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Euro Area Financial Fragmentation and Bond Market Stability

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ABSTRACT: This paper investigates the phenomenon of financial fragmentation within the euro area and focuses on its implications for bond market stability. A three-step approach is used to assess the sensitivity of credit risk premiums to identified global risk shocks, distinguishing between regimes of higher and lower fragmentation. First, a time-varying indicator of euro area financial fragmentation is constructed on the basis of a principal component analysis of sovereign yield changes. The indicator reflects the extent to which yields across different country groupings—often characterized by differing structural and financial market conditions—move in opposite directions. Second, we construct a series of identified global risk shocks using a sign-restricted Bayesian vector auto-regression model applied to a set of financial market variables. Third, we assess bond market stability/fragility in terms of the responsiveness of credit risk premiums to global risk shocks, using a non-linear panel local projections method, distinguishing between regimes of higher and lower fragmentation. We find that during times of elevated fragmentation, both sovereign CDS premiums and corporate option-adjusted spreads react more strongly to a given global risk shock. This elevated sensitivity appears across both country groupings, suggesting that in the higher-fragmentation regime, bond markets are more vulnerable throughout the euro area. These findings indicate that efforts to strengthen financial integration could contribute to greater bond market resilience.

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1 Introduction

History shows that fragmentation comes not only with high economic cost to growth and jobs, but also a potentially high political one, with loss of public confidence in European institutions

Financial Times, June 24 2022

Financial fragmentation refers to the breakdown of financial markets into fragments or segments, either geographically, by product type, or participant type.[1] It can be the result of, for example, regulatory and legal differences between countries, market inefficiencies, or foreign exchange risk. Financial fragmentation can also have a self-reinforcing dynamic. Financial fragmentation can lead to a sub-optimal capital allocation and price-inefficiencies. And within the context of a single monetary union –like the euro area–, it can hamper the transmission of monetary policy. This paper assesses yet another aspect: the relationship between financial fragmentation and the stability/fragility of financial markets. Understanding of this relationship can help policymakers take actions to foster resilience and stability through effective harmonization efforts and market integration. This paper focuses on the euro area, where the notion of financial fragmentation is often associated with the period of the European sovereign debt crisis.[2] During this period, financial markets showed signs of severe stress, and a break-up of the single monetary union was considered a real possibility.

This paper investigates the relationship between euro area financial fragmentation and the stability of sovereign and corporate bond markets. It does so through a three-step approach. In the first step, a time-varying indicator of euro area financial fragmentation is constructed on the basis of a principal component analysis of sovereign yield-changes. In the second step, we construct a series of identified global risk shocks using a sign-restricted Bayesian Vector Auto-regression (BVAR) model on a set of financial market variables; these global risk shocks feed into the third step of our analysis. In the third step, we assess bond market stability/fragility in terms of the responsiveness of credit risk premiums to global risk shocks, using a nonlinear panel local projections method, whereby we distinguish between regimes of higher and lower levels of financial fragmentation, based on our fragmentation indicator. A natural hypothesis is that bond markets are more fragile in the higher-fragmentation regime, as reflected by a relatively larger responsiveness of euro area bond market risk premiums to a normalized global risk shock.

A crucial step in our methodology is the construction of an indicator of euro area financial fragmentation. This is challenging, as there is no generally accepted technical definition of financial fragmentation (see Annex A). In the euro area, the concept of financial fragmentation is often associated with large yield spreads that emanated between the sovereign curves of its member states during the European sovereign debt crisis. During this period, bond market dynamics became increasingly segmented across two distinct country groupings, whereby one group is generally perceived as more vulnerable and the other as more resilient. However, spread-divergences should not be seen as a defining characteristic of financial fragmentation. Spread-divergences do not necessarily point to financial fragmentation, and financial fragmentation does not always lead to spread-divergences. Spread-divergences also arise in integrated and efficient markets, to the extent that they reflect differences in risks and fundamentals (Horny et al. (2018)). In other words, differences in yield spreads are not sufficient to define financial fragmentation, nor necessary.

In this paper we construct an empirical indicator of euro area financial fragmentation on the basis of

[1]Financial fragmentation is not equivalent to geopolitical or geo-economic fragmentation. While geopolitical or geo-economic fragmentation can contribute to financial fragmentation, the reverse is not necessarily true. Financial fragmentation can arise even in the absence of formal barriers to international trade and finance, such as tariffs, legal discrepancies, or capital controls.

[2]The European Sovereign Debt crisis occurred approximately between 2010 and 2014.

divergences in market *dynamics*. In an integrated market, the prices of similar assets respond –to some extent– homogeneously to common shocks. This insight is used to construct a time-varying indicator of euro area financial fragmentation, based on a principal component analysis (PCA) of weekly sovereign bond yield changes for the five largest economies of the union. The first principal component captures co-movements in sovereign yields across the euro area. By contrast, the second principal component reflects a pattern in which yield changes diverge between two country-blocks. These country-blocks coincide exactly with the aforementioned groups of more vulnerable and more resilient countries, typically characterized by differing structural and financial market conditions. In other words, the second principal component reflects dynamics whereby yields of those two country-blocks move in opposite directions. We construct an indicator of financial fragmentation by computing the variance of yield movements explained by the second principal component over a twelve-month moving window.[3] This indicator peaks during the period of the European sovereign debt crisis, and declines afterwards. Our indicator of fragmentation correlates with other proposed measures, such as the quanto-CDS spreads, which capture re-denomination risk.

We subsequently investigate the relationship between financial fragmentation and market stability by assessing the market's sensitivity to identified global risk shocks. We employ the methodology of Brandt et al. (2021) to identify global risk shocks, using a sign-restricted Bayesian vector autoregression (BVAR) model on a set of financial market variables. Our primary focus is on the effects of global risk shocks on credit risk premiums. The global risk factor is described as an important driver of sovereign CDS premiums in the existing literature (see, for example Longstaff et al., 2011; Pan and Singleton, 2008; Augustin, 2018). The BVAR also produces identified euro area monetary policy shocks, which are of secondary interest. Armed with these identified shocks, we then use the local projections method of Jordà (2023) to examine the dynamic reaction function of sovereign and corporate credit spreads to global risk and euro area monetary policy shocks, distinguishing between higher and lower fragmentation regimes. Similar to the approach taken by Augustin (2018), our work investigates the conditional correlations between euro area credit risk premiums and global risk shocks, whereby in our case, we distinguish between regimes of higher and lower fragmentation.

The data used for the construction of the euro area financial fragmentation indicator includes the five-year sovereign and corporate bond yields for the five largest euro area economies: France (FR), Germany (DE), Italy (IT), Spain (ES) and the Netherlands (NL). The sample is based on weekly data and covers the period between January 2001 and September 2024. The construction of the identified global risk shocks is based on daily data, in line with Brandt et al. (2021), whereby the data includes euro 10-year overnight-index swap (OIS) rate, equity returns for the EURO STOXX and S&P 500 indices, the EUR/USD exchange rate, and the 10-year US Treasury yield. The local projections analysis uses daily sovereign credit default swap spreads at the 5-year maturity, and daily option-adjusted corporate spreads at index-level.

Our main finding is that euro area financial fragmentation can be associated with heightened fragility in bond markets. This elevated sensitivity appears across both country-blocks, suggesting that in the higher-fragmentation regime, bond markets are more vulnerable throughout the euro area. The effect *is* most pronounced in the country-block of more vulnerable jurisdictions. Specifically, our local projections approach shows that global risk shocks induce a larger response in sovereign credit risk premiums in the higher-fragmentation regime. Similar to the sovereign CDS premiums, corporate bond spreads (option-adjusted spreads) are found to react more strongly to global risk shocks in the higher fragmentation regime.

This paper adds to the existing literature on euro area fragmentation in multiple ways. Whilst not unique

[3]This indicator was first introduced by the authors of this paper in De Vette and Mosk (2022), where it was called the Dynamics Divergence Indicator (DDI).

in its use of a principal component analysis, our construction of a time-varying fragmentation indicator is novel. This fragmentation indicator subsequently allows us to investigate the relationship between fragmentation and market fragility in the second part of our analysis. To the best of out knowledge, this is the first paper that combines a fragmentation indicator based on a principal component analysis with an empirical assessment of bond market stability. Fontana and Scheicher (2016), Fabozzi et al. (2016),Candelon et al. (2022) use PCA or similar techniques in identifying two country-block factors in CDS prices, but these papers do not construct fragmentation indicators, and they also do not fully delve into the financial stability implications of fragmentation.

Our paper is most closely related to Fontana and Scheicher (2016), who perform a principal component analysis of sovereign CDS spread-changes, and find –similar to our analysis– that the first principal component reflects co-movements, whilst a divergence between the two country-blocks emanates in the second principal component. Their focus is different from our paper: Fontana and Scheicher (2016) use the PC vector loadings as an explanatory variable in the analysis of the CDS-bond basis, whilst our paper exploits the PCA variance decomposition to construct a time-varying indicator of fragmentation. Candelon et al. (2022) also employ a principal component analysis to investigate fragmentation, but do so on sovereign yield *levels*; this is fundamentally different from our approach, which focuses on yield *dynamics* (first differences) instead of levels.[4] Fabozzi et al. (2016) investigate the drivers of sovereign CDS spreads and employ a so-called independent component analysis (ICA), a technique similar to principal component analysis. Similar to Candelon et al. (2022), Fabozzi et al. (2016) perform a PCA and ICA on CDS premiums, and also finds a homogeneous first principal component, and a two-country-block split in the second; however, Fabozzi et al. (2016) argue that the second PC2 is economically insignificant as it only explains a small share of the variance over their short sample (2009-2014). Differences between credit risk premium levels (or yields levels) may well be explained by differences in fundamentals, and do therefore not consistently and unambiguously point to financial fragmentation. For this reason, this paper considers divergences in spread or yield dynamics in its construction of a fragmentation indicator. An interesting alternative approach is offered by Kakes and van den End (2023), who construct a measure capturing fragmentation based on the higher moments of the sovereign-spread distribution, to the extent that these higher moments are not explained by fundamentals.

This paper does not seek to *explain* the causes of euro area financial fragmentation. While structural factors—such as differences in policies and regulations—are widely considered contributors, additional drivers include concerns around debt sustainability, sovereign credit risk, and even euro area break-up risk. Moreover, self-reinforcing dynamics and behavioral biases may amplify these fundamental factors in a non-linear or even unpredictable manner. Given the complexity of these underlying drivers, this paper adopts a practical and pragmatic stance. It treats financial fragmentation as a latent state variable—one that cannot be directly observed, but can be proxied through divergences in the dynamics of the euro area financial system. To explore variables potentially associated with fragmentation, Section 4.3 presents a probit regression. Results suggest that indicators such as debt-to-GDP ratios, fiscal deficits, and unemployment are correlated with our fragmentation measure. Strikingly, however, even with a broad set of explanatory variables, a large share of the variance in the fragmentation indicator remains unexplained, and variables like debt-to-GDP have an economically insignificant coefficient. This supports the notion that fragmentation dynamics are not fully captured by fundamental variables alone, and may instead be driven—at least in part—by non-linear feedback

[4] Candelon et al. (2022) finds –similar to Fontana and Scheicher (2016) and this paper– that the first principal component features homogeneous signs, whilst the second principal component shows country-block divergences. Nonetheless, the PCA analysis of yield *levels* is fundamentally different, and consequently, the interpretation of the principal components is different as well.

loops and behavioral mechanisms.

Our findings provide valuable insights for policy makers. Our paper shows that euro area financial fragmentation can be associated with heightened fragility in bond markets - not only for the country-block of more vulnerable jurisdictions, but across the euro area, as well as in corporate bond markets. Policies aimed at reducing financial fragmentation within the euro area could therefore enhance market stability.

This paper is structured as follows: section 2 presents the key methodology used in this paper, starting with the construction of the PCA-based fragmentation indicator, followed by the construction of the identified financial market shocks and our implementation of the local projections method. Before presenting the key results of our analysis, section 2.1.2 presents descriptive statistics with respect to our fragmentation indicator, as well as some heuristics (correlations) related to financial fragmentation. Results are presented in section 3, which centers around the local projections method's response functions, in terms of sovereign CDS premiums and corporate option-adjusted spreads, in response to the identified global risk shocks. In Section 4, we test the robustness of our euro area financial fragmentation indicator, and we establish confidence intervals for our analysis that capture the combination of uncertainty in our estimates from various steps. Section 5 follows with conclusions and a further discussion of our results.

Note: *in the remainder of this paper will use the terminology of "core" and "periphery" jurisdictions, referring to the two country groupings that are typically associated with differing structural and financial market conditions. We adopt this nomenclature to remain consistent with the terminology commonly used in the public discourse and academic literature on euro area financial fragmentation. The authors wish to express that the use of this terminology is not intended to diminish the importance or contributions of any of the euro area member states, nor to suggest a hierarchy among them.*

2 Data & Methodology

The methodology for assessing the relationship between financial fragmentation in the euro area and fragility in bond markets follows a three-step approach, as outlined below. In the first step, a fragmentation indicator is constructed on the basis of a principal component analysis of yield changes. In the second step, we follow Brandt et al. (2021) to construct a series of identified shocks or innovations using a sign-restricted BVAR on a set of financial market variables. In the third step, we assess the fragility of the bond market in terms of the response of credit risk premiums to global risk shocks, using the local projection method of Jordà (2023). In this third and last step, we distinguish between regimes of higher and lower levels of financial fragmentation, on the basis of our fragmentation indicator. Table 1 provides an overview of the data used in the analysis.

We construct a panel data set that covers five countries in the euro area - Germany, France, Italy, Spain, and the Netherlands - over the period 2008 to September 2024. The main dataset includes sovereign credit risk indicators (CDS spreads and option-adjusted spreads), financial market variables (equity returns and euro area volatility, measured via the VStoxx), and BVAR-identified structural shocks capturing global risk, euro area macroeconomic and policy shocks, and US spillovers. Macroeconomic conditions are represented by the Citi Economic Surprise Index (CESI). Table 2 reports summary statistics for key variables. For the heuristic analysis in Section 2.1.2 additional macroeconomic variables are downloaded from the ECB data repository; country-level unemployment, government debt-to-GDP ratios, government deficits, GDP growth. Finally, the Citi Suprise Index is sourced from Bloomberg.

At this point, it should be noted that bond market stability has many different aspects and at least as many stability measures. Our focus is on the dynamical behavior of credit risk premiums in response to risk shocks. Other popular measures focus on market volatility, market liquidity, draw-downs, or investor behavior under stress (e.g., fund flows and redemptions). Our choice of stability measure reflects the compounded effect of some of the aforementioned aspects.

Table 1: Datasets used in the three-step approach

	Step 1	*Step 2*	*Step 3*
Objective	Construct financial fragmentation indicator	Construct identified global risk shocks	Assess risk premium responsiveness to shocks
Methodology	Principal Component Analysis	Sign-restricted Bayesian vector autoregression	Non-linear panel local projections method
Data sources	Bloomberg, Datastream	Bloomberg, Datastream	Bloomberg, Datastream
Frequency	Weekly	Daily	Daily
Range	Jan. 2001 - Sep. 2024 (1286 data points)	Jan. 2008-Sept. 2024 (20012 data points)	Jan. 2008-Sept. 2024 (20012 data points)
Variables	a) Sovereign yields -maturities: 2y, 5y, 10y -DE, ES, FR, IT, NL b) IG corporate yields -index weighted yield -DE, ES, FR, IT, NL	10y euro OIS rate 10y US Treasury yield EURO STOXX index US S&P500 index EUR/USD	a) Sovereign CDS spreads -maturities: 5y -DE, ES, FR, IT, NL b) IG corporate OAS -index weighted OAS -DE, ES, FR, IT, NL
Other inputs			-Financial fragmentation indicator (*Step 1*) -Identified global risk shocks (*Step 2*) -Other shocks as control variables (*Step 2*)

2.1 A Statistical Indicator of Euro Area Financial Fragmentation

In this subsection we first construct our euro area financial fragmentation indicator. This indicator is an *empirical* measure, and *not* a universal construct. Its construction follows a pragmatic approach that also reflects that financial fragmentation should be thought of as a latent variable. Consequently, this part of the *Methodology* section contains (perhaps unusually) both theoretical as well as some empirical aspects.

