Ph.D. THESIS

TITLE: Analysis and forecasting of asset quality, risk management and financial stability for the Greek banking system

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This Ph.D thesis is devoted to my late parents, Nikolaos Kanellopoulos and Maria Kanellopoulos, for their continuous efforts to raise me and equip me with knowledge and ethos. May God bless their souls and may they rest in heaven.

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ABSTRACT

The increase in non-performing loans (NPLs) during the financial crisis of 2008, which has been converted into a fiscal crisis, as well as the risk of a medium-term increase due to the COVID-19 pandemic has put into question the robustness of many banks and the financial stability of the whole sector. As far as the banking sector is concerned, the management of non-performing loans represents the most significant challenge as their stock reached unprecedented levels, with the deterioration in asset quality being widespread. Addressing the problem of non-performing loans with the assistance of credit risk modeling is important from both a micro and a macro-prudential perspective, since it would not only improve the financial soundness and the capital adequacy of the banking sector, but also free-up funds to be directed to other more productive sectors of the economy.

This Thesis extends earlier research by employing a short-term monitoring system with the aim to forecast "failures" i.e. NPL creation. The creation of such a monitoring system allows the risk of a "failure" to change over time, measuring the likelihood of "failure" given the survival time and a set of explanatory variables. The application of Cox proportional hazards models and survival trees to forecast NPLs can be usefully employed in the Greek corporate sectors.

The research aim of this thesis consists of two domains: The first aim is the investigation of the determinants that contribute to the NPLs formation. Two GAMLSS models are being tested, a linear GAMLSS model and a nonlinear semi-parametric GAMLSS model which includes smoothing functions that capture potential nonlinear relationships between the explanatory variables to model the parameters favorably. The explanatory variables of the models consist of credit risk variables, macroeconomic variables, bank-specific variables and supervisory and market variables, while the response variable is the non-performing loans.

The second aim is to provide answers on whether proportional hazards Cox models and survival tree models can forecast NPLs of loans that are provided in specific corporate sectors in Greece by the use of the most granular data set of corporate borrowers. By evaluating a series of Cox models, a short-term monitoring system has been created with the aim to forecast "failures" i.e. NPL creation. The Cox proportional hazards regression models are incorporating time-to-event, involving a timeline, described by the survival function, indicating the probability that a loan becomes an NPL until time

t. The time period counts from the origination of the loan until the “death” of the loan, i.e. its termination, incorporating an “in between” observation point. The event is when the loan is initially being “infected”, i.e. has become NPL. Regarding survival trees, the data set was divided into more subsets, which are easier to model separately and hence yield an improved overall performance. Such models are then beneficial to implement with different machine learning techniques. Predictors (or covariates) are defined as the sectors of the Greek economy and the model is fitted both for the whole sample and for the sample of early terminated loans.

The Thesis is organized as follows: Chapter 1 - Introduction addresses the role of banks in financial intermediation, the evolution of credit risk and some issues regarding the Greek banking sector. Chapter 2 constitutes a literature review on research focused on improving the predictive performance of different credit risk assessment methods. Chapter 3outlines the competitive conditions in the banking sector to demonstrate whether the increase in concentration had affected the competitive conditions in the Greek banking system. In Chapter 4, the funding and the liquidity conditions in the Greek banking sector are being addressed. Chapter 5 contains the selection of aggregate sample, results and analysis of GAMLSS models that have been used for determining NPLs. Chapter 6 provides an introduction to the granular database on Large Exposures, which is used for deriving the panel sample of corporate borrowers whereby models of forecasting and prediction are being employed. Chapter 7 contains the application of Cox models and decision trees, the estimation procedure, parameters, model fit, estimation results and empirical findings. Chapter 8 provides an evaluation and applicability of models as well as the implications for further research. Finally, a conclusion is provided by summarizing my contribution to the research community and my recommendations to the banking industry.

CHAPTER 1 Introduction

The activity of banks is associated with risk-taking. Whenever a bank makes a financial decision on an investment, it is highly likely that the counterparty may breach the obligations. This uncertainty affects its asset valuation, though the bank has all the necessary tools to assess the risk parameters and to assess the potential loss. It can proceed to a write-off of a claim which, under normal conditions will be absorbed by profitability and increased provisioning. The business model of each bank is structured around this approach and the aforementioned process is the classic treatment of a "bad investment". The approach presupposes that there are no adverse conditions in the macroeconomic environment. In case the external conditions become extremely adverse and the number of defaults increase, it is probable that profitability and the setting aside of provisions to cover risks will not be sufficient for expected loss, so the capital of the bank will also be affected, but if the situation persists, a question may arise on its solvency. The problem could be magnified given the effect of the lack of data on the reliability of the results, while the toxic characteristics of "unhealthy" assets can affect healthy elements in the bank itself.

1.1 The historic role of banks in financial intermediation at a global scale and main drivers for increased risk taking

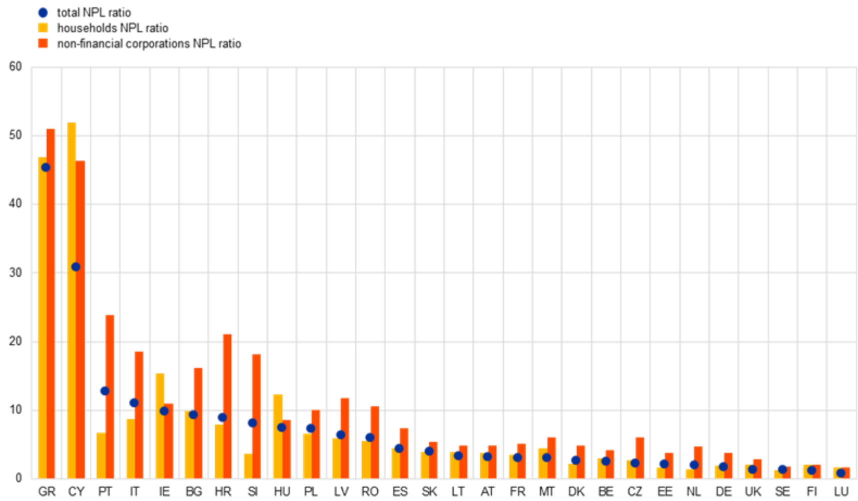
Historically, the difficulties in the business model transitions in European banks (Global Financial Stability Review [145]) as well as the increased legal costs have led to extraordinarily weak earnings results many of the large European banks, while market turbulence has also affected other income sources, especially trading income results and wealth management. The Return on Assets for European banks ranges to low structural levels between 0.25% to 0.50%, being lower in comparison to about 1% for U.S. banks. Accordingly, the weak banking profitability in the euro area increases the difficulty of dealing with non-performing loans due to the reduction of the banks' capacity to build capital buffers through retained earnings (Global Financial Stability Review [145]). The elevated levels of non-performing loans in many banking systems is a sign of structural weakness.

The increase in non-performing loans affects economic decisions, such as investments, the conduct of the undertakings, consumer behaviour, loan behaviour of banks etc., and may lead to the credit stagnation. In such an environment, the ability of banks to move forward with active management is limited, especially when it is expected that they will meet the market demands, i.e. increased margins, and supervisory response in terms of an increase in the capital requirements.

The financial crisis of 2008, which hit the global and the European economy, capital markets and banking industry, had a profound impact on the increase in NPLs. As shown in Figure 1.1, debt levels increased significantly in some EU countries, (see Castellani, S., Pederzoli, C. and Torricelli, C [73] & Castro, V. [75]) making NFCs and households particularly vulnerable to negative shocks to income and/or to an increase in interest rates and/or to a sharp depreciation of the exchange rate.

FIGURE 1.1

NPL ratios by sector in the second quarter of 2018 Source: ECB Consolidated Banking Data



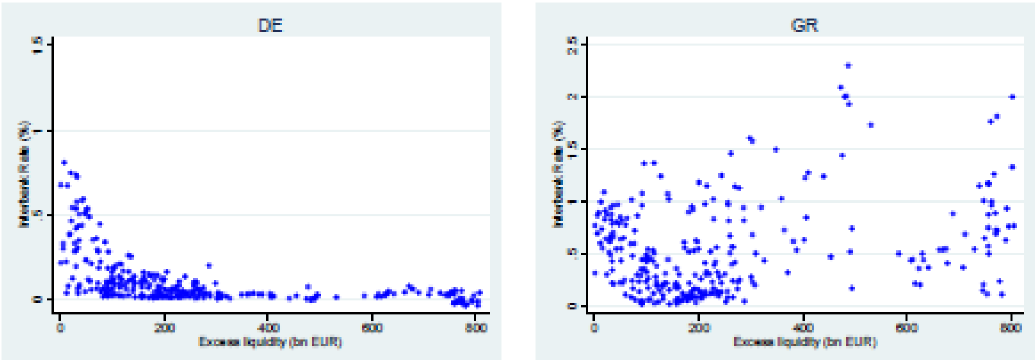
Notes: The NPL ratios are computed as a percentage of total gross loans and advances for the relevant portfolio (total, households or NFCs). Ordered by the total NPL ratio.

Supply factors can be a deterrent for the inability of banks to grant loans to households. Garcia de Andoain et. al [113] conducted a study through which they established that there is an interrelationship between the provisions of excess liquidity and interbank interest rates, although this relationship is not uniform amongst Euro area countries. For example, in Germany, which was the least affected country by the Euro area stresses related to the debt crisis, a negative correlation between excess liquidity and interest rates was observed. In Greece, on the other hand, which was the highest affected country by stresses related to the debt crisis, there is no clear interrelationship between excess liquidity and interest rates (Figure 1.2).

Apart from the liquidity constraints, the inability of banks to grant loans to households is also influenced by demand factors. However, lower lending capacity in conjunction with the inability of the borrowers to repay is contributing to the increase in NPLs. While the key driver of the increase in residential mortgage arrears was due to the sharp rise in unemployment rates, the impact of the increase in NPLs on non-financial corporations was more diverse. As such, certain countries have been affected in specific sectors such as construction, real estate, and hotels and restaurants, while in others the effect was mainly in small and medium-sized enterprises (SMEs) (Kelly, R. and McCann, F. [182]).

FIGURE 1.2

Relationship between excess liquidity and interest rates in Germany and Greece



The main drivers of the system-wide increases in NPLs are business cycle and asset price shocks as a downturn of the business cycle and/or negative asset price shocks may trigger a system-wide increase in NPLs, while in some cases such increases may also be associated with instances of significant resource reallocation within the economy (Anastasiou, D. et. al [23], Bofondi, M. and Ropele, T. [46], Castro, V. [75], Charalambakis, E. [76]).

In addition, the rapid growth of aggregate demand without a corresponding increase in its potential growth translated into large external imbalances and led some countries to a hard landing when the global financial crisis erupted. Inadequate bank practices have also been a driver as they may contribute to the worsening of credit quality throughout the whole lifecycle of a loan if the following steps are not properly managed: origination, monitoring and early intervention (including NPL management at an early stage), and repayment, resolution or disposal. Finally, several structural factors (ESRB [99]) contribute to the increase and persistence of system-wide NPL, such as the legal and judicial systems (ESRB [100]). From a bank's perspective, the effect is through the determination of the contract enforcement and collateral repossession framework as well as pre-insolvency and insolvency laws. From an investors' perspective, complex and overburdened legal systems and judiciary proceedings might also hinder investment in distressed assets.

1.2 The banking capital as value optimizer and credit risk mitigant

The role of regulatory capital in optimizing the value of credit institutions is important given the fact that there is interdependence between the level of regulatory capital and the value of credit institutions. The existence of regulatory requirements has an indirect impact on the level of accounting capital that banks hold, which affects the change in leverage and finally - according to Berger, Herring and Szego [34] - the change in the value of credit institutions.

The empirical analysis of supervisory own funds leads to the conclusion that the higher level of own funds is associated with a decrease of banking risks. Moreover, from the analysis of banking models, it is demonstrated that an increase in the own funds as a percentage of total assets leads to a reduction in the probability of financial distress (Lane, Looney, Wansley [210], Avery and Berger [20], Cole and Gunther [94]). In the paper, which explains why large banking institutions in the United States hold considerable amounts of equity capital - above the regulatory minimums - (Berger et. all [39]), it is stated that during the period of 1992-2005, observed prices have reached the level of the average in the distribution of Tier I capital. This is explained by the fact that credit institutions that did not have very comfortable capital adequacy levels, they undertook measures in order to increase their capital adequacy ratios. Also, credit institutions which were adequately capitalized, undertook measures to reduce their respective ratios. Nevertheless, in all cases credit institutions have maintained a "capital buffer" which was significantly above the minimum regulatory requirements.

The argument that the high level of equity capital can be preserved by capital buffers has been questioned by Gropp and Heider [140]. In their empirical analysis they couldn't find evidence of the impact of regulatory own funds in the optimal capital structure of credit institutions. Unlike Peura and Keppo [246], Gropp and Heider do not support the argument that the excessive capital may be used as a capital buffer in periods of crisis that could prevent credit institutions to issue new capital at a greater cost in a very shortperiod of time. The empirical analysis of Gropp and Heider demonstrates that despite the fact that credit institutions with higher profitability levels - that distribute more dividends - are the ones that are expected to have a lower cost of capital, such credit institutions maintain lower levels of debt and more equity. In spite of all the aforementioned, even Gropp and Heider believe that there is some impact of regulatory capital on the optimal capital structure. This is constrained, however, only to credit institutions that maintain capital, "close" to the regulatory minimums. They support that the same rules do not apply in this case , hence the impact of supervisory own funds in the capital structure of credit institutions is a factor that should be taken into consideration.

Banks can be financed by measures that do not affect the rights of existing shareholders and creditors (e.g. guarantee of previous debts, purchase of troubled assets, equity injection) and measures that affect the rights of existing shareholders and creditors ("Bad Bank", debt exchange with shares).

The implementation of the precautionary recapitalization measure requires that the pre-measure supervision exercise, which should be carried out, includes two key elements in determining whether a bank can be classified as eligible. First, an Asset Quality Review (AQR) is required to examine the true economic value in relation to the capital strength of the bank and second, the preparation of a stress test. With the latter, it is assessed whether the bank remains financially sound in the long run (going concern), as well as whether it has sufficient capital when the economic and financial conditions deteriorate in order to be able to finance the economy.

Based on the results of the simulation exercise with the distinction in baseline and adverse scenarios, when a bank has a shortfall of regulatory capital in the adverse scenario, it will be entitled to recapitalization with the participation of the State, after any potential deficit of the basic has been covered by individuals . This deficit in the supervisory funds resulting from the exercise must be considered as the minimum recapitalization amount.

Therefore, the basic assumptions for determining the amount of additional funds for the recapitalization of the banking system concern:

• Possible change in other NPLs and total loans, which will depend on:

• Sales of NPLs under the NPLs securitization and asset protection program in the form of state guarantees (Hellenic Asset Protection Scheme - HAPS) and the participation of banks in HAPS

• the case of application of an additional solution for NPLs

• the impact of the loan moratorium application due to the crisis on the creation of new NPLs and the possibility of extending the measure

• the effects of a crisis on the creation of new NPLs and the possibility of granting new loans

• The potential need to form additional provisions - which will depend on the previous ones - in the context of the application of IFRS 9

• The use of the deferred tax claim

- The amount of the existing capital adequacy ratio and the goal that the supervisor will set
- The participation of the private sector

Elsinger & Summer [109] examined different forms of recapitalization and concluded that the choice of designing a banking system recapitalization policy without using taxpayers' money exists only superficially, as the current recapitalization policies that minimize taxpayer costs will inevitably affect the rights of both shareholders and creditors. On the other hand, the belief that supporting the financial system and the benefits of ensuring financial stability - even with taxpayers' money - is particularly strong in the eyes of taxpayers, as the effects of a deep systemic crisis would have a much greater impact for the economy and society as a whole.

Evaluating the various government intervention options based on their effectiveness, they are ranked according to the amount of capital support required. In addition, provided that the existing shareholders' rights remain intact, the capital injection is the most favorable option for the taxpayer. Buying troubled assets is the second best solution, and debt guarantees are either ineffective or cost - relatively - more expensive. In case a change in the existing rights is required, the cost of the recapitalization is borne by the existing creditors, with the solutions of "Bad Bank" and the debt to equity swap being equivalent options.

Philippon & Schnabl [254] examined the cost of recapitalization and concluded that, since the program is mandatory for all banks, it does not matter if the State intervenes by direct participation in equity (equity injection), buys problematic assets or guarantees the debts of banks, as well as that the three measures require the same cost. However, if participation in the program is voluntary and the private sector is better informed about the quality of the assets, then a direct equity investment is preferred. In such a case, the public sector faces a problem of "self-selection", as banks with lower quality assets will participate in the program, which, however, is offset by the benefit of financing new projects. In other words, Philippon & Schnabl [254] demonstrate that direct equity investment solves the above compromise more effectively than debt guarantees or the purchase of risky assets. Kocherlakota [198] concludes with similar results, arguing that the purchase of problem assets and the direct investment of equity in the bank are equivalent options if the State is able to accurately assess the quality of assets. Conversely, if the information about the bank's assets is questionable, then direct investment in equity is preferred.

The experience of the three recapitalizations of Greek banks during the last decade (2008-2018), totalling 45 billion euros, with different forms of support from the Greek State should undoubtedly act as a guide for assessing the costs and effectiveness of possible state support of the Greek banking sector. This should assess, inter alia: (i) the impact on banks' balance sheets and results, including the quality of assets and capital; (ii) the budgetary impact (e.g. the total expected cost, timing and type of financial support, as well as any potential compensation, i.e. if and how government intervention will be rewarded); (iii) the speed with which these effects are achieved; and (iv) the banks ", etc. (see IMF, 2019).

