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NPL Spillovers in Europe: Credit Risk contagion mechanisms in the aftermath of the global financial crisis

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Abstract

This chapter investigates the interconnectedness of non-performing loans (NPLs) across 30 European economies, including the UK, using the Diebold–Yilmaz spillover index. Employing a linear VAR model of order 2 and Lanne–Nyberg variance decomposition on 12-period-ahead forecast errors over 2010Q1–2022Q2, the analysis reveals a persistently high total spillover index, indicating strong cross-country linkages in NPL dynamics. The results uncover an important asymmetry: economies that emerged from the global financial crisis in a relatively resilient position often act as net transmitters of NPL spillovers, while more vulnerable banking systems typically absorb them as receivers. This finding challenges the conventional view that fragility is the primary source of contagion, instead highlighting the role of resilient systems in propagating shocks through regional financial networks. The paper contributes to understanding the interplay between macroeconomic stability and credit risk transmission, with implications for European financial stability policy and cross-border supervision.

1. Introduction

The study of contagion and interdependence has always been an important part of financial stability and risk assessment of one country's financial system. Both IMF and ECB are very interested (Bricco and Xu, 2019 and Roncoroni et al., 2019) in the study of contagion and interconnectedness especially when keeping in mind the financial sector assessment programme and the macro-financial surveillance, spillover reports and the global financial stability report GFSR. The current paper starts by reviewing current approaches for analysing interconnectedness, contagion and interdependence through an overview and examples of the data and methodologies used in pre-existing literature. I will then be choosing the best approach to assess interdependence between NPLs in Europe. Finally, I provide the reasons for following the DY approach when analysing spillover effects in NPLs along with a method of interpreting results and financial stability policy recommendations.

2. Contagion, interdependence and spillovers

Contagion of any kind has always been one of the most pivotal topics of study in a financial context. The academic literature is rich in studies investigating what drives shocks amongst countries and trying to understand their propagation mechanisms behind them (Rigobon, 2019). The vast majority of the literature around contagion crises was released after the Mexican 1994, Asian 1997 and Russian 1998 currency downfalls, with the transmission of these shocks around the globe drawing a lot of academic interest. More specifically, although some contagion can be explained due to trading connection between countries –see for example Russian fall in 1980s followed by the Finnish collapse– some of them cannot be explained by only analysing pre-existing trading routes. For the latter, i.e. the contagion that cannot be explained by only analysing pre-existing trading routes, the most prominent example is the beginning of defaulting and sovereign debt renegotiation in various Latin America countries after Costa Rica and Mexico's debt default in early 1980s. Moreover, the subprime crisis in the United States in 2008, followed by the fiscal crises in Europe in 2010 have rekindled the academic interest in contagion and have alarmed Central Banks on the importance of crises' prevention. Modelling contagion is crucial in a financial regulation setting where banks are interconnected.

Kollemand and Malherbe (2011) argued that the 2007-9 crisis in the US mortgage market was transmitted to the rest of the world mainly via cross-country banking linkages, while balance sheets of global banks and other financial institutions are the key channel of international transmissions. Most bank assets come from short-term debt which refers to domestic and foreign securities (Diamond & Rajan, 2001). If there is an adverse macroeconomic or financial shock in one country, which lowers the capital of global banks, it would lead to a global recession because of a global credit crunch (Bernanke, 2018). This explains the importance of this paper. By studying Non-Performing Loans and how they interconnect with each other we can outline those propagations mechanisms and potentially help in the prevention of uncontrolled transmission future global financial shocks.

3. Formal Definitions

There is no academic consensus around the definition of contagion and interdependence. Contagion is generally perceived as shift of crisis from one area to another which could not be explained generally by the macroeconomic fundamental channels[1]. Classical examples of financial contagion throughout history are the Asian currency crisis of 1997, the Russian financial crisis in 1998, the USA mortgage crisis of 2007 that spread to several world markets and finally the European sovereign debt crisis of 2010 originated in Greece and spread to other major European countries.

The most widely utilised in academic papers definition of financial contagion was given by Forbes and Rigobon (2002) where they defined contagion as a notable increase in cross-market linkages after a shock to one or multiple countries. Special attention must be paid to

[1] Dornbusch et al. (2000) argues that it is mostly related to investor behaviour changes.

the fact that contagion only exists when there is an increase in co-movement after a shock and not during periods of stability. The advantages of this definition are mainly two. First, by calculating linkages between two markets ex-post and ex-ante financial shocks, we can diagnose some contagion easily and, secondly, this method can be used to test different propagation of shock definitions.

Interdependence, spillovers, and contagion in financial systems are critical concepts for understanding systemic risk and its implications. Forbes (2012) defines interdependence as the financial linkages or correlations between the market prices of financial institutions ***across all states*** of the world. Unlike contagion, which refers specifically to high correlations emerging ***after crises***, interdependence implies consistently high correlations regardless of economic conditions. Both interconnectedness and contagion, however, can stem from direct or indirect linkages between financial institutions. Direct linkages arise from balance sheet exposures, such as interbank transactions, while indirect linkages may result from shared exposures to common assets, mark-to-market losses from fire sales (Shleifer and Vishny, 1992; Cifuentes et al., 2005), information spillovers (Aghion et al., 2000; Acharya and Thakor, 2016), or market and investor perceptions. Diebold and Yilmaz (2014) further emphasise that interconnectedness in financial institutions is closely associated with systemic risk, which arises from widespread vulnerabilities across the financial system and can adversely affect the real economy.

It is crucial to mention here that Rigobon (2019) challenges the distinction between contagion and spillovers, arguing that the difference is often model-dependent. A change in the analytical framework could alter how these terms are defined and interpreted, underscoring the fluidity of these concepts within financial research.

Both the International Monetary Fund (IMF) and the European Central Bank (ECB) have prioritised the study of interconnectedness and contagion due to their critical importance in understanding and mitigating systemic risks. The IMF's approach, outlined in Working Paper WP/19/220, proposes a comprehensive framework for analysing a country's financial system in three phases. The first phase involves mapping the financial system to understand its structure. The second phase focuses on modelling interbank, cross-sectional, and cross-border linkages to identify how risks propagate within and across borders. Finally, the third phase centres on policy discussions to inform new reporting standards and enhance systemic risk management. The IMF recommends incorporating granular balance sheet data alongside aggregate-level information to capture cross-sector variations and risk transmissions effectively. This paper will endeavour to follow this approach by collecting data at the most granular level available.

The IMF also advises adopting a holistic perspective on contagion channels within the financial system. Contagion analysis should be integrated with broader financial stability assessments, such as banking sector stress tests, solvency reports, liquidity stress tests, and second-round effect analyses of interbank exposures. Viewing contagion within this broader context ensures a comprehensive understanding of systemic vulnerabilities.

The ECB, in its report (No. 1866 / Nov 2015), focuses on the interconnectedness of the banking sector using macro-network analysis. The findings highlight that a central position of the banking sector within the macro-network significantly increases the likelihood of a banking crisis. The ECB’s framework is grounded in the early warning literature, which seeks to predict vulnerable states preceding crises using a wide range of macroeconomic, financial, and banking sector indicators.

The ECB’s analytical approach comprises three key components: constructing the macro-network to map the interconnections within the financial system, measuring the centrality of the banking sector within this network, and using this information to predict early warning signs of a crisis. The findings are then integrated with policy recommendations to mitigate systemic risks. By combining macro-network analysis with predictive modelling, the ECB provides a robust framework for identifying and addressing vulnerabilities in the banking sector.

In summary, the methodologies employed by the IMF and ECB provide valuable frameworks for analysing financial interconnectedness and contagion. These approaches emphasise the importance of granular data, comprehensive system mapping, and integration with broader financial stability analyses. This paper adopts these principles, aiming to contribute to the understanding of systemic risk and provide actionable insights for policymakers and regulators.

For the purposed of this analysis, in order to examine the association of NPLs I will be ***employing the spillover approach***. I do that because I want to semantically associate spillovers with a constant existence and keep the definition of contagion more closely related to crises or periods of observed financial stress. My analysis will be focusing on data collection in the lowest level possible, accompanied with modelling the linkages between NPLs and closing with some policy discussion.

This paper refers to the branch of the NPL literature that has to do with finding and measuring the interdependence and risk across banks in a system or across countries. I want to describe the system from a within perspective as opposed to examining, from the outside, the macro factors that affect the system. On top of that I will be focusing solely on NPLs and examining their interconnectedness in Europe. Herreiras and Moreno (2012) have contacted NPL spillover analysis using Diebold and Yilmaz (2009) to decompose spillovers observed among banks' portfolio risk for a collection of banks in Mexico. They found that approximately 70 percent of the credit risk in the long run is attributable to systemic risk and that there is a two-way diffusion of risk channel among banks, meaning that small banks affect big ones and vice versa. Olorogun (2020) applied the Diebold and Yilmaz index to explore spillover effects of Covid-19 on non-performing loans (NPLs) of the Turkish agricultural sector on the banking system. They found that there is an acceptable interconnectedness among the group. Again, this study didn't rely only in spillover among NPLs but included other variables as well. To my knowledge, there is no other up-to-date study analysing spillovers in NPLs in a pan-European level.

4. Technical Literature Review

There are plenty of papers utilising different types of GARCH models to examine co-movement between different markets. Engle and Kroner (1995) came up with the GARCH-BEKK model by applying a new parametrisation of the multivariate ARCH model. In order to be easily estimated, they imposed a vector representation of the multivariate GARCH and by assuming that covariances depend solely on past own cross-products of residuals, in what Bollerslev, Engle, and Wooldridge (1988) called diagonal representation, they created a model well-known for its flexibility of modelling spillover effects for low dimensions (Alexander (2008)). However, there is a key limitation of the BEKK model (Caporin & McAleer, 2012) that makes it suboptimal for our analysis; the BEKK model requires certain parameters equal to zero. Not only these restrictions lead to the extinction of some valuable information, such as volatility spillovers, but they are usually rejectable. This makes this model inappropriate for our study.

A second model of the GARCH family widely used in financial applications is the Dynamic Conditional Correlation model of Engle (2002) which combines a univariate GARCH with parsimonious parametric models for correlations. The flexibility of the DCC models lies in being a univariate GARCH hence lacking the complexity of the MVGARCH models. Contrary to the BEKK model, the DCC model is not characterised by dimension limitations and, therefore, it could be applied to any dimension. These benefits exist because this model can be estimated in two steps: starting with the univariate GARCH estimation and then constructing a two-parameter maximum likelihood function. Nevertheless, the DCC model requires more restrictions on dynamic effects than the BEKK model which then will lead to some volatility spillovers to be excluded again (Dhesi and Xiao (2010)). Hence this model would not be optimal to adopt for our analysis.

Several relevant recent studies have utilised VAR models to explore interdependence mainly via estimating volatility spillovers. One of the most popular methodologies to do that is the Diebold-Yilmaz (2014), DY thereafter, which follows Engle's (1990) meteor shower approach. DY used equity returns and/or return volatility data to examine interconnectedness between publicly trade financial entities (FEs). The DY approach has as a first step the estimation of a vector autoregression (VAR) model with market data followed by the derivation of an interconnectedness measure from the generalised variance decomposition of the underling VAR based on Pesaran and Shin (1998). The DY approach combines variance decomposition in VARs with network topology by recognising that variance decomposition of VARs form networks. According to Demirer et al. (2018), the Diebold-Yilmaz index is superior to other approaches to the measurement of connectedness and systemic risk due to minimal data requirements. However, DY does have some disadvantages. Its main disadvantage is that it doesn’t respond well in high-dimensional data (Barigozzi and Hallin, 2016) but with the adoption of appropriate shrinkage techniques such as Demirer et al. (2018) LASSO technique, it can be used for higher dimensions and/or shorter estimation periods. Another criticism that the DY has received refers to the Generalised Forecasts Error Variance Decompositions not adding up to unity. Yet Lanne and Nyberg (2016) came up with a modified DY index that solved the problem and allows the interpretation of the shocks to the system economically (Koop et al., 1996).

Antonakakis et al. (2017) provided a dynamic-estimation extension to the Diebold and Yilmaz (2014) by applying a time-varying parameter vector autoregressive model (TVP-VAR) with a time-varying covariance structure, versus the constant-parameter rolling-window VAR approach. This TVP-VAR method extends the originally proposed connectedness approach of Diebold and Yilmaz (2014) by allowing the variance-covariance matrix to vary via a Kalman filter estimation with forgetting factors in the spirit of Koop and Korobilis (2014). This drastically helps with the pre-existing randomly selecting rolling window size which could potentially lead to very erratic or flattened parameters while avoiding the loss of viable observations. With this transformation it’s now possible to examine dynamic connectedness for low-frequency and limited time-series data.

Barunik and Krehlik (2018) explained that it is when connectedness is created at lower frequencies that shocks are persisting for longer periods. Following the work of Geweke (1982) and Stiassny (1996) they were mostly interested in measuring spillovers in a specific frequency domain. In order to produce frequency-dependent measurements, they defined a spectral representation of GFEVD using Fourier transformations of the IRFs.

5. Deciding methods: Why Spillovers

The main advantage of a MVGARCH model is minimising errors in forecasting by accounting for errors in prior forecasting and enhancing the accuracy of ongoing predictions. However, those models don't come without limitations. Firstly, a basic limitation of GARCH models is the non-negativity of parameters in order to ensure the positivity of the conditional variance. Since I am interested in the directional connectedness information from a systemic perspective (directional system-wide interactions) we are prone to using a VAR approach like the DY. Secondly, and most importantly, a MVGARCH model estimation is highly demanding in terms of degrees of freedom something that requires high data frequency and large system size. Given the anticipated NPL data frequency being quarterly or monthly a MVGARCH approach will not be optimal.

Given the outlined reasons, I will be deploying the DY method to identify the interdependence between NPLs and their connectedness across European countries. Thus, for 30 European countries we will estimate a VAR model for aggregate NPLs (or change in NPLs) over 2010Q1 to 2022Q2. I will use Forecast Error Variance Decompositions and the Diebold-Yilmaz framework to estimate spillovers and connectedness. The main advantage of this method is that it allows to examine how large is the magnitude of the NPLs; this will help determine whether global shocks impact NPLs (or even vice-versa). Furthermore, thus far, almost all NPL studies cover a single country or several countries, consequently there is a need for a broader multi country investigation to build a more detailed picture of NPL linkages and their drivers. In addition, one of the DY method is that it can be used to inform us on the percentage of forecast error variance from one entity that can be attributed to other entities, i.e., the diffusion effect on the NPL ratio, something that we are especially interested in.

Furthermore, analysing interconnectedness and interdependence is a very crucial component of a financial stability and risk assessment work. The poor understanding of financial crises' transmission mechanisms has initiated an increase interest in understanding interdependence (Claessens and Forbes, 2001). By analysing interdependence and contagion we could also have a more holistic view about different systems and how they operate. For example, contagion analysis reports can be looked during supervisory and resolution assessments in conjunction with banking sector stress test of the incorporation of solvency liquidity stress testing.

In selecting the Diebold-Yilmaz spillover index as the primary methodological framework for this study, a deliberate decision was made to adopt a system-wide, multilateral approach to understanding inter-country spillovers in NPLs, as opposed to simpler comparative methods such as a bilateral country comparison or group-averaged analysis. The principal advantage of the Diebold-Yilmaz methodology lies in its capacity to capture the dynamic and directional nature of spillovers across a large set of countries simultaneously. While a comparative study between two countries or predefined regional groups may yield useful descriptive insights, such methods are inherently limited in their ability to account for the complexity of interconnectedness within a globalised financial system. They risk oversimplifying the analysis by neglecting the role of third-country effects and by failing to distinguish between net transmitters and net receivers of shocks.

In contrast, the spillover matrix derived from the Diebold-Yilmaz framework provides a detailed decomposition of forecast error variance, enabling the identification of which countries exert systemic influence, and which are more susceptible to external financial disturbances. This granularity is crucial in the context of NPLs, where transmission channels are likely to be highly asymmetric and influenced by a variety of country-specific financial structures, policy environments, and exposure levels. In addition, by applying this method to the full panel dataset rather than to aggregated regional indices, the analysis retains the heterogeneity of national experiences and avoids masking important idiosyncratic dynamics. This approach is not only more empirically rigorous but also more policy-relevant, aligning with analytical techniques employed by institutions such as the IMF, ECB, and BIS in the assessment of systemic risk and financial contagion. As such, the Diebold-Yilmaz methodology offers both methodological sophistication and substantive insight, making it a more appropriate and powerful tool for analysing cross-country NPL spillovers than simpler, more reductionist alternatives.

