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“Banking systems in the euro zone and transmission of monetary policy”

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ABSTRACT

This study examines the transmission of monetary policy in the eurozone from 2005 to 2021. The novelty of this research lies in defining the European Central Bank’s monetary policy through three dimensions extracted via principal component analysis. These components, examined across various neural network models, enable the exploration of the heterogeneity of monetary policy within the Eurozone. Specifically, dimension 2, which represents the yield curve structure and the ECB’s interventions in debt markets, serves to categorize the transmission of monetary policy into two groups of countries. The study concludes that variations in banking system characteristics such as margins and leverage, among others, lead to diverse outcomes in the transmission of monetary policy within the credit channel.

1. Introduction

Current monetary policy faces significant challenges in meeting inflation targets. Various conventional and unconventional monetary policies have been employed to avert deflation. These measures, implemented by both the European Central Bank (ECB), solely focused on price stability, and the Federal Reserve, which also prioritizes economic growth, have led to an era of negative interest rates. This unorthodox approach by central banks can, however, create issues in the transmission of monetary policy. Research by Brunnermeier and Koby (2019) indicates that the reduction of banks’ margins has a greater impact than recapitalization due to margin mismatch. Moreover, Heider et al. (2019) illustrate banks’ reluctance to pass negative rates on to depositors, while Eggertsson et al. (2019), Michail (2019), and Borio et al., (2017) document transmission problems attributed to negative rates. Also, Present et al. (2023) studied the effect of the Zero Lower Bound on household deposits on bank lending margins in the Eurozone. Their findings demonstrate that with every 100-basis-point increase in the deposit rate gap, banks offset this by adding approximately 44 basis points to the lending margin. As a result, they conclude that accommodative policy near the lower bound is less effective when contrasted with a scenario featuring positive interest rates.

The transmission of monetary policy unfolds through several channels, namely the savings and investment channel, the exchange rate channel, and the asset and wealth channel. These channels, responsive

to expansive policies, collectively bolster aggregate demand, consequently stimulating price growth. Interest rate reductions play a pivotal role within these channels, rendering more investment ventures viable and escalating asset values owing to increased discounted cash flows. This surge in asset values, attributable to the wealth effect, prompts heightened consumption and enhanced access to credit, buoyed by augmented collateral values. Moreover, the resultant decrease in interest rates augments the trade balance by depreciating the exchange rate, fortifying aggregate demand. The multifaceted mechanism of monetary policy transmission encompasses various facets such as asset valuation, cash flows, banking capital, and risk assumption, delineating pathways through which central bank decisions reverberate within the economy. Within the realm of cash flows, interest rate decreases alleviate debt servicing, amplify liquidity, and consequently uplift aggregate demand. Furthermore, such rate cuts curtail default rates and enhance capital ratios, empowering banks to extend more loans, thereby fostering further aggregate demand. Finally, the adjustment of risk assumption through decreases in interest rates stimulates risk appetite, driven by an intensified pursuit of profitability and increased collateral values that support lending activities.

However, recent years have proven challenging for the European Central Bank in meeting inflation targets, with approaches bordering on deflation and moving away from the 2 % target, as documented by Mazumder (2018), Van der Crujisen and Demertzis (2011), and Olson and Wohar (2016). Inflation differentials across eurozone countries have

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also varied in recent years, [Blanchard et al. \(2010\)](#) and [Summers et al., \(2018\)](#) argue for increasing the inflation target beyond 2 %, highlighting the lack of maneuverability with the current target in efficiently overcoming crises.

Banks play a crucial role in the transmission of monetary policy, especially in Europe, which has a more bank-centric economy compared to the United States.¹ These banks, particularly in Europe, face challenges in financing smaller companies in the market. The transmission of monetary policy by banks occurs through the credit channel, where an exogenous increase in reserves via securities purchases by the European Central Bank enables banks, through the fractional reserve system, to expand credit. Banks maintaining reserves beyond the regulatory minimum pose difficulties in policy transmission. Lower and especially negative interest rates tend to increase risk-taking, potentially creating financial system fragility, as indicated by various authors. In the eurozone, risk appetite, influenced by monetary policy rates, is influenced by diverse banking characteristics. [Boungou \(2020\)](#) highlights how risk-taking is contingent on factors such as bank capitalization and size. In our analysis, risk appetite will be measured by different loan margins set by banks, while the leverage coefficient will serve as an indicator of capitalization.

In the study, the main questions addressed are firstly which components of monetary policy exert greater influence on the transmission of monetary policy, specifically in the credit channel in the Eurozone. Additionally, it aims to verify whether transmission occurs uniformly across the identified monetary components or, conversely, if there are blocs of countries experiencing different reactions. If so, the objective is to identify the monetary component that drives these transmission differences.

The key contributions to the literature are twofold. Firstly, it innovatively approaches the transmission of monetary policy holistically across its instruments, defining dimensions for the Eurozone that yield the latent structure of monetary policy through three components. Secondly, it delineates the reactions of banking systems in Eurozone countries to the previously identified dimensions of monetary policy, alongside various banking structural variables and risk appetite indicators, such as applied margins. This assessment of monetary policy transmission will be carried out using neural networks, enabling the classification of Eurozone banking systems according to the importance level of the utilized variables.

The study begins with a review of the current literature in Section 1. Section 2.1 defines the ECB's monetary policy through principal component analysis (PCA) involving various monetary variables, interest rates, and ECB balance sheet items. This process derives three monetary policy dimensions utilized in the neural network models. Finally, in Section 2.2, these components, along with other banking system variables, are used to predict loan approvals. This analysis employs neural networks and Olden and Leakprofile algorithms to interpret the results. Neural networks, chosen for their predictability, exhibit higher precision in model validation compared to linear models.

2. State of the art

The current study distinguishes itself through the application of principal component analysis to delineate three dimensions characterizing monetary policy, subsequently serving as the foundational basis for analyzing its transmission. Researchers such as [Lombardi and Zhu \(2014\)](#) and [Favero et al. \(2005\)](#) have previously employed principal component analysis, applying the dynamic factor model in the context of the United States. Furthermore, [Favero et al. \(2005\)](#) conducted a

principal component analysis for the four largest countries in the Eurozone—specifically, Germany, France, Italy, and Spain—with the specific aim of scrutinizing monetary policy. In contrast to their methodology, our study undertook a unified analysis of monetary components for the entire Eurozone, facilitating an evaluation of its impact on each of the studied Eurozone countries. Other studies utilizing this technique include [Giannone et al., \(2004\)](#) research in the United States, where they employed a two-factor model to predict both the federal funds rate and gross domestic product (GDP). In the European context, [Laine \(2020\)](#) investigated the effect of the ECB's conventional monetary policy on the real economy using a Factor-Augmented Vector Autoregression model (FAVAR), specifically examining how unanticipated changes in the ECB's policy rate influenced the unemployment rate and industrial production. Our study stands out in that it does not incorporate economic variables, focusing on financial and monetary policy aspects. In the Asian context, [Ang \(2008\)](#) applied principal component analysis to construct a summarized measure of interest rate policies, considering the joint influence of various interest rate controls imposed on Malaysia's financial system. Additionally, [Heckel and Nishimura \(2022\)](#) delved into the unconventional monetary policies of the Bank of Japan from 2002 to 2019, focusing on open market operations and employing principal component analysis to investigate the complexity of monetary policy.

Among authors examining divergent banking responses within nations sharing a unified monetary policy, the work of [Buchholz et al. \(2020\)](#) stands out prominently. They investigated the impact of the deposit facility rate, a conventional monetary policy tool, on portfolio management within Euro area banks from 2009 to 2014. Their findings highlight those banks, which exhibit heightened sensitivity to interest rates in their business models as measured by the net interest margin, tend to decrease reserves when the deposit facility rate declines. This emphasizes the potential for divergent outcomes among banks and, consequently, across countries, contingent upon the distinct characteristics of the banking sector. Additionally, [Heryán and Tzeremes \(2017\)](#) shed light on the divergent responses of commercial banks to monetary policy shocks, particularly during crisis periods. They argue that in former Economic and Monetary Union (EMU) countries, banking lending channels exhibit greater sensitivity to changes in M2 compared to short-term interest rates during financial crises. Conversely, their analysis suggests that bank lending channels in new European Union countries show increased responsiveness to short-term market interest rates. These observations will be examined in our study by creating monetary dimensions. Moreover, [Grandi \(2019\)](#) outlines the variability in the transmission of both conventional and unconventional monetary policies to bank credit within the Eurozone, covering the period 2007–2016. They find that transmission mechanisms seem to be less effective for banks located in countries more vulnerable to the sovereign debt crisis. [Grandi \(2019\)](#) highlights that existing monetary policy tools may not sufficiently address these disparities and emphasizes that rectifying such heterogeneities is not within the ECB's mandate.

In the investigation of clusters responsive to monetary policy within the Eurozone, the work of [Domínguez-Torres and Hierro \(2020\)](#) stands out prominently. Spanning from 2001 to 2017, their study employed Vector Autoregressive (VAR) models and hierarchical clusters. Their primary focus revolves around addressing banking systems in crisis and stabilizing sovereign debt, deeming these as pivotal elements for the effective transmission of expansionary monetary policies. While their emphasis lies in economic variables to determine cluster formation, our research delves into the loan channel and exclusively financial variables. We introduce various components of monetary policy to discern transmission from a novel perspective across different Eurozone countries, utilizing a methodology capable of capturing non-linear relationships.

Additionally, [Brana et al. \(2019\)](#) demonstrate a non-linear relationship within unconventional monetary policies, highlighting how effects intensify below a certain threshold. They propose that when interest rate indicators fall below this threshold, the negative correlation between

¹ The Bank credit to the private non-financial sector as a percentage of GDP has averaged 93 % in the Eurozone since the inception of the euro, while in the United States, it has averaged 51 % over the same period (data sourced from the Basel Committee).

bank risk measures and monetary policy intensifies. They conclude that an excessively accommodating monetary policy might lead to the accumulation of financial imbalances and pose challenges to the banking industry. For the transmission of monetary policy, other authors have identified banking risk appetite as another pivotal variable, which we will address in our work using distinct measures. For instance, [Dang and Dang \(2020\)](#) have substantiated the significant and multifaceted relationship between monetary policy and bank risk-taking. [Segev's \(2020\)](#) research specifically illustrates that banks tend to become less sensitive to risk when operating under prolonged periods of accommodative monetary conditions, specifically observed in the United States. This association underscores a link between monetary policy and banks' risk preference, prompting the recommendation to establish better risk appetite measures for financial intermediaries.

In the context of the Eurozone, [Neuenkirch and Nockel \(2018\)](#) present compelling evidence of a monetary policy transmission channel that amplifies risk by relaxing credit standards for borrowers. Spanning from the first quarter of 2003 to the second quarter of 2016, their study indicates that banks in the Netherlands, Portugal, Spain, and Ireland eased credit standards following expansionary monetary policy shocks. This trend was particularly pronounced in crisis-affected countries, namely Greece, Ireland, Italy, Portugal, and Spain. The findings suggest that if banks are unable to safeguard their interest rate margins by assuming more risks, it may lead to a decline in profits, potentially exacerbating instability in the financial system. A similar line of reasoning is echoed in the work of [Altavilla et al. \(2020\)](#) concerning the Eurozone, covering the period from 2007 to 2017. Their study demonstrates that certain banks adopted a more cautious approach, charging higher rates to customers than anticipated based on the dynamics of the monetary policy rate. This shift is attributed to the deterioration of assets in balance sheets and challenges in securing financing. In a comparable vein, [Matthys et al. \(2020\)](#) examine the impact of monetary policy on loan spreads using data on corporate loans issued by US banks from 2008 to 2015, employing VAR models. Their findings indicate that loose monetary conditions can stimulate banks to increase their risk appetite by offering lower-margin loans to riskier companies.

The role of bank capital in the transmission of monetary policy has been extensively explored in existing literature, employing three primary approaches. The traditional bank loan channel theory suggests that as a bank's capital approaches regulatory minimums, the impact of an expansionary monetary policy shock on bank loans diminishes, given the limited capacity for loan supply expansion without additional capital. Consequently, the effects of monetary policy are more pronounced in well-capitalized banks but subdued when bank equity is low. The revised perspective of the credit channel departs from conventional beliefs by suggesting that an expansionary policy could significantly impact weakly capitalized banks due to the decrease in wholesale financing costs, potentially enhancing the significance of the bank credit channel.

The third approach, the bank-capital channel of monetary policy, accentuates a mechanism where bank capital gains occur due to declining interest rates, exhibiting the most pronounced effect in banks with lower capitalization levels. [Halvorsen and Dag Henning \(2016\)](#) scrutinized the role of bank capital in Norway's monetary policy transmission from January 1993 to August 2008, utilizing a VAR models. Their study confirmed a risk-oriented channel that operates through bank loans facilitated by wholesale financing. Their findings highlighted the dependency of monetary policy effectiveness on the financial strength of banks, showcasing stronger effects in weaker capitalized banks. Conversely, [Gomez et al. \(2021\)](#) supported a conventional bank credit channel over a balance channel, analyzing quarterly data from US bank holding companies spanning from 1986 to 2014. The role of bank capital in the transmission of monetary policy is further emphasized by [Rubio \(2020\)](#), utilizing a Dynamic Stochastic General Equilibrium model with a financial accelerator. Their results imply that the capital requirements of banks, combined with an

imperfect rate of monetary policy transmission, could diminish effectiveness. [Boeckx et al. \(2020\)](#) corroborate this for the Eurozone between 2007 and 2012, highlighting the necessity for banks to maintain a sufficient cushion above minimum capital requirements for an effective transmission mechanism.