1.3 Towards a more systemic approach for credit risk management

The smooth management of credit risks depends on the possibility of losses absorption, i.e. the regulatory capital. The impairment of an asset is an element that the bank must recognize and record in the balance sheet totally or partially (write-offs). The write-offs may not be the preferred option, but if there are not enough provisions, banking capital will be affected. Consequently, the first line of defense for a bank is the adequacy of its provisions (coverage of non-performing loans by provisions) and any supervisory intervention tries to sort this out first.

Banks proceed to impairment testing of the value of the claims and shape provisions when they have objective evidence that they will not recover the whole amount in cash for each contract. Of course, there is a degree of discretion, which can be used to reveal information on expected losses or to overshadow the actual loss. The accounting provisions are not always consistent with supervisory provisions and therefore the supervisory intervention aims to bridge the gap and to prevent opportunistic behaviors. If, however, the provisions are not sufficient, the second line of defence in one bank is the existence of capital buffers in order to absorb bank losses with the smallest vibrations. The regulatory framework uses the minimum required capital adequacy as an effective measure and as a lever in the robustness of a bank. Banks have to meet the minimum requirements and calculate a margin security. Basel III has recognized the need to identify with clarity the amount of extra capital cushion, which must be held by a bank, as well as the limits imposed by the supervisory authorities. According to the Bank of International Settlements [51], additional sectoral capital requirements could in principle take a number of forms, i.e. raising the Pillar 1 sector risk weights directly through a multiplicative scalar; raising the floor under risk weights for certain exposures; or imposing capital buffer add-ons.

The micro-level lines of defence create the preconditions for smooth absorption of vulnerabilities that create NPLs, but they have certain limitations, identified primarily from the external environment. In case of adverse conditions, the problem gets different characteristics and escapes from the narrow limits of a bank. In this case central intervention is required to solve the case, i.e. NPLs write-offs share capital increase or transfer of NPLs off - balance sheet to an SPV plus capital enhancement, thus more macro-prudential measures are required.

Therefore, the accumulation of problems requires a more systemic approach. The State can help in this direction with the aim to strengthen the restructuring process of their balance sheets and restore the creditor-borrower relationship and to re-enable the smooth flow of credit to enterprises and households.

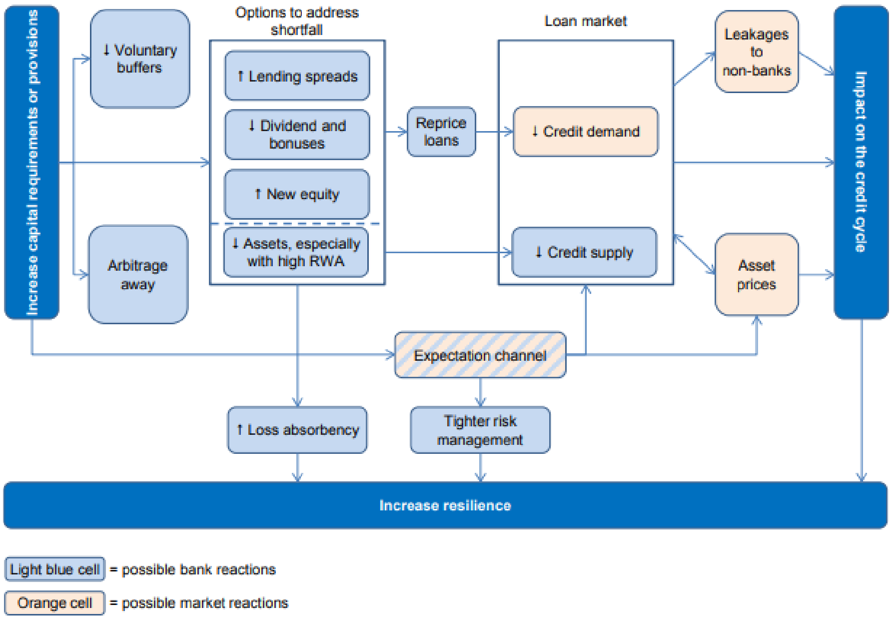
Interventions can be distinguished in two categories: the reorganization with open bank resolution and consolidation with bank closure (closed bank resolution). In the first case, the banks can be refinanced or recapitalized or an immediate intervention in their restructuring portfolios can be implemented, especially if non-performing loans increase significantly. In all restructuring processes, the determination of the optimal capital structure is crucial and will enable the tackling of the non-performing loans in the long term.

Regarding macro prudential measures, a number of specific actions could be helpful to avert an NPL increase caused by a future crisis. In particular, macro prudential authorities should develop short-term monitoring systems to monitor risks of credit portfolio deterioration. Authorities should include borrower-based measures in their national toolkits, given the important role these instruments play in mitigating the vulnerabilities underlying the first stage of the lifecycle of a potential NPL. They should use the countercyclical capital buffer (CCyB) and the systemic risk buffer (SyRB), the latter in particular when the potential systemic increase in NPL flows is associated with developments in specific market segments.

Macro prudential authorities can also use capital measures aimed at addressing excessive exposure concentration when systemic risk appears to be building up in specific sectors/asset classes (Ferrari, S. [117], ESRB [115]). The main transmission channels for capital measures are shown in Figure 1.3. Capital-based measures play a key role in addressing the issue of the underlying unexpected losses associated with the build-up of NPLs. In particular, during periods of economic downturn, the authorities should allow banks to use their capital buffers to address increases in NPLs in a timely manner (BIS [45], ESRB [101]).

FIGURE 1.3

Transmission channels underlying a capital requirement increase. Source: Bank for International Settlements - Committee on the Global Financial System.

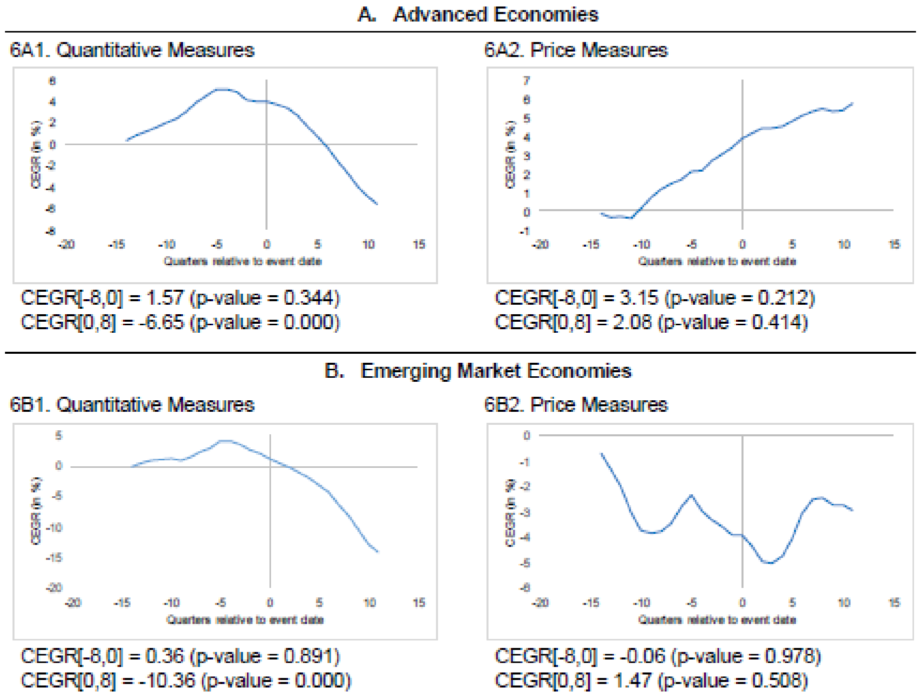


It should also be noted that some capital-based measures can also have procyclical features, as they depend on the level of own funds. Macro prudential authorities should therefore seek to adopt a comprehensive approach by assessing and avoiding procyclical features of this type and, if necessary, by combining different measures with different activation and release timings.

It should be noted that some of the vulnerabilities and structural factors cannot be addressed by macro prudential measures. Nevertheless, they determine the circumstances in which any macro prudential policy approach will need to be developed, possibly conditioning the need for the policy as well as its effectiveness. As such, they merit consideration in the design of future macro prudential approaches to NPLs.

FIGURE 1.4

Impact of macroprudential policies to bank credit



Bank credit	All Instruments	Quantity Measures	Price Measures
All	-7.7***	-8.7***	1.7
AEs	-3.2**	-6.6***	2.0
EMEs	-9.9***	-10.4***	1.5

Note: The Figures illustrate the Cumulative Excess Growth Rates (CEGR) after the activation of macroprudential policies both using the Quantitative measures and Price measures. The table reports the effects both at a comparable level but also in total the effects during the 2- year period following the activation of macroprudential policies, for standard errors * p <.1, ** p <.05, *** p <.01. Source: authors' calculations.

According to Wierts P. et. all [66], the effects from the activation of macro prudential policies on bank credit are statistically significant and generally stronger in EMEs than in AEs (Figure 1.4). In AEs, bank credit slows by 3.2 percentage points below the baseline scenario of two years after the activation of macro-prudential policies, whereas in EMEs the slowdown is close to 10 percentage points. The results both from the activation of quantity-based as well as price-based measures demonstrate that most of the decline in bank credit in both AEs and EMEs comes from quantity-based constraints (contraction of 6.6 percentage points in AEs and 10.4 percentage points in EMEs). This supports the view that quantity limits are more binding than measures that increase the cost of credit. Given that bank credit growth is above the baseline scenario before the activation of quantity-based measures, this suggests that authorities respond to periods of high credit growth by implementing stronger constraints. On the other hand, macro prudential policies based on price-based measures have no statistically distinguishable impact on banks both in AEs and in EMEs.

1.4 The main challenges for the Greek banking system

Greek banks have faced a range of crises starting from the financial crisis of 2008, which has been converted into a fiscal crisis during the period 2010-2018. We are currently facing the COVID-19 pandemic, of a more unprecedented global health nature, with serious consequences for every aspect of daily life, the economy and the financial sector. During every crisis, the ECB and national authorities have taken immediate monetary, supervisory, budgetary and other measures to contain it, protect citizens and mitigate the economic impact. Coordinated action and a decisive response to the economic recovery at EU level is imperative. Facing such challenges for more than a decade, the Greek economy has to move towards a new long-term equilibrium, and consequently towards new adjusted consumer, investment and savings standards. In this context, the role of banks and the financial sector in general, needs to be revised in order to adapt to the new normality. The challenges are multifaceted as each sector of the economy is part of a complex multivariate system of functions, with common factors, a particularly high degree of interaction between them, and many unknown terms, both on the demand and the supply side.

In this context, the main and immediate priority is the financing of the real economy and ensuring the stability of the Greek financial system.

According to the Bank of Greece Financial Stability Review Special Feature [56], the challenges of the banking sector have been ignited during the last 2 major crises have led to the following consequences: (i) the high stock of non-performing loans (NPLs) with prospects of further deterioration; (ii) the low or negative operating profitability; (iii) the low quality of regulatory capital with the participation of deferred tax; and (iv) the macroeconomic outlook. The aforementioned challenges need to be addressed simultaneously. Any other proposal for addressing the individual challenges individually will not be so suboptimal, as it will not provide the perspective of a comprehensive solution to the problems and the momentum required to restart the economy.

The goal is twofold, on the one hand to solve the problem of the large existing stock of NPLs as well as the new NPLs that may be created by the Covid-19 pandemic, and on the other hand to address the problem of low quality of regulatory equity.

In this way, the banking system will change its operating model and will be able to substantially finance the real economy, but at the same time to enhance its operating profitability by creating conditions for the creation of internal capital. However, the capital effect of relieving the NPLs problem and improving the quality of regulatory capital may translate into the need to recapitalize the Greek banking sector.

Accordingly [56], the main challenges for the Greek financial system stability, in view of the new normality that has arisen in the context of the current crisis, are:

• the inability to finance the real economy[1] as unemployment rises, the number of companies with low creditworthiness and low prospects for sustainability, while income and average labour costs are revised downwards as a result of the crisis.

• the uncertain outlook for economic activity (both domestically and at European - global level), which is expected to exert significant pressure on the banking sector in the medium to long term.

• The already high cumulative reserve of NPLs. In addition, the already planned actions and the NPLs reduction strategies developed by the banks and the previous positive results on this front, have been abruptly stopped and need a complete reassessment in order to respond to the new reality. Despite the flexible framework for the determination of NPLs by the European Banking Authority (EBA) due to the crisis, the existing high stock of NPLs may increase further during the next period, including moratorium loans.

• Low or negative operating profitability, which limits the ability of banks to generate internal capital, as operating income was affected by increased financing costs and the absence of interest income from new financing.

According to Homar & van Wijnbergen [163], timely and adequate support of banks during the initial phase of the crisis significantly reduces the duration of the recession, highlighting the disruption caused by "zombie" banks and the cost of forbearance. Moreover, according to Brei, M et. All [64], the consolidation of banks' balance sheets by NPLs and the strengthening of bank lending are successful only if the separation of assets is combined with the recapitalization of banks. In this light, it is necessary as a first step to identify the funds that may be required.

[1] By applying a static approach (based on methods for calculating the countercyclical capital buffer (CCyB) according to which the long-term trend of the “credit-to-GDP gap” is taken into account), the financial gap of the Greek economy is estimated at 58.7 billion euros for 2019.

CHAPTER 2 Literature Review

In the recent years, there has been bourgeoning literature on research focused on improving the predictive performance of different credit risk assessment methods and in some instances with some illusion of progress as showcased by Hand (2006). Also important is the fact that research focused on behavioral assessment of existing loan obligors increased, as aforementioned. Even though there is increasing research on behavioral scoring, little research is available on modelling recovery from delinquency to normal performance on loan obligors (Ha, 2010; Ho Ha and Krishnan, 2012).

This Chapter will address the literature on the factors that influence the formation of the NPLs, the research work that has already been done on the modeling of delinquencies by using a series of models. On the basis of this, I will make a comparison between GMM models and my approach using GAMLSS models and provide a justification of is use in identifying the triggering factors for NPL creation. But it will also address the use of time-failure models that have been used to predict delinquencies and compare this with my approach. Even though multiple failure-time data are abundant in the credit risk domain, statistical techniques that do not take into account the subsequent events are commonly used to analyze such data. Applying standard statistical methods without addressing the recurrence of the events produces biased and inefficient estimates, thus offering erroneous predictions. I will thus explore various ways of modelling and forecasting delinquency events on corporate loans. Using corporate loans data from a severely distressed economic environment, I will illustrate and empirically compare extended Cox and survival tree models for delinquency events and contribute to research by providing a comprehensive analysis of how to model delinquencies., To do so, I will use survival analysis in the context of corporate loans by including time dependent variables. In this context, I will take into account the recurrent nature of delinquencies.

To my knowledge, this is the first research to apply survival analysis to model the delinquency of Greek corporate loans, including time dependent variables, while also exploring the determining factors for the formation of NPLs.

2.1 Factors that influence the formation of the NPLs

A number of studies have indicated that there is a relationship between the economic cycle and banks' loan losses and this is very relevant for addressing financial stability. Additionally, the bank specific variables have also played a role in NPL formation in the Greek banking sector. Finally, market fragmentation in the peripheral euro area markets in comparison to the core ones is an important factor that explains the accumulation of NPLs in those markets.

2.1.1 The effect from the macroeconomic environment

Whenever there is a slowdown in economic growth or recession, NPL ratio increases whereas NPL ratio decreases after economic growth. NKusu [237] demonstrated that whenever macroeconomic environment deteriorates, a deterioration which is associated with the decrease in asset prices or high unemployment rates, this is related to debt servicing capacity issues. On the other hand, an improvement in macroeconomic conditions brings about a decrease in non-performing loans. Louzis et. al [218] suggest that in literature business cycle has already been linked with business stability and this has enabled us to study the interrelationship between the macroeconomic environment and loan quality. Apart from GDP growth as a determinant of NPLs which is very well documented in the literature, it is worth investigating macroeconomic variables such as unemployment, as these provide more highlights on the macroeconomic effect on firms and households.

In general, macroeconomic variables with more cyclical characteristics seem to affect more the NPL ratio. Quagliariello [229] found than the business cycle affects NPLs by taking into account a large panel of Italian banks for an extensive period between 1985 and 2002. Beck et. al [38] utilized panel data to investigate the effect of variables that address the macroeconomic environment on NPLs, taking a sample of 75 countries over the last decade. His research concluded that NPLs are inversely related both to the real GDP growth rate and to the share prices, while interest rates are positively related.

2.1.2 The effect from bank lending behaviour variables

Louzis et. al [218] have used a panel data set and investigated that inferior bank management may have negative effects on NPLs. Furthermore, profitability and efficiency indicators may have extra explanatory power on the model. For instance, loan loss provisions may be used for cleaning part of the NPLs in the portfolio or taking a more forward-looking approach associated to the probability of loan losses. In either case, this practice reduces the potential of higher earnings. A short-sighted approach in this respect will not take into account credit risk considerations and proceed to a reduction of loan loss provisions mostly with the potential for increased earnings in mind. As a consequence, past earnings, which normally should have been provisioned for loan losses, may demonstrate a positive relationship to future NPLs. Despite the fact that several studies highlight the presence of the procyclicality of loan loss provisions over the business cycle (e.g. Laeven and Majnoni [202]; Bikker and Metzemakers [36]; Craig et al. [97]), only Bouvatier and Lepetit ([47] and [48]) assess how provisioning affects bank lending. Messai et. al [228] conducted a study of NPLs, whereby they used a sample of 85 banks over the period 2004-2008 from the south European banking sectors. More specifically, they found that the explanatory variables for NPLs are related to balance sheet and P&L items, such as the ROA, the provisions for loan losses and the credit dynamics, i.e. to what extent credit growth accelerates or decelerates; and concluded that banks' provisions are increasing with NPLs. Cifter [77] has investigated the role of bank concentration in financial stability, by taking a sample of Central and Eastern European countries, but did not find any evidence on the relationship between bank concentration and financial stability.