2.1.1 Construction of the Fragmentation Indicator

For the construction of our euro area financial fragmentation indicator we utilize the sovereign yields for the five largest euro area economies: France (FR), Germany (DE), Italy (IT), Spain (ES) and the Netherlands (NL), using weekly data over the period from January 2001 to September 2024. Our focus is on benchmark yields for the 5-year maturity, but to illustrate that our fragmentation indicator does not critically depend on the selected maturity, we also consider 10-year benchmark yields. To further illustrate the robustness of the

Table 2: Summary Statistics of Key Variables

Variable	Mean	St. Dev.	Min	Max	N
Sovereign CDS	0.03	4.25	−67.56	79.45	20,012
Corporate OAS	0.01	1.71	−34.12	30.51	20,012
Equity returns	0.003	1.46	−18.54	13.48	20,012
VSTOXX	23.41	9.19	10.68	87.51	20,012
Citi Surprise Index	1.10	67.22	−304.60	212.40	20,012
EA Policy Shock	−0.004	0.83	−4.86	5.72	20,012
EA Macro Shock	0.02	0.86	−4.71	5.77	20,012
Global Risk Shock	0.01	0.93	−7.44	5.37	20,012
US Macro Shock	−0.02	0.85	−5.31	5.40	20,012
US Policy Shock	−0.01	0.84	−7.15	4.72	20,012

Notes: This table presents summary statistics for the main variables used in the empirical analysis. The sample includes daily data for five euro area countries from 2008 to September 2024. CDS and OAS are measured in basis points. Shocks are identified using the BVAR model of Brandt et al. (2021). Reported statistics are pooled at country level for CDS, OAS and Equity market returns.

constructed measure, we also apply our methodology to the weighted option-adjusted spreads for investment grade corporate bond indices (for the above-mentioned countries).

To construct our euro area financial fragmentation indicator, we first compute the first differences for weekly yield-data, as we are interested in yield *dynamics* (and not yield *levels*). Let Δy be the $T \times n$ matrix of $T = 1286$ weekly yield-changes for the $n = 5$ jurisdictions under consideration. The principal component analysis of Δy shows, in line with Fontana and Scheicher (2016), that the first two principal components, $PC1$ and $PC2$, have an intuitive interpretation (see Figure 1):

PC1 ***Co-movements***

The components of $PC1$ each have the same sign, and $PC1$ therefore reflects co-movements of yields. The magnitude of the individual components varies: the larger magnitude for Italian and Spanish yield-changes implies that the sovereign yields for these jurisdictions tend to be more volatile. One could also see the magnitude of these vector components as a kind of "market beta".

PC2 ***Core-periphery divergences***

The components of $PC2$ can be divided into two distinct groups based on their relative sign. The first group consists of Italy and Spain, the two major countries among the so-called periphery jurisdictions. The second group consists of France, the Netherlands and Germany; the three major countries among the core-jurisdictions. $PC2$ reflects yield-dynamics whereby core and periphery yields move in opposite directions.

Interestingly, a similar pattern emanates for the first two principal components of the option-adjustment spreads for corporate bonds (Figure 2).

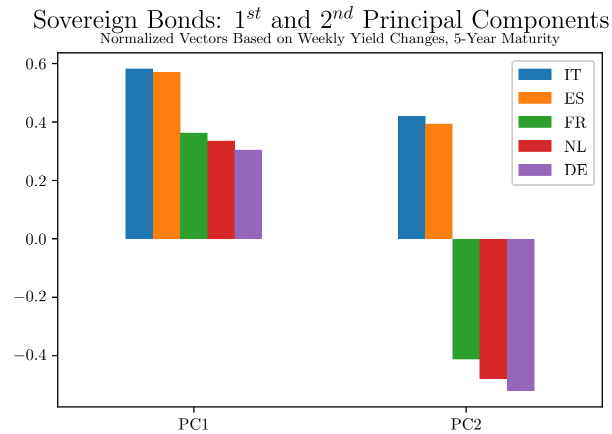


Figure 1

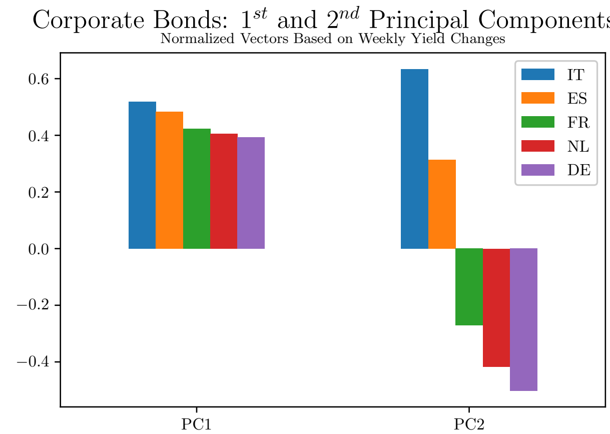


Figure 2

Our euro area financial fragmentation indicator is based on the share of the variance that can be explained by the second principal component, computed over a twelve-month moving window. To recall: the second principal component reflects yield dynamics whereby core and periphery yields move in opposite directions. For the full sample period, we see that patterns of co-movements are predominant (see Figure 3): for the 5-year sovereign yields, around 68 percent of the variance can be explained by the first principal component. For corporate bond OAS the first factor even accounts for 85% of the variance over the full sample. The second factor explains around 20% of the variance in our sample for sovereign bonds and around 5% for corporate bond OAS. Appendix B discusses the statistical significance and presents Supporting Statistics for Principal Component Analysis

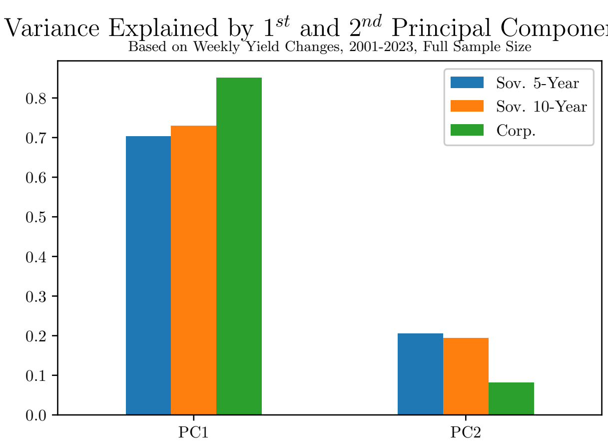


Figure 3

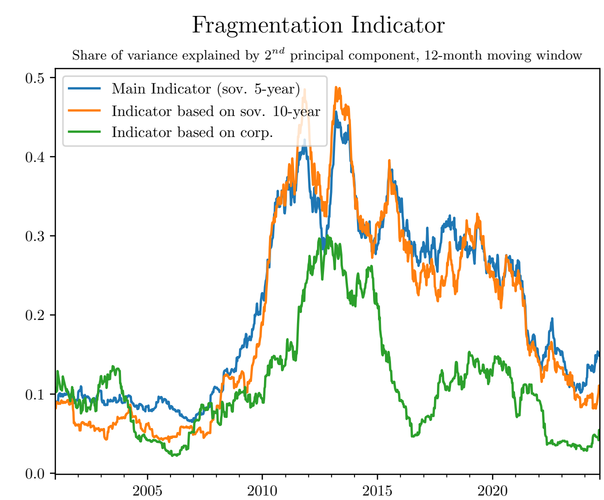


Figure 4

Figure 4 shows the resulting fragmentation indicator -based on a twelve-month moving window- over time.

During the period before the Global Financial Crisis (GFC) and European Sovereign Debt crisis, the measure shows lower readings, accounting for around 10% of the variance. This increases to almost 50% for sovereign yields and 30% for corporate bond OAS during the euro area sovereign debt crisis. Thereafter, both the sovereign and corporate fragmentation indicators declined gradually. In recent years, the bulk of euro area bond yield dynamics can be explained by the common factor.

In principle, divergences in yield-dynamics could be driven by divergences in underlying fundamentals, such as macro-economic conditions and fiscal conditions. However, idiosyncratic news about a single country's macro-fundamentals does not necessarily lead to a high loading on either PC1 or PC2, unless single jurisdiction-specific news affects other jurisdictions in patterns that are consistent with the dynamics captured in PC1 or PC2, respectively. Persistent divergence in yield dynamics -especially when systematic across groups of countries- suggests segmentation in investor behavior or pricing, indicative of fragmentation.

In addition, at the weekly frequency on which our analysis is based, external –often global– shocks that affect investor sentiment and risk perception are key drivers of variance in yield and risk premium dynamics (see Srivastava et al., 2016, Longstaff et al., 2011 and Corzo et al., 2020). During times of higher fragmentation, flight to safety dynamics as described by Kekre and Lenel (2024) likely play a key role in driving divergences in weekly yield-moves. In the context of the European sovereign debt crisis, "flight to safety" often refers to investor flows out of the "periphery" segment, and into the "core" segment, as the market fragments into these two country-blocks. Evidence suggests that under these dynamics, outflows were driven largely by investment funds, while investors domiciled in the "periphery" jurisdictions stepped in to absorb the sales (Longaric et al. (2025)). While investor sentiment and risk perception are key drivers of variance in yield and risk premium dynamics, the manifestation of changes in risk-sentiment in terms of yield-change patterns is different as a function of the prevailing fragmentation regime. The first principal component unveils a pattern whereby yields co-move, but with different amplitudes -resembling how assets with different risk characteristics have a different "market beta". By contrast, the second principal component reflects divergent yield-moves, signaling asymmetric pricing and fragmentation. The extent to which variations in risk sentiment translate into the manifestation of PC2-like dynamics (as opposed to PC1-like dynamics) is captured by our indicator. As discussed in sections 2.1.2 and 4.1, the extent to which PC2-like patterns appear is not just a reflection of CDS premiums or the level of the sovereign spreads.

Lastly, it is important to highlight that our euro area financial fragmentation indicator is an empirical construct that relies on several discrete choices, including the length of the moving window, the decision to apply a moving average, the selection of jurisdictions, the maturity of the bond yields considered, and the focus on sovereign yields (as opposed to spreads or CDS premiums). The choice of sovereign yields is motivated by the fact that sovereign yields –and their divergence during the European Sovereign Debt Crisis– are central in the phenomenon of euro area financial fragmentation, and sovereign bonds trade in relatively liquid markets.

We have limited the sample to the five largest euro area economies, as they offer the deepest and most liquid markets, whilst spanning both core and periphery countries. While a broader country sample -e.g., including Greece, Portugal, Austria, or Ireland— could add additional granularity, it would also introduce challenges related to data comparability (e.g., missing values[5], illiquidity, or the absence of a benchmark yield at the 5-year maturity) and the stability of principal component estimation in high-dimensional settings. Nonetheless, the patterns we observe—such as divergence between country groupings and time-varying sensitivity to global shocks—are likely to extend beyond the five-country sample, given their consistency with broader euro area

[5]For example, Greece was subject to a credit event in 2012 (see https://www.isda.org/2012/03/09/isda-emea-determinations-committee-restructuring-credit-event-has-occurred-with-respect-to-the-hellenic-republic) and its 5-year yield spiked at 50%.

dynamics reported in the literature (e.g. Fontana and Scheicher (2016) use panel of ten countries and still finds a core-periphery split in the second principal component).

Furthermore, sovereign yields reflect –in addition to the credit risk premiums reflected by CDS pricing– a more complete spectrum of drivers, including the inflation premium, term risk premiums, and the risk-free component. Nonetheless, we do note that Fontana and Scheicher (2016) finds similar principal components based on CDS premiums. We have conducted experiments with different maturities (see Figure 4), revealing that the resulting measures exhibit close correspondence. Additionally, we explored various aggregation methods, including both shorter and longer averaging windows. Shorter time windows yield a more volatile measure, reflecting immediate and idiosyncratic market fluctuations, while longer time windows tend to smooth out these variations and present a more backward-looking perspective. Ultimately, we have determined that the twelve-month window strikes a pragmatic balance between stability and responsiveness, effectively capturing the dynamics of financial fragmentation within the euro area.

2.1.2 Heuristics of the Fragmentation Indicator

Before moving to the second and third steps of our methodological approach, this subsection explores some characteristics of our euro area financial fragmentation indicator and how it relates to related –but not equivalent– measures such a the quanto-CDS spreads that relfect re-denomination risk pricing. We also explore how sovereign bond market liquidity behaves in higher and lower fragmentation regimes –measured through our indicator–, and how our fragmentation indicator relates to potential fundamental drivers and sources of fragmentation. It is important to emphasize that at this stage, these heuristics reflect mere correlations.[6] We look at government CDS premiums government bond market liquidity and euro area re-denomination risk pricing.

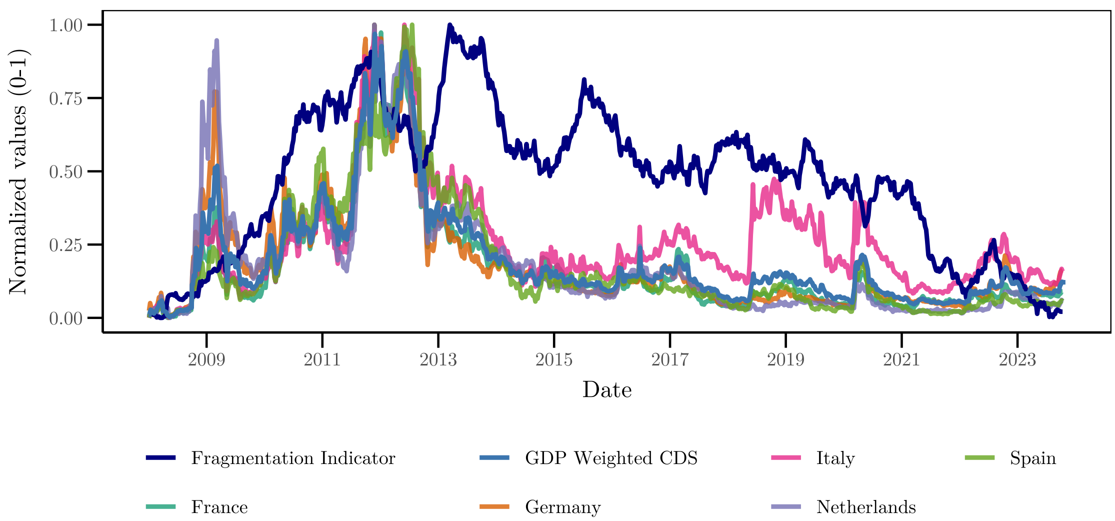
Our Fragmentation Indicator Does Not Simply Reflect Sovereign CDS Premiums

Our fragmentation indicator measures is not simply a one-for-one reflection of the CDS premiums on sovereign debt. Even though our measure is constructed on the basis of sovereign yield *dynamics*, one could hypothesize that yield-change-pattern are related to fundamentals. The objective of this paper is not to identify the drivers of euro area financial fragmentation; nonetheless, the phenomenon *is* likely related to various underlying factors – in a complex and possibly non-linear fashion. Some of these factors may also be reflected in the *levels* of risk premiums; our premise is that fragmentation dynamics constitute a phenomenon that goes above and beyond its potential impact on risk premiums. To illustrate this point, Figure 5 compares the indicator with the (USD-denominated) sovereign CDS spreads for the euro area countries in our sample. Although one might jump to the conclusion that the indicator primarily reflects a credit spread between core and periphery countries, Figure 5 demonstrates this is not the case. The fragmentation indicator focuses on the divergence in yield dynamics, independent of the yield or spread levels, whereas the CDS measure captures market perceptions of credit risk. For example, during the 2014-2018 period, the fragmentation indicator remains elevated even though the CDS premiums are relatively subdued, suggesting that yield dynamics may diverge between countries due to factors other than credit risk. By contrast, during the Global Financial Crisis, credit premiums increased across the board, while the fragmentation indicator remained relatively low, reflecting a common shock affecting all jurisdictions. Thus, while the two measures sometimes coincide — particularly during the sovereign debt crisis — the indicator captures distinct dimensions of market behavior beyond those reflected in the levels of CDS premiums.

[6] Causal relationships may exist, but we do not attempt to investigate them here.

