as those of sounder countries like Austria and Netherlands, could have in part been attributed to the enhanced global risk-aversion resulting to market participants flee to the Bund. This finding is supported by Caceres, Guzzo and Segoviano (2010) as well as Beber et al. (2009), who both suggest that liquidity concerns might cause a similar flow, through a "flight-to-liquidity". Though, market spreads being higher than fundamentally estimated spreads may also be linked to financial institutions' regulatory framework. An explanation comes from De Santis (2012), who, in addition to the former finding, has also highlighted that downgrades of government bonds can cause portfolio reallocation to safer assets, as certain financial institutions are bounded to invest in securities of a minimum rating and regulators use debt ratings to assign capital requirements to banks. Barrios et al. (2009) came to a similar conclusion, citing both risk aversion and credit risk as reasons for such behavior of financial institutions portfolio managers.

Beber et al. (2009) concept of "flight-to-liquidity" has been of particular interest in the sovereign bond spreads fair value field, after all the market liquidity shock resulting from the Russian crisis in 1998 was a prominent cause of the failure of Long-Term Capital Management (LTCM). Indeed, De Grauwe and Ji (2012) compared the market spreads' reactions to enlargements in debt-to-GDP ratios of country in the Euro Area and stand-alone countries (such as Australia or Japan). They found no evidence of non-linearities of debt-to-GDP ratio for stand-alone countries but found evidence for Euro Area ones. Their conclusion was thus that since the Euro Area sovereign debt is

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[5] PIIGS: Portugal, Italy, Ireland, Greece and Spain

issued in a currency the single governments don't control, countries are not able to guarantee that cash will always be available to pay the bondholders, creating the possibility of a liquidity crisis. If such an occurrence was to happen, investors would sell the bonds, worsening the financing conditions of the country in question and enlarging a liquidity crisis into a solvency crisis, in a self-fulfilling way. Ultimately these findings provide evidence for the previously formulated hypothesis by De Grauwe (2011) that sovereign bond markets in monetary unions are more vulnerable to self-fulfilling liquidity crisis. However, the latter two studies defined liquidity as the money available to pay bondholders, not as market wide measure of liquidity, such as the size of bid-ask spreads, which could represent more of a financial variable rather than indicator related to a country's fundamentals.

Research on the latter type of liquidity evidenced mixed results. Favero et al. (2010) explored the determinants of yield in the Euro Area and discovered that liquidity differentials (difference between bid-ask spread of country in question and a reference country) are only priced in a subset of nine countries out of the 16 investigated. In addition, Delatte et al. (2017), who studied the potential drivers of non-linearities in bond pricing, discovered that, in periods of crisis, investors attach extra premium to a country's competitiveness and international risk than they do to market liquidity measures [6].

Because of the mixed results regarding the significance of market liquidity in bond pricing, this paper will not focus on this branch of literature, but rather on market sentiment, financial variables and their additional contribution, on top of economic fundamentals, in determining market spreads. This focus arises from the fact that in the literature covered thus far, economic fundamentals seem to be a driver of spreads, as reasonable to expect, though fair value models are unable to explain a considerable portion of market spreads, especially in times of crisis and uncertainty. These time periods are associated with enhanced financial markets volatility, greater investors and businesses uncertainty, and lower equity performance for certain industries. Consequently, there is the possibility that indicators related to this phenomenon could capture an additional portion of the spreads than the one explained by economic variables. Some of the papers covered in this section have hinted at such a possibility. For example, Di Cesare et al. (2013) despite their efforts to include

[6] Non-linearities in bond pricing are often observed in periods of enhanced uncertainty as evidenced in Di Cesare et al. (2013)

in their model various orders and interactions terms between time periods and debt-to-GDP ratios, their fair-value models were unable to explain a considerable portion of market spreads. Hence, the authors also investigated the components of the sovereign risk premia in the Euro Area stemming from financial markets. They used three different proxies of country specific financial risk: volatility of sovereign spreads, volatility of bank stocks and spread on corporates bonds of the same rating as the sovereign. The econometric analysis suggested that all three proxies had significant explanatory power, especially the volatility of sovereign spreads. Longstaff et al. (2011) also studied the relationship between financial variables and sovereign risk premia, focusing on CDS spreads from 26 economically developed and less economically developed countries. Although their investigation centers on CDS spreads rather than sovereign bond spreads, the two securities are expected to behave coherently with one another, making the authors' findings relevant for this paper. First, they find that CDS spreads from different countries tend to be much more correlated than the respective equity indices of those countries. Second, they suggest that this higher correlation in countries' CDS spreads can be attributed to the dependence of sovereign credit spreads on a common set of global market factors, risk premiums and liquidity patterns. Third, they attribute much of the credit spreads movements to US equity and high-yield markets factors. Returning to the Euro Area and bond markets, Codogno et al. (2003) came across similar results, concluding that changes in international risk factors are the main drivers of yield differentials in the Euro Area, defining international risk factors as the difference between the 10Y US interest rate swap's fixed leg and the 10Y Treasury and the spread between AAA corporate bond with respect to the 10Y Treasury.

Lastly, it is important to expand further on Di Cesare et al. (2013) discovery of the relevance of banking domestic banking sector on sovereign bond spreads pricing. The financial sector is a very important industry in a country's economy, thus expected future economic fundamentals. On the one hand, shocks in the financial service industry propagate considerably to the real economy, affecting consumption and investments, thus reducing economic activity, which in turns impacts government revenues. On the other hand, when the sector comes under stress, governments are likely to propose banks rescue packages of different forms, hence creating expectations of greater budget deficits and higher levels of debt-to-GDP in the future. Consequently, strains of domestic commercial financial institutions tend to cause downward adjustments of the credit position of a country, by impacting both government inflows and outflows. Attinasi et al. (2009) investigated the effects of governments' commitments to rescuing the banking sector on sovereign yield spreads. Their results highlight that on top of economic fundamentals, international risk-aversion and liquidity proxies, announcements of rescue packages lead to upward reassessments of the market spreads. Moreover, they specified that what influences sovereign yield spreads is the not the size of the package announced, but rather the credibility of the commitment the government takes to stand ready to intervene. Accordingly, the authors formulated the "credit risk transfer hypothesis" whereby banks rescue packages are viewed by investors as commitments by the government to take over part of the risk and liabilities from the banks, which reflects to "reassessment of sovereign credit risk vis-à-vìs the private financial sector". However, the interaction between banks and governments may be more circular than unidirectional. European banks have considerable amounts of government debt in their balance sheet, hence a widening of the spreads for reasons unrelated to the healthiness of the financial sectors may in turn impact the financial services industry by devaluing the assets present in their balance sheet. Gennaioli et al. (2012) has in fact highlighted the role that strong financial institutions play in disciplining governments to be responsible in their fiscal expenses.

Therefore, financial and sentiment variables, whether they come under the shape of risk-aversion proxies or as the stock market performance and equity performance of the financial sector, seem to explain an additional portion of the sovereign bond spreads, on top of the fair spread estimated by economic fundamentals. Consequently, it comes as no surprise that a considerable portion of literature on sovereign spreads and yield estimates includes financial variables. Examples of the latter include papers previously mentioned, such as Di Cesare et al. (2013) and Delatte et al. (2017), as well as Cecchetti (2020), who investigated the drivers of sovereign CDS and bond spreads in the Euro Area and will be discussed in Section 3.

2.3 Estimating the fair values

In order to study how market sentiment and financial variables relate to the mispricing of government bond spreads, the model from Ceci and Pericoli (2022) "Sovereign Spreads and Economic Fundamentals: An Econometric Analysis" was used. Since fair value estimate was defined as the spreads estimated according to economic fundamentals, the latter model uses a set of economic variables and a set of control financial variables to estimate the fitted (fair) values of the spreads. The following is the equation estimated:

$$s_{it} = \alpha + \delta_i + \beta_0 Z_{it} + \beta_1 X_{it} + \beta_2 F_t + \epsilon_{it} \qquad (1)$$

s_{it} refers to country's i market spread at time t measured as the 10Y yield difference with respect to the German Bund, α is the constant, δ_i represents country-fixed effects, Z_{it} are the economic variables for the various countries, $X_{it}$and F_t are defined as variables representing the "risk attitude" of investors and are country specific and common to all countries, and lastly, ϵ_{it} are the residuals.

Focusing on the economic variables: i) is the debt-to-GDP ratio – OECD historical time series were used; ii) is the 5-years ahead average inflation rate iii) is the 1-year ahead average real GDP growth rate iv) is the average medium term growth forecast (5-year ahead real GDP growth average); v) is the unemployment rate. Unlike Barclays (2022), Ceci and Pericoli (2022) didn't take the difference respective to Germany of these five variables, rather they used the levels. Moreover, the data was either downloaded from DataStream or Bloomberg.

With regards to the risk attitude, non-fundamentals, variables ($X_{it}$and F_t) that were included as controls. X_{it} is the country specific ISDA Basis, which is the difference between sovereign CDS issued under the ISDA 2014 and those issued under ISDA 2003 protocol. The difference between the two protocols is that while the former considers debt redenomination in a different currency as a credit event, the latter doesn't. Hence, Gros (2018), as well as the authors, suggest that the ISDA basis proxies redenomination risk of a specific country's debt. Conversely, F_t is not country specific and is the Sentix index, which depicts the volume of "euro break-up" or similar phrases google searches. Accordingly, the Sentix represents the risk of the euro risk, rather than the domestic exiting risk. The inclusion of the latter variable in the regression can be attributed to the method followed by Di Cesare et al. (2012), which is also followed by the creators of the model.

Following Ceci and Pericoli (2022) methodology, the data collected was of monthly frequency[7] and from three Euro Area countries: Italy, France and Spain. Though, while the sample in the original research started in 2007 and ended in 2022, our sample started in 01-2014 and ended in 12-2022. The reason for starting our sample 7 years later resides in the impossibility in accessing previous data as the licenses at disposable were different than those of the authors of the model.

[7] For variables that are published on a quarter basis, the value was kept constant throughout the three months within the quarter, while data published on a daily frequency was aggregated to monthly by taking the average.

Table 1: Fair value model variables

Variable	Mean	Standard deviation
Market Spreads		
Italy	164.61	47.537
France	39.03	11.255
Spain	105.02	28.404
Debt-to-GDP		
Italy	138.8	6.526
France	104.1	7.604
Spain	106.8	6.741
Average expected inflation		
Italy	1.03	0.654
France	1.33	0.721
Spain	1.03	0.655
Average short-term expected real GDP growth		
Italy	1.49	1.679
France	1.84	1.655
Spain	2.25	1.727
Average medium-term expected GDP growth		
Italy	0.77	0.399
France	1.39	0.604
Spain	1.92	0.622
Unemployment rate		
Italy	10.11	1.783
France	8.46	1.121
Spain	16.56	3.948
ISDA Basis		
Italy	37.22	23.991
France	7.92	4.660
Spain	13.02	8.145
Sentix	10.26	8.875

The coefficients of the panel model with country fixed effects (equation (1)) were estimated using the Ordinary Least Squares method, which is the approach used by Ceci and Pericoli (2022). Moreover, the two authors deem appropriate employing a multi-country model as the three countries belong to an economically and financially integrated area and the securities in question are denominated in the same currency. After obtaining the coefficient, the in-sample estimate of the fair value can be carried out. Since fair value is defined as the spread determined exclusively by economic fundamental factors (current or expected), the fair spreads are the values fitted by using just Z_{it} and the country fixed effects:

$$\hat{s}_{it} = \hat{\alpha} + \widehat{\delta_\iota} + \widehat{\beta_0} Z_{it} \qquad (2)$$

2.4 Results from the estimation

The following are the coefficients estimated following Ceci and Pericoli (2022) methodology and using the Newey-West adjustment for addressing the heteroscedastic and autocorrelated nature of the residuals displayed in times of enhanced economic uncertainty. This adjustment doesn't influence the point estimates of the model, rather it modifies the standard errors to account for the two issues.

Table 2: Panel estimates using Italy, France and Spain

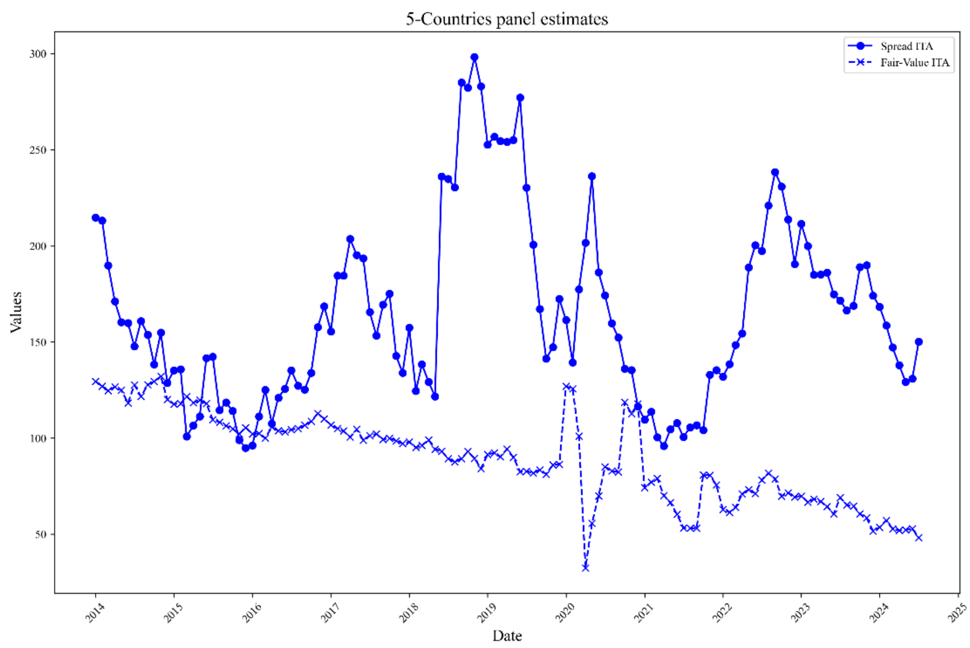
	Coefficients	***Standard Errors***	***t-Stat***	***P-values***
Constant	-66.732	23.563	-2.832	0.005
Debt-to-GDP	0.064	0.203	0.317	0.751
Inflation	82.592	29.775	2.774	0.006
Unemployment	8.563	0.934	9.169	0.000
GDP 1Y	-6.490	1.080	-6.009	0.000
GDP 5Y	10.268	2.963	3.465	0.001
Sentix	-0.225	0.170	-1.326	0.185
ISDA Basis	1.754	0.182	9.658	0.000
Italy Fixed Effects	70.735	9.951	7.109	0.000
Spain Fixed Effects	-13.576	8.720	-1.557	0.119
Number of Observations	306			
Degrees of Freedom (Error)	296			
R-squared	0.86			
Adjusted R-squared	0.85			
F-statistic (vs Constant Model)	226.04			

The coefficients displayed in Table 2 are somewhat different than those obtained by Ceci and Pericoli (2022). For example, both the unemployment and the inflation coefficient are of magnitudes considerably different than that of the original authors, who obtained 17.59 and 179.86 for unemployment and inflation, respectively. Moreover, the positive sign of the 5Y GDP coefficient is economically unreasonable despite being statistically significant. The coefficient being positive implies that if the average 5-year rate of growth for a country was to increase by 1 percentage point, the fair spread would increase by 10.3 if everything else remained equal. The latter scenario is counterintuitive as greater economic activity should result in higher government revenue, thus a lower risk of default and lower risk premia. Of course, greater GDP has important implications on monetary and could also be the case that it's government spending driven growth, though typically, and as in Ceci and Pericoli (2022), better growth outlook should have the opposite effect on spreads. Additionally, the Sentix and ISDA Basis coefficients are not perfectly in line with the ones of the original paper, who obtained 2.08 and 1.01 respectively. Lastly, there is a slight difference between the coefficient that result to be statistically significant in this regression as opposed to the outputs obtained by Ceci and Pericoli (2022): their only not statistically significant coefficient was that of medium-term growth, whereas the ones of this regression are those of debt-to-GDP and Sentix. Given the importance of the differences, greater investigation was needed to address the issue.

First of all, the sample used by the two authors covered the sovereign debt crisis of the Euro Area, while the one in this paper did not. Secondly, both samples cover a period of economic stagnation and very low inflation, with Ceci and Pericoli (2022) sample covering periods of higher inflation in the early data points while the sample of this regression started in 2014. Consequently, coupling these differences with the issue of having a small sample (306 observations only), thus greater likelihood of in-sample overfitting, it is possible that the different coefficients are rooted in the model fitting slightly different economic environments. This explanation reconciles with obtaining values for both the R-Squared and the Adjusted R-Squared that were higher than the original paper (0.858 vs. 0.72 and 0.855 vs. 0.715). To check whether this hypothesis could be reasonable, the sample was lengthened, and coefficients were compared again to those estimated by Ceci and Pericoli (2022).

Below, the graphic comparison between fitted spreads and market spreads for Italy can be found, while the graphs of the remaining two countries are in the appendix (Graphs 8 and 9).

Graph 1: Market spread vs. fitted values – Italy



Since this is a panel model, a possible way to widen the sample size is by including additional countries in the regression. As Ceci and Pericoli (2022) relied on Cesare et al. (2013) to determine the specifications of the model, the latter paper was in turn employed to decide which other countries to include. Cesare et al. (2013) estimated their fair value models using Italy, Spain, Portugal and Ireland, while excluding Greece because of the events of 2009. Therefore, it was decided to include Ireland and Portugal to the panel and carry out the estimates of the coefficient as done for the panel regression using 3 countries. In addition, the sample was also lengthened by ending it in 07-2024, adding two years of data points. By carrying out these procedures, another 328 observations were used to estimate the equation (1) in the 5-countries panel model. The results were the following:

Table 3: Panel estimates using 5 countries

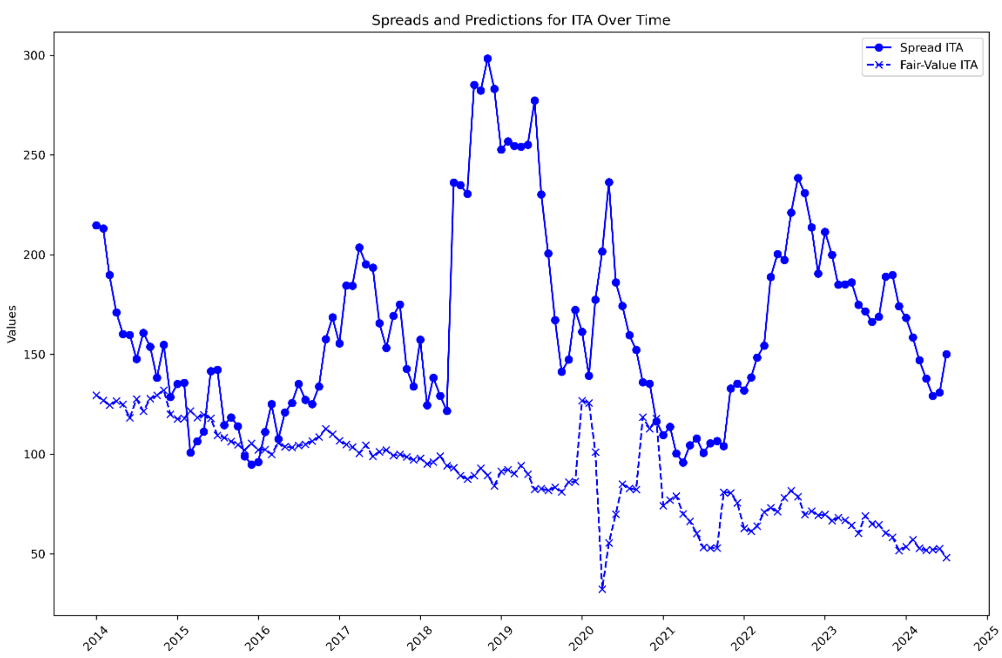
	Coefficients	***Standard Errors***	***t-Statistics***	***P-values***
Constant	-285.646	23.465	-12.173	0.000
Debt-to-GDP	2.020	0.227	8.914	0.000
Inflation	59.499	5.938	10.021	0.000
Unemployment	13.767	0.987	13.942	0.000
GDP1Y	-11.996	1.337	-8.971	0.000
GDP5Y	-1.670	0.435	-3.840	0.000
Sentix	0.077	0.217	0.355	0.723
ISDA Basis	1.986	0.147	13.543	0.000
Italy Fixed Effects	-29.614	9.545	-3.102	0.002
Spain Fixed Effects	-53.726	8.422	-6.379	0.000
Irelands Fixed Effects	55.588	3.928	14.152	0.000
Portugal Fixed Effects	52.589	3.463	15.187	0.000
Number of Observations	634			
Degrees of Freedom (Error)	622			
R-squared	0.79			
Adjusted R-squared	0.79			
F-statistic (vs Constant Model)	237.31			

By including Ireland and Portugal to the panel, it can be seen from Table 3 that the coefficients have changed. Not only the 5 years ahead average real GDP growth coefficient is now negative, but also unemployment, 1-year ahead GDP growth and Debt-to-GDP coefficients are closer to the ones reported by Ceci and Pericoli (2022). The biggest difference in the coefficients is the constant term, with which we obtain -285.65, whereas Ceci and Pericoli (2022) obtained -538.86, and the inflation coefficient which was 179.85 in the original paper and only 59.5 in this second regression.

However, the difference in time periods observations assessed had a role in these differences. Moreover, due to inaccessibility of the same data sources as Ceci and Pericoli, instead of using the Consensus Economics medium term inflation forecast, we employed the market consensus expectations by utilizing the 5Y breakeven inflation of each country. Similarly, the real GDP 1 year ahead average growth was obtained from Bloomberg's aggregation of professionals' estimates instead of Consensus Economics, thus the constituent list used in the aggregation may differ. Taken together, these differences in the underlying data set are likely the reason for mismatches of the coefficients, also considering that the transformations made by the two authors were the same as those carried out in our series and that the same estimation methodology, namely OLS, was used.

After the 5-country panel coefficients were estimated, the fitted (fair) spread values were obtained by employing equation 2. The following are the results for Italy, in the appendix the fair spreads for France, Spain, Ireland and Portugal can be found in the appendix (Graph 10- to 13).

Graph 2: Market spreads vs. fitted spreads - Italy



As expected from the findings of previous literature, there is a considerable divergence between the fair value estimates and the market spreads. On average, in the sample period the difference amounts to 74 basis points and the observations range between -21 and 209 b.p., with the peak difference reached in November 2018. Moreover, Graph 4 illustrates that mispricing tends to widen in periods that the market spreads increase substantially and decreases in periods that the spreads tighten. Though, the fair estimates tend to be quite persistent in level, with the only exception being the Covid-19 period, which can be considered reasonable as debt-to-GDP ratios widen due to the denominator effect and the 1-year ahead growth expectations spiked amid the lockdown, as a bounce back of the economy was expected with the withdrawing of the lockdown measures. Although regarding different periods, these findings coincide with Cesare et al. (2013), who recorded significant differences between the fair value estimates and the market spreads even after accounting for nonlinear relationships in times when the economic fundamentals didn't experience such spikes and trough as in 2020.

3. Data

After having obtained the fair value estimates of spreads for the 5 countries in the period between 01-2014 and 07-2024, the following step was delving into the market sentiment and financial variables. Accordingly, the investigation continued by looking for specific market sentiment variables, as proxied by volatility on financial markets and uncertainty in economic prospects, and financial variables, i.e. returns of stock markets and its specific sectors. This section explains the data set employed and the reasons for the variables' inclusion in the set of data.

3.1 Market sentiment and financial variables

In order to determine the variables to include in this analysis present literature has been considered. Most variables were cited in the various papers discussed in Section 2.2, though special contributions came from Cecchetti (2020), Borri (2018), Delatte et al. (2017), Longstaff et al. (2011) and the ECB's May 2014 Financial Stability Review Report. Out of the variables cited in literature some were not available due to sources inaccessibility with the available subscriptions to data providers. Additionally, the variables in the literature included were previously analyzed in the context of sovereign CDS spreads rather than sovereign bond spreads, thus creating room for potential new findings. The following is an exhaustive list of the sentiment and financial variables used:

<u>Sentiment variables</u>

- VSTOXX: Euro Area's implied stock market volatility (European VIX). Taken in monthly percentage change and downloaded from DataStream.
- Economic Policy Uncertainty: FRED provides indexes of countries' economic policy uncertainty. Out of the 5 countries in the panel, only 4 countries had their corresponding index, with Portugal being the exception. Accordingly, the Euro Area's index of economic uncertainty was included instead of Portugal's. The data was available from DataStream and was taken as monthly percentage changes of the index.

- CISS indicators[8]: 4 different indicators on equity, bond market, bank's equity and FX financial stress for Euro Area as a whole. Source: DataStream.

Financial variables

- TOTMKEN (PE): The Price-Earnings ratio of the aggregate Euro Area stock market index. The series was transformed by taking the monthly percentage changes and was downloaded from DataStream. According to Cecchetti (2020), after the transformation this series should proxy the variation in the equity risk-premium.
- A Country's banking sector returns: the monthly returns of the banking sector stock price index for each country of the panel (Italy, France, Spain, Ireland and Portugal). The source is DataStream.
- MSCI EUROPE: the monthly returns of the European stock market index aggregated by MSCI. The data was downloaded from DataStream.
- S&P 350: Europe's 350 leading 350 blue chip companies' monthly returns, downloaded from DataStream.
- Europe's banking sector returns: the monthly returns of the European banking sector index provided by DataStream (BANKSER)

The sample covered the period between 01/2001 and 07/2024 with monthly frequency. Moreover, each series was tested for stationarity, by firstly plotting the series, and subsequently by analyzing the ACF and the PACF, carrying out the Augmented Dickey-Fuller Test using AIC criterion, and lastly inspecting the unit circle. If the series were deemed not stationary, the first difference was taken, and the examination was carried out again. Most series didn't require any further transformation than those previously explained (most variables were taken as monthly percentage changes), while the few remaining ones only required to be differenced ones. The summary statics of the series in questions can be found in the appendix (Tables 8 and 9).