6. Methodology and Data

6.1 Spillovers a la Diebold and Yilmaz

Diebold and Yilmaz (2009) spillover index uses the error in forecast variance decomposition estimated with a VAR equilibrium process. The variance decomposition acknowledges the diffusion of risk among agents, which will be countries for this paper, in a closed system. It provides an intuitive measure of interconnectedness by assessing the degree of connection between returns and the volatility of different equity markets. Some of the main advantages of this method is that it reports the percentage of forecast error variance from one entity that can be attributed to other entities (the diffusion effect on the NPL ratio in our case) and it allows to estimate changes in connectedness when changing the time frame. When allowing for the forecast horizon to get expanded, it becomes possible to describe how the diffusion process takes place and how the systemic risk becomes relevant over time as measured by the spillover index.

Another advantage of applying the DY spillover effect methodology applied in NPLs is that it can identify how many percent of the level of the NPL ratio, in the long run, is mostly attributed to systemic risk vs the intrinsic risk in each bank or country, effective when an expansion of the forecast period is applied.

From the DY approach three spillover indices can be estimated. The first one, called **to-index**, captures contribution of individual agents to systemic network events (outward spillover). The **from-index** shows exposure of individual agents to systemic shocks from the network (inward spillover). Finally, the **net-index** (the difference between to and from) describes the relative contribution to systemic risks from each financial entity.

Historically, Diebold and Yilmaz developed their methodology as follows: in 2009, following Engle et al. (1990), Diebold and Yilmaz introduced a new way of estimating spillovers, allowing to produce spillover indices, tables and plots to analyse aggregate spillover effects across markets. Their method entailed variance decompositions associated with an N-variable VAR model. In 2012, they expanded their spillover index definition so that it is invariant to variable ordering, and it can produce directional spillovers (along with the total ones). They achieved variable ordering independence by using a Koop, Pesaran and Potter (1996) and a Pesaran and Shin (1998) variance decomposition framework instead of the Cholesky factorisation originally used as well as introducing directional and net spillover definitions. Finally, in 2014, Diebold and Yilmaz presented a unified framework to measure connectedness and presented a new way of depicting pairwise directional connectedness. They also referred to the importance of stress testing.

6.2 The model

Original DY index

Following Berger and DeYoung (1997, 2009, 2012), let the long-run aggregate credit risk of the banking system of a specific country be represented in terms of the individual NPL ratios of the banks in each country we are examining. Let's also consider that the long-run aggregate national bank risk u_t (aka shocks or innovations in the literature) relates to the profile of an existing individual country's risk Rt, following a vector autoregressive (VAR) equilibrium representation:

$$\boldsymbol{R}_t = \boldsymbol{\Phi}(L)u_t \qquad (1)$$

where L denotes the number of lags in the moving average representation of the risk contagion process.

If we recover the **Φ**(L) vector using mlVAR estimation, we can transform the model in terms of the normalized moving average representation as:

$$\boldsymbol{R}_t = \boldsymbol{A}(L)\varepsilon_t \qquad (2)$$

Where $\boldsymbol{A}(L) = \boldsymbol{\Phi}(L)Q_t^{-1}$, $\varepsilon_t = Q_t u_t$, $E(\boldsymbol{\varepsilon_t \varepsilon_t'}) = \boldsymbol{I}$ and Q_t^{-1} is the unique lower-triangular Cholesky factor of the covariance matrix of u_t.

Now let ${}_{t}\boldsymbol{R}_{t+k}$ be the prediction generated by a Wiener-Kolmogorov linear least-square forecast of the future risk for each country using date "t" for information future period t+k, where k refers to the number of forward periods in the estimation.

Given the processes described we will then have:

$${}_{t}\boldsymbol{R}_{t+k} = [A(L)]^{k}\boldsymbol{R}_{t} \qquad (3)$$

Which implied that the corresponding prediction error will be:

$$\boldsymbol{e}_{t+k} = \boldsymbol{R}_{t+k} - {}_{t}\boldsymbol{R}_{t+k} = \boldsymbol{A}(L)_{t+k}\varepsilon_{t} \qquad (4)$$

With $\boldsymbol{A}(L)_{t+k}$ being the implicit normalised matrix essential for the Cholesky decomposition of the V matrix so that it includes ε.

The covariance matrix will then be:

$$V_{t+k} = E[\boldsymbol{e}_{t+k}\boldsymbol{e}'_{t+k}] = E[\boldsymbol{A}(L)_{t+k}\boldsymbol{A}(L)_{t+k}{}'] \qquad \textit{(5)}$$

All these transformations can now allow us the identification of the various VAR system shocks comprising a. the element of risk contagion coming from the k-periods-ahead variance in the error in forecasting the risk of a country j that is due to the bank's own shocks; and b. the amount of this variance of error for each country j coming from the secondary diffusion of risk from other countries.

Following now Diebold and Yilmaz (2009), we can define:

- the *own-variance shares* to be the fractions of the k-step-ahead error variances in forecasting due to each country's own shocks and
- the *cross-variance shares (spillovers)* to be the fractions of the k-step-ahead error variances in forecasting due to other risks.

Now let's use some matrix representation to make this clearer. Le the k-periods forward Cholesky matrix of J banks in the VAR system to be:

$$\boldsymbol{A}(L)_{t+k} = \begin{bmatrix} a(L)_{11} & \cdots & a(L)_{1j} \\ \vdots & \ddots & \vdots \\ a(L)_{j1} & \cdots & a(L)_{jj} \end{bmatrix}$$

Where if we now recall that:

$$\boldsymbol{e}_{t+k} = \boldsymbol{A}(L)_{t+k}\varepsilon_t \qquad \textit{(6)}$$

It can be implied that the error in the variance of the forecast for k-periods ahead risk for each bank j can be defined as:

$$[v_{jj}]_{t+k} = \sum_{n=1}^{j}[a(L)_{jn}^2]_{t+k} \qquad (7)$$

Which will, finally, imply that the overall DY spillover index over an L-th lag order and J-variables VAR using K-periods-ahead forecasting is:

$${}_kS = \frac{\sum_{k=0}^{K-1}\sum_{i,j=1;i\neq j}^{J}[a(L)_{ij}^2]_{t+k}}{\sum_{k=0}^{K-1} tr(\boldsymbol{A}(L)_{t+k}\boldsymbol{A}(L)_{t+k}{}')}\ 100 \qquad (8)$$

The S index is defined to calculate the cross variance share of the total variance over the k-step-ahead prediction of the risk of country j relative to the whole variation of the error in prediction by using the ratio of the sum of the risk inputs of each of the J countries to the total variation of the error forecast for country j relative to the total variation of the error forecast for k periods ahead.

Modified Lanne-Nyberg DY

The original DY spillover index, although able to overcome the VAR variables ordering shortcoming, doesn't help much with assigning an economical interpretation to the system shocks (Koops et al., 1996) nor allows for an assessment of the changes in the systemic contributions of a variable throughout time.

Following Pesaran and Shin (1998) let

$$y_t = G\left(y_{t-1}, \dots, y_{t-p}; \theta\right) + \varepsilon_t \qquad (9)$$

be a K-dimensional nonlinear multivariate model with G(.) representing a nonlinear function of past values of y and a parameter vector θ while ε_t is an iid disturbance term.

If we concentrate on shocks hitting only one equation at a time, we can define the General Impulse Response function (GIRF) of y_t to the shock δ_{jt} at horizon l as:

$$Gl\left(l, \delta_{jt}, \omega_{t-1}\right) = E\left(y_{t-1} \middle| \varepsilon_{jt} = \delta_{jt}, \omega_{t-1}\right) - E(y_{t-1}|\omega_{t-1}) \qquad (10)$$

for any $l = 0,1,2 \dots$

This function represents the time profile of the effect of the shock δ_{jt} hitting at time t, obtained as a difference between the expectations conditional on the shock and history ω_{t-1} and the expectations condition only on the history ω_{t-1}. Following Koop et al. (1996), each history ω_{t-1}consists of the matrix of initial values needed to compute the two conditional expectations (forecasts) which are typically obtained by averaging many realizations from equation (1) with and without the shock δ_{jt}, respectively.

Different from the Pesaran-Shin generalised forecast variance decomposition approach based on the orthogonalized impulse response function, the Lanne-Nyberg GFEVD is not restricted to the linear VAR(*p*) model with normally distributed errors and is constructed by replacing the orthogonalized IRF in Pesaran-Shin GFEVD with the GIRF shown in equation (2).

The corresponding Lanne-Nyberg GFEVD component for horizon h equals

$$\lambda_{ij,\omega_{t-1}}(h) = \frac{\sum_{l=0}^{h} Gl(l,\delta_{jt},\omega_{t-1})}{\sum_{j=1}^{K}\sum_{l=0}^{h} Gl(l,\delta_{jt},\omega_{t-1})_i^2}, i,j = 1,\dots,K \qquad (11)$$

Where j and i refer to shock and variable, respectively, h is the horizon and ω_{t-1} denotes the history. The denominator estimates the aggregate cumulative effect of all the shocks, whereas the numerator is the cumulative effect of the j^{th} shock. By construction, λ lies between 0 and 1, measuring the relative contribution of a shock to the j^{th} equation in relation to the total impact of all K shocks on the i^{th} variable in y_t after h periods, and these contributions sum to unity.

In the linear VAR model with infinite-order moving-average representation $y_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j}$, with no identification restrictions imposed, the GIRF in equation (2) reduces to $Gl(l,\delta_{jt},\omega_{t-1}) = A_l\delta$, which is independent of history ω_{t-1}, but depends on the hypothetical $K \times 1$ vector of shocks of size $\delta = (\delta_1, \dots, \delta_K)$, with only one of the elements being non-zero. Assuming normality of the error term ε_t and setting a shock to the j^{th} element of ε_t, the unscaled GIRF of the shock δ_j is given by:

$$Gl(l,\delta_{jt},\omega_{t-1}) = A_l \sum e_j \sigma_{jj}^{-1} \delta_j \qquad (12)$$

Then, following Chan-Lau (2017) and Diebold and Yilmaz (2012), the MLNDY total spillover index (thereafter "TOTAL"), which measures the contribution of spillovers of shocks across the variables to the total forecast error variance, is then constructed as:

$$S^{LN}(h) = \frac{\sum_{i,j=1;i\neq j}^{K} \lambda_{ij,\omega_{t-1}}(h)}{\sum_{i,j=1}^{K} \lambda_{ij,\omega_{t-1}}(h)} 100 = \frac{\sum_{i,j=1;i\neq j}^{K} \lambda_{ij,\omega_{t-1}}(h)}{K} 100 \qquad (13)$$

The MLNDY directional spillover index imparted by all other variable j to variable i (thereafter "FROM") is measured as:

$$S^{LN}{}_{i\bullet}(h) = \frac{\sum_{j=1;i\neq j}^{K} \lambda_{ij,\omega_{t-1}}(h)}{\sum_{j=1}^{K} \lambda_{ij,\omega_{t-1}}(h)} 100 \qquad (14)$$

In a similar vein, the MLNDY directional spillover from variable *i* to all other variable *j* (thereafter "TO") is calculated as:

$$S^{LN}{}_{\bullet i}(h) = \frac{\sum_{j=1;i\neq j}^{K} \lambda_{ji,\omega_{t-1}}(h)}{\sum_{j=1}^{K} \lambda_{ji,\omega_{t-1}}(h)} 100 \qquad (15)$$

Correspondingly, given these directional spillovers, the MLNDY net spillovers (thereafter "NET") from variable *i* to variable *j* can be calculated as the difference between gross shocks transmitted to ("TO") and gross shocks received from all other variables ("FROM"):

$$S^{LN}{}_{i}(h) = S^{LN}{}_{i\bullet}(h) - S^{LN}{}_{\bullet i}(h) \qquad (16)$$

Under this logic, a MLNDY net directional spillover measure for each pair (thereafter "NET PAIRWISE") can be constructed as:

$$S_{ij}^{LN} = \left(\frac{\lambda_{ij,\omega_{t-1}}(h)}{\sum_{k=1}^{K} \lambda_{ik,\omega_{t-1}}(h)} - \frac{\lambda_{ji,\omega_{t-1}}(h)}{\sum_{k=1}^{K} \lambda_{jk,\omega_{t-1}}(h)} \right) 100 \qquad (17)$$

6.3 Data collection

One of the main contributions of this paper is the creation of a data set for NPLs in Europe. The data collection for this data set has been a very complicated process as I had to access multiple data sources along with using data extrapolation and interpolation methods to complete the time series. I started with the online IMF data base finding NPL ratios under the Financial Soundness Indices category. The ratio refers to NPLs over total loans in individual economies. I am aiming for a pan-European approach, so I gathered data for 30 European countries including the UK: Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Czech

Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the UK. Note here these are EU countries plus Norway, Switzerland, and the UK. Lichtenstein and Iceland were left outside this group because of limited data availability and specific financial regulations unique to those countries because of geographical and legal characteristics.

Unfortunately, some time series were incomplete, so I had to access all individual central banks in the European countries I had data for to complete the series. This has been a very long and meticulous operation since the majority of Central Banks websites are in local languages and we used translation services to pinpoint the data. This led to around 95% data completion. In order to have complete time series we used an MA(3) forecasting model to complete the series.

Finally, the dataset includes quarterly data from the first quarter of 2010 to the second quarter of 2022. That means we have 540 observations (30 countries, 12 years, quarterly) which is an adequate sample size for our VAR analysis without using and data reduction techniques. Last but not least, the data collection process was in line with our literature review findings that NPL data became generally available from 2010 onwards.

6.4 Summary Statistics

In this section I present the descriptive statistics for each county's NPLs separately along with some graphs showing the evolution of the NPLs through time and a unit root test to help us understand if the series are stationary or not. The NPL time evolution graphs are presented individually for each country. Finally, at the last column, I provide the MacKinnon approximate p-value for a Dickey–Fuller test for unit root for each series, with H_0: Random Walk without drift. I will be then using the following notation $p < 0.001$ ***, $p < 0.01$ **, $p < 0.05$ *, which means three asterisks for p-values of less than 0.1%, two asterisks for 1% and one for 5% respectively.

Variable	*Mean*	*Std. dev.*	*Min*	*Max*	*p-value*
Austria	2.49	0.78	1.15	4.10	0.95
Belgium	3.00	0.77	1.87	4.32	0.92
Bulgaria	11.83	4.27	5.08	16.88	0.99
Croatia	11.44	3.70	4.90	16.76	0.98
Cyprus	23.73	14.02	4.80	47.75	0.71
Czech	4.10	1.60	1.57	5.85	0.98
Denmark	3.00	1.40	1.06	5.95	0.76
Estonia	2.66	1.37	0.96	6.22	0.35
Finland	0.90	0.41	0.44	1.57	0.79
France	3.53	0.74	2.36	4.50	0.98
Germany	2.89	1.73	1.23	6.59	0.44
Greece	26.47	13.56	4.66	47.20	0.75
Hungary	8.98	5.42	1.51	17.32	0.94
Ireland	12.35	7.06	2.07	24.06	0.98
Italy	11.80	4.92	3.35	18.06	0.98
Latvia	6.96	4.17	2.21	15.77	0.28
Lithuania	8.07	7.45	0.51	22.74	0.16
Luxembourg	0.58	0.30	0.15	1.03	0.73
Malta	5.79	2.08	3.08	9.39	0.96
Netherlands	2.46	0.49	1.61	3.23	0.82
Norway	1.17	0.32	0.72	1.68	0.63
Poland	4.32	0.62	2.82	5.21	0.98
Portugal	35.64	3.52	30.38	40.50	0.53
Romania	10.52	5.82	3.01	22.26	0.96
Slovakia	4.15	1.13	2.05	5.33	1.00
Slovenia	8.26	4.75	1.93	17.97	0.86
Spain	4.74	1.36	2.65	7.12	0.91
Sweden	0.75	0.26	0.35	1.24	0.58
Switzerland	0.74	0.09	0.62	0.97	0.08
UK	2.00	1.24	0.73	3.96	0.74

Table 1: NPL ratio descriptive statistics and MacKinnon approximate p-value for a Dickey–Fuller test, created by author

The above table 4 provides an overview of Non-Performing Loan (NPL) ratios for various European countries, along with mean, standard deviation, minimum, and maximum values, as well as p-values from unit root tests. The mean NPL ratios indicate substantial variation among the countries. Portugal stands out in the table with an exceptionally high mean NPL ratio of 35.64, higher only to Greece. This indicates a significant prevalence of non-performing loans in its banking sector over the period considered. The standard deviation for Portugal is relatively low at 3.52 compared to its high mean, suggesting that while the NPL ratio is high, it has been relatively stable over time. The minimum and maximum values, 30.38 and 40.50 respectively, further illustrate this stability, showing that the NPL ratio has consistently remained within a high range. Furthermore, Cyprus (23.73) and Greece (26.47) showing extremely high averages, signalling significant issues with loan performance and financial distress. In contrast, Luxembourg (0.58), Sweden (0.75), and Switzerland (0.74) have very low mean NPL ratios, indicating strong financial health and stability in their banking sectors.