Moreover, we test the fragmentation indicator for structural breaks to validate its use as an identifier for regimes in which sovereign debt markets are more fragmented. To this end, we first apply a Chow break test to assess whether a specific threshold of the indicator—defined as a dummy variable equal to one when fragmentation exceeds its median—can identify a structural break in the time series (Chow (1960)). The Chow test strongly confirms this, with a p-value $< 2.2e\text{-}16$, indicating a significant structural break on 07/05/2010 when the fragmentation indicator is above its median for the first time in the sample. Additional analysis using the Bai-Perron (Bai and Perron, 2003) procedure supports these findings. When testing for multiple structural breaks, the identified breakpoints align closely with the periods we classify as higher fragmentation regimes (see Appendix G).

Figure 5: 5Y sovereign Fragmentation Indicator versus country CDS spreads



Source: ECB, Refinitiv and author calculations *Note:* Figure shows the Fragmentation Indicator as defined in Equation 1 versus the country and GDP-weighted USD-denominated CDS spreads for the countries in our sample between January 2008 and December 2024.

Fragmentation and Re-denomination Risk

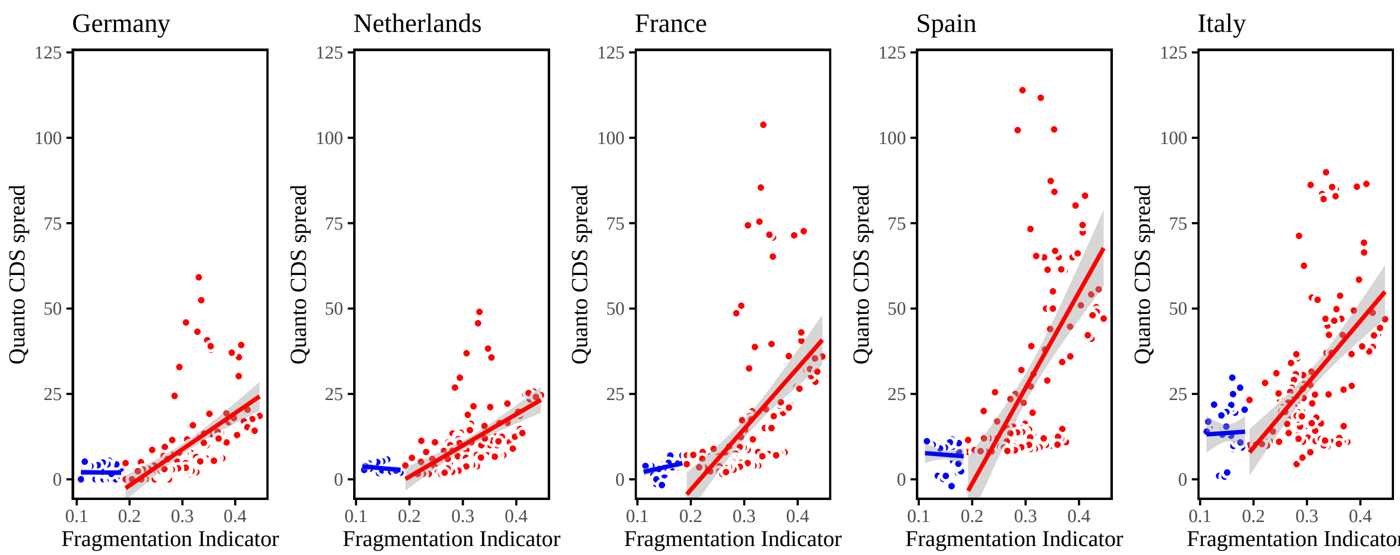
In an extreme scenario, self-reinforcing euro area financial fragmentation could ultimately have led to a break-up of the single monetary union. In turn, this could have led to a re-denomination of assets into post-break-up currencies, the risk of which is termed "re-denomination risk". Such a tail risk scenario would come with a country specific economic cost, and is therefore reflected in asset prices. We examine how our euro area financial fragmentation indicator relates to market-based measures of re-denomination risk. Concepually, this measure is more related to our Fragmentation Indicator, hence we follow De Santis (2015, 2019) and construct a measure of re-denomination risk as the spread between euro and US dollar denominated CDS contracts, also know as the quanto credit default spread. A higher quanto-CDS spread signals that investors price an additional premium for the euro denominated contract on the same underlying asset, reflecting the risk and cost of re-denomination. Historically, the quanto CDS spread peaked during the European sovereign debt crisis, as well as periods of policy uncertainty, such as the Italian elections of March 2018. Ex-ante we would expect our financial fragmentation indicator to positively correlate with the re-denomination risk for all jurisdictions, but in particular for periphery countries such as Italy and Spain.

At the same time, fragmentation can be elevated even in the absence of redenomination risk. For example, during episodes of market dislocation, liquidity may deteriorate unevenly across jurisdictions due to differences in market depth, investor base, or regulatory frameworks. This can lead to a divergence in yield dynamics among sovereign bonds, even when there is no perceived risk of a country exiting the euro area. In such cases, fragmentation reflects impaired market functioning rather than concerns about monetary union integrity. Conversely, redenomination risk may rise without a corresponding increase in fragmentation if market concerns are concentrated in a single jurisdiction. For instance, if investors begin to question the political commitment of one member state to the euro, this may be reflected in higher quanto CDS spreads or widening sovereign bond spreads for that country, without necessarily triggering broader dislocations across the euro area bond market. In this scenario, redenomination risk is elevated, but fragmentation—as measured by cross-country yield dispersion—may remain contained.

Nonetheless, during systemic episodes such as the euro area sovereign debt crisis, both measures tend to move in tandem. This is because broader doubts about the cohesion of the monetary union can simultaneously affect market integration (leading to fragmentation) and increase perceived credit and currency risk (raising redenomination risk).

Quanto-CDS spreads are indeed positively correlated with our fragmentation indicator. The relationship is reflected by the upward-sloping curves in Figure 6. The steepness of these curves appears higher for the periphery jurisdictions –Italy and Spain– and also shows some positive convexity.

Figure 6: 5Y sovereign Fragmentation Indicator versus Quanto CDS spread

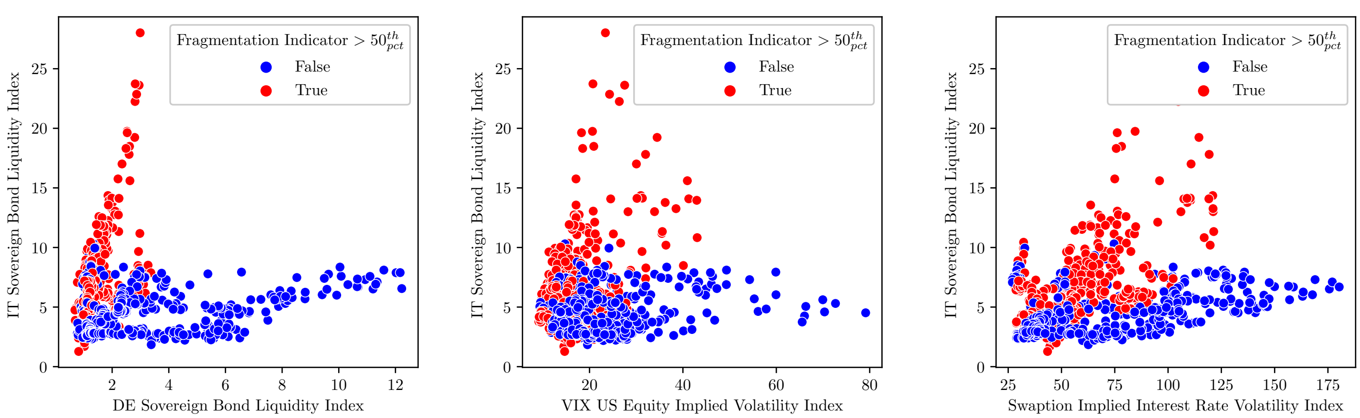


Source: Refinitiv and author calculations *Note:* Figure shows the correlation between the fragmentation indicator as defined in sub-section 2.1 and the quanto CDS spread in basis points as defined in De Santis (2015). The red dots represent the higher fragmentation regime, when the indicator is above its 50^{th} percentile over the period Jan. 2001- Aug. 2024. The charts include a linear fit between the fragmentation Indicator and the quanto CDS spread with robust confidence bands in light grey.

Fragmentation and Liquidity

Market liquidity –and in particular liquidity under stress– is an important aspect of a market's robustness/fragility. If liquidity evaporates quickly under stress, risk shocks can have an out-sized impact. Under such conditions, small trading volumes can drive larger price moves, providing first-mover advantages which can lead to self-reinforcing dynamics. Below, we assess whether market liquidity in euro area sovereign bond markets –and its "flightiness under stress" in particular– changes with the degree of financial fragmentation. The analysis is based on a liquidity measure provided by Bloomberg L.P., which reflects sovereign bond yields' deviations from a smooth spline fit.[7] Under this measure, higher values point to lower liquidity. It should be noted that many other measures of liquidity exist. Figure 7 assesses the liquidity of sovereign bonds in regimes of higher and lower fragmentation. These regimes are defined by splitting the sample at the fiftieth percentile of our fragmentation indicator. Figure 7(a) shows that in the lower fragmentation regime, the liquidity of German sovereign bond is more closely aligned with the liquidity of Italian sovereign bonds (blue), as compared to the higher fragmentation regime. This suggests that in the higher fragmentation regime, liquidity may evaporate much more quickly in the "periphery countries", as compared to "core jurisdictions". Figures 7(b) and (c) illustrate the empirically observed liquidity-stress relationship in the Italian sovereign market, whereby stress is proxied by the US VIX Implied Volatility index[8] and the swaption implied interest rate volatility, respectively.[9] For both measures of stress, a faster deterioration of liquidity conditions can be seen in the higher fragmentation regime.

Figure 7: Liquidity, Fragmentation and Stress



(a) (b) (c)

[7]The rationale for this liquidity measure is that deviations from a smooth yield-curve fit point to arbitrage opportunities. In a very liquid market, traders should be better able to exploit –and thereby remove– such arbitrage opportunities quickly.

[8]One could also consider the VSTOXX implied volatility index for European stocks; here we have opted for the VIX Index as reverse causality would be less significant in terms of the interpretation of the observed correlation.

[9]The VIX Index, short for Chicago Board Options Exchange Volatility Index, is based on S&P 500 Index (SPX) option prices. SMOVE is short for the Swaption Merrill Option Volatility Estimate. This is a yield curve weighted index of the normalized swaption-implied volatility, reflecting implied-volatilities for 2-year, 5-year, 10-year, and 30-year interest rate swaps.

Fundamental Drivers of Fragmentation

This paper does not seek to *explain* the causes of euro area financial fragmentation. While structural factors —such as differences in policies and regulations— are widely considered contributors, additional drivers could include concerns around debt sustainability, sovereign credit risk, and euro area break-up risk. Moreover, self-reinforcing dynamics and behavioral biases may amplify these fundamental factors in a non-linear or unpredictable manner. Given the complexity of these underlying drivers, this paper adopts a practical and pragmatic stance. It treats financial fragmentation as a latent state variable —one that cannot be directly observed, but can be proxied through the dynamics of the euro area financial system.

To explore potential drivers of financial fragmentation, Table 3 presents one of the probit regression models we estimated to examine correlations between the fragmentation regime and various macroeconomic variables. We choose to explore the fragmentation regime instead of the indicator level, as the regime indicator is consistently employed in the empirical setup throughout the remainder of the analysis. The results suggest that factors such as the debt-to-GDP ratio, fiscal deficits, citi surprise index, unemployment rate and economic uncertainty are associated with our measure of fragmentation. However, after testing a range of specifications and variable combinations, two key insights emerge. First, the estimated coefficients are not robust to changes in model specification, indicating some instability. Second, even with a comprehensive set of explanatory variables, a substantial portion of the variation in the fragmentation indicator remains unexplained (Pseudo $R^2 = 0.291$). These findings support the idea that financial fragmentation in the euro area cannot be fully explained by fundamental variables alone. Instead, it may be shaped by nonlinear dynamics, feedback loops, and behavioral mechanisms that go beyond traditional macroeconomic indicators.

Table 3: Panel Probit Estimation of High Fragmentation Episodes

Variable	**Estimate**	**Std. Error**	**t-value**	**p-value**
Unemployment (%)	0.557	0.048	11.662	0.000
Government debt-to-GDP (%)	0.019	0.003	6.822	0.000
Government Deficit (%)	0.172	0.025	6.967	0.000
Citi Surprise Index	0.003	0.001	4.696	0.000
Economic Policy Uncertainty	0.002	0.001	2.235	0.025

Notes: This table presents the results from a random-effects panel probit regression estimating the probability of high financial fragmentation episodes. Standard errors are robust. McFadden's pseudo-$R^2 = 0.291$. The dependent variable is a dummy that is one when higher fragmentation equals one. Panel includes DE, NL, FR, IT and ES. Model includes an intercept. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

2.2 Construction of Identified Market Shocks

We assess the fragility of bond markets by analyzing the response of sovereign CDS premiums and corporate OAS to identified shocks. For the construction of these daily shocks, we follow the methodology of Brandt et al. (2021). Here we recap the key elements of this methodology; the reader can find more details in the original paper.

Brandt et al. (2021) use asset price movements in a sign-restricted Bayesian vector auto-regression (BVAR) to derive the extent to which euro area rates and US yields, equity prices, and the EUR/USD exchange rate are jointly driven by monetary policy, macro-news, and global risk factors. Brandt et al. (2021) show the resulting identified factors correlate with the VIX Index (global risk factor), and euro area and US Citi surprise indices (EA macro and US macro factor). Disentangling the drivers of financial asset prices provides us with identified shocks that can be used in our empirical setup to test their impact on euro area debt markets. The analysis uses daily data for the 10-year euro OIS rate, the EURO STOXX and S&P 500 equity index returns, the EUR/USD exchange rate, and the 10-year US Treasury yield for our sample period.

For the analysis in this paper, the global risk shock is most relevant.[10] Moreover, previous literature finds that sovereign CDS premiums are largely driven by a global risk factor (see Srivastava et al., 2016, Longstaff et al., 2011 and Corzo et al., 2020). Investigating the sensitivity of CDS pricing to this factor can therefore provide insights into bond market stability; if CDS pricing becomes more sensitive to the global risk factor this might imply that markets become more prone to flight-to-safety or disorderly dynamics, which could impair financial stability (see De Santis (2014)).

The identification of the distinct types of shocks is based on the sign restrictions in Table 4. A favorable global risk shock is assumed to drive up euro area rates and US yields, boost equity prices, whilst weakening the US dollar vis-a-vis the euro. A restrictive euro area monetary policy shock is assumed to drive up euro area yields, whilst depressing euro area stock prices, strengthening the euro vis-a-vis the US dollar, and increasing the spread between euro area rates and US yields. We implement the methodology of Brandt et al. (2021) using the BEAR-toolbox of Dieppe et al. (2016). Further details and visualizations can be found in Appendix C.

	Euro Area		**United States**		**Global**
	Restrictive mon. policy	*Favourable macro news*	*Restrictive mon. policy*	*Favourable macro news*	*Favourable Global risk*
EA long-term yields	+	+	+	+	+
EA equity prices	-	+			+
US equity prices			-	+	+
USD/EUR exchange rate	+	+	-	-	+
EA-US long-term spread	+	+	-	-	-

Table 4: Sign-restrictions used by Brandt et al. (2021) for the identification of shocks.

2.3 Assessing Market Fragility with a Local Projections Method

This section outlines how we measure the responsiveness of credit risk premiums to the identified global risk shocks from sub-section 2.2. This responsiveness serves as our measure of market stability. As mentioned before, market stability has many different dimensions; our approach assesses one specific (albeit important) aspect. Specifically, we consider the sensitivity of credit risk premiums –measured through 5-year sovereign CDS premiums and corporate option-adjusted spreads – in response to identified global risk shocks, distinguishing between regimes of higher and lower fragmentation.

As our dependent variable, we consider the log-difference of the sovereign CDS premium, and OAS for corporate bonds. For relatively small changes of the CDS premium we have, for country i and time-period t:

$$\log\left(\frac{\text{CDS}_{i,t}}{\text{CDS}_{i,t-1}}\right) \times 100 \approx \frac{\Delta\text{CDS}_{i,t}}{\text{CDS}_{i,t-1}} \times 100. \qquad (1)$$

[10]For the application of analyzing euro area CDS premiums, we do not shock the euro area macro news shocks, as the issue of endogeneity (in particular, reverse causality) could be a challenge.