Additionally, studies such as [Hosono \(2006\)](#) demonstrated a traditional lending channel by observing Japanese banks' responses to monetary policy from 1975 to 1999. Their analysis revealed a more substantial impact of monetary policy on smaller, less liquid, and more abundantly capitalized banks. Similar results were observed by [Jim-borean \(2009\)](#) in Central and Eastern European countries and by [Ler-skullawat \(2017\)](#) and [Ippolito et al. \(2017\)](#) in Southeast Asian countries, indicating that higher capitalization and liquidity in banks weaken the transmission channel. Studies such as [Wang \(2016\)](#) indicate that the financial structure significantly influences unconventional monetary policy effects. They suggest that the Federal Reserve's provision of liquidity stabilizes financial markets and positively influences asset prices, encouraging lending by major banks in the United States. However, Japan's Quantitative Easing Policy by the Bank of Japan lacked a robust connection between the monetary base and bank loans, resulting in an excess of reserves in the system.

Our study aims to contrast some of these findings in Europe through derived monetary dimensions impacting the Eurozone banking systems. The novelties that the work presents with respect to the analyzed literature are presented in two aspects. Firstly, the monetary policy instruments in the euro zone are reduced by a component analysis to three dimensions. This allows us to have a broader vision of the possible monetary policy variables that affect the credit channel. Secondly, the monetary components are used to form eleven neural network models on the countries, to study their influence on the credit channel. This will allow us to observe the operation of the credit channel according to the banking characteristics of the countries, such as risk appetite, from three perspectives of monetary policy established by the factors. Finally, it is observed how, in each country, its own banking characteristics can determine a greater or lesser influence of each monetary component in the credit channel.

3. Analysis

This section is structured, firstly, with a component analysis that will be carried out on different variables related to the ECB's monetary policy. Using the components obtained, the sensitivity of loan approvals to these factors, along with other banking variables in most of the eurozone countries, is analyzed. For this latter part of the analysis, neural networks and other algorithms are employed to facilitate interpretation. The neural networks are ordered according to the weights of their architecture, which determine one of the monetary components and therefore, one of the dimensions of monetary policy transmission.

3.1. Component analysis

In this section of the study, a component analysis is conducted on various monetary policy variables. The aim is to uncover the latent structure within the data, enabling the definition of monetary policy through new variables that encapsulate the data's variability. A total of 38 variables from the European Central Bank are collected. [Appendix A](#) displays the evolution of the collected series for the period the period spanning from 2005 to 2021 at monthly frequency, while [Table 1](#) presents the variables alongside the components formed. The analysis employs the Principal Component Analysis, method for non-stationary time series based on detrended cross-correlation analysis developed by [Zhao and Shang \(2016\)](#). The traditional principal component analysis is effective for reducing dimensions and constructing indices in stationary time series. However, it becomes susceptible to external trends present in real-world data when non-stationarity exists. The non-stationary principal component analysis, based on detrended cross-correlation

Table 1
Variables and Components formed.

Principal component 1	correlation	p.value
Euribor 1-year	0.9359316	0.0000
Euribor 6-month	0.9339334	0.0000
Euribor 3-month	0.924364	0.0000
bond(all issuers) 5-month	0.9236207	0.0000
bond(all issuers) 6-month	0.9231393	0.0000
bond(all issuers)7-month	0.9223827	0.0000
bond(all issuers) 9-month	0.9212045	0.0000
bond (all issuers) 1-year	0.9210521	0.0000
bond(issuers) 3-month	0.9201868	0.0000
bond (all issuers) 2-year	0.9164483	0.0000
Euribor 1-month	0.9129507	0.0000
Eonia	0.9009324	0.0000
bond(all issuers) 3-year	0.8688952	0.0000
Principal Component 2	correlation	p.value
bond(all issuers) 30-year	0.9208141	0.0000
bond (all issuers) 25-year	0.9107072	0.0000
bond (all issuers) 20-year	0.895992	0.0000
bond (all issuers) 15-year	0.8832711	0.0000
bond (all issuers) 10-year	0.8609777	0.0000
Claims non-euro area res.	0.7893371	0.0000
bond(all issuers) 5-year	0.6613417	0.0000
bond(all issuers), 4-year	0.5542034	0.0000
Liab. to other euro area	-0.6322504	0.0000
Securities euro res.	-0.6530682	0.0000
Current accounts (Min. Res.system)	-0.6599954	0.0000
M1	-0.7941904	0.0000
Principal component 3	correlation	p.value
Longer-term ref. Opr.	0.8054039	0.0000
Lend. Credit Inst.	0.7698845	0.0000
Liabilities euro area credit inst.	0.6277329	0.0000
Banknotes	0.5947286	0.0000
M2	0.5423082	0.0000
Liab. to other euro area	0.5189726	0.0000
M3	0.5077725	0.0000
Liab. to non-euro area	0.5034972	0.0000
General gov. debt	0.4978459	0.0000
Deposit facility	0.4492771	0.0000

Source: Own elaboration

analysis, overcomes these limitations by theoretically deriving coefficients that represent combinations of original variables.

The detrended cross-correlation matrix is depicted in Fig. 1, showcasing various blocks of high correlation (The variables and components formed are presented in Table 1). These findings indicate the suitability of the analysis, in fact, the KMO² obtained has a value of 0.70, which indicates the good fit of the analysis.

Table 1 displays the variables utilized for the component analysis, encompassing aggregates such as M1, M2, and M3, alongside various indicators sourced from the European Central Bank. Additionally, short-term interest rates from the public debt and interbank market, as well as longer-term rates, are included to represent the interest rate curve.

² The measure of adequacy of the sample (Kaiser-Meyer-Olkin) is defined by the following formula: $KMO = \frac{\sum_{i,j} r_{ij}^2}{\sum_{i,j} r_{ij}^2 + \sum_{i,j,m} r_{ij,m}^2}$ [1] Being r_{ij} the simple correlation

coefficient between the variables i and j ; and $r_{ij,m}$, the partial correlation coefficient between the variables eliminated the effect of the remaining m variables. The partial correlation between two variables should be small when the component principal analysis is adequate, approaching a value of 1.

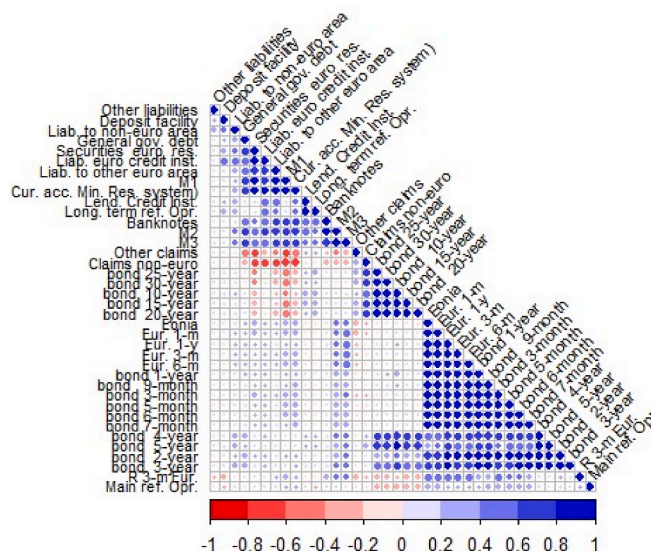


Fig. 1. Detrended cross-correlation matrix.
Source: own elaboration

Appendix A illustrates the temporal evolution of these variables, all observed from 2005 to 2021 in monthly values, revealing their non-stationary nature and justifying the application of the previously mentioned method. Furthermore, Table 1 categorizes these variables based on their correlation within each of the three components, distinguished by color according to the respective component.

Table 2 shows that with the three components obtained through non-stationary principal component analysis, 78,80 % of the variance of the data structure is explained.

Short-term bond yields are grouped into the Component 1, as well as interbank market rates. The EONIA and the EURIBOR are benchmark interest rates used in the euro interbank market. These rates influence Eurozone monetary policy as key indicators in determining funding conditions between banks, consequently impacting credit supply and demand in the economy.

Short-term bond yields also have a significant impact on monetary policy. These rates reflect market expectations about future monetary policy, as short-term bond yields can mirror central bank decisions and forecasts concerning short-term interest rates. Changes in these rates can influence investors' willingness to take risks and investment decisions, thereby affecting economic activity and inflation. Higher rates mean that borrowing will be more expensive for banks and borrowers in general. This can slow consumer spending and corporate investment, as borrowing becomes costlier, impacting economic activity.

The Component 2 shows a negative correlation between long-term bond yields and the monetary supply. An increase in long-term bond yields can discourage investment and borrowing as borrowing costs rise. If M1 shows an opposing trend, it may suggest that available liquidity isn't being utilized for investments or loans, indicating a constraint on economic growth. As M1 increases, a portion of these funds typically ends up as reserves in the central bank, hence correlating with the same sign in this component.

Therefore, this component includes the instruments of monetary policy that affect the creation of a significant amount of money supply. It

Table 2
Components.

	Component1	Component2	Component3
Proportion Var	0.392	0.229	0.159
Cumulative Var	0.392	0.621	0.780

Source: Own elaboration

also captures the interaction arising from ECB interventions in public debt markets and long-term bond yields. Due to the correlation in this component, a flattening of the yield curve is observed through ECB interventions, particularly in the purchase of euro resident securities, which predominantly consist of long-term bonds.

The Component 3 includes different items on the ECB balance sheet and direct injections into European banks such as longer-term refinancing operations, Lending credit institutions. It must be considered that this greater liquidity in turn increases the liability side of the ECB, current accounts minimum Reserves and deposit facility. As an indirect effect, it would also increase the M2 M3, hence positively correlating with them. A higher value of this component will represent a more expansive monetary policy through direct liquidity injections to the banks.

3.2. Loan prediction through neural networks

In this section of the analysis, predictions regarding loan approvals across Eurozone countries are made using neural networks. One advantage of neural networks is their capability to detect intricate non-linear relationships between independent and dependent variables. During the training phase, the neural network adjusts its weights to capture these complex relationships among the variables. Another advantage is their ability to identify all potential interactions between predictors. To achieve this, the bank risk variables illustrated in **Table 3** are utilized. Additionally, the monetary components obtained in the preceding section are incorporated to explore the transmission of monetary policy alongside the variables represented in **Table 3**. All these variables are obtained from the ECB and compiled for each of the 11 countries included in the study, along with the loans. In total, 110 series are collected from the European Central Bank, covering the period from 2005 to 2021 with monthly frequency. The analyzed countries include Austria, Belgium, Finland, Greece, Germany, Ireland, Spain, Italy, Luxembourg, the Netherlands, and Portugal. Many of these variables, as highlighted in the literature review, directly influence the transmission of monetary policy, particularly impacting the risk appetite of banks. This section utilizes the Leakprofile³ and Olden⁴ algorithms, through these algorithms, we conducted a sensitivity analysis for loan predictions in each country. **Appendix B** presents the historical evolution of each explanatory variable by country (excluding monetary components, which are common across all countries). Additionally, it includes the variable denoted by the 'L' code, referring to loans granted in each country. The analysis spans from 2005 to 2021, except for Austria, where the available data starts from 2009 until 2021. Monthly data was utilized to enhance the robustness of results and enable model precision evaluation. **Appendix C** demonstrates the variable correlations across countries, showcasing differences, particularly observed in the relationship between loans and monetary components due to varying banking system characteristics.

Before delving into the neural network results, the achieved precision with the algorithms is demonstrated. To accomplish this, the neural network was trained using 80 % of the data from each country, while the

³ The lekprofile function (see Lek et al., 1996) evaluates the effects of the input variables by returning a plot of predictions of the model in the range of values of each variable. The rest of the explanatory variables are kept constant when evaluating the effects of each input variable. The implementation of lekprofile, which is used in our work, is to group the explanatory variables by grouping k-means, since the covariance between predictors can present unlikely scenarios if all the non-evaluated variables are kept at the same level.

⁴ Algorithm developed by Olden et al., (2004), the advantage of this algorithm over others such as Garson (1991) to obtain the most important variables is that each connection weight of the neural network is maintained both in magnitude and sign. Another added benefit is that the old function can evaluate neural networks with multiple hidden layers and response variables.

Table 3
Explanatory variables used.

Codes	Variables	Explanation
LM1	Lending margin on new business loans to non-financial corporations and households	These four measures are defined as the difference between the interest rates charged on loans specifically extended to a particular group and the cost of funds. Lending margins help assess the risk associated with different types of loans. Based on these margins, financial institutions can make decisions on whether to grant loans, to whom, and at what interest rates.
LM2	Lending margins on loans for house purchase	It is defined as the proportion of loans that banks extend to other banking institutions (interbank loans) compared to their total loan portfolio. This metric indicates the extent to which banks rely on interbank loans as a source of funding or liquidity. It highlights the portion of their lending activities that involve transactions between banks rather than loans extended to other entities, such as individuals or businesses.
LM3	Lending margins on loans to non-financial corporations	
LM4	Lending margin on outstanding loans to non-financial corporations and households	
IL	Share of interbank loans in total loans	It's defined as a financial metric that measures the adequacy of the bank's capital by comparing its regulatory capital to its total exposure. This ratio serves as a measure of the bank's ability to absorb potential losses and withstand financial stress, indicating the level of financial leverage and risk that the institution carries in relation to its assets.
LR	Leverage ratio	The maturity gap for the bank is defined as the difference between the weighted maturity of all assets and liabilities considered, representing the percentage of short-term deposits used to finance long-term loans.
MM	Maturity mismatch	It is defined as funds acquired by financial institutions that do not originate from customer deposits. These funds typically come from sources other than traditional deposits, such as interbank loans, issuance of debt securities, or other forms of borrowing distinct from customer deposits.
NDF	Non deposit funding	It is defined as the proportion or percentage of funding that the bank acquires from short-term sources compared to its overall market funding. It indicates the bank's reliance on short-term funding sources such as overnight loans, commercial paper, or other short-term instruments in comparison to its total funding obtained from the market. This metric helps assess the bank's liquidity and potential vulnerabilities to short-term market disruptions.
STF	Share of short-term funding in total market funding	

Source: own elaboration

precision was assessed using the remaining 20 % of the data. This precision assessment was conducted individually for each country, comparing the neural network's precision against that of a linear model. **Table 4** and **Fig. 2** present these results, confirming the favorable outcomes achieved by the neural network models across all countries. In **Table 4** and **Fig. 2**, 'NN' refers to the neural network models, while 'LM' denotes the linear models.