2.1.3 The effect from market specific variables

The drive for the effect of market variables on the NPLs was initiated since the advent of the financial crisis whereby Greek sovereign bond, corporate bond and interbank markets became fragmented as the risk premium paid became too high and therefore it was not possible to get any access to these markets. In general, the peripheral countries have experienced a larger pressure in comparison to the core European markets. Mayordomo et al. [226] conducted a study in the euro-area interbank market. In their study, they found that counterparty risk, economic sentiment and high levels of debt to GDP are important factors which explain that market fragmentation in the periphery is higher compared to market fragmentation in most central euro area markets. Anastasiou, Louri & Tsionas [24] addressed the issue of peripheral market fragmentation and found that the effect from macroeconomic environment and bank-specific variables to NPLs is more profound in the periphery markets as compared to the main euro area markets. They found a significant level of fragmentation in the peripheral markets. The cost of borrowing adjusted for risk also plays a significant role. Nevertheless, core market variables, such as share prices did not seem to affect NPLs.

2.2 Modeling the deliquency by using non parametric models

The econometric models have been using statistical inference tools to estimate the values of a parameter vector in a parametric model. However, non-parametric models are increasingly being constructed on a more frequent basis, based almost exclusively on data with no (or relaxed) underlying distribution assumptions.

2.2.1 The use of GMM and FDML models for finding the determinants of NPL formation

The econometric techniques for parameter estimation in the dynamic panel model have traditionally been based on the generalized method of moments, GMM. Two GMM based methods for dynamic panels have been particularly successful: the difference GMM estimator, which is attributed to Arellano and Bond (1991), and the system GMM of Arellano and Bover (1995) and Blundell and Bond (1998). A likelihood-based estimator, the first differenced ML (FDML), was developed by Hsiao et al. (2002).

Louzis et. al [218] have used the Generalized Method of Moments (GMM) to find the determinants for NPL formation in Greece. In line with the dynamic panel data literature used in the moment conditions as well as the assumption of serial independence of the residuals, they tested the overall validity of the instruments using the Sargan specification test proposed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundel and Bond (1998). The Sargan test for over-identifying restrictions is based on the sample analog of the moment conditions used in the estimation process so as to determine the suitability of the instruments.

Kumar et. al (1998) [195] used GMM to investigate the determinants of NPLs of the Indian banking system for the period 2000-01 to 2015-16. They found that among macroeconomic specific variables, the economic growth has greater impact on reducing the Gross NPLs ratio, whereas expansionary fiscal policy escalates Gross NPLs ratio. Other macroeconomic specific variables, such as stock market index and market capitalization ratio of the stock market have statistically significant inverse relationship with Gross NPLs ratio.

Apan and İslamoglu (2019) [18] investigated the relationship between participation banks, nonperforming loans, gross domestic product, and asset size in the period 2005: Q1-2018: Q2 by using the co-integration, Granger causality tests and regression analysis methods.

Han and Phillips (2013) [157] found that the first difference maximum likelihood (FDML) seems an attractive estimation framework in dynamic panel data modeling because differencing eliminates fixed effects and, in the case of a unit root, differencing transforms the data to stationarity, thereby addressing both incidental parameter problems and the possible effects of no stationarity. FDML uses the Gaussian likelihood function for first differenced data and parameter estimation is based on the whole domain over which the log-likelihood is defined.

Mehic (2021) [227] compares the two methods. Overall, although the FDML has slightly higher bias than the GMM, its high power and correct size makes it a viable option to the hitherto dominating GMM-based methods in most empirical settings. Precision in econometric estimates is crucial for making correct investment decisions. While GMM-based estimators are widely used by practitioners, for instance the one and two step estimators, FDML could be used as an alternative to the GMM when, for example, monitoring for bubbles in equity prices, or for comparing capital structure and payout policy between firms.

2.2.2 The analytical power in the use of GAMLSS models for finding the determinants of NPL formation

Ljung and Svedberg (2020) [217] used GAMLSS models to estimate loss given default (LGD) of non-performing consumer loans. This is a contribution to a credit risk evaluation model compliant with the regulations stipulated by the Basel Accords, regulating the capital requirements of European financial institutions.

In general, Generalized Additive Models for Location, Scale and Shape (GAMLSS) are semi-parametric regression type models, that is, regression is performed for the parameters of the distribution. GAMLSS models are parametric in the sense that they require a parametric distribution assumption for the response variable and "semi" because the modeling of the distribution parameters, as functions of explanatory variables, may include non-parametric smoothing functions. GAMLSS was introduced by Rigby and Stasinopoulos [261] as a way to overcome some limitations related to the Generalized Linear Models (GLM) and Generalized Additive Models (GAM) -see Nelder and Wedderburn [236] and Hastie and Tibshirani [166], respectively. As an example, in GAMLSS, the exponential family distribution assumption for the response variable, which is used in GLM and GAM, is relaxed and instead replaced by a general distribution family, including distributions which are skewed and/or kurtotic continuous and discrete.

GAMLSS as described in Stasinopoulos and Rigby [258] and Stasinopoulos D. M. , Rigby R.A., Voudouris V. and Bastiani F. [267], is an extremely flexible model class which allows the utilization of a wide variety of distributions to characterize the response variable. This flexibility is important, as Rigby and Stasinopoulos [256] showed that both refraining from and incorrect modelling of skewness and kurtosis can lead to distorted fitted percentiles. As a result, this set of methods is well suited to verify the impact of external factors to credit risk levels at the Greek banking system. Macro-models have already provided evidence that both macro-economic and bank-specific variables affect credit risk levels in the Greek banking system, however the GAMLSS model found that only macroeconomic variables with certain cyclical characteristics and certain distributions, such as GDP, appeared to affect credit risk levels.

2.3. The use of Cox models and survival analysis trees for prediction

Previous domestic studies always use financial ratios in the quantitative research of bank loans analysis. However, traditional parametric and semi-parametric analysis has some limitations as credit institutions do not constitute a closed system and can be influenced by the macroeconomic and market environments.

Even by introducing industry-relative ratios and non-financial ratios on traditional models, their predictive power would be significantly improved only if a neural network approach is being used compared to the Bayesian discriminate model.

In 1985, Frydman et al. [121], [122], [123] were the first to use decision trees to predict business failure. They found their decision tree to be a superior predictor of business failure compared with discriminant analysis.

Lane et al. [190] pioneered the use of survival analysis for financial distress prediction in 1986. Their use of the Cox model was empirically comparable to discriminant analysis but with fewer Type I Errors. Similar encouraging results were also found by Crapp and Stevenson [92]. Laitinen and Luoma [200], [201] also used the Cox model, but found it slightly inferior to both discriminant and logit analysis. Shumway [277] used an accelerated failure time survival analysis model that outperformed the traditional techniques in predicting financial distress. More recently in 2008, Gepp and Kumar [138], [139], [176] found the Cox model to be comparable at equal misclassification costs but inferior in adapting to higher Type I Error costs when compared with discriminant analysis and logistic regression. They have highlighted research questions about whether the proportional hazards assumption of the Cox model is appropriate for financial distress prediction.

The last two decades experienced a shift from static models towards the use of dynamic methods such as survival analysis for credit risk modelling. Among other reasons, survival models have proved to be more informative compared to the other static statistical and machine learning approaches since they do predict not only whether an event will occur but also when it is likely to occur (Tong et al. 2012). Survival analysis also allows the prediction of default probabilities over many different time periods (Einav et al. 2013), thus providing lending institutions important information which facilitates decision making and action taking to prevent default (Lim and Sohn, 2007). It also allows the analysis of the seasoning effects where the probability of default or recovery varies with time as the loan matures (Tong et al., 2012).

Early published research on credit risk assessment using survival analysis methods dates back to Narain et al., (1992). Banasik et al. (1999) further developed the idea using the accelerated life exponential model. A few years later, Stepanova and Thomas (2002) also explored survival analysis methods for personal loan data analysis. In a closely related subject, Whalen (1991) evaluated the application of the Cox proportional hazard model in predicting bank failure. Lando [208] (1994) proposed the use of proportional hazard model to model time until bond default. Henebry [167] (1997) also used the proportional hazard model to assess the role of cash flow variables in predicting bank failure. As noted by Tong et al. (2012), the semi-parametric Cox PH model (Cox, [95] 1972) has been widely used as a survival model in the field. However, there is limited literature on the application of such models in recovery prognosis.

Ha (2010) as well as Ho Ha and Krishnan (2012) successfully used the Cox proportional hazard (PH) model in a hybrid approach to predict recovery of credit cards debts. Overall, their approach showed satisfactory results with good model calibration. However, these studies are different from my approach as they did not address the typical problem of recurrence of delinquency. Furthermore, they focused on discriminating clients based on the potential to recover but did not address the effects of macroeconomic conditions to the overall recovery of obligors.

Mbuthia (2014) [233] designed an improved cox proportional hazard (ph) model to analyze the loans default by customers and thereby reduce the NPLs in order to maximize the net returns on loans. The objectives of the project are to determine the survival time of loans, assess if the survival time differs on the basis of the loan category, study the influence of predictors on survival of a loan and determine to what extent a cox ph model can aid in prediction of the loans default prediction by improving it. The results have shown that account balance and loan classification are highly significant in the improved cox ph model than compared to credit amount and value saving stock in determining the default rates of loans. The study recommends further

studies on coarse classification schemes such as clustering.
Chamboko and Bravo (2016) [83] addressed the area of modelling recovery from delinquency to normal performance on retail consumer loans taking into account the recurrent nature of delinquency and also including time-dependent macroeconomic variables. The findings vividly showed that behavioral variables were the most important in understanding recovery patterns of obligors and point to the need for policy measures aimed at promoting economic growth for the stabilization of consumer welfare and the financial system.

Cox et all [75] use the Cox Proportional Hazards Model, examining the operating and financial characteristics of banks as well as market and economic conditions, to demonstrate what caused US bank failures.

Mungasi [2019] [234] provided a comparison between the Cox PH model, frailty model, and mixture and non-mixture models. He assumed different distributions that were assessed using the AIC, where a lower AIC value indicates a better model fit. The study concluded that the Cox PH model is more efficient in the analysis of Kenyan real data set compared to the frailty, penalized spline, and the mixture cure and non-cure model.

Arents [2019] [19] examined whether the statistical technique of survival analysis (SA) would be applicable in the modelling of the LGL component, used in the LGD model for retail mortgage portfolios of Rabobank. The results show high potential of applying SA in the modelling of the LGL component, used in the LGD model for retail mortgage portfolios.

Belotti et. all [2021] [27] tested a wide set of regression techniques and machine learning algorithms for predicting recovery rates on non-performing loans, using a private database from a European debt collection agency. They found that rule-based algorithms such as Cubist, boosted trees and random forests perform significantly better than other approaches.

Joubert et. all [2021] [179] adapted the DWSA method (used to model Basel LGD) to estimate the LGD for International Financial Reporting Standard (IFRS) 9 impairment requirements by making use of survival analysis to estimate the LGD. The proposed survival analysis methodology to produce the IFRS 9 LGD was validated and tested on a South African retail bank portfolio by comparing the empirical and estimated LGD by deciles.

2.4 Purpose and research question of the Thesis

The first research aim of this thesis is to investigate how NPL formation is associated with various external factors according to risk class and predict future cash flows. It explores GAMLSS models for determining the factors for NPL formation and empirically evaluates how these models perform and which of them can be used in practice. It is consistent with the methods used for deriving the determinants of delinquencies, nevertheless I have used NPLs as the response variables and not LGDs. First of all, the use of NPLs as the response variable is more consistent, as all research efforts that have been utilizing GMM models so far have concentrated in using the NPLs as the response variable. Secondly, my approach considers a corporate loan portfolio which is much larger in magnitude compared to the consumer loan portfolio. In addition, it is challenging to adjust the amount of NPLs for loss given default (LGD) and to incorporate such a change in the model due to the lack of data for the distribution of bank loan portfolio exposure and losses by location for a large sample of borrowers. Finally, government loan guarantees may influence the potential losses that a bank may face from assets exposed at potential risk of losses.

I also extend the previous research efforts, by utilizing GAMLSS models to analyse credit risk by means of NPL formation taking into account the impact of macroeconomic and market factors as well. In this respect, I use aggregate data formed from datasets, which provides information on credit risk levels and then use GAMLSS models to investigate whether macroeconomic, bank specific and market factors play a significant role in affecting credit risk levels by borrower, thus prescribing with more accuracy the drivers that affect credit risk levels. The analysis conducted in this thesis incorporates the compound influence of different macroeconomic variables with the explanatory variables concerning the bank-specific characteristics, leading to an improved NPL model performance.

Regarding the variety of models, apart from using a linear GAMLSS model, a nonlinear semi-parametric GAMLSS model was also created, by the use of smoothing functions that capture potential nonlinear relationships between the explanatory variables to model the parameters favourably. To estimate the functions, a method for automatic selection of the smoothing parameters has been used, which is specially developed for GAMLSS objects by Rigby and Stasinopoulos [262]. As some of the explanatory variables included in the model formulation of the parameters were not significant, a variable selection procedure was carried out. In particular, the variable selection was performed using step-wise elimination based on an Akaike Information Criterion (AIC) together with model assessment measured as fitted global deviance (GD). Once the model formulation was identified, the model accuracy was investigated further by performing a residual and prediction analysis to evaluate the difference between observed values and estimated values.

The second element of the thesis attempts to provide answers on the main empirical question on which proportional hazards model can forecast NPLs for loans that are provided in specific corporate sectors. In that sense, reliable and efficient estimation models of NPLs are crucial. The demand for these models is constantly increasing and the effectiveness of conducting credit risk relating business will further increase as these models develop. The forecasting models used in this research include - apart from the industry sectors - the bank size and the loan value amount. Enduring sectors that have a smaller probability of becoming NPLs are the shipping, and the energy sectors, whereas the probability of loans becoming NPLs is magnified by the construction and commercial real estate sectors.

The time-dependent Cox models have been utilized in this research alongside the following lines:

- The Cox proportional hazards regression models have incorporated time-to-event. It involves a timeline, described by the survival function, indicating the probability that a loan becomes an NPL until time t. The time period counts from the origination of the loan until the “death” of the loan, i.e. its termination incorporating an “in between” observation point, i.e. 31.12.2013. The event is when the loan is initially being “infected”, i.e. become NPL.
- The purpose to use Cox proportional hazards models is that it handles “right censoring” and “left truncation”. Right censoring occurs as only some loans will have experienced the event (death) by the end of the panel data period, and left truncation occurs as loans may “die” even before they enter the panel data period i.e. they are not detected. In my case, the data sample is left truncated because most of the loans were issued before December 2013, so some loans may have failed even before the panel data period 2013-2017. So an unknown number of loans have failed before a certain time and the “subjects” didn’t get into the study. Right censoring occurs because loans survive after 2017, which is the end of the panel data period.

- Each loan has been "tagged" to a specific economic sector in accordance with the statistical specification in order to evaluate simultaneously the impact of the various sectors of the economy on the "infection of the loan" and its subsequent "death". Predictors (or covariates) are the sectors of the economy whereby loans have been granted. Loans per borrower have been grouped to sectors according to the NACE statistical classification. Next, I analyze the joint impact of covariates.

Survival trees are the best for making accurate predictions without the risk of violating statistical assumptions. Trees can deal with missing data flexibly, they handle interaction between variables and they can be used in conjunction with other survival methods.

- In this case, the data set was divided into more subsets, by survival trees, which is easier to model separately and hence yield an improved overall performance. Such models are then beneficial to implement with different machine learning techniques.
- One category of trees that have been used is the LTRCIT trees, i.e. LTRC (left truncated right censored based on Conditional Inference Tree). Another category is the Left-truncated Right Censored Relative Risk tree (LTRCART). In each node, we need to choose the optimal predictor on which to split and to choose the optimal threshold value for splitting.
- Predictors (or covariates) are defined as the sectors of the economy and the model is fitted both for the whole sample and for the sample of early terminated loans.
- Compared to Cox models, tree models account for the interaction between variables and this is one of their main advantages compared to the Cox model. Interaction terms are modeled appropriately by decision trees simply due to the way in which decision trees are built. In my research for LTRCIT, I have found an interaction between Shipping and Energy Sectors with Bank size and an interaction in Trade and Manufacturing Sectors with Loan Value. For LTRCART, it appears to be an interaction between Shipping with Bank size and an interaction in Construction with Loan Value.

In the end, the main contribution of this Thesis is that it provides a short-term monitoring system to forecast "failures" i.e. NPL creation. The users of this short-term monitoring system include investors, bank management, and financial regulators. In particular, banks and regulators will have a lead time warning that may enable them to take action to determine whether NPLs are likely to form in loans that are granted to specific sectors of the Greek economy.

This is very important because even since the beginning of the financial crisis in 2008, regulators tried to cope with the spike in bank failures and the resultant threat to the global financial system. By enabling them a lead time to take actions, bank managers can identify which corporate sectors have a higher probability of becoming NPLs and divert their loans to those sectors that demonstrate durability. Investors can construct investment strategies to take advantage of corporates that may show deteriorating operations but have a significant growth potential. Finally, financial institution regulators can intervene with policies to circumvent failure and disruption to the financial markets, borrowers, and depositors.