With regards to the rationale of the choice of variables, the sentiment variables included are related to implied volatility present in financial market and economic policy uncertainty. The former, may help capture the "flight to safety" and "flight to liquidity" phenomenon that are uncaptured by a

[8] CISS: Composite Indicator of Systemic Stress. Introduced by the ECB with "CISS – A Composite Indicator of Systemic Stress in the Financial System" – Working Paper Series, March 2012

country’s economic fundamentals, while the latter should proxy the uncertainty and possible future deteriorations underlying the current economic fundamentals and the expected future ones. The financial variables are on the one hand linked to the financial sectors of the countries, thus proxy the risks associated to possible banks rescue packages and the negative economic spillovers of a distressed banking sector. On the other hand, financial variables could help explain the portfolio reallocations and flows to varying levels of risky securities that performance of equity markets may cause.

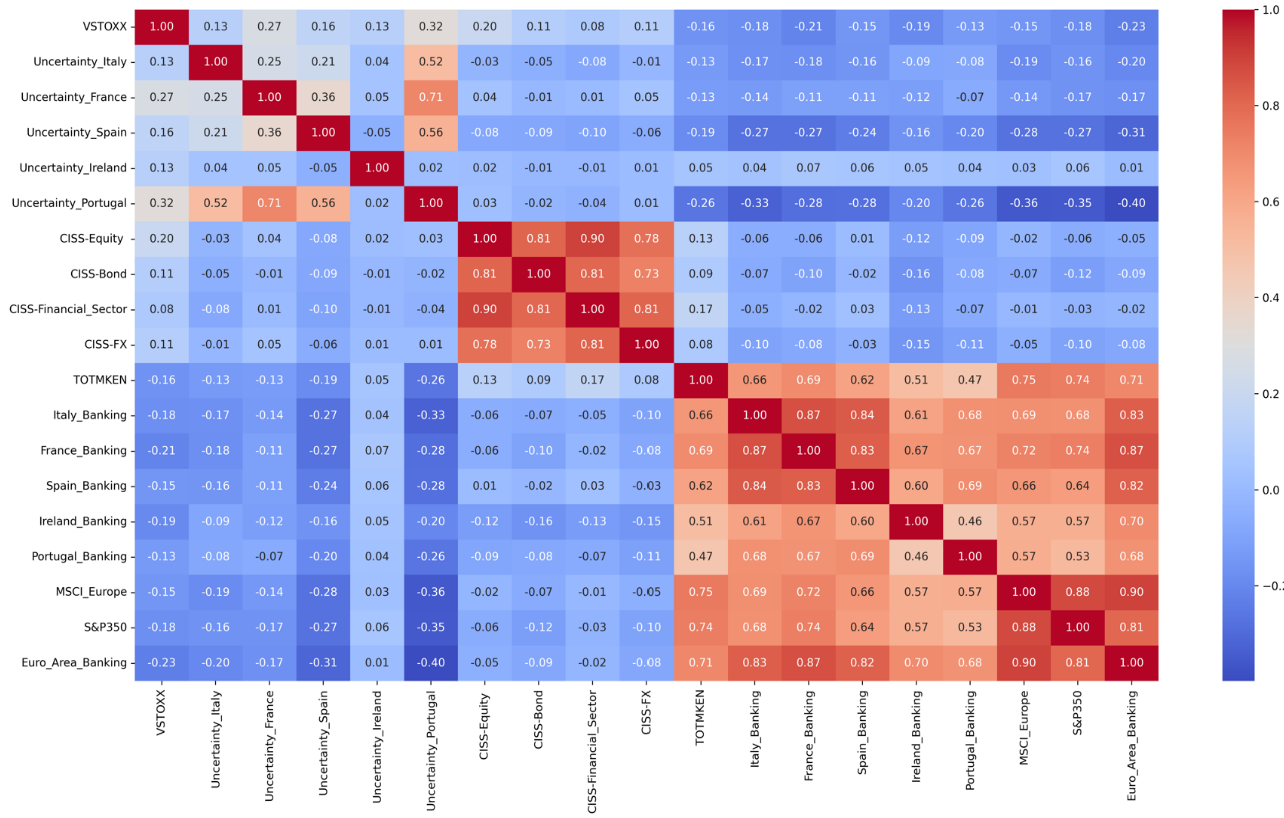
Additionally, it must be noted that all the series are related to the European geographical area instead of a mix between European and global variables. The reasoning behind this can partly be attributed again to the limited access to the data, but more importantly the fact that in more recent literature mostly European variables have been studied, whereas past research on global variables is more extensive.

Lastly, since the composition of European stock indices is extensively made up of banks equity and economic uncertainty, systemic stress and implied volatility tend to have close links, the following subsections will deal with how the dataset was reduced and used.

3.2 Data cleaning and reduction

In order to ease the understanding of the reasoning behind the procedures utilized in rendering the data useful for the investigation, a brief contextualization is needed before exploring the methodology with which the dataset was reduced to a smaller subset of the set explained in Section 3.1. Given the aim of this research is to investigate the effects financial and market sentiment variables on the mispricing of spreads obtained using Ceci and Pericoli (2022), the initial research methods focused on using a multivariate linear regression to see if the aforementioned variables could explain the variations mispricing. Accordingly, as there were concerns that the time series from section 3.1 could be highly correlated to one another, thus resulting in multicollinearity issues in the regression model, the correlation matrix was estimated and analyzed:

Figure 1: Correlation matrix of sentiment variables



By looking at the figure above it is evident that the data presents clusters of variables that are highly correlated to one another. This is not surprising as amongst the data set various time series are stock indices, some of which include shared equity securities, and the banking sector makes up a considerable part of the European equity markets as well. Furthermore, the CISS indicators also display high intra-group correlations, though they correlate little with other sentiment variables.

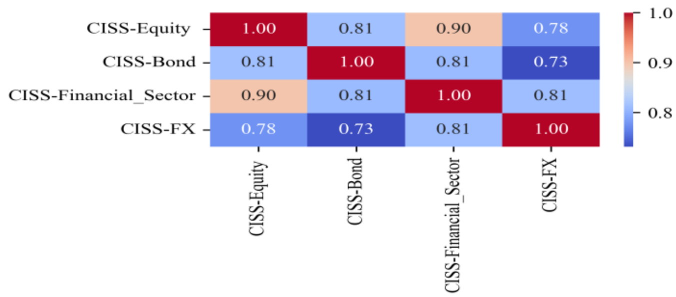
Following these findings, some adjustments were required. Starting from the financial variables, since the MSCI Europe and the S&P350 if regressed one on the other have a high R-squared and can be deemed to be substitutable with one another, only the MSCI Europe was kept in the following steps of the analysis. In addition, by following the same reasoning, only one between the European banking sector index and the country specific banking sector index was needed. Accordingly, only the country specific banking sector was kept, given that such regressor was used in Cecchetti (2020), while the European banking sector was included as found on DataStream when searching for the time series. With regards to the market sentiment variables, on the one hand, the economic policy uncertainty indicators are country specific, thus one of the five was regressed on the mispricing per country, meaning that even if amongst them considerable correlation was present, it would not pose multicollinearity concerns. On the other hand, the only subset of series that displayed correlations of truly worrying levels was composed by the CISS indicators, hence those four indicators could be dealt with separately.

Therefore, the time series remaining after the first discretionary reduction were VSTOXX, country specific policy uncertainty indices and CISS indicators with regards to financial variables, and a country's banking sector monthly equity performance, TOTMKEN and MSCI Europe with regards to the financial variables. Moreover, because the CISS indicators could not be included together in a multivariate model as displayed very high correlations between each other, the Principal Component Analysis was used to deal with the issue.

3.3 Principal component analysis of CISS indicators

The aim of employing the Principal Component Analysis (PCA) is to obtain a different representation of the four aforementioned dimensions in terms of four principal components that are orthogonal (uncorrelated) with each other, where the first principal component explains the greatest amount of variance of the underlying dimensions out of the four components. Thus, this method solves the issues related to multicollinearity and identifies the common drivers behind the variations of the four CISS indicators. Consequently, instead of discretionarily deciding which indicator to include and the ones to exclude, through the PCA a certain threshold of explanation of the original covariance matrix of the dataset is used to determine how many of the principal components to include. Despite the problems this methodology solves, there are also some limitations with the principal components obtained. Firstly, the principal components are linear combinations of the original variables that are weighted sums of the underlying observations. Consequently, while the CISS indicators have a clear financial meaning, the principal components do not, leaving the interpretation of each component open to discussion. This weakness will also complicate the interpretation of the coefficients in the later parts of sections 4 and 5. Secondly, the PCA does not capture relationships that are more complex than the linear ones, hence this methodology might fail if the relationships between the CISS indicators were not linear.

Figure 2: Correlation matrix of CISS indicators[9]



In section 3.1 it was ensured that all time-series included in the analysis were stationary before carrying out any further investigation, hence before proceeding with the PCA the four indicators only had to be standardized. Then the covariance matrix was computed, which allowed to proceed with the Eigen Decomposition from which the Eigenvalues and the Eigenvectors were obtained. The results are summed up in the table below, where the explained variance of each component, the cumulative explained variance and the eigenvectors can be seen.

Table 4: Principal Component Analysis of CISS Indicators

Principal Component	*Explained Variance*	*Cumulative Explained Variance*
PC1	0.856	0.856
PC2	0.068	0.924
PC3	0.051	0.975
PC4	0.025	1

Table 5: Eigenvectors of each Principal Component

	PC1	***PC2***	***PC3***	***PC4***
CISS-Equity	0.511	0.178	0.519	0.662
CISS-Bond	0.489	0.590	-0.641	-0.034
CISS-Financial Sector	0.515	0.003	0.435	-0.739
CISS-FX	0.484	-0.787	-0.362	0.122

The first principal component explains over 85% of the total variation of the 4 indicators, which aligns with what could be expected by looking at the very high correlations in Table 2. As a rule of thumb, the number of principal components to keep corresponds to the first principal component whose cumulative explained variance amounts to 80%. Therefore, two considerations were made. First, having few regressors in the regression carried out in the next part of the research would help

[9] The following correlation matrix was computed before the series were standardized; thus it is simply a snapshot of Figure 1 with only CISS indicators included.

dealing with the relatively small sample at disposable (634 observations). Second, the first principal component already explains a big portion of the original covariance matrix. As a result, it was decided to keep just the first principal (PC1) component and discard the other ones.

As previously mentioned, the financial interpretation of principal components is more ambiguous than the indicators in their original form. However, by inspecting the eigenvectors an idea can be formulated as to what the principal components could potentially signify financially, especially considering that the 4 features used are very similar in their workings (an increase in the indicator implies enhanced financial stress), thus easier to interpret. Since only PC1 was kept, the attempt to interpret the meaning will only focus on this component. As shown in Table 5, the components of the eigenvectors are positive for all underlying series of PC1, implying that as any of the four CISS indicators rises, so does PC1, assuming all else equal. Thereby, the first principal component could be an indicator of Euro Area financial market stress. In other words, monitoring PC1 could provide insights into the healthiness of the Euro Area's financial system. Accordingly, an increase in PC1 could mean an improvement in the confidence amongst investors. Conversely, a decrease PC1 may indicate a deterioration in investors' confidence. Having established a rough definition of this component is beneficial for the next parts of the research, as interpreting the meaning of the coefficients from the multivariate regressions is going to be simpler and identifying financially dubious results more straightforward.

4.Multivariate panel regression model

The fair value spread estimates of Section 2.4, and the past literature highlights how there are additional influences on the sovereign risk premia on top of a country's current and expected economic fundamentals. Accordingly, by analyzing the portion of market spreads unexplained by fundamentals, i.e. the mispricing, with respect financial and market sentiment variables, the aim is to find that a part of the mispricing can be captured.

4.1 Specifications

Di Cesare et al. (2013) provided inspiration on the means through which to assess the impacts of market sentiment and financial variables on mispricing. They used a multivariate regression, which is the methodology that was followed in this investigation as well and which motivates the reductions of the features carried out in the previous section. However, unlike Di Cesare et al. (2013) who carried out regressions at country level and not by employing a panel model, we decided to first investigate the 5 countries together, using panel regression. Consequently, an initial assessment between the independent variables and the mispricing was done using the following equation:

$$\Delta Mispricing_{i,t} = \alpha + \delta_i + \beta_1 VSX_t + \beta_2 TOT_t + \beta_3 BnkSec_{i,t} + \beta_4 EconP_{i,t} + \beta_5 PC1_t + \varepsilon_{i,t} \quad (3)$$

Where $Mispricing_{i,t}$ was obtained by taking the difference between $s_{it} - \widehat{s_{it}}$ of equation (1) and (2) using the spreads fair value estimates from the 5 country panel model; δ_i represented country fixed effects[10]; VSX_t stands for VSTOXX, TOT_t stands for TOTMKEN (price-earnings of the European stock market); $BnkSec_{i,t}$ is the monthly performance of a country's banking sector stock index; $EconP_{i,t}$ a country's economic policy uncertainty index; and $PC1_t$ the first principal component computed in the Section 3.3[11]. Since the mispricing computed in Section 2.4 are available from 01/01/2014 until 01/07/2024 for Italy, France, Spain, Ireland and France, the sample

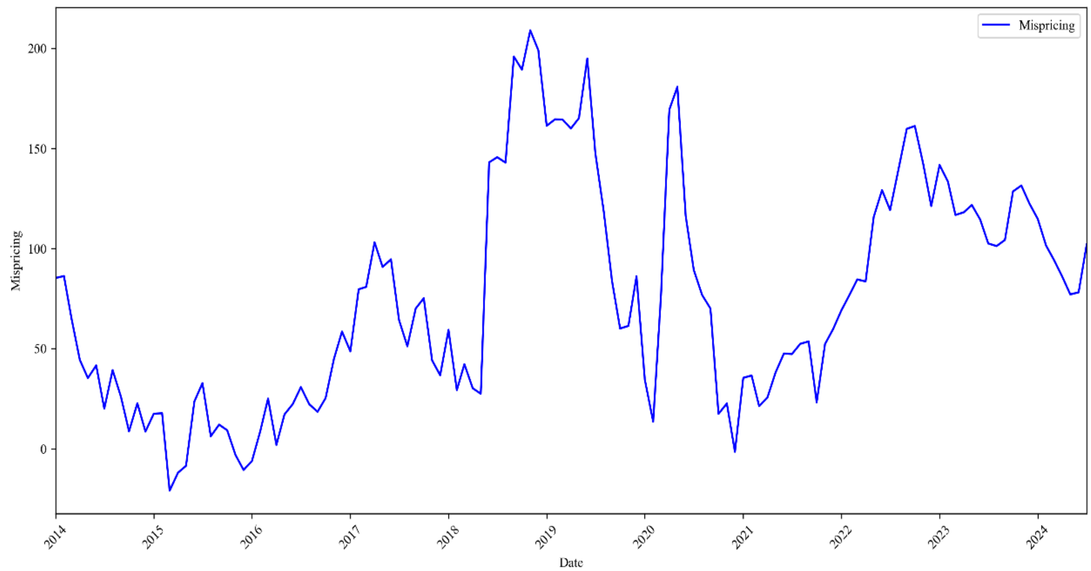
[10] The dummies included were for Italy, Spain, Ireland and Portugal. France was left out to avoid incurring in multicollinearity errors.
[11] The PCA analysis was carried out with monthly observations starting in 01/01/2008. Therefore, in equation (3), the values of PC1 were taken from 01/01/2014, which is date from which the mispricing is available.

used to estimate equation (3) contains the latter countries and with data belonging to the former time period.

The reader will have noticed that equation (3) does not include the MSCI Europe equity index in its specification. The reasoning behind this decision can be found in Figure 1, the correlation matrix, where the MSCI Europe is estimated be positively correlated with the *BnkSec* of each country, especially France, and with TOT_t. Therefore, initially a slightly different version of equation (3) was estimated, which included the MSCI Europe and the residuals obtained from simple univariate regressions of each country's banking sector equity performance on MSCI Europe. However, various considerations were made regarding the latter specification. First, the financial meaning of the residuals from the *BnkSec* on MSCI Europe regressions was unclear, making the interpretation of the coefficient very difficult and open to extensive discussion. Second, the financial reasoning behind including MSCI Europe in the specification of the variant of equation (3) was questionable. This is because in literature the rationale for the inclusion of the MSCI Europe in an estimation of the sovereign bond spread is related to the possible ability of the stock index to capture the expectations of future GDP growth of the geographic area, which is something that was already done at country level in Ceci and Pericoli (2022) model. Third, despite these two issues, a trial using MSCI Europe and the *BnkSec* residuals in the specification was made, however there was no evidence of statistical significance of the two variables and, as expected, their coefficients lacked interpretability. Consequently, though MSCI Europe is a financial variable and though it might capture expectations of other variables besides economic growth, it was decided to drop the time series and rely solely on the countries' financial sectors' equity performance.

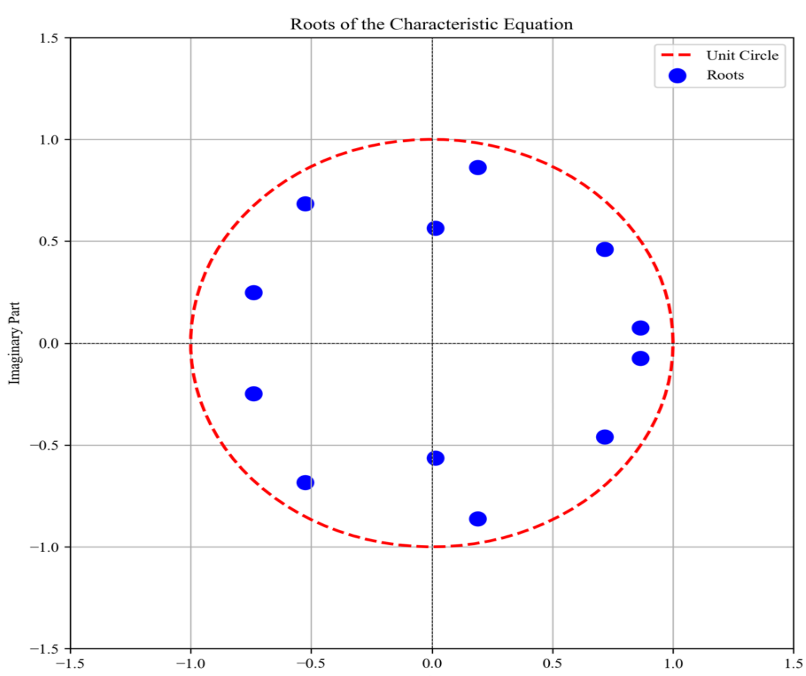
Moreover, it doesn't go unnoticed that the first difference was taken of the spreads mispricing ($\Delta Mispricing_{i,t}$). This is because by plotting the mispricing at country level, take Italy as an example, it was noticed that series did not resemble a stationary one.

Graph 3: Italy's Mispricing



Because of this doubt a stationarity test was carried out using the ADF Test. The result was a P-Value of 0.07, which is not definite as the null hypothesis (Mispricing non-stationary) could be rejected if the 10% significance level is, but not the 5%. Accordingly, we looked at the roots of the Characteristic Equation. By graphing the results, the following image was obtained:

Graph 4: Roots of the Characteristic Equation for Italy Mispricing



The roots all lying within the unit circle gave a much clearer interpretation of whether the mispricing series for Italy was stationary or not. As further evidence for the non-stationarity of the time series, an AR (2) model estimated on the mispricings resulted to the coefficient of the first lag being equal to 1.04 and of that of the second lag equal to -0.23. Therefore, having established that the series was not stationary, the first difference was taken. The procedure was carried out for all other countries, and the results were similar.

4.2 Results and interpretation

Following these adjustments to the data at our disposal, equation (3) was estimated. The outputs obtained were the following:

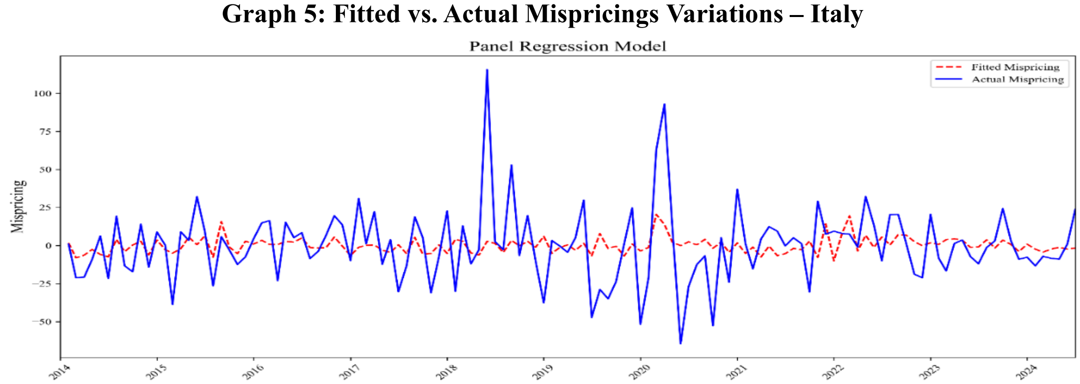
Table 6: Multivariate Panel Model Regression Outputs

	Coefficient	***Standard Error***	***t-stat***	***Probability***
Constant	0.605	1.177	0.514	0.607
VSTOXX	0.150	0.031	4.779	0.000
TOTMKEN	0.078	0.158	0.497	0.619
Banking Sector	-3.995	7.266	-0.550	0.582
Economic Policy Uncertainty	0.018	0.013	1.379	0.168
PC1	1.835	0.587	3.127	0.002
Italy Fixed-Effects	0.155	2.324	0.066	0.947
Spain Fixed-Effects	0.283	1.791	0.158	0.875
Ireland Fixed-Effects	0.064	1.426	0.045	0.964
Portugal Fixed-Effects	-1.106	2.388	-0.463	0.643
Number of Observations	629			
Degrees of Freedom (Error)	619			
R-squared	0.08			
Adjusted R-squared	0.07			
F-statistic	4.62			

Starting from the R-Squared and the Adjusted R-Squared, it is evident that the independent variables included in the model explain little of the variability of $\Delta Mispricing_{i,t}$. However, by looking at the singular coefficients, it is noticeable that the coefficient for VSTOXX is statistically relevant at a 1% significance level and has a positive value. Therefore, besides the statistical relevance, also the financial interpretation of the coefficient is reasonable: higher equity market implied volatility is likely to result to an increase in the variation of the mispricing following the flee of investors from riskier securities to safe havens, with the economic fundamentals being unable to capture, at least not fully, these portfolios rebalance. In addition, the first principal component drawn from the CISS indicators is also statistically relevant at a 1% significance level and with a positive coefficient. The PC1 coefficient has thus a logical financial interpretation, which is similar to the one of the VSTOXX coefficient. With regards to the remaining coefficients, none are statistically significant, but what is more confusing is that the sign of the TOTMKEN is the opposite of what would be expected from reasoning financially. TOTMKEN should proxy the equity risk premium, whereby when the price-earnings decrease, the equity risk premium increases. The series is included in the regression as the monthly percentage changes in the index, hence a decrease with respect to the previous month signifies an increase in the risk premia, which could be expected to enhance the variation in the mispricing (thus have a negative coefficient) but doesn't seem to do so. It must be reminded that the coefficient is not statically significant, though its positive sign is still puzzling. Conversely, despite being not statically significant, the banking sector coefficient is negative, which aligns with Attinasi et al. (2009) hypothesis of "Transfer of Risk". This is because if a country's financial sector performs poorly, it should indicate possible repercussions on the future economic fundamentals, some of which might not be captured by the market consensus expectations, and thus potentially result to increases in the mispricings, bringing them further away from the average. With regards to the economic policy uncertainty, the coefficient is of the expected sign, but not statistically significant. Lastly, the F-Statistics is 4.62, suggesting that the null hypothesis of the coefficients being jointly zero is rejected for 5% significance level, after considering the degrees of freedom (619 and 9).

Below, the graph of the fitted vs. the actual mispricings monthly variations for Italy can be found. As the low R-Squared anticipated, the model from equation (3) displays difficulties in promptly fitting the observed variations. The graphs for the remaining countries are in the appendix.

Graph 5: Fitted vs. Actual Mispricings Variations – Italy



Slightly different specifications of the model were tested as well, with the VSTOXX, Economic Policy Uncertainty and PC1 always kept as regressors, while the TOTMKEN and the Banking Sector were inserted and dropped one at the time. The coefficients of the latter three independent variables remained relatively unchanged in all the specifications, both in their values and in statistical significance. Moreover, the R-Squared of the model underwent minimal changes, while the R-Squared Adjusted slightly improved in the regression with just the three aforementioned independent variables and the country fixed effects.

These low proportion of significant coefficients was not expected before running the regression. This is because Di Cesare et al. (2013) obtained greater explicability of spreads and yields by using sentiment (as proxied by market volatility) and financial variables as regressors. Therefore, we reasoned that while a panel model is appropriate for estimating the fair value of spreads in a financially and economically integrate area, the heterogeneity of each country's debt may play an important role when assessing mispricings in reference to financial and sentiment variables. By looking at the different countries estimates of the fair spread value obtained under the 5 countries panel mode, the divergence of the market spreads relative to the fitted ones was considerably different for each country, both in terms of moments and magnitudes. Consequently, the reactions of investors to enhanced uncertainty and deterioration of the banking sectors may vary depending on the country. This implies that the country fixed effects included in equation (3) may not capture the discriminations held by investors on different countries sovereign securities. Additionally, Di Cesare et al. (2013) did not employ panel regressions in their investigation, but rather separate regressions on each country. Because of these reasonings and literature evidence, we decided to try an alternative method of assessment of the relationships between mispricings and financial/sentiment variables.

5. Multivariate time series model

As a reaction to the unexpected results, we tried this second approach to see whether further insights could be added to the research and if the outputs of this second method would reconcile with the expectations based on previous literature.

5.1 Specifications

As previously mentioned, we substituted the panel model with a country specific multivariate regression. The specifications of the estimated regression were the following:

$$\Delta Mispricing_t = \alpha + \beta_1 VSX_t + \beta_2 BnkSec_t + \beta_3 EconP_t + \beta_4 PC1_t + \varepsilon_t \quad (4)$$

Like for equation (3), the sample used to estimate this regression included Italy, France, Spain, Ireland and Portugal, and contained observations of the period between 01/01/2014 and 01/07/2024.