In **Fig. 2**, the red points represent the predictions of the neural

Table 4
Accuracy of the models.

	Accuracy										
	Austria	Belgium	Finland	Germany	Spain	Greece	Italy	Ireland	Netherlands	Luxembourg	Portugal
NN	0.970	0.989	0.983	0.945	0.968	0.925	0.908	0.997	0.998	0.956	0.847
LM	0.897	0.969	0.634	0.731	0.903	0.917	0.461	0.982	0.301	0.947	0.363

Source: own elaboration

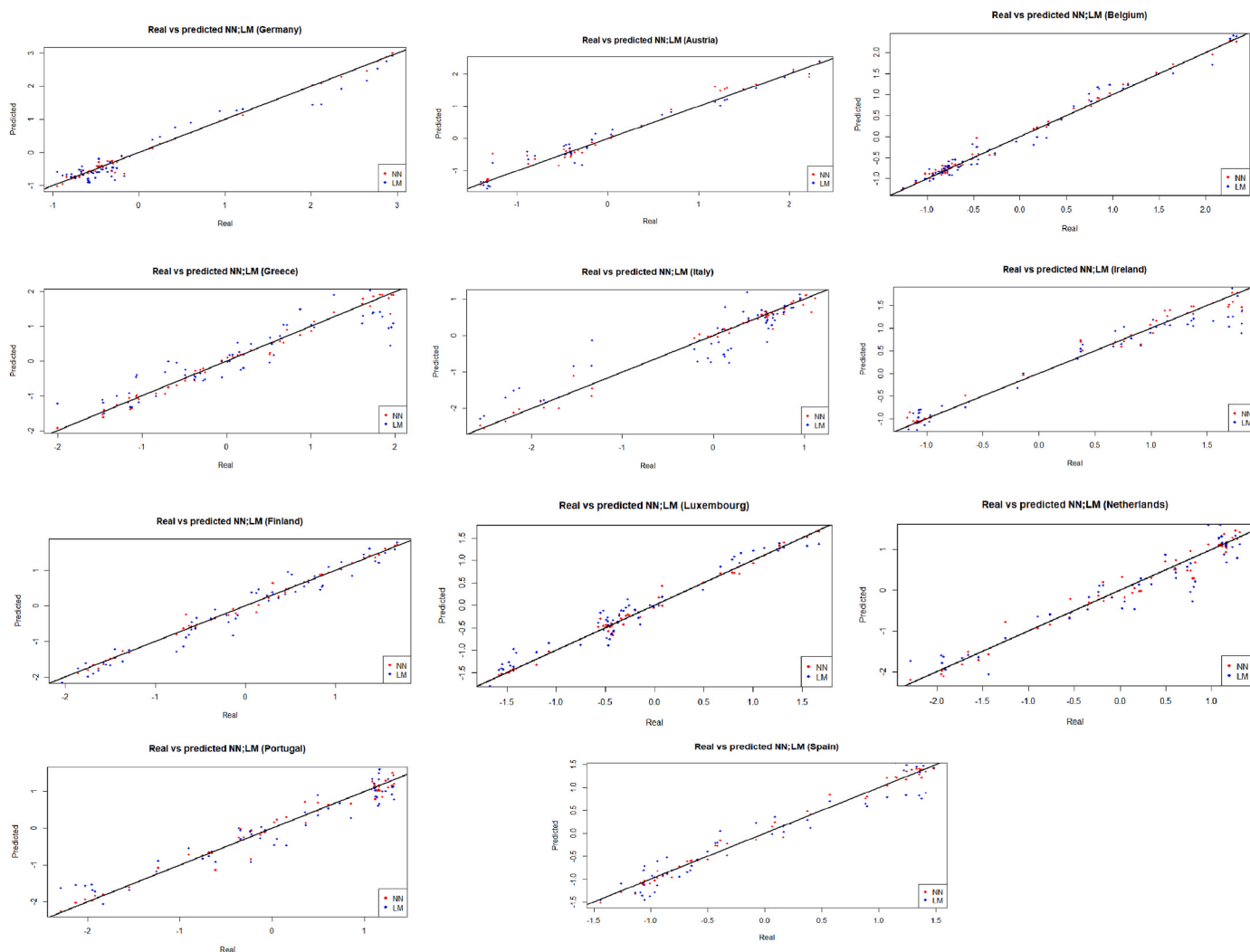


Fig. 2. Accuracy of the models.
NN refers to neural networks and LM to regression.
Source: own elaboration

networks, while the blue points represent the predictions of the linear model. It is evident that the neural networks produce a better fit.

The results are presented below for each of the 11 countries in the euro area, for which the analysis is carried out. In Fig. 3, the weights for monetary component 2 (based on the olden algorithm, see note 8) are depicted for the 11 neural networks created for each country. The countries (in ISO codes) are arranged along the horizontal axis. The countries have been ordered from displaying the most negative influence for the Netherlands to the most positive for Italy (see Fig. 3). This serves to visualize the similarities and differences among the neural networks. This order will be maintained to present the architecture and analysis of the neural networks, starting with The Netherlands, where the sum of weights shows the highest negative value for monetary component 2, and concluding with Italy, where the highest positive sum

of weights for this component is achieved. Choosing component 2 for establishing this order is because it encompasses long-term rates along with the monetary base, aiding in distinguishing divergences in the credit channel effects across countries within the transmission itself. It also enables the observation of two blocks in the transmission of said monetary policy. The countries in red would experience a good transmission because the increases in component PC2 work against loan granting, while the block of countries in green, where such transmission would be inadequate as the component acts positively.

In the country-specific results, three figures are provided to aid in the interpretation of the neural networks. Firstly, the neural network itself comprises an intermediate layer of neurons, using the original explanatory variables as input and the variable being explained, i.e., loans, as the output. In the figure depicting the neural network

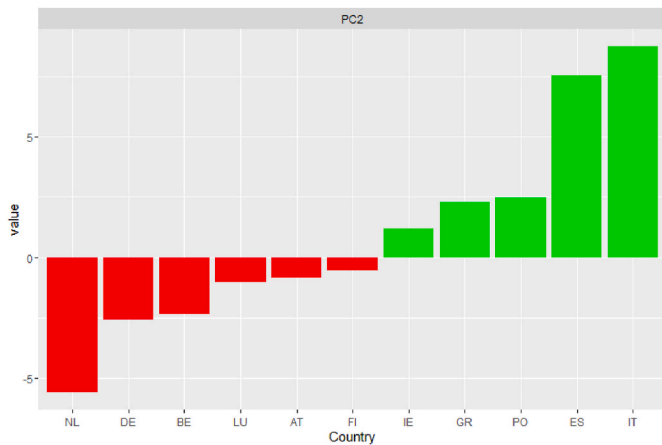


Fig. 3. Principal Component 2 (Weights in the neural networks).

architecture, gray lines indicate negative relationships, while black lines represent positive relationships, illustrating the weights of connections between neurons. Additionally, the Olden graph, employing the Olden algorithm, illustrates the net effect of the explained variable. Finally, the Lekprofile graph provides a sensitivity analysis showing how loans respond to each of the explanatory variables. The lines are grouped accordingly (refer to note 3 for further details).

3.2.1. Neural network for Netherlands

In Fig. 4 (4a), the architecture of the neural network is presented, while in Fig. 4b, for Netherlands, it is observed how the variables the Leverage Ratio (LR) and the lending margins on loans to non-financial

corporations (LM3) have a positive influence. All three Monetary Components show a negative impact on loan issuance. This suggests that both Components 1 and 2 have an effective transmission of monetary policy. The negative influence of Component 3, which deals with direct bank injections, has a negative effect. This could be due to several factors, including internal banking policies, loan demand, or risk perceptions, leading banks to exercise more caution.

3.2.2. Neural network for Germany

In Germany, it is observed that among the margins, particularly the lending margins on loans for house purchase (LM2), is the most important margin in predicting loans (L), having a negative impact (Fig. 5b and c). Additionally, within the margins, it is notable how the variable LM4 experiences the greatest decline compared to other countries (Appendix B) since 2010, potentially indicating a perception of risk in Germany. Regarding monetary components, Component 2 is clearly observed in Fig. 6b and c, displaying a negative behavior and being the most important variable in determining loans. This suggests an effective transmission of monetary policy through this component. For instance, the increase in the monetary base and the reduction of long-term rates have a positive effect on loan issuance.

3.2.3. Neural network for Belgium

The Maturity Mismatch (MM) and leverage ratio variables are the most positively influential in the neural network weights (see Fig. 6a and b); meanwhile, interbank loans (IL) are the variables exerting the most negative influence through the weights (graph 6b). Banks might prioritize lending amongst themselves rather than extending loans to businesses or individuals. Moreover, interbank loans could signal caution or uncertainty in the financial market, leading banks to be hesitant in lending to the real economy if they perceive heightened risks or have

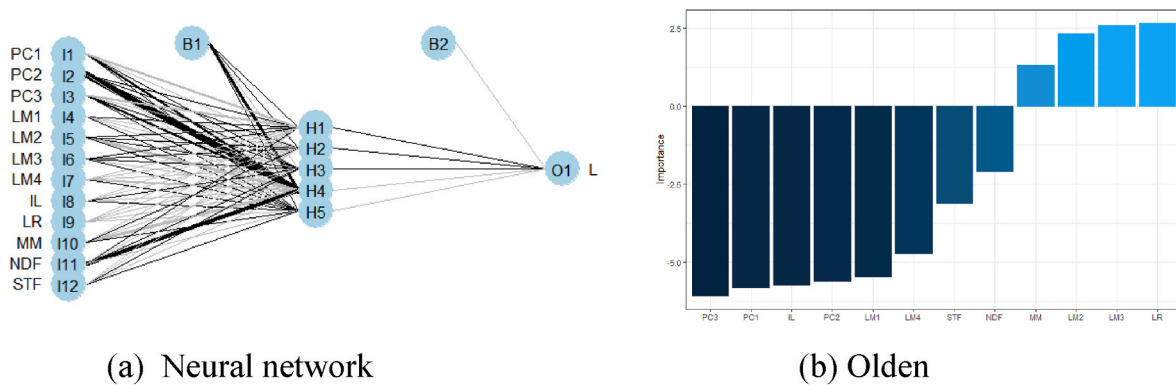


Fig. 4. Interpretation of the neural network of Netherlands. Source: Own elaboration

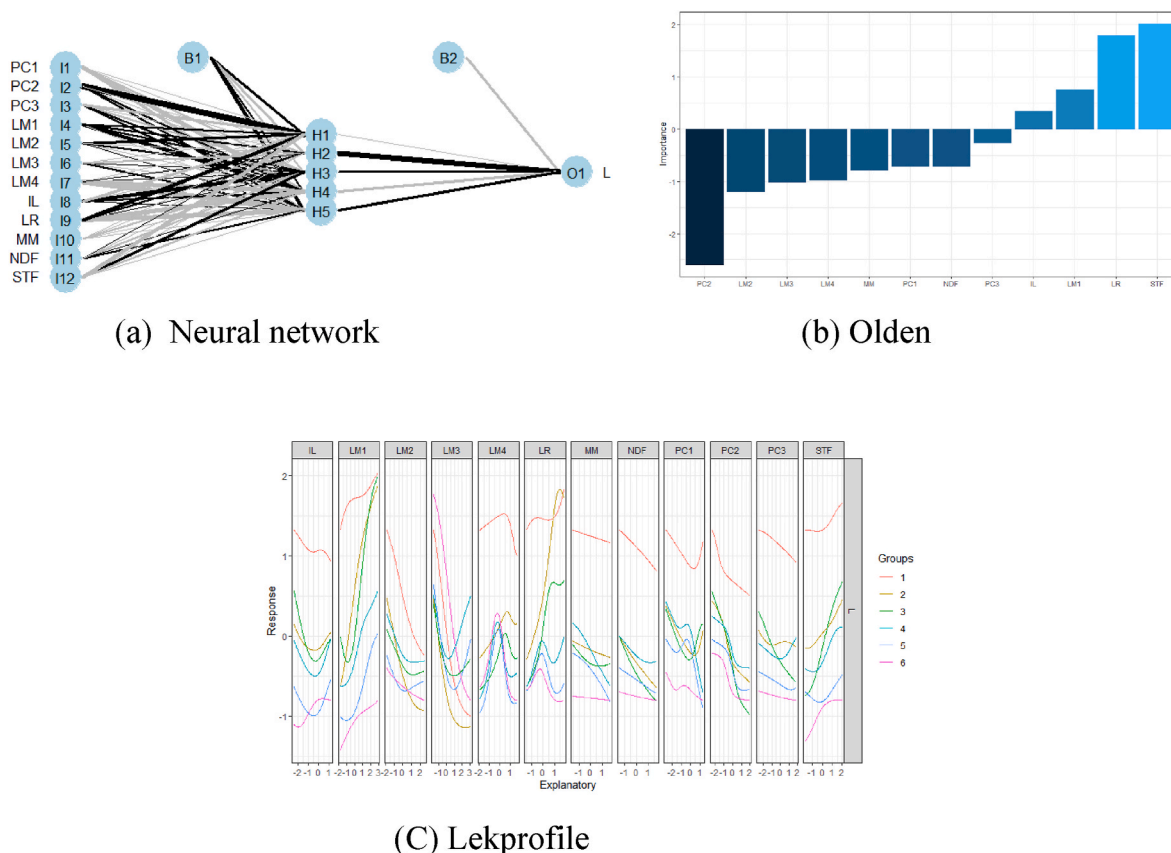


Fig. 5. Interpretation of the neural network of Germany. Source: Own elaboration

concerns about the credit quality of borrowers. Component PC2 holds the greatest negative influence on loan issuance among the three obtained components. In the case of Monetary Component 3 (representing direct injections of funds into banks), a negative behavior is observed in loan issuance, indicating potentially low demand periods or liquidity issues (see Fig. 6c). An effective transmission of monetary policy is observed, as evidenced by the decrease in loan issuance with increases in components 1 and 2, and vice versa (see Fig. 6c).