The standard deviation values further illustrate the variability within each country. High standard deviations in countries like Cyprus (14.02) and Greece (13.56) reflect considerable fluctuations in NPL ratios, while lower standard deviations in countries such as Switzerland (0.09) and Luxembourg (0.30) suggest more consistent loan performance.

The minimum and maximum values provide additional insights into the range of NPL ratios. Countries like Cyprus and Greece not only have high average NPL ratios but also significant maximum values of 47.75 and 47.20, respectively, indicating extreme peaks in non-performing loans. On the other hand, Luxembourg, Sweden, and Switzerland maintain low maximum NPL ratios, reinforcing their financial stability.

The p-values from the unit root tests are crucial for understanding the persistence of NPL ratios over time. Most p-values are above 0.05, indicating that the null hypothesis of a unit root (implying non-stationarity) cannot be rejected for most countries. This suggests that NPL ratios in these countries are persistent and potentially influenced by long-term economic factors. Notably, Switzerland has a p-value of 0.08, which, while still above the 0.05 threshold, is closer to suggesting some degree of stationarity compared to other countries.

In summary, the table highlights significant disparities in NPL ratios across European countries, with some facing severe challenges in managing non-performing loans, while others exhibit strong financial health. The unit root test p-values suggest that in most cases, NPL ratios are persistent over time, reflecting underlying economic conditions.

Let’s now explore now the graphical representation of the NPL series. I will be providing 33 graphs, one for each country individually (moved in the appendix), one with the 3 top performers (lowest average NPL ratio), one with one with the 3 top underperformers (highest average NPL ratio), and one with the top performer vs the country with the highest NPLs, just to help us visualise the extend of the difference.

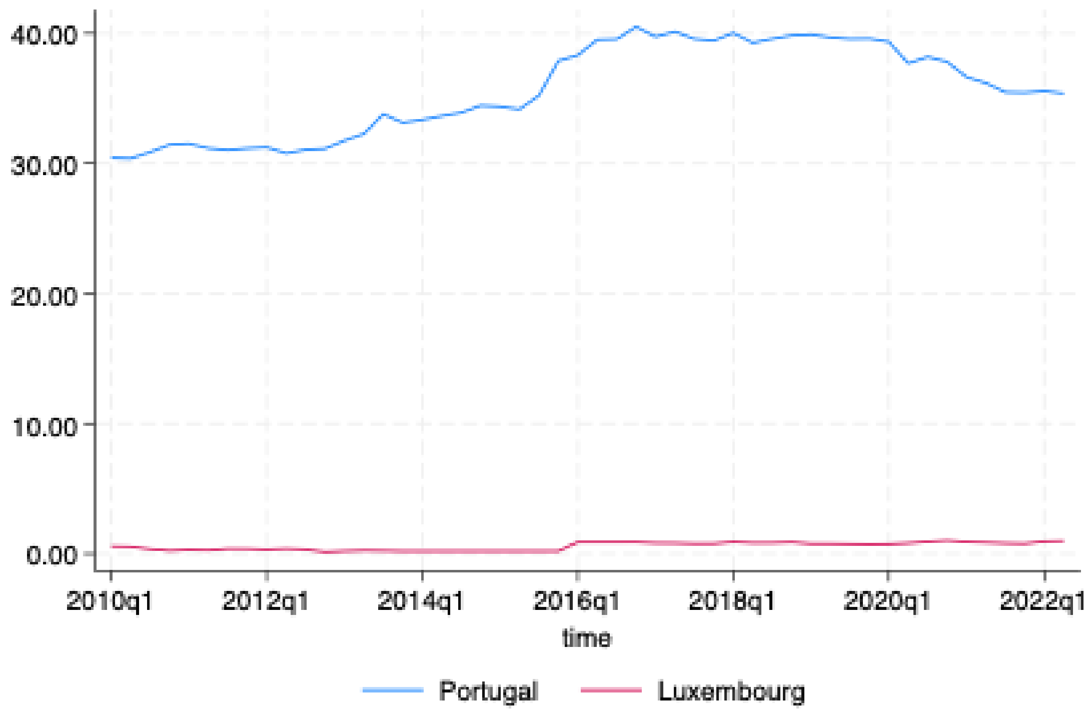

Figure 1. NPLs for Portugal which has the highest average NPLs vs the country with the lowest NPL ratio (Luxembourg), created by the author

The graph (figure 1) illustrates the trends in non-performing loans (NPLs) for Portugal and Luxembourg from 2010 to 2022, highlighting a stark contrast between the two countries. Portugal's NPL ratio shows a significant increase starting in 2010, peaking around 2016, followed by a gradual decline from 2018 onwards. This trend suggests that the Portuguese banking sector faced substantial challenges with loan performance, likely due to the lingering effects of the 2008 financial crisis, economic instability, and subsequent austerity measures. In contrast, Luxembourg maintains a consistently low NPL ratio throughout the period, indicating a robust banking sector with effective risk management and possibly more conservative lending practices. The differences can be attributed to Portugal's economic vulnerabilities during the period, which resulted in higher loan defaults, while Luxembourg, as a financial hub, benefitted from strong regulatory frameworks and a stable economic environment, minimizing the incidence of non-performing loans.

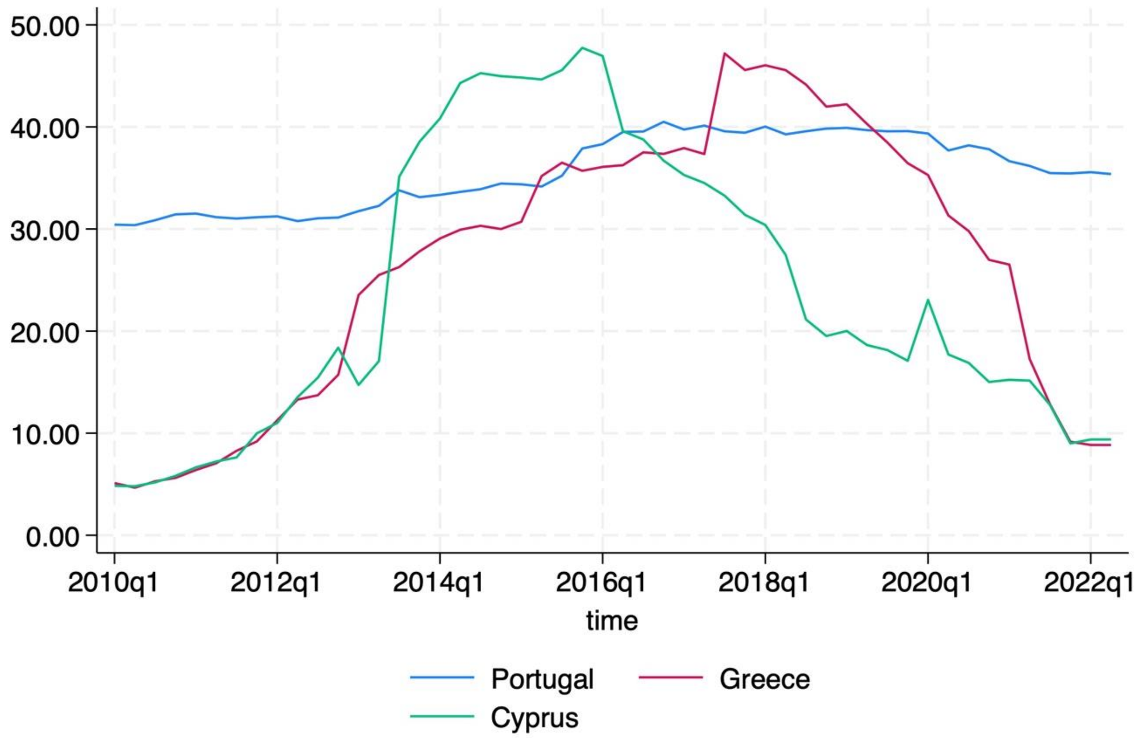

Figure 2. The three countries with the highest average NPL ratio, created by the author

This graph (figure 2) includes data for Greece and Cyprus along with Portugal, providing a comprehensive overview of non-performing loans (NPLs) trends from 2010 to 2022, revealing unambiguous contrasts among these three countries. Greece and Cyprus exhibit dramatic surges in NPL ratios beginning around 2011-2012, reaching their zenith around 2016, followed by significant declines. This pattern underscores the severe economic crises both countries endured: Greece's sovereign debt crisis and Cyprus's banking sector collapse led to substantial loan defaults. The sharp rise and subsequent decline in NPLs in these countries reflect the impact of severe financial instability, poor regulatory oversight, and stringent austerity measures that strained borrowers' ability to repay loans. In contrast, Portugal's NPL ratio, while higher than Greece's and Cyprus's, shows a more moderate and stable increase until 2016, followed by a gradual decline. Portugal's less dramatic NPL fluctuations can be attributed to a combination of more effective regulatory measures, gradual economic recovery, and continuous reforms that helped stabilise its banking sector. The differences in NPL trends among these countries may be a by-product of the varying effectiveness of post-crisis policy interventions and financial support mechanisms. The EU and IMF's intervention played a crucial role in stabilising the banking sectors of Greece leading to improved loan performance and a marked reduction in NPLs post-2017.

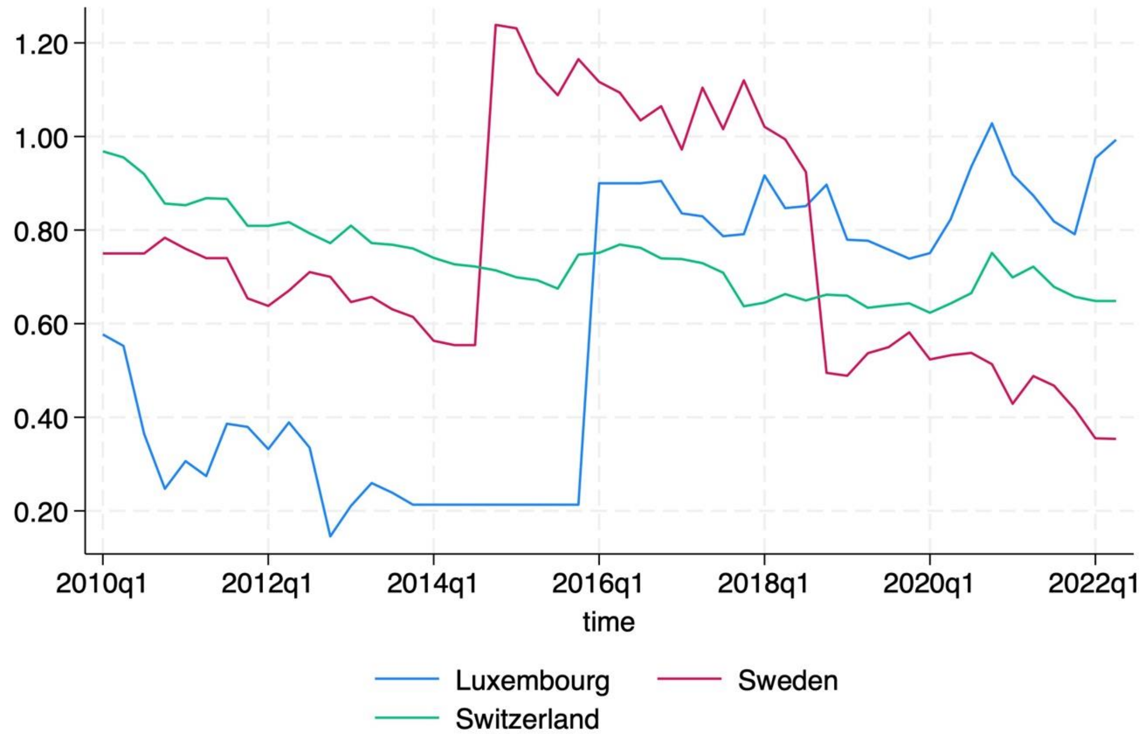

Figure 3. The three countries with the lowest average NPL ratio, created by the author

Figure 3 presents the non-performing loans (NPLs) trends for Luxembourg, Sweden, and Switzerland from 2010 to 2022. Luxembourg's NPL ratio starts relatively low and shows a downward trend until around 2015, after which it fluctuates but remains below 0.50. Sweden's NPL ratio remains consistently higher than Luxembourg's, with a slight increase around 2016 but generally stable, peaking around 1.20 before declining again towards the end of the period. Switzerland maintains an NPL ratio consistently higher than Luxembourg but lower than Sweden, showing a gradual decline over the years. The differences in NPL ratios among these countries highlight varying levels of economic stability and banking sector health. We will be examining each country's NPLs separately to try and demarcate those trends.

7. Empirical Results

In this section I present the empirical results from my analysis. Starting with the Static spillover table for the European NPLs and then followed by a detailed review of the findings, instructions on how the table can be read as well as the uncover connections between various countries' NPLs. Before the connections' discussion I also present a graphical representation of the interconnectedness using a visualisation network graph.

Due to formatting constraints, the table presented in this section is divided across two consecutive pages. Part I, found on the second page, contains the initial portion of the table, while Part II, on the following page, provides the continuation. This division ensures the table remains legible and appropriately formatted within the document. Readers are advised to consider both sections together for a complete interpretation of the data.

Additionally, to enhance visual comprehension, the results within the table are colour-coded, with green indicating positive values and red denoting negative values. This colour scheme is employed to facilitate a more intuitive understanding of the data, allowing for a quick distinction between positive and negative figures. While the numerical values remain the primary focus, the use of colour serves as an additional interpretative aid, improving readability and aiding pattern recognition.