CHAPTER 3 Competitive conditions and developments in the Greek banking sector

Analysis of competitive conditions and moral hazard is vital for the proper designing of a short-term monitoring system. Bäckman P. et all [27] investigated whether individual banks within a macro-network, aiming to undertake higher risks, could take advantage of information asymmetry. They conducted a survey on moral hazard measurement for macro-networks and found that individual banks' competitors could possess less information within the network, due to the diffusion of risk through specialized financial tools. In addition, they investigated the characteristics of these banks. In a nutshell, they found that individual behavior of various banks, which are part of a macro-network may have incentives that contribute to the beginning of a banking crisis.

This chapter, based on data from the fourth quarter of 2015 to the second quarter of 2021, initially investigates the functioning of competition in the Greek banking system. Furthermore, the evolution of the margin between lending and deposit rates is being examined *(hereinafter: margin)* as an indication of competition.

3.1 An investigation on the functioning of competition and market power

This chapter investigates competition be means of analyzing the market share in assets, loans and deposits of the Greek commercial banks on a solo basis *(hereinafter: commercial banks)*. In particular, the following portfolios are being studied in detail: (a) assets of commercial banks; (b) total loans to customers (non-financial institutions); (c) loans by category (i.e. mortgages, consumer loans and corporate loans); and (d) customer deposits. Furthermore, the evolution of the margin between lending and deposit rates is being examined *(hereinafter: margin)* as an indication of competition.

Regarding the investigation on margin, it should be noted that the increase in the margin implies an increase in interest income, while the decrease in the margin implies a reduction in interest income, and this contraction is caused - under certain conditions - by the intensity of the level of competition.

This chapter also investigates the effect of macroeconomic risks and uncertainty regarding the prospects of the Greek economy on the increase of banking risks, i.e. credit risk and liquidity risk. Further reference is made to the political risk and country risk. Finally, this chapter explores the resilience of the banking system to shocks, given the adverse financial results of banks during this period by making use of performance indicators and capital adequacy.

The results of this chapter, based on the assessment of the changes in the market shares of assets, loans and deposits of commercial banks, as well as the behavior of the margins, show that the level of competition, in particular for the 4 systemic banks, has been maintained while the high level of concentration has not been a deterrent for the competition of Greek banks.

In addition, this chapter explores the liquidity conditions of the banking system following the period of restrictions on capital movements to the gradual recovery due to confidence-building for households and businesses up to the Covid-19 crisis. Finally, the resilience of the banking system is examined on the basis of capital adequacy ratios.

3.2 Market developments

3.2.1 The Greek sovereign bond market

The Greek sovereign bond market showed a downward trend since the recapitalization of the 4 systemic banks in December 2015, which took place mainly from hedge funds, and to a lesser extent through the involvement of the Hellenic Financial Stability Fund (HFSF), as market developments have become more intertwined with policies and macroeconomic developments. Both the volume of transactions and pricing in the bond markets were affected by the outcome of the negotiations between Greece and its international creditors, which led to the successful completion of the 3rd Economic Adjustment Program[2] and the course of the economy following this program.

In this framework, it is important to monitor an indicator, which signals the market sentiment in the sovereign bond markets, i.e. the spread between the 10-year Greek government bond and the respective German one. The assumption is that Germany is able to place debt in the markets and investors can purchase this debt expecting to receive a rate of return (yield) which is close to the risk-free rate of return. Any other country in the Euro-area can place debt in the markets expecting that investors will require a higher yield, compared to the German one. Such a spread signifies the "premium" for the additional risk. The difference between the yield of a representative 10-year Greek Government bond and the yield of the respective German government

2 The third economic adjustment program was agreed between Greece and its official creditors in July 2015.

bond constitutes the spread. It is normal to expect that this spread will have a positive sign, signaling the higher risk of possessing Greek government bonds compared to the German ones[3]. However, a long-term analysis of the evolution of spreads reflects the market sentiment of the investors on the Greek government bond market.

During January 2016, spreads increased markedly due to heightened uncertainty regarding the process for the program review on pension reforms and additional budgetary measures. Therefore, spreads reached their highest level of 1139 basis points as of 11.02.2016.

However, on 23.05.2016 spreads fell significantly to 708.7 basis points as the IMF published the analysis of its Debt Sustainability Report (DSA) for Greece, whereby "a realignment of the DSA assumptions should take place while the revised objectives of the program remain ambitious and justify continued support from the European partners of Greece"[4].

In November 2016 spreads fell significantly to 630 basis points on 30 November 2016 given the optimism about the outlook for Greek debt reduction and expectations for the successful completion of the second review of the third economic adjustment program.

On 07.02.2017 spreads rose to 748 basis points reflecting the negative market sentiment due to the difficulties of Greece joining the ECB's quantitative easing program in view of the pessimistic revision of Greece's debt by the IMF[5].

Thereafter, however, the downward trend in spreads was virtually uninterrupted for a longer period, resulting in a rise of 525.9 basis points on 08.05.2017 due to positive developments that could trigger a more favorable settlement on the long-term Greek debt relief, while on 02.02.2018 spreads fell significantly to 290.8 basis points. This profound decline in government bond yields is attributed to the increase in Greece's

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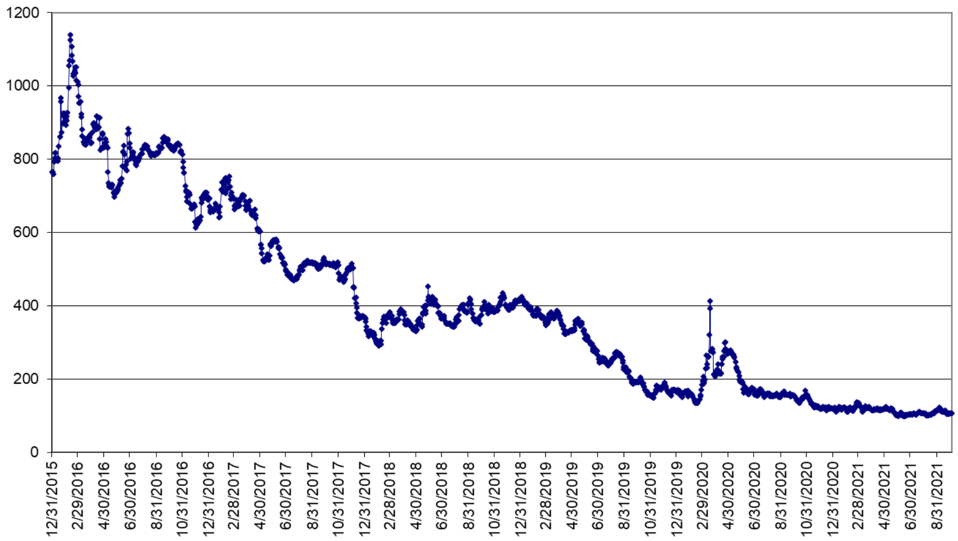
3 This assessment has been maintained during a period of protracted low interest rate environment in Greece and negative interest rates in Germany.

4 Greece : Preliminary Debt Sustainability Analysis-Updated Estimates and Further Considerations. https://www.imf.org/en/Publications/CR/Issues/2016/12/31/Greece-Preliminary-Debt-Sustainability-Analysis-Updated-Estimates-and-Further-Considerations-43915

5 Greece : 2017 Article IV Consultation-Press Release; Staff Report; and Statement by the Executive Director for Greece. https://www.imf.org/en/Publications/CR/Issues/2017/02/07/Greece-2017-Article-IV-Consultation-Press-Release-Staff-Report-and-Statement-by-the-44630

creditworthiness to one notch by S & P Global Ratings, while Eurogroup approved the disbursement of 6.7 billion, i.e. the fourth installment of the third economic adjustment program[6].

FIGURE 3.1
Evolution of spreads between the yields of the 10-year Greek government bonds with the respective 10-year German government bonds (in basis points)



Source: Bloomberg.

Then there was a volatility of spreads, which has nevertheless never exceeded the 454 basis points to date. Specifically on 29.05.2018 the spreads reached 453.9 basis points given the political turmoil in Italy that hit the regional bond markets[7] and then the yields declined as investors re-evaluated their risks due to positive expectations for the creation of a new government coalition in Italy. This volatility, including investors' fears of a more expansionary fiscal policy in Italy, has contributed to increasing the volatility of spreads in the bond market.

Government bond yields in the fourth quarter of 2018 are kept at relatively high levels and above 400 basis points as they were partly influenced by uncertainties in the international environment (Italy, emerging markets, increased trade protectionism), but also by the process of the United Kingdom leaving the European Union.

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6 Eurogroup statement on Greece. https://www.consilium.europa.eu/en/press/press-releases/2018/01/22/eg-statement-on-greece/

7 EU leaders spar as Italy’s political crisis deepens. https://www.ft.com/content/8edfb128-631f-11e8-90c2-9563a0613e56

During January and February 2019, spreads declined both due to the positive news from S & P Ratings on Greece's positive credit outlook and by Fitch Ratings that the proposed plans to reduce non-performing exposures would offer real hopes in the banking sector.

From May 2019 onwards, the rate of this decline became steeper registering 311.3 basis points as of 31.05.2019, echoing the improvement of health in the Greek manufacturing sector[8], as steep upturns in output and new orders supported overall growth, while the economic climate has slightly improved. In August 2019, spreads decreased further registering 265 basis points in light of the encouraging macroeconomic data and expectations of further economic growth, mainly boosted by tourism and planned construction projects.

In November 2019, the rate of decline eased as IMF published the 2019 Article IV Staff Report for Greece[9] noting that Greece's economic recovery continues, but it has fallen far short of expectations. On November 14th spreads amounted to 182bps, while on November 19th spreads amounted to 177.9bps.

According to the Bank of Greece Financial Stability Review [55], volatility in the bond markets increased tremendously during March 2020. More specifically, on March 18th spreads climbed to 417bps as bond markets struggled for stability while investors expected fiscal stimulus policies to cushion the anticipated economic blow from the COVID-19 pandemic. However, on March 19th spreads declined significantly to 265bps as ECB's Governing Council announced a new Pandemic Emergency Purchase Programme with an envelope of €750 billion until the end of the year, in addition to the €120 billion on 12 March 2020. The two programs amount to 7.3% of euro area GDP. Thereafter, stress in the financial markets subsided considerably and spreads registered 166.8 basis points as of 30th June 2020. Still as a disconnect between markets and the real economy has emerged, this raises the risk of another correction in risk asset prices should investor risk appetite fade (June 2020 IMF Global Financial Stability [145]).

10-year bond spreads during the second half of 2020 showed a downward trend, with the result that a decade (2010-2020) record low of 1.15% was recorded on 16.12.2020. Spreads increased to 1.37% on 26.02.2021 due to the uncertainty about the continuation

8 IHS Markit Greece Manufacturing PMI releases

9 Greece : 2019 Article IV Consultation-Press Release; Staff Report; and Statement by the Executive Director for Greece. https://www.imf.org/en/Publications/CR/Issues/2019/11/14/Greece-2019-Article-IV-Consultation-Press-Release-Staff-Report-and-Statement-by-the-48806

of the political support in view of the extension of the restrictive measures due to the challenges related to the pandemic. However, on March 11, 2021, 10-year Greek bond spreads fell to 1.11% as the European Commission approved the Greek program of 60 million euros to support micro, small and medium-sized enterprises affected by the pandemic, while the authorities announced new measures. business support through tax breaks and loan subsidies. The yield then stabilized as the ECB increased its weekly bond buying rate under the PEPP program, while according to Fitch Ratings, Greece's high debt level is sustainable despite the pandemic, as it is supported by continued economic flexibility as a significant risk mitigation factor.

According to the Bank of Greece Financial Stability Review [52], the implementation of strict measures to limit mobility as well as the uncertainty about the course of the Greek economy, led to an increase in Greek bonds spreads in the first five-months of 2021, reaching 1.19% on 19.5.2021. Subsequently, during the period May-September 2021, the performance of the 10-year spreads followed a downward course. The lifting of the restrictive measures in May 2021, the restart of the Greek economy, as well as the upgrade of Greece's debt from BB- to BB with positive prospects for further upgrading by the rating agency Standard & Poor's on 23.04.2021 contributed to the decrease in the 10-year Greek bond spreads. Specifically, on 10.8.2021 its performance recorded a low of 1.01%. On 7.9.2021 spreads were temporarily increased to 1.22% due to the concern caused by the possibility of restricting bond purchases under the PEPP by the ECB, but returned to 1.06% on 28.09.2021 after its announcement to maintain the market pace bonds at moderately lower levels compared to previous quarters.

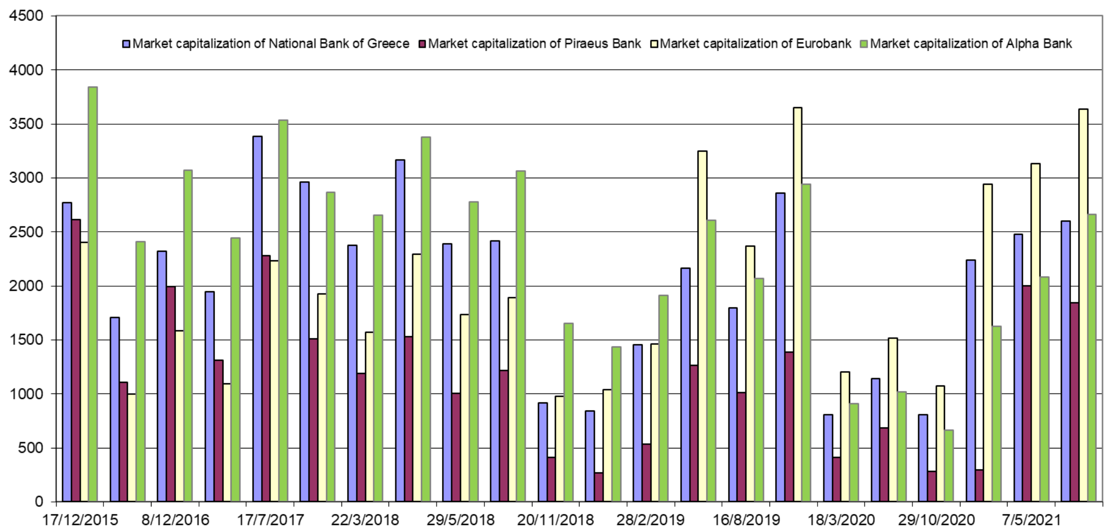
3.2.2 The market capitalization of Greek listed banks

The market capitalization of Greek banks is mainly affected by the course of events in the Greek banking system and the Greek economy. Following the recapitalization of the 4 systemic banks in December 2015, mainly by hedge funds and with lesser participation of the Hellenic Financial Stability Fund, the Greek systemic banks (National Bank of Greece, Alpha Bank, Eurobank, Piraeus Bank) had a market capitalization of € 11.6 billion at 17.12.2015.

However, in January 2016, market capitalization declined as progress in the economic adjustment program slowed down, a fact which is linked to meeting the requirement for improved proposals for pension reform. This has resulted in a further delay of debt relief negotiations. In February 2016, the market capitalization fell significantly to € 4.2 billion on 11 February 2016, namely National Bank had € 1.1 billion, Alpha Bank had € 1.8 billion, Piraeus Bank € 707 million, and Eurobank € 2.4 billion. This was due to increased uncertainty about the program's evaluation process for pension reform and other fiscal measures, which was a prerequisite for the successful completion of the 3rd Financial Adjustment Program.

FIGURE 3.2

Market capitalization of the four Greek systemic banks (by bank - in mil. €)



Source: Bloomberg.

The market capitalization rose to 10.3 billion euros on 09.05.2016, as the Eurogroup welcomed a package of reforms approved by the Greek Parliament regarding the pension system, income tax, VAT, reforms of the public sector and non-performing exposures[10]. It was decided that after the completion of the first review and the disbursement of additional funding, further possible measures would be discussed to ensure the sustainability of Greece's refinancing needs. However, in June 2016, instability increased as the positive effect of disbursing the second tranche of ESM funding of EUR 10.3[11] was offset by investor concerns about tensions over the withdrawal of UK from the EU as well as worries regarding the capital needs of

10 Eurogroup statement on Greece. https://www.consilium.europa.eu/en/press/press-releases/2016/05/09/eg-statement-greece/

11 ESM releases aid of €10.3 for Greece. https://agenceurope.eu/aewebsite_dev/en/bulletin/article/11575/4

European banks. For this reason, the stock market value declined to € 6.2 billion on 30.08.2016.

In the first quarter of 2017, market capitalization remained at the same level reflecting the negative climate in the markets related to the difficulties of implementing the Economic Adjustment program amid worsening of economic and market indicators. But in June 2017 market capitalization rose due to a compromise agreement on debt sustainability. In particular, the IMF agreed to participate in discussions on debt relief on the basis of the "agreement in principle"[12]. The IMF will no longer require specific measures, but will merely assure that debt relief measures are specific enough to ensure its viability in the future.

In July 2017, market capitalization rose, reflecting the improved investment climate that allowed positive estimates of the macroeconomic outlook as well as improved bank liquidity prospects. Following the conclusion of the negotiations, the ESM's Board of Directors on 07.07.2017 approved the third installment of financial assistance to Greece of € 8.5 billion[13] after the approval of the Supplementary Agreement. As a result, the market value stood at € 11.4 billion on 17.07.2017, namely National Bank had € 3.4 billion, Alpha Bank had € 3.5 billion, Piraeus Bank € 2.3 billion and Eurobank € 2.2 billion.