3.2.4. Neural network for luxemburgo

In Fig. 7, it's observed how the variable Maturity Mismatch (MM) is the most influential variable in determining loans, positively impacting them. It's followed by the STF and LR variables with a positive influence. As a negative factor, the Share of interbank loans in total loans (IL) and the lending margins on loans to non-financial corporations (LM3) show a negative influence on loans (L). For this country, Monetary Components 1 and 2 have a negative influence, suggesting an efficient transmission of monetary policy.

3.2.5. Neural network for Austria

In Fig. 8 (8a), the architecture of the neural network is presented, while in Fig. (8b), for Austria, it is observed how the variable of the lending margins on loans to non-financial corporations (LM3) stands out as the most important in terms of weights in the neural network. The second most influential variable is Maturity Mismatch (MM), its increase results in a greater number of loans. An increase in Maturity Mismatch indicates strategies where short-term funds are used to lend in the long term. This broadens the financial base and improves flexibility, enabling banks to offer more competitive loans. Additionally, the proportion of interbank loans in total loans (IL) emerges as one of the most critical variables in terms of weights in the neural network, negatively

impacting the quantity of loans (L). In Austria's case, interbank loans are observed to have a negative effect on loan approval, possibly due to increases occurring when capital regulations aren't adhered to, resulting in a reduction in loans during these instances. An increase in the variable Lending margin on new business loans to non-financial corporations and households (LM1) negatively impacts loan approvals, indicating a higher perceived risk. In contrast, Lending margins on loans to non-financial corporations (LM3) positively influence loans, suggesting more favorable conditions in this market segment. Regarding the monetary components, a good transmission of monetary policy can be identified, observing the negative influence of monetary components 1 and 2 on loans as these variables increase.

3.2.6. Neural network for Finland

In the case of Finland, it can be observed in Fig. 9 that LM4 (Lending margin on outstanding loans to non-financial corporations and households) is the most important variable in determining loans, acting negatively. Both Component 1 and Component 2 are seen to have a negative influence in Fig. 9 (b) and (c), where the former represents short-term rates, and the latter represents long-term rates. Finland is one of the economies that experienced significant loan growth during the studied period (see Appendix B). There is also an effective transmission of monetary policy observed in this country, effectively responding to the monetary components. The behavior of monetary component 3 can apply the same explanation given for Belgium.

3.2.7. Neural network for Ireland

In the case of Ireland (see Fig. 10), the variables that most explain loan issuance are, negatively, the Lending Margin on Outstanding Loans to Non-Financial Corporations and Households (LM4), along with the leverage ratio (LR), and, positively, Monetary Component 2. However,

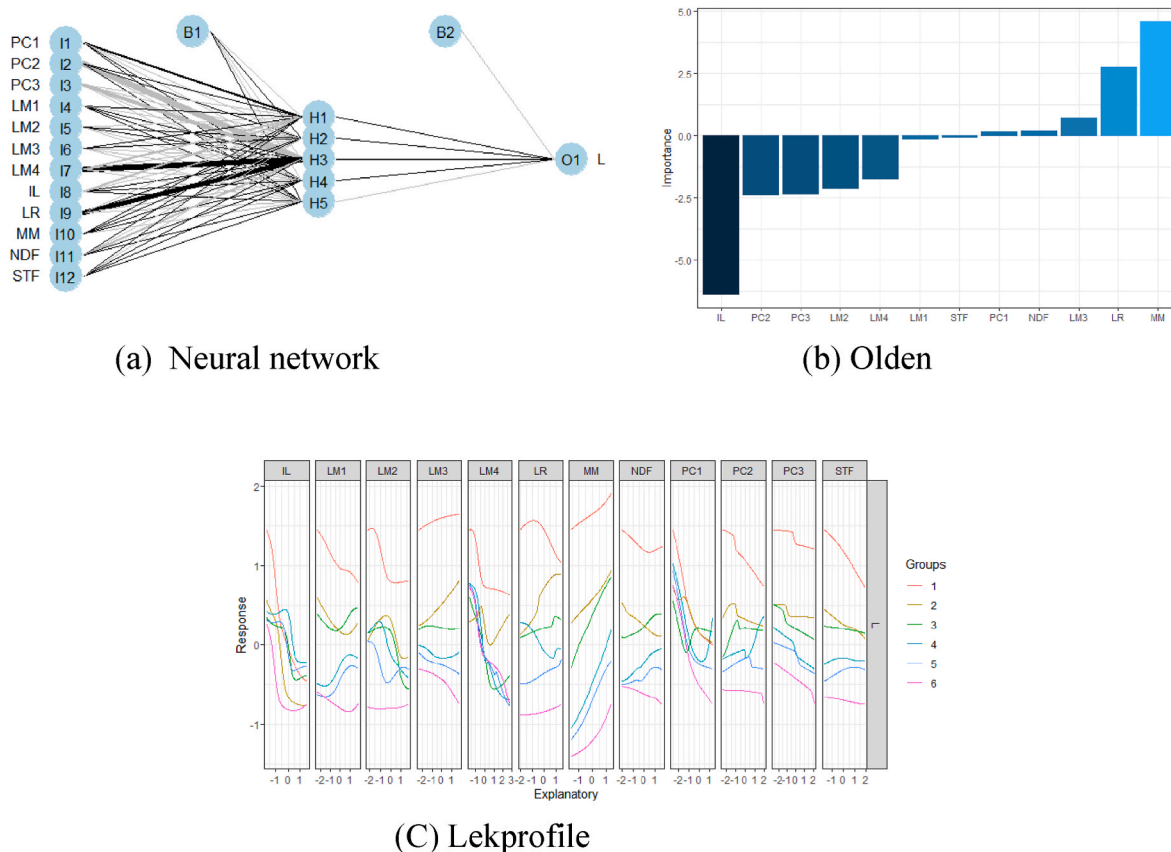


Fig. 6. Interpretation of the neural network of Belgium. Source: Own elaboration

the expected expansive effect is present in Monetary Component 3, representing direct injections of funding into banks. Therefore, an ineffective transmission of monetary policy is observed for this country regarding Monetary Component 2.

3.2.8. Neural network for Greece

In the case of Greece (see Fig. 11), it is observed that the most negatively impactful variable in determining loans (L) is the Lending margin on outstanding loans to non-financial corporations and households (LM4). Greece exhibits the widest dispersion in both its bank leverage and short-term bank funding (see Appendix B). A high proportion of short-term funding can jeopardize the financial stability of banks and limit their lending capacity, as excessive reliance on these funds may lead to liquidity issues and higher financial costs. It is also notable how Monetary Components 1 and 2 exert a positive influence, suggesting a less effective transmission of monetary policy for these components. However, the expected expansive effect is present in monetary component 3, representing direct injections of funds into banks.

3.2.9. Neural network for Portugal

In Fig. 12, it is observed that the Leverage Ratio (LR) is the most significant variable in determining the dependent variable for loans (L), maintaining a negative significance. Portugal initially displays one of the lowest LR values in the analyzed period, progressively increasing over time (refer to Appendix B). Alongside Ireland and Greece, it stands among the countries reaching the highest LR values. Regarding the monetary components, Component 2 is seen to most positive impact loan approvals, suggesting an inefficient transmission of monetary policy. On the other hand, Component 3 fails to increase the quantity of loans with its increases, possibly due to a prevalence of risk perception

over direct bank injections.

3.2.10. Neural network for Spain

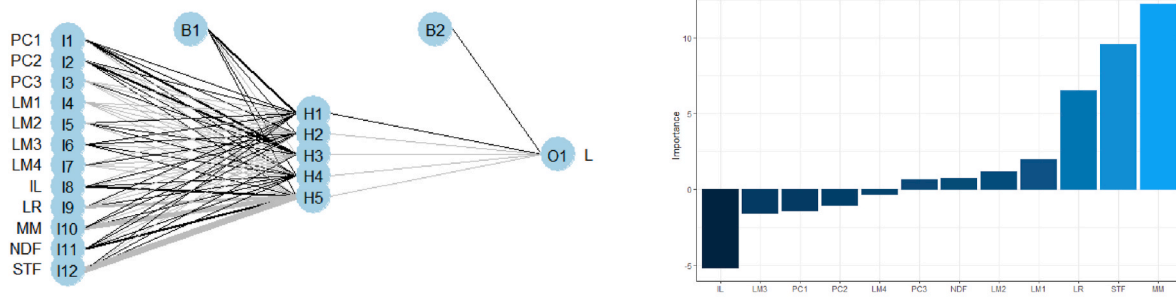
In Spain, one of the main contributors to the reduced loan issuance is the maturity mismatch variable (see Fig. 13). In fact, as observed in Appendix B, this variable has experienced growth in Spain since 2015, currently reaching 80 %. Despite this increase, Spain still lags countries like Belgium, Luxembourg, or Greece, which stand at 90 %. The Lending Margin on Outstanding Loans to Non-Financial Corporations and Households (LM4), as depicted in Fig. 13, negatively impacts credit issuance. In other words, in Spain, banks increase margins based on their perception of risk. The positive variables with the greatest influence on loan issuance in Spain are short-term bank funding (STF) and monetary components 2, indicating a less efficient monetary transmission for those components, as well as component 1.

3.2.11. Neural network for Italy

In the case of Italy, the Monetary Component (PC2), as observed in Fig. 14, is the most significant variable for positively determining loans (L). Negatively, there is the Non-deposit Funding (NDF) variable, being one of the countries experiencing the most significant decline in this variable (see Appendix B). It's evident that in this country, Monetary Component PC2 doesn't result in an efficient transmission of monetary policy.

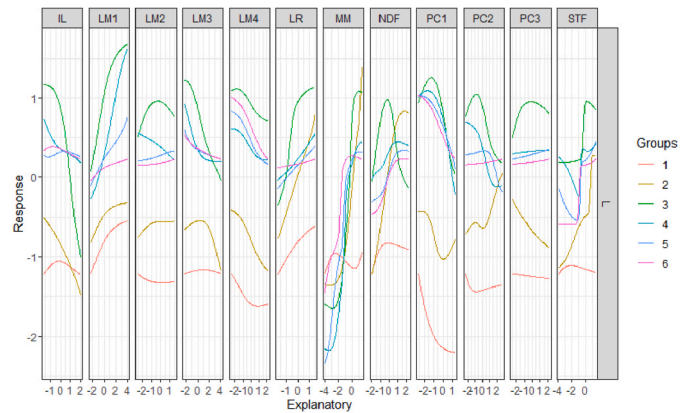
4. Conclusion

The monetary policy of the European Central Bank is categorized using the detrended component analysis methodology. Three components are derived to capture the underlying structure of various variables related to monetary policy. Component 1 includes short-term



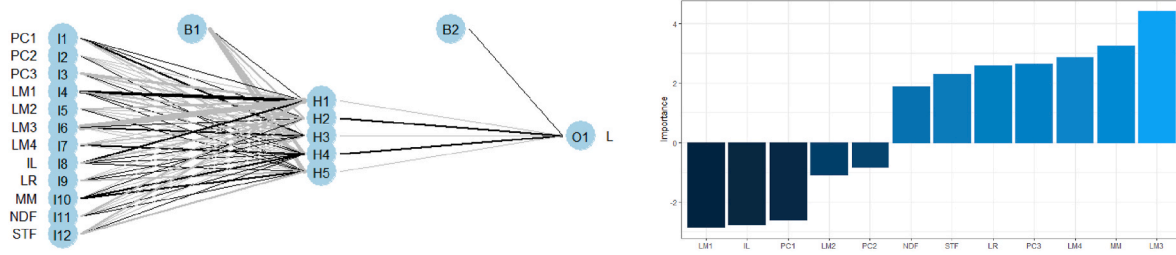
(a) Neural network

(b) Olden



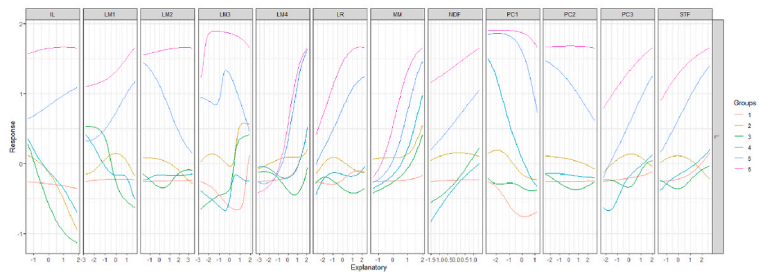
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Fig. 7. Interpretation of the neural network of Luxembourg. Source: Own elaboration