	Lithuania	Luxembourg	Malta	Netherlands	Norway	Poland	Portugal	Romania	Slovakia	Slovenia	Spain	Sweden	Switzerland	UK	FROM	SUM
Austria	2.27	1.34	1.27	1.74	7.5	9.79	0.86	4.13	10.6	2.72	0.29	1.5	0.23	3.17	86.06	100
Belgium	1.21	1.56	1.48	5.38	9.05	6.69	1.71	4.66	7.07	3.57	0.54	0.32	0.21	3.34	87.3	100
Bulgaria	3.12	0.33	0.03	0.96	9.9	11.25	1.33	5.38	10.73	3.05	0.27	1.69	0.08	2.82	91.75	100
Croatia	2.55	0.55	0.29	1.36	9.68	11.96	1.17	4.83	9.74	3.15	0.46	0.24	0.12	3.77	94.78	100
Cyprus	0.5	1.69	1.08	2.31	9.89	3.46	0.48	6.77	5.54	1.41	1.33	1.21	1.66	1.66	81.03	100
Czech	2.05	0.56	0.62	2.39	7.92	9.46	2.41	3.77	9.29	2.03	0.33	2.03	0.21	2.48	88.55	100
Denmark	2.79	0.6	1.19	2.51	5.57	10.91	3.98	2.61	6.67	8.3	0.74	0.41	0.7	8.88	78.49	100
Estonia	3.44	0.06	2.71	0.13	1.13	6.77	0.74	0.22	4.42	0.17	0.4	4.67	0.08	0.16	60.9	100
Finland	2.91	0.31	0.9	0.28	8.83	6.37	1.78	3.11	4.24	1.56	3.81	1.02	1.83	3.92	68.62	100
France	2.93	1.29	0.27	2.16	7.29	10.76	3.2	3	9.9	3.21	0.53	0.59	0.08	3.99	90.59	100
Germany	0.17	2.85	2.3	1.44	2.71	2.79	0.61	0.68	2.2	6.21	0.14	0.83	0.45	6.32	65.4	100
Greece	2.25	0.08	3.49	1.02	12.32	4.7	0.72	5.49	4.19	0.93	1.2	0.83	3.59	0.72	77	100
Hungary	0.44	2.17	2.09	4.71	4.93	4.15	3.74	1.43	4.3	1.89	0.19	0.53	0.17	2.76	66.82	100
Ireland	2.45	0.3	0.06	1.64	11.74	10.1	1.48	5.74	10.38	2.77	1.13	0.46	0.22	2.87	96.67	100
Italy	1.25	0.57	0.15	1.32	11.09	9.17	0.85	6.15	9.07	1.54	0.62	0.26	0.53	1.45	80.2	100
Latvia	5.41	1.31	2.33	1.48	2.25	5.36	0.51	0.43	5.32	0.75	0.31	4.15	0.98	0.2	78.68	100
Lithuania	9.36	0.2	0.49	0.09	7.32	12.57	1.03	2.56	10.68	3.32	0.04	2.56	0.38	3.91	90.64	100
Luxembourg	2.61	48.51	0.81	4.2	0.78	3.32	3.64	0.68	1.68	2.55	1.57	0.32	2.51	3.38	51.49	100
Malta	1.9	2.58	11.22	5.2	5.62	9.09	3.26	3.69	5.8	4.47	0.6	0.16	0.6	6.04	88.78	100
Netherlands	2.05	1.06	2.89	13.88	8.52	8.73	2.75	4.37	7.14	2.97	1.88	0.28	0.19	3.15	86.12	100
Norway	1.39	0.28	0.96	0.54	28.09	6.45	0.75	5.89	8.53	1.07	0.19	0.68	1.98	0.88	71.91	100
Poland	6.53	0.16	0.9	0.17	6.08	21.07	0.34	2.18	6.01	4.45	0.54	1.06	0.14	4.65	78.93	100
Portugal	0.83	0.91	1.76	3.39	2.76	0.91	31.4	1.33	1.45	2.14	2.73	1.06	1.93	3.72	68.6	100
Romania	3.01	0.32	0.31	1.31	9.57	11.91	1.94	10.63	8.21	6.27	0.39	0.34	0.11	5.57	89.37	100
Slovakia	4.06	0.32	0.11	0.32	8.58	13.17	0.81	3.87	14.57	3.36	0.18	1.72	0.03	3.43	85.43	100
Slovenia	4.33	0.31	0.14	0.41	4.19	10.06	0.77	2.74	4.02	23.68	0.28	0.31	0.18	14.02	76.32	100
Spain	2.06	0.42	0.45	2.59	7.98	8.08	2.36	5.16	6.72	2.7	19.25	1.68	0.41	2.94	80.75	100
Sweden	1.57	0.01	0.32	0.08	0.02	1.21	0.05	0.1	2.05	0.47	1.44	74.6	1.9	1.97	25.4	100
Switzerland	1.52	1.9	1.96	0.43	1.68	4.97	2.44	0.48	3.43	0.22	1.38	2.88	36.47	0.15	63.53	100
UK	5.08	1.77	0.42	0.52	0.37	7.88	0.7	0.81	1.31	14.21	0.42	1.24	0.57	24.73	75.27	100
To	72.69	25.81	31.79	50.07	185.28	222.03	46.41	92.26	180.69	91.45	23.92	35.05	22.06	102.31		
Net	-17.95	-25.68	-56.99	-36.05	113.37	143.11	-22.2	2.89	95.25	15.13	-56.83	9.65	-41.47	27.04		

	Austria	Belgium	Bulgaria	Croatia	Cyprus	Czech	Denmark	Estonia	Finland	France	Germany	Greece	Hungary	Ireland	Italy	Latvia
Austria	13.94	0.68	3.55	0.32	3.46	2.36	2.49	4.41	0.1	4.84	2.33	3.54	2.2	0.84	6.93	0.57
Belgium	1.56	12.7	3.31	0.78	5.94	2.02	2.63	2.51	0.13	3.84	0.27	2.57	8.51	0.69	4.46	1.29
Bulgaria	3.34	0.07	8.25	0.14	1.92	1.46	2.43	8.96	0.34	6.32	0.56	3.5	2.87	1.06	7.2	0.65
Croatia	2.45	0.51	4.52	5.22	2.72	3.58	2.99	4.38	0.11	5.09	0.53	4.41	3.85	1.04	8.04	0.7
Cyprus	1.69	3.8	5.38	1.04	18.97	2.74	0.95	0.46	1.31	1.6	0.81	7.11	5.03	0.55	8.59	0.96
Czech	3.25	0.83	2.94	3.34	2.24	11.45	3.16	4.7	0.81	5.2	2.27	2.25	4.96	1.66	5.18	0.22
Denmark	0.61	0.43	2.15	0.4	0.65	1.31	21.51	2.6	0.55	3.73	1.78	2.05	1.44	1.09	3.41	0.43
Estonia	4.93	2.51	0.2	1.05	0.06	0.54	0.05	39.1	7.67	4.79	7.61	0.49	0.21	0.64	2.39	2.69
Finland	1.12	0.25	1.9	0.39	0.26	2.6	0.95	9.58	31.38	2.74	0.24	2.24	0.89	1.05	2.56	1
France	2.97	0.24	3.15	0.74	2.88	1.89	3.52	5.88	0.17	9.41	0.71	2.31	10.25	1.15	4.19	1.32
Germany	7.58	0.85	0.51	3	3.47	4.88	2.05	6.56	0.53	2.12	34.6	1.06	0.96	0.53	0.77	0.83
Greece	0.5	0.31	7.38	0.35	1.41	3.26	0.18	0.75	0.62	1.24	0.36	23	0.26	1.01	15.04	2.8
Hungary	0.81	1.71	1.87	3.14	5.93	1.71	3.42	0.22	0.13	2.43	1.35	0.49	33.18	0.21	0.74	9.15
Ireland	2.75	0.69	5.68	0.22	2.63	1.85	2.15	6.01	0.53	6.64	0.3	3.37	4.27	3.33	7.91	0.33
Italy	2.62	1.35	8.05	0.28	3.84	2.79	1.29	4.22	0.06	4.38	0.32	3.05	2.42	0.59	19.8	0.92
Latvia	3.21	2.23	0.51	0.86	1.01	0.07	0.11	20.62	2.97	3.01	3.78	1.21	4.49	0.46	3.35	21.32
Lithuania	3.31	0.31	2.4	0.42	0.19	0.93	1.9	13.15	1.27	6.94	0.54	3.22	0.48	1.53	4.88	3.99
Luxembourg	1.23	2.77	0.83	1	2	1.3	4.33	0.63	0.83	0.95	5.08	0.57	0.26	0.54	0.86	0.27
Malta	1.11	1.46	1.85	0.65	2.95	2.66	6.33	2.45	0.37	3.72	2.12	2.27	7.8	0.54	2.42	1.08
Netherlands	1.96	3.22	3.06	0.39	2.49	1.72	3.38	4.52	0.3	5.47	0.25	3.16	4.62	0.53	4.33	0.74
Norway	1.83	1.51	5.46	0.26	1.33	1.1	0.75	6.65	1.51	4.03	1.72	5.57	2.94	0.26	6.89	0.5
Poland	1.44	0.66	2.89	1.64	0.06	2.78	2.24	9.72	0.89	3.87	0.97	5.77	0.06	0.87	8.19	3.67
Portugal	2.44	0.44	1.46	1.77	3.01	0.99	4.46	2.48	1.62	4.88	9.91	2.37	0.76	1.55	4.46	1.08
Romania	1.79	0.24	3.9	0.39	1.81	2.2	4.26	5.47	0.24	5.28	0.18	3.72	3.87	1.11	5.08	0.55
Slovakia	3.7	0.18	4.25	0.44	1.31	1.41	2.7	9.23	0.42	5.83	0.32	3.95	1.12	1.2	7.52	1.89
Slovenia	0.87	2.47	1.4	0.34	0.11	0.8	8.05	2.99	0.93	2.5	3.44	2.83	0.3	2.67	3.08	1.79
Spain	1.86	0.15	3.36	0.59	1.62	1.54	1.95	5.02	2.99	6.43	0.07	2.93	2.69	0.97	4.6	0.45
Sweden	0	1.61	0.1	0.23	0.4	3.54	0.29	2.73	1.3	0	1.06	0.49	0.77	1.21	0.42	0.07
Switzerland	3.22	0.43	0.28	0.18	0.72	0.79	0.88	14.7	5.63	2.75	2.53	0.44	3.5	1.33	2.04	0.66
UK	1.13	2.02	0.15	2.38	1.64	1.09	7.42	2.82	2.13	1.96	11.48	1.21	0.18	0.98	0.24	3.15
To	65.28	33.96	82.48	26.77	58.07	55.92	77.31	164.43	36.48	112.55	62.91	78.13	81.95	27.85	135.75	43.75
Net	-20.78	-53.34	-9.27	-68.01	-22.96	-32.63	-1.19	103.52	-32.14	21.96	-2.49	1.13	15.14	-68.82	55.55	-34.93

Table 2 NPL SPILLOVERS PART I (page 28) and PART II (page 27): The ijth item represents the pairwise connectedness a la Diebold and Yilmaz. The From (To) column (row) presents the row (column) summation without the diagonal elements. The Net connectedness is the difference between To and From.

After running a linear VAR model of order 2, and Lanne-Nyberg variance decomposition of 12-periods ahead forecast errors[2] over the period 2010q1-2022q2, I examine the static total spillover index matrix of NPLs in Table 2. More specifically, the table includes:

- ***off-diagonal elements:*** the ijth off-diagonal elements show the proportion of forecast error variance of NPLs of country i explained by shocks originated in country j
- ***on-the-diagonal elements:*** own connectedness measures
- ***To Others (To) row:*** total directional spillover from country j to others, which is the sum of all off-diagonal elements of each column demonstrating influence of country's j NPLs on each country's i NPLs (j→i's)
- ***From Others (From) column:*** total directional spillovers from all others to country i, which is the sum of all off-diagonal elements of each row mirroring the total impact on country i's NPLs due to all other counties' NPLs in the system (j's→i)
- ***Sum row:*** accounts for the total effect on country i's NPLs originated from other countries and country i itself and, therefore, it shall be equal to 100%
- ***Net row:*** net spillover which is the result of the operation **"**To" minus "From", with a positive value indicating this country is a net transmitter of shocks to other markets and a negative value suggesting a net receives of shocks from others.

$$S^{LN}(12) = 77.52\%$$

Let's now begin our analysis, the total spillover index calculated by equation (13) was found to be 77.52% for the whole system. This means that an average of around 78% of the NPLs series' forecast error variance is originated in other countries, which indicates that the NPL connectedness in Europe is more than substantial and there is a high degree of interconnectedness.

[2] The results were found to be robust to the choice of those parameters after using alternative VAR orders, forecast horizon, rolling window sizes, and taking into consideration the limitations of the sample size.

As far as Net Spillovers are concerned, for the countries with positive net spillovers, Poland is the largest return transmitter in the system with net spillover almost double the system's value, that is 143.11%. Second comes Norway followed by Estonia, with net spillovers of 113.37% and 103.52 respectively.

One the other hand, Ireland is the is found to be the most prevailing NPL spillovers receiver, with negative net spillovers of 68.82%, followed by Malta and Slovenia, with net NPL spillovers of 56.99% and 56.83%, respectively.

It is of great interest that although Portugal, Greece and Cyprus have the highest average NPL ratio, when it comes to the way the interconnect with the other countries' NPLs in Europe, Portugal and Cyprus are NPL spillover receivers and Greece is a transmitter.
Contrary, Luxemburg and Switzerland, the lowest NPL ratio countries, have negative net spillover indices as expected to be receivers (-25.68% and, -41.47%, respectively) but Sweden is a transmitter with net spillovers index of almost 10%. Therefore, although Sweden has had a relatively low and stable level of NPLs in the early part of the period, followed by a brief increase around 2015-2016, and a subsequent decline it ends up being a transmitter. We can conclude here that many countries whose NPLs spiked because of the global financial crisis end up being transmitters independently of the overall low NPL ratio.

In order now to examine the pairwise connectedness between the various countries' NPLs I have created a network analysis graph (please see next page) capturing all the different sources and channels of interconnectedness in the system. More specifically, each country is represented as a node. The colour of the node, oscillating between light and dark green, specifies the net connectedness from weak to strong, whereas the size of the node represents the average NPLs of each country.

The edge size shows the magnitude of the pairwise spillovers, which is also reflected in the edge colour (from light to dark green).

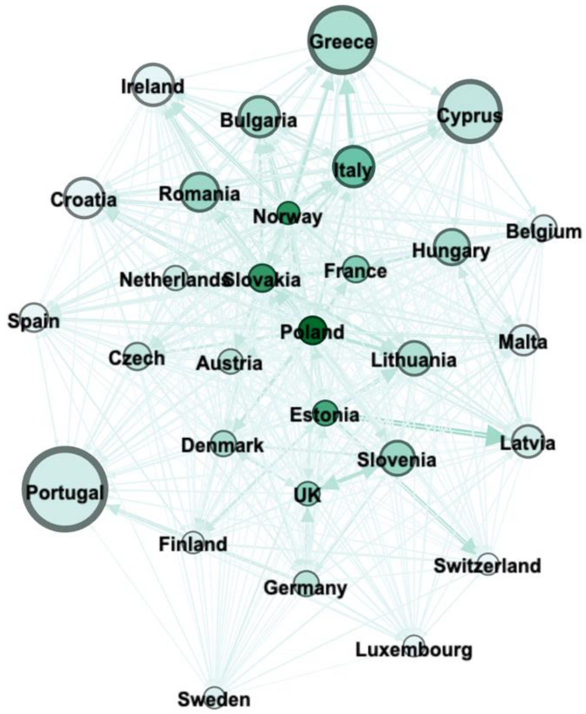

Figure 4 NPL connectedness in Europe, created by the author

Figure 4 presents the network graph of non-performing loan (NPL) connectedness across European countries, constructed using the Diebold-Yilmaz spillover framework and visualised through Gephi. In this graph, each node represents a country, and the edges denote the direction and intensity of NPL spillovers between them. The size of the nodes reflects their overall level of connectedness (i.e., the sum of outgoing and incoming spillovers), while the thickness and opacity of the edges correspond to the strength of bilateral NPL shock transmission. This visualisation provides an intuitive, system-wide depiction of financial contagion risk, capturing how shocks in one national banking system may propagate across borders via deteriorating loan performance.

Several features of the network are immediately noteworthy. First, countries such as Greece, Portugal, and Cyprus appear as dominant nodes in terms of both size and outbound links, suggesting that they are major transmitters of NPL-related shocks to the rest of the European financial system. This is consistent with historical vulnerabilities observed in the sovereign-bank nexus within Southern Europe, particularly during and after the Eurozone debt crisis. These countries' positions highlight the potential for regionally concentrated instability to act as a source of wider systemic risk, even when absolute NPL levels may have declined in recent years.

In contrast, countries located more centrally in the network — such as France, Germany, and Poland — are characterised by dense connectivity with moderate node sizes. These appear to function more as intermediaries within the spillover architecture, simultaneously transmitting and absorbing shocks. Meanwhile, smaller economies like Luxembourg, Malta, and the Baltic states tend to occupy more peripheral positions, although they are not entirely isolated; their exposure to inbound spillovers suggests a degree of vulnerability even in the absence of systemic outward influence. This network structure supports the notion that interconnectedness, rather than absolute size alone, is a key determinant of systemic importance.

Overall, the graph reinforces the utility of network-based approaches for identifying hidden fragilities in Europe's financial landscape. It highlights how NPL risk is not confined within national borders but rather diffuses through a complex web of bilateral exposures and feedback loops. By translating the numerical outputs of the VAR and FEVD-based spillover framework into a relational topology, this visualisation provides both analytical depth and communicative clarity, offering policymakers a tool for monitoring systemic risk and prioritising regulatory coordination across jurisdictions.

Focussing now on more detailed connections, from the network graph (figure 8) we can see that Poland has the darkest colour and occupies a central position, surrounded by all other countries. This shows how big a transmitter is and how greatly connected is with other countries' NPLs. Norway has a central position with a dark green node and many edges initiating from it. This shows how big of a transmitter is, although the general NPL ratio trend was downwards and there was a significant decline in NPLs after the global financial crisis. This is very interesting as it was observed that Norway experienced its strongest, most durable economic boom in decades with the highest employment ever after the GFC[3]. This indicates that countries that handled well their economy during the global financial crisis managed to keep the ex-post credit risk in optimal levels.