This choice of dependent variable is motivated by the observation that other factors –besides the extent of financial fragmentation– can contribute to the market's responsiveness to risk shocks. The key insight is that other factors –notably credit fundamentals– that determine the responsiveness of CDS premiums to risk shocks are likely to be reflected in the level of the CDS premium itself (CDS_{t-1}). Factors that contribute to the responsiveness of credit risk premiums to risk shocks could include the debt/GDP ratio, primary and overall deficits, and economic growth. Our choice of dependent variable (see equation 1) absorbs any linear relationship between the level of the credit risk premium (CDS_{t-1}) and its response (ΔCDS_{t-1}). Admittedly, non-linear relationships could exist between credit fundamentals and the responsiveness of credit risk premiums to risk shocks. An implicit assumption of our methodology is therefore that such nonlinear contributions are small or negligible – a common assumption in linear regression. This assumption is in line with market practice: market participants often consider the (de-)compression of credit spreads. For example, market participants consider the ratio (compression) of high-yield and investment grade CDS premiums, rather than their nominal spread, as a measure of relative risk pricing. This corresponds with the empirical observation that –given a change in risk sentiment– the percentage change of different risk premiums tends to have a similar magnitude.[11]

We estimate the following dynamic panel data model to capture the effect of global shocks in scenarios of higher and lower fragmentation, using a smooth transition function (STF) approach[12]:

$$\Delta CDS_{i,t+h-1} = \beta_{0,h} + \beta_{1,h}\, S_t + \gamma_h\, G(z_t;\theta)\, S_t + \sum_{k=0}^{H} \delta_{k,h}\, X_{t-k} + \alpha_i + u_{i,t+h-1}, \qquad (2)$$

where:

- i indexes the cross-section (countries) in the panel,
- t represents time,
- h represents the local projections horizon,
- ΔCDS is short for $\log\left(\frac{CDS_{i,t}}{CDS_{i,t-1}}\right) \times 100$. For the analysis of corporate bonds, we use a similar construct based on the option-adjusted spreads.
- $\beta_{0,h}$ represents the intercept that varies across horizons,
- $\beta_{1,h}$ captures the effect of the shock S_t that also varies across horizons,
- S_t is the shock variable (e.g., global risk) at time t,
- H is the number of lags of the exogenous variables included in the model,
- X_{t-k} represents the exogenous variables lagged by k periods, with $k = 0, 1, 2, \ldots, H$,
- $G(z_t;\theta)$ is the smooth transition function that governs the varying impact of the shock depending on the transition variable z_t (high/low fragmentation) and the parameter vector $\theta = (\kappa, c)$,
- z_t is the fragmentation indicator,

[11] Consider the following example as an illustration of this empirical observation. A CDS premium of 100 basis points increases to 110 basis points, due to a change in risk sentiment, and a CDS premium of 300 basis points increases to 330 basis points. In this case, the compression remains constant at 3.

[12] We explicitly tested for autocorrelation in ΔCDS_t using ACF diagnostics, as well as a Wooldridge test, and found no significant evidence of serial correlation in our panel setup. Moreover, Annex D provides a model where ΔCDS_t is included. The coefficient is not significant. Annex H provides further details on the performed autocorrelation tests.

- γ_h is the coefficient associated with the interaction between the shock variable and the transition function,
- α_i are the individual country-fixed effects,
- $u_{i,t+h-1}$ is the error term.

The dynamic response of the shock is modulated by the transition function, $G(z_t;\theta)$, which allows the impact to vary smoothly depending on the value of the transition variable z_t. The transition function $G(z_t;\theta)$ is the sigmoid function, as used in Auerbach and Gorodnichenko (2013):

$$G(z_t;\theta(\kappa,c)) = \frac{1}{1+\exp\left(-\kappa(z_t-c)\right)},$$

whereby the parameter κ governs the smoothness of the transition, and the parameter and c is sets the threshold determining the transition between the two regimes. In our analysis, κ is set to 10, and c reflects the 50th percentile of the fragmentation indicator. The choice of κ thereby implies a relatively sharp transition between a market that is fragmented and one that is not. Section F demonstrates that the results of our main analysis are robust to alternative values of κ between 1 and 10, confirming that our findings hold under both gradual and relatively sharp transitions between regimes.

To compute the nonlinear impulse responses, we follow Adämmer (2019). This framework ensures that the response of CDS spreads depends not only on the size and direction of the shock but also on the degree of fragmentation, capturing potential regime-dependent differences within the euro area.

The exogenous variables $\mathbf{X}_t$ used to control for the other factors that could drive changes in risk premiums are:

$$\mathbf{X}_t = [\text{EA policy}_t,\quad \text{EA macro}_t,\quad \text{US policy}_t,\quad \text{US macro}_t] \tag{3}$$

In this model, the smooth transition function $G(z_{it};\theta)$ allows for a more continuous relationship between fragmentation regimes and credit premium responsiveness (or any other variable captured by z_{it}). Specifically, when z_{it} moves beyond a certain threshold, the effect of the shock changes in a continuous and smooth manner across regimes, rather than through a sharp break as in a dummy-variable approach. "EA policy", "EA macro", "US policy", and "US macro" refer to structural shocks identified via a sign-restricted Bayesian Vector Autoregression model following Brandt et al. (2021). "EA policy" and "US policy" capture monetary policy shocks in the euro area and United States, respectively. "EA macro" and "US macro" represent macroeconomic news shocks in the respective regions. These shocks are derived from asset price movements and reflect changes in interest rates, equity prices, and exchange rates consistent with the imposed sign restrictions (see Table 4 and Section C).

Our local projections approach (equation 2) seeks to uncover a relationship between the credit risk premium's response $\Delta\text{CDS}_t/\text{CDS}_{t-1}$ and the global risk shocks S_t, distinguishing between regimes of higher and lower financial fragmentation, and controlling for a number of other factors. This approach raises the question of possible sources of endogeneity, whereby a key issue is that the shocks –see section 2.2– are *identified* and orthogonal but not strictly *exogenous*. Below, we discuss three distinct aspects.

A first concern arises with the potential for reverse causality, whereby a move in euro area CDS premiums becomes globally systemic and thereby drives a global risk shock. Here, the inclusion of euro area-specific shocks (see Table 4) –orthogonal to the global risk shock– forms a first line of defense, as they should absorb the non-globally systemic component of any major move in euro area CDS premiums. Additionally, we assess granger causality to determine whether there is a causal relationship from peripheral sovereign CDS premiums to global risk shocks, or if global risk drives CDS premiums as argued in existing literature (see Srivastava et al., 2016, Longstaff et al., 2011 and Corzo et al., 2020). Details can be found in appendix E.

A second concern is the omitted variable bias that might arise if important control factors are missing. To address this concern, our specification (equation 2) includes the other factors identified in the BVAR model (see section C) as controls. These factors capture the macro-economic shocks and monetary policy shocks for the euro area as well as the US, as described in Brandt et al. (2021).

A third –and perhaps important– concern is that the relationship between euro area credit risk premiums' response $\Delta \mathrm{CDS}_t/\mathrm{CDS}_{t-1}$ and the global risk shocks S_t is fundamentally driven by common confounders. One might argue that global risk shocks are driven by new information – and generally speaking, this new information has implications for the underlying fundamentals of euro area sovereign and corporate bond issuers, which in turn impacts their CDS prices. This question commonly occurs in econometrics, as ultimately, micro-fundamentals underlie macro- and market variables. There is no a priori solution for this issue, but the focus of our methodological setup does offer some reprieve: our interest is primarily in differences between the higher and lower fragmentation regimes. In effect, we investigate if the "elasticity" of a CDS premium's response vis-a-vis global risk shocks depends on the fragmentation regime. Moreover, by augmenting our local projections with US and EU macroeconomic and monetary policy shocks, we are effectively controlling for other sources of risk that might otherwise be conflated with global risk shocks. This approach has several benefits. In addition to enhanced identification by isolating key US/EU-specific dynamics affecting CDS premiums these additional shocks serve as controls that capture regional influences, thereby reducing the risk of attributing effects from domestic policy or economic conditions to global risk shocks.

3 Results

This section presents our results. Section 3.1 outlines how sovereign CDS premiums respond differently to global risk shocks under higher and lower fragmentation regimes. Section 3.2 addresses the same question for corporate credit risk premiums in the euro area. Finally, Section 3.3 differentiates between core and periphery countries in the euro area.

Throughout this section and the results presented in it, a standardized global risk shock is introduced in the first period $h(1)$, using a non-linear panel local projection framework. The magnitude is consistently normalized to one standard-deviation, i.e. the magnitude is consistent across the analyses of the responsiveness of various types of sovereign and corporate credit risk premiums. To recall, the dependent variable is the log-difference of the credit risk premium (Δ CDS), multiplied by a hundred. Approximately, this responsiveness can be thought of as the percentage change of the credit risk premium under consideration. At each subsequent lag, the results are presented on the basis of first-differences.

3.1 Sovereign credit risk

Our results show that the higher fragmentation regime is associated with increased sensitivity of euro area credit risk premiums to global risk shocks. This finding aligns with ex-ante expectations, as higher fragmentation can undermine the efficiency of markets, prompting investors to demand higher risk premiums in response to a given shock.

Table 5 presents our findings for the non-linear panel local projections at horizons $h = 1 - 3$ for both the sovereign CDS premiums as well as the corporate option-adjusted spreads; first, we will focus on the sovereign

CDS premiums. The dependent variable in both panels is the log-difference of the credit risk premium (x 100). We analyze the responsiveness of the risk premiums under two fragmentation regimes, where "+" indicates the higher fragmentation regime (above the median) and "-" indicates the lower fragmentation regime (below the median).

The standardized shock is introduced at the first time period $h(1)$, where we observe a positive and statistically significant impact of a standardized global risk shock on CDS premiums in the higher fragmentation regime. Specifically, in this regime, a one standard deviation increase in the global risk factor leads to a 1.4 percent rise in sovereign CDS premiums. This effect is both economically and statistically significant, as it accounts for about half of the typical daily fluctuations in CDS premiums. This suggests that even a relatively mild increase in global risk (one standard deviation) can have a substantial effect on sovereign CDS premiums, significantly raising borrowing costs for governments.

Figure 8 illustrates the dynamic responses to the global risk shock under the higher and lower fragmentation regimes across horizons $h(1)$ to $h(15)$. The impact of a standardized global risk shock on CDS premiums appears to be fully absorbed at $h(1)$, as no further significant *increases* are observed in subsequent horizons $(h(2)-h(3))$. At the same time, the initial impact at $h(1)$ is fairly persistent.

Among the control factors included in the model, we find a positive and significant relationship between sovereign CDS premiums and the euro area macro-news factor, the euro area monetary policy factor, and the US macro-news factor. Notably, factors directly affecting the euro area economy emerge as the most significant drivers. US-related factors also spill over to euro area sovereign CDS premiums, but with a somewhat delayed response, also observed at $h(2)$. This lag may stem from differences in trading hours between the US and Europe. Illiquidity in the sovereign CDS market could also contribute to a lagged response (see Fontana and Scheicher, 2016).

In the lower fragmentation regime, the responsiveness of sovereign CDS premiums to a standardized global risk shock is significantly lower than in the higher fragmentation regime (see Table 7). The immediate reaction of CDS to global risk shocks at $h(1)$ is no longer observed. The shock has a much weaker impact in $h(1)$, reflected in the smaller coefficient. This suggests that in a less fragmented market, the impact of the standardized global risk factor is less pronounced, pointing to greater resilience. Another key finding is that sovereign CDS premiums are less sensitive to macroeconomic news factors during periods of lower fragmentation. For both euro area monetary policy factors, we observe a significant upward impact on sovereign CDS premiums following a tightening shock. This aligns with the direct transmission of monetary policy to interest rates and, subsequently, to credit fundamentals. However, during periods of lower fragmentation, the impact of a tightening shock becomes statistically insignificant, suggesting that in a low-fragmentation regime, credit risk premia are less sensitive to monetary policy shocks—possibly indicating higher economic resilience.

Qualitatively, our findings are consistent with the existing literature, which identifies the global risk factor as a key determinant of sovereign CDS premiums (Longstaff et al., 2011, Pan and Singleton, 2008, Augustin, 2018). Moreover, the outcomes of the local projections (LP) exercise are consistent with the results of the fixed effects (FE) panel model described in Annex D. For example, the contemporaneous impact of a global risk shock on sovereign credit risk during periods of higher fragmentation is estimated at 1.5 percent in the FE panel model and approximately 1.4 percent in the LP panel model, which incorporates dynamic responses (see Figure 8).

Table 5: Global risk shock on Sovereign ΔCDS

	$h(t)$		
	(1)	(2)	(3)
shock$^+$	1.427***	0.014	−0.207
	(0.134)	(0.124)	(0.129)
shock$^-$	−0.200	0.801**	0.430
	(0.289)	(0.330)	(0.328)
euro area macro$^+$	1.977***	0.122	−0.064
	(0.152)	(0.137)	(0.139)
euro area pol$^+$	1.033***	−0.074	0.097
	(0.156)	(0.168)	(0.228)
US macro$^+$	0.347**	0.549***	−0.059
	(0.150)	(0.140)	(0.132)
US policy$^+$	−0.051	−0.070	−0.019
	(0.119)	(0.149)	(0.128)
euro area macro$^-$	−0.276	0.855**	0.696*
	(0.358)	(0.353)	(0.363)
euro area pol$^-$	0.166	−0.009	0.182
	(0.345)	(0.382)	(0.384)
US macro$^-$	−0.095	0.473	0.128
	(0.301)	(0.312)	(0.314)
US policy$^-$	0.366	0.877***	0.280
	(0.243)	(0.323)	(0.265)

Table 6: Global risk shock on IG Corporate ΔOAS

	$h(t)$		
	(1)	(2)	(3)
shock$^+$	0.551***	0.283***	0.171***
	(0.049)	(0.045)	(0.043)
shock$^-$	0.114	−0.149	−0.002
	(0.125)	(0.113)	(0.104)
euro area macro$^+$	0.654***	0.197***	0.166***
	(0.053)	(0.043)	(0.047)
euro area pol$^+$	0.419***	0.153***	0.113
	(0.071)	(0.057)	(0.086)
US macro$^+$	0.268***	0.382***	0.100**
	(0.068)	(0.073)	(0.050)
US policy$^+$	0.005	0.173***	0.094*
	(0.061)	(0.049)	(0.051)
euro area macro$^-$	0.221	−0.092	−0.174
	(0.183)	(0.142)	(0.145)
euro area pol$^-$	0.230	0.200	−0.020
	(0.158)	(0.130)	(0.154)
US macro$^-$	−0.005	0.023	−0.211*
	(0.136)	(0.127)	(0.122)
US policy$^-$	−0.009	0.229*	0.135
	(0.149)	(0.119)	(0.120)

Table 5 and Table 6 report the impact of global risk shocks on sovereign CDS spreads (ΔCDS) and corporate option-adjusted spreads, respectively. The "+" indicates a fragmentation regime that is above the median and "-" indicates a fragmentation regime where the indicator is below its median. Estimates are based on three different specifications of the model ($h(t)$), with robust statistical significance indicated by *p<0.1, **p<0.05, and ***p<0.01, computed using HAC-robust standard errors.

Figure 8: Impulse response of Sovereign ΔCDS to global risk shocks during higher (left) and lower (right) fragmentation regimes

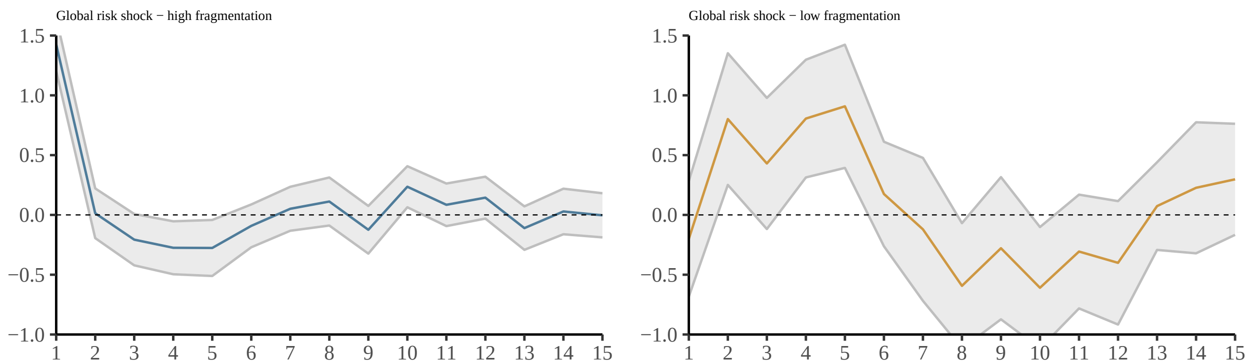


Figure reports the impact of global risk shock on changes in sovereign CDS spreads (ΔCDS). The shocks as identified in a BVAR-model of financial market dynamics Brandt et al. (2021). The response is estimated using non-linear local projections at $h(1) - h(15)$. Impulse responses are shown with 90% confidence intervals, computed using HAC-robust standard errors.