After a period of decline, market capitalization increased in December 2017 and stood at € 9.3 billion on 02.01.2018, because of improved liquidity conditions and bank revenue growth prospects, as well as a schedule for targeted sales of non-performing loan portfolios. On 22 March 2018 the market capitalization fell to € 7.8 billion on 02.01.2018, while the negative climate deteriorated due to "shorting" positions in banks from some aggressive hedge funds.

On 30.04.2018 the market capitalization increased to € 10.4 billion as the Greek authorities showed a commitment to fiscal consolidation and a reform process after the end of the program. On 29.05.2018 the market capitalization fell significantly to € 7.9

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12 IMF Executive Board Approves in Principle €1.6 Billion Stand-By Arrangement for Greece. https://www.imf.org/en/News/Articles/2017/07/20/pr17294-greece-imf-executive-board-approves-in-principle-stand-by-arrangement

13 ESM Board of Directors approves €8.5 billion loan tranche to Greece. https://www.esm.europa.eu/press-releases/esm-board-directors-approves-%E2%82%AC85-billion-loan-tranche-greece

billion as political instability in Italy hit regional European markets. On 18.07.2018 the market capitalization increased to € 8.6 billion due to the improvement in banks' liquidity conditions. On 20.11.2018 the market capitalization fell significantly to € 3.9 billion, following MSCI's decision to remove the 3 systemic banks (National Bank of Greece, Piraeus Bank, Eurobank) from the MSCI Standard Greece index. As a result, the market value for the National Bank of Greece amounted to € 917 million, Alpha Bank to € 1.7 billion, Piraeus Bank to € 410 million and Eurobank to € 977 million. Although the impact was systemic, Alpha Bank was less affected by this development as was expected.

On 21 January 2019, the market capitalization fell significantly to € 3.9 billion, as investors' concerns about the challenges that banks have to face in reducing their non-performing exposures had a negative impact on the Greek banking index. However, during February 2019, there was a strong rise with the market capitalization reaching € 5.4 billion on 28.02.2019 due to the positive market dynamics. This has been boosted by signs of stabilization in Greek bond markets after a five-year bond issuance of 2.5 billion euros, with investors taking more long-term positions. The positive sentiment in the markets is attributed to the Deutsche Bank's report that the changes provided by the new law on the protection of the main residence are positive for dealing with strategic defaulters. In addition, Morgan Stanley's report notes that steps have been taken to drastically reduce Greek bank non-performing loans (the reduction targets are expected to be achieved by 2021), despite the ongoing challenges for the implementation of non-performing exposures securitization schemes.

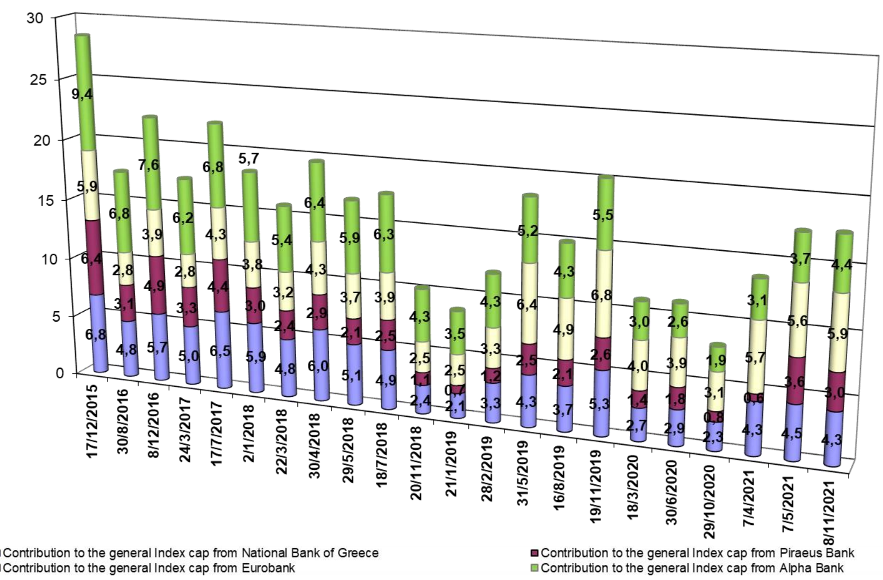
On 31 May 2019, market capitalization has already been increased to € 9.3 billion. During that time, Moody's published a report [229] according to which the outlook for Greece's banking system remained positive on expected improvements in banks' funding and asset risks, while more deposit growth and a gradual fall in problem loans was expected. Systemic banks also had plans to securitize a large amount of non-performing loans ahead of future developments on NPL securitization schemes. On 16 August 2019, market capitalization amounted to € 7.3 billion, as the reduction of non-performing loans and the control of staff expenses in banks’ balances will be the major factors of enhancing banks’ profitability in the next quarters.

On November 2019, market capitalization increased, reaching € 10.8 billion on 11 November 2019, as Greece has finalized the draft bill for Hercules Asset Protection

Scheme (HAPS) to be subsequently sent to DG comp and ECB for approval[14]. However, on March 2020, market capitalization declined significantly amounting to € 3.3 billion on 18.03.2020 as markets struggled for stability while investors expected fiscal stimulus policies to cushion the anticipated economic blow from the COVID-19 pandemic. Thereafter as market pressures eased, volatility in the banking index subsided and the market capitalization amounted to €4.4 billion as of 30 June 2020.

FIGURE 3.3

Contribution to the total banking FTSE/ATHEX cap of the four systemic banks (%)



Source: Bloomberg.

According to the Bank of Greece Financial Stability Review [52, 53, 54, 55], after the four-year low recorded on 16.03.2020, market capitalization recorded a low period on 29.10.2020 amounting at € 2.8 billion as a result of investors' concerns about the recurrence of COVID-19 cases. But then, the stock market showed a continuous recovery and the key index of the Athens Stock Exchange and the market capitalization amounted at € 7.1 billion on 07.04.2021 amid further support measures on both European and national level. The improvement of investor confidence and the belief in ensuring the sustainability of the Greek debt played a catalytic role in this recovery, as it is supported by the continuing economic flexibility as an important factor in reducing

14 According to a Moody's Report dated 17 March 2020, Greece's Asset Protection Scheme (HAPS) will help lenders to reduce nonperforming exposures (NPE) by packaging them into asset-backed securities. HAPS protects senior noteholders by aligning their interests (that is maximizing timely recoveries from underlying assets in the workout process), with those of key transaction counterparties, such as servicers. A state guarantee will protect senior noteholders against the non-payment of principal or interests due and it is unconditional, irrevocable and on first request.

the risk. As a result, the market risk in the Greek financial system decreased despite the fact that the risk of interconnectedness remains high.

Market capitalization during April-November 2021 continued an upbeat course, as Greek banks took initiatives to increase their capital through share capital increases (Piraeus Bank and Alpha Bank) and the issuance of bonds. As a result, market capitalization reached its highest point since December 2019 amounting at € 10.7 billion on 18.11.2021.

The contribution of each systemic bank to the total market capitalization of banks has changed significantly since the recapitalization of the 4 systemic banks in December 2015. While on 17.12.2015 the contribution of the 4 systemic banks to the total market capitalization of the Athens Exchange Index was 28.5%, this figure decreased to 22.1% on 17.07.2017 and 17.5% on 18.07.2018. This figure was further reduced to 10.2% on 20.11.2018 while on 19.11.2019 and 08.11.2021 there was a significant increase to 20.2% and 17.6% respectively due to the positive market dynamics.

More specifically, the impact of MSCI's decision to remove the 3 systemic banks (National Bank of Greece, Piraeus Bank, Eurobank) from the MSCI Standard Greece index is noteworthy[15]. Thus, while the National Bank of Greece before the decision participated on 18.07.2018 by 4.9% in the value of the Athens Exchange Index, Piraeus Bank by 2.5%, Eurobank by 3.9% and Alpha Bank by 6, 3%, after the decision, the National Bank of Greece reduced its participation in the Athens Exchange Index to 2.4%, Piraeus Bank to 1.1%, Eurobank to 2.5% and Alpha Bank to 4.3%. However, the positive dynamics of markets in February 2019 played a key role in increasing systemic bank contributions to the stock market index. In particular, on 28.02.2019, National Bank of Greece increased its contribution to the Stock Index to 3.3%, Piraeus Bank to 1.2%, Eurobank to 3.3% and Alpha Bank to 4.3%. Thereafter, as market capitalization increased, the contribution of the 4 systemic banks to the general index cap in November 2019 surpassed even the 2018 levels. More specifically, on 19.11.2019, National Bank of Greece increased its contribution to the Stock Index to 5.3%, Piraeus Bank to 2.6%, Eurobank to 6.8% and Alpha Bank to 5.5%. It is worth noting that the impact of COVID19 reduced the contributions of the systemic banks in March and June 2020. More specifically, on 30.06.2020, the National Bank of Greece decreased its

15 MSCI decision to downgrade shares of 3 Greek systemic banks drags down ATHEX banking index. https://www.naftemporiki.gr/story/1413555/msci-decision-to-downgrade-shares-of-3-greek-systemic-banks-drags-down-athex-banking-index

contribution to the Stock Index to 2.9%, Piraeus Bank to 1.8%, Eurobank to 3.9% and Alpha Bank to 2.6%. However, on 08.11.2021, National Bank of Greece increased its contribution to the Stock Index to 4.3%, Piraeus Bank to 3.0%, Eurobank to 5.9% and Alpha Bank to 4.4%.

3.3 Structure and Competitive Conditions in the Greek Banking System

This section examines to which extent the competitive conditions have changed in the Greek banking system, following the major restructuring and consolidation process during this period, by the examination of the following portfolios: (a) assets of commercial banks; (b) total loans to customers (non-financial institutions); (c) loans by category; and (d) customers deposits during the period from the fourth quarter of 2015 until the second quarter of 2021. In addition, the evolution of the margin (lending rate – deposit rate) is being investigated as an indication of competition. It should be noted that the increase in the margin implies an increase in interest income, while the decrease in the margin implies a reduction in interest income, and this contraction is caused - under certain conditions - by the intensity of the level of competition.

3.3.1 Analysis of portfolio structure

During 2015-2020, the Greek banking system demonstrated a mild contraction which was mainly attributed to the cessation of activities of a number of cooperative banks that have been operating in Greece, while the commercial banks as well as foreign banks established in a form of a branch have remained largely unaffected.

However, the picture of the financial aggregate volumes of the credit system is more mixed. While there has been a significant contraction as a whole during 2015-2018, mainly due to continued deleveraging and an increase in the rate of write-off of bad debts, there has been an increase during 2019-2021Q2, mainly due to the improvement of liquidity conditions.

Thus, while the total number of credit institutions decreased mildly from 39 in December 2015 to 37 in December 2018, there was a significant decrease in total assets from € 385.4 in December 2015 to € 292 billion in December 2018. However, during the period of 2019-2021Q2, while the number of credit institutions remained fairly stable to 36, in June 2021, total assets increased from € 292 billion in December 2018 to € 335 billion in June 2021, as debt securities increased during this period despite the decrease in outstanding loan balances (deleveraging). According to the Bank of Greece Financial Stability Review [52], improved liquidity conditions due to the increase in customer deposits, the participation of banks in targeted operations and longer-term use of Eurosystem refinancing operations (TLTROs III), led to an increase in cash and cash equivalents, while there has been an increase in bond and derivative positions.

The change in the number of credit institutions is depicted in Table 3.1. According to the Bank of Greece's Bulletins of Conjunctural Indicators [62] as of December 2020, financial products and services are offered to Greece by 36 credit institutions with headquarters or branch in Greece, 287 financial intermediaries and finally 58 finance companies in the financial system. There are also 35 insurance companies and 25 pension funds although the last two entities are not engaged in financial intermediation.

Undoubtedly, banking intermediation in Greece is traditionally been carried out from commercial banks, which were nine in 2021Q2. More specifically, 9 of them are headquartered in Greece (National Bank of Greece, Alpha Bank, Piraeus Bank, Eurobank, Attica Bank, Optima Bank, Aegean Baltic Bank, Viva Payments, Pancreta Bank), while none of them are subsidiaries of foreign banks. It should be mentioned that commercial banks constitute 98.2% of the total assets of the banking system, while the 4 systemic banks, (National Bank of Greece, Alpha Bank, Eurobank, Piraeus Bank) listed in the Athens Exchange (hereinafter: listed) constitute approximately 95.5% of the total assets of the banking system.

TABLE 3.1
Number of Credit Institutions in Greece

Credit Institutions	2013	2014	2015	2016	2017	2018	2019	2020	2021Q2
Commercial Banks – of which:	10	9	8	8	8	8	8	9	9
Domestic Banks:	7	6	5	5	6	6	6	9	9
Subsidiaries of foreign banks:	3	3	3	3	2	2	2	0	0
Branches of foreign banks:	20	20	21	20	21	22	20	21	21
Other credit institutions:	11	11	10	9	9	7	7	6	6
Total credit institutions:	40	40	39	37	38	37	35	36	36

Source: Bank of Greece (BoG) Bulletins of Conjunctural Indicators [62].

In Table 3.2, the market share of the total assets of each bank on a solo basis to the total assets of the commercial banks is being portrayed from the 4th quarter of 2015 up to the

2nd quarter of 2021, indicating the intermediate values for 2018, 2019, 2020 and 2021. From the analysis, the following conclusions are being derived:

(a) The four systemic banks have reduced - albeit very little - the share of their assets in the period 2015: Q2-2021, compared to the market share of other commercial banks. However, these banks have maintained considerable size in the banking market, allowing them to compete with each other. It should be noted that as part of the implementation of their restructuring plans approved by the European Commission[16], Greek banking groups continued to dispose of their non-banking activities in the domestic market and to sell their subsidiaries abroad. More specifically, the presence of Greek banking groups abroad shrank further in 2019, as Piraeus Bank withdrew from Albania and completed the transfer of its subsidiary in Bulgaria to Eurobank, while the National Bank sold its subsidiary in Romania. Moreover banks restructured further their activities during 2020, as Alpha Bank transferred to Luxembourg the activities of the branch that maintained in UK due to uncertainty relating to the withdrawal of the UK from EU, while Piraeus Bank ceased the operations of its branch in UK and transferred its activities to Greece.

TABLE 3.2

Market share in total assets of commercial banks (%)

Commercial banks	Period									
	2015:Q4	2016:Q4	2017:Q4	2018:Q2	2018:Q4	2019:Q2	2019:Q4	2020:Q2	2020:Q4	2021:Q2
National Bank of Greece	26.28	25.46	24.94	25.55	25.84	25.63	24.93	26.96	26.88	27.14
Alpha Bank	22.15	22.45	23.84	24.17	24.16	24.73	24.37	24.56	24.27	23.16
Attica Bank	1.25	1.38	1.52	1.58	1.49	1.44	1.48	1.41	1.42	1.31
Piraeus Bank	28.28	29.03	27.53	26.00	26.36	25.48	25.74	24.99	26.05	27.28
Eurobank Ergasias	21.87	21.53	21.97	22.51	21.92	22.41	23.06	21.64	20.76	20.37
Optima Bank	0.05	0.06	0.08	0.07	0.09	0.09	0.13	0.22	0.37	0.47
Aegean Baltic	0.09	0.09	0.10	0.11	0.12	0.15	0.21	0.22	0.23	0.26
Viva Payments	0.02	0.01	0.02	0.02	0.02	0.06	0.08	0.01	0.02	0.02
All commercial banks (%)	100	100	100	100	100	100	100	100	100	100
Total loans (bn)	293.5	269.1	234.2	222.0	229.3	232.7	237.9	257.3	267.9	279.1

Sources: (a) Bank of Greece (BoG) for Less significant institutions and (b) Published financial statements for the systemic banks

16 State aid: Commission approves amended restructuring plans for Alpha Bank and Eurobank. https://ec.europa.eu/commission/presscorner/detail/en/IP_15_6184
State aid: Commission approves aid for Piraeus Bank on the basis of an amended restructuring plan https://ec.europa.eu/commission/presscorner/detail/en/IP_15_6193
State aid: Commission approves aid for National Bank of Greece on the basis of an amended restructuring plan https://ec.europa.eu/commission/presscorner/detail/en/IP_15_6255

Nevertheless, international activities of Greek banking groups remained profitable in 2019, as they focused on a number of specialized banking products in investment banking, while gradually withdrawing from activities in the retail banking sector abroad. During 2020-2021Q2, the profitability of international operations decreased mainly due to the formation of increased provisions for credit risk in the context of the consolidation of the loan portfolio.

(b) From the evolution of the above market shares, between the four systemic banks, two of them (National Bank of Greece & Alpha Bank) slightly increased their market shares between 2016 and 2021H1, one of them has broadly maintained its market share (Eurobank) while one of them witnessed a considerable decrease up to 2020Q2 (Piraeus Bank). Moreover, the National Bank of Greece started to follow a more aggressive strategy of attracting customers by being more generous in the restructuring of the client portfolios and at the same time more strict and coherent in auctions and foreclosures. In addition, the National Bank of Greece has been engaging in initiatives, which aspire to strengthen critical sectors of the economy and aim to modernize the country's productive model, enhance business innovation and extroversion, and add value to the dynamically growing rural sector. In addition, the increase in Alpha Bank's market share is due to the strengthening of strategic partnerships in the retail banking sector and the support of the dynamic growth and investments in Greece, through new financing to the real economy and through an expanded set of value-added services to facilitate and develop the activity of customers. As far as Eurobank is concerned, it emphasizes the important role of recycling and waste management in the new growth model within the context of green growth and the circular economy.