Other useful observations are Greece's and Cyprus's position, located very close to each other and having many thick arrows pointing them. Greece has a strong connection with Italy, which was expected given the geographical location of the two countries. Portugal and Spain are also placed very close indicating a strong interconnection, similarly to UK and Germany. Hence geographical connections are very important in NPL inter-dynamics, which can be explained by the existence of trade networks.

Moving on another interesting remark, there is a strong connection between Portugal and Finland in the graph, indicated but the size and deepness in colour of their node connecting them. This may come as a surprise since it is not widely recognized that Portugal and Finland share connections in their political histories, especially considering their locations at opposite ends of the European continent. However, if you check their political history, you can see a constant attempt of a trade route creation between Portugal and Finland, which could explain this interconnection in NPL dynamics.

Last but not least, someone can easily notice the two-side full-sized edge between Slovenia and UK. This shows a strong connection between those countries. Upon checking the relationships between those two countries it can become obvious that there is a great willingness to cooperate and connect, verified by the UK-Slovenia joint statement of intent on enhancing bilateral relations, that aims to enhance business links, security cooperation and exchanges in science and education.

In conclusion, there are two main insights from my analysis. First, the way different countries handled their economy after the 2007-2008 global financial crisis was crucial to the evolution of NPLs and it is reflected in NPL dynamics by the fact that countries that managed well the GFC end up being spillover transmitters. Secondly, geographical characteristics, political

[3] Dølvik, Jon Erik, and Johannes Oldervoll, 'Norway: Averting Crisis through Coordination and Keynesian Welfare Policies', in Stefán Ólafsson, and others (eds), Welfare and the Great Recession: A Comparative Study

interests and joint trade agreements can serve as the body of evidence explaining the various streams of NPL interconnections among the European countries.

8. Conclusion

This paper explored and analysed the interconnectedness among NPLs in 30 European countries including the UK using the Diebold-Yilmaz spillover index. Special attention was paid in the evolution of NPLs and their contagion dynamics after the global financial crisis of 2007-2008. After running a linear VAR model of order 2, and Lanne-Nyberg variance decomposition of 12-periods ahead forecast errors over the period 2010q1-2022q2 the total spillover index was found to be almost 78% demonstrating a significant degree of connectedness among NPLs in Europe.

The analysis reveals that the total spillover index, calculated at 77.52%, highlights the substantial interconnectedness of non-performing loans (NPLs) across European countries, with around 78% of forecast error variance originating from other nations. Poland stands out as the largest transmitter of NPL spillovers, with a net spillover of 143.11%, followed by Norway (113.37%) and Estonia (103.52%). Conversely, Ireland is the most significant receiver, with negative spillovers of 68.82%, followed by Malta (56.99%) and Slovenia (56.83%). Interestingly, countries with high average NPL ratios, such as Portugal and Cyprus, act as receivers, while Greece emerges as a transmitter. On the other hand, countries like Luxembourg and Switzerland, with low NPL ratios, are receivers, whereas Sweden, despite its stable and low NPL levels, acts as a transmitter. This suggests that countries which effectively managed their economies during the 2007-2008 financial crisis became significant transmitters, regardless of their NPL ratios.

Network analysis further stresses the role of geographical proximity and economic ties in NPL dynamics. Poland's central position with the darkest node highlights its significant role as a transmitter. Norway also features prominently, reflecting its robust post-crisis economic performance. Greece and Cyprus are closely connected, with Greece strongly linked to Italy, reflecting their geographical and economic ties. Similarly, Portugal and Spain's proximity mirrors their strong interconnection, as do the UK and Germany. Unexpectedly, Portugal and Finland display a notable connection, potentially explained by historic trade routes and shared political interests. Additionally, the strong bilateral edge between Slovenia and the UK underscores their deep economic and cooperative ties, as evidenced by their agreements to enhance relations.

Policy-wise, the findings of this study carry important policy implications for both national authorities and supranational regulators within the European financial framework. The evidence of significant and asymmetric NPL spillovers across countries accentuates the need for coordinated macroprudential surveillance and cross-border supervisory collaboration. Policymakers should recognise that vulnerabilities in one national banking system—particularly those identified as net shock transmitters, such as Greece or Portugal—can have systemic repercussions beyond their borders. This necessitates early intervention mechanisms, harmonised resolution frameworks, and enhanced transparency around asset quality. Furthermore, the network structure revealed by the analysis suggests that systemic risk does not necessarily align with economic size alone; even smaller or peripheral countries can act as channels of contagion. These insights advocate for a more nuanced and network-aware approach to risk monitoring, where interconnectedness metrics complement traditional indicators in guiding supervisory focus, stress testing, and crisis management planning. Ultimately, the spillover-based approach employed here provides a valuable diagnostic tool for assessing the resilience of the European banking system and for informing timely, pre-emptive policy responses.

Future studies could focus on several key areas to deepen our understanding of NPL dynamics. A comparative analysis of policy responses to the global financial crisis across different countries could reveal the long-term impacts on financial stability. Additionally, a longitudinal study of NPL trends might identify sustained patterns and vulnerabilities. This would be achievable in the future when the NPL datasets will increase in size, thus, surpassing the limitations of a limited data set. Exploring how recent economic challenges, such as the COVID-19 pandemic, interact with the legacy of the crisis could provide crucial insights. Further research could also examine regional variations in spillover effects and the role of international cooperation in addressing NPL issues. Finally, investigating the potential of financial technology and data analytics in improving NPL management could offer innovative solutions for future financial stability.

Appendix

Figure 5 Nonperforming Loan ratio for Austria, 2010-2022, created by author

The graph illustrates the Non-Performing Loan (NPL) ratio for Austria from the first quarter of 2010 to the first quarter of 2022. Initially, from 2010 to 2014, the NPL ratio experienced a steady rise, indicating increasing financial distress among borrowers or worsening economic conditions. This upward trend culminated in a peak around the second quarter of 2014, where the ratio exceeded 4.0, marking the highest level of loan delinquency during this period. This can be attributed to the Vienna Initiative which prioritised for action plan to deal with NPLs in central and south-eastern Europe. Following this peak, there was a noticeable decline in the NPL ratio, particularly sharp between 2014 and 2016, after which the decrease continued at a steadier pace. From 2018 to 2022, the NPL ratio showed a more stable and consistent decline, reaching levels just above 1.0 by the first quarter of 2022. This suggests a significant improvement in loan performance, possibly due to better economic conditions or more effective financial regulations and management. Overall, the trend from 2010 to 2022 indicates that after a period of increasing loan delinquencies, Austria managed to significantly reduce the NPL ratio, reflecting an improvement in the health of the banking sector and borrower repayment behaviour.

Figure 6 Nonperforming Loan ratio for Belgium, 2010-2022, created by author

The graph depicts the Non-Performing Loan (NPL) ratio for Belgium from the first quarter of 2010 to the first quarter of 2022. Initially, the NPL ratio remained relatively stable around 3.0 from 2010 to 2012. However, from 2012 onwards, there was a noticeable increase, peaking in early 2014 at approximately 4.5. This peak indicates a period of heightened financial stress and increased loan delinquencies. After reaching this peak, the NPL ratio began a steady decline, with occasional fluctuations, particularly between 2014 and 2016.

From 2016 to 2018, the decline continued more sharply, reflecting improvements in loan performance and possibly better economic conditions or regulatory measures. Post-2018, the NPL ratio further decreased, stabilising around 2.0 by early 2022, despite some minor fluctuations during this period. Overall, the trend suggests that Belgium experienced a significant reduction in loan delinquency rates after a peak in 2014, indicating improved financial stability and borrower repayment behaviour by 2022.

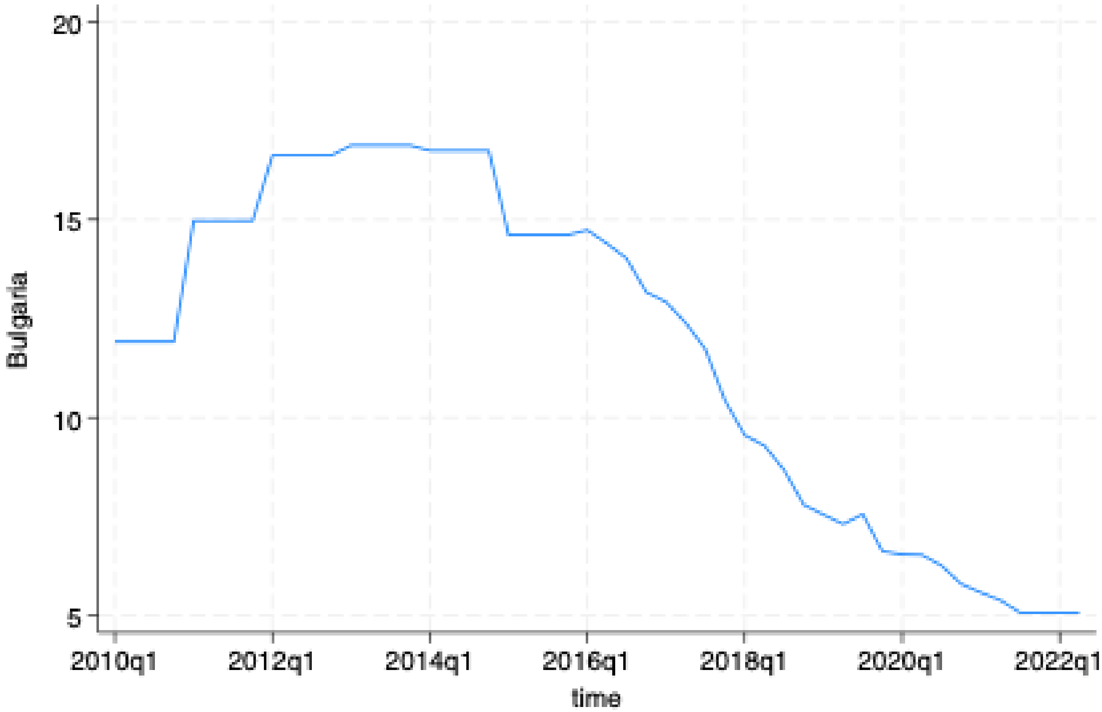

Figure 7 Nonperforming Loan ratio for Bulgaria, 2010-2022, created by author

The graph depicts the Non-Performing Loan (NPL) ratio for Bulgaria from the first quarter of 2010 to the first quarter of 2022. Starting in 2010, the NPL ratio was around 10.0 and saw a marked increase, peaking at approximately 17.0 by 2012. This elevated level persisted until around 2015, indicating a prolonged period of significant financial stress and high loan delinquency rates. From 2016 onwards, there was a pronounced and steady decline in the NPL ratio. This downward trend continued with some minor fluctuations, reflecting a gradual improvement in loan performance and potentially more effective financial management or better economic conditions. By early 2022, the NPL ratio had decreased to just above 5.0, showcasing a significant reduction in non-performing loans over the decade. Overall, the trend for Bulgaria shows a high level of NPLs maintained through the early 2010s, followed by a consistent improvement leading to much lower delinquency rates by 2022.

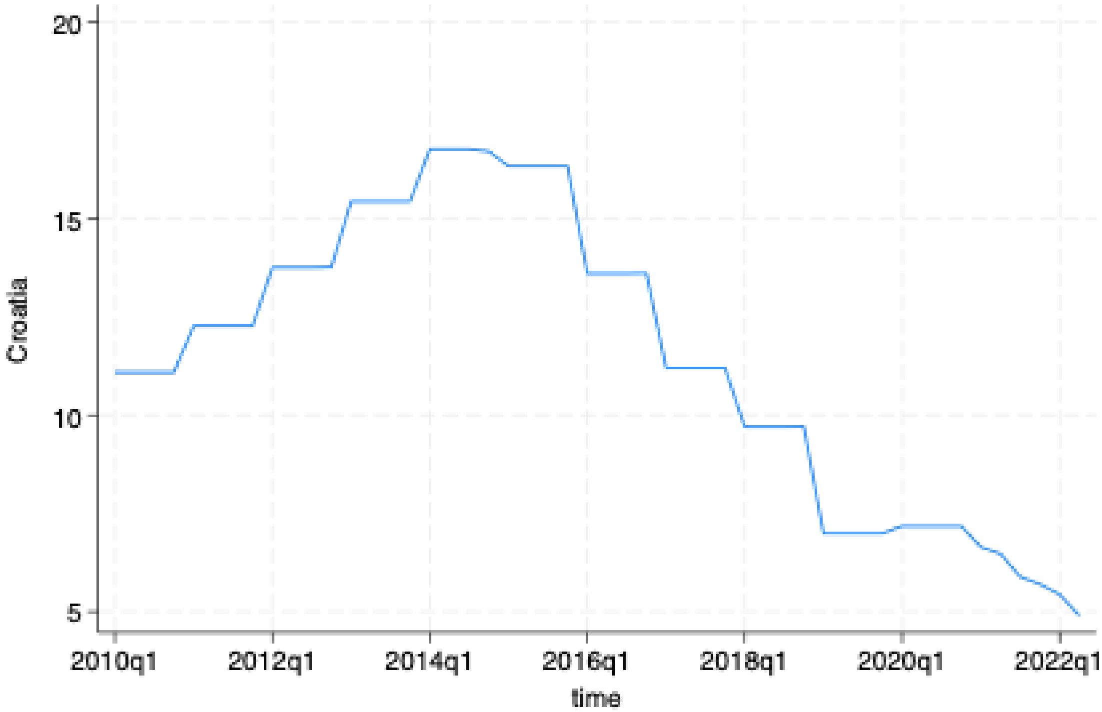

Figure 8 Nonperforming Loan ratio for Croatia, 2010-2022, created by author

The graph illustrates the trend in non-performing loans (NPLs) for Croatia from 2010 to 2022. Initially, the NPL ratio in Croatia shows a gradual increase from 2010, peaking around 2014-2015 at approximately 17%. This period of rising NPLs can be attributed to the economic challenges Croatia faced during the European debt crisis, which impacted borrowers' ability to repay loans. However, post-2015, there is a significant and steady decline in the NPL ratio, falling to around 5% by 2022.

Figure 9 Nonperforming Loan ratio for Cyprus, 2010-2022, created by author

The graph illustrates the trend in non-performing loans (NPLs) for Cyprus from 2010 to 2022. Starting from a relatively low base in 2010, the NPL ratio in Cyprus shows a sharp increase beginning around 2012, peaking at approximately 47% in 2015-2016. This significant rise is indicative of the severe banking crisis Cyprus experienced, characterized by high levels of loan defaults due to economic instability and the collapse of major financial institutions. Post-2016, the graph depicts a steady decline in the NPL ratio, dropping to around 10% by 2022.

Figure 10 Nonperforming Loan ratio for Czech Republic, 2010-2022, created by author

The graph displays the trend in non-performing loans (NPLs) in the Czech Republic from 2010 to 2022. It shows a consistently decreasing trend in NPL ratios over the years, starting from around 5.5% in 2010 and sharply falling to below 2% by 2022. This decrease suggests a strong and resilient banking sector, underpinned by effective regulatory frameworks, sound risk management practices, and economic stability in the country.

Figure 11 Nonperforming Loan ratio for Denmark, 2010-2022, created by author

The graph illustrates the trend in non-performing loans (NPLs) for Denmark from 2010 to 2022. Initially, Denmark's NPL ratio hovers around 4% but experiences a sharp spike to approximately 6% around 2013. This peak likely reflects the aftereffects of the global financial crisis and subsequent economic challenges that impacted the Danish banking sector. Following this peak, the NPL ratio shows a steady and significant decline, reaching around 1% by 2022.

Figure 12 Nonperforming Loan ratio for Estonia, 2010-2022, created by author

The provided graph illustrates the time series data of Non-Performing Loans (NPLs) in Estonia from the first quarter of 2010 to the first quarter of 2022. At the outset of the period, NPLs were notably high, exceeding 6% in early 2010. This high level reflects the aftermath of the global financial crisis, which significantly impacted many economies, including Estonia's. Following this peak, there is a clear downward trend, indicating an improvement in the health of the Estonian banking sector and possibly the broader economy. By 2012, NPLs had dropped to around 3%, and the downward trajectory continued, albeit with occasional fluctuations. From 2014 onwards, the NPL ratio stabilized somewhat, oscillating between 1.5% and 3%. There were short periods of increases, such as in early 2016 and mid-2018, but these spikes were followed by subsequent declines, suggesting that the banking sector was able to manage and resolve periods of distress relatively effectively. Post-2020, the data show a more pronounced downward trend, coinciding with the period during and following the COVID-19 pandemic.