Table 7: Sovereign CDS: Significance of Difference between Higher and Lower Fragmentation Regimes

Shock Type	$h(k)^+$	$h(k)^-$	**Δ Coeff.**	**SE Diff**	**T-stat**	**P-value**
Global Risk Shock $h(1)$	1.427	-0.200	1.626	0.319	5.101	0.000
Global Risk Shock $h(2)$	0.014	0.801	-0.788	0.352	-2.235	0.025
Global Risk Shock $h(3)$	-0.207	0.430	-0.637	0.353	-1.807	0.071

Note: The t-statistics were calculated based on the difference in coefficients for each shock type, using the formula $t = \frac{\text{Diff Coeff}}{\text{SE Diff}}$. The degrees of freedom for the t-test are approximated as $N - 1$, where N represents the number of observations. The p-values are computed using a two-tailed t-test. $h(1)^+$ ($h(1)^-$) is the shock coefficient at $h(k)$ in the high (low) fragmentation regime.

3.2 Corporate credit risk

In a similar vein to Zaghini (2016) and Bedendo and Colla (2015), we extend our analysis to the corporate debt market and find that fragmentation affects the dynamics of corporate credit risk premiums. By exploring this channel, we provide new insights into the broader economic consequences of euro area financial fragmentation. Consistent with the findings for sovereign CDS premiums, we observe significantly higher sensitivity to a standardized global risk shock in the higher fragmentation regime.

Table 6 provides the results of the exercise for corporate investment grade OAS. Starting with the impact of a global risk shock on corporate credit risk we observe a positive and significant impact in the higher fragmentation regime, which is different from the lower fragmentation regime at the 1% significance level (see Table 8). Compared to the responsiveness of the sovereign CDS risk premium we find a somewhat more muted impact at the first horizon $h(1)$, where the OAS increases by around 0.6 percent for a one standard deviation global risk shock. However, the responsiveness of corporate OAS to a global risk shock is not limited to the first period, as the responses in $h(2) - h(3)$ are also positive and significant, cumulating to around 1 percent at the end of the third horizon $h(3)$. This might be the result of lower market liquidity in euro area corporate debt markets, which makes price adjustment less efficient (Novick et al., 2016). We find that both euro area macro and monetary policy factors significantly increase the risk premiums in corporate debt markets in the higher fragmentation regime. Similarly, it takes some time for these shocks to be fully priced into corporate credit risk premiums as we also find a positive and significant impact beyond the first period ($h(1)$). The impact of US monetary policy is less clear as we find a similar coefficients in both the lower and higher fragmentation regimes ($h(2)$).

Table 8: Corporate OAS: Significance of Difference between Higher and Lower Fragmentation Regimes

Shock Type	$h(k)^+$	$h(k)^-$	**Δ Coeff.**	**SE Diff**	**T-stat**	**P-value**
Global Risk Shock $h(1)$	0.551	0.114	0.436	0.135	3.238	0.001
Global Risk Shock $h(2)$	0.283	-0.149	0.432	0.122	3.543	0.000
Global Risk Shock $h(3)$	0.171	-0.002	0.173	0.112	1.543	0.123

Note: The t-statistics were calculated based on the difference in coefficients for each shock type, using the formula $t = \frac{\text{Diff Coeff}}{\text{SE Diff}}$. The degrees of freedom for the t-test are approximated as $N - 1$, where N represents the number of observations. The p-values are computed using a two-tailed t-test. $h(1)^+$ ($h(1)^-$) is the shock coefficient at $h(k)$ in the high (low) fragmentation regime.

Figure 9: Impulse response of Euro Corporate Investment Grade ΔOAS to global risk shocks during higher (left) and lower (right) fragmentation regimes

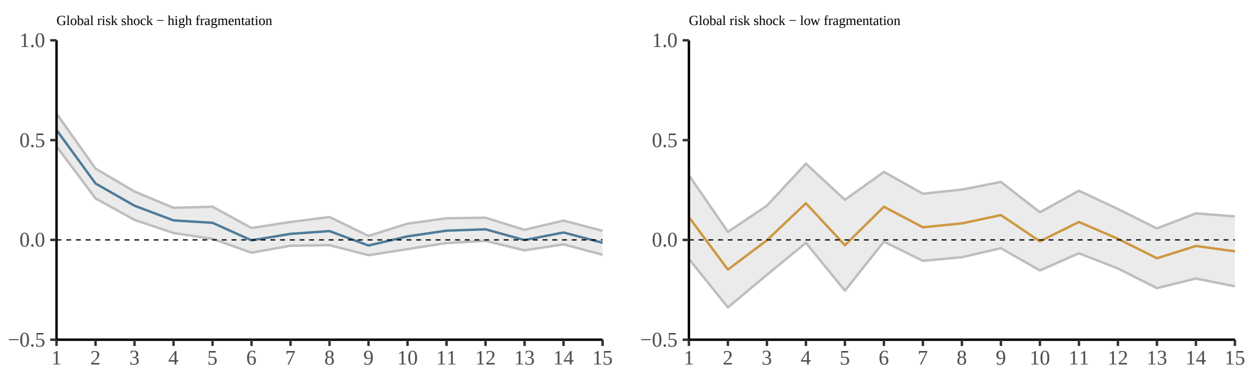


Figure reports the impact of a global risk shock on log-differences in corporate OAS spreads (ΔOAS). The shocks as identified in a BVAR-model of financial market dynamics Brandt et al. (2021). The response is estimated using non-linear local projections at $h(1) - h(15)$. Impulse responses are shown with 90% confidence intervals, computed using HAC-robust standard errors.

3.3 Core and periphery credit risk

The results presented so far are based on a panel local projections method, whereby all five major euro area jurisdictions are included. But given the public discourse's emphasis on differences between core and periphery jurisdictions, one might wonder if our results are driven only by the periphery jurisdictions. In a more extreme scenario, one could hypothetically observe a divergence in terms of the impact of higher fragmentation on credit risk premium responsiveness. In this sub-section, we split our sample of countries into core and periphery jurisdictions, and assess whether the results for the full sample hold for the core and periphery sub-samples.

Figure 10 summarizes the results at $h(1)$ for all different specifications in the above sub-sections, but distinguishes between core and periphery countries. Starting from the impact on sovereign CDS, several observations can be made. First, the amber dots indicate that in a higher fragmentation regime the impact of a global risk shock is positive and significant for both the core and periphery countries, with a relatively small economic difference between the impact (1.13 percent for the core countries versus 1.46 percent for the periphery countries), albeit statistically significant. Second, the difference between core and periphery in the global risk shock-response under lower fragmentation is limited (0.12 percent).

An interesting observation is that in both regimes, core sovereign CDS spreads widen in response to a global risk shock. This might appear counterintuitive, as "risk-off" or "flight-to-safety" dynamics imply that safe asset prices increase (per definition), or equivalently, the yields on "safe" bonds decline. However, this perhaps counterintuitive effect is well-documented, and our findings align with Beber et al. (2009) who show that liquidity premiums are an important driver in flight-to-safety dynamics, in addition to credit risk risk premiums. In times of stress, investors may have a higher preference for more liquid assets; and this effect can also be self-reinforcing. For example, a German government bond might have a relatively low CDS spread to begin with, and in response to a risk shock, a limited widening of the credit risk premium may be more than offset by the additional liquidity premium. Lastly, the fact that credit risk premiums widen for both core as well as periphery jurisdictions also hints at spillovers among euro area countries as described in Drago and Gallo (2016).

The second panel in Figure 10 shows the results for corporate investment grade OAS. Similar to the result of the main analysis, the global risk shock has a less pronounced impact in $h(1)$, but the results for the higher fragmentation regime show a larger responsiveness, although the estimate has a wider confidence interval. Interestingly, the impact on core bond markets seems to be more pronounced for core euro area firms than for bond issuers that are domiciled in periphery countries.

Figure 10: Contemporaneous Response of Sovereign ΔCDS and Euro Corporate Investment Grade ΔOAS to global risk shocks

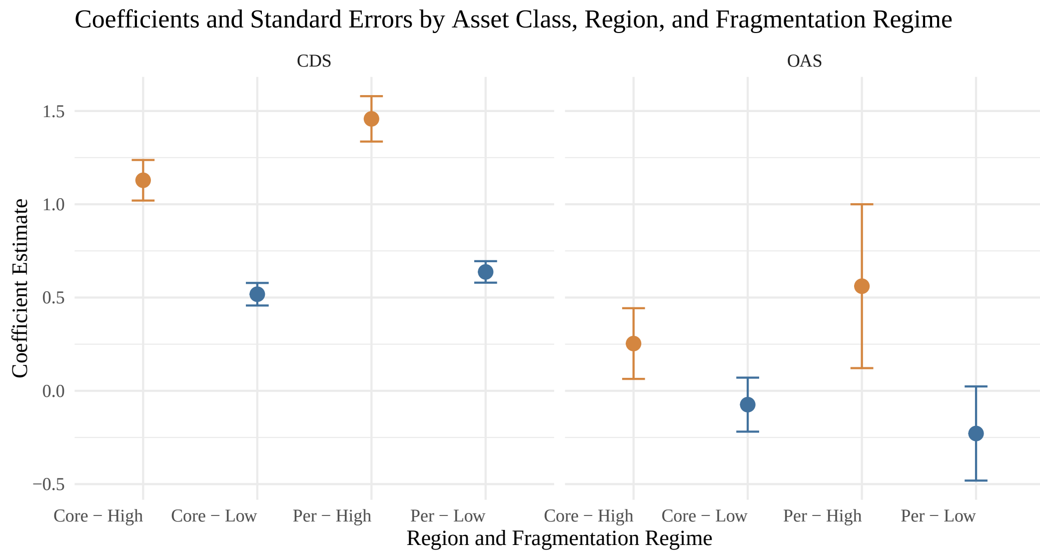


Figure reports the direct response $h(1)$ for the non-linear panel local projections of the main specification (Table 5 Panel A). Core countries are France, Germany and The Netherlands, periphery countries are Italy and Spain.Impulse responses are shown with 90% confidence intervals, computed using HAC-robust standard errors.

4 Robustness

This section assesses the sensitivity of our results to key sources of uncertainty. First, we focus on the construction of our novel fragmentation indicator, which represents a central contribution of the paper. As the indicator is designed to capture a latent, non-directly observable state variable, there is no uniquely correct specification. Within the scope of our PCA-based approach, we examine a range of alternative constructions for a time-varying euro area financial fragmentation indicator and find that these alternatives yield similar dynamics, supporting the robustness of our baseline measure.

Second, we evaluate the propagation of estimation uncertainty arising from the second and third steps of our empirical strategy—namely, the construction of identified shocks using the sign-restricted BVAR and the estimation of dynamic responses via local projections. By jointly incorporating these sources of uncertainty, we construct confidence bands that reflect the full estimation variability inherent in these stages. We do not formally integrate uncertainty from the indicator construction into these bands, given the conceptual nature of the latent variable it seeks to represent.

Third, as a robustness check, we present a series of panel regressions as a substitute for steps two and three of the analysis. While this approach is more rudimentary, it offers a useful benchmark and allows us to more transparently assess the influence of different control variables and fixed effects on our core results.

4.1 Euro Area Financial Fragmentation Indicator

This subsection assesses the robustness of the euro area financial fragmentation indicator. We conceptualize financial fragmentation as a latent state variable—an underlying condition of the financial system that cannot be observed directly. Accordingly, we remain within the framework of principal component analysis (PCA) applied to yield dynamics, where the state of the system is inferred from its behavior over time rather than from directly measurable quantities such as credit spread levels.

First, we assess the uncertainty in our indicator arising from the PCA decomposition itself, using a bootstrap approach to gauge the sensitivity of the estimated principal components. Second, we explore the robustness of the aggregation method used in constructing the indicator, specifically by varying the 12-month moving window used to compute the average variance explained in yield dynamics. These exercises demonstrate that the indicator's behavior is stable across plausible variations in both the decomposition and aggregation steps.

The bootstrap analysis is based on 10,000 samples drawn with replacement from the 1,287 weekly observations, with each bootstrap sample matching the original dataset in size. As shown in Figure 11, the second principal component consistently captures the "core-periphery" divergences described in Section 2. Applying the 12-month moving window to compute the average variance explained by these diverging dynamics, Figure 12 demonstrates that the resulting indicator trajectories from the bootstrap decompositions are broadly similar. While the confidence bands are somewhat wider during periods of lower indicator values, the resulting uncertainty appears limited for the purpose of distinguishing between regimes of higher and lower fragmentation. Moreover, our use of a smooth transition function in the local projections framework further mitigates the impact of marginal variation in indicator values, helping ensure stability in the estimated impulse responses.

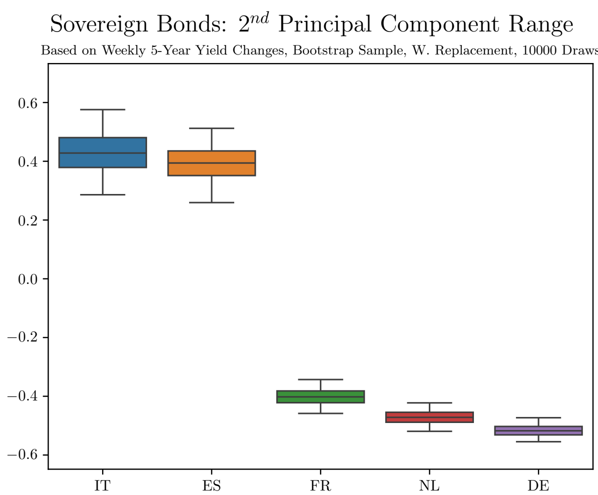


Figure 11

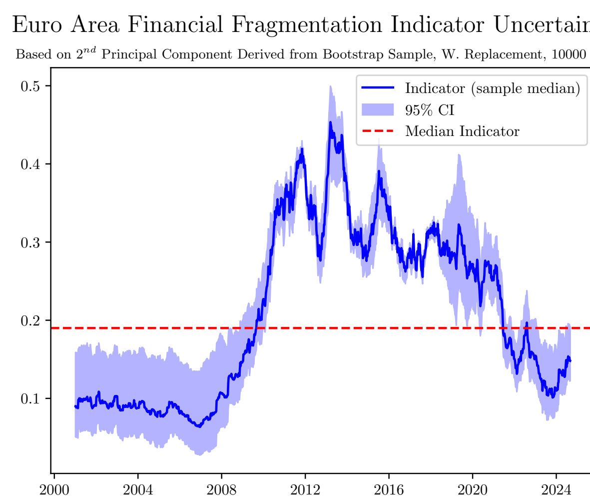


Figure 12

Next, we consider alternative aggregation methods for the indicator. In Figure 13, we retain the moving average approach but vary the length of the averaging window. The figure highlights a trade-off between the indicator's responsiveness, stability, and sensitivity to idiosyncratic market fluctuations. Shorter averaging windows (e.g., 3 months) result in a more volatile indicator that is quicker to reflect abrupt changes, while longer windows yield a smoother, more stable series that tends to lag underlying shifts—effectively producing a delayed or right-shifted depiction of fragmentation dynamics.