From the above comparative analysis of the market shares in total assets, it appears that the four systemic banks maintained a satisfactory market share with significant banking activities, allowing them to maintain the level of competition in the domestic market.

FIGURE 3.4

Distribution of Total Assets of Commercial Banks in Quartiles (in € bn)

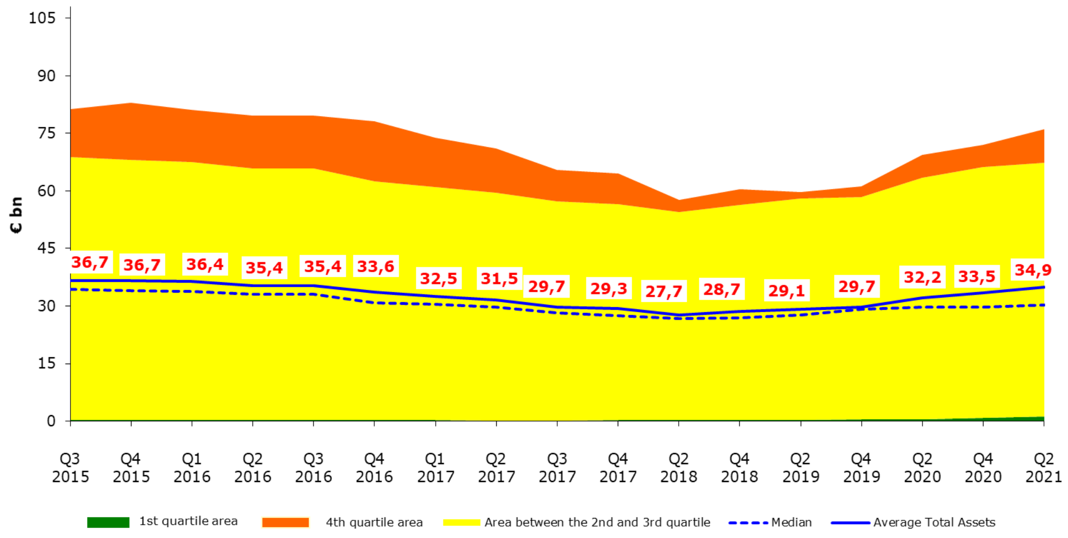


Figure 3.4 depicts the distribution of assets of commercial banks in quartiles. According to this distribution, the average assets of commercial banks decreased from € 36.7 billion in the third quarter of 2015 to € 28.7 billion at the end of 2018 and increased to € 34.9 billion in the second quarter of 2021, while the total number of credit institutions has slightly decreased during this period [See Table 3.1]. However, the maintenance of the average assets at fairly similar levels in 2017-2019 and a subsequent increase in 2020-2021Q2 during a deleveraging period observed in all credit institutions suggests that competitive conditions were maintained irrespective of the very high concentration in the banking system. The existence of the aforementioned competitive conditions is maintained through the period of 2018-2019 as no significant change in the average assets was observed. The subsequent increase in average assets during 2020-2021Q2 was not attributed to a particular institution, while the number of credit institutions remained almost unchanged. According to Angeloni [2], bank concentration is, at best, an imperfect proxy of bank competition. Markets can be competitive, even if relatively concentrated, if they are "contestable", that is, competitive pressure can also be exercised by outsiders. For this reason, it is important to combine the concentration indicators with other measures, notably focused price performance.

The maintenance of a relatively large area, which is covered from the 2nd and 3rd quartiles is mainly attributed to the fact that 2 systemic banks are included in it. On the other hand, the decline in area covered by the fourth quartile is due to the decrease in assets held by the Piraeus Bank that is included in the 4th quartile, compared to 2015, whereby its asset size was far more important. In Table 3.3, the distribution of commercial banks depending on the quartile they belong to in the 2nd quarter of 2021 is being portrayed.

TABLE 3.3

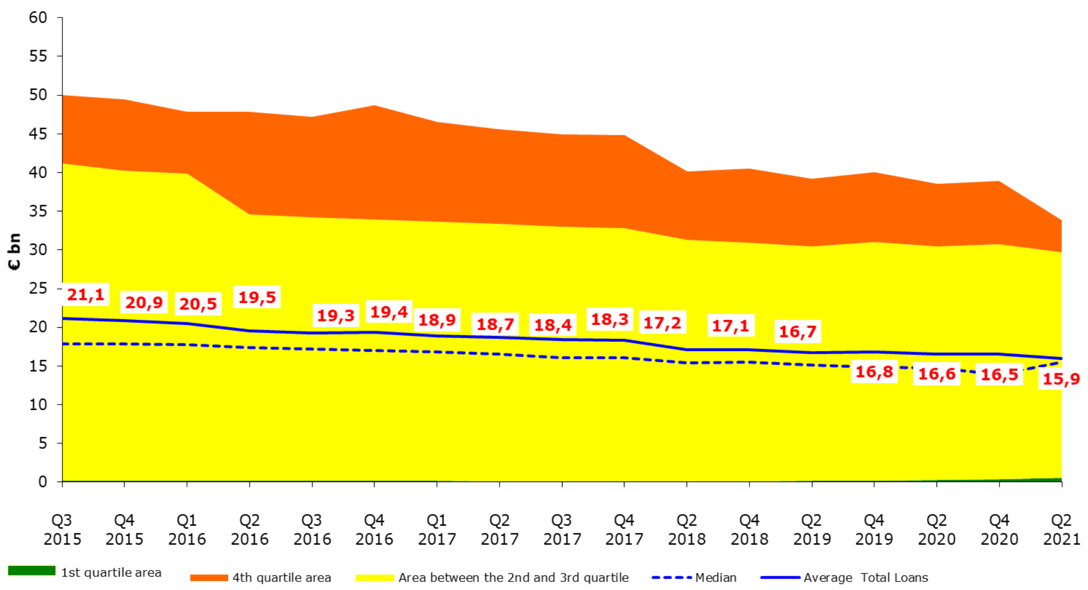
Distribution of Commercial Banks in Quartiles (Q2 2021)

1st quartile: banks with assets ≤ 1.2 bn	2nd quartile: banks with assets ≤ 30.2 bn	3rd quartile: banks with assets ≤ 67.4 bn	4th quartile: banks with assets ≤ 76.1 bn
Aegean Baltic Bank Viva Payments Pancreta Bank	Attica Bank Optima Bank	Alpha Bank Eurobank	National Bank of Greece Piraeus Bank

Sources: (a) Bank of Greece (BoG) for Less significant institutions and (b) Published financial statements for the systemic banks

FIGURE 3.5

Distribution of Total Loans of Commercial Banks in Quartiles (in € bn)



Sources: (a) Bank of Greece (BoG) for Less significant institutions and (b) Published financial statements for the systemic banks

Regarding the evolution of loans [see Figure 3.5], average loans decreased from €21.1 billion in the 3rd quarter of 2015 to €15.9 billion in the 2nd quarter of 2021, despite only a small decline in the total number of credit institutions during this period. Table 3.4 lists the market shares of all loans (mortgages, consumer and corporate) per bank.

TABLE 3.4

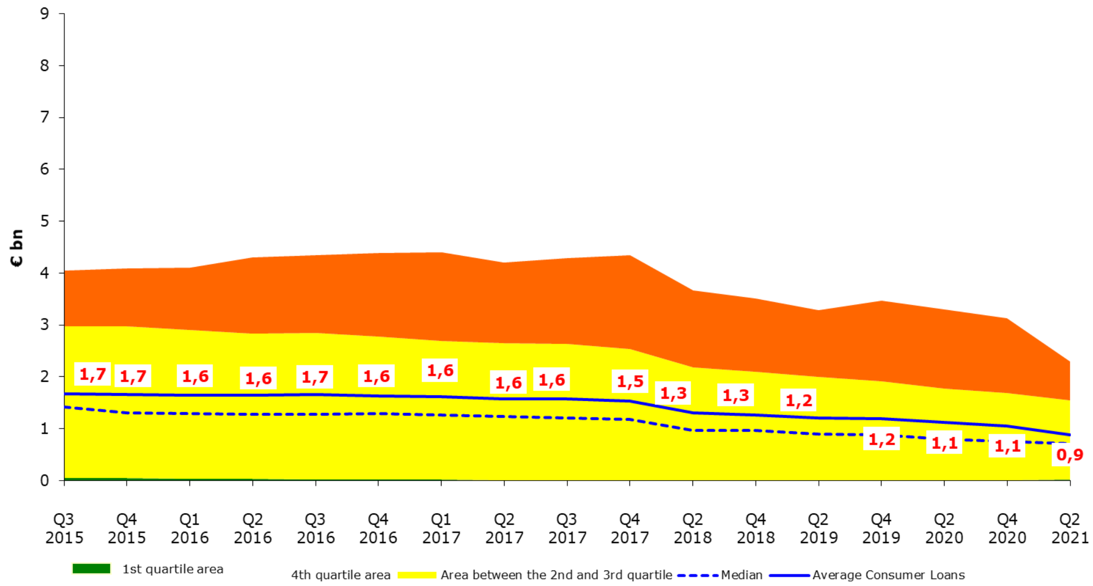
Market Share in total loans of commercial banks (%)

Commercial banks	Period									
	2015:Q4	2016:Q4	2017:Q4	2018:Q2	2018:Q4	2019:Q2	2019:Q4	2020:Q2	2020:Q4	2021:Q2
National Bank of Greece	23.88	20.20	20.43	21.04	21.26	21.51	20.69	20.86	19.27	22.41
Alpha Bank	24.91	25.80	26.27	26.52	26.21	26.21	26.75	26.47	26.71	25.84
Attica Bank	1.65	1.79	1.49	1.48	1.42	1.39	1.39	1.38	1.83	1.86
Piraeus Bank	29.62	31.45	30.62	29.27	29.16	29.15	29.00	29.13	29.46	26.57
Eurobank Ergasias	19.76	20.60	21.06	21.55	21.61	22.04	21.62	21.79	22.16	22.47
Optima Bank	0.01	0.02	0.03	0.03	0.03	0.05	0.10	0.14	0.29	0.51
Aegean Baltic	0.14	0.13	0.09	0.11	0.14	0.17	0.21	0.23	0.28	0.33
Viva Payments	0.03	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
All commercial banks (%)	100	100	100	100	100	100	100	100	100	100
Total loans (bn)	166.9	154.9	146.6	137.2	136.9	133.8	134.7	132.5	132.1	127.5

Sources: (a) Bank of Greece (BoG) for Less significant institutions and (b) Published financial statements for the systemic banks.

FIGURE 3.6

Distribution of Total Consumer Loans of Commercial Banks in Quartiles (in € bn)



Sources: (a) Bank of Greece (BoG) for Less significant institutions and (b) Published financial statements for the systemic banks

Table 3.4 shows a consistent decline in lending over the period 2015Q3-2021Q2, More specifically, the decline in average lending during this period depicted in Figure 3.5 is taking place in an environment of continued deleveraging observed in all credit institutions while there is no appreciable change in the credit standards for all types of loans in the credit institutions, leading to the maintenance of the continued adoption of stricter criteria. This is confirmed by the gradual decline in average loans from the third quarter of 2015 to the second quarter of 2021, while during 2018 this decline accelerated as a result of the larger decline in loans observed in Alpha Bank and Piraeus Bank in 2018.

TABLE 3.5

Market Share in consumer loans of commercial banks (%)

Commercial banks	Period									
	2015:Q4	2016:Q4	2017:Q4	2018:Q2	2018:Q4	2019:Q2	2019:Q4	2020:Q2	2020:Q4	2021:Q2
National Bank of Greece	18.74	18.58	18.38	17.45	18.25	17.50	17.33	16.82	16.27	18.19
Alpha Bank	30.72	33.58	35.34	34.98	34.64	34.19	36.29	36.76	37.09	32.37
Attica Bank	1.07	1.11	0.89	1.11	1.11	1.03	1.20	1.21	1.60	1.79
Piraeus Bank	28.89	27.47	26.75	27.79	27.97	29.19	27.36	28.63	27.37	27.45
Eurobank Ergasias	20.13	19.06	18.53	18.55	17.93	17.97	17.68	16.45	17.54	19.88
Optima Bank	0.04	0.04	0.06	0.08	0.08	0.12	0.12	0.12	0.14	0.31
Aegean Baltic	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01
Viva Payments	0.40	0.16	0.05	0.03	0.01	0.01	0.00	0.00	0.00	0.00
All commercial banks (%)	100	100	100	100	100	100	100	100	100	100
Total loans (bn)	13.3	13.1	12.3	10.5	10.1	9.6	9.5	9.0	8.4	7.1

Sources: (a) Bank of Greece (BoG) for Less significant institutions and (b) Published financial statements for the systemic banks

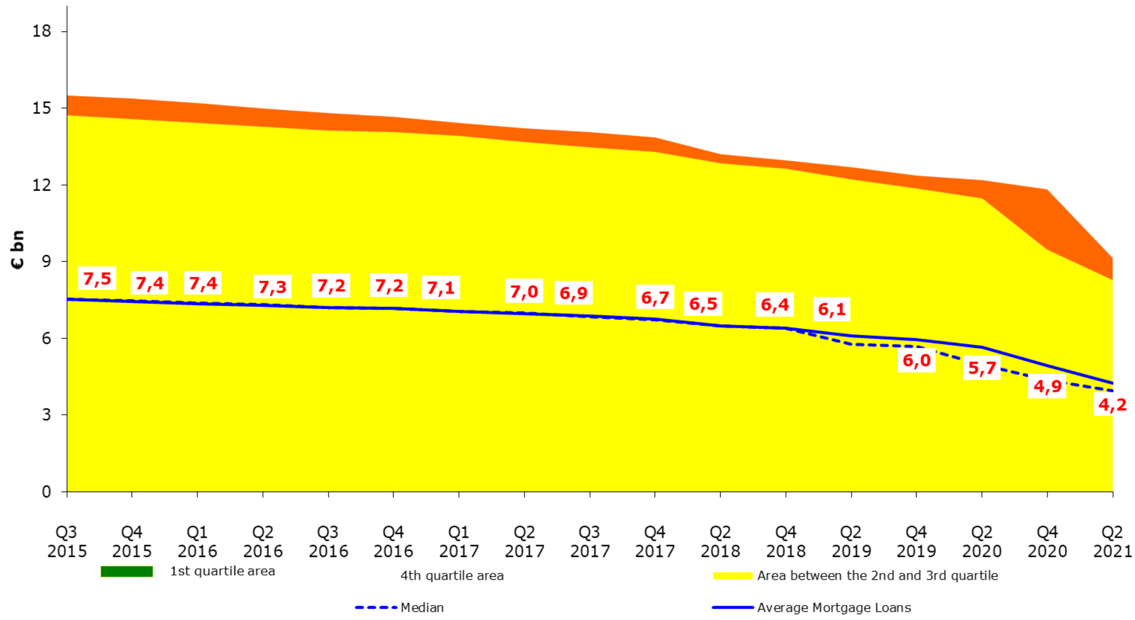
It should be noted that the general trend in the evolution of total loans is also confirmed in each category of loans but with the following observations:

(a) Regarding the evolution of consumer loans [See Figure 3.6], during the reference period from the third quarter of 2015 to the second quarter of 2021, a significant downward trend in lending reflects the efforts by banks to write off non-performing consumer loans, especially after 2018. However, the rate of decline in the consumer loan portfolio is not the same for all systemic banks but is more pronounced for the banks residing in the 3rd quartile, such as Alpha Bank and Eurobank and less pronounced for banks residing in the 4th quartile (National Bank of Greece, Piraeus Bank).

(b) Regarding the evolution of the mortgage portfolio [See Figure 3.7 and Table 3.6], there has been a significant decrease witnessed during the above-mentioned period. In particular, mortgage lending was reduced from € 59.5billion from 2015 to € 47.7billion in 2019 and € 33.9billion the second quarter of 2021. Loan sales and securitizations have accelerated in particular after 2019, from all systemic banks. This suggests that banks are made use of either established securitization schemes (such as HAPS) or individual initiatives in order to proceed to more extensive write-offs of the mortgage portfolios.