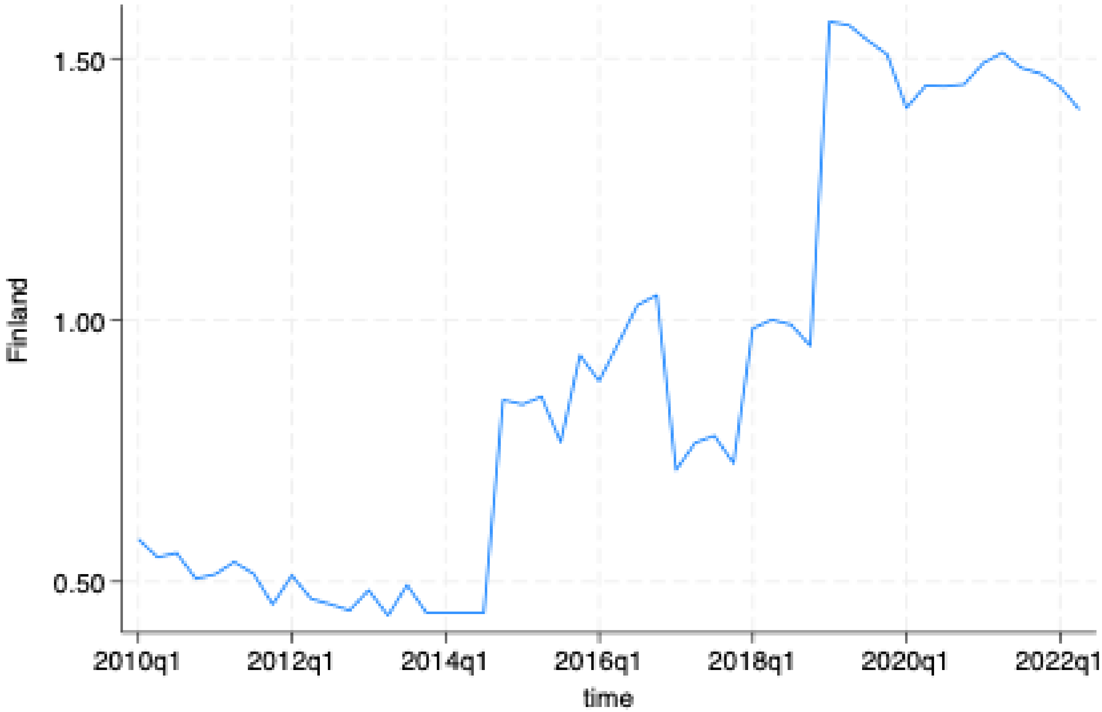

Figure 13 Nonperforming Loan ratio for Finland, 2010-2022, created by author

The graph presented shows the time series data of Non-Performing Loans (NPLs) in Finland from the first quarter of 2010 to the first quarter of 2022. Unlike the steep initial decline observed in Estonia, Finland's NPLs started at a relatively low level, around 0.5%, and exhibited more variability over the period. In the early years, from 2010 to 2014, Finland maintained a low and stable level of NPLs, typically below 0.5%. This indicates a period of stability in the Finnish banking sector, with relatively few loans becoming non-performing. However, from 2015 onwards, there is a noticeable upward trend. The NPL ratio increased gradually at first, with occasional dips, but it did not revert to the low levels seen in the earlier period. By 2016, NPLs had risen to around 1%, and this marked the beginning of a more volatile phase. The NPL ratio experienced several spikes, notably in 2016 and 2018, reaching levels close to 1.5%. This period likely reflects a combination of economic factors and changes in the banking sector, potentially including more stringent reporting standards or economic challenges impacting borrowers' ability to repay loans. A significant surge occurred around 2019 and early 2020, where NPLs spiked dramatically, peaking at approximately 1.5%. This rise could be associated with the onset of the COVID-19 pandemic, which posed severe economic disruptions globally, leading to increased loan defaults. Despite the peak, the NPL ratio remained relatively high throughout the subsequent quarters, hovering around 1.5% with minor fluctuations.

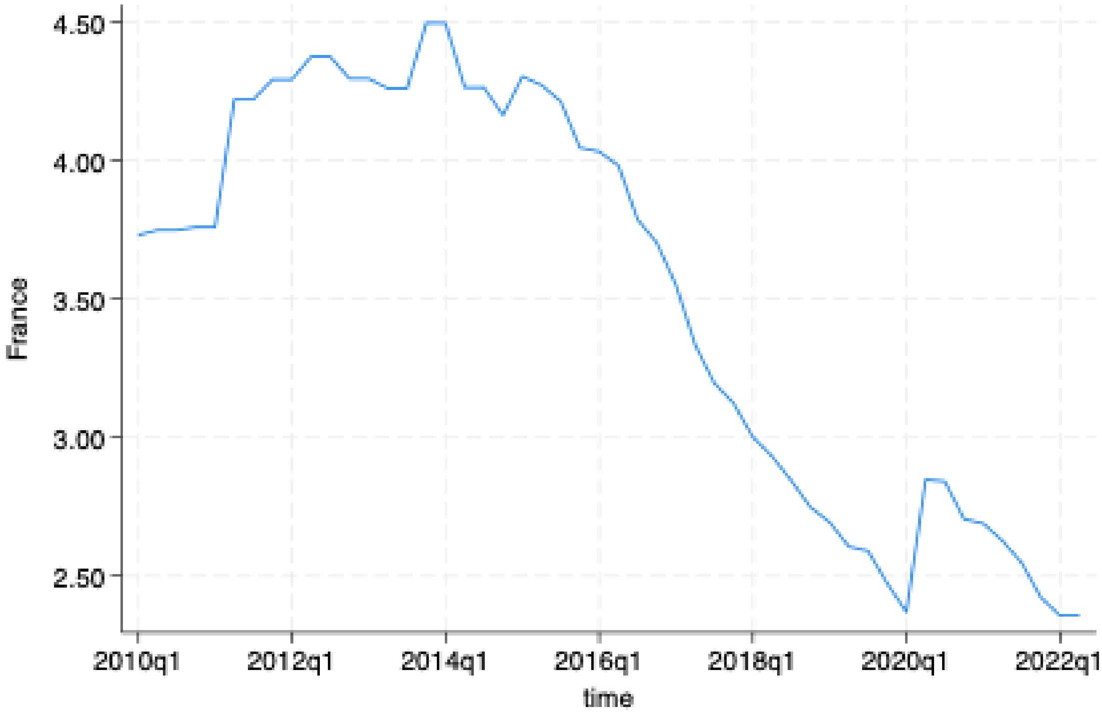

Figure 14 Nonperforming Loan ratio for France, 2010-2022, created by author

The graph provided illustrates the time series data of Non-Performing Loans (NPLs) in France from the first quarter of 2010 to the first quarter of 2022. At the beginning of the period, NPLs in France were relatively high, starting at around 3.5%. This initial level reflects the lingering effects of the global financial crisis, which had a significant impact on the French banking sector. Throughout the early part of the decade, from 2010 to 2014, NPLs in France increased, reaching a peak of around 4.5%. However, starting around 2015, there is a clear downward trend in the NPL ratio. By 2016, NPLs began to decline more rapidly, falling from approximately 4.5% to around 3.5% by 2017. This decline continued, and by the beginning of 2020, NPLs had dropped to approximately 2.5%. This improvement suggests a combination of better economic conditions, improved credit risk management by banks, and possibly supportive regulatory measures. The onset of the COVID-19 pandemic in early 2020 caused a brief increase in NPLs, reflecting the sudden economic shock and its impact on borrowers' ability to repay loans. Despite this spike, the trend quickly resumed its downward trajectory, indicating effective crisis management and recovery efforts. By the end of the period, in the first quarter of 2022, NPLs in France had fallen to their lowest levels, close to 2%.

Figure 15 Nonperforming Loan ratio for Germany, 2010-2022, created by author

The graph provided illustrates the time series data of Non-Performing Loans (NPLs) in Germany from the first quarter of 2010 to the first quarter of 2022. Initially, the NPL ratio in Germany was relatively stable, starting at around 2% and maintaining this level through to early 2014. This period of stability indicates that the German banking sector was able to manage credit risk effectively in the aftermath of the global financial crisis. However, starting around mid-2014, there is a significant upward shift in the NPL ratio. By 2015, NPLs had increased sharply, reaching a peak of over 6% by the beginning of 2016. The NPL ratio remained elevated through 2017, indicating persistent challenges in managing non-performing loans during this period. From 2018 onwards, there is a marked decline in the NPL ratio. By early 2020, NPLs had decreased to around 2%, similar to the levels seen at the beginning of the period. This decline reflects significant progress in resolving non-performing loans and improving the financial health of the banking sector. The onset of the COVID-19 pandemic in early 2020 did not cause a significant spike in NPLs, suggesting that the sector was relatively resilient to the immediate economic shock. Post-2020, the NPL ratio remained low, with a brief dip below 1.5% towards the end of the period.

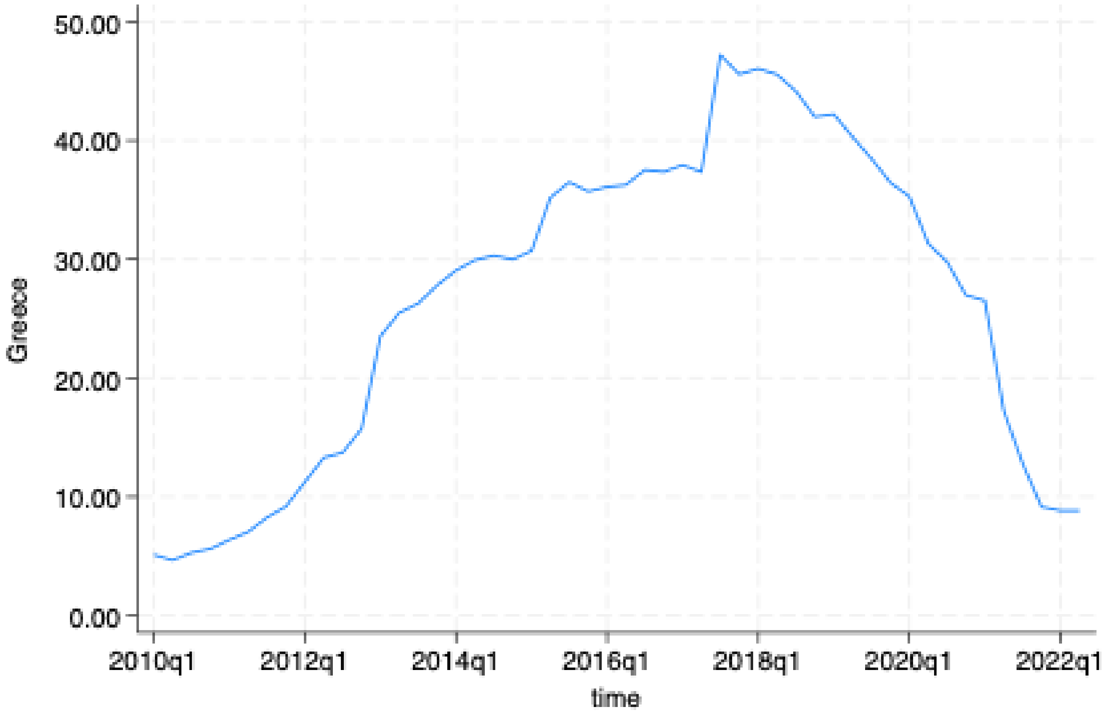

Figure 16 Nonperforming Loan ratio for Greece, 2010-2022, created by author

The graph shows the trend in non-performing loans (NPLs) for Greece from 2010 to 2022. Greece's NPL ratio starts relatively low around 10% in 2010 but increases significantly, peaking at around 45% in 2017. This sharp rise in NPLs reflects the severe economic and financial crisis Greece experienced during this period, which led to widespread defaults as borrowers struggled to meet their loan obligations. Post-2017, the graph shows a marked decline in NPL ratios, falling sharply to below 10% by 2022. This substantial decrease is indicative of Greece's recovery efforts, including financial reforms, restructuring of debt, and policy interventions aimed at stabilizing the banking sector. International financial support, coupled with stringent austerity measures, also played a critical role in improving the financial health of Greek banks as advised and imposed by IMF policy. The trajectory of NPLs in Greece highlights the profound impact of economic crises on loan performance and the effectiveness of sustained recovery and reform measures. The significant reduction in NPLs by 2022 underscores the resilience of Greece's financial sector and the success of its efforts to restore stability and manage financial risks effectively.

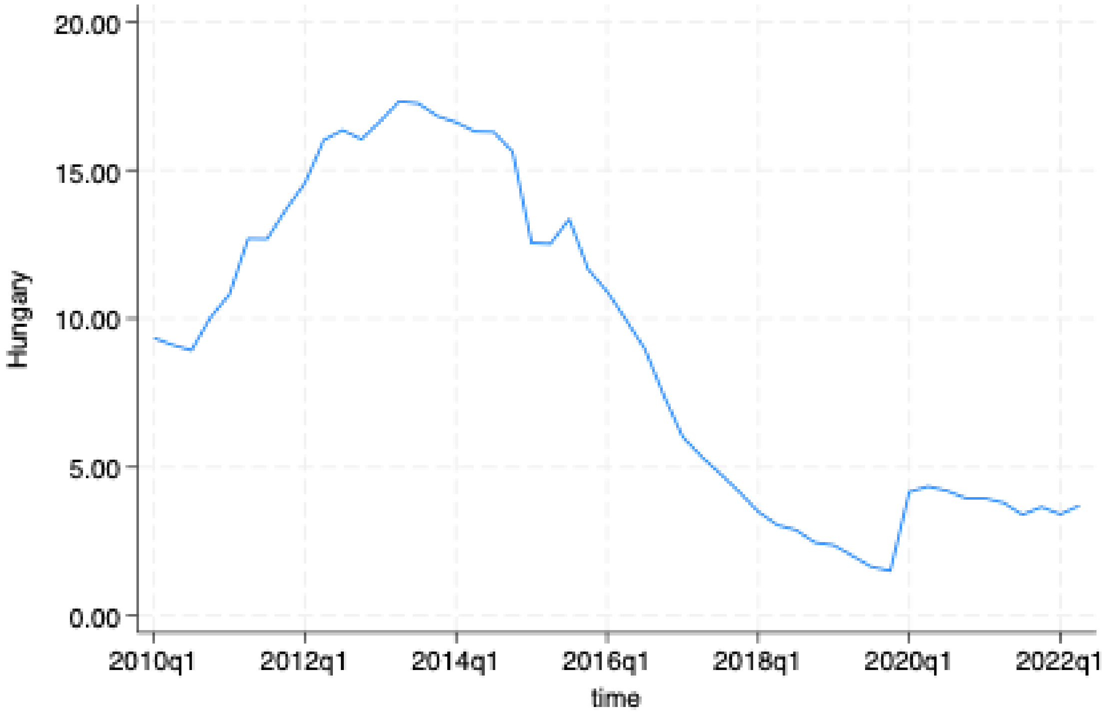

Figure 17 Nonperforming Loan ratio for Hungary, 2010-2022, created by author

The graph illustrates the trend in non-performing loans (NPLs) for Hungary from 2010 to 2022. Initially, the NPL ratio in Hungary shows a gradual increase, peaking at around 17% in 2013-2014. This peak corresponds to the aftermath of the global financial crisis and the European debt crisis, which adversely affected Hungary's economy and the ability of borrowers to repay loans. After reaching its peak, the NPL ratio begins a notable decline, dropping steadily to below 5% by 2018. Post-2018, the NPL ratio stabilizes, maintaining levels around 4-5% up to 2022, with a slight increase observed around 2020, possibly due to the economic impact of the COVID-19 pandemic.

Figure 18 Nonperforming Loan ratio for Ireland, 2010-2022, created by author

The graph shows the trend in non-performing loans (NPLs) for Ireland from 2010 to 2022. Initially, Ireland's NPL ratio rises steadily, peaking at around 25% in 2013-2014. This peak reflects the severe impact of the global financial crisis and the subsequent European debt crisis on Ireland's economy, leading to widespread loan defaults. After reaching its peak, the NPL ratio begins a significant decline, falling consistently to below 5% by 2020. The decline continues, albeit more gradually, stabilizing around 3-4% by 2022.