Given the nature of our problem—measuring an underlying state variable in the presence of noise—we also explore a Kalman filter approach to constructing the fragmentation indicator. Figure 14 presents two specifications: one using a univariate Kalman filter without exogenous inputs, and another incorporating the Italian-German government bond yield spread as an exogenous driver. Both versions produce smooth indicator dynamics, notably avoiding the "right-shift" bias associated with the moving average approach. Including the yield spread leads to only marginal adjustments, reinforcing the notion that financial fragmentation is not synonymous with yield differentials. Conceptually, the univariate Kalman filter approach is problematic, as it assumes the fragmentation indicator evolves independently, without any relationship to fundamental economic drivers. This limitation reduces its ability to capture meaningful underlying dynamics linked to observable market factors. The Kalman filter approach that incorporates exogenous variables is more promising, as it allows the indicator to be linked to observable economic drivers. However, this raises important questions: which variables are most relevant to include? Does the indicator reflect self-reinforcing dynamics driven by (ir)rational behavioral biases? Moreover, should exogenous variables enter the model only linearly, or is it necessary to consider non-linear effects and interactions to fully capture the complexity of financial fragmentation? As in previous robustness checks, we emphasize that the smooth transition function used in the third step of our analysis further mitigates the impact of such differences in indicator construction.

Lastly, it is worth motivating why we opted for the 12-month moving average approach to construct our euro area financial fragmentation indicator as opposed to e.g. the Kalman filter approach that incorporates exogenous variables, or different time-windows. First, our 12-month moving-average specification provides a transparent and intuitive means of smoothing short-term volatility in the underlying principal component dynamics, while remaining sufficiently responsive to capture meaningful shifts in market fragmentation. Compared to shorter windows, it mitigates the influence of transient noise and idiosyncratic market fluctuations; compared to more model-dependent alternatives like the Kalman filter, it preserves a high degree of methodological simplicity, replicability, and interpretability. This balance between responsiveness, stability, and transparency makes the 12-month moving average a natural and robust baseline for our analysis.

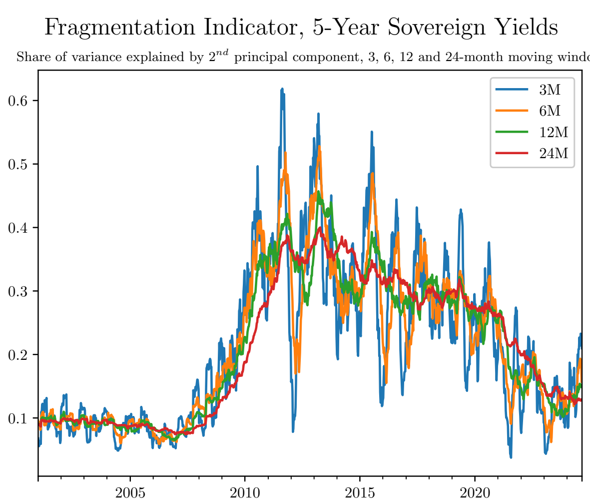


Figure 13

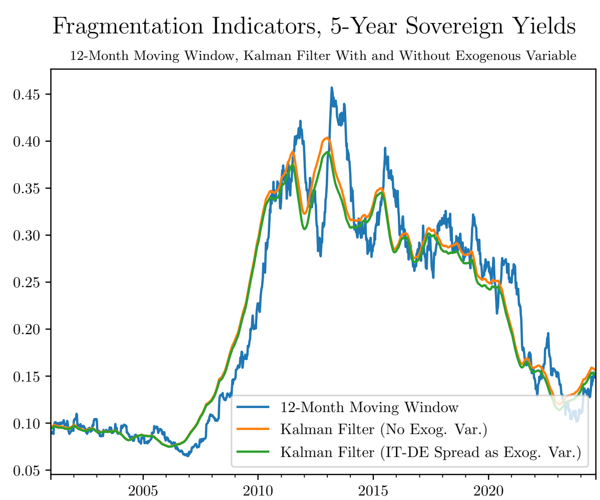


Figure 14

4.2 Combined Uncertainty in Shock Identification and Impact Estimation

As outlined in Table 1, our methodology proceeds in three steps to estimate the impact of global risk shocks under conditions of high and low financial fragmentation. While this method presents a straightforward and practical structure, the confidence intervals reported in Table **??** may understate the true extent of estimation uncertainty. In particular, the reported intervals reflect uncertainty from the local projection (LP) regression, but do not account for the additional uncertainty introduced by the BVAR-based identification of the global risk shock. To address this, we construct a fully integrated estimate by re-estimating the LP model across a large set of BVAR identification matrix draws, thereby combining both sources of uncertainty in an estimated density of the regression coefficient for shock^{+} at $h(1)$. Given the computational intensity of the calculations, we provide results for the global risk shock coefficient in $h(1)$ only.

The distributions shown in Figure 15 incorporate two sources of uncertainty: (i) the variability in identified structural shocks across 500 BVAR draws, and (ii) LP estimation uncertainty. For each BVAR draw, we simulate 20 values uniformly within the reported LP confidence interval (see Figure 16) to approximate the full conditional distribution of the IRF in $h(1)$. This nonparametric procedure allows for asymmetric responses across draws. Note that uniform drawing is a conservative approach; assuming normality of the distribution would provide (even) tighter confidence intervals.

Figure 15 presents the resulting distributions of the regression coefficient for shock$^{+/-}$ at $h(1)$ for high (+) and low (−) fragmentation regimes. Under the high fragmentation, global risk shocks trigger a significantly larger increase in sovereign CDS spreads, with the distribution centered well above one. In contrast, the IRF distribution under low fragmentation is concentrated around zero and exhibits lower dispersion. A Kolmogorov–Smirnov test strongly rejects the null hypothesis of equal distributions (D = 0.997, p < 0.001), providing statistical evidence that the coefficient remain significantly different from each other - also when accounting for the additional uncertainty introduced by the BVAR estimation procedure. [13]

[13] In addition to the Kolmogorov–Smirnov test, a Wilcoxon rank-sum test confirms that the distributions of impulse response coefficients under high and low fragmentation differ significantly, rejecting the null hypothesis of equal medians ($p < 0.001$).

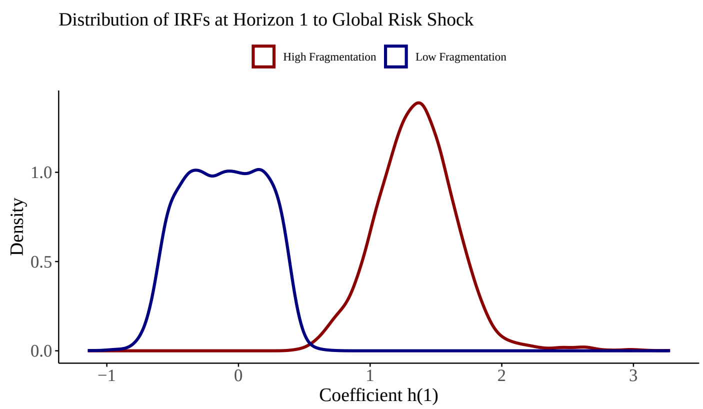


Figure 15

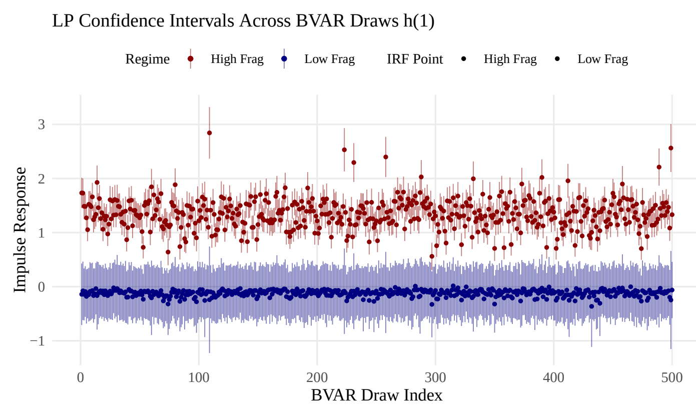


Figure 16

Figure reports the direct response at horizon $h(1)$ based on the non-linear panel local projections from the main specification (Table 5). The distributions (Figure 15) incorporate both uncertainty from the BVAR-estimated global risk shocks and local projection estimation. For each of the 500 BVAR draws, we re-estimate the panel LP model and simulate from the reported confidence interval to generate a distribution of impulse responses under high and low fragmentation. This procedure yields a nonparametric approximation of the total uncertainty i.e., we make no assumptions about the distribution of the standard errors.

4.3 Validation of Results via Panel Regression Evidence

To support the interpretation and robustness of the local projections, we also employ a fixed effects panel regression that examines the impact of BVAR-identified shocks on changes in sovereign CDS spreads (see Annex D). Since local projections yield direct estimates at each horizon h, the panel regression offers complementary insights—particularly regarding the sensitivity of the LP estimates at $h = 1$, to various model specifications.

The panel regressions incorporate interaction terms to capture differential effects under varying levels of financial fragmentation, represented by a dummy variable, and include controls for key macroeconomic and policy variables. Several model specifications are estimated, gradually introducing interaction effects, a lagged dependent variable, a sovereign debt crisis dummy, and time-fixed effects to account for unobserved, time-specific shocks. The results indicate that in periods of low fragmentation, global risk and euro area macroeconomic shocks are significantly associated with increases in sovereign CDS premiums, confirming the findings in the main specification. Notably, during high-fragmentation episodes, these shocks exert a significantly stronger marginal effect, particularly global risk shocks, which contribute an additional 0.6 percentage points to the change in CDS spreads. Overall, the panel regression analysis confirms the validity of the local projections specification and underscores the role of financial fragmentation in shaping the impact of macro-financial shocks on sovereign risk pricing in the euro area.

5 Conclusions and Discussion

This paper addresses how financial fragmentation in the euro area impacts the stability of sovereign and corporate bond markets. To achieve this, we employ a three-step methodological framework. First, we develop a time-varying indicator of euro area financial fragmentation, enabling us to examine bond market stability and fragility across different fragmentation regimes. While market stability encompasses various dimensions, our primary focus is on the sensitivity of credit risk premiums to risk shocks. In the second step, we identify and construct a series of global risk shocks, which serve as a basis for evaluating the response of credit risk premiums to these shocks in the third and final step. The third step employs a non-linear panel local projections method, allowing for a nuanced understanding of how credit risk premiums react to identified global risk shocks across different fragmentation environments.

Our key result is that both sovereign and corporate credit risk premiums appear more reactive to global risk shocks during times of elevated euro area financial fragmentation. This conclusions holds for both "core" as well as "periphery" jurisdictions, showing that financial fragmentation is not just a problem for "the periphery", but affects market stability across the single monetary union. We also find that corporate option-adjusted spreads show a larger and more persistent response to a global risk shock when fragmentation is elevated. Interestingly, this result appears to be more pronounced for bonds issued by firms that are domiciled in core countries.

This study has a number of limitations and relies on certain assumptions; technical aspects are discussed in the methodology section (section 2), but here we will highlight the most important choices in the design of this study. First, our euro area financial fragmentation indicator is an empirical measure, the construction of which relies on a number of discrete choices. This measure reflects that euro area financial fragmentation is a latent variable that cannot be measured directly. Moreover, it transcends the naive idea of using sovereign spreads as a measure of fragmentation: indeed, intra-euro area sovereign spreads could just as well reflect differences in underlying credit fundamentals, rather than the fragmentation of markets. Second, this study follows a three-step approach, which may look overly complex. An alternative approach could seek to remove the third step –based on the local projections method– by integrating sovereign and corporate credit premiums into the BVAR framework. However, identification would be non-trivial with both sovereign and corporate credit premiums for five jurisdictions. For this reason we have chosen to construct a series of global risk shocks first, which then allow for a comparison of the response of the different credit premiums on an equal footing.

Third, it should be noted that this study does not seek to "explain" euro area financial fragmentation, and we aim to measure fragmentation through its effects on market dynamics, rather than investigating its drivers. A disadvantage of this approach is that divergences in market dynamics could also be explained by divergences in fundamentals. But as we argue, we expect that macro and credit fundamentals are more slowly-moving and help explain long-run variation, but only a small share of the variance in weekly yield-changes. At the weekly frequency, (global) risk sentiment is a key driver of yield-changes, see for instance Costantini et al. (2014) and Attinasi et al. (2010). In addition, idiosyncratic country-specific news tends to be less frequent and does not necessarily give a large loading on PC2.

Fourth, our measure of market fragility –the responsiveness of credit premiums to global risk shocks– could be affected by factors other than fragmentation. For example, a high primary deficit could make investors more nervous about any additional adverse shocks. However, such factors would likely be reflected in the credit premiums, and our definition of responsiveness absorbs –through its scaling with the credit risk premium itself– the impact of such factors at linear level. By the same token, to the extent that financial fragmentation drives credit risk premiums (e.g. directly through a liquidity premium or re-denomination risk premium, or indirectly through any relationship with relevant fundamental variables), our measured effect in terms of risk premium responsiveness may be an underestimate.

Our three-step approach could also be applied to other manifestations of fragmentation. Financial fragmentation can be driven by different forces, and future fault lines may delineate across different dimensions as compared to those that appeared during the European sovereign debt crisis. For example, on a global scale, geopolitical tensions and trade-protectionism may be at the roots of financial fragmentation (see Catalan et al. (2024)). Our measure of market stability –the responsiveness of credit risk premiums to identified global risk shocks– could be applied to geopolitical fragmentation as measured by Fernández-Villaverde et al. (2024).[14] Lastly, it should be noted that even within the euro area, future fault lines may appear along different fault lines than those that emerged during the European Sovereign Debt crisis. While the PCA-based fragmentation indicator could still be useful, in such a different regime, a recalibration of the fragmentation indicator should be done based on the time-window relevant for that era. For example, a PCA-analysis on a shorter and more recent time-interval shows a smaller component for France in PC2, suggesting that France has moved away from the other core countries and more towards the periphery countries. Nonetheless, the fragmentation indicator remains low compared to historical episodes.

[14]When the number of credit risk premiums of interest is limited –contrary to our case–, a Threshold BVAR or Markov-switching BVAR approach would be more appropriate than our combination of the sign-restricted BVAR from Brandt et al. (2021) and the local projections method of Jordà (2005).

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A Definitions of Financial Fragmentation

There is no commonly accepted definition of financial fragmentation, and international organizations as well as academics have used different definitions in different contexts. Conceptually, this paper follows the Financial Stability Board in its definition (see below). As a loose definition of the concept, we consider financial fragmentation as *a situation wherein financial markets are segmented, whereby there is a breakdown of market efficiency across these segments.* This segmentation disrupts the smooth operation of financial markets, leading to disparities in access to capital, interest rates, and investment opportunities. Inefficiencies emerge around the fault lines between these segments, hindering the optimal allocation of resources and potentially affecting economic growth and financial stability. This segmentation can be driven by a variety of underlying factors, such as geopolitical relationships, differences in legal frameworks and law enforcement's, demographic and geographic factors, varying degrees of market development, and differences in investor base, among other factors.

International organizations have described financial fragmentation in a similar fashion, but from different perspectives:

Financial Stability Board (FSB) The FSB choses a market-based angle and describes fragmentation as the breakdown of markets into fragments either geographically or by product type or participant. In the context of securities markets, the FSB characterizes fragmentation by the trading or clearing of economically similar assets across multiple venues, whereby the fragmentation of international banking might refer to pools of capital and liquidity being segregated within local markets and unable to move freely across jurisdiction. (see Financial Stability Board (2019))

Organisation for Economic Co-operation and Development (OECD) The OECD focuses on the economic dimensions of fragmentation, defining it as heterogeneous economic systems, policies, rules, laws and industry practices that create perverse incentives and block business efficiency and productivity growth (see OECD (2016)).

International Monetary Fund (IMF) The IMF does not explicitly state a definition of "financial fragmentation", but in its April 2023 Global Financial Stability Report, the IMF discusses factors that affect cross-border investment, international payment systems, and asset prices, whilst focusing on geopolitical tensions as a key driver of financial fragmentation (see IMF (2023)). Catalan et al. (2024) define financial fragmentation as a policy-driven weakening of financial links between countries –a particular form of deglobalization.

B Supporting Statistics for Principal Component Analysis

This appendix provides additional detail on the statistical basis for the use of the second principal component (PC2) in the construction of the financial fragmentation indicator.

Figure 17 presents a scree plot, together with two common criteria used to assess the number of components to retain in principal component analysis (PCA): the Kaiser criterion and parallel analysis. The Kaiser criterion suggests retaining components with eigenvalues greater than one, based on the rationale that a component should explain at least as much variance as an individual standardized variable (Kaiser (1960)). In terms of variance explained, this equates to $1/n$, where n is the number of variables; in our case this is 20% since we are considering yield-changes for $n = 5$ countries.