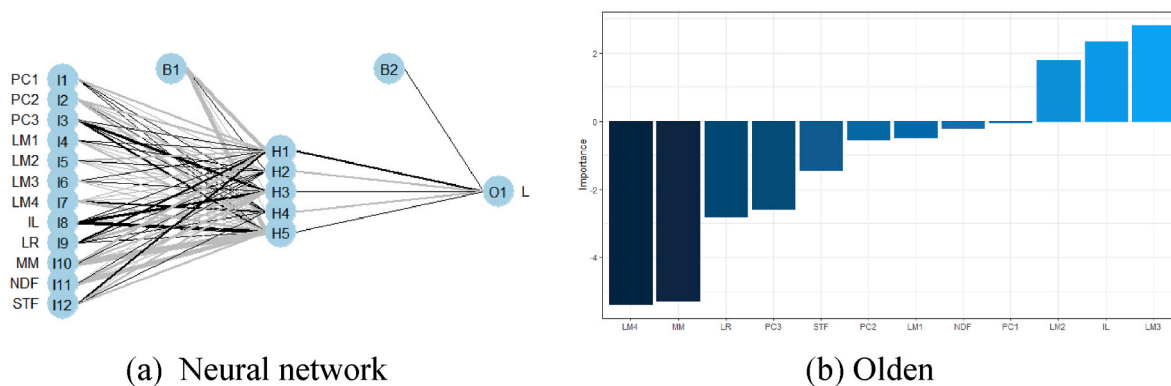
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(b) Olden



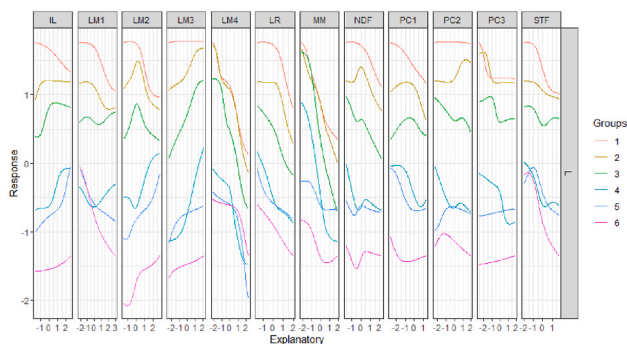
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Fig. 8. Interpretation of the neural network of Austria. Source: own elaboration



(a) Neural network

(b) Olden



(C) Lekprofile

Fig. 9. Interpretation of the neural network of Finland. Source: Own elaboration

interbank rates and short-term bond yields. Component 2 comprises long-term bond yields, elements in the ECB’s balance sheet, and the monetary aggregate M1. Lastly, Component 3 encompasses various items in the ECB’s balance sheet, both in assets (bank financing operations) and liabilities (claims on credit institutions, among others), as well as the monetary aggregate M3, and elements in the ECB’s balance sheet such as banknotes.

The effects of the monetary policy defined by principal components, along with other risk measures, on loan approval are determined. Fig. 15 provides a summary of the variables’ importance in loan determination. The Netherlands, Germany, Belgium, Luxembourg, and Finland are the countries where the loan channel is more pronounced due to the transmission of their monetary policy via the monetary component (PC2). These countries exhibit the lowest average values of the leverage ratio during the studied period; it is observed that lower values enhance the trend of the loan channel. Countries like Greece, Ireland, Italy, and Spain have the highest leverage rates and the widest range of variation. In these countries, there is a poorer transmission of monetary policy for the monetary component (PC2). Regarding the monetary component (PC1), which captures short-term interest rates, it has a negative impact on loan approval in all countries, indicating effective transmission, except for Spain and Greece, where it has a positive influence. In the monetary component (PC3), the cumulative effects in most countries carry a more negative weight, leading to a greater preference for maintaining liquidity, especially during moments of uncertainty or financial stress, when this monetary component is more frequently utilized.

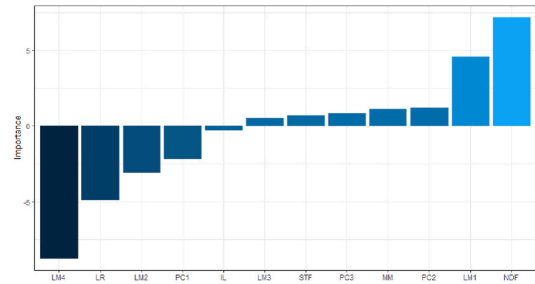
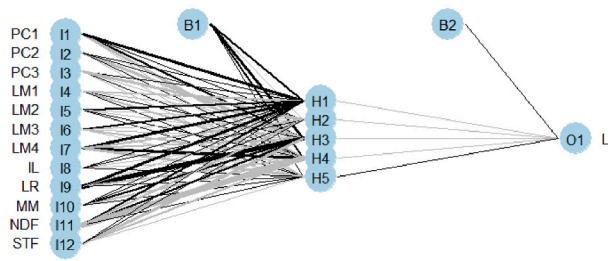
Concerning the risk appetite studied through the influence of margins on loan approval, these margins serve as an explanatory factor that adversely affects loan approval, particularly in the case of LM4, reflecting a notably negative impact for Spain, Greece, and Ireland. It is

worth noting that the LM4 margin decreases in most countries, leading to an increase in loans, signaling a heightened risk appetite in these nations. Conversely, in countries with higher leverage rates, it curtails their risk appetite, and the LM4 margin exhibits an upward trend in recent years. The LM3 margin, which does not take household margins into account, positively contributes to loan approval in most countries, with some exceptions such as Portugal. On its part, the variable of interbank loans shows a negative impact (refer to the summary in Fig. 15) in most countries. This suggests an elevated perception of risk and a shortage of liquidity, consequently influencing a decrease in loan approvals.

The policy implications underscore the varied responses of countries to different monetary components, highlighting the necessity for tailored policies. Some banking systems exhibit greater sensitivity to short-term rates, while others are more responsive to long-term bond yields or liquidity measures. Policies need to recognize and address these sensitivities to optimize their impact effectively. Additionally, understanding risk perception is crucial. Banking systems with heightened risk awareness might require distinct policy interventions compared to those with a more risk-tolerant stance. Aligning policies with these risk perceptions ensures their effectiveness. Furthermore, enhancing harmonization concerning leverage and capitalization aspects within banking systems could significantly strengthen the execution and impact of monetary policies across diverse economic landscapes.

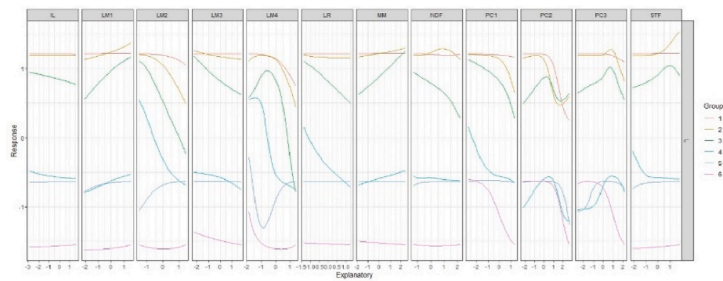
Statements and declarations

- Competing Interests: I declare that I have no conflict of interest with this article
- The article is the result of a research project financed by FUNCAS



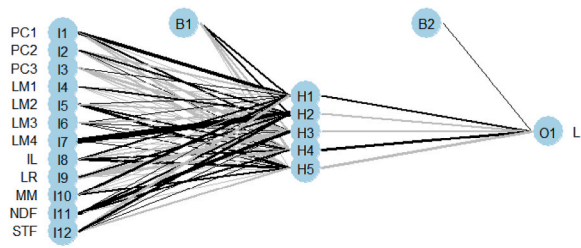
(a) Neural network

(b) Olden

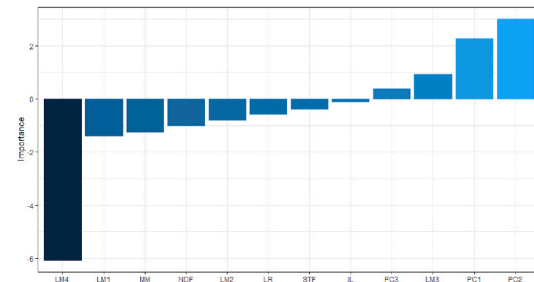


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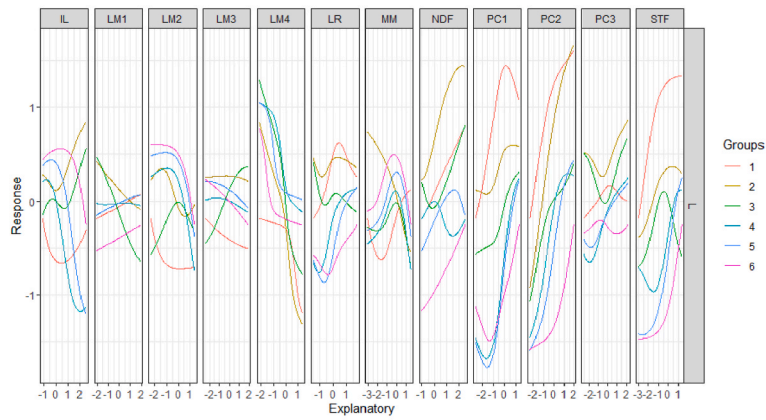
Fig. 10. Interpretation of the neural network of Ireland.
Source: Own elaboration



(a) Neural network

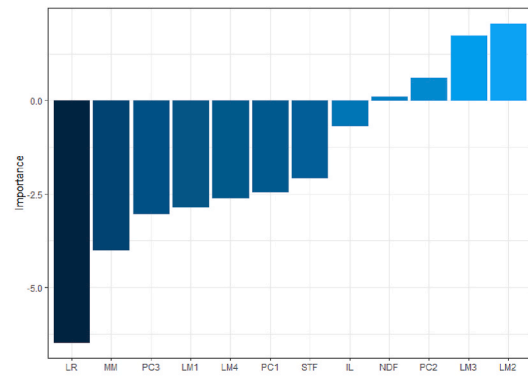
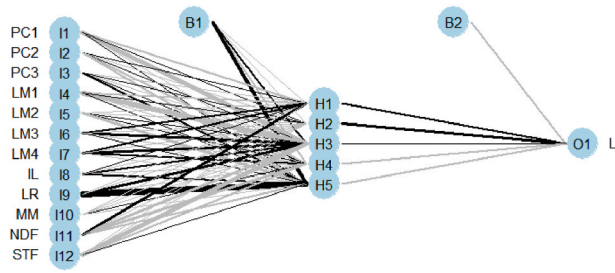


(b) Olden



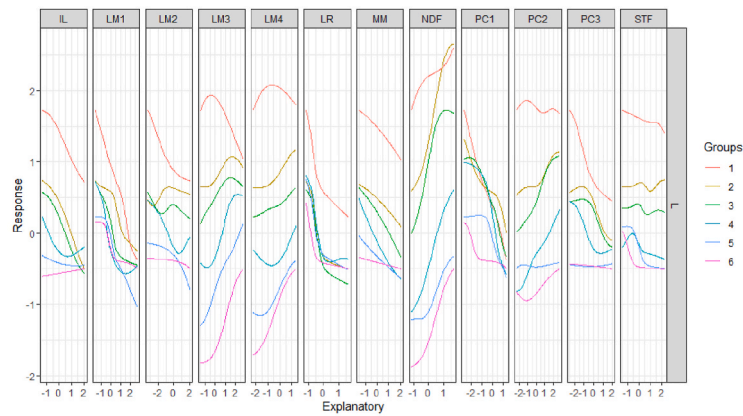
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Fig. 11. Interpretation of the neural network of Greece.
Source: Own elaboration



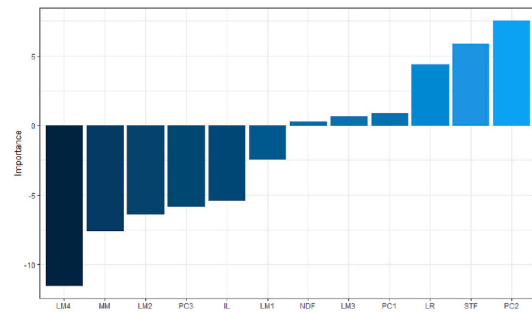
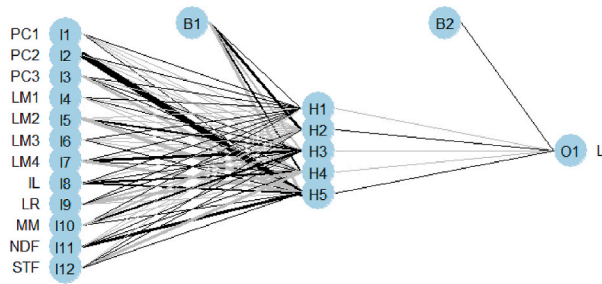
(a) Neural network