Besides the common differences between a panel model and time series regression, equation (4) also does not contain TOTMKEN as an independent variable. We decided to drop TOTMKEN because of various considerations. First, a preliminary analysis, which included TOTMKEN, displayed that its coefficient was not statistically significance for any of the five countries. Second, the Adjusted R-Square improved in all countries in the regressions without the TOTMKEN, while the R-Squared only saw minor changes. Third, the measure was found only in Cecchetti (2020), whereas the other variables could be found in multiple papers which provide thorough reasons for their inclusion. Accordingly, considering these three arguments and in the interest of making the model parsimonious, the TOTMKEN was not included in the specification for this time series model.

5.2 Results and explanations

The equation was estimated using the Ordinary Least Squares and the following results were obtained:

Table 7: Time-Series Model Outputs

	Coefficient	*Standard Error*	*t-stat*	*Probability*
Italy				
const	0.493	2.689	0.183	0.854
VSTOXX	0.236	0.089	2.663	0.008
Banking Sector	-4.654	16.600	-0.280	0.779
Economic Policy Uncertainty	0.097	0.034	2.839	0.005
PC1	2.592	1.667	1.555	0.120
Number of Observations	126			
Degrees of Freedom (Error)	121			
R-squared	0.14			
Adjusted R-squared	0.11			
F-statistic	5.09			
France				
const	-0.015	1.538	-0.010	0.992
VSTOXX	0.118	0.063	1.855	0.064
Banking Sector	14.924	9.191	1.624	0.104
Economic Policy Uncertainty	0.042	0.029	1.447	0.148
PC1	0.890	1.074	0.829	0.407
Number of Observations	125			
Degrees of Freedom (Error)	120			
R-squared	0.11			
Adjusted R-squared	0.08			
F-statistic	3.43			
Spain				
const	0.974	1.843	0.528	0.597
VSTOXX	0.100	0.067	1.488	0.137
Banking Sector	10.862	13.487	0.805	0.421
Economic Policy Uncertainty	0.054	0.027	1.989	0.047
PC1	2.148	1.271	1.690	0.091
Number of Observations	126			
Degrees of Freedom (Error)	121			
R-squared	0.10			
Adjusted R-squared	0.07			
F-statistic	3.62			
Ireland				
const	0.434	1.136	0.382	0.702
VSTOXX	0.094	0.041	2.271	0.023
Banking Sector	-1.544	9.884	-0.156	0.876
Economic Policy Uncertainty	-0.010	0.011	-0.882	0.378
PC1	0.376	0.788	0.478	0.633
Number of Observations	126			
Degrees of Freedom (Error)	121			
R-squared	0.07			
Adjusted R-squared	0.04			
F-statistic	1.89			
Portugal				
const	0.256	2.616	0.098	0.922
VSTOXX	0.169	0.092	1.841	0.066
Banking Sector	-6.657	15.719	-0.423	0.672
Economic Policy Uncertainty	0.105	0.102	1.032	0.302
PC1	3.509	1.898	1.849	0.065
Number of Observations	126			
Degrees of Freedom (Error)	121			
R-squared	0.11			
Adjusted R-squared	0.08			
F-statistic	3.22			

Out of the four explanatory variables, the VSTOXX recorded the greatest proportion of statistically significant coefficients. For Italy and Ireland, this regressor was relevant at 1% and 5% significance levels respectively. However, when increasing the significance level to 10%, four out of five countries displayed statistically relevant coefficients, with France and Portugal joining Italy and Ireland. Moreover, the coefficient is positive for all five countries, but the magnitude is slightly different in each, with Portugal's and Italy's variations in mispricings being the most sensitive with coefficients of 0.089 and 0.092 respectively. All VSTOXX coefficients having a positive sign is financially logical as explained in the results of the multivariate panel model in the section above. Additionally, 4/5 countries having at least a p-value smaller than 0.1 is supportive of the findings from the previous section.

Economic policy uncertainty also resulted to have p-values below 0.05 in 2 countries, but this time the couple was composed by Italy and Spain. Though, unlike the VSTOXX coefficients, when significance level is brought to 10%, no other countries join the group. In addition, all countries except Ireland have a positive coefficient for the explanatory variable in question, making Ireland the only country with illogical results financially speaking. Furthermore, it is also the country whose p-value falls the furthest away from the levels that can suggest statistical relevance.

With regards to the PC1 of the CISS indicators, only Spain and Portugal obtained coefficients that fall below 0.1 p-value, though not below the 0.05 threshold. All of the five countries display positive coefficients, which again is logical given that an increase of PC1 signals a deterioration of the health of financial markets of the Euro Area. The fact that the coefficient is considerably bigger for Italy, Spain and Portugal is also interesting to note, as, out of the sample group, those countries have been known to have the most issues with keeping their spreads under control in the last 10 years. Nevertheless, these results somewhat contrast those of the panel regression model, which indicated at a statistically significant PC1 with p-value of 0.002.

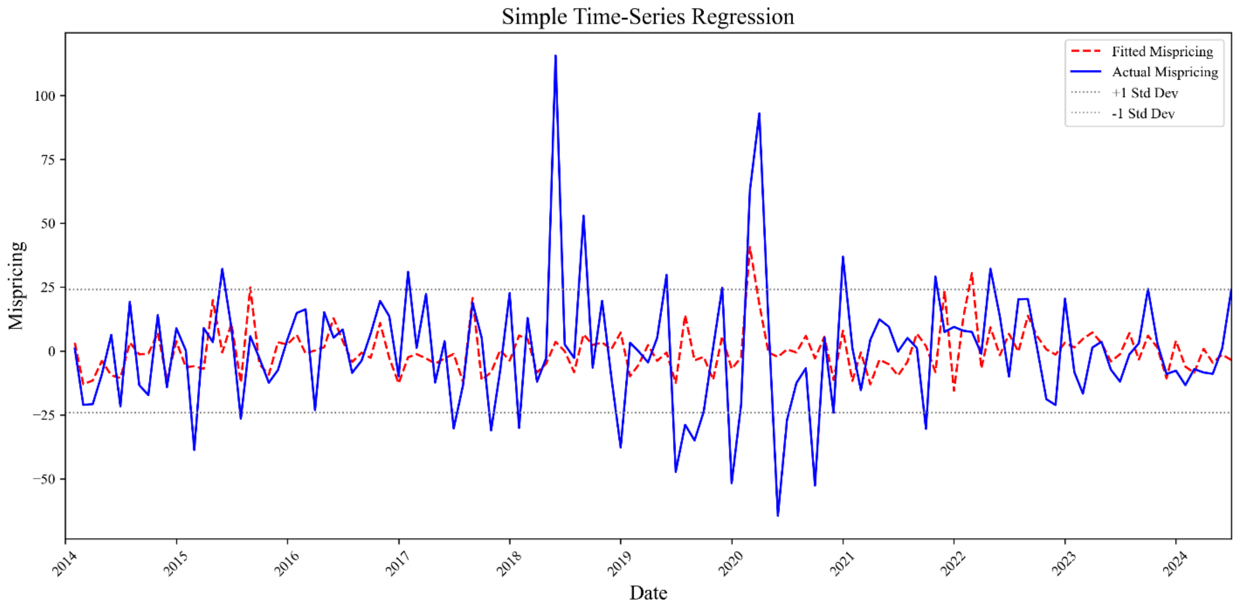
The fourth and last explanatory variable, the banking sector, was not significant in any of the 5 regressions. Additionally, the coefficient was negative for Italy and Ireland and positive for the other three countries. Though there is no statistical evidence of this explanatory variable influencing the variations in the mispricing variations, it is interesting to see the difference in the signs amongst the various countries. Attinasi et al. (2009) suggested "transmission of risk hypothesis" while Gennaioli et al. (2012) concluded that domestic banks are sensitive to devaluations of sovereign securities through the devaluations of the assets on their balance sheets. Consequently, the differences displayed by the countries might be partly attributable to the forces having the better on one another, with the one coming out on top varying country by country. Again, the fact that none of 5 coefficients was statistically significant signifies that the latter statement must be taken with caution.

The F-tests suggest that in four out of the five countries the null hypothesis of all regression coefficients to be equal to zero with at least a 5% significance level is rejected. Ireland is the only country that fails to reject to the null hypothesis, even when enlarging the significance level at the 10% threshold. Additionally, Ireland is also the country with the lowest R-squared and Adjusted R-Squared values, 0.07 and 0.04 respectively. On the other hand, Italy has the highest values of the latter two measures (0.14 and 0.11), followed by France and Portugal (0.11 and 0.08 for both countries), and then by Spain (0.10 and 0.07). Therefore, like what was found with the panel model, these sentiment and financial variables only explain small fractions of the variations in mispricings, even when accounting for discriminations at country level by investors.

The interesting aspect of the outputs of the F-tests and the various R-Squares is that while the former is found to be high (low p-value) in various countries, the latter is constantly low. Thereby, while sentiment and financial variables may explain little of the overall variations in the mispricings, these variables are arguably statically relevant.

For Italy, when these statistical measures are translated into a graph, the reasons why the R-Squared is low is immediately clear. The deviations from the fitted values increase considerably when the actual mispricings variations exceed the 1 standard deviation boundaries, both in spikes and troughs. Moreover, while pre-2018 the fitted values seem to pinpoint the actual observations roughly well, after 2018 it does not seem to be the case, with the portion of the graph from 2022 onwards depicting an unambiguously poor fit by the model. The graphical representation of the fitted vs. actual mispricing variations for the remaining four countries can be found in the appendix.

Graph 6: Fitted vs. Actual Mispricing Variations – Italy



The residuals of the regressions were tested for autocorrelation and heteroskedasticity. According to the Durbin-Watson Statistics there was no evidence of autocorrelation in any of the countries' residuals. Moreover, heteroskedasticity was assessed using the White's Test, which resulted to raisings concerns for France and Ireland by giving p-values that suggested the rejection of the null hypothesis of homoscedasticity. Accordingly, the White adjustment was made for those two countries, such that the results displayed in Table 7 are following the latter procedure.

On another note, the results obtained for this second model were again quite surprising in terms of the low R-squares and Adjusted R-Squares. Nevertheless, before comparing our results with those of other studies it must be noted that there are various methodological differences to consider. Though, before moving on to the latter discussion, a third model was tried.

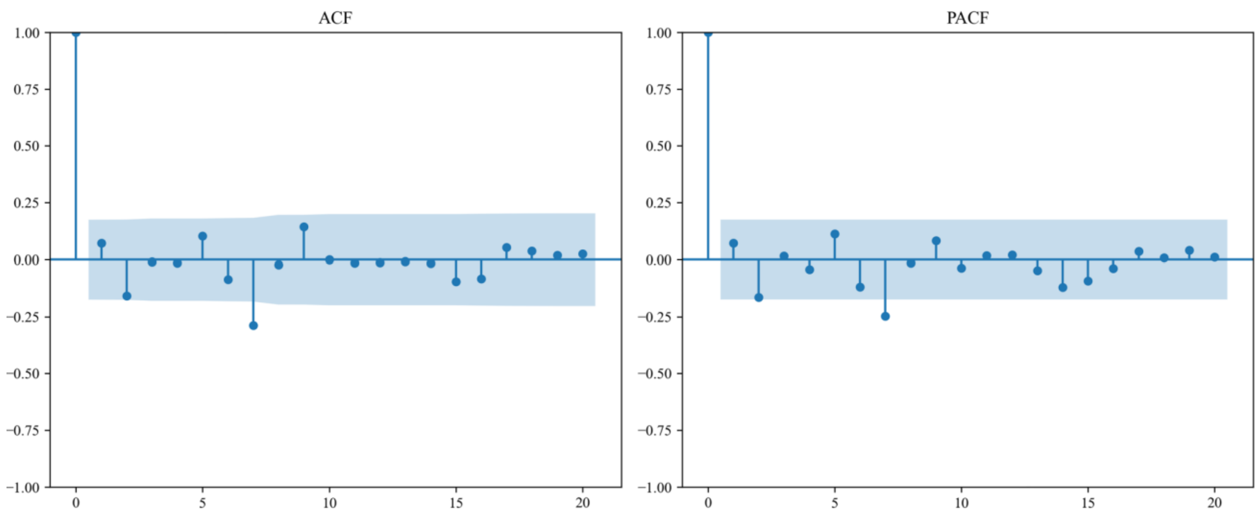
5.3 The AR-X model – Trial

Because of the low R-squared obtained in the two previous models, a trial was made with an autoregressive model. The idea was to employ the 4 explanatory variables used in the simple time series model (sections 5.1 and 5.2) and add a lagged value of $\Delta Mispricing_t$, such that the model would be of the following form:

$$\Delta Mispricing_t = \alpha + \phi \Delta Mispricing_{t-1} + \beta_1 VSX_t + \beta_2 BnkSec_t + \beta_3 EconP_t + \beta_4 PC1_t + \varepsilon_t \quad (5)$$

And possibly include more lagged terms in case there were the statistical fundamentals to do so. Accordingly, we proceeded by estimating the ACF and the PACF to see if $\Delta Mispricing_t$ displayed autocorrelation and determine whether it was appropriate to carry on with the estimation of the model in question, as well as form an idea regarding how many lags to includes. However, the ACF and PACF displayed that an autoregressive model was not appropriate in this context as $\Delta Mispricing_t$ was not autocorrelated with its lagged terms in the sample used (01/01/2014 – 01/07/2024). These are the results for Italy, the graphs of the remaining countries can be found in the appendix.

Graph 7: ACF and PACF of the variations in mispricing - Italy



As a check an AR-X with 1 lag was estimated and the results evidenced what had already emerged from the ACF and PACF analysis. Therefore, no further investigation was carried out on the model.

6. Discussion on the findings

6.1 The outputs of the models

Different explanatory variables were found to be statistically significant across models, as well as across countries in the context of the multivariate time series model. Out of 6 regressions (Table 6 and Table 7), the VSTOXX turned out to be the explanatory variable with the greatest statical evidence of its relevance in driving mispricings variations. The VSTOXX coefficient turned out to be statistically significant at the 5% threshold 3 out of 6 times. Therefore, even after taking into account the possibility of type I error, it can still conclude that an increase in the implied volatility of the EURO STOXX 50 market results to an increase in the monthly variation in mispricing, which when thought of in levels, it means that there is an upward revision of the mispricing. Second, the first principal component of the CISS Indicators turned out to be significant with p-value 0.002 in the panel regression but the result was not replicated at country level. This is reasonable as the CISS Indicators are computed at Euro Area level; therefore, the panel regression may be capturing an effect that holds across different countries, but that is weaker at individual country level, thus suggesting that a country level measure of financial distress could have been a better explanatory variable of the variations in mispricings.

Conversely, the statistical relevance of the Economic Policy Uncertainty index by FRED was only found significant for specific countries, namely Italy and Spain, and not in the panel. Interestingly, those two are the countries from sample that have been closely monitored, and possibly disciplined, by the market for the majority of the 10-year period of the sample. Portugal on the other hand, does not have a statistically relevant coefficient despite it being the third in the bunch to also be under the investors' eyes. This can be because the index pertaining to the Euro Area was used as regressor instead of the country specific one, as the FRED does not publish an index specifically for Portugal. Lastly, the banking sector monthly equity performance was not found to be a driver in the variations in mispricings for the countries in question, for the time period of the sample and according to the methodology used. In none of the 6 regressions the coefficients of the latter regressor turned out to be statistically significant, not even when enlarging the significance level to 10%.

The F-tests for all regressions except the one for Ireland, with the time-series model, hinted at rejecting the null hypothesis of all coefficients being equal to zero. This can be interpreted as out of the variables analyzed in the two models, at least do in influence the variations of mispricings. Considering the F-test and p-values of the singular coefficients we can deem market sentiment as proxied by VSTOXX and PC1 of the CISS indicators demonstrate detectable influence on the movements in the mispricing of the 5 countries sovereign bond spreads mispricings. On the other hand, at country level the uncertainty regarding the economic policies seems to be a better indicator of the variations in mispricings. Thirdly, the banking sector does not seem to have enough statistical evidence to ensure that it has an influence on the first difference of the mispricing. This was unexpected as it implies that our results are not aligned with those of Delatte et al. (2017) and Di

Cesare et al. (2013) of domestic banking being a driver of sovereign spreads. However, it must be highlighted that the time period of our investigation is considerably different to the one of the of the latter two papers, which studied the period surrounding the sovereign debt crisis. Consequently, this divergence may be attributable just to the different extraordinary events that the underlying data are subject to.

6.2 Contextualizing the findings with existent literature

Though evidence was found for market sentiment being a driver of sovereign bond spreads mispricing, the amount of variation in mispricing captured was low. The R-squared and the Adjusted R-Squared values were low in both models and even in the tests with slightly different specifications. We were expecting that there would be numerous more factors influencing the part of the sovereign spreads that remains unexplained by economic fundamentals. Nevertheless, we found these results surprising given our very low R-squares and Adjusted R-squares, which have not appeared in the previous literature covered. As a result, we went back to look more attentively at the methods, the data and the specific conclusions of the papers from which we got the ideas of the variables to include in models. When re-reading we tried to understand what possible reasons for the differences in our results could be.

First of all, the data used in Di Cesare et al. (2013), which uses the methodology most similar to ours, was of daily frequency when assessing the effects of financial factors on market spreads. Therefore, while the frequency of macroeconomic data is at most monthly, if not quarterly, and thus calls for monthly observations to be used, proxies for market sentiment can be found with daily frequencies, and the same is true for financial variables. Given that market sentiment might vary considerably on a daily basis, when taking the monthly average of this variable a lot of information is lost in this process of smoothening the time series. Consequently, we fear that although monthly market sentiment measures can still be found to affect mispricings, they are a better explanatory variable on short time horizons, where investors might overact to a certain news or data release, which then gets corrected away in the later days of the months, reducing the variation of monthly data as well as its explanatory power for bonds' prices deviations from economic fundamentals.

Another important aspect is our dependent variable of the investigation, namely the variations in the theoretical mispricing obtained through the application of Ceci and Pericoli (2022) model. The papers covered in the literature review section investigated the role financial and proxies of market sentiment and financial variables in the determination of either sovereign yields or sovereign spreads. Therefore, the coefficients they obtained for the various proxies of the market sentiment and the financial variables have a different meaning than those of this paper. By using the difference in mispricing as dependent variable, the coefficient of regressions of equations (3) and (4) represent the contribution to the enlargements (or reduction if the coefficient is negative) of the mispricings of the explanatory variables, not the enlargements of spreads or the yields. In addition, our mispricings are unrelated to the economic fundamentals, as they are the residuals of equation (2). Accordingly, if financial and sentiment variables were to include information regarding the macroeconomic outlook of the country, in equation (3) and (4) it would not be detected, reducing the variations in the dependent variable explained by the set of independent variables when compared to regressions where the y-variable equals spreads or yields.

Still related to our dependent variables, the first difference of mispricing needed to be taken, as the time series was not stationary. This was done to avoid encountering spurious regression issues and all the consequential invalidities of the statistical interpretations of the results. However, taking the first difference of series also results in the loss of information. Consequently, when considering that information was first lost by using monthly frequencies as opposed to weekly or daily ones and then by taking the difference of mispricings, finding evidence of the statistical relevance of the market sentiment in explaining these variations in mispricing becomes a more valuable result than what the low R-squares values capture.

The differences in the period of the sample must also be considered as possible source of the differences in the results between our research and those Di Cesare et al. (2013) and Delatte et al. (2017). Since 2001, the Euro Area sustained various distinct periods economically speaking, besides the periods of crisis, which often result in models fitting those periods poorly. The period between 2012 and 2019 was characterized by very low economic growth and inflation, with the ECB introducing quantitative easing roughly around the notorious Mario Draghi sentence "Whatever it takes" in July 2012. Quantitative Easing (QE) had impacts on the term structure of the yield curves and arguably on the portfolio allocation of investors. Accordingly, there could be influences of the latter unconventional monetary policy tool on the interactions of financial and sentiment variables with the mispricing of spreads. Therefore, depending on how many years of QE are present in the sample, the results of the analysis could be impacted differently by the instrument. This issue is often present in studies on the Euro Area given the relatively short time series available, which implies that if a subset of the full time series is used to study a certain relationship the data points might be too few to capture to represent the population accurately, lowering the generalizability of the results.

A final point to make regarding the results obtained from the regression is related to the explanatory variables included. The explanatory variables used were local to the countries in question or to the European geographical area. Longstaff et al. (2011) deemed global risk factors as the main drivers of CDS spreads. Though sovereign bonds and sovereign CDS are not the same security, many of the underlying drivers can be expected to be similar. Accordingly, it could be the case that by using international financial variables and international proxies of market sentiment, greater fit may be obtained in the model. Delatte et al. (2017) in fact used financial variables that accounted for both the Euro Area and either comparison between yields in the EU vs. the USA or simply US variables. However, it was decided to focus just on European values.

To summarize the discussion, it is important to keep in mind that the results obtained do indeed suggest that market sentiment, as proxied by implied volatility, economic policy uncertainty and distress of financial markets, is found to be a driver of mispricing. While, countries' banking sectors were statistically relevant drivers in the sample. The models employed, however, exhibit a low fit to data, suggesting that there may be considerably more variables influencing the portion of the spreads unexplained by economic fundamentals, or that more complex relationships could exist between the explanatory and dependent variables investigated.

7. Further research

As evidenced in Section 6, there are various trajectories that further research can build upon this investigation. The most obvious one is simply enlarging the dataset of the explanatory variables. Both in terms of features used and in terms of length of the sample. The low R-squares obtained in the panel model and the time series model definitely are supportive of this direction, as there are lots of additional drivers of mispricings to research.

Another interesting development of the model would be to account for quantitative easing. In fact, Broeders et al. (2023) suggested that QE lowered the bond market volatility, contributing to lowering the sovereign bond spreads. QE can be studied by controlling for this variable and assessing the changes caused to the variables of interest or by investigating the additional explanatory power obtained when taking QE into consideration.

These first two possibilities are mainly focused on adding data to the model estimation to try account for various events and information present on financial markets. However, the other approach to further research could be trying different types of models.

Recalling Graph 5 and 6, the models in question struggled to provide accurate fitted values when the actual mispricing variations fell outside the one standard deviation interval. Therefore, it is possible that in certain periods of high uncertainty and financial markets volatility, the relationships between our explanatory variables and the independent variable rather than being linear is quadratic. Accordingly, it could be interesting to explore a wider range of the models and apply Gonzalez et al. (2005) panel smooth threshold regression model to financial and market sentiment variables, rather than on economic fundamentals like it was used in Delatte et al. (2017).

Additionally, the loss of information arising from the monthly frequency of data and the first differencing of the mispricing was previously addressed. Thereby, a possible field for expanding the research is moving from monthly to weekly frequency data, at the expense of needing to deal with the lower frequency of macroeconomic variables. By increasing the frequency, the samples can be shortened in terms of years covered but not necessarily have fewer observations. Shorter periods may allow for mispricings to be found stationery in levels while still having enough variation to carry out an analysis upon. Accordingly, if that was the case, much more information would be present in the mispricing series and autoregressive models could be employed in the analysis, if some autocorrelation was to be found, and possibly improve the fit of the estimated values.

8. Conclusion

This paper investigated in what means the mispricings of sovereign bond spreads is driven financial and market sentiment variables. In the paper mispricing was defined as the difference between the market observed spreads and the theoretical fair value estimates obtained by considering only the current and the future economic fundamentals of a Euro Area country and following the estimation procedures put forth by Ceci and Pericoli (2022).

In the investigation two approaches were followed. In the first approach, the investigation was carried out with a multivariate panel model inspired by Ceci and Pericoli (2022) rationale for using panel regressions for highly economically and financially integrated geographical areas like the Eurozone. In the second approach, a simple multivariate time series regression was used individually for Italy, France, Spain, Ireland and Portugal, with the aim of mimicking the methodology by Di Cesare et al. (2013). The results obtained suggested that at panel level, VSTOXX and the first principal component of the CISS indicators for the bonds, equity, financial sector and FX market systemic stress, were statistically relevant drivers of the mispricings. Conversely, the indicator of economic policy uncertainty by FRED resulted to be a more important driver statistically than the first principal component of the CISS indicators. VSTOXX on the other hand, was statistically significant both in the panel model and in single countries regressions for Italy and Ireland. The former and the later country are joined by France and Portugal when significance level is extended to 10%. Furthermore, despite previous research evidenced the importance of the financial sector in determining the spreads of Euro Area countries, this paper was not able to find statical evidence supporting the country's banking sector equity monthly performance as a driver of mispricing.

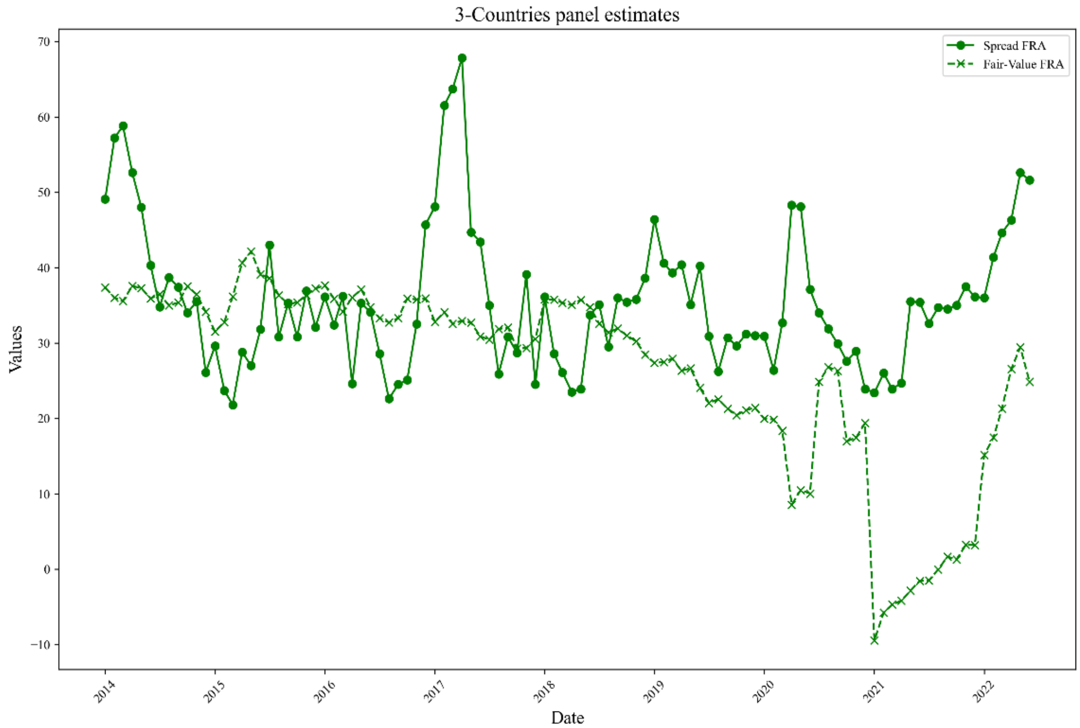
In the process of choosing the specifications of the two models estimated numerous financial variables were excluded from the investigation to address the multicollinearity concerns that were raised by the correlation matrix of the full dataset at our disposal. Other financial variables, such as the TOTMKEN price-earnings European index, were dropped from the specifications as their financial meaning was doubtful, their inclusion raised concerns of invalidating the results of the model, or they simply were not able to capture the mispricings according to the statistical tests conducted.