A second indicator for the significance of a principal component is based on parallel analysis. Parallel analysis compares the observed eigenvalues to those obtained from randomly generated data with the same dimensions. A component is typically considered significant if its eigenvalue exceeds the 95th percentile of the simulated distribution (Horn (1965)).

Under these criteria, the significance of PC2 is nuanced. It is borderline significant under the Kaiser criterion, and inconclusive under parallel analysis, falling clearly below the conventional 95% threshold for inclusion, but within a 95% confidence interval of the median of the random draws. However, PC2 still explains approximately 20% of the total variance in yield changes over the full sample, placing it near standard inclusion thresholds.

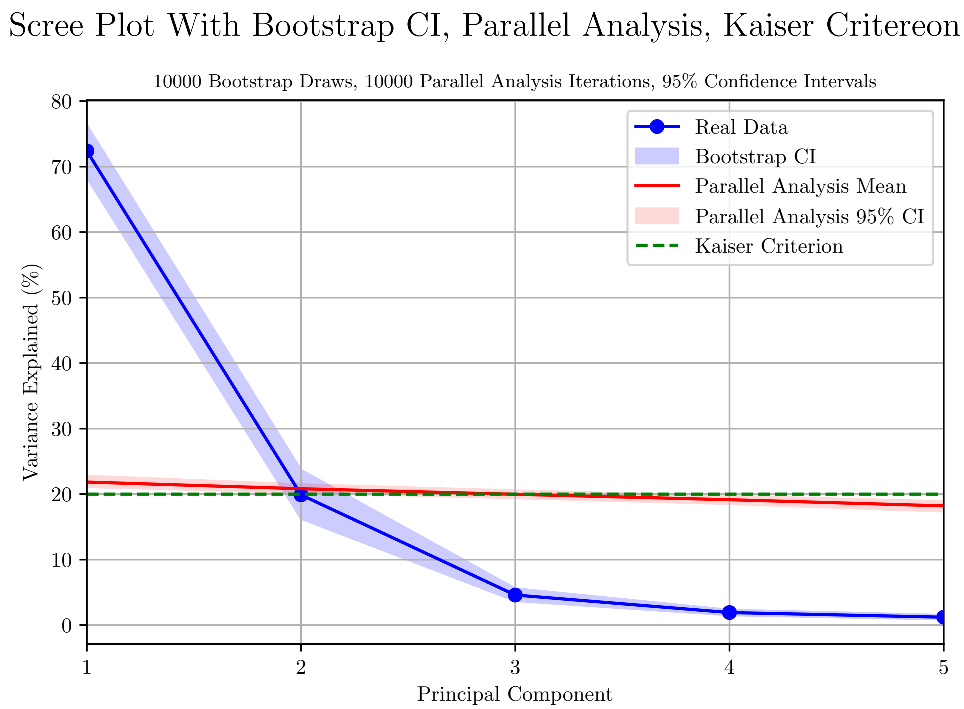


Figure 17

A more granular analysis reveals that the explanatory power of PC2 varies substantially over time (see also Figure 20). During periods of higher fragmentation —defined as weeks in which the fragmentation indicator is above its median— PC2 accounts for 31.0% of the variance in yield changes. By contrast, in periods of lower fragmentation, it explains only 11.4%. This pattern is conceptually consistent with the interpretation of PC2 as a fragmentation indicator: its influence is episodic rather than constant, becoming more pronounced as fragmentation intensifies. This dynamic behavior supports the view that PC2 captures a meaningful underlying structure in the data.

Further support for the relevance of PC2 comes from a bootstrap analysis of its loadings. Figure 11 shows that the composition of PC2 is highly stable across resampled datasets. While one could also consider bootstrap-based confidence intervals for eigenvalues, we view the stability of PC2's components as stronger evidence that it reflects a persistent, interpretable pattern rather than noise. Lastly, as mentioned before, the principal component structure -—whereby PC1 captures common co-movements and PC2 reflects core–periphery divergence—-

has been documented in the existing literature (see Fontana and Scheicher (2016); Fabozzi et al. (2016)), including for different country samples and in analyses based on sovereign CDS spreads. We also find similar patterns in our own analysis when using alternative bond maturities and even in corporate bond markets (see Figure 2). The consistency of this principal component structure across a range of instruments, sample periods, bootstrapped samples, and different country selections strongly suggests that it is unlikely to have emerged by mere statistical coincidence.

An interesting avenue for future research would be to explicitly model the time variation and non-linear dynamics that appear to characterize the second principal component (PC2). While we classify regimes using the share of variance explained by the fixed PC2 factor, the episodic behavior of PC2 suggests that a more dynamic framework could have advantages. In this context, regime-switching models—such as hidden Markov models (HMMs) or Markov-switching vector autoregressions (MS-VARs) could be used instead.

Additionally, dynamic factor models (DFMs) provide yet another framework for capturing the evolving influence of latent components like PC2 (see, for example, Fernández-Villaverde et al. (2024) for an application of a DFM to measuring geopolitical fragmentation).[15] Extensions of DFMs with time-varying loadings or stochastic volatility could account for changing relationships between observed variables and latent fragmentation patterns.

However, these alternative approaches also come with disadvantages relative to our simpler PCA-based methodology. Dynamic factor models and regime-switching frameworks capture evolving structures and nonlinear dynamics, but the interpretation of the identified factors becomes less stable by construction, as they evolve over time. In contrast, the PCA-based approach provides a simple, transparent, and interpretable decomposition of yield dynamics, allowing for the clear identification of a "fragmentation factor" —orthogonal to other factors— whose importance varies across regimes. The stability of the PC2 vector components (see Figure 11) supports the use of comparative analysis over time; accordingly, PC2 is well-suited for structural interpretation, making the indicator a useful diagnostic and monitoring tool.

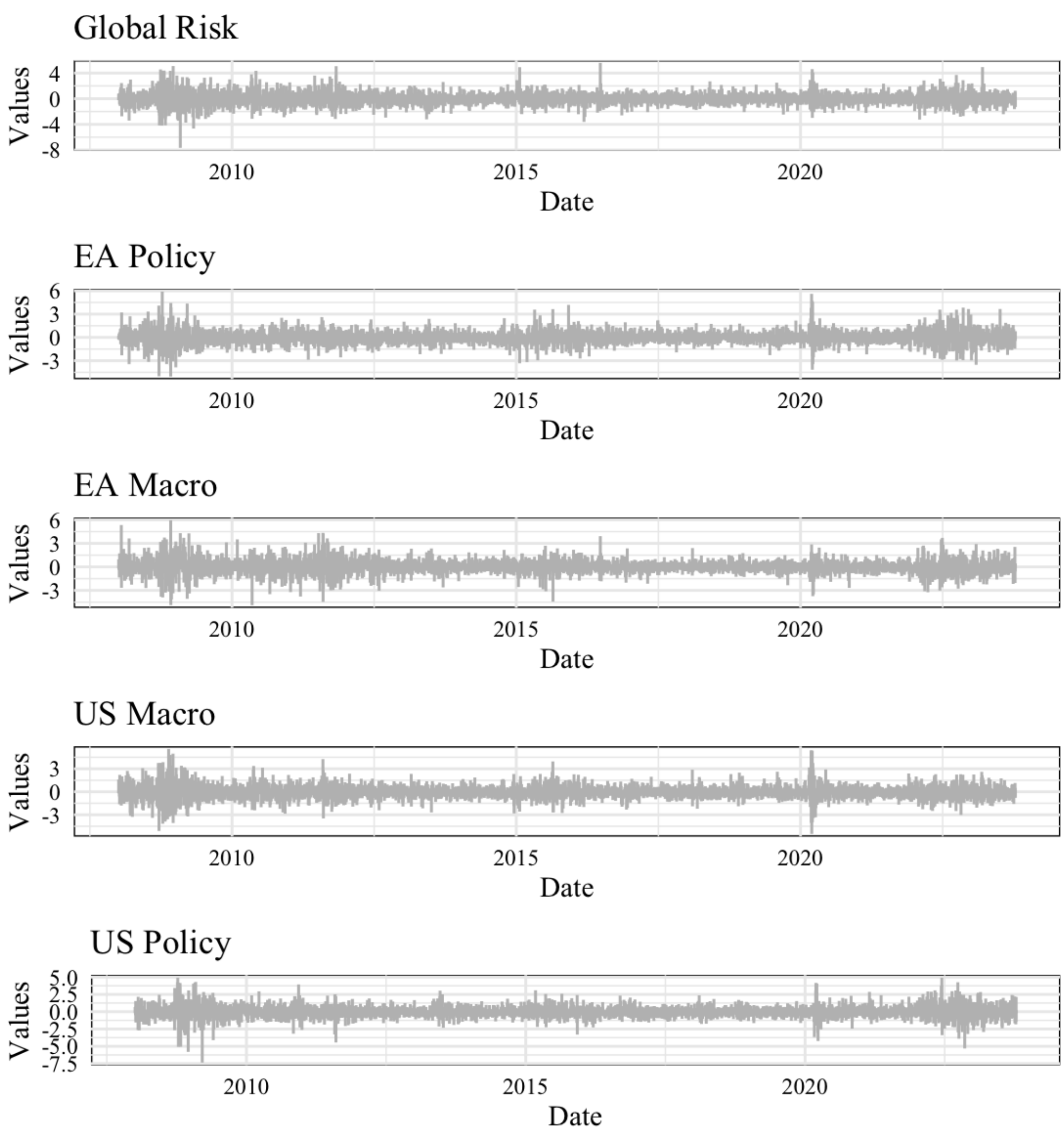
C Construction of Shocks (BVAR)

To asses bond market fragility we start with constructing identified shocks on global financial markets by following Brandt et al. (2021). This methodology uses financial market data and sign restriction to arrive at *identified* monetary policy shocks, macro fundamental shocks in both the US and euro area and global risks shocks.

Figure 18 shows the resulting median value of the estimated shocks. The figure shows the BVAR model is capable of identifying spikes in risk events, such as the Global Financial Crisis, and monetary policy shocks, such as the start of Quantitative Easing (QE) and upward spikes during the COVID-19 pandemic. Moreover the global risk factor exhibits notable spikes during the Lehman collapse and the COVID-19 pandemic. Brandt et al. (2021) show the global risk factor correlates with equity market implied volatility (the VIX and VSTOXX index) and the euro zone CISS index Hollo et al. (2012), but with the added benefit of being symmetrical, i.e. measuring both adverse and benign risk sentiment episodes.

[15]This paper considers various aspects and drivers of geopolitical fragmentation. The authors conclude that for their application "the factor derived from PCA appears largely consistent" with their DFM-based indicator.

Figure 18: BVAR shocks.



Note: Sign-restrictions used by Brandt et al. (2021) for the identification of shocks, see Table 4.

D Financial Fragmentation and Bond Market Stability: a Panel Regression Approach

As a means of robustness checking, we use a panel data setup with dummies to investigate the contemporaneous impact of the various BVAR shocks. This exercise thus substantiates the specification chosen in the local projections approach we take for the main specification. We examine how changes in sovereign CDS premiums relate to these shock variables Φ during times of high and low fragmentation in a simple fixed effects panel model, controlling for the same other identified BVAR factors in X, and θ the dummy for the fragmentation indicator being above the median:

$$\Delta CDS_{i,t} = \beta_0 X_t + \gamma_0 \Phi_t + \gamma_1 \theta_t + \gamma_3(\theta_t \times \eta_t) + \alpha_i + u_{i,t} \tag{4}$$

where $\Delta\text{CDS}_{i,t}$ is defined as in section 2.

These shocks are then used in a fixed effects panel model. More specifically we use the specification:

$$\begin{aligned}\Delta\text{CDS}_{it} &= \beta_1 \text{ global shock}_t + \beta_2 \text{ euro area pol}_t + \beta_3 \text{ euro area macro}_t + \beta_4 \text{ crisis}_t + \beta_5 \text{ high frag}_t \\ &+ \beta_6 \text{ (high frag} \times \text{global shock)}_t + \beta_7 \text{ (high frag} \times \text{euro area pol)}_t + \beta_8 \text{ (high frag} \times \text{euro area macro)}_t + \alpha_i + \varepsilon_{it}\end{aligned} \tag{5}$$

Table 9 includes multiple specifications of the fixed effects panel model. Model (1) starts with the most basic specification where we only assess the relation with the different indentified BVAR shocks. Specifications (2)-(5) then gradually add the interactions for the different fragmentation regimes, the lagged dependent variable and a dummy that equals one during the sovereign debt crisis (defined as the period between May 2010-January 1, 2014). Finally, model (4) adds time-fixed effects to control for unobserved time-specific shocks, that are potentially not identified by our BVAR shocks, ensuring that the estimated impact of Δ CDS reflects variation independent of common time trends.[16]

Model(5) presents the results for the main specification in this exercise, thereby controlling for the euro area sovereign debt crisis with a crisis dummy and country fixed effects. When examining the relationship between the identified macro, policy and global risk shocks and sovereign CDS premiums several messages come to the fore. *First*, in a lower fragmentation regime both the global risk shocks and euro area macro shocks have a significant ($p<0.05$) positive relationship with the sovereign CDS, indicating that sovereign CDS premiums react symmetrically with global risk shocks. These findings are in line with our ex-ante hypothesis, the results form the main local projections at $h(1)$ and the findings in multiple other analytical works (c.f. Blommestein et al. 2016, Fabozzi et al. 2016 Fontana and Scheicher 2016, Longstaff et al. 2011 and Bampinas et al. 2023). *Second*, Model (5) also provides valuable insight into the exacerbated effects of these shocks during periods of higher fragmentation. The results indicate that all interaction terms for the BVAR shocks with the high-fragmentation regime show a positive and significant additional additional impact. Moreover, during higher fragmentation regimes we observe an significant additional marginal effect on sovereign credit risk premia when an global risk shock hits the euro area. The global risk adds 0.6 to the change in credit spread during these periods. Moreover, the coefficients and significance hold when adding time-fixed effects to the model (Model (6)), which suggests adding those to the main specification is redundant.

E Granger causality

We employ a *Granger causality tests* to explore the directional relationship between sovereign *CDS premiums* and *global risk shocks* for the five countries in our sample (IT, ES, FR, DE and NL). The granger causality test assesses whether past values of one variable contain information useful in predicting another. Tests are

[16] Our BVAR model identifies a range of economic and policy shocks, therefore time-fixed effects only control for unobserved, time-specific factors that may influence Δ CDS changes but are not fully captured by the identified shocks.

Table 9: Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ CDS	Δ CDS	Δ CDS	Δ CDS	Δ CDS	Δ CDS
Global Shock	0.998***	0.627***	0.637***	0.628***	0.615***	0.601***
	(0.061)	(0.031)	(0.025)	(0.031)	(0.032)	(0.035)
EA Macro	1.422***	1.404***	1.415***	1.404***	0.849***	0.845***
	(0.162)	(0.160)	(0.151)	(0.160)	(0.067)	(0.067)
US Macro	0.204***	0.212***	0.202**	0.213***	0.125**	0.112**
	(0.043)	(0.044)	(0.052)	(0.044)	(0.033)	(0.032)
EA Policy	0.854***	0.866***	0.875***	0.868***	0.600***	0.591***
	(0.133)	(0.134)	(0.127)	(0.134)	(0.079)	(0.080)
US Policy	0.065*	0.051	0.048	0.054	0.159**	0.160**
	(0.025)	(0.026)	(0.025)	(0.026)	(0.040)	(0.040)
ΔCDS_{t-1}			−0.042			
			(0.054)			
Crisis Dummy				−0.064***		
				(0.013)		
Global Shock$^+$		0.615***	0.612***	0.614***	0.615***	0.628***
		(0.081)	(0.084)	(0.081)	(0.081)	(0.081)
EA Macro$^+$					0.860**	0.865**
					(0.284)	(0.285)
US Macro$^+$					0.167	0.182*
					(0.079)	(0.078)
EA Policy$^+$					0.323	0.330*
					(0.154)	(0.153)
US Policy$^+$					−0.171	−0.174
					(0.102)	(0.103)
Constant	0.005*	0.127***	0.127***	0.020***	0.137***	0.601***
	(0.002)	(0.012)	(0.023)	(0.004)	(0.013)	(0.070)
Observations	20012	20012	20006	20012	20012	20012
Country FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time FE	*No*	*No*	*No*	*No*	*No*	*Yes*

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

conducted for lags ranging from 1 to 5 to account for potential autocorrelation in returns (which might be redundant in our case, see Annex H). Separate tests examine whether CDS premiums Granger-cause global shocks or vice versa. Aditionally, we are also testing is CDS is granger causing the fragmentation index, or the other way around.