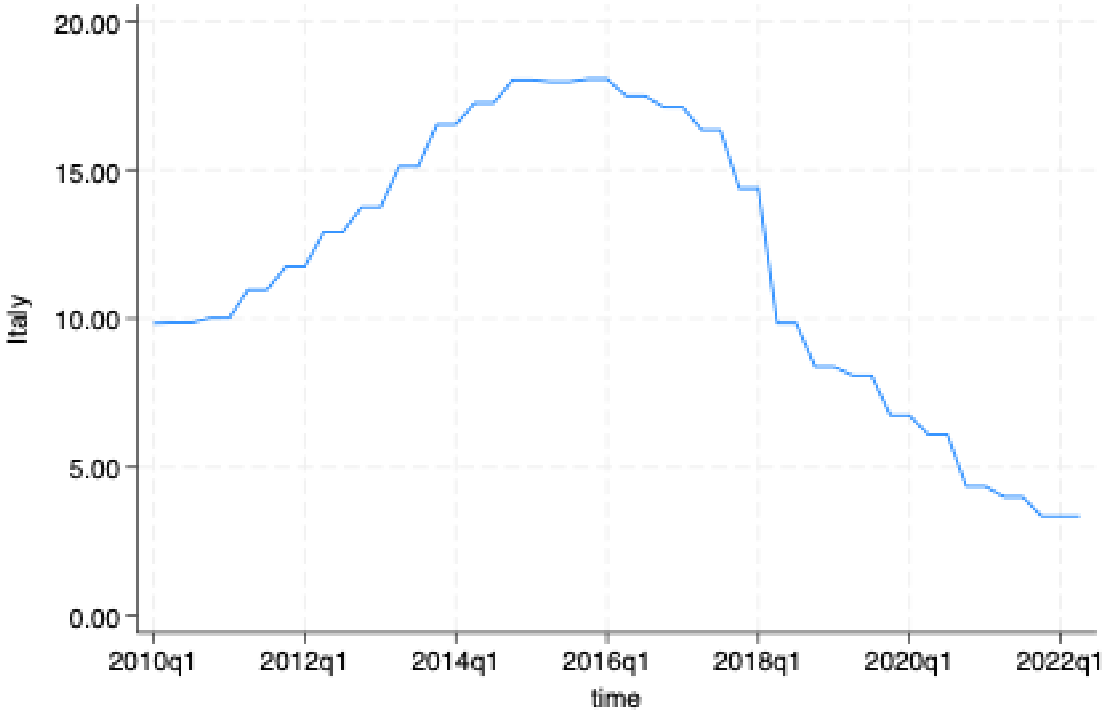

Figure 19 Nonperforming Loan ratio for Italy, 2010-2022, created by author

The graph illustrates the trend in non-performing loans (NPLs) for Italy from 2010 to 2022. The NPL ratio in Italy begins at around 10% in 2010 and rises steadily, peaking at approximately 18% in 2015-2016. This increase reflects the lingering effects of the global financial crisis and the subsequent European debt crisis, which significantly impacted Italy's economy and banking sector, leading to higher loan defaults. Following this peak, there is a notable decline in the NPL ratio, with a steady decrease observed from 2016 onwards, falling to around 4% by 2022.

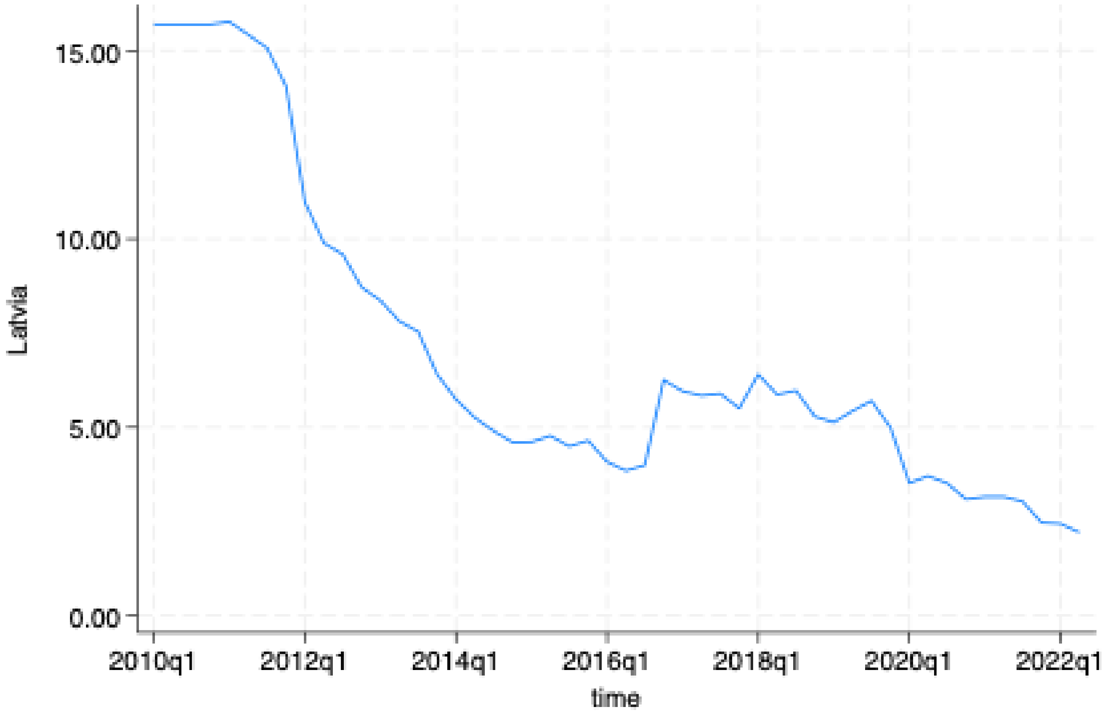

Figure 20 Nonperforming Loan ratio for Latvia, 2010-2022, created by author

The graph shows the trend in non-performing loans (NPLs) for Latvia from 2010 to 2022. At the beginning of the period in 2010, the NPL ratio is relatively high, around 15%. This high level is indicative of the aftermath of the global financial crisis, which severely impacted Latvia's economy and banking sector. From 2010 onwards, there is a sharp decline in the NPL ratio, falling below 5% by 2014. Following this sharp decline, the NPL ratio remains relatively stable with minor fluctuations, maintaining levels around 3-5% from 2014 to 2020.

There is a slight increase observed around 2018-2019, likely due to economic fluctuations, but the overall trend continues to show a downward movement, dropping below 3% by 2022.

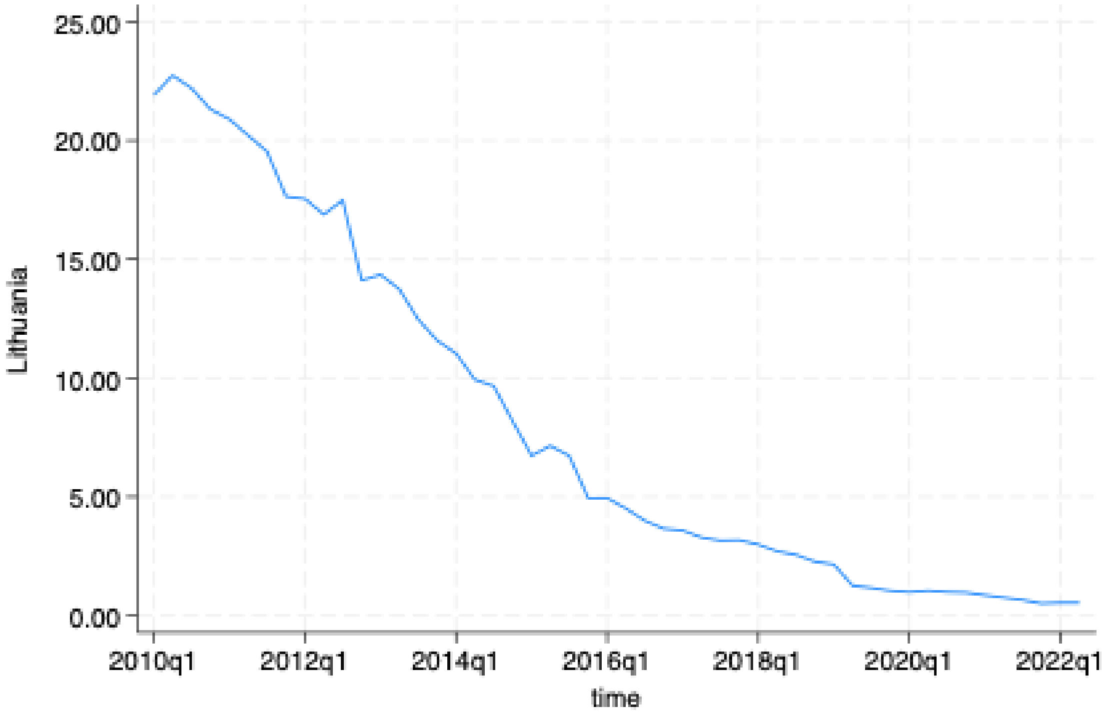

Figure 21 Nonperforming Loan ratio for Lithuania, 2010-2022, created by author

The graph provided illustrates the time series data of Non-Performing Loans (NPLs) in Lithuania from the first quarter of 2010 to the first quarter of 2022. The trend demonstrates a significant and steady decline in NPLs over this period, reflecting substantial progress in improving the financial health of the banking sector. At the beginning of the period in early 2010, NPLs in Lithuania were exceptionally high, starting at around 22%. This high level is indicative of the severe impact of the global financial crisis, which led to widespread loan defaults and financial instability. Over the next few years, there was a consistent and steep decline in NPLs. By early 2012, the NPL ratio had decreased to around 17%, and this downward trend continued steadily. From 2012 to 2014, NPLs continued to decline, falling to approximately 10% by 2014. The period from 2014 to 2016 saw a further reduction in NPLs, with the ratio falling to below 7%. By 2018, the NPL ratio had decreased to around 5%, and this downward trend persisted, albeit at a slower pace. Despite the economic shock caused by the COVID-19 pandemic in early 2020, the NPL ratio in Lithuania continued its downward trajectory, reflecting resilience in the banking sector. By the end of the period in early 2022, NPLs had fallen to their lowest level, below 2%.

Figure 22 Nonperforming Loan ratio for Luxembourgh, 2010-2022, created by author

The graph provided shows the time series data of Non-Performing Loans (NPLs) in Luxembourg from the first quarter of 2010 to the first quarter of 2022. The trend indicates a relatively low level of NPLs throughout the period, with some fluctuations and a notable shift around mid-2015. Initially, in early 2010, the NPL ratio in Luxembourg was around 0.6%. This level was relatively low compared to other countries, suggesting a stable financial environment with effective credit risk management. Over the next few years, from 2010 to 2014, the NPL ratio fluctuated between 0.2% and 0.6%, indicating minor variations in the financial sector's health but overall stability. A significant change occurred around mid-2015, where the NPL ratio increased sharply to approximately 1%. This marked a new phase where NPL levels stabilized at this higher range, fluctuating between 0.8% and 1%. Despite the onset of the COVID-19 pandemic in early 2020, the NPL ratio in Luxembourg did not show a significant spike, unlike in many other countries. The ratio remained stable with minor fluctuations, indicating resilience and effective management of the financial sector during this period of economic uncertainty. By early 2022, the NPL ratio was around 1%, similar to the levels seen since mid-2015. This sustained low level of NPLs highlights the robustness of

Luxembourg's banking sector and its ability to maintain financial stability over the past decade despite various economic challenges.

Figure 23 Nonperforming Loan ratio for Malta, 2010-2022, created by author

The graph provided shows the time series data of Non-Performing Loans (NPLs) in Malta from the first quarter of 2010 to the first quarter of 2022. The trend illustrates an initial rise in NPLs followed by a substantial decline over the period, indicating significant improvements in the financial health of the banking sector. In early 2010, the NPL ratio in Malta was around 6%. This level was moderately high, reflecting some degree of financial stress within the banking sector. Over the next few years, from 2010 to 2014, the NPL ratio increased, peaking at nearly 10% by mid-2014. From 2014 onwards, the trend shifts, showing a clear and sustained decline in NPLs. By 2016, the NPL ratio had decreased to around 6%, returning to the levels observed at the beginning of the period. The downward trend continued, and by 2018, NPLs had fallen further to around 4%. Despite some minor fluctuations between 2018 and 2020, the overall trend remained downward. The onset of the COVID-19 pandemic in early 2020 caused a brief stabilisation in the NPL ratio, but it did not lead to a significant increase, indicating resilience in the Maltese banking sector. By early 2022, the NPL ratio had decreased to its lowest level in the period, around 3%.

Figure 24 Nonperforming Loan ratio for The Netherlands, 2010-2022, created by author

The graph provided shows the time series data of Non-Performing Loans (NPLs) in the Netherlands from the first quarter of 2010 to the first quarter of 2022. The trend indicates an overall decline in NPLs over this period, reflecting improvements in the financial health of the banking sector. In early 2010, the NPL ratio in the Netherlands was around 3%. This level indicates moderate financial stress within the banking sector at the time, likely due to the lingering effects of the global financial crisis. Over the next few years, from 2010 to 2013, the NPL ratio fluctuated between 2.5% and 3.5%, indicating some instability but no significant long-term increase. From 2013 onwards, the NPL ratio began a gradual and sustained decline. By 2015, NPLs had decreased to around 2.5%. The downward trend continued steadily from 2015 to 2018, with the NPL ratio falling to around 2%. Despite some minor fluctuations between 2018 and 2020, the overall trend remained downward. The onset of the COVID-19 pandemic in early 2020 did not lead to a significant increase in NPLs, indicating resilience in the Dutch banking sector. By early 2022, the NPL ratio had decreased to its lowest level in the period, around 1.5%.

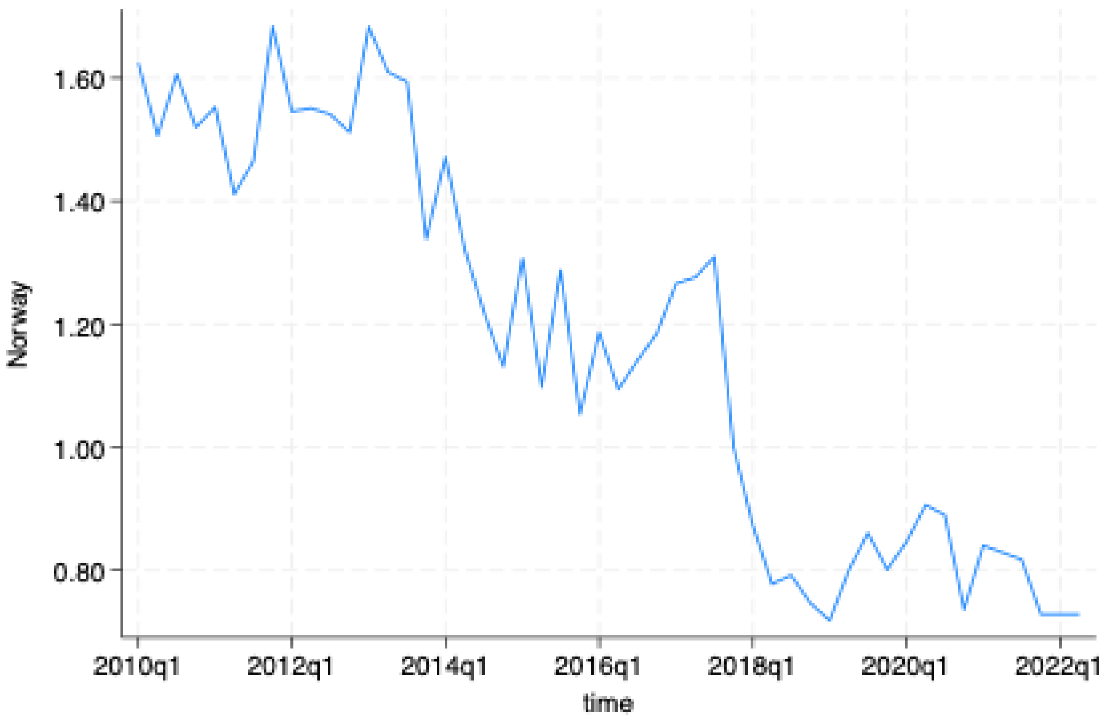

Figure 25 Nonperforming Loan ratio for Norway, 2010-2022, created by author

The graph provided illustrates the time series data of Non-Performing Loans (NPLs) in Norway from the first quarter of 2010 to the first quarter of 2022. The trend shows a notable decline in NPLs over this period, indicating improvements in the financial health of the banking sector. In early 2010, the NPL ratio in Norway was around 1.5%. This level indicates moderate financial stress within the banking sector at the time, likely influenced by the lingering effects of the global financial crisis. Over the next few years, from 2010 to 2014, the NPL ratio fluctuated between 1.2% and 1.6%, indicating some instability but no significant long-term increase. Starting around 2014, the NPL ratio began a gradual decline. By 2016, NPLs had decreased to around 1.2%. The most significant change occurred around 2017, when the NPL ratio began to decline more steeply. By early 2018, NPLs had fallen to around 0.8%. Despite the onset of the COVID-19 pandemic in early 2020, the NPL ratio in Norway did not show a significant increase, indicating resilience in the Norwegian banking sector. The ratio remained relatively stable with minor fluctuations, hovering around 0.8%. By early 2022, the NPL ratio had decreased to its lowest level in the period, below 0.8%. This significant reduction over the 12-year period highlights the progress made in resolving non-performing loans and enhancing the financial stability of the banking sector.