(b) Olden



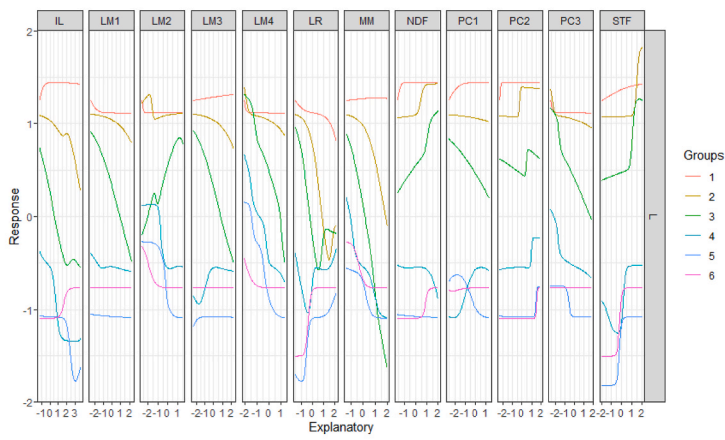
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Fig. 12. Interpretation of the neural network of Portugal.
Source: Own elaboration



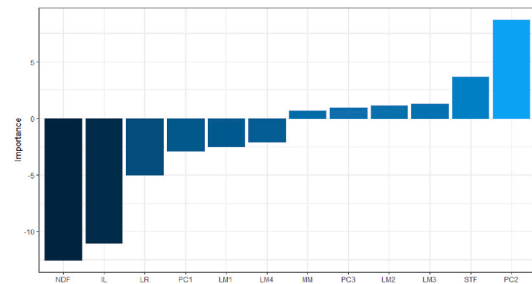
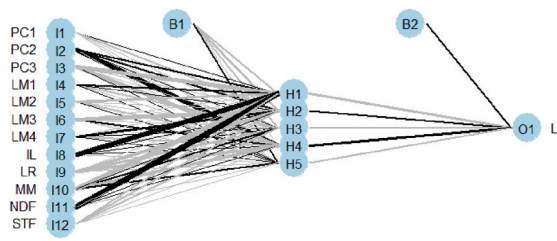
(a) Neural network

(b) Olden



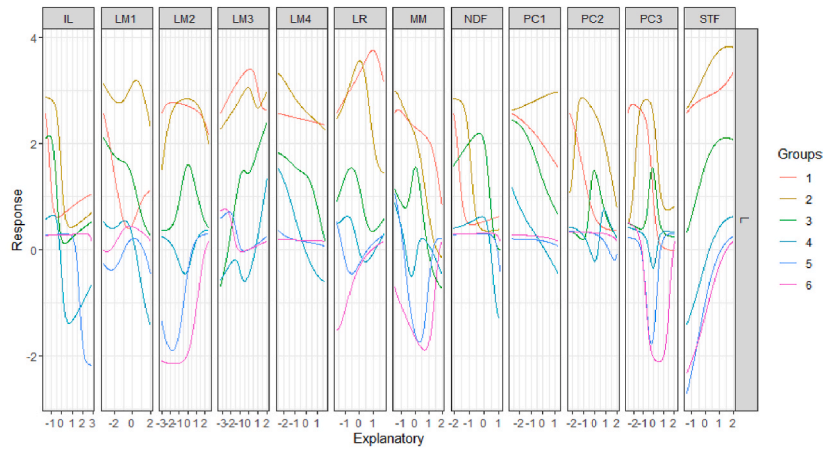
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Fig. 13. Interpretation of the neural network of Spain.
Source: Own elaboration



(a) Neural network

(b) Olden



(C) Lekprofile

Fig. 14. Interpretation of the neural network of Italy.
Source: Own elaboration

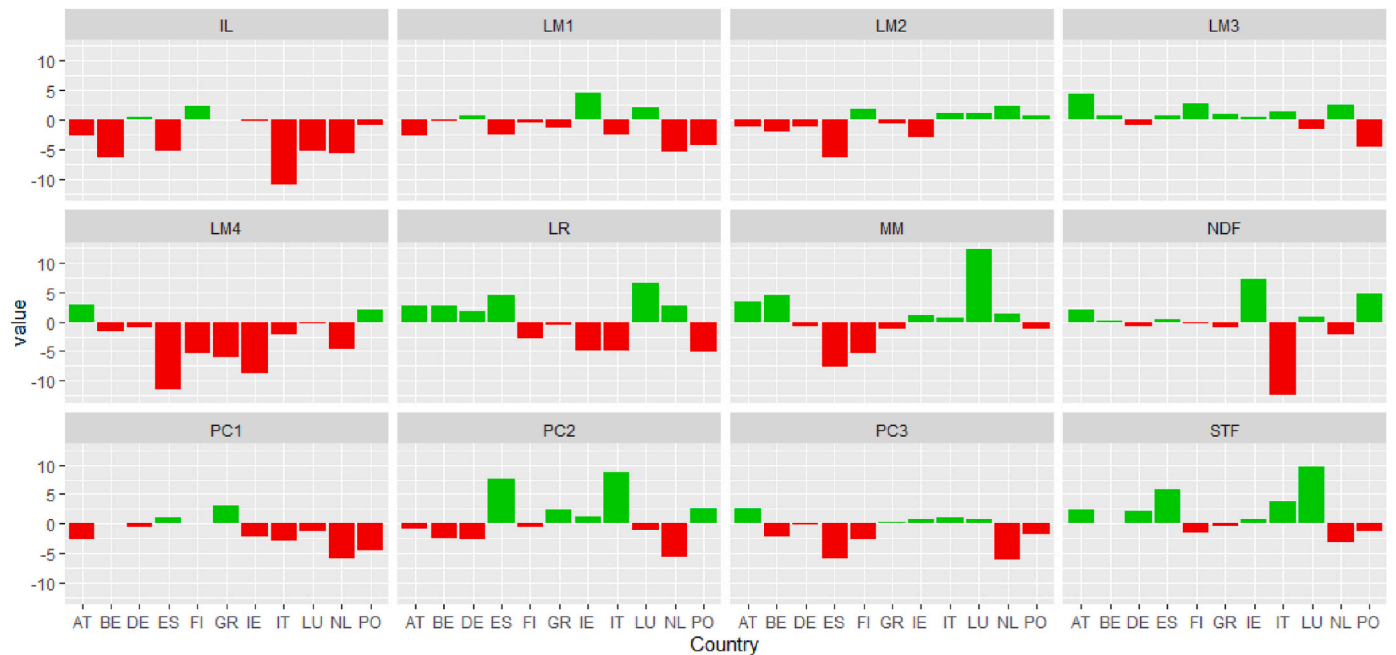
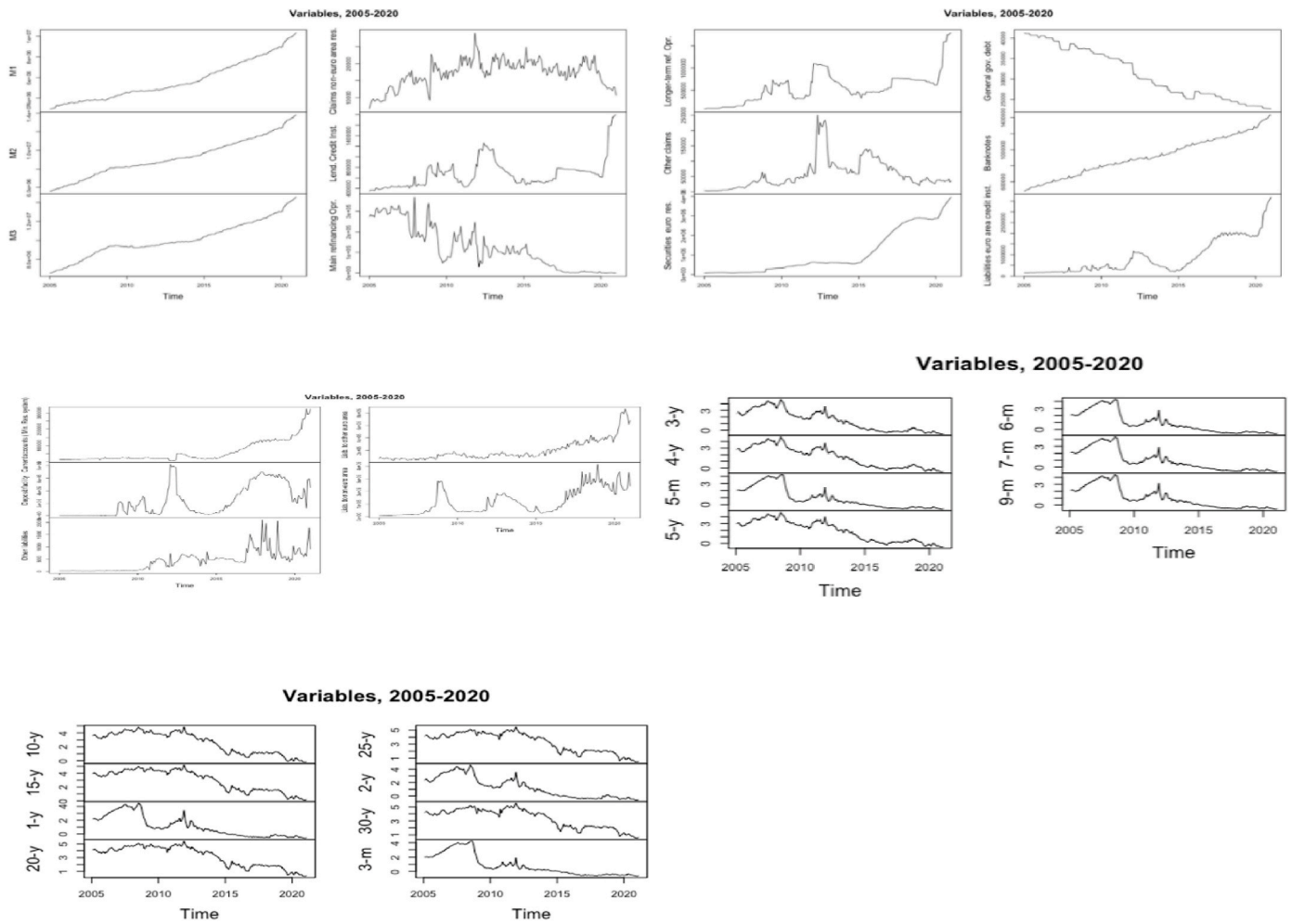


Fig. 15. Summary of important variables of neuronal network.
Source: Own elaboration

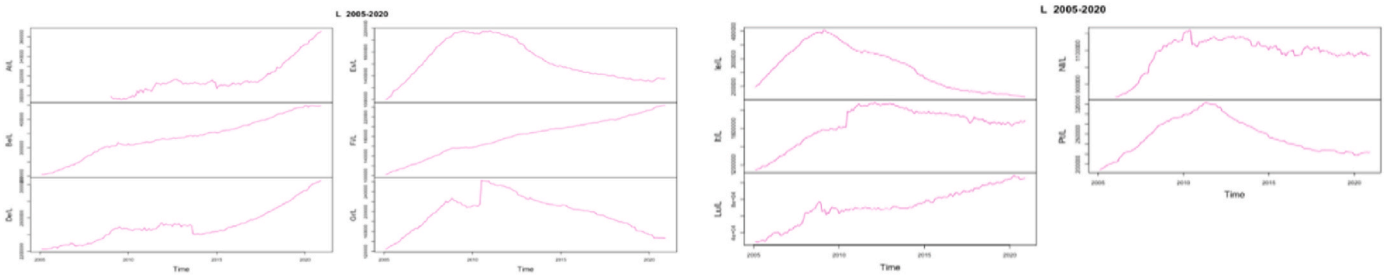
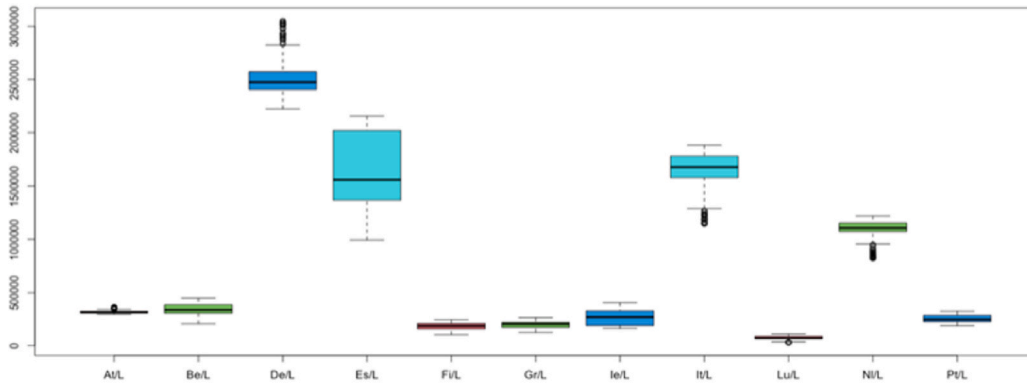
Appendix

Appendix A. (variables component analysis)