The results indicate bidirectional Granger causality for most countries, suggesting an environment in which CDS premiums and global shocks influence each other or are affected simultaneously. Therefore, the test does not provide a conclusive answer regarding the directionality of the correlation between sovereign CDS and global risk shocks. For most countries, there is no clear causal direction, as the correlations run in both directions. This suggests that both CDS premiums and global risk shocks react simultaneously to risk events that impact the global economy. However, this does not hold true for Italian CDS, where global shocks primarily lead the response in the CDS market, rather than the other way around. This finding reduces the likelihood that global risk shocks originate in Italian CDS markets, thereby helping to mitigate potential endogeneity concerns.

Country	Lags	F Statistic	P Value	Significance
France	1	11.08	0.00	***
France	2	5.36	0.00	***
France	3	3.68	0.01	***
France	4	2.92	0.02	***
France	5	2.36	0.04	***
Germany	1	18.54	0.00	***
Germany	2	9.21	0.00	***
Germany	3	6.22	0.00	***
Germany	4	5.29	0.00	***
Germany	5	4.35	0.00	***
Italy	1	0.93	0.34	
Italy	2	0.58	0.56	
Italy	3	0.39	0.76	
Italy	4	0.32	0.86	
Italy	5	0.30	0.92	
Netherlands	1	22.93	0.00	***
Netherlands	2	12.57	0.00	***
Netherlands	3	8.94	0.00	***
Netherlands	4	7.10	0.00	***
Netherlands	5	5.97	0.00	***
Spain	1	6.68	0.01	***
Spain	2	3.67	0.03	***
Spain	3	2.87	0.04	***
Spain	4	2.18	0.07	**
Spain	5	2.15	0.06	**

Table 10: Granger Causality: CDS → Global Shock

Country	Lags	F_Statistic	P_Value	Significance
France	1	18.91	0.00	***
France	2	12.43	0.00	***
France	3	8.60	0.00	***
France	4	6.50	0.00	***
France	5	5.30	0.00	***
Germany	1	10.56	0.00	***
Germany	2	9.10	0.00	***
Germany	3	6.11	0.00	***
Germany	4	4.84	0.00	***
Germany	5	5.41	0.00	***
Italy	1	5.78	0.02	***
Italy	2	4.21	0.01	***
Italy	3	2.78	0.04	***
Italy	4	2.10	0.08	**
Italy	5	1.90	0.09	**
Netherlands	1	7.27	0.01	***
Netherlands	2	10.75	0.00	***
Netherlands	3	7.21	0.00	***
Netherlands	4	5.39	0.00	***
Netherlands	5	4.29	0.00	***
Spain	1	4.57	0.03	***
Spain	2	4.15	0.02	***
Spain	3	2.77	0.04	***
Spain	4	2.10	0.08	**
Spain	5	1.91	0.09	**

Table 11: Granger Causality: Global Shock → CDS

F Sensitivity to the Smoothness Parameter κ

An important modeling choice in our local projections framework with a smooth transition function (STF) is the selection of the smoothness parameter, κ. This parameter governs the steepness of the transition between regimes of higher and lower financial fragmentation. For our main specification, we follow Auerbach and Gorodnichenko (2013) and set $\kappa = 10$, which implies a relatively sharp transition between regimes.

To assess the robustness of our findings to alternative parameterizations of the STF, we conduct a sensitivity analysis by varying κ between 1 and 10, re-estimating the local projection model at both 1 and 10. This exercise tests whether the regime-dependent responses of credit risk premiums to global risk shocks are sensitive to the choice of transition smoothness.

Figure 19 presents the results of this robustness analysis for both sovereign CDS spreads and corporate option-adjusted spreads (OAS). For both values of κ, we plot the impulse responses of credit risk premiums to a standardized global risk shock, distinguishing between the higher and lower fragmentation regimes.

The results confirm that our main conclusions hold across different values of κ. Specifically, the impulse responses of both sovereign CDS spreads and corporate OAS in the higher fragmentation regime consistently exhibit larger and more persistent effects compared to the lower fragmentation regime, regardless of the smoothness of the regime transition. While lower values of κ produce a more gradual transition between regimes, the differential responses remain statistically and economically significant across the full range of specifications, and do not significantly vary across the values for κ.

These findings underscore the robustness of our empirical results and indicate that the heightened sensitivity of euro area credit risk premiums to global risk shocks during periods of elevated financial fragmentation is not driven by a particular choice of κ. Instead, it reflects a stable feature of euro area bond market dynamics, observable in both sovereign and corporate credit markets.

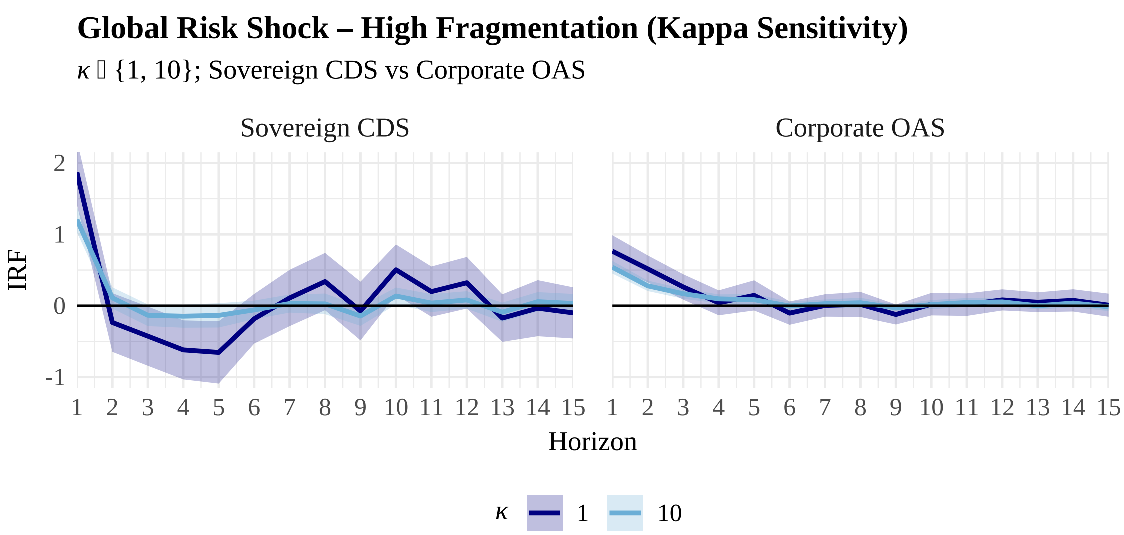


Figure 19: Sensitivity of Δ sovereign CDS global risk shocks across smoothness parameter κ.
Robust standard errors. presents the results of this robustness analysis for both sovereign CDS spreads and corporate option-adjusted spreads (OAS). For each value of κ, we plot the impulse responses of credit risk premiums to a standardized global risk shock, distinguishing between the higher and lower fragmentation regimes.)

G Structural Breaks in Sovereign fragmentation indicator

To assess whether our indicator of market fragmentation effectively captures structural changes in sovereign risk pricing, we applied the Bai-Perron multiple breakpoint test of Bai and Perron (2003). This method endogenously identifies statistically significant structural breaks in the mean of a time series without requiring a priori knowledge of the break dates. Figure 20 summarises the results, where red dashed lines indicate the estimated breakpoints. The grey shaded areas represent periods in which the fragmentation indicator exceeds its historical median, interpreted as episodes of higher fragmentation, while the first such instance is marked with a black dotted line. To complement the Bai-Perron analysis, we also performed a Chow test (see Chow 1960) at this first identified point of higher fragmentation, treating it as a known breakpoint. The test strongly rejects the null hypothesis of parameter stability, indicating a statistically significant shift in the level of sovereign fragmentation at that date. All-in-all, close alignment between the Bai-Perron breakpoints and the periods of higher fragmentation, together with the statistically significant Chow test result, provides support for the fragmentation indicator's ability to capture meaningful regime shifts in sovereign bond markets.

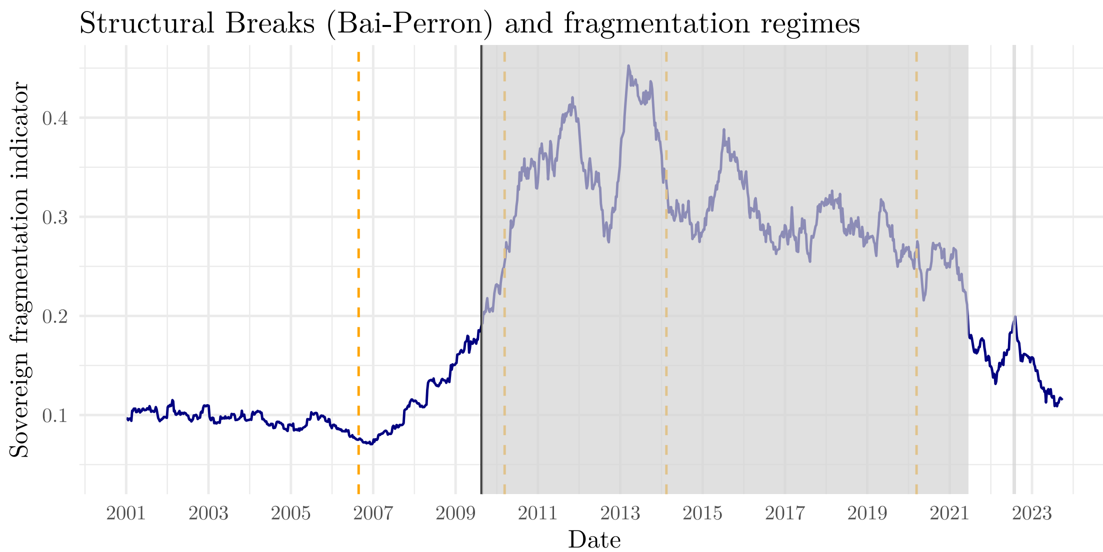


Figure 20: Fragmentation indicator and Bai-Perron breakpoints
The figure shows the sovereign fragmentation indicator with structural breaks estimated using the Bai-Perron multiple breakpoint test (Bai and Perron, 2003), which endogenously identifies significant changes in the mean level of the series. Orange dashed lines indicate detected breakpoints. The grey shaded areas represent periods of high fragmentation, defined by a binary indicator that equals 1 when the fragmentation indicator exceeds its historical median. The black line marks the first occurrence of this high-fragmentation regime. The alignment between shaded regimes and idenitified structural breaks suggests that the indicator captures meaningful shifts in market conditions.

H Autocorrelation in Sovereign CDS Spreads.

Figure 21 displays the autocorrelation functions (ACFs) of sovereign CDS spreads for five euro area countries, focusing on the first ten lags. As expected, autocorrelation at lag 0 is mechanically equal to one. However, across all countries, autocorrelation at lag 1 is modest and quickly decays, with most subsequent lags falling within the 95% confidence bounds. This indicates that CDS spreads exhibit limited serial dependence beyond contemporaneous movements. To formally test this, we estimate a fixed effects panel model regressing CDS spreads on their first lag. The Wooldridge test provides no evidence of first-order serial correlation in the panel residuals (F = 1.26e5, p-value = 0.9972). These findings confirm that there is little persistence in daily CDS dynamics after controlling for fixed effects in our sample. These results are also confirmed by the panel regressions in Table 9, where Model (3) includes CDS_{t-1}, but the coefficient is insignificant. The lack of serial correlation in residuals or spread changes show that sovereign CDS respond quickly and efficiently to underlying risk drivers, without obvious predictable patterns at the daily frequency. This finding might contradict literature on equity reruns that find high return persistent, but is in line with other emperical works on sovereign CDS. For instance Augustin (2018) and Klingler and Lando (2018) find minimal first-order autocorrelation in daily CDS spread changes, suggesting efficient price adjustment on aggregate.

By means of completeness, Table 12 provides the local projection results when ΔCDS_{t-1} is included in the model. In line with expectations, coefficients for ΔCDS_{t-1} are not significant in the local projections setup. Moreover, adding the lagged first difference for the CDS also does not alter any of the conclusions made based on the main specifications. Consequently, we do not include lagged CDS spreads (CDS_{t-1}) in the main specification of our model, as they offer no explanatory gain and would unnecessarily complicate the empirical setup.

Table 12

	$h(t)$		
	(1)	(2)	(3)
shock$^+$	1.433***	0.017	−0.205
	(0.135)	(0.124)	(0.127)
shock$^-$	−0.187	0.788**	0.434
	(0.291)	(0.325)	(0.327)
euro area macro$^+$	1.991***	0.126	−0.060
	(0.156)	(0.137)	(0.138)
euro area policy$^+$	1.052***	−0.071	0.101
	(0.162)	(0.168)	(0.227)
US macro$^+$	0.339**	0.545***	−0.061
	(0.148)	(0.140)	(0.132)
US policy$^+$	−0.057	−0.072	−0.021
	(0.119)	(0.149)	(0.128)
Δ CDS$_{t-1}$	−0.049	−0.017	−0.011
	(0.043)	(0.025)	(0.034)
euro area macro$^-$	−0.274	0.843**	0.691*
	(0.362)	(0.352)	(0.358)
euro area policy$^-$	0.149	−0.012	0.176
	(0.347)	(0.379)	(0.383)
US macro$^-$	−0.115	0.488	0.126
	(0.297)	(0.313)	(0.310)
US policy$^-$	0.374	0.881***	0.284
	(0.247)	(0.322)	(0.266)
Δ CDS$_{t-1}$	−0.025	0.064	−0.001
	(0.114)	(0.077)	(0.083)

Note: Robust standard errors are reported, for further specification see Table 5. *p<0.1; **p<0.05; ***p<0.01

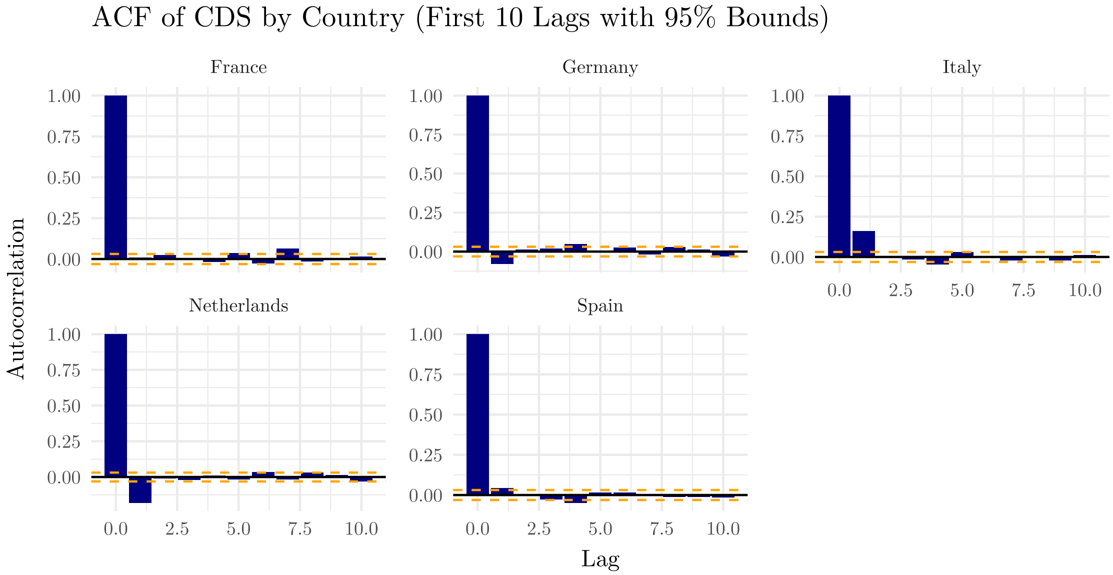


Figure 21: autocorrelation functions (ACFs) of sovereign CDS spreads for five euro area countries
Autocorrelation functions (ACFs) of daily sovereign CDS spreads for five euro area countries, including 95% confidence bounds, to assess the persistence and statistical significance of CDS dynamics.

PUBLICATIONS

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