Regardless of the attempts to follow different approaches and the evidence from previous literature of the relevance of the financial variables and market sentiment proxies included, the explained variance of the first difference in mispricing was low. The maximum R-squared obtained was of 0.14, and it was in the singular country regression for Italy. Therefore, the spreads mispricings is influenced not only by the explanatory variables we studied, but also by other factors, which are not included in this investigation, as well as possibly by non-linear relationships with VTSOXX, FRED's economic policy uncertainty index, country's banking sector equity returns and the first principal component of the CISS indicators.

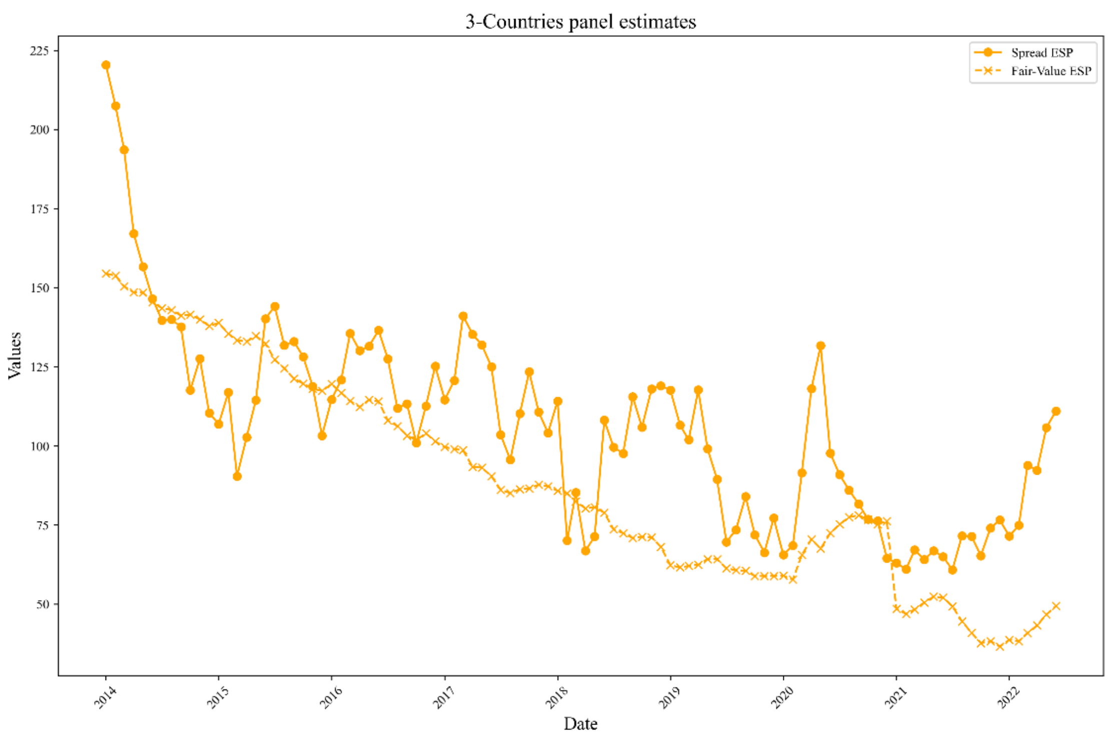
Further reasons as to why the explanatory power of the independent variables included in the investigation is low are related to the loss of information that occurred in the process of transforming the variables to a state that was useful in a linear regression context. Firstly, because the mispricings were estimated with a monthly frequency, the financial and market sentiment series were also taken at monthly observations, thus considerable information was filtered out. Secondly, the mispricings were differentiated ones to ensure stationarity, again resulting in the loss of information in the case that an autoregressive model was to be fitted. Consequently, to ensure econometric validity of the results, information originally present in the time series' raw form was sacrificed.

9. Appendix

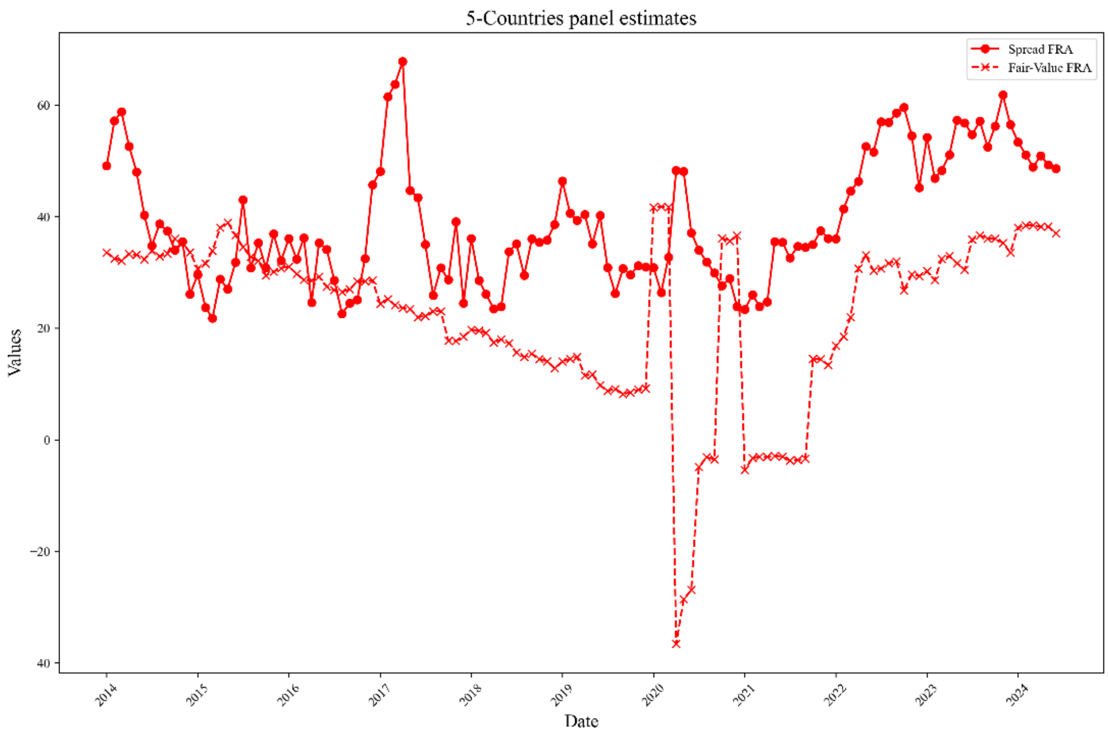
Graph 8: Market spreads vs. fitted values – France



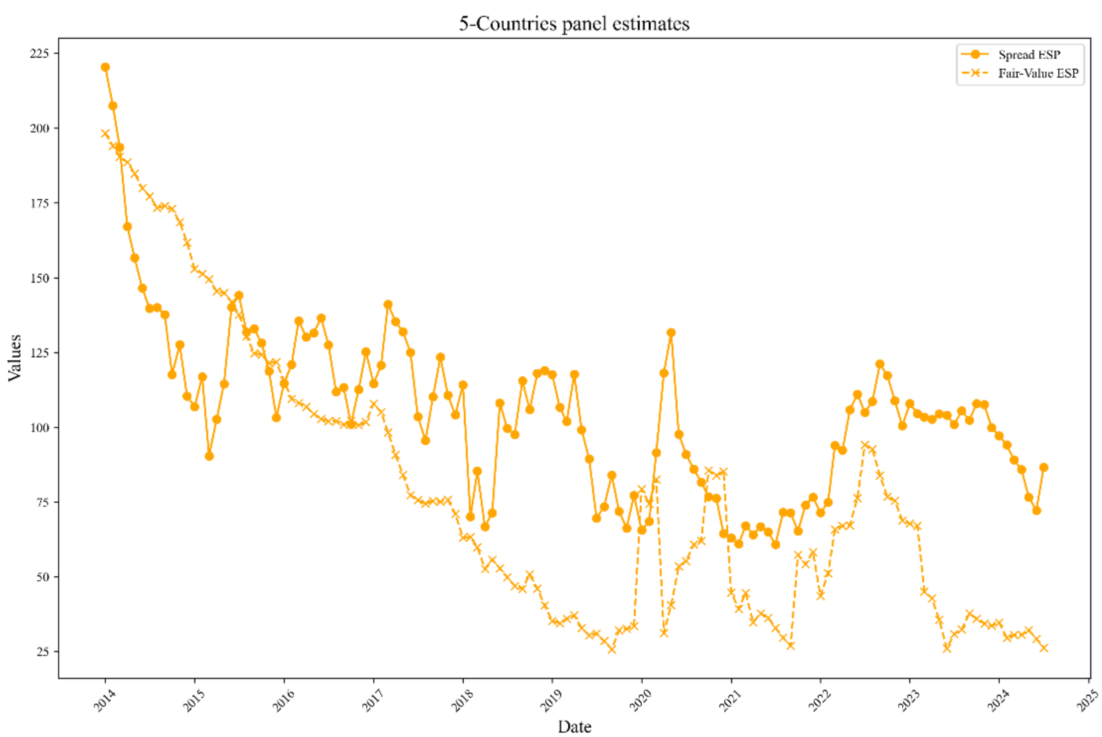
Graph 9: Market spreads vs. fitted values – Spain



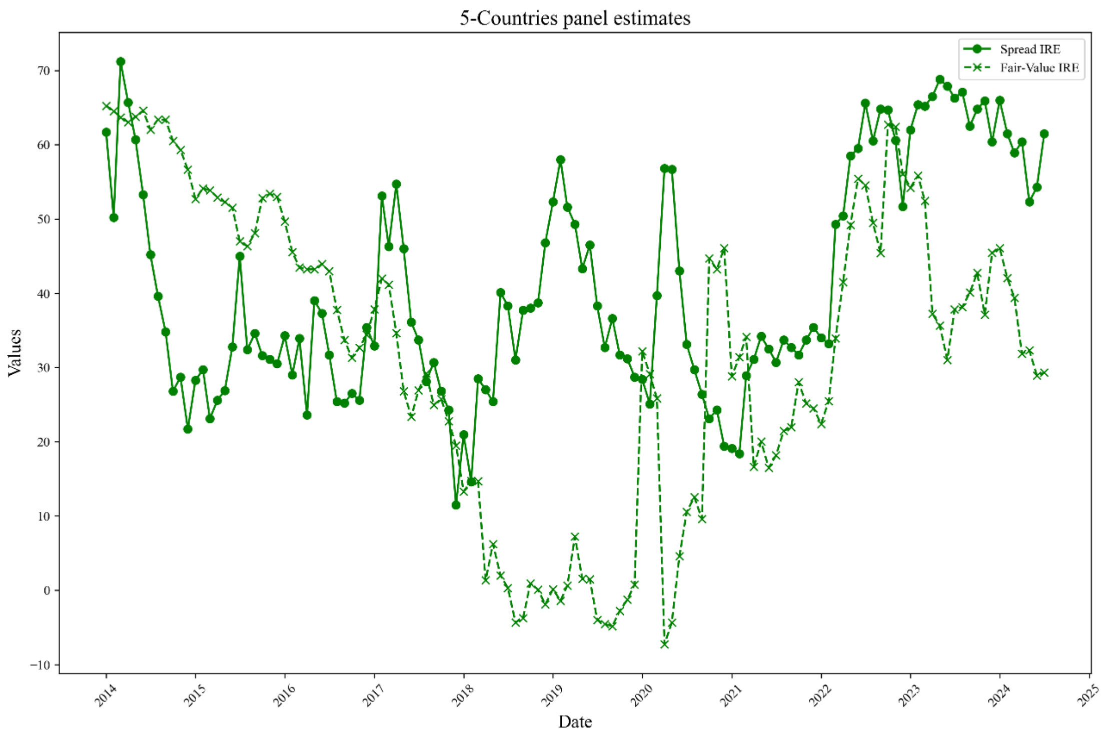
Graph 10: Market spreads vs. fitted values – France



Graph 11: Market spreads vs. fitted values – Spain



Graph 12: Market spreads vs. fitted values – Ireland



Graph 13: Market spreads vs. fitted values – Portugal

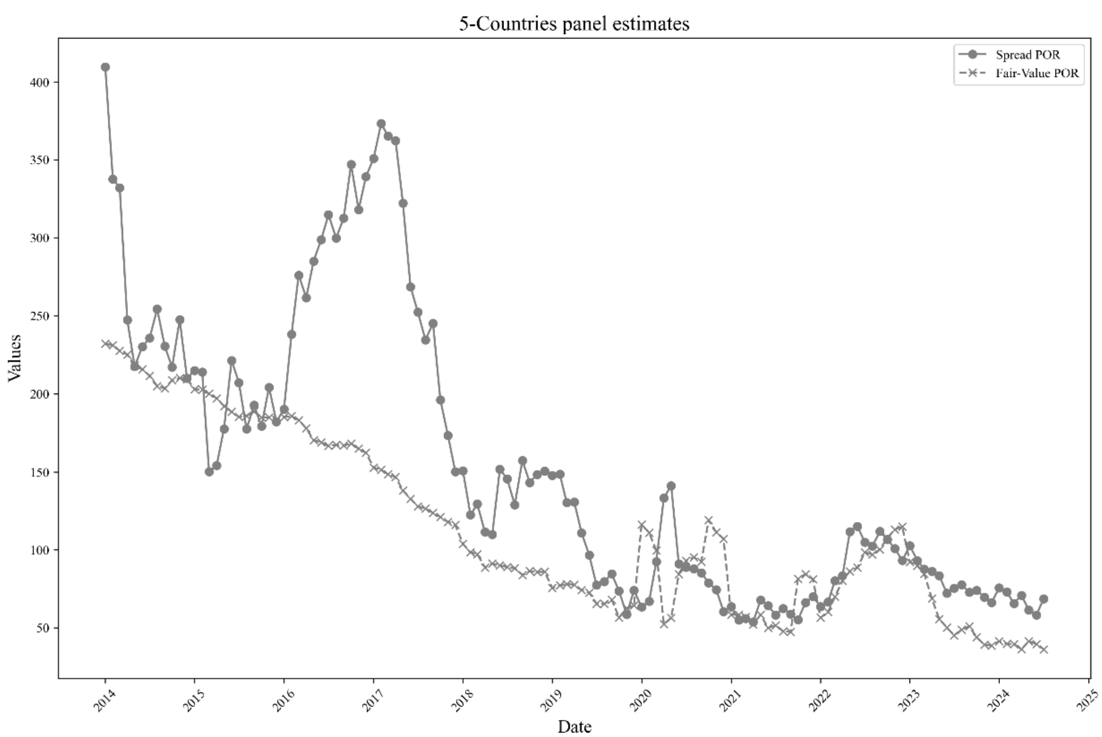


Table 8: Market sentiment variables

Variable	*Mean*	*Standard Deviation*
VSTOXX	2.467	24.8
Italy Policy Uncertainty	5.679	37.43
France Policy uncertainty	5.701	33.35
Spain Policy Uncertainty	7.673	44.48
Ireland Policy Uncertainty	16.206	84.33
*Portgual Policy Uncertainty**	2.884	22.49
CISS - Equity	0.087	0.05
CISS - Bond Market	0.061	0.03
CISS - Banking Sector	0.127	0.06
CISS - FX	0.047	0.03

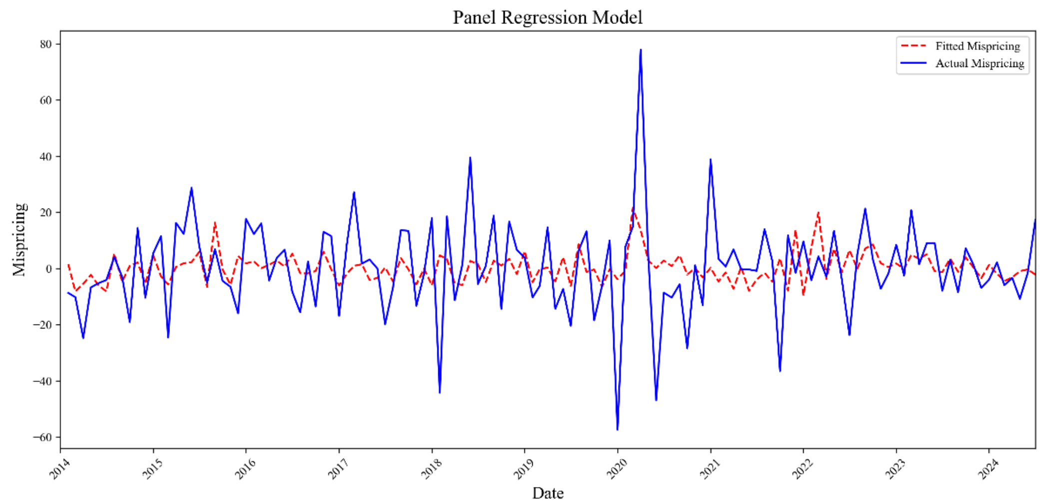
**Since FRED does not estimate an Economic Policy Uncertainty Index for Portugal, these statistics to the Euro Area's index.*

Table 9: Financial Variables

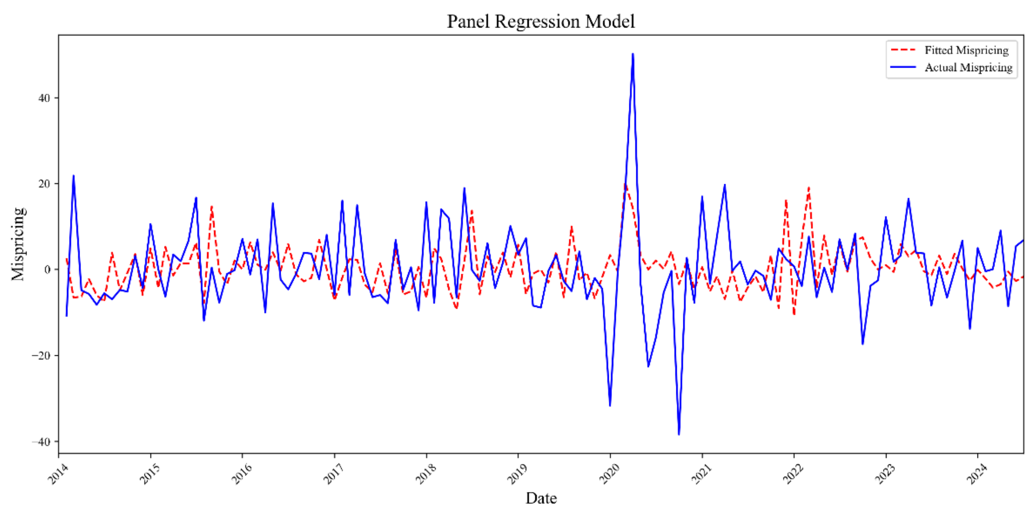
Variable	*Mean*	*Standard Deviation*
TOTMKEN	0.286	6.62
Italy Banking Sector	-0.004	0.1
France Banking Sector	-0.002	0.1
Spain Banking Sector	-0.004	0.1
Ireland Banking Sector	-0.018	0.19
Portugal Banking Sector	-0.014	0.13
MSCI Europe	0	0.06
S&P350	0.002	0.04
European Banking Sector	-0.005	0.09

Graph 14: Fitted vs. actual mispricings variations – France

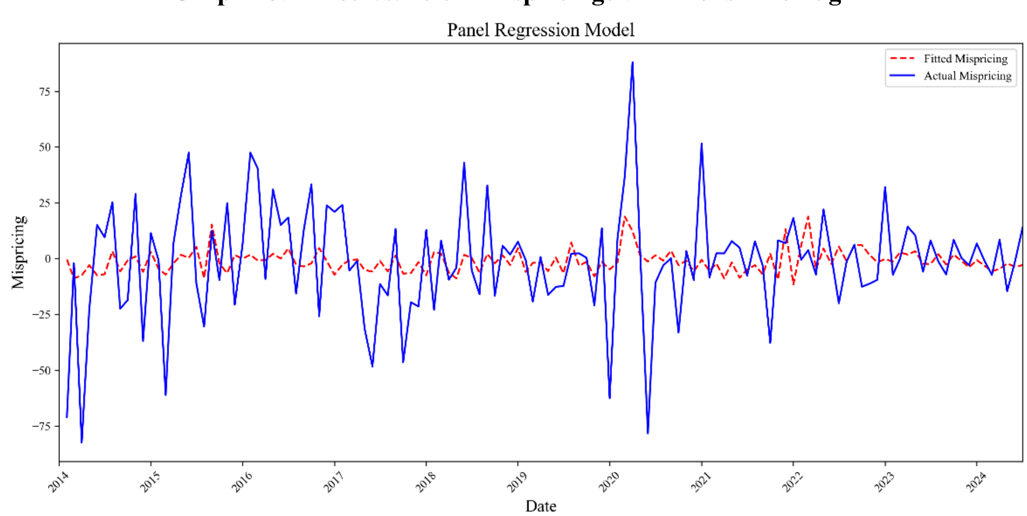
Graph 15: Fitted vs. actual mispricings variations – Spain



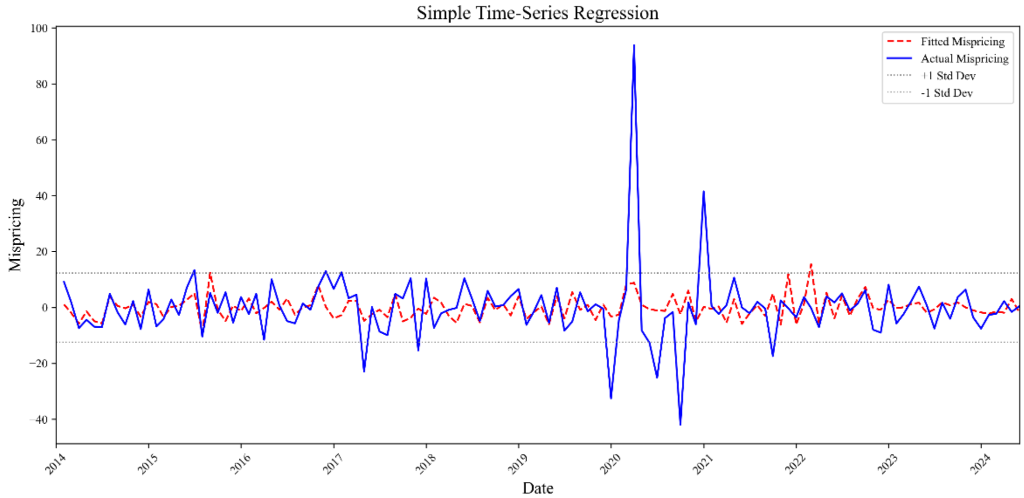
Graph 16: Fitted vs. actual mispricings variations – Ireland



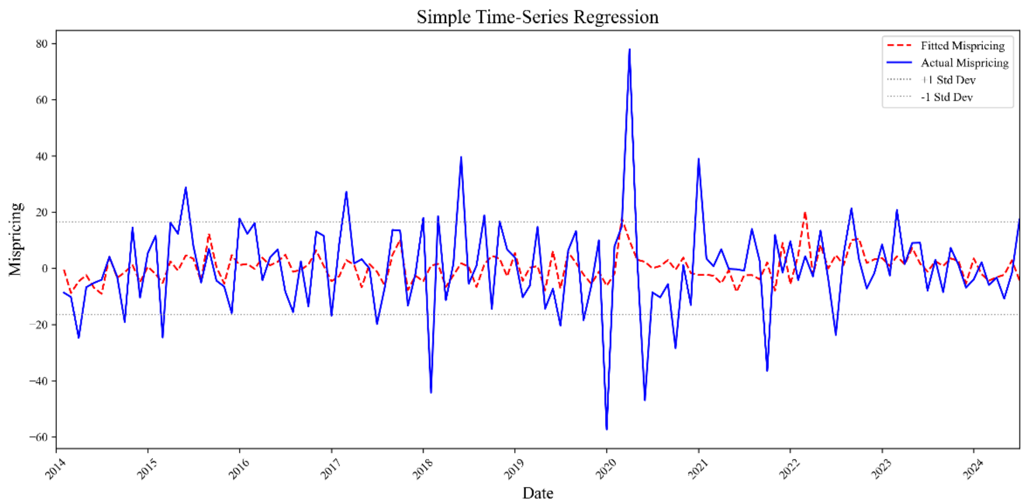
Graph 17: Fitted vs. actual mispricings variations – Portugal