FIGURE 3.7

Distribution of Total Mortgage Loans of Commercial Banks in Quartiles (in € bn)



Sources: (a) Bank of Greece (BoG) for Less significant institutions and (b) Published financial statements for the systemic banks

TABLE 3.6

Market Share in mortgage loans of commercial banks (%)

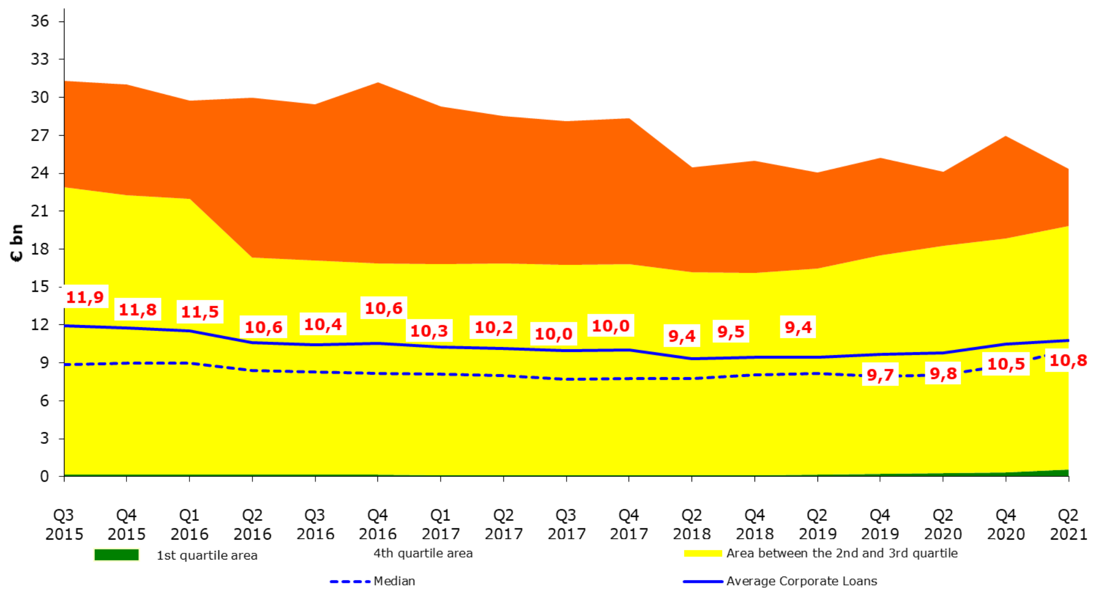
Commercial banks	Period									
	2015:Q4	2016:Q4	2017:Q4	2018:Q2	2018:Q4	2019:Q2	2019:Q4	2020:Q2	2020:Q4	2021:Q2
National Bank of Greece	25.88	25.60	25.66	25.05	24.68	24.99	24.64	24.97	21.16	23.96
Alpha Bank	24.55	25.01	24.91	25.40	25.35	26.08	25.95	26.87	29.87	25.77
Attica Bank	0.76	0.75	0.70	0.71	0.73	0.73	0.77	0.79	0.89	1.01
Piraeus Bank	24.46	24.26	24.49	24.59	24.90	25.27	25.56	26.21	24.29	22.28
Eurobank Ergasias	24.35	24.39	24.24	24.25	24.34	22.92	23.08	21.16	23.78	26.94
Optima Bank	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03
Aegean Baltic	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Viva Payments	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
All commercial banks (%)	100	100	100	100	100	100	100	100	100	100
Total loans (bn)	59.5	57.3	54.0	51.9	51.1	48.7	47.7	45.3	39.6	33.9

Sources: (a) Bank of Greece (BoG) for Less significant institutions and (b) Published financial statements for the systemic banks.

(c) As regards the category of corporate credit [See Figure 3.8 and Table 3.7], most of the decline in corporate loans was witnessed during 2015-2016 due to business portfolio restructuring, and the increase in the rate of recovery of non-performing loans in cash, while the rate of decline during 2017-2018 eased somehow as it was partially offset by increasing demand for new lending to growth-enhancing sectors and the cyclical economy. During 2019-2020Q1, the corporate climate has been improved, despite the pandemic, and in 2019Q4 the outstanding balances of corporate loans increased for the first time since 2013. More encouraging results regarding the stabilization of loan balances in the corporate loan portfolio are observed in National Bank of Greece and Alpha Bank, while Piraeus Bank has seen a larger decline in this portfolio from the 2nd quarter of 2016 to the second quarter of 2020. During the period of 2016-2019, GDP growth was positive, while the negative effects from COVID19 were incorporated in a GDP decline in 2020, although a sharp rebound in 2021 is expected to support loan balances during the forthcoming periods.

FIGURE 3.8

Distribution of Total Corporate Loans of Commercial Banks in Quartiles (in € bn)



Sources: (a) Bank of Greece (BoG) for Less significant institutions and (b) Published financial statements for the systemic banks

(d) From the comparison of distributions of loans by category, it can be observed that in the loan categories mortgages and consumer loans, the range in the areas of the 2nd and 3rd quartiles is decreasing to the same rate compared to the decline in the 4th quartile from 2016 up to the second quarter of 2021. However, regarding the corporate loan portfolio, the range in the areas of the 2nd and 3rd quartiles is increasing during the period 2015-2021Q2 while there is a decline in the 4th quartile during the same period. There are therefore a number of banks belonging to the 3rd quartile (e.g. Eurobank) which penetrate a larger part of the corporate base due to the outlook for expansion to new, more dynamic enterprises. On the other hand, the banks that belong to the 4th quartile, appear to be unable to change their customer base significantly so that they can channel new lending to extrovert enterprises and thus offset the losses from their existing borrowers.

TABLE 3.7

Market Share in corporate loans of commercial banks (%)

Commercial banks	Period									
	2015:Q4	2016:Q4	2017:Q4	2018:Q2	2018:Q4	2019:Q2	2019:Q4	2020:Q2	2020:Q4	2021:Q2
National Bank of Greece	23.34	16.79	17.23	18.77	19.34	19.77	18.67	18.94	18.68	22.15
Alpha Bank	24.30	25.13	25.80	26.11	25.42	25.66	24.61	25.06	24.19	25.33
Attica Bank	2.30	2.61	2.11	2.06	1.97	1.90	1.83	1.74	2.30	2.20
Piraeus Bank	32.99	36.93	35.34	32.72	33.06	31.84	32.52	30.88	32.10	28.18
Eurobank Ergasias	16.80	18.27	19.31	20.10	19.96	20.49	21.94	22.77	21.86	20.94
Optima Bank	0.01	0.03	0.04	0.05	0.05	0.06	0.11	0.22	0.44	0.72
Aegean Baltic	0.25	0.23	0.17	0.20	0.21	0.28	0.32	0.39	0.44	0.49
Viva Payments	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.00
All commercial banks (%)	100	100	100	100	100	100	100	100	100	100
Total loans (bn)	94.0	84.5	80.3	74.8	75.6	75.5	77.5	78.2	84.1	86.5

Sources: (a) Bank of Greece (BoG) for Less significant institutions and (b) Published financial statements for the systemic banks

For this reason, and despite the general decrease in all the categories of lending during the reporting period, the only increase in the case of corporate lending is witnessed in the area of the 2nd and 3rd quartiles, while the area of the 4th quartile is not substantially decreased during the period considered. An interpretation of this may be that, in the enterprise loans market, all banks are trying to maintain their market share by expecting that growth will come from extrovert enterprises, while on the other hand banks do not wish to lose to their competitors their corporate loan portfolios that traditionally have high added value (e.g. tourism, infrastructure etc.).

(e) The degree of concentration did not significantly change throughout all portfolios, i.e. consumer, mortgage and corporate loans, reaching an average of 2.385 units in the 2nd quarter of 2021 from 2.465 units in the 3rd quarter of 2015 as measured by the Herfindahl Index[17]. However, some activity from the smaller ones, (i.e. Attica Bank,

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17 Herfindahl Index is defined as the sum of the squares of the market shares of banks and has values from 0 to 10,000. A market is defined to be highly concentrated when Herfindahl Index exceeds 1,800,

Optima Bank) is picking up. At the same time, during the period 2015Q3-2020Q3, the growth of concentration in the portfolio of consumer loans was higher while the growth of concentration in the portfolio of mortgage loans remained overall virtually unchanged. As a result, concentration in the portfolio of consumer loans is the highest amounting to 2.531 units in the 2nd quarter of 2021, the concentration in the portfolio of corporate loans is the lowest and it amounts to 2.370 units, while the concentration for the mortgage portfolio amounts to 2.462 units.

The apparent similarity in the distributions and partly in the lower degree of concentration in corporate loans may be regarded as evidence of the existence of a relatively higher competition in these markets, as the portfolio of consumer loans is formed by high interest rates, due to the higher risk premium and the high rates of delinquencies. As a result, regional as well as portfolio specificities prevail and may dictate the relationship between the level of concentration and the level of delinquencies. This is confirmed by Çifter [77] who analyzed the effect of bank concentration on the non-performing loans (NPLs) for ten Central and Eastern European (CEE) countries. He found that bank concentration does not reduce the credit risk for all of the CEE countries and concluded that the relationship between the bank concentration and the NPLs, in regard to the CEE countries, is ambiguous.

With respect to the relationship between bank concentration and competition, in earlier studies of the theory of Industrial Organization (See Bain [25]) is has been argued that there is a negative correlation between concentration and competition, i.e. higher concentration could lead to lower competition, since the market is concentrated in very few companies. However, in more recent empirical studies (see Guevara & Maudos [141], Ferreira C. [119], and Liu G., & Mirzaei A. [207]), it is concluded that there is not necessarily a direct correlation between concentration and competition in the banking system and that the increase in the concentration of this industry could only provide some indications for the lack of competition. In addition, a significant concentration (moderate or high concentration) in the banking sector, may also be interpreted in a different way, i.e. that it is positively correlated with competition by arguing that inefficient banks have already been acquired from the efficient ones (Broye G. & Weill L [66]). In the case of the Greek banking system, the significant increase in

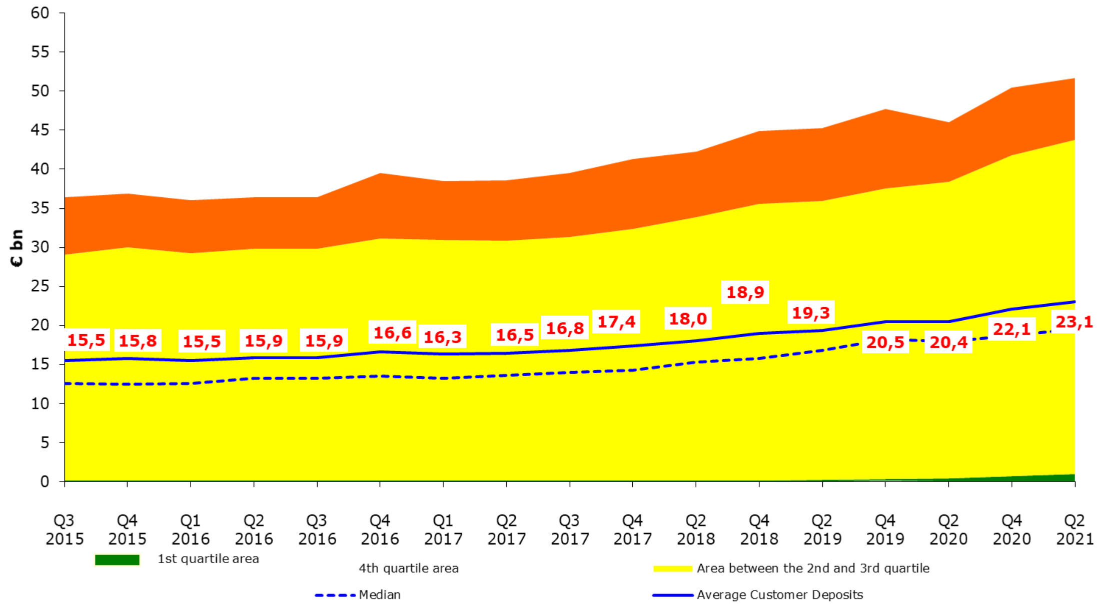
moderate concentrated when the value is between 1,000 and 1,800, and relatively low concentrated when the value is lower than 1.000.

concentration of total assets which was observed during 2013, is driven – to a very large extent – from the restructuring of the banking system as the "good assets" of banks have been retained and absorbed by the systemic banks which were deemed as «sustainable" and were recapitalized by the HFSF and the private sector. This trend is consistent with other European countries where economic adjustment programs had been initiated. Angeloni [2] illustrates this by comparing the values of the Herfindhal index for euro area countries before the crisis (2007) and after (2014). The evidence suggests that the increase in concentration between the two years is greater for the countries that have undergone an adjustment program. This is due, at least in part, to the fact that the program has included interventions on banks that have increased, e.g. via mergers or resolution, the concentration of the market.

However, in the case of the Greek banking sector, the increase in the concentration of total assets continued as well during the years 2015-2017 despite the fact that mergers and acquisitions of the period 2012-2014 had already been completed. This is because non-systemic banks lost market share to the benefit of systemic banks. However, a degree of competition is observed even amongst systemic banks. In this vein, Alpha Bank and the National Bank of Greece increased their market share of total assets during 2018 and 2019 to the detriment of Piraeus Bank. This is also evidenced by the improvement of the efficiency indicator "cost to income" ratio during the period 2016-2019, under conditions of a significant concentration due to economies of scale. However, during 2020-2021Q2, a decrease in concentration is observed both in the total loan portfolio and the portfolios by sector (consumer, mortgage, enterprise) and also a deterioration of the cost-of-income ratio is observed. The decline in the concentration during 2020-2021Q2 is due to the improvement in the market share of non-systemic banks, particularly in the corporate loan portfolio. In this vein, domestic entrepreneurs, foreign investment schemes and international groups are more favorably viewing that smaller banks (Attica Bank, Optima Bank, Aegean Baltic) will be able to compete in the Greek financial services market and benefit from its expected growth. Many investors expect increased demand in the advisory area (consultants for M&As, restructuring proposals, funding availability, corporate bonds) as well as further improvement of the macroeconomic environment. The increase in the cost of income ratio from 2017 onwards is attributable to the reduction in interest income due to the negative impact of the application of IFRS 9 and the revaluation of loan portfolios (such as mortgages) that cannot offset the cost reduction [See Table 13].

FIGURE 3.9

Distribution of Total Deposits of Commercial Banks in Quartiles (in € bn)



Sources: (a) Bank of Greece (BoG) for Less significant institutions and (b) Published financial statements for the systemic banks

TABLE 3.8

Market Share in total deposits of commercial banks (%)

Commercial banks	Period									
	2015:Q4	2016:Q4	2017:Q4	2018:Q2	2018:Q4	2019:Q2	2019:Q4	2020:Q2	2020:Q4	2021:Q2
National Bank of Greece	29.15	28.07	27.93	26.79	27.18	26.65	26.51	27.26	27.23	27.52
Alpha Bank	21.93	21.82	21.75	22.45	22.23	22.11	21.69	22.19	22.39	22.43
Attica Bank	1.71	1.51	1.39	1.43	1.51	1.55	1.60	1.63	1.60	1.58
Piraeus Bank	29.07	29.73	29.69	29.37	29.63	29.25	29.13	28.16	28.50	28.00
Eurobank Ergasias	18.03	18.76	19.10	19.83	19.31	20.21	20.62	20.26	19.57	19.55
Optima Bank	0.03	0.04	0.04	0.03	0.04	0.05	0.13	0.25	0.44	0.58
Aegean Baltic	0.08	0.07	0.09	0.09	0.10	0.14	0.23	0.26	0.25	0.32
Viva Payments	0.00	0.00	0.00	0.00	0.00	0.04	0.09	0.00	0.02	0.02
All commercial banks (%)	100	100	100	100	100	100	100	100	100	100
Total loans (bn)	126.5	133.0	139.0	144.0	151.6	154.8	163.8	163.6	177.1	184.6

Sources: (a) Bank of Greece (BoG) for Less significant institutions and (b) Published financial statements for the systemic banks

Regarding the evolution in the portfolio of customer deposits [See Figure 3.9] in the commercial banks, they increased from € 15.8 billion in the 4th quarter of 2015 to € 23.1 billion in the 2nd quarter of 2021; however, average deposits fluctuated by the end quarter of each year, due to seasonality effects. In any case, the course of deposits in the years 2017-2021Q2 is steadily increasing due to the strengthening of business confidence in the Greek banking system. Household deposits also increased due to the decline in banknote repository, as uncertainty subsided, while a gradual build-up of economic confidence in the stability of the banking system and solid macroeconomic prospects as a whole was observed.

It should be noted that the 2nd and 3rd quartile already constitutes the larger area compared to the 4th quartile. During 2016-2021Q2, there was no significant change in the specific weight of certain quartiles amid a total increase in commercial bank deposits.

3.3.2 Analysis of Interest Rate Margins

The indications of a potential existence of competition in the Greek banking system can be better observed from the differences in average lending and deposit rates [See Figure 3.16], i.e. the margin. Historically, the margin in the Greek banking system stood to the levels between 3.5% - 4.5%, however during 2016-2019, this limit was lifted up to 4.0%-5.0%, primarily due to the reduction of deposit interest rates. Since 2020 the margin is hovering around 4%.