Figure 26 Nonperforming Loan ratio for Poland, 2010-2022, created by author

The graph provided shows the time series data of Non-Performing Loans (NPLs) in Poland from the first quarter of 2010 to the first quarter of 2022. The trend illustrates an initial period of stability and moderate increase, followed by a significant decline in NPLs over this period, reflecting improvements in the financial health of the banking sector. In early 2010, the NPL ratio in Poland was around 4.5%. Over the next few years, from 2010 to 2013, the NPL ratio fluctuated between 4.5% and 5%, indicating some instability but no significant long-term increase. Starting around 2014, the NPL ratio began a gradual decline. By 2016, NPLs had decreased to around 4%. The downward trend continued steadily from 2016 to 2018, with the NPL ratio falling to around 3.5%. Despite a brief spike in early 2018, the overall trend remained downward. The onset of the COVID-19 pandemic in early 2020 did not lead to a significant increase in NPLs, indicating resilience in the Polish banking sector.

By early 2022, the NPL ratio had decreased to its lowest level in the period, around 3%.

Figure 27 Nonperforming Loan ratio for Portugal, 2010-2022, created by author

The graph provided shows the time series data of Non-Performing Loans (NPLs) in Portugal from the first quarter of 2010 to the first quarter of 2022. The trend illustrates a significant rise in NPLs until the mid-2010s, followed by a substantial decline, reflecting changes in the financial health of the banking sector over this period. In early 2010, the NPL ratio in Portugal was around 30%, indicating a high level of financial distress within the banking sector. Over the next few years, from 2010 to 2014, the NPL ratio increased gradually, reaching approximately 34% by 2014. This increase reflects ongoing economic challenges and the slow recovery process from the global financial crisis. Starting around 2014, there was a sharp increase in the NPL ratio. By early 2016, NPLs had risen to nearly 40%, indicating a period of significant financial stress. From 2016 onwards, the NPL ratio began to stabilize and then decline. By early 2018, NPLs had decreased to around 37%. The downward trend continued more markedly from 2018 to 2020, with the NPL ratio falling to around 36%. The onset of the COVID-19 pandemic in early 2020 did not cause a significant spike in NPLs, indicating some resilience in the Portuguese banking sector. By early 2022, the NPL ratio had decreased further to around 35%, showing continued improvement but still reflecting a relatively high level of non-performing loans compared to other countries.

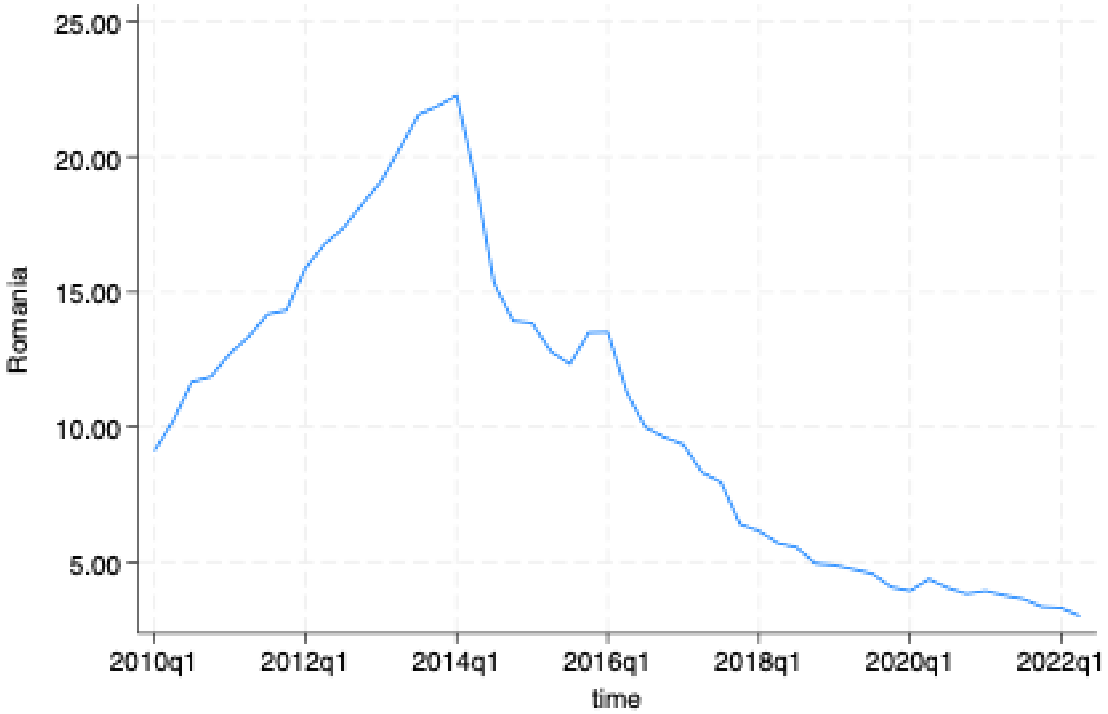

Figure 28 Nonperforming Loan ratio for Romania, 2010-2022, created by author

The graph provided shows the time series data of Non-Performing Loans (NPLs) in Romania from the first quarter of 2010 to the first quarter of 2022. The trend indicates a significant rise in NPLs until the mid-2010s, followed by a substantial decline, reflecting changes in the financial health of the banking sector over this period. In early 2010, the NPL ratio in Romania was around 10%, indicating a moderate level of financial stress within the banking sector. Over the next few years, from 2010 to 2014, the NPL ratio increased gradually, reaching a peak of nearly 22% by mid-2014. This peak represents a period of significant financial distress, likely influenced by the slow recovery from the global financial crisis and specific economic challenges within Romania. Starting around 2014, the NPL ratio began a sharp decline. By early 2016, NPLs had decreased to around 13% with the downward trend continuing steadily from 2016 to 2018, with the NPL ratio falling to around 6%. Despite some minor fluctuations between 2018 and 2020, the overall trend remained downward, reflecting ongoing improvements in the financial health of the banking sector. The onset of the COVID-19 pandemic in early 2020 did not lead to a significant increase in NPLs, indicating resilience in the Romanian banking sector. By early 2022, the NPL ratio had decreased to its lowest level in the period, around 3%.

Figure 29 Nonperforming Loan ratio for Slovakia, 2010-2022, created by author

The graph provided shows the time series data of Non-Performing Loans (NPLs) in Slovakia from the first quarter of 2010 to the first quarter of 2022. The trend indicates a relatively stable level of NPLs in the early part of the period, followed by a significant decline, reflecting improvements in the financial health of the banking sector over this period.

In early 2010, the NPL ratio in Slovakia was around 5%, indicating a moderate level of financial stress within the banking sector. Over the next few years, from 2010 to 2014, the NPL ratio remained relatively stable, fluctuating slightly around the 5% mark. Starting around 2014, the NPL ratio began a gradual decline. By 2016, NPLs had decreased to around 4%. The downward trend continued steadily from 2016 to 2018, with the NPL ratio falling to around 3%. Despite minor fluctuations, the overall trend remained downward. The onset of the COVID-19 pandemic in early 2020 did not lead to a significant increase in NPLs, indicating resilience in the Slovak banking sector. By early 2022, the NPL ratio had decreased to its lowest level in the period, around 2%.

Figure 30 Nonperforming Loan ratio for Slovenia, 2010-2022, created by author

The graph provided shows the time series data of Non-Performing Loans (NPLs) in Slovenia from the first quarter of 2010 to the first quarter of 2022. The trend illustrates an initial rise in NPLs until the mid-2010s, followed by a substantial decline, reflecting significant changes in the financial health of the banking sector over this period. In early 2010, the NPL ratio in Slovenia was around 6%, indicating a moderate level of financial stress within the banking sector. Over the next few years, from 2010 to 2013, the NPL ratio increased significantly, reaching a peak of around 18% by early 2013. Starting around 2014, the NPL ratio began a sharp decline. By early 2016, NPLs had decreased to around 10%. The downward trend continued steadily from 2016 to 2018, with the NPL ratio falling to around 5%. Despite a brief spike in early 2018, the overall trend remained downward. The onset of the COVID-19 pandemic in early 2020 did not lead to a significant increase in NPLs, indicating resilience in the Slovenian banking sector. By early 2022, the NPL ratio had decreased to its lowest level in the period, around 2%.

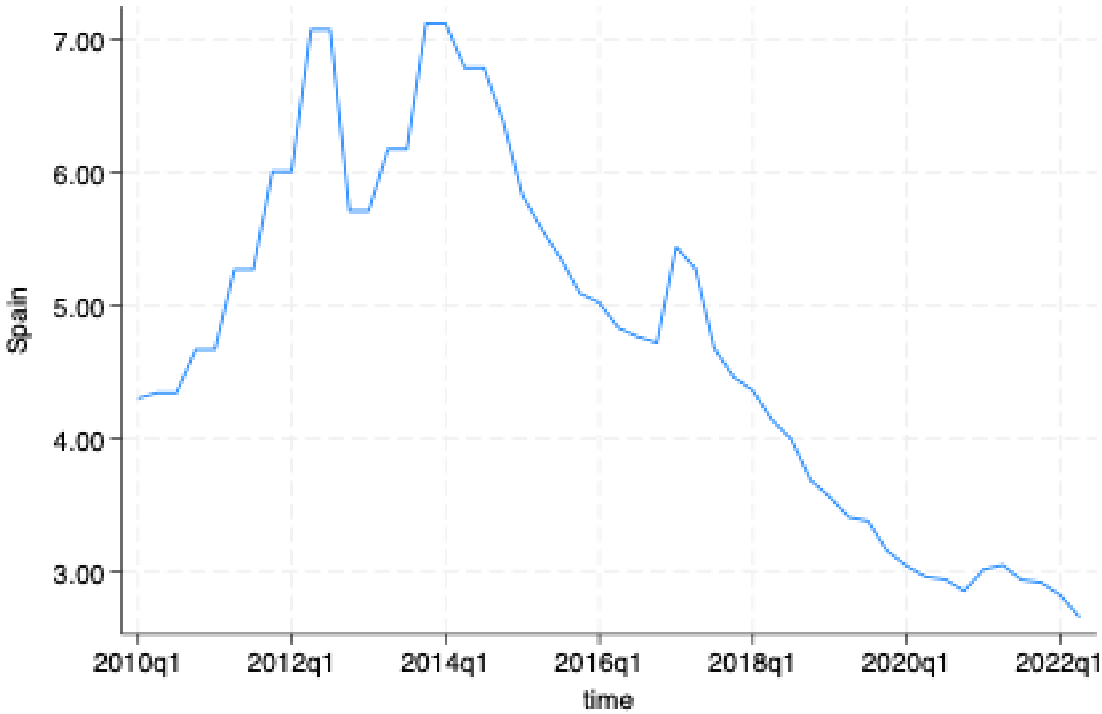

Figure 31 Nonperforming Loan ratio for Spain, 2010-2022, created by author

The graph provided shows the time series data of Non-Performing Loans (NPLs) in Spain from the first quarter of 2010 to the first quarter of 2022. The trend indicates a significant rise in NPLs in the early part of the period, followed by a substantial decline. In early 2010, the NPL ratio in Spain was around 4.5%, indicating moderate financial stress within the banking sector. Over the next few years, from 2010 to 2013, the NPL ratio increased significantly, reaching a peak of nearly 7% by early 2013. This peak represents a period of severe financial distress, likely influenced by the slow recovery from the global financial crisis and the specific economic challenges Spain faced, including a severe real estate crisis. Starting around 2014, the NPL ratio began a decline. By early 2016, NPLs had decreased to around 5.5%. The downward trend continued steadily from 2016 to 2018, with the NPL ratio falling to around 4%. Despite some minor fluctuations, including a brief spike in early 2018, the overall trend remained downward. The onset of the COVID-19 pandemic in early 2020 did not lead to a significant increase in NPLs, indicating resilience in the Spanish banking sector. By early 2022, the NPL ratio had decreased to its lowest level in the period, around 3%.

Figure 32 Nonperforming Loan ratio for Sweden, 2010-2022, created by author

The graph provided shows the time series data of Non-Performing Loans (NPLs) in Sweden from the first quarter of 2010 to the first quarter of 2022. The trend indicates a relatively low and stable level of NPLs in the early part of the period, followed by a brief increase around 2015-2016, and a subsequent decline, reflecting changes in the financial health of the banking sector over this period. In early 2010, the NPL ratio in Sweden was around 0.8%, indicating a relatively low level of financial stress within the banking sector. Over the next few years, from 2010 to 2014, the NPL ratio decreased gradually, reaching around 0.6% by early 2014. Starting around 2015, there was a significant increase in the NPL ratio. By early 2016, NPLs had risen to approximately 1.3%, representing a notable shift from the previously stable low levels. However, from 2016 onwards, the NPL ratio began a steady decline. By early 2018, NPLs had decreased to around 0.6%. This decline continued, and despite minor fluctuations, the overall trend remained downward. The onset of the COVID-19 pandemic in early 2020 did not lead to a significant increase in NPLs, indicating resilience in the Swedish banking sector. By early 2022, the NPL ratio had decreased to its lowest level in the period, around 0.3%.

Figure 33 Nonperforming Loan ratio for Switzerland, 2010-2022, created by author

The graph provided shows the time series data of Non-Performing Loans (NPLs) in Switzerland from the first quarter of 2010 to the first quarter of 2022. The trend indicates a gradual decline in NPLs over this period, reflecting improvements in the financial health of the banking sector, despite some fluctuations. In early 2010, the NPL ratio in Switzerland was close to 1%. Over the next few years, from 2010 to 2014, the NPL ratio gradually decreased, reaching approximately 0.7% by 2014. From 2014 to 2016, the NPL ratio continued to decline, albeit with some fluctuations. By early 2016, NPLs had decreased to around 0.6%, marking a period of significant improvement. Despite a brief increase in 2016, the overall trend remained downward. From 2017 to 2020, the NPL ratio fluctuated between 0.6% and 0.8%, indicating a stable but slightly variable financial environment. The onset of the COVID-19 pandemic in early 2020 led to a brief increase in NPLs, peaking at around 0.8%, reflecting the economic uncertainty and challenges posed by the pandemic.

However, by early 2022, the NPL ratio had stabilized around 0.7%, indicating an overall resilience in the Swiss banking sector and effective measures to manage NPLs despite the economic impacts of the pandemic.

Figure 34 Nonperforming Loan ratio for the UK, 2010-2022, created by author

The graph provided shows the time series data of Non-Performing Loans (NPLs) in the UK from the first quarter of 2010 to the first quarter of 2022. The trend illustrates an initial high level of NPLs, followed by a substantial decline, reflecting significant improvements in the financial health of the banking sector over this period. In early 2010, the NPL ratio in the UK was around 4%, indicating a high level of financial stress within the banking sector. Over the next few years, from 2010 to 2013, the NPL ratio remained relatively high, fluctuating around 4%. This period suggests ongoing challenges in managing non-performing loans in the aftermath of the global financial crisis. Starting around 2014, the NPL ratio began a sharp decline. By early 2016, NPLs had decreased to around 2%. From 2016 onwards, the NPL ratio continued to decline, albeit at a slower pace. By early 2018, NPLs had decreased further to around 1%. This level was maintained with minor fluctuations until 2020, indicating a period of stability and effective management of non-performing loans. The onset of the COVID-19 pandemic in early 2020 did not lead to a significant increase in NPLs, indicating resilience in the UK banking sector. By early 2022, the NPL ratio remained stable at around 1%, highlighting the sustained improvements in the financial stability of the banking sector.

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