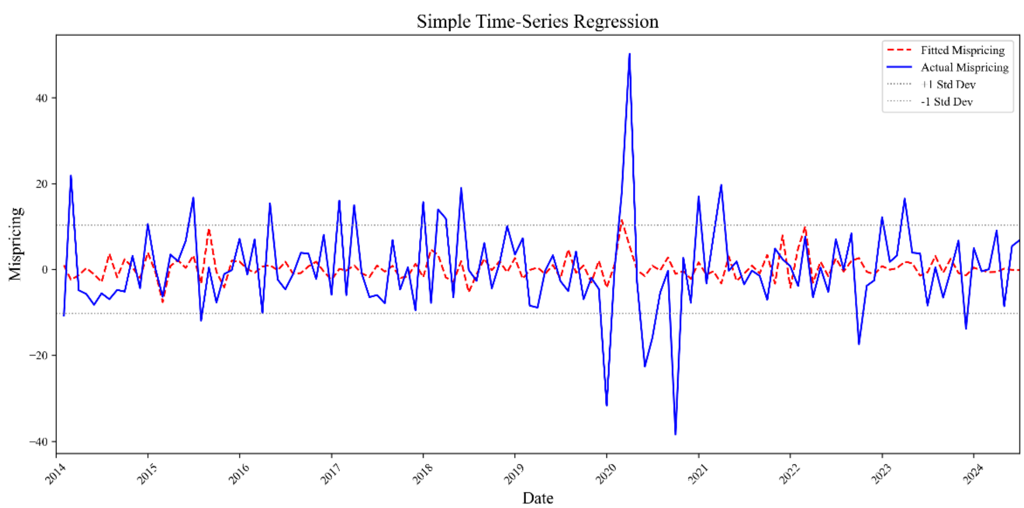
Graph 18: Fitted vs. actual mispricings variations – France



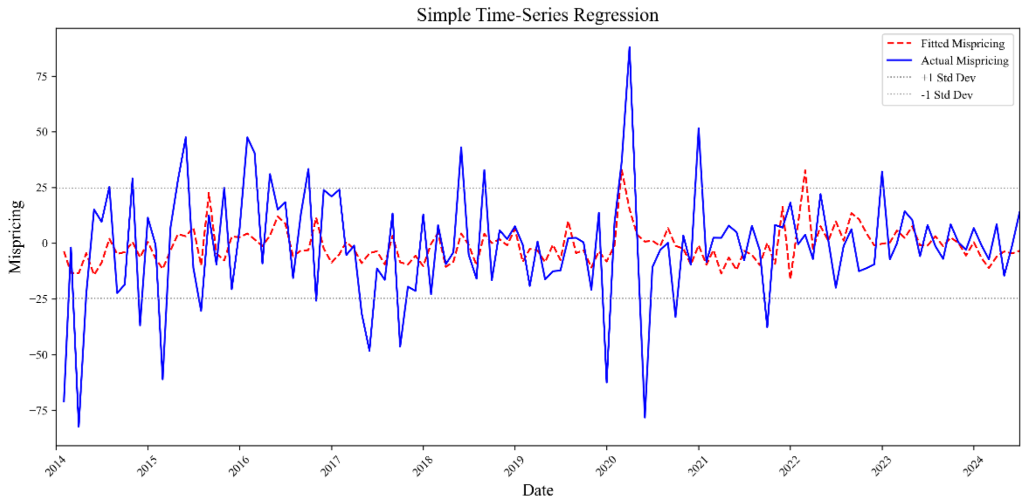
Graph 19: Fitted vs. actual mispricings variations – Spain



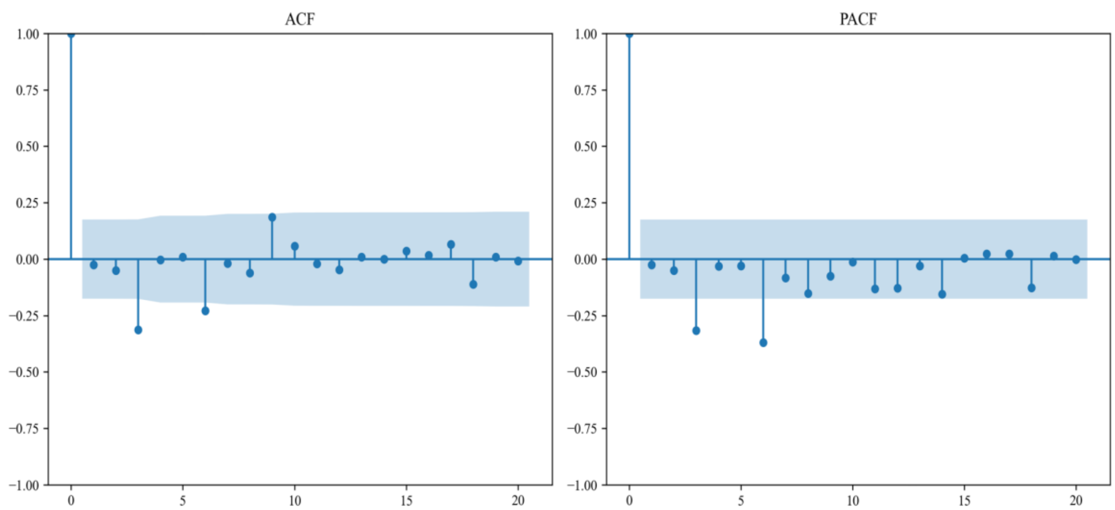
Graph 20: Fitted vs. actual mispricings variations – Ireland



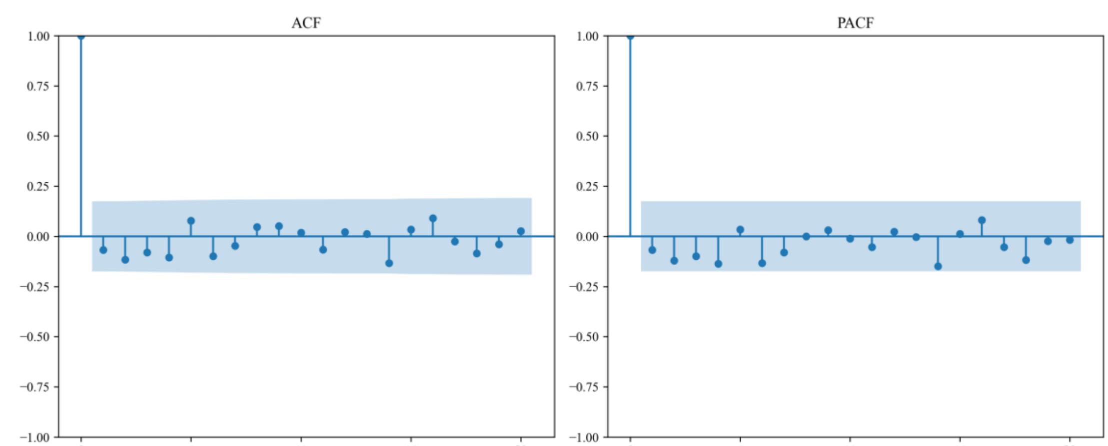
Graph 21: Fitted vs. actual mispricings variations – Portugal



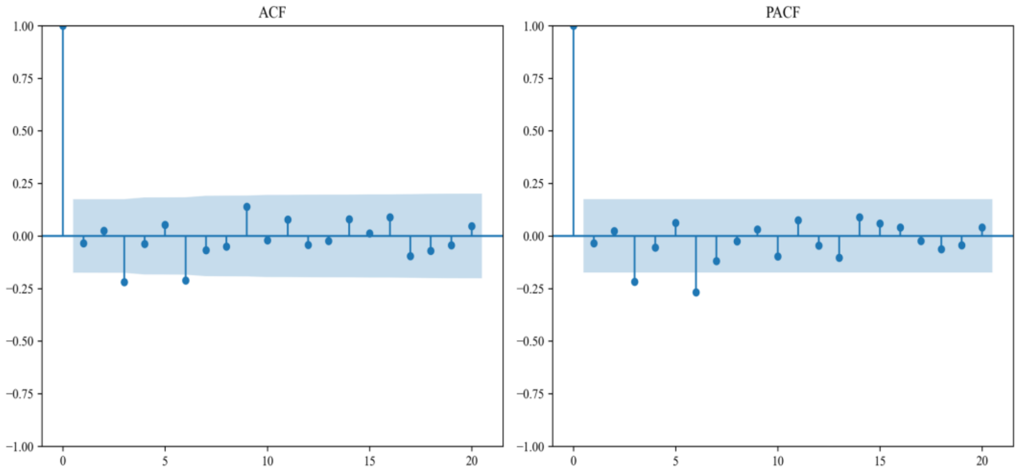
Graph 22: ACF and PACF – France



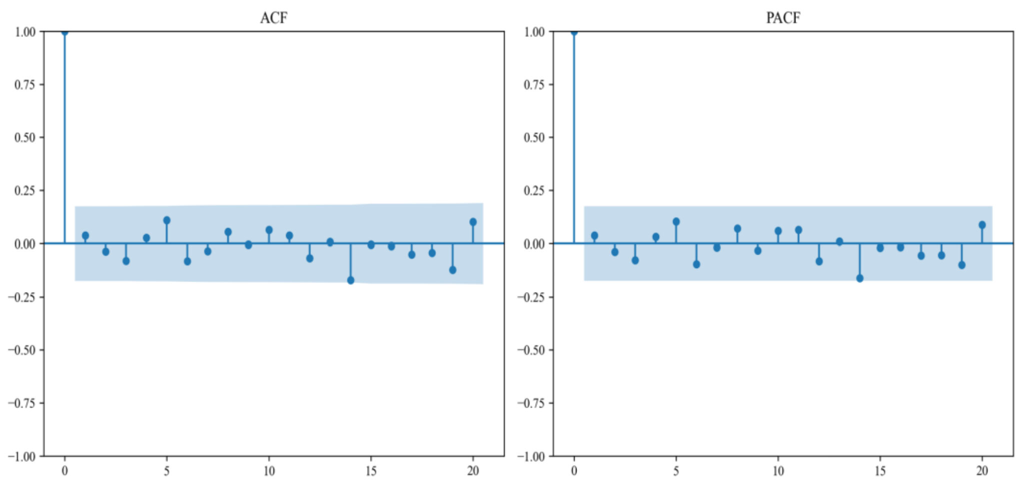
Graph 23: ACF and PACF – Spain



Graph 24: ACF and PACF – Ireland



Graph 25: ACF and PACF – Portugal



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Market sentiment as driver of Euro Area Sovereign Bonds 10-Year Term Premium

MATTEO MONTANI – 42693

STOCKHOLM SCHOOL OF ECONOMICS
Department of Finance
4350 Master’s thesis in Finance
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Market sentiment as driver of Euro Area Sovereign Bonds 10-Year Term Premium

Abstract:

This paper investigates the relationship between market sentiment proxies and innovations in the 10-year term premium of Germany, France, Italy, and Spain. The analysis uses quarterly term premium estimates for the period 2000–2025 from Favero and Srivastava (2023) and five market sentiment proxies, examined within two empirical frameworks: country-by-country multivariate regressions and panel regressions. The results provide limited evidence that market sentiment systematically influences euro-area government bond term premiums, with statistical significance emerging only for specific sentiment proxies and in particular geographical areas of the euro area.

Keywords: Sovereign debt, term premium, sentiment, euro area

Author: Matteo Montani (42693)

Tutor: Gualtiero Azzalini, Assistant Professor, Department of Finance, Stockholm School of Economics

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Stockholm School of Economics

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1. Introduction

This paper extends the Bocconi University thesis *"Market Sentiment and Financial Variables as Drivers of Sovereign Spreads Mispricing"* by investigating the relationship between market sentiment and the 10-year term premiums of Germany, France, Italy, and Spain.

The two investigations are linked by the fact that sovereign yields can be decomposed into two components: the expected average nominal monetary policy rate over the remaining life of the bond, and the term premium required by investors for holding a bond of a given maturity. Differences in term premiums across euro area countries are often interpreted as what constitute sovereign spreads with respect to the German Bund, as expectations of future monetary policy rates are shared among all countries under the European Central Bank's (ECB) monetary policy. However, expected monetary policy rates vary over time as ECB's decisions evolve and markets revise their expectations and interpretation of the forward guidance, affecting the level of yields across all countries. For this reason, while spreads primarily capture cross-country differences (generally the differences in the credit worthiness of the countries), this thesis focuses on the term premium itself, abstracting from the common variation in expected monetary policy rates over time and isolating the component of yields more directly related to the overall risk compensation. This compensation is not only linked to sovereign credit related concerns but also to inflation related risk beyond expected inflation.

Because term premiums are not directly observable in the market, they must be extracted using a model. This study utilizes the quarterly term premium estimates of Favero and Srivastava (2023), who apply the methodology of Adrian et al. (2013), for the period 2000–2025. The market sentiment variables employed were selected based on existing literature and aligned with those used in the Bocconi University thesis. These include the VSTOXX, the P/E ratio of the euro area stock market, national banking sector stock performance, national economic policy uncertainty indices, and the CISS financial stress indicators.

Two approaches were used to investigate the relationship between market sentiment and term premiums, both focusing on linear relationships. The first approach follows the multivariate regression methodology of Di Cesare et al. (2013), estimating separate regressions for each country. The second approach is a panel regression model inspired by the multi-country model of

Ceci and Pericoli (2022), which they applied to construct fair-value estimates of sovereign spreads with respect to the German Bund for Italy, France, and Spain.

The results obtained from the two models suggest that market sentiment plays only a moderate part in driving the quarterly changes of the term premiums of the four countries, with periphery countries' (Italy and Spain) term premiums innovations being the most affected by market sentiment.

The remainder of the paper is organized as follows: Section 2 reviews the existing literature, Section 3 describes the data and the transformations applied, Section 4 presents the country-specific multivariate regressions and the panel regression models, Section 5 discusses the results, and Section 6 concludes the investigation.

2. Literature Review

2.1. Decomposition of the yield

The nominal yield of a bond can be decomposed into two components. The first is the expected average nominal monetary policy rate over the remaining life of the bond (the federal funds rate in the United States and the Deposit Facility Rate in the euro area). The second is the term premium, defined as the additional risk compensation investors require to hold a bond of a given maturity. This two-part decomposition represents the most common interpretation of the term structure of interest rates in financial markets and is the framework adopted by Adrian et al. (2013) in the construction of their affine term structure model.

Yields, however, can be decomposed further. For instance, D'Amico et al. (2018) first distinguish between the expected average nominal policy rate over the life of the bond and the nominal term premium, consistent with Adrian et al. (2013). They then decompose nominal policy rate expectations into the expected average real policy rate and expected inflation over the bond's maturity. Finally, within the nominal term premium, they separate an inflation premium, capturing inflation risk net of expectations, from the real term premium, which is associated with fiscal considerations, issuance volumes at different maturities, and a range of other supply and demand factors.

Although expectations of the average monetary policy rate and term premia are market-determined, they are not directly observable and therefore require a model-based approach for identification. These models can be relatively simple. For example, within the two-component definition of Adrian et al. (2013), the expected average monetary policy rate can be proxied using forecasts of short-term interest rates from the ECB's Survey of Professional Forecasters, as suggested by Favero and Srivastava (2023). The term premium is then computed as the difference between the observed bond yield at a given maturity and the corresponding expected average short-term rate implied by the survey. The same approach can be applied to U.S. Treasury yields.

Nevertheless, the shortcomings of this very basic model are easy to identify. When the market expects a policy rate path that differs from the one forecasted by the ECB, estimates of both components become unrepresentative of the market expectations and risk attitudes. Consequently, models used to extract the various components of the term structure tend to be more sophisticated.

A prominent example is Adrian et al. (2013), who propose a regression-based approach to decompose yields. More specifically, the authors employ an affine model that imposes a no-arbitrage condition and uses five risk factors to estimate the nominal term premium. These five factors correspond to the first five principal components extracted from yields at various maturities along the yield curve, adjusted to satisfy both the affine structure and the no-arbitrage restriction.

D'Amico et al. (2018) also provide a model to estimate the term premium. However, whereas Adrian et al. (2013) model can be applied to the yields of various financial instruments, D'Amico et al. (2018) model is specific to U.S. Treasuries. This specificity arises because the latter authors initially focused on estimating the TIPS liquidity premium, and the decomposition of the nominal Treasury yield emerges as a by-product of jointly modelling nominal and real yields[1].

Adrian et al. (2013) and D'Amico et al. (2018) are the two most well-known models for estimating the Treasury term premium. However, several other models have been developed, including those by Crump and Gospodinov (2019), Duffee (2011), Lemke and Werner (2017), and Favero and Fernandez-Fuentes (2023).

The last two publications are of relevance to this investigation, as their models were designed for decomposing euro area sovereign bond yields. Lemke and Werner (2017) specifically focused on the decomposition of long-term Bund yields in the run-up to the ECB's Public Sector Purchase Program announced in January 2015, whereas Favero and Fernandez-Fuentes (2023) extended the analysis to other euro area countries. Both studies develop an affine macro term structure model in which yields co-move, sharing a common stochastic trend driven by short-term interest rate movements (monetary policy), while excess returns remain stationary.

Favero and Srivastava (2023), using the model proposed by Favero and Fernandez-Fuentes (2023), provide an updated decomposition of the 10-year yields of Bunds, BTPs, OATs, and Bonos at a quarterly frequency, alongside other estimates obtained using the Adrian et al. (2013) approach. These decompositions are essential for this paper, as the investigation is not aimed at developing a model for estimating the term premium but rather at understanding the relationship between market sentiment and term premiums. Hence, in the investigation, Favero and Srivastava (2023) estimates of the term premium were used as dependent variables.

[1] TIPS: Treasury Inflation Protected Securities

2.2. Market sentiment influence on sovereign bond yields

Having defined the concept of the term premium, the focus now shifts to understanding its relationship with market sentiment, which lies at the core of this investigation. A first piece of evidence on the interaction between these two variables is provided by Kim et al. (2019), who, in a Federal Reserve research note, explain that the inflation expectation and inflation premium components of U.S. Treasury yields exhibit pairwise correlations with sentiment proxies, namely weekly changes in the high-yield spread and the VIX. This link between U.S. sentiment variables and the inflation premium component of the nominal term premium of the 10-year Treasury yield may suggest that analyzing the relationship between market sentiment in the euro area and the term premiums of European Government Bonds (EGBs) – what this investigation covers – would yield similar findings. Moreover, this first piece of evidence by Kim et al. (2019) suggests that this investigation represents an interesting extension of the thesis *"Market Sentiment and Financial Variables as Drivers of Sovereign Spreads Mispricing"* written for Bocconi University.

Kim et al. (2019) are not the only researchers to report evidence of interactions between market sentiment and term premiums. Di Cesare et al. (2013) attempted to use the debt-to-GDP ratios of France, Italy, Spain, Belgium, Portugal, and Ireland in regressions of various orders to construct a fair-value model estimating the spreads of these six countries relative to the German Bund. They found that this approach could not explain a significant portion of the market spreads observed. Consequently, they extended their analysis by employing three different sentiment proxies: sovereign spread volatility, bank stock volatility, and spreads on corporate bonds of the same rating as the sovereign bonds in question. Their findings indicated that these three sentiment measures had high explanatory power. Since the six countries and Germany operate under the same monetary policy regime – the one established by the ECB – their sovereign spreads can be interpreted as differences in term premiums relative to Germany. Accordingly, the results of Di Cesare et al. (2013) suggest that this investigation may find term premiums in the euro area to be linked to market sentiment, when proxied with volatility indexes.

The findings of Di Cesare et al. (2013) are consistent with earlier evidence emphasizing the role of contagion risk and portfolio reallocation to safer sovereign bonds during periods of financial stress. Metiu (2012) argues that, between January 2008 and February 2012, divergences between market-based spreads and fundamentals were partly driven by contagion effects, with Italian spreads influenced by developments in Spain and Portugal, which in turn were affected by shocks originating in Greece. At the same time, episodes of heightened risk aversion triggered a "flight-to-safety" phenomenon, whereby investors reduced exposure to higher-risk sovereigns in favor of German Bunds, amplifying yield differentials across countries. De Santis (2012) shows that this "flight-to-safety" mechanism contributed not only to widening spreads in the PIIGS countries (Portugal, Italy, Ireland, Greece, and Spain) but also in fiscally sound economies such as Austria and the Netherlands, reflecting broader global risk aversion. Related findings by Caceres, Guzzo, and Segoviano (2010) and Beber et al. (2009) further indicate that liquidity concerns may reinforce these dynamics through a "flight-to-liquidity", underscoring the central role of sentiment and risk perceptions in shaping euro-area term premia[2]. Taken together, these mechanisms imply that market sentiment may exert heterogeneous effects across countries' term premiums, motivating a differentiated analysis between core (Germany and France) and periphery (Italy and Spain) countries.

Research on the interaction between spreads and sentiment is not the only evidence that market sentiment affects term premia. The influence of sentiment on credit default swaps (CDS) is also relevant, as default risk contributes to the compensation investors require in the form of a term premium. Longstaff et al. (2011) examine the relationship between financial variables and sovereign risk premium by analyzing CDS spreads across 26 countries, both advanced and less developed. They find that CDS spreads are far more correlated across countries than the corresponding equity indices, and that U.S. equity and high-yield market dynamics account for much of the variation in credit spreads. Similarly, Codogno et al. (2003) show that changes in international risk factors—measured as the difference between the 10-year U.S. interest rate swap fixed leg and the 10-year Treasury yield, and the spread of AAA corporate bonds over the 10-year Treasury—are the main drivers of euro-area sovereign yield differentials. Nevertheless, Cecchetti (2020) suggests that both global and euro-area factors influence credit risk premia, implying that an investigation of the relationship between market sentiment and term premiums using euro-area variables and sovereign bonds may still uncover meaningful links between the two.

[2] "flight-to-liquidity": the action of selling a riskier sovereign bond to buy a safer one (Bund) as euro area sovereign debt is issued in a currency that individual member states do not control, national authorities cannot ensure the unconditional availability of liquidity to service their obligations, thereby introducing the risk of a liquidity crisis.

A final remark concerns the finding by Di Cesare et al. (2013) that the domestic banking sector also plays a crucial role in shaping sovereign term premia. Shocks in the financial sector propagate to the real economy, as observed during the 2008 financial crisis, affecting consumption and investment, which reduces government revenues and increases the compensation investors require for holding sovereign debt – i.e., the term premium. Banking stress also triggers government rescue packages, creating expectations of higher future deficits and debt-to-GDP ratios, similar to those observed in 2008. Consequently, strains in domestic financial institutions can raise term premium by affecting both government inflows and outflows. Attinasi et al. (2009) show that announcements of rescue measures lead to upward revisions in term premium, driven by the credibility of the government's commitment rather than the size of the package. This mechanism is formalized in the "credit risk transfer hypothesis," whereby investors interpret rescue packages as a transfer of risk from banks to the sovereign, prompting a reassessment of sovereign credit risk and, consequently, the term premium. The interaction is also circular: European banks hold substantial government debt, so widening term premium for reasons unrelated to financial-sector health can weaken banks by devaluing their assets. Hence, Gennaioli et al. (2012) note that strong financial institutions can discipline governments to maintain responsible fiscal policies, the so called "Bond vigilantes". Consequently, when jointly considering the findings of these authors, the conclusion is that it is imperative to include banking sector variables in the investigation of the relationship between market sentiment and EGBs term premiums.

Overall, the existing literature highlights several channels through which market sentiment may influence sovereign yields, yield spreads, CDS premia and, indirectly, the nominal term premia of government bonds. However, despite the extensive body of research examining the relationship between market sentiment and sovereign risk, limited attention has been devoted to the role of sentiment in shaping model-based term premium innovations for euro-area sovereign bonds, particularly when using data at quarterly frequency. Most contributions in the literature focus either on sovereign spreads (e.g. Di Cesare et al., 2013), on credit risk indicators such as CDS spreads (e.g. Longstaff et al., 2011), or on analyses of term premium components conducted at higher frequencies and primarily for the United States (e.g. Kim et al., 2019).

This paper contributes to the existing literature by investigating whether commonly employed market sentiment proxies retain explanatory power for quarterly movements in 10-year term premiums of the four major euro-area economies, using the term premium estimates from Favero and Srivastava (2023). In doing so, the analysis connects the literature on sovereign spreads and market sentiment with the term structure decomposition framework and evaluates the relevance of sentiment both in country-specific regressions and within a multi-country panel setting. The following sections describe how the sentiment measures identified in prior research are operationalized in this study and outline the empirical strategies adopted.

3.Data

The data utilized in this investigation was inspired mainly by the publications of the Cecchetti (2020), Borri (2018), Delatte et al. (2017), Longstaff et al. (2011) and the ECB, in its May 2014 Financial Stability Review Report, with regards to market sentiment proxies. Whereas the term premium data, is from Favero and Srivastava (2023), one of the few computed estimates of the term premium for EGBs as explained in section 2.1.

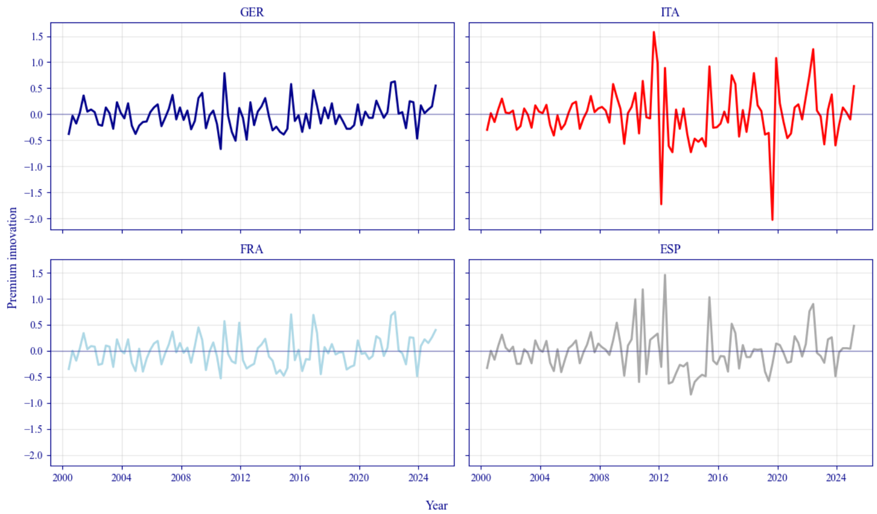
3.1 Term premium

Favero and Srivastava (2023) publish estimates of both the term premium and the expected average nominal short-term monetary policy rate for the 10-year Bund, BTP, OAT, and Bono. This investigation focuses exclusively on the term premium component; accordingly, the four series were downloaded for the period 01/01/2000–31/03/2025, which represents the full set of observations made available by the authors. Specifically, the decomposition based on the methodology of Adrian et al. (2013) was chosen over the approach of Favero and Fernandez-Fuentes (2023). The data are at quarterly frequency, yielding 101 observations per country. The four series are illustrated in the graph below.