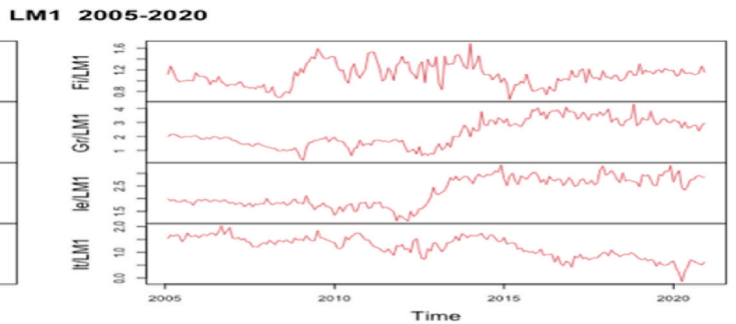
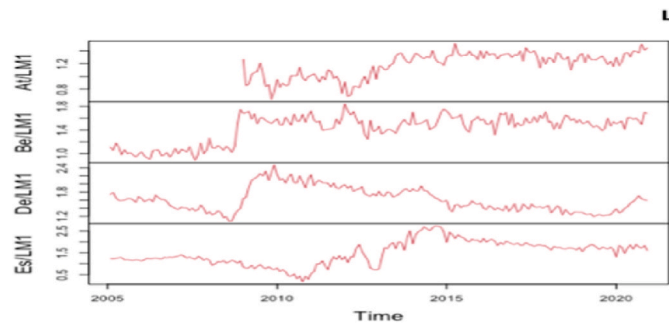
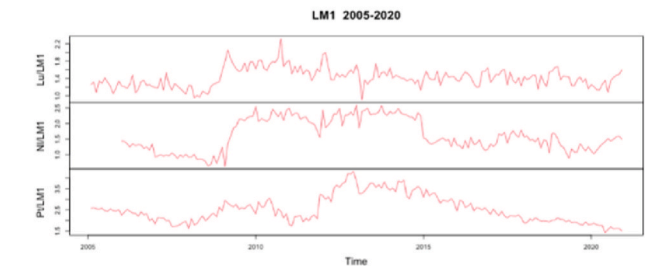
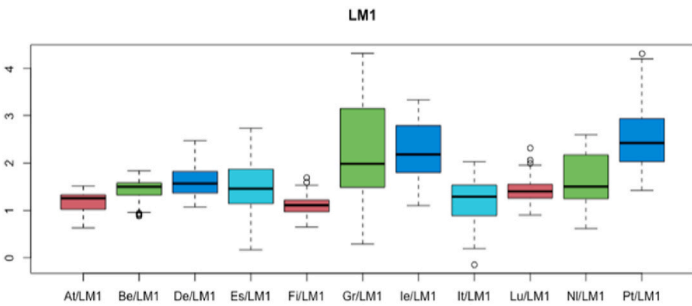


Appendix B. Historical evolution and boxplot of the variables used for neural networks

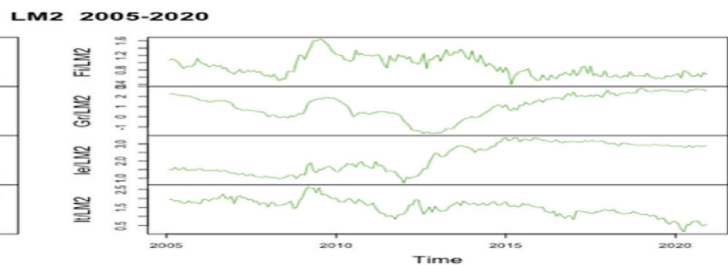
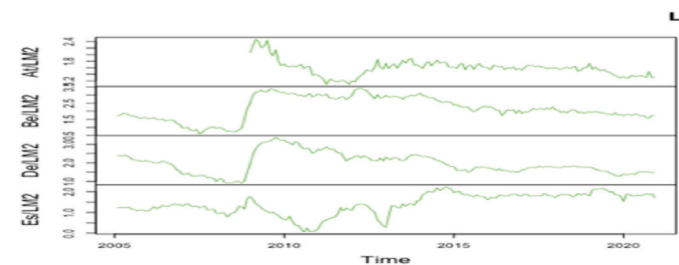
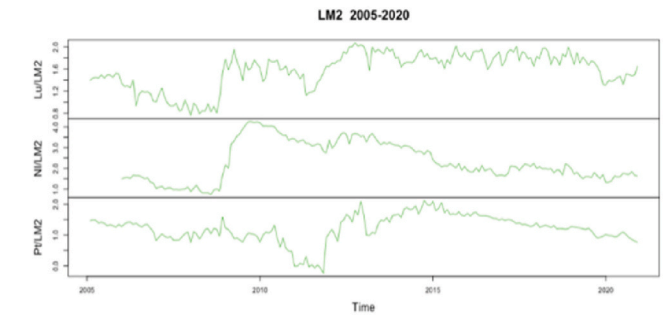
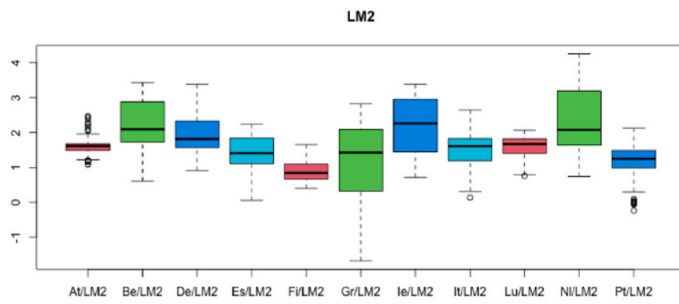
Loans for countries (L)



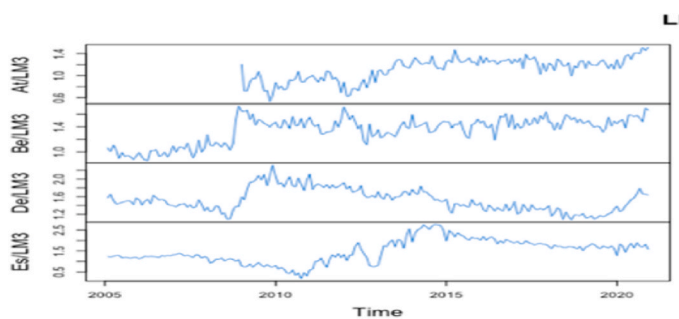
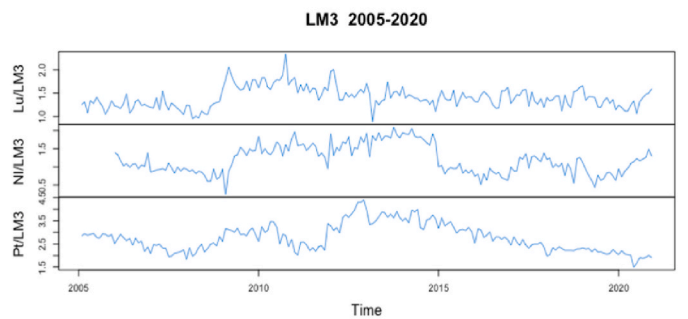
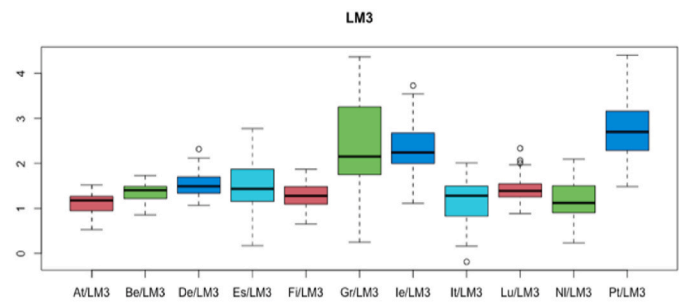
Lending margin on new business loans to non-financial corporations and households (LM1)



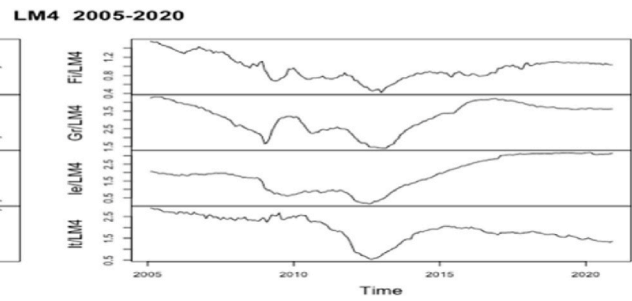
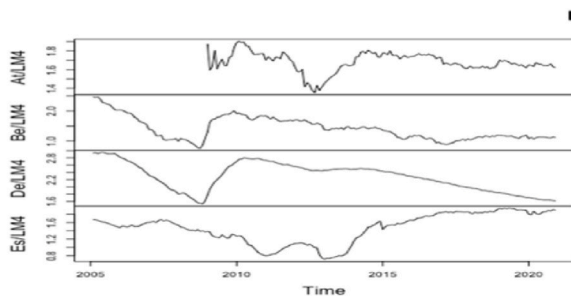
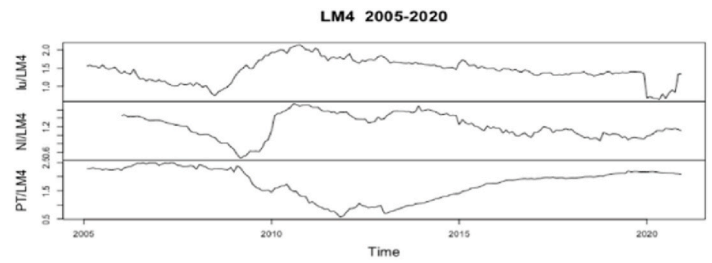
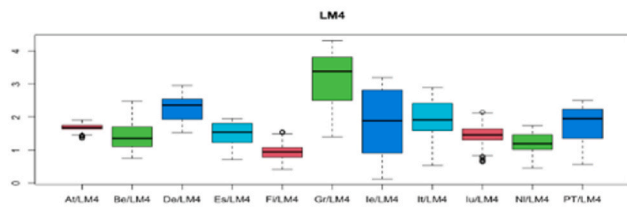
MFIs lending margins on loans for house purchase (LM2)



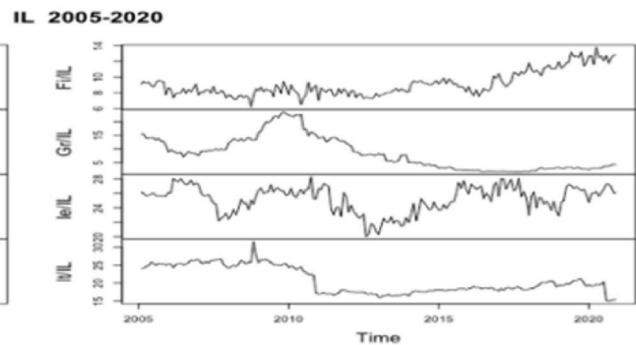
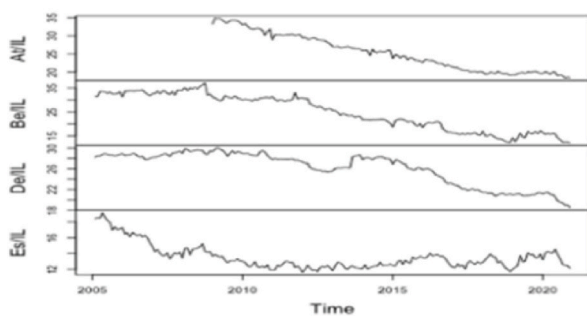
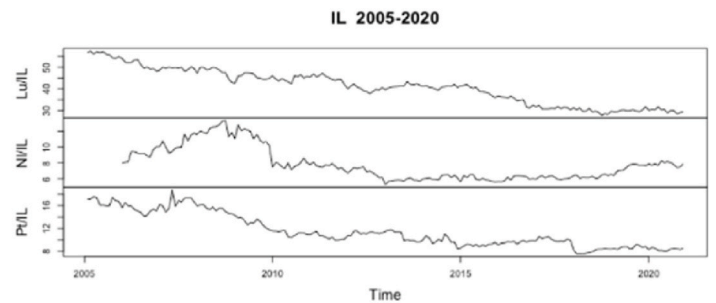
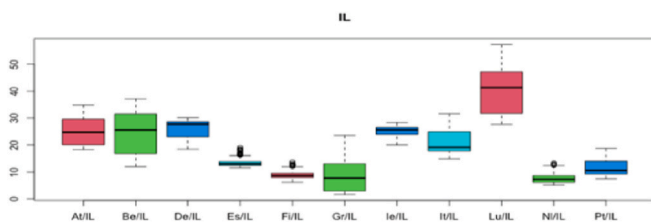
MFI's lending margins on loans to non-financial corporations (LM3)



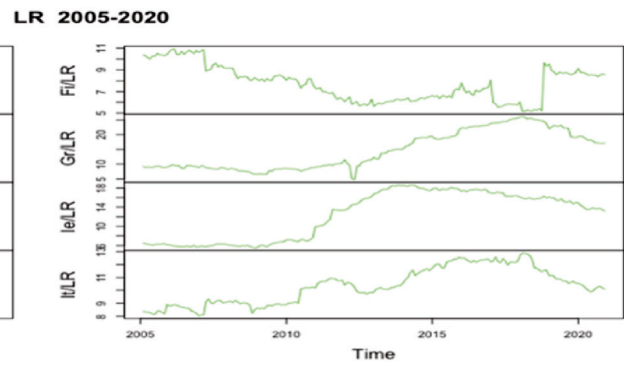
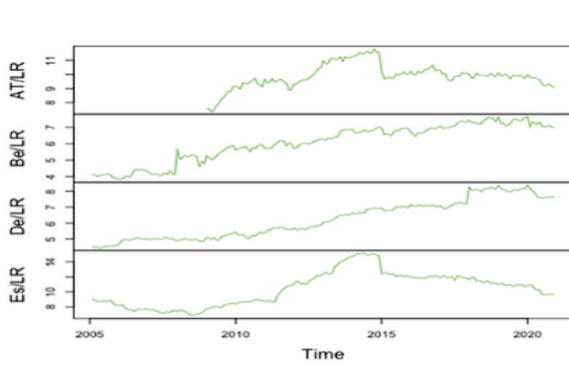
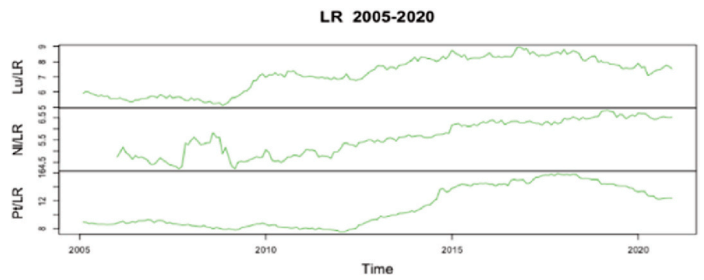
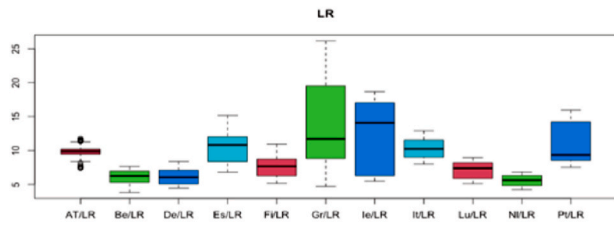
Lending margin on outstanding loans to non-financial corporations and households (LM4)