Figure 1: Term premiums of Germany, France, Italy and Spain

The term premiums were checked for stationarity, through the Augmented Dickey Fuller (ADF) Stationarity Test, as well as by inspecting the ACF and the PACF. According to these assessments, the four term premium series were deemed not stationarity, requiring the first difference to be taken. Accordingly, from this point on in the analysis, the discussion will be regarding the innovations in the term premiums, i.e. the quarterly increments and decrements of the term premiums. This decision to transform the term premiums in such a way is dictated by the statistical requirements of working in a linear regression setting, though reasoning in the delta (innovations) of the term premium is common practice in the finance field. In the following figure, the term premium innovations can be seen.

Figure 2: 1st difference (innovations) of the term premiums



3.2 Sentiment variables

The sentiment variables used in this study were selected based on the existing literature on the interaction between market sentiment and sovereign yields. However, unlike most of the studies reviewed in the literature section, which rely on weekly or monthly data, the sentiment proxies in this investigation were utilized at a quarterly frequency due to the availability of term premium data only at that frequency. Accordingly, variables that are expressed as weekly or monthly percentage changes in the present literature were converted into quarterly percentage changes in this study, while variables commonly used in levels were averaged over each quarter.

The following explanatory variables were downloaded using Refinitiv DataStream.

- VSTOXX: euro area's implied stock market volatility (European VIX). Taken in quarterly percentage changes.
- P/E euro area: The Price-Earnings ratio of the aggregate euro area stock market index, which, according to Cecchetti (2020), should proxy the variation in the equity risk-premium. This series was downloaded as the quarterly percentage change of the index.
- A Country's banking sector returns: the quarterly returns of the country's banking sector stock index (Germany, Italy, France and Spain).

- Economic Policy Uncertainty: FRED provides indexes of countries' economic policy uncertainty. The quarterly percentage change of the indexes was used.
- CISS indicators[3]: 4 different indicators on equity, bond market, banks' equity and FX financial stress for Euro Area as a whole. These indicators became popular following the 2012 sovereign debt crisis in the euro area. The four indicators are not country specific and were downloaded as the quarter averages.

These variables were downloaded for the same period as the term premiums, from Q1 2000 to Q1 2025. As with the term premium series, stationarity and correlation checks were performed on all series[4]. Before discussing the correlation analysis, it is important to explain the rationale for choosing these variables.

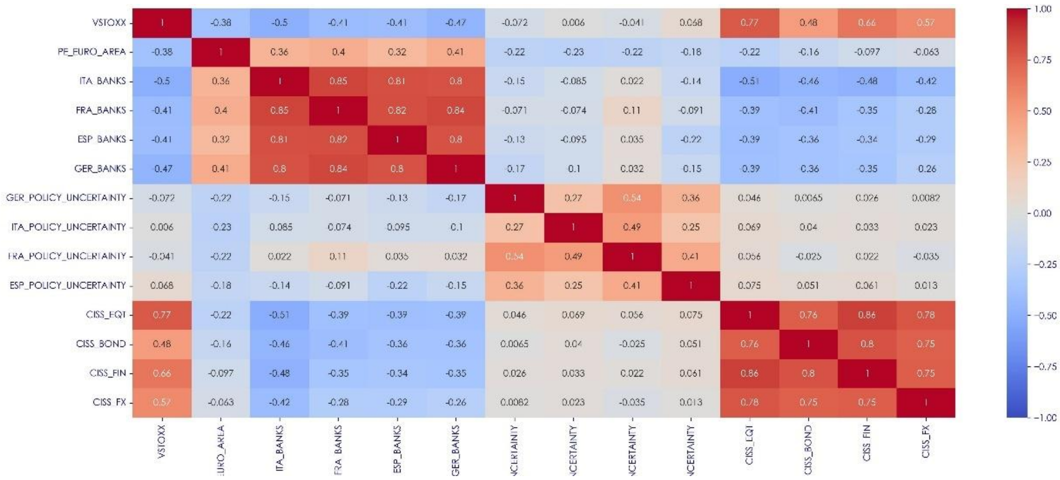
First, VSTOXX serves as the primary measure of market fear for euro area assets, capturing periods when investors are panicking and adjusting their portfolios accordingly. This indicator can thus provide a proxy for the "flight-to-safety" phenomenon. Second, the P/E ratio of the euro area stock market reflects the current risk appetite in the region, as it proxies the equity risk premium demanded by investors. Third, the countries' banking sector returns are included to capture potential "transfer of risk" phenomena. Fourth, the Economic Policy Uncertainty (EPU) index from FRED captures concerns about government measures, such as fiscal packages that may not be welcomed by the market. Finally, the CISS indicators are intended to function similarly to VSTOXX, but with greater specificity for different asset classes.

With regards to the stationarity checks, likewise the term premiums, both the ADF Stationarity test and the ACF and PACF were used in the assessment. The only group of variables that were deemed not stationary were the four CISS indicators, which were made stationary through differentiation.

After all series were made stationary, correlations checks were made to avoid multicollinearity problems in the regressions. Therefore, the correlation matrix of figure 3 was estimated, and it became immediately clear that the correlation amongst the CISS indicator was worryingly high.

[3] CISS: Composite Indicator of Systemic Stress. Introduced by the ECB with "CISS – A Composite Indicator of Systemic Stress in the Financial System" – Working Paper Series, March 2012
[4] Figure 16 in the appendix summarizes all the transformations carried out.

Figure 3: correlation matrix of all explanatory variables (in heatmap form)



Besides the CISS indicators (bottom right corner), two additional clusters of correlated series are visible in Figure 3. However, these clusters do not raise concerns regarding multicollinearity, as they consist of country-specific variables that are not simultaneously used to estimate individual country term premium.

For the CISS indicators, principal component analysis (PCA) was employed as a dimensionality reduction tool. This approach avoids the need to exclude three of the four CISS indicators, which would have been the result of arbitrarily selecting a single indicator as representative. The purpose of applying PCA is to obtain alternative representations of the original dimensions in the form of mutually orthogonal (uncorrelated) principal components, thereby resolving the multicollinearity problem. However, this method involves some trade-offs. First, principal components are weighed linear combinations of the four original variables. Hence, while the CISS indicators are economically interpretable, the resulting components lack direct financial meaning, making their interpretation less straightforward when used as explanatory variables in a regression. Second, PCA captures only linear dependencies and may be unsuitable if the relationships among the CISS indicators are nonlinear.

Once the principal components were estimated, it was noticed that the first principal component alone accounted for explaining nearly 0.83 of the variances of the four series (Figure 4). Consequently, there was no need to utilize more than the first principal component for the future analysis as generally the number of principal components to retain coincides with an explained cumulative variance of 70-80%.

Figure 4: explained cumulative variance of the four principal components estimated using the CISS indicators

Component	*Explained Variance*	*Cumulative Variance*
PC1	0.826	0.826
PC2	0.086	0.912
PC3	0.054	0.966
PC4	0.034	1.000

Though principal components tend to have ambiguous financial meaning, inspecting the eigenvectors (loadings) can give some information as to what the component can possibly represent. The first principal component of the CISS indicators has negative loadings (figure 5), meaning that an increase in the component implies a sounder financial situation as stress levels across the four asset classes are reducing. Accordingly, the first principal component can be interpreted as representing easing financial market stress when it increases, and rising stress when it decreases.

Figure 5: Eigenvectors (loadings) of the four principal components

	PC1	*PC2*	*PC3*	*PC4*
CISS_EQT	-0.513	-0.345	-0.260	0.742
CISS_BOND	-0.504	-0.058	0.858	-0.074
CISS_FIN	-0.509	-0.388	-0.383	-0.666
CISS_FX	-0.473	0.853	-0.221	-0.008

Following the dimensionality reduction of the CISS indicators from four to one, the five explanatory variables for each country's term premium were ready for use in the linear regression analysis. Section 4 presents the country-specific regression models, while Section 5 explains the panel regression approach.

4. Models

4.1 Country level regression specification

The first approach utilized for assessing the relationship between market sentiment proxies and the EGBs term premium was inspired by Di Cesare et al. (2013), who investigated both the impact of macro and sentiment variables on sovereign spreads using multivariate regressions estimated at country level. Consequently, in this investigation, the specification of the regression estimated at country level is the following:

$$\Delta Term\ premium_t = \alpha + \boldsymbol{\beta X_t} + \varepsilon_t$$

Where the dependent variable was a country's term premium innovation, and the explanatory variables were the VSTOXX (quarterly percentage change), the P/E of the euro area (quarterly percentage change), the domestic banking sector's performance (quarterly percentage change), the country's economic policy uncertainty (quarterly percentage change) and the first principal component of the four CISS indicators. In total, eight regressions were estimated, two regressions for each country, and using the data from the second quarter of 2000 until the first quarter of 2025[5]. The second regression estimated for each country included 2012 dummies, such that the specification of the regression was the following:

$$\Delta Term\ premium_t = \alpha + \boldsymbol{\beta X_t} + \varphi_t + \varepsilon_t$$

Where φ_t stands for a time dummy, which is set equal to 1 in 2012, and is supposed to capture the peak of the euro area sovereign debt crisis.

Coefficients were estimated using Ordinary Least Squares (OLS). Residual diagnostics, including the Durbin-Watson statistic, the Breusch-Pagan test, and the White test, revealed no concerns regarding autocorrelation or heteroskedasticity[6]. Therefore, no adjustments, such as Newey-West standard errors, were made. With respect to stationarity, various checks and transformations were conducted in Section 3 to ensure that no non-stationary series were included in the regressions.

[5] The term premium data was available from the first quarter of 2000. However, after taking the first difference of the term premium to make it stationary, one observation was lost.
[6] Consult figure 17 in the appendix if interested in the residual diagnostic.

4.2 Country level regressions output

From the four separate regressions for the four different countries the following results were obtained.

Figure 6: Country level multivariate regressions outputs

	Germany		*France*		*Italy*		*Spain*	
Const	-0.1017	-0.1094	-0.1289	-0.1383	-0.1818	-0.1761	-0.1322	-0.1338
	(0.2246)	(0.1905)	(0.1386)	(0.1060)	(0.2212)	(0.2335)	(0.2579)	(0.2545)
VSTOXX	0.0042	0.0048	0.0051	0.0061*	0.0065	0.0070	0.0048	0.0050
	(0.2032)	(0.1437)	(0.1411)	(0.0768)	(0.2782)	(0.2404)	(0.3066)	(0.2897)
P/E euro area	0.0104*	0.0119**	0.0066	0.0092	0.01046	0.0131	0.0132*	0.0139*
	(0.0605)	(0.0355)	(0.2807)	(0.1357)	(0.2869)	(0.1866)	(0.0945)	(0.0867)
Banking sector	0.0007	0.0007	0.0021	0.0018	-0.0075*	-0.0064	-0.0020	-0.0019
	(0.7025)	(0.7146)	(0.3681)	(0.4350)	(0.0693)	(0.1282)	(0.5330)	(0.5638)
Policy uncertainty index	-0.0011	-0.0010	-0.0001	0.0001	0.0068***	0.0067***	0.0062***	0.0063***
	(0.1724)	(0.1956)	(0.9944)	(0.8982)	(0.0011)	(0.0013)	(0.0092)	(0.0089)
CISS_PC1	-0.0149	-0.0108	-0.0140	-0.0069	-0.0967***	-0.0863***	-0.0115	-0.0094
	(0.3803)	(0.5285)	(0.4454)	(0.7055)	(0.0018)	(0.0063)	(0.6357)	(0.7060)
2012 dummy		-0.1944		-0.3226**		-0.3739		-0.0865
		(0.1624)		(0.0311)		(0.1393)		(0.6734)
Number of Observations	100	100	100	100	100	100	100	100
Degrees of Freedom	94	93	94	93	94	93	94	93
R-squared	0.0791	0.0984	0.0354	0.0826	0.1908	0.2098	0.0925	0.0942
Adjusted R-squared	0.0302	0.0402	-0.0160	0.0234	0.1478	0.1588	0.0442	0.0358
F-statistic	1.6167	1.6919	0.6891	1.3956	4.4347	4.1143	1.916	1.6125

Values reported in parenthesis are the p-values of the coefficients

Starting with the coefficient of VSTOXX, it is positive in all four countries. However, the coefficient is statistically significant only for France when including the 2012 dummy, and only at 0.1 significance level. Accordingly, even though the sign of the coefficients are positive, thus in line with what would the expected impact of a increase in stock market volatility on the innovations of term premium, the results provide limited statistical evidence of a meaningful relationship between VSTOXX and changes in the term premiums.

The coefficient of the P/E euro area stock index is also positive across all four countries. In Spain and in Germany (in the specification without the 2012 dummy), the coefficient is statistically significant at the 10% level, while it reaches the 5% level in the German regression including the 2012 dummy variable. Although this significance is relatively weak, the positive signs of the coefficients are somewhat puzzling. This is because according to Cecchetti (2020), the P/E ratio represents the equity risk premium, so an increase in P/E growth implies a decrease in the equity risk premium. Consequently, one would expect a negative coefficient rather than a positive one.

The banking sector coefficients are positive but not statistically significant in Germany and France, whereas they are negative in Italy and Spain. In Italy, the coefficient for national banking sector returns is statistically significant in the no 2012 dummy specification, providing a little bit of evidence that concerns about a troubled banking sector increase worries about the country's economic and fiscal outlook, thereby raising changes in the sovereign term premium relative to the previous quarter.

The banking sector coefficients are positive but not statistically significant in Germany and France, whereas they are negative in Italy and Spain. In Italy, the coefficient for national banking sector returns is statistically significant in the specification without the 2012 dummy, providing some evidence that deteriorating banking sector performance is associated with increased concerns about the country's economic and fiscal outlook, thereby raising innovations in the sovereign term premium relative to the previous quarter.

Finally, the coefficients of the first principal component of the CISS indicators are all negative, with Italy being the only country where the coefficient is statistically significant at the 1% level. The negative sign is consistent with expectations, as a decrease in the first principal component corresponds to an increase in financial market stress (see Section 3.2 for further details regarding the interpretation of the principal component).

Overall, considering the statistical significance of the coefficients across the four countries, there is limited evidence that market sentiment proxies meaningfully explain the quarterly movements of EGB term premiums in a linear regression framework. The specification including the 2012 dummy generally leads to very similar results compared with the specification without the sovereign debt crisis dummy, and the minor differences observed do not alter the overall picture.

The adjusted R-squared obtained for the four countries paint a similar picture. Only Italy obtains an adjusted R-squared above 0.1, while the other three countries all have adjusted R-squared below 0.05. Even the R-squared, which does not account for sample size nor for the number of regressors present in the specification, has values below 0.1 in Germany, France and Spain. These findings suggest that the proportion of the variation of the innovation of term premium explained by the sentiment proxies of the specification is very low, especially for countries whose sovereign debt has been perceived safer in past two decades (Germany and France).

The mediocre fit of the estimates with respect to the actual term premium innovations values is clearly visible in a graphical representation too, even for Italy. Below the graphs of the fitted vs.

actual values of the changes in the German, French, Italian and Spanish 10Y term premium can be seen[7].

Figure 7: Fitted values vs. actual innovations in German 10Y term premium obtained with the country level regression, without the 2012 dummy variable

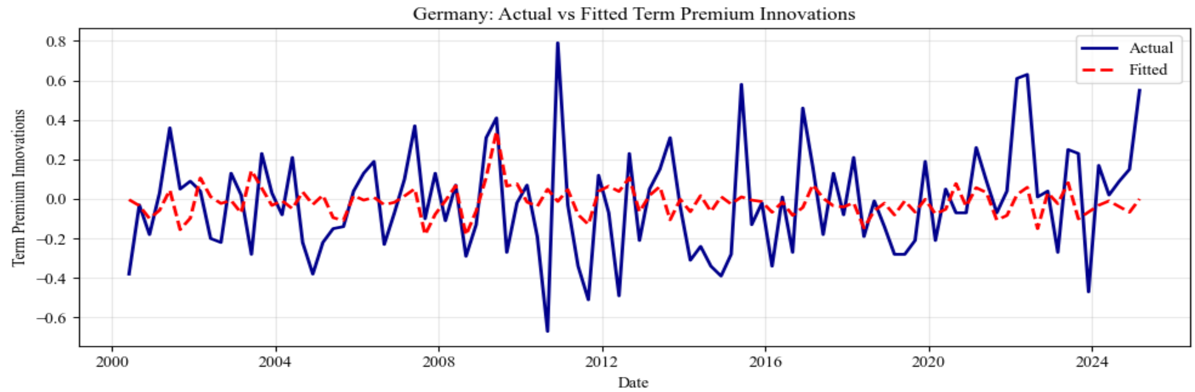


Figure 8: Fitted values vs. actual innovations in French 10Y term premium obtained with the country level regression, without the 2012 dummy variable

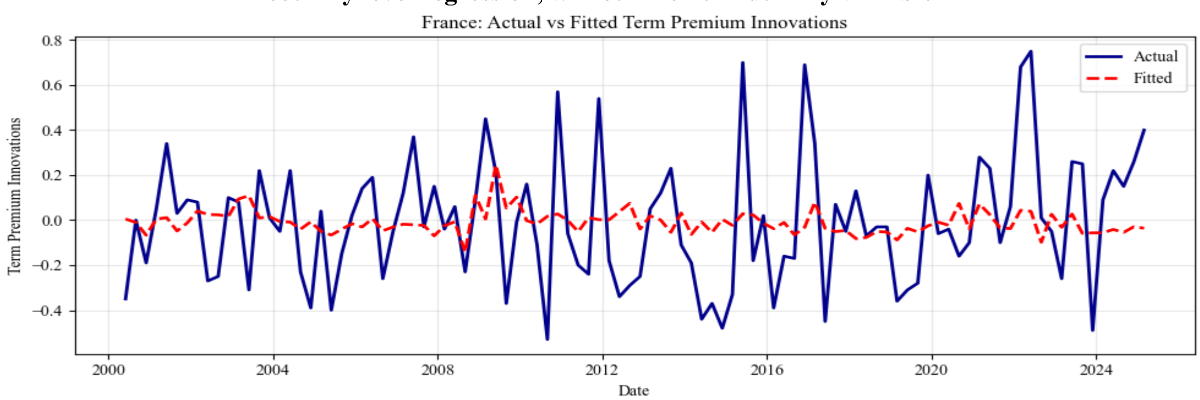
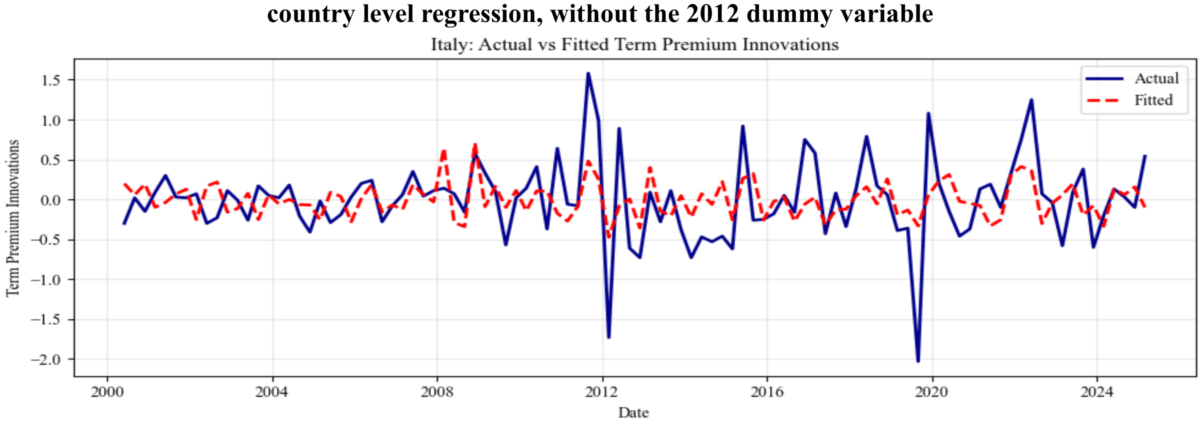
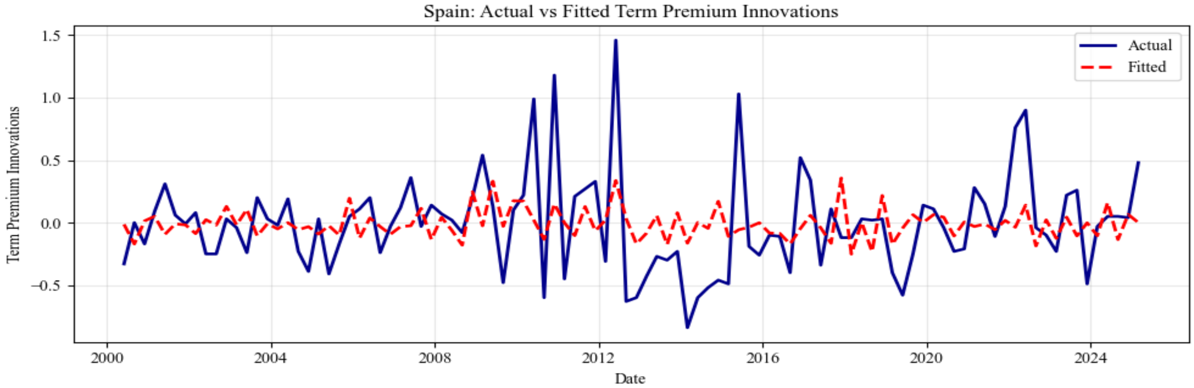


Figure 9: Fitted values vs. actual innovations in Italian 10Y term premium obtained with the country level regression, without the 2012 dummy variable



[7] The graphs for the specification with the 2012 dummy are available in the appendix.

Figure 10: Fitted values vs. actual innovations in Spanish 10Y term premium obtained with the country level regression, without the 2012 dummy variable



The unexpected results obtained with the multivariate country specific regressions model prompted the creation of a second model, which is covered in the next subsection.

4.3 Multivariate panel regressions specifications

Because of the mediocre results obtained with the first model, a second approach was tried. This time the model departed from Di Cesare et al. (2013) methodology of country specific regressions and tried to exploit the benefits of expanding the sample size by estimating panel regression. The approach resembles that of Ceci and Pericoli (2022), who suggested that countries inside a highly economically integrated system, such as the Euro System, could be studied through a multi-country model. A panel regression, using two or more countries, falls under the category of multi-country model according to the definition of Ceci and Pericoli (2022).

In this second attempt, the regression specification was the following:

$$\Delta Term\ premium_{t,i} = \alpha + \boldsymbol{\beta X}_{t,i} + \delta_i + \varepsilon_{t,i}$$

Where the $\boldsymbol{X}_{t,i}$ contains the VSTOXX, the P/E of the euro area stock market, the first principal component of the CISS indicators, the country's banking sector equity performance and the country's economic policy uncertainty index. Additionally, δ_i stands for country specific dummies, which are fixed in time[8] .

The specification was estimated on three different sets of countries: the entire panel (Germany, France, Italy and Spain) and two pairs of countries. The first pair, referred to as the "core

[8] Since the panel is composed of two countries, the dummy takes values of 0 and 1. In the case of the "core countries", Germany is 0 and France is 1, while for the "periphery countries", Italy is 0 and Spain is 1.

countries”, comprises Germany and France, which are historically considered the core of the euro area and whose sovereign debt has been perceived as safer than that of Italy and Spain. The second pair, the “periphery countries”, includes Italy and Spain. This split is justified by the fact that the term premiums of the two groups have behaved quite differently over the past 25 years, particularly during the period 2008–2015 (Figure 1). Moreover, Italy and Spain were part of the PIIGS countries during the euro-area sovereign debt crisis in 2012. Considering these two characteristics, it is plausible that the direction in which market sentiment proxies influence term premium innovations differs between the groups, making the split into core and periphery countries a reasonable approach.

For each of the three groups of countries, an additional specification, which included a 2012 dummy φ_t, was also estimated, so that the model becomes:

$$\Delta Term\ premium_{t,i} = \alpha + \boldsymbol{\beta X}_{t,i} + \delta_i + \varphi_t + \varepsilon_{t,i}$$

Moreover, for the panel containing all four countries, a third specification was estimated that included year fixed effects for each year in the sample. This specification was estimated only for the full panel, as the inclusion of a full set of year dummies (24 dummies for the 25 years the data spans across) substantially increases the number of estimated parameters and absorbs a large share of the time-series variation. Therefore, estimating this specification on the smaller core and periphery subsamples would result in a significant loss of degrees of freedom and statistical power, leading to imprecise coefficient estimates.

As in the regressions of Section 4.1 and 4.2, data from Q2 2000 to Q1 2025 was used. All specifications were estimated using OLS with country fixed effects and, where applicable, year fixed effects. Standard errors are clustered at the country’s level in order to allow for heteroskedasticity and serial correlation within countries.

4.4 Panel regression output

From the estimation of the two panel regressions the following outputs were obtained:

Figure 11: Panel multivariate regressions outputs

	Full Panel			*Core*		*Periphery*	
Const	-0.1383**	-0.1439**	-0.3186**	-0.1211*	-0.1301	-0.1500	-0.1506
	(0.0344)	(0.0266)	(0.0182)	(0.0519)	(0.0346)	(0.1291)	(0.1265)
VSTOXX	0.0050**	0.0057**	0.0077**	0.0049**	0.0058**	0.0053	0.0058
	(0.0285)	(0.0124)	(0.0454)	(0.0394)	(0.0157)	(0.1614)	(0.1268)
P/E euro area	0.0095**	0.0115***	0.0142***	0.0083	0.0103**	0.0118*	0.0136**
	(0.0136)	(0.0032)	(0.0023)	(0.1018)	(0.0124)	(0.0605)	(0.0337)
Banking sectors	-0.0024	-0.0020	-0.0027	0.0016	0.0015	-0.0045*	-0.0039
	(0.1106)	(0.1708)	(0.1834)	(0.2679)	(0.3036)	(0.0862)	(0.1364)
Policy uncertainty index	0.0013*	0.0014**	0.0011	-0.0006	-0.0005	0.0065***	0.0065***
	(0.0586)	(0.0461)	(0.1168)	(0.3205)	(0.3852)	(0.0002)	(0.0001)
CISS_PC1	-0.0304**	-0.0243**	-0.0123	-0.0137	-0.0081	-0.0525***	-0.0464**
	(0.0101)	(0.0408)	(0.3275)	(0.2674)	(0.5087)	(0.0071)	(0.0192)
Country fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
2012 dummy		-0.2622***			-0.2585**		-0.2384
		(0.0072)			(0.0103)		(0.1408)
Year fixed effects	*No*	*No*	*Yes*	*No*	*No*	*No*	*No*
Number of Observations	400	400	400	200	200	200	200
R-squared	0.0419	0.0595	0.2453	0.0496	0.0817	0.1285	0.1384
Adjusted R-squared	0.0223	0.0378	0.1772	0.0201	0.0482	0.1015	0.1069
F-statistic	2.1385	2.7428	3.6039	1.6798	2.4411	4.7448	4.4044

Values reported in parenthesis are the p-values of the coefficients

Starting with the coefficients of VSTOXX, both country pairs and full panel exhibit positive coefficients. However, only for the core countries and the "full panel" is the p-value of the coefficient below the 5% significance threshold. This suggests that heightened volatility in the euro-area stock market is positively associated with changes in term premiums in samples that include Germany and France, providing some statistical evidence of a relationship between VSTOXX and term premium innovations.

Regarding the P/E ratio of the euro area stock market, the coefficients are positive in all specifications and statistical significance is not observed only in the "core" countries when the 2012 dummy is not included. The statistical significance is not always high, only the coefficients of the full panel have significance level at 1%, while those of the periphery countries at the 10% and 5% level depending on the specification. Consistent with the conclusions from Section 4.2 and the results of this second model, the P/E ratio appears to demonstrate the opposite relationship to what would be expected from financial theory regarding term premiums and the equity risk premium. A possible explanation for the positive sign of the euro area P/E coefficient is interaction with other regressors. It is plausible that VSTOXX, national banking sector performance, and the first principal component partially capture information about the equity risk premium. As a result, the residual variation in the P/E ratio may be less closely aligned with movements in the equity risk premium.

The banking sector coefficients differ in sign between the two country groups: they are positive for the core countries and negative for both the periphery countries and the full panel. Nonetheless, statistical significance is observed only for the periphery countries, where the coefficient is significant at the 10% level in the specification without the 2012 dummy. The negative coefficient for the periphery is economically plausible, as a troubled banking sector can affect sovereign yields through the "credit risk transfer hypothesis", as suggested by Attinasi et al. (2009), operating via the term premium channel by influencing perceived sovereign credit risk rather than monetary policy concerns. Though, the statical evidence of this phenomenon visible in the table is very limited.

For the remaining coefficients, namely the economic policy uncertainty indexes and the first principal component of the CISS indicators, statistical significance is observed only for the periphery countries and, in two out of three specifications, for the full panel as well, though at weaker significance levels. In the periphery pair, both coefficients are significant at the 1% level in the specification without the 2012 dummy: the economic policy uncertainty coefficient is positive, indicating that increases in policy uncertainty are associated with rises in term premium innovations, while the CISS coefficient is negative, in line with standard theoretical expectations.

With regards to the R-squared, the periphery registered an adjusted R-squared slightly above 0.1, whereas the core adjusted R-squared was below that threshold. The regression made on the full panel yielded adjusted R-squared values similar to those of the core countries for the specifications with the 2012 dummy and the one without. However, the full panel regression with year fixed effects yielded the highest adjusted R-squared, 0.1772, that is however largely attributable to the year fixed effects rather than the market sentiment. Accordingly, these results are similar to the ones obtained in section 4.2, as sentiment proxies seem to be able to explain only a small proportion of the variations of the term premium innovations[9].

[9] There was concern that the inclusion of country fixed effects in the specification affected the interpretation of the regression, causing the specification to capture cross-country spreads. Consequently, a specification without country fixed effects was estimated for every regression reported in Figure 11. The resulting coefficients differed from those obtained with country fixed effects only at the fourth decimal place, implying that the specification does not capture cross-country spreads.

More generally, the inclusion of a dummy for the peak of the sovereign debt crisis in 2012 and the introduction of year fixed effects in the full-panel regression do not lead to substantial changes in coefficient estimates, their statistical significance, nor the portion of variation in term premium innovations explained by market sentiment across the four countries. The figures below report the fitted values of term premium innovations for Germany, France, Italy, and Spain, obtained from the panel regressions estimated on the core and periphery samples without the 2012 dummy[10].

Figure 12: Fitted values vs. actual innovations in German 10Y term premium obtained with the "core" regression, without the 2012 dummy variable

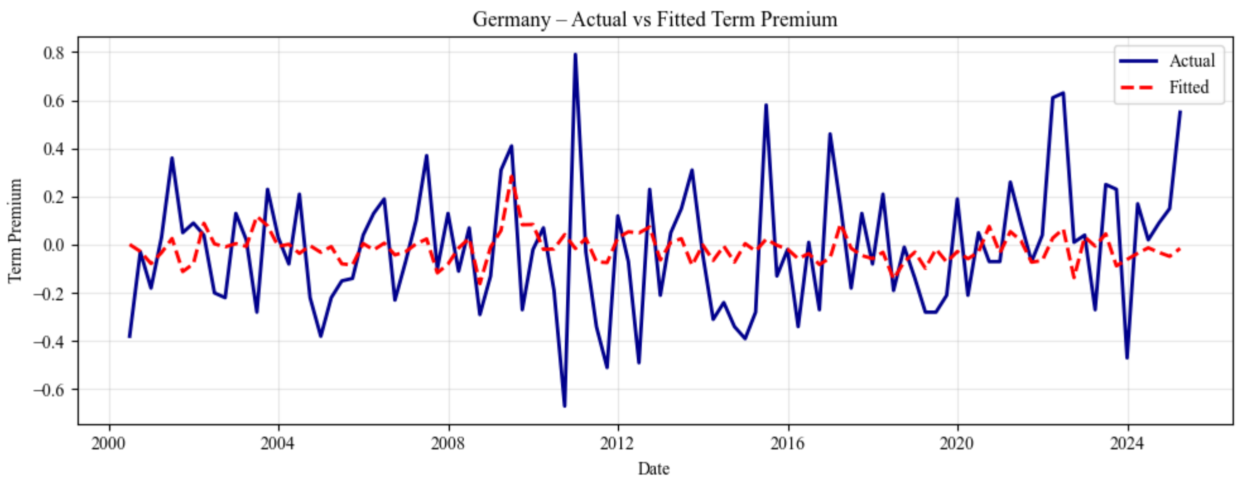
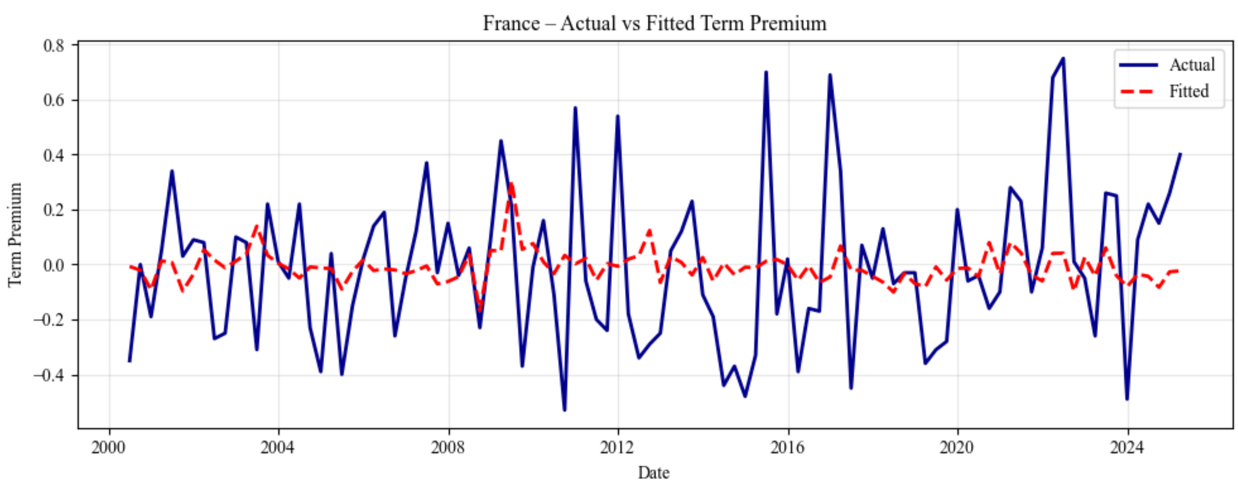


Figure 13: Fitted values vs. actual innovations in French 10Y term premium obtained with the "core" regression, without the 2012 dummy variable



[10] The graphs for the remaining regressions can be found in the appendix.

Figure 14: Fitted values vs. actual innovations in Italian 10Y term premium obtained with the "periphery" regression, without the 2012 dummy variable

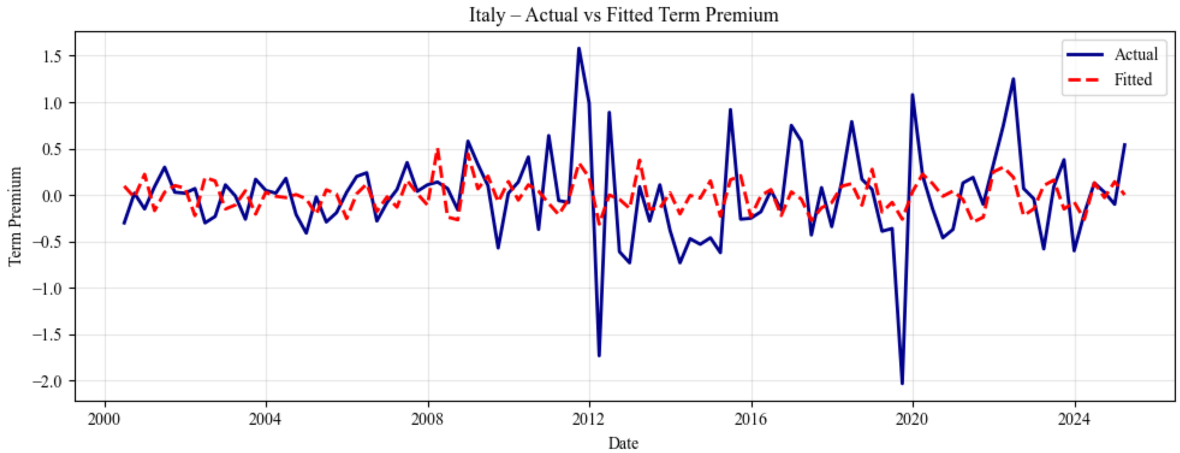
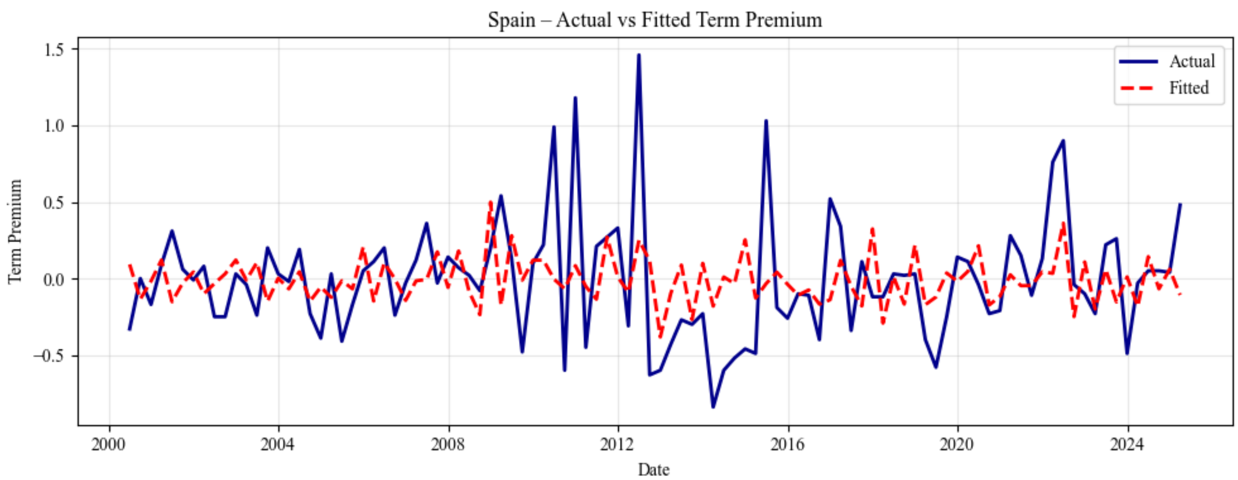


Figure 15: Fitted values vs. actual innovations in Spanish 10Y term premium obtained with the "periphery" regression, without the 2012 dummy variable



Overall, also by employing the panel regression approach, and increasing the sample upon which the regressions were estimated, the proportion of explained variance remained low and only some improvements were noticed in the number of statically significant coefficients. Nevertheless, the evidence of the importance of market sentiment in driving quarterly innovations of the EGBs term premium is not overwhelming.

5. Discussion of the findings

Overall, different sentiment variables were found to be statistically significant across models and across countries in explaining the quarterly changes in the 10-year term premiums of Germany, France, Italy and Spain. Among the variables considered, national economic policy uncertainty emerges as the most robust proxy, displaying statistically significant coefficients in several specifications and across different empirical frameworks. This finding suggests a consistent positive association between increases in policy uncertainty and term premium innovations. On the other hand, the remaining four explanatory variables investigated were only in singular cases statistically significant and did not exhibit a stable pattern throughout the various countries and specifications.

In addition, the adjusted R-squared of the six regressions were generally very low, with Italy being the country with the highest adjusted R-squared value in the country specific regression setting (in both specifications), while in the panel regression setting the periphery pair (Italy and Spain) obtains the highest adjusted R-squared among the models without year fixed effects. The only exception is the full-panel regression with year fixed effects, which yields a considerably higher adjusted R-squared. Nevertheless, as discussed earlier, the high adjusted R-square of the latter regression is largely attributable to the inclusion of year fixed effects rather than to the explanatory power of market sentiment variables.

Therefore, not much evidence was found of market sentiment being a driver of the EGBs 10-year term premium innovations. This outcome of the investigation was somewhat unexpected, as existing literature on the relationship between market sentiment and yields, term premiums, spreads and CDS, tends to evidence a greater impact of sentiment on the dependent variable. As result, a revision of the existing literature took place, with the aim of formulating hypotheses as to why these differences in findings occurred.

The main hypothesis is that in this investigation quarterly data is used. The reason for this choice is linked to the unavailability of monthly nor weekly data of term premiums for the euro area. Consequently, it was preferred to carry out the study using all data at quarterly frequency, instead of keeping the term premium data constant in the months within the quarter[11]. However, both Di Cesare et al. (2013) and Kim et al. (2019) used higher frequency data in their studies, daily frequency and weekly frequency respectively. Additionally, market sentiment fluctuates at relatively high frequencies, so aggregating it to the quarterly level smooths the underlying series and leads to information being lost. While quarterly sentiment measures may still be related to term premium, their explanatory power is likely stronger at shorter horizons, when investors may temporarily overreact to news and events. These reactions are often corrected within the quarter, reducing the variability of sentiment at lower frequencies and, in turn, weakening the ability to explain movements in term premia. Furthermore, using data at quarterly frequency required certain transformations to be made, both to the dependent and the independent variables. These transformations are another source of information being lost, hence if using lower frequency meant avoiding some of the transformations that were required for quarterly data, it could result having data that retains more information and possibility of explaining a greater proportion of the variation of the term premiums.

A second important consideration to be made is that in this paper only the linear relationship between market sentiment proxies and term premiums was investigated. Di Cesare et al. (2013) highlighted that in times of turbulence in the sovereign bond markets, like the 2012 sovereign debt crisis, spreads – hence the difference in term premium between the Bund and the other euro area sovereign bonds – tend behave in non-linear manners. Thereby, the low proportions of variations of the dependent variable explained by the independent variables may also be related to the models not capturing the non-linear nature of the movements of term premium in times of enhanced sovereign bond market volatility.

These two hypotheses regarding why the results differ from existing literature also provide potential directions for further research and should not be interpreted merely as critiques of the investigation conducted.

[11] This decision arises from the experience of the Bocconi University thesis discussion, during which was suggested by one of the committee professors that if one of the variables in the regression is of quarterly frequency, bringing the entire data set to quarterly frequency should improve the fit of the regression.

6. Conclusion

This investigation extended the Bocconi University thesis *"Market Sentiment and Financial Variables as Drivers of Sovereign Spreads Mispricing"* by analyzing the relationship between quarterly innovations in the 10-year term premiums of Germany, France, Italy, and Spain and measures of market sentiment.

The market sentiment proxies used were the VSTOXX, the P/E ratio of the euro area stock market (as an indicator of the equity risk premium), the country's banking sector equity performance, the country's economic policy uncertainty index provided by FRED, and the first principal component of the CISS indicators. All independent variables were included at a quarterly frequency to match the term premium data from Favero and Srivastava (2023).

Two approaches were employed to investigate these relationships. The first was a multivariate regression model estimated at the country level, using two different specifications, and following the approach of Di Cesare et al. (2013). The second was a multivariate panel regression inspired by the multi-country model suggested by Ceci and Pericoli (2022) for analyzing countries within a highly economically integrated system, such as the euro area.

The results provided limited evidence that market sentiment systematically explains variations in 10-year term premium innovations. Italy, and more broadly the periphery peer (Italy and Spain), exhibited the highest adjusted R-squared values, though these were modest, slightly above 0.1. Among the sentiment proxies considered, national economic policy uncertainty stands out as the most robust indicator, showing a consistently positive association with term premium innovations across multiple specifications. In contrast, the other proxies are statistically significant only in isolated cases and do not exhibit stable patterns across countries or models.

The use of quarterly data may partially explain why these findings differ from much of the existing literature, which generally finds a stronger influence of market sentiment on term premiums. Accordingly, further research could explore the use of higher-frequency data and extend the analysis to non-linear settings to better capture the dynamics of term premiums in response to market sentiment.

Appendix

Transformations applied to the time series

Figure 16: Description of the transformations applied to the series

Series name	Transformation	Source
Term Premiums		
Germany 10Y term premium	Quarter-on-Quarter difference	IEP@BU
France 10Y term premium	Quarter-on-Quarter difference	IEP@BU
Italy 10Y term premium	Quarter-on-Quarter difference	IEP@BU
Spain 10Y term premium	Quarter-on-Quarter difference	IEP@BU
Market Sentiment		
VSTOXX	Quarter-on-Quarter percentage change	Datastream
P/E euro are stock market	Quarter-on-Quarter percentage change	Datastream
Germany's banking sector returns	Quarter-on-Quarter percentage change	Datastream
France's banking sector returns	Quarter-on-Quarter percentage change	Datastream
Italy's banking sector returns	Quarter-on-Quarter percentage change	Datastream
Spain's banking sector returns	Quarter-on-Quarter percentage change	Datastream
Germany's economic policy uncertainty	Quarter-on-Quarter percentage change	Datastream
France's economic policy uncertainty	Quarter-on-Quarter percentage change	Datastream
Italy's economic policy uncertainty	Quarter-on-Quarter percentage change	Datastream
Spain's economic policy uncertainty	Quarter-on-Quarter percentage change	Datastream
CISS equity	Quarter-on-Quarter difference	Datastream
CISS bond	Quarter-on-Quarter difference	Datastream
CISS FX	Quarter-on-Quarter difference	Datastream
CISS baking sector equity	Quarter-on-Quarter difference	Datastream

Additional statistics and graphs on the multivariate country level regressions (section 4.1 & 4.2)

Figure 17: Residuals diagnostic for the country level regressions of section 4.1 and 4.2

	Test	*Germany*	*France*	*Italy*	*Spain*
Specification without 2012 dummy	*Durbin–Watson*	1.852	1.740	2.160	2.089
	Breusch–Pagan p-value	0.892	0.585	0.607	0.254
	White p-value	0.514	0.111	0.340	0.147
Specification with 2012 dummy	*Durbin-Watson*	1.870	1.848	2.147	2.080
	Breusch-Pagan p-value	0.920	0.558	0.499	0.330
	White p-value	0.171	0.142	0.194	0.124

Figure 18: Fitted values vs. actual innovations in German 10Y term premium obtained with the country level regression, with the 2012 dummy variable

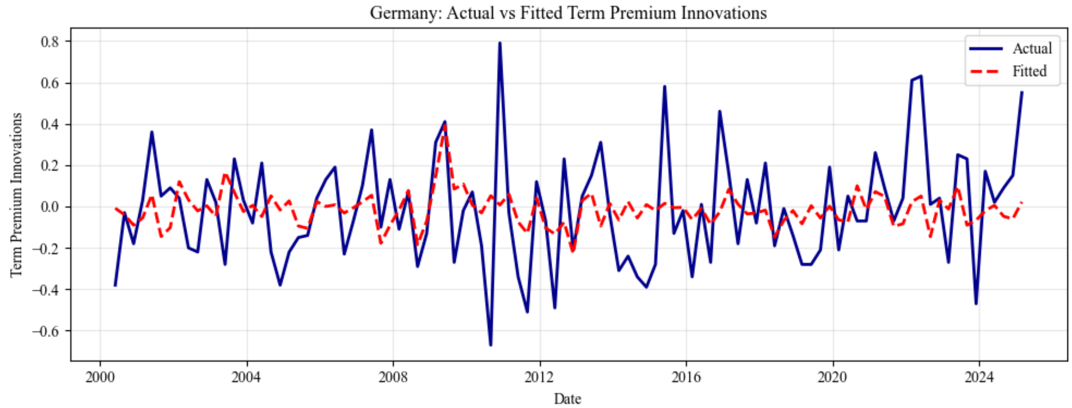


Figure 19: Fitted values vs. actual innovations in French 10Y term premium obtained with the country level regression, with the 2012 dummy variable

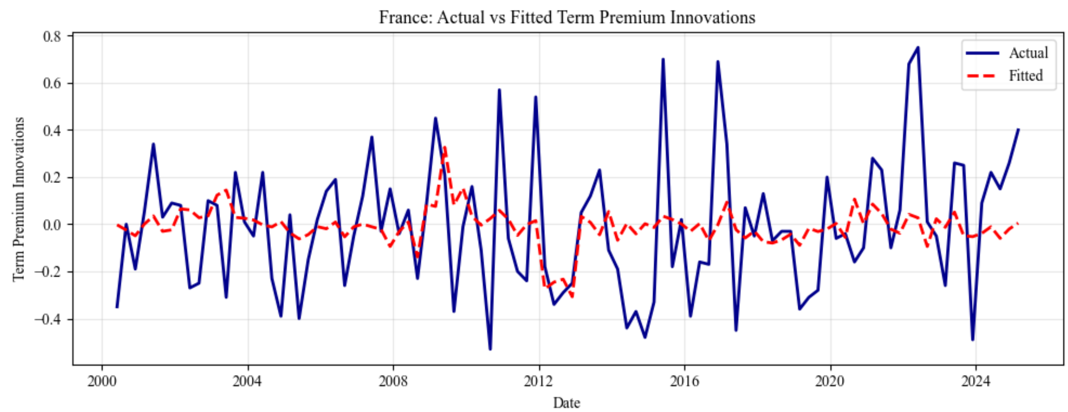


Figure 20: Fitted values vs. actual innovations in Italian 10Y term premium obtained with the country level regression, with the 2012 dummy variable

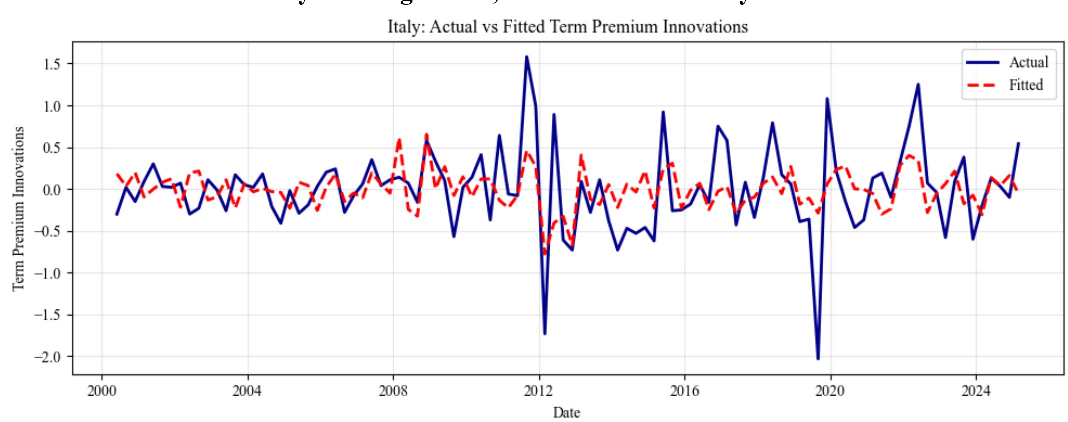
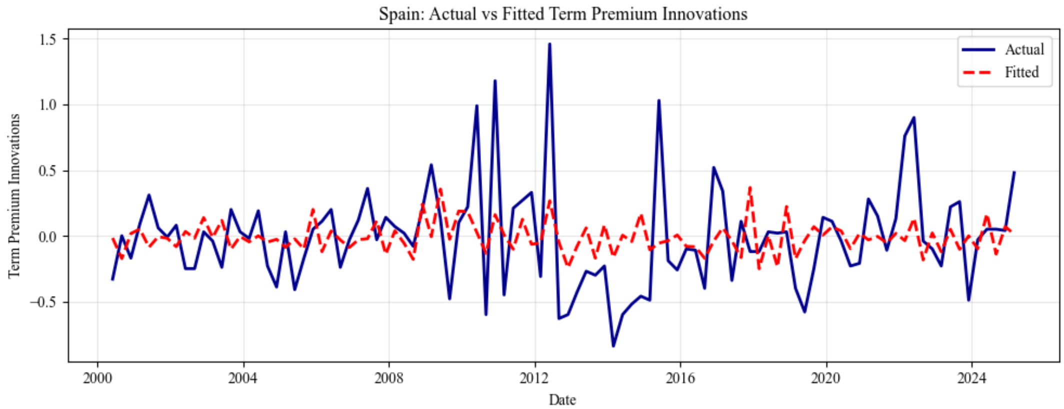