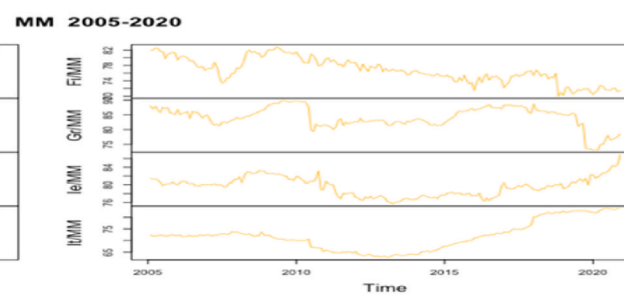
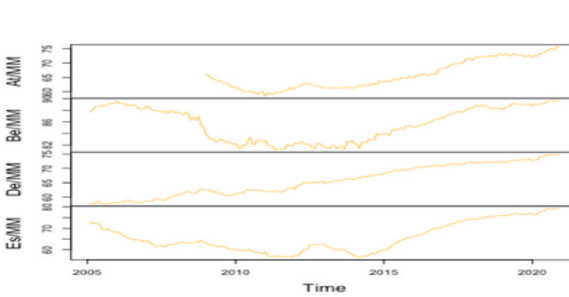
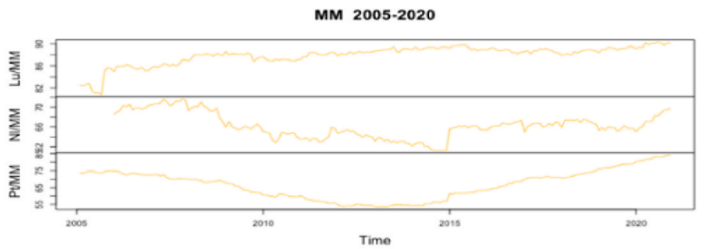
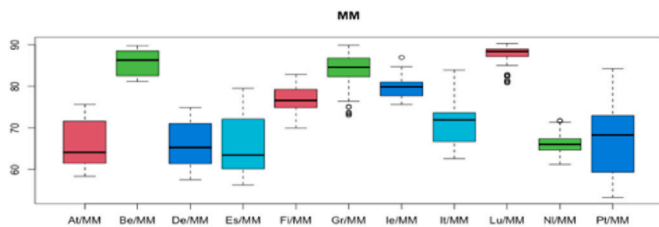
Share of interbank loans in total loans (IL)



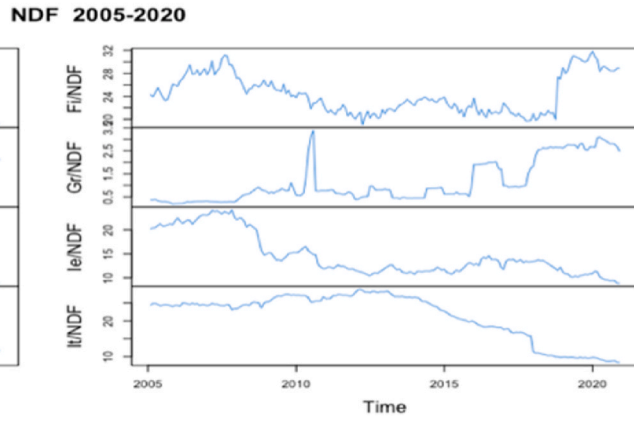
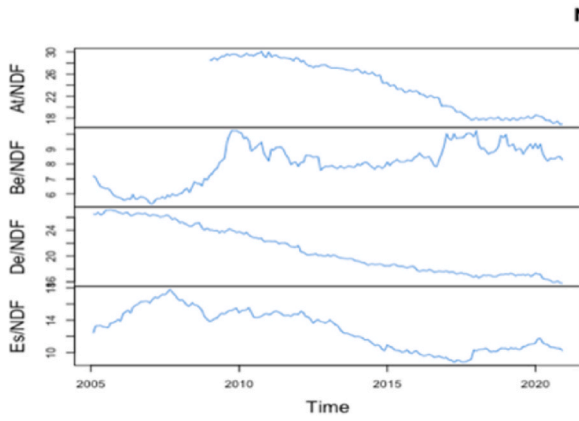
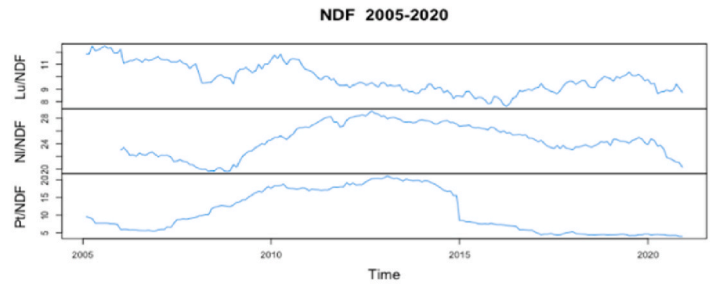
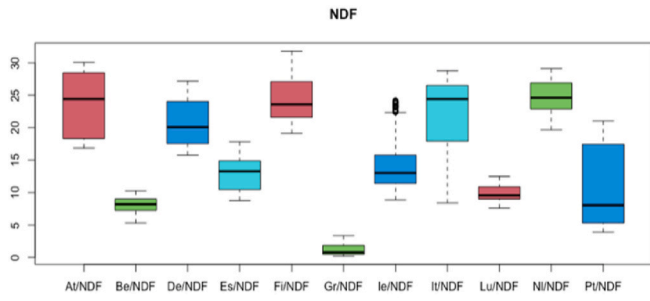
Leverage ratio (LR)



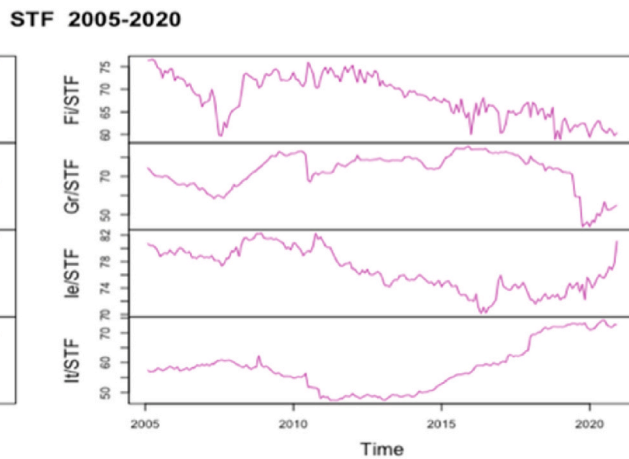
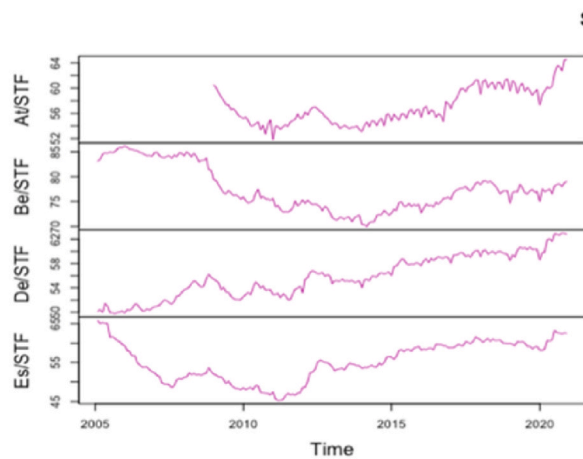
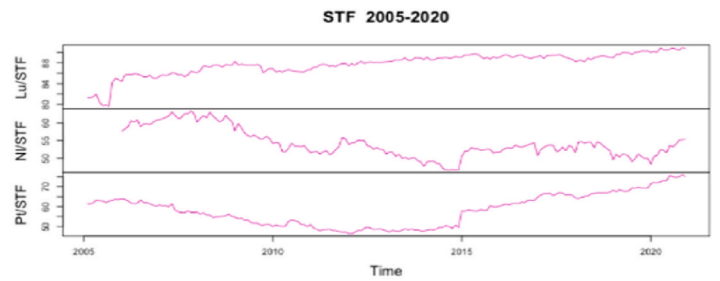
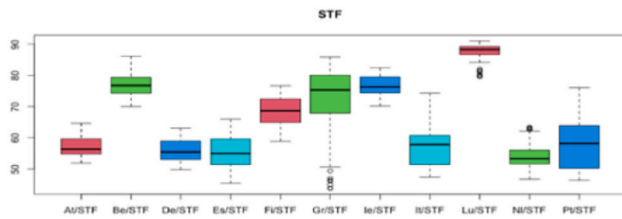
Maturity mismatch (MM)



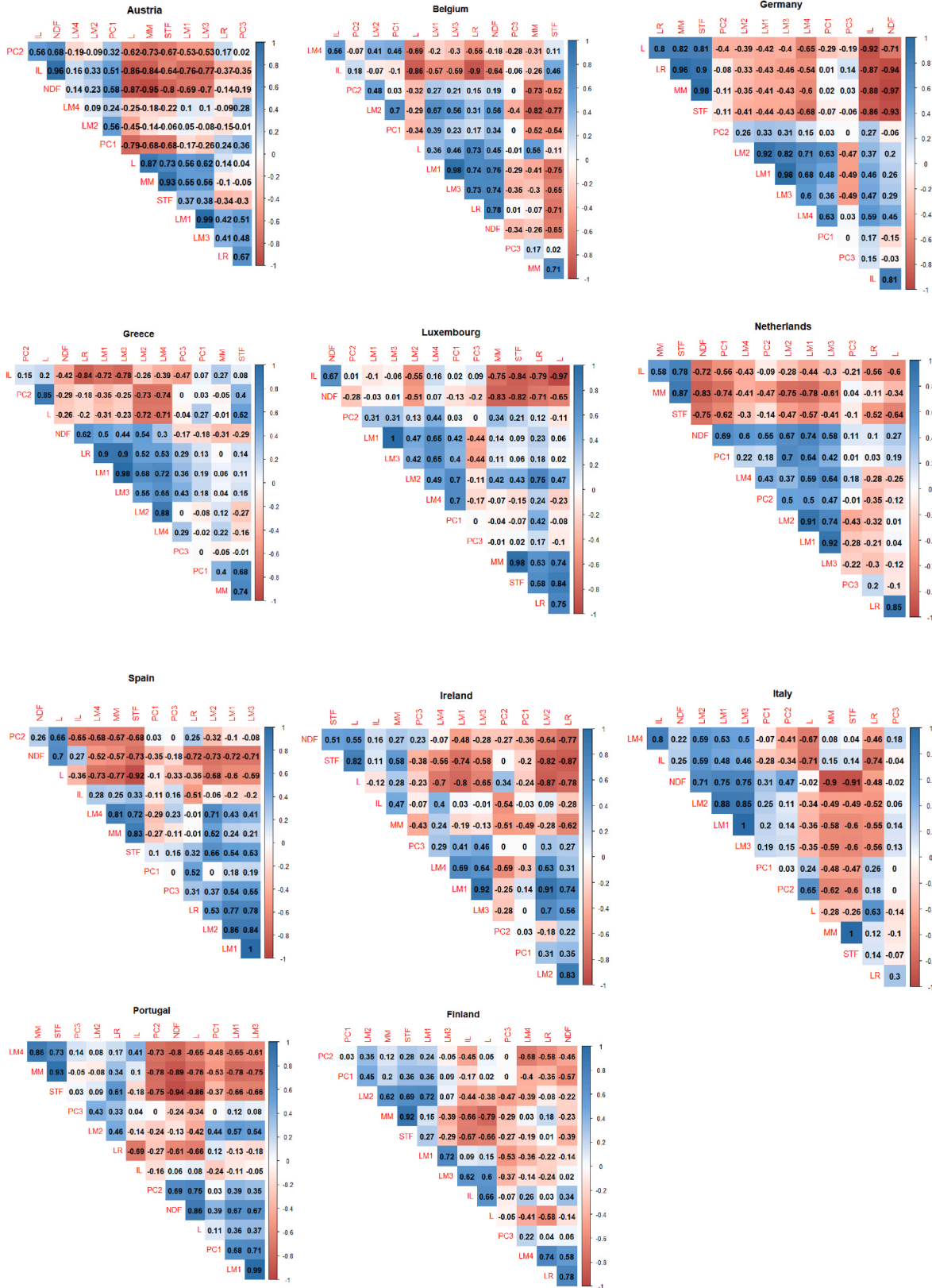
Non deposit funding (NDF)



Share of short-term funding in total market funding (STF)



Appendix C. Correlation matrix



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