Figure 21: Fitted values vs. actual innovations in Spanish 10Y term premium obtained with the country level regression, with the 2012 dummy variable



Additional graphs of the panel regressions (sections 4.3 & 4.4)

Figure 22: Fitted values vs. actual innovations in German 10Y term premium obtained with the "full panel" regression, without the 2012 dummy

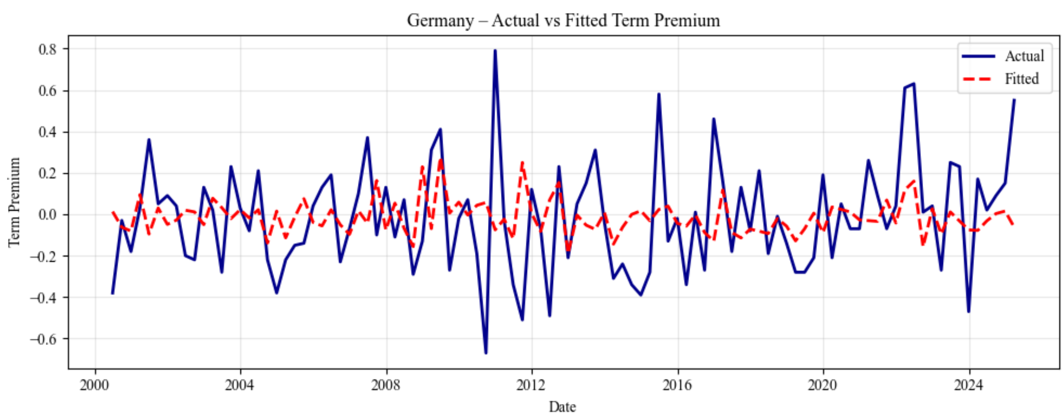


Figure 23: Fitted values vs. actual innovations in French 10Y term premium obtained with the "full panel" regression, without the 2012 dummy

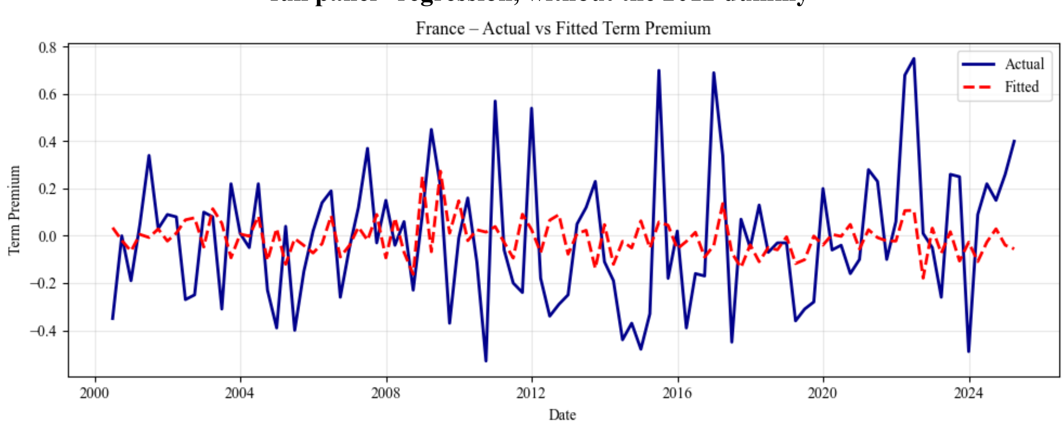


Figure 24: Fitted values vs. actual innovations in Italian 10Y term premium obtained with the "full panel" regression, without the 2012 dummy

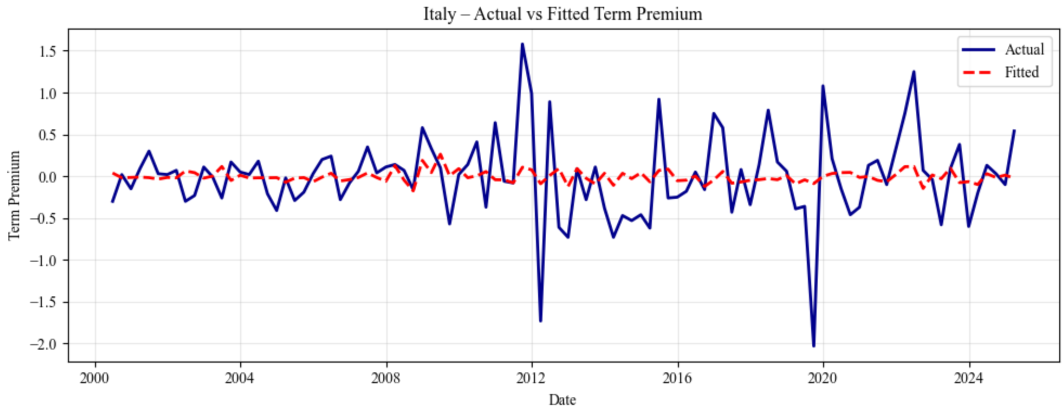


Figure 25: Fitted values vs. actual innovations in Spanish 10Y term premium obtained with the "full panel" regression, without the 2012 dummy

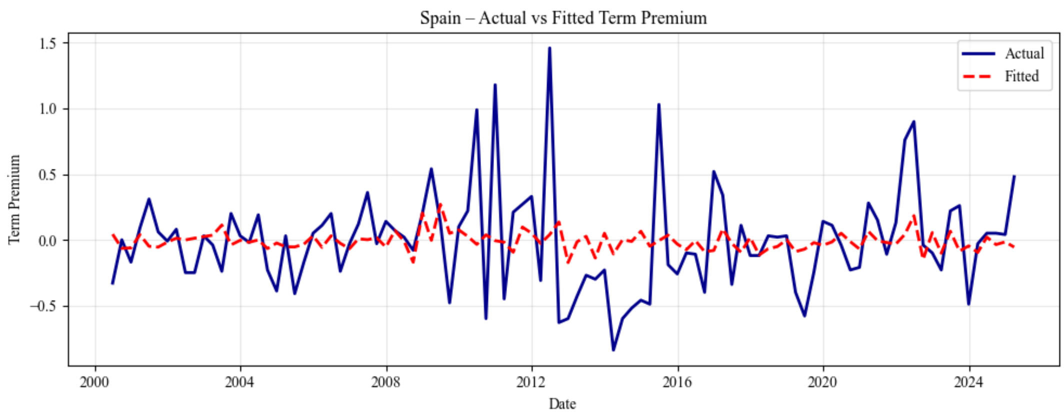


Figure 26: Fitted values vs. actual innovations in German 10Y term premium obtained with the "full panel" regression, with the 2012 dummy

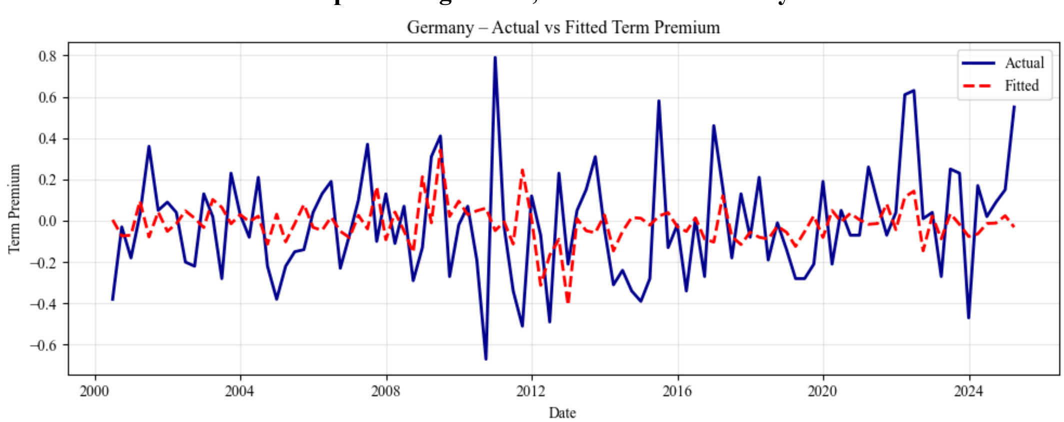


Figure 28: Fitted values vs. actual innovations in French 10Y term premium obtained with the "full panel" regression, with the 2012 dummy

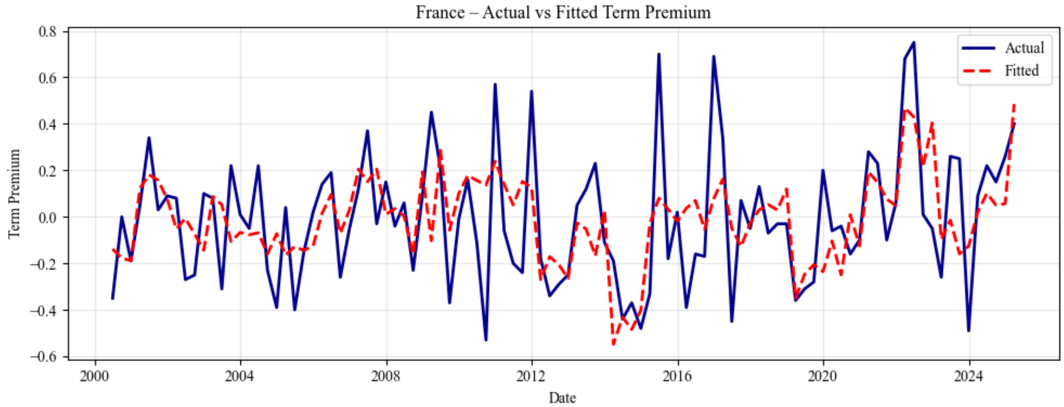


Figure 29: Fitted values vs. actual innovations in Italian 10Y term premium obtained with the "full panel" regression, with the 2012 dummy

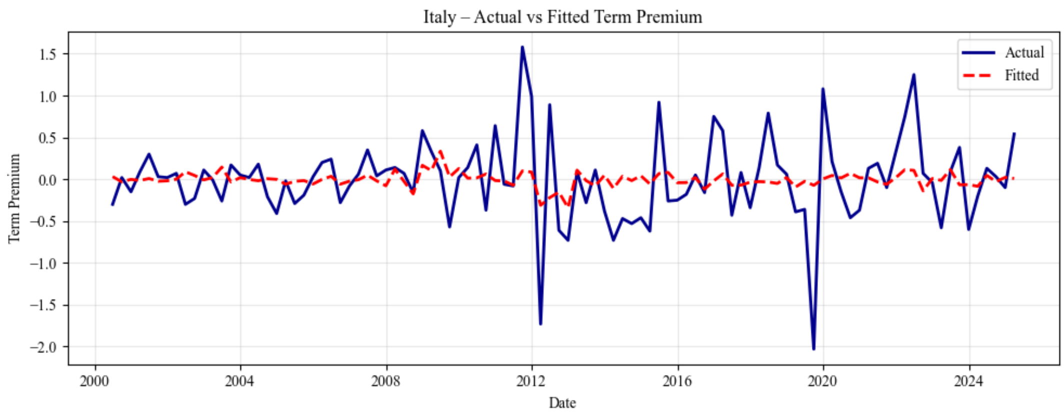


Figure 30: Fitted values vs. actual innovations in Spanish 10Y term premium obtained with the "full panel" regression, with the 2012 dummy

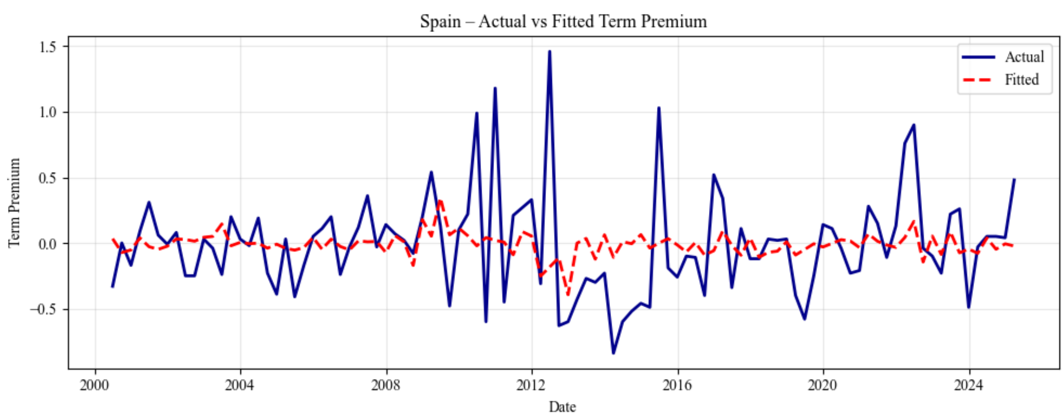


Figure 31: Fitted values vs. actual innovations in German 10Y term premium obtained with the “full panel” regression, with the year fixed effects

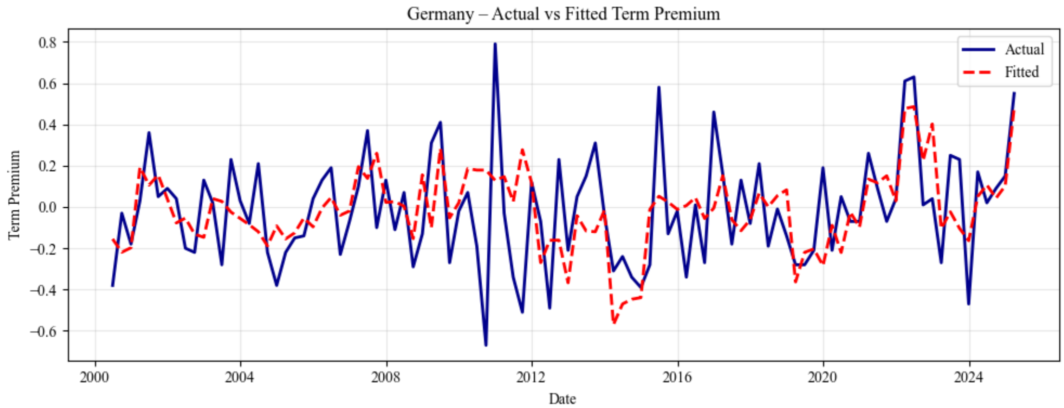


Figure 32: Fitted values vs. actual innovations in French 10Y term premium obtained with the “full panel” regression, with the year fixed effects

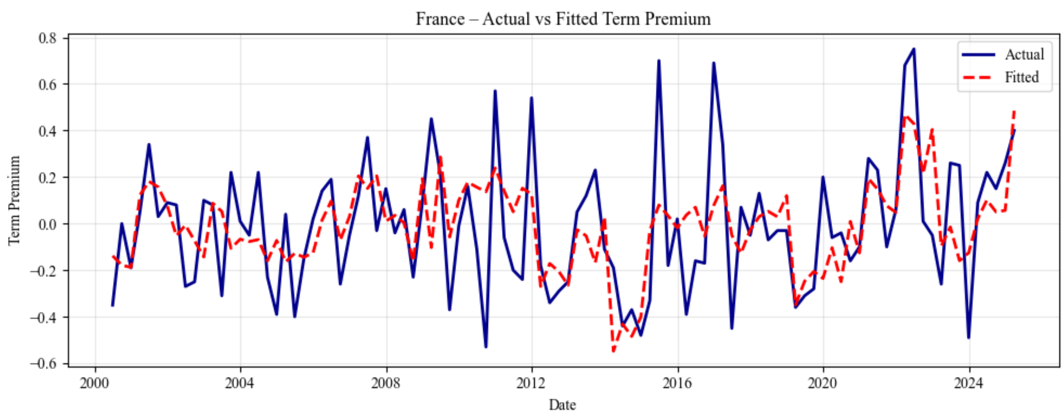


Figure 33: Fitted values vs. actual innovations in Italian 10Y term premium obtained with the “full panel” regression, with the year fixed effects

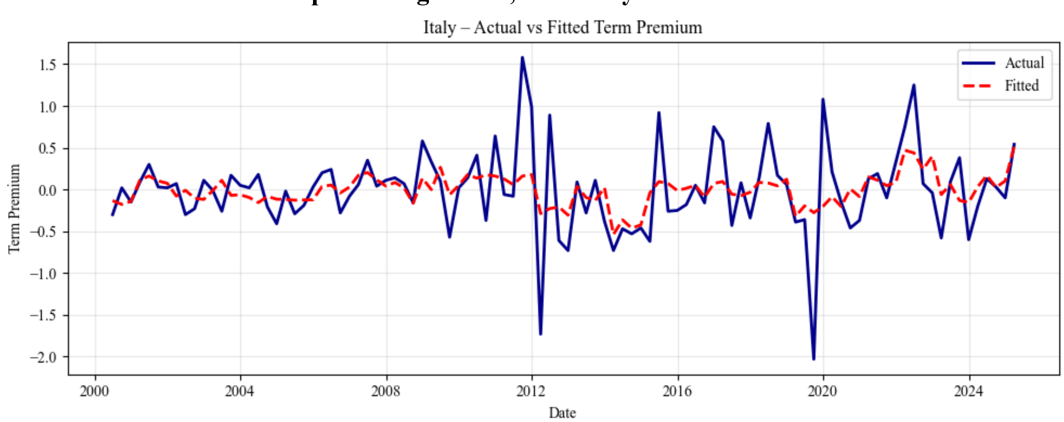


Figure 34: Fitted values vs. actual innovations in Spanish 10Y term premium obtained with the "full panel" regression, with the year fixed effects

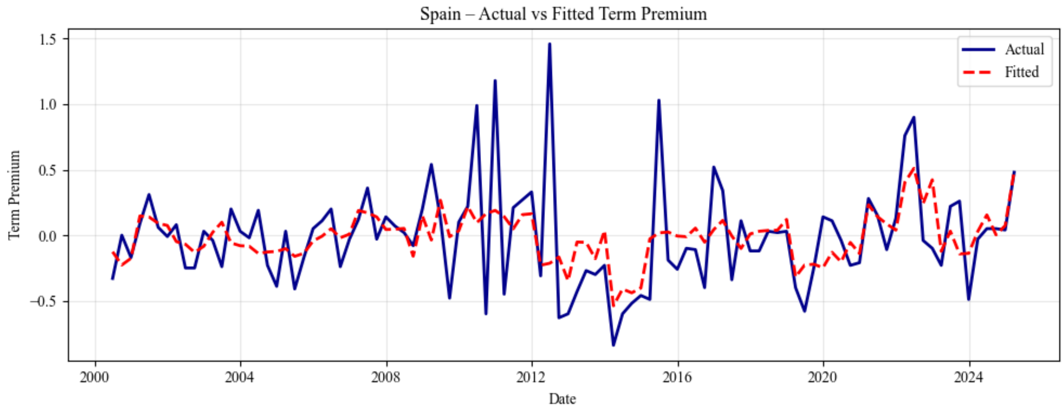


Figure 35: Fitted values vs. actual innovations in German 10Y term premium obtained with the "core" regression, with the 2012 dummy

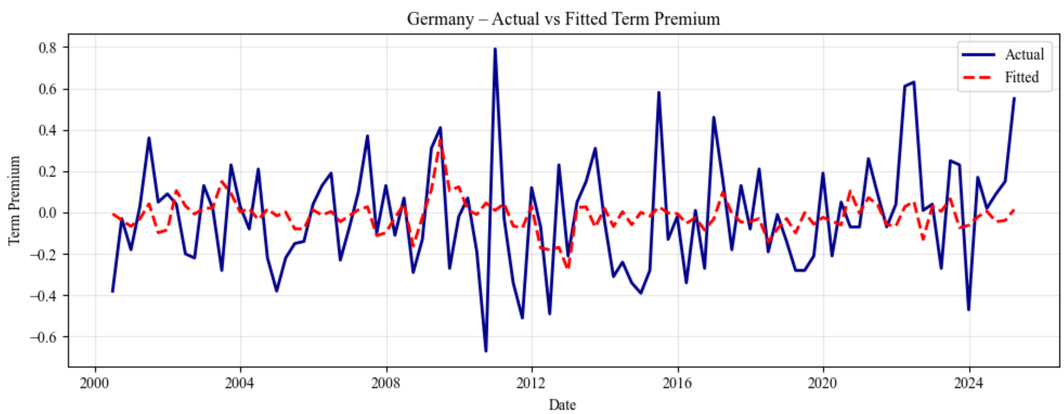


Figure 36: Fitted values vs. actual innovations in French 10Y term premium obtained with the "core" regression, with the 2012 dummy

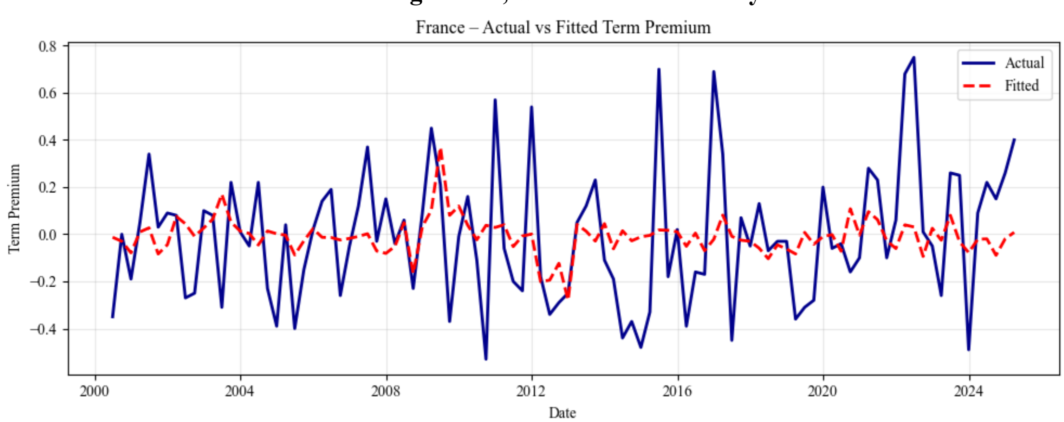


Figure 37: Fitted values vs. actual innovations in Italian 10Y term premium obtained with the "core" regression, with the 2012 dummy

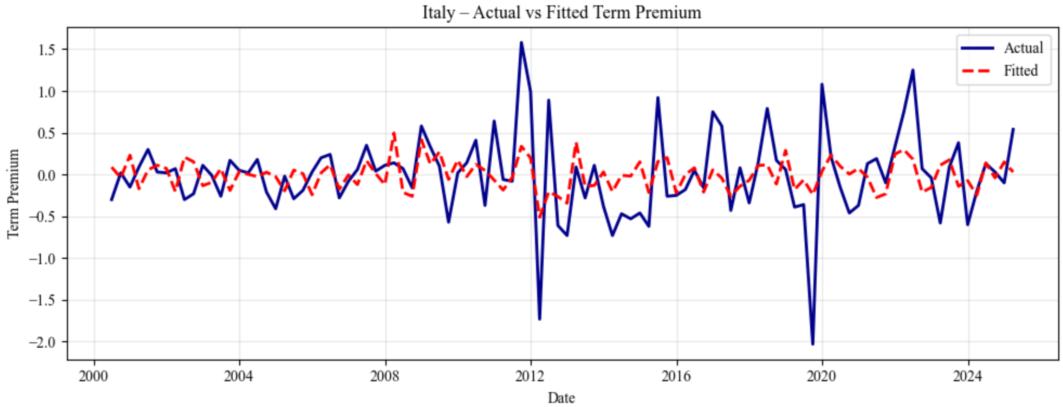
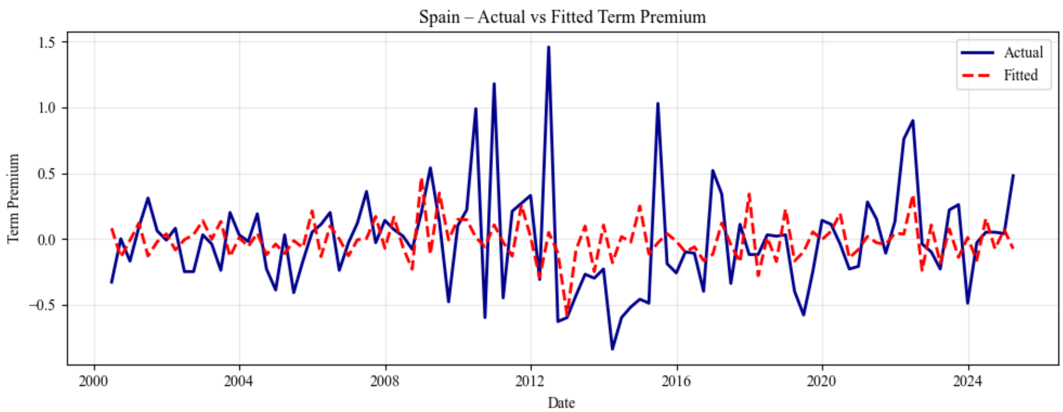


Figure 38: Fitted values vs. actual innovations in Spanish 10Y term premium obtained with the "core" regression, with the 2012 dummy



AI Disclaimer

In line with SSE guidelines, artificial intelligence was used as a support tool during both the coding and the writing phases of this thesis. The only artificial intelligence tool used was ChatGPT.

For the coding part, ChatGPT was used in both theses and primarily for debugging when more complex errors arose and for suggesting alternative python syntax aimed at simplifying certain specific procedures. The main benefits of this support were linked to the data management part of the code, through a reduction in debugging time and the exploration of alternative graphical representations of the data. However, ChatGPT proved less effective in debugging or simplifying the statistical parts of the code. For this reason, any AI suggestions related to statistical code snippets were carefully verified and corrected when necessary.

With respect to the writing process, ChatGPT was used as an advanced support tool for proofreading, including the identification of typos and unclear sentences, beyond what the Microsoft Word grammar checker offers. While this assistance was useful in highlighting potential issues in the text, some suggested revisions occasionally altered the intended meaning or reduced the emphasis on key points. Consequently, in both coding and writing, ChatGPT outputs were used as inspiration and/or warning signal, whilst its outputs were never incorporated directly without independent verification and revision. In the Bocconi University thesis, no artificial intelligence was utilized for the writing part.

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