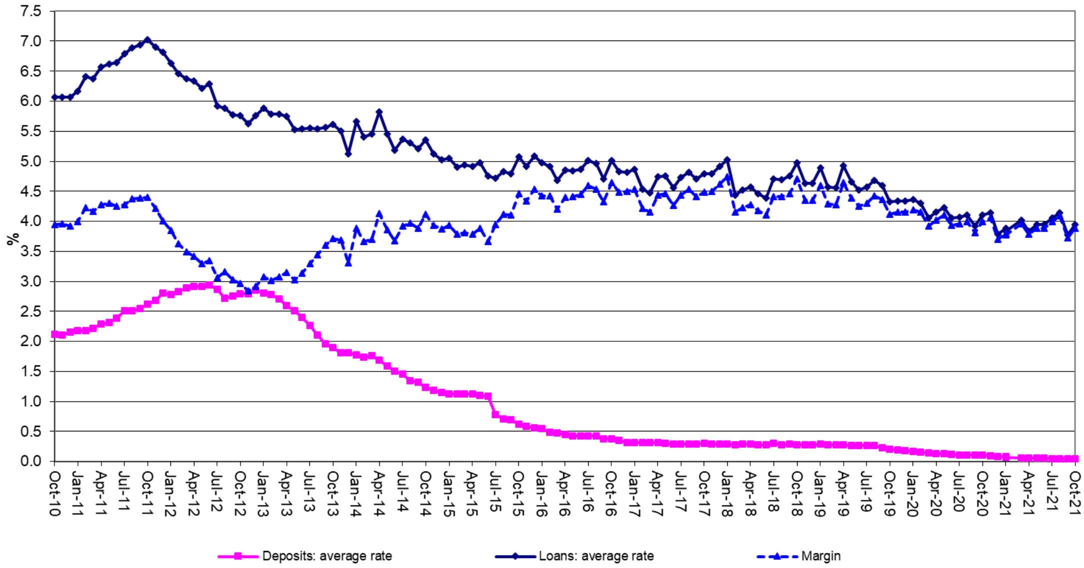
From the empirical examination of the margins, a downward trend in deposit rates was observed since June 2015 and up until December 2016, while lending rates remained stable on average during the same reporting period. This led to an increase in the interest margin. The factors that led to the reduction of deposit rates are due to the ECB's accommodative policy that proceeded in a double reduction of its benchmark interest rates on 09.12.2015 and then on 16.03.2016. The reason for this decline is due to the prolonged financial crisis that forced the ECB to pursue a policy of providing cheaper liquidity through monetary policy operations. However, while the decrease in Euribor and the ECB interest rate has affected deposit rates, it did not have the same effect on their associated lending rates, which remained high, albeit with variations, over the reporting period. This has taken place amid a reduction in banks' dependence on ELA funding, the interest rate of which is much higher compared to other sources of funding. The main reason for the one-sided reduction in deposit rates can be attributed to the increase in alternative sources of funding by banks, and in particular from the interbank market. Thus, while the volume of transactions on the interbank market, mainly from foreign banks, amounted to just € 1.7 billion in March 2015, this amount increased to € 18.2 billion in December 2016 with continuous improvement in transaction terms and conditions. Thus, the increase in alternative sources of funding led to a decline in deposit rates. In addition, the banks continued to compete with each other not so much for the level of deposit rates but for the flexibility in the terms and conditions for the supply of time deposit products. However, lending rates remain relatively high, mainly due to consumer loan rates, but in any case there is little room for the compression of lending rates even on the most fundamental portfolios of enterprise loans, that are rendered the most competitive, due to the high level of delinquencies of the period until the end of 2016.

Subsequently, deposit rates remained stable between December 2016 and August 2019 due to the policy of maintaining very low interest rates by the ECB. During this period, any fluctuations in the interest margin are exclusively due to changes in lending rates, which are however in the range of 4.5% -5%. As a result, the interest margin ranges between 4.2% -4.7% over the same period.

On 18 September 2019, ECB lowered the deposit facility rate[18] from -0.4 to -0.5%. By lowering the perceived lower bound of central bank rates, negative rates allow the monetary accommodation to propagate through the entire yield curve. This has resulted to the decrease in deposit rates from 0.23% in September 2019 to 0.13% in May 2020 and 0.05% in October 2021. This has subsequently pushed lending rates down – to a further extent – from 4.59% in September 2019, to 4.23% in May 2020 and 3.94% in October 2021. As a result, interest rate margins decreased from 4.36% in September 2019, to 4.10% in May 2020 and 3.89% in October 2021. Banks were provided a strong incentive to rebalance in favor of credit origination, by either rebalancing their portfolios through credit expansion or by purchasing securities.

18 The deposit facility rate is one of the three interest rates the ECB sets every six weeks as part of its monetary policy. The rate defines the interest banks receive for depositing money with the central bank overnight.

FIGURE 3.16
Average Deposit Rate, Lending Rate and Interest Rate Margin



Source: Bank of Greece (BoG) – Bulletins of Conjunctural Indicators [62]

As structural and cyclical factors have brought nominal interest rates closer to zero, the need to ease financing conditions further has prompted ECB to adopt a negative interest rate policy. So far, margins have been maintained at these levels due to the current ECB policy that remains accommodative, prolonging even further the low interest rate environment. According to Bank of Greece's Financial Stability Review [52], there are risks due to rising raw material prices and energy costs, which could maintain inflationary pressures in the period ahead. ECB's future policy will also take into account a reassessment of the prospects for economic recovery, combined with any increased risk-taking by investors, which could lead to significant fluctuations in the stock and bond markets. Of course, under the current level of competition, banks will be able to maintain their loan portfolios - mainly corporate and, secondarily, mortgages - with these interest rates. In any case, the reduction in the lending rate provides increasing difficulties for all - and not just for individual banks - as long as the problem of the high level of delinquencies persists.

As observed above, the level of banking interest rates in Greece and other countries of the euro area is formed according to the key ECB interest rates and the competitive conditions between banks in the local markets. Overall, the positive difference between the Greek and the corresponding Eurozone lending interest rates was maintained during this period, but there are variations depending on the loan portfolio. The largest discrepancy is still observed in lending rates to households (consumer loans), which reflects the highest credit risk and managerial costs that this borrowing entails. As a result, in this category covering the total cost of the loan (APRC), the interest margin in Greece in October 2021 stood at 11.75% and in the euro area at 5.83% and the difference between them has widened considerably in comparison to December 2017 (Greece: 9.78%, Eurozone: 5.80%) and December 2015 (Greece: 9.73%, Eurozone: 6.25%)[19]. Regarding corporate loans up to one year with amounts up to € 250 thousand, a lesser divergence is observed in this category given that the margin in Greece in October 2021 stood at 4.55% and in the euro area at 2.09%. It is important to note that the difference between Greece and the Eurozone is converging compared to December 2017 (Greece: 5.34%, Eurozone: 2.46%) and December 2015 (Greece: 5.87%, Eurozone: 3.18%)[19]. Regarding housing loans with an interest rate covering the total cost of the loan (APRC), the interest margin in Greece in October 2021 stood at 3.26% and in the euro area at 1.6% and the difference between them remains relatively low but it is widening compared to December 2017 (Greece: 3.52%, Eurozone: 2.15%) and December 2015 (Greece: 3.03%, Eurozone: 2.55%)[19] .

It should be noted that the difference in interest rates between loans and deposits in Greece is higher compared to the average of the euro area countries. Given that delinquencies remain at very high levels, this implies an increase in risk premia, which is incorporated into the lending rates. In this sense, to the extent that borrowing costs and non-performing assets of Greek credit institutions are maintained at high levels, bank lending rates in Greece will continue to remain high in the near future. Nevertheless, the largest divergence is still observed in loans to households (consumer loans). This implies that the category of lending which is considered attractive for banks comprises of corporate loans, where competition mainly from systemic banks has intensified.

3.4 Risk Analysis in the Greek banking system

This section examines the extent to which important factors that explain the course of the banking system have strengthened systemic risks (credit risk, liquidity risk, political risk, country risk). Of course, the international financial crisis that has been transposed

19 MFI interest rate statistics in Greece and the euro area.

into a sovereign and private debt crisis - in the case of Greece, has led to the maintenance of the non-performing exposures at very high levels, which in turn undermines the intermediation role of the banks. However, this is reversible under the preconditions of appropriate macroeconomic conditions and targeted actions to reduce non-performing exposures, Greek banks will be able to recover part of their intermediation role that they have lost in the past periods, which in turn is expected to bring positive effects to the real economy.

First of all, the undisputed achievement in the decrease in non-performing loans, coupled with the increase in accumulated provisions, reinforces the argument that total credit risk at system level has declined during 2018-2021Q2. Obviously, the COVID-19 pandemic has disrupted global financial stability and overturned Greece's growth for 2020 bringing it in negative territory although there has been a sharp rebound in 2021. Nevertheless, a reversal of the downward trend of non-performing loans in the short-term has not been observed while a deterioration in the medium term cannot be precluded if the Greek State support measures are prematurely terminated. Regardless of the impact of the COVID-19 pandemic, restarting the real economy through the intermediary role of banks requires the resolution of the historical stock of non-performing loans. In this context, the Hellenic Asset Protection Scheme (HAPS), although a positive development, is not sufficient and therefore there should be other complementary plans to address this problem.

In the medium to long run, the successful tackling of the problem of non-performing exposures will not only alleviate the debt burden of borrowers, but will also - in particular - allow credit institutions to release funds that will be able to target the most dynamic and outward-looking enterprises. In this way, credit institutions will contribute to the overall restructuring of the economy, resulting in an increase in overall productivity and potential growth even in the short term.

It should also be noted that there are a number of exogenous risks that could overturn this path. The uncertainty due to the Covid-19 pandemic reduced international risk appetite and induced heightened volatility in the markets. The broad range of measures undertaken both by central banks and national authorities, have been a major factor in the market recovery, by reducing market stress to a great extent. Still, there are risks ahead. The decline in consumer confidence, has not resulted in a decline in equity markets. As the divergence between market prices and fundamentals of the real economy has grown considerably, this raises the risk of another correction in risk asset prices should investor risk appetite fade, posing a threat to the recovery.

3.4.1 Developments in the asset quality of the Greek banking system

Since the inauguration of the financial crisis in 2008, the unfavorable macroeconomic conditions led to the decline in disposable income of both households and corporates. Due to the unfavorable macroeconomic environment, the demand for business funding was reduced, taking into account increased business risk, but also from households as a result of uncertainty about the future course of their economic potential. As a result of the aforementioned developments, the asset quality of the loan portfolios of Greek credit institutions deteriorated and credit risk reached its highest level until December 2016.

According to Bank of Greece's Financial Stability Review [52], [53], [54], [55], [56] and the Reports on the Overview of the Financial System [57] since the second and third quarters of 2017 to the second quarter of 2021, there has been a continuous improvement in the quality of banks' loan portfolio. On the one hand, banks have restructured non-performing loans, improved the rate of recovery of non-performing loans to cash and accelerated the write-offs of non-performing consumer credit portfolios, as well as old business loans that remained in banks' balance sheets. On the other hand, the improvement in macroeconomic conditions has helped stabilize the demand for credit from non-financial firms, as specific sectors have shown interest in more lending, such as the start-up small and medium-sized enterprises, as well as enterprises that promote employment for young people.

Although no short-term effects have been witnessed, the COVID-19 pandemic is expected to re-weigh the asset quality of the Greek banking system through the creation of new non-performing loans in the medium term, but such a development cannot be accurately assessed. One of the factors that complicates the assessment for the creation of new NPLs in the medium term is the suspension of the payment of interest-bearing installments on loans and other debt obligations until the end of the year, according to the support framework for households and enterprises that have been rendered extremely vulnerable by the coronavirus pandemic.

Based on the latest available data [52], [53], [54], [55], [56], [57], the ratio of non-performing loans has declined in all sectors during 2018-2021Q2 (2021Q2: 20.3%; 2020: 30.1%; 2020Q2: 37.2%; 2019: 40.6%; 2019Q2: 43.6%; 2018: 45.4%; 2018Q2:

47.8%; 2017: 47.2%). In absolute terms, the total amount of non-performing loans was reduced to € 29.4 billion in 2021Q2 from € 47.2 billion in 2020, € 68.5 billion in 2019, € 81.8 billion in 2018 and € 94.4 billion in 2017. During the same period, the coverage of non-performing exposures by provisions improved from 46.3% in 2017 to 47.4% in 2018, while it subsequently fell but was maintained fairly stable to 43.9% in 2019, 44% in 2020 and 43.5% in 2021Q2.

It should be noted that the successful completion of the scheduled sales of NPLs through securitizations with the simultaneous use of the Hellenic Asset Protection Scheme (HAPS) will contribute to a further reduction in the existing stock of NPLs. However, a NPLs ratio of 20.3% is still the highest compared to the average of the countries of the medium-sized banks in the European Union (2.3% as of June 2021) [20].

3.4.2 Liquidity Conditions in the Greek Banking System

The liquidity of the banking system will be examined next, as the financing of the economy through loans can be supported only by strengthening the deposit base of Greek banks[21].

The examination of the data shows that banks' funding from the Eurosystem (ECB and ELA) sources has declined significantly since the end of 2015 as, following the imposition of controls on capital movements, Greece reached an agreement with international creditors in July 2015, which resulted in the stabilization of deposits. Additionally, in December 2015, the successful recapitalization of the Greek banking system resulted in the buildup of investor confidence in the domestic banking system.

However, the course of improving liquidity conditions was not always smooth. In the

20 Source: ECB, ECB Statistical Data Warehouse https://sdw.ecb.europa.eu/browse.do?node=9691533

21 It should be noted that during the crisis, banks' deposit base was significantly compressed and, given that banks could not maintain sufficient liquidity, they sought other external sources of funding. The main alternative source of funding was Eurosystem funding, which includes both direct funding from the ECB and the Emergency Liquidity Assistance (ELA) facility. ECB funding is provided in cases where (a) the collateral held by banks is of high quality, low risk and hence of high credit rating (i.e. debt securities issued by EFSF) and (b) high credit rating, but still fall short of the aforementioned category (for example, covered bonds, government bonds, loans and advances, securitizations). ELA funding is extraordinary and takes place to replace ECB funding if the ECB does not recognize securities as eligible to those with a high credit rating and in other exceptional cases where there is a sudden and large-scale outflow of deposits.

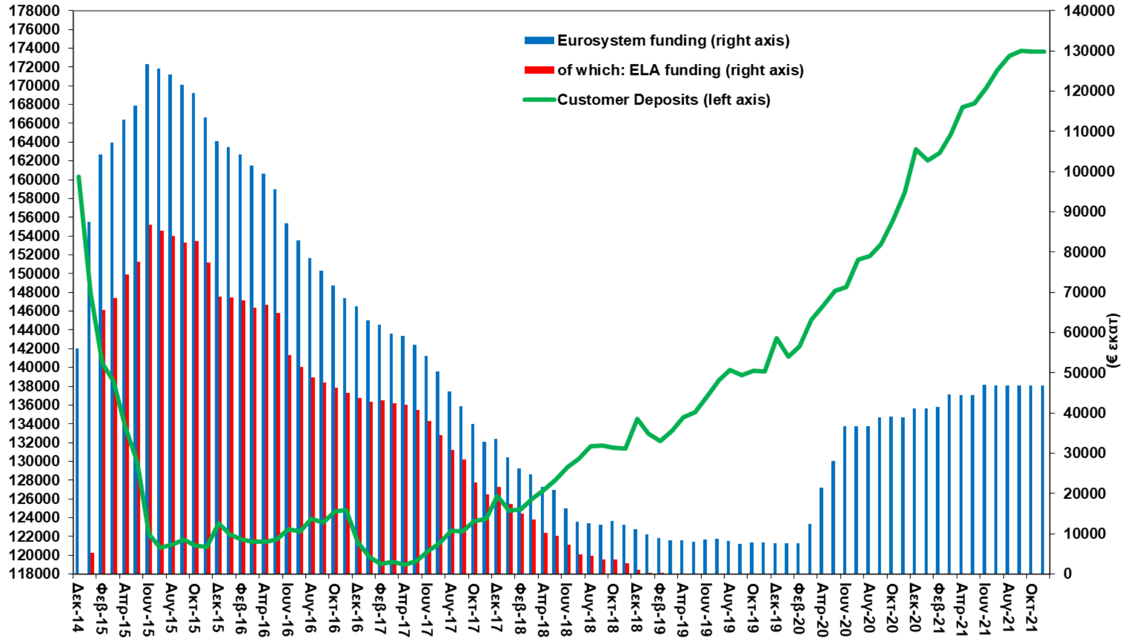
first quarter of 2017, banks underwent significant pressures on their liquidity, as despite the progress of negotiations between the Greek authorities and international creditors, the second review of the Third Economic Adjustment Program (Memorandum) was not completed. According to data from the Bank of Greece [62], Greek customer deposits declined to 119 billion euros in April 2017 compared to 121.4 billion in December 2016. On the other hand, the outstanding balances of the emergency liquidity facility (ELA) rose in February 2017 to 43.1 billion, reversing a downturn that started after June 2015, as Greek banks tried to offset their declining deposits from other sources in order to meet their financing needs.

During May 2017, liquidity risks declined as the Greek government reached an agreement with international lenders on the actions to be taken (prerequisite measures) to complete the second review of the 3rd Financial Adjustment Program. Lastly, a compromise agreement on debt sustainability criteria between the IMF and European creditors was reached in June 2017 (agreement in principle), as debt relief does not need to be fully defined but the IMF requires assurance that the relief measures of debt is quite specific to preserving the sustainability of debt in the future. As a result, Greek customer deposits increased to 120.4 billion in June 2017 with an upward trend. Correspondingly, ELA declined to 37.9 billion in June 2017 compared to 43.7 billion in December 2016.

Then, since the fourth quarter of 2017 until now, the upward trend in the bank deposit base continued uninterrupted (May 2020: EUR 148.1 billion; December 2019: EUR 143.1 billion June 2019: EUR 136.9 billion; December 2018: EUR 134.5 billion; March 2018: EUR 126 billion; September 2017: EUR 122.6 billion). It should be noted that the review of the third economic program adjustment was completed in the Eurogroup meeting on 12 March 2018 and subsequently the European Stability Mechanism on 27 March 2018 approved the immediate disbursement of the first tranche of EUR 5.7 billion. The upward trend in household deposits was due to a decline in uncertainty and a gradual recovery of confidence in the stability of the banking system as a whole and it led to the definitive lifting of the cash withdrawal restrictions as of 1.10.2018.

FIGURE 3.17

Customer Deposits and Eurosystem Funding (ECB and ELA)



Sources: Bank of Greece (BoG) - Monthly Balance Sheet of the Bank of Greece for ELA funding and *Bulletins of Conjunctural Indicators for Eurosystem funding and customer deposits [62]*

Then, during 2018, banks significantly reduced dependence on the Emergency Support Facility (ELA), while since March 2019, all banks have become completely independent of ELA[22].

Figure 3.17 shows the evolution of deposits and the provision of liquidity by the Eurosystem through monetary policy operations and the ELA, respectively. Total Eurosystem funding (including ELA) declined significantly since 2015 and in December 2019 amounted to € 7.6 billion (December 2018: € 10.9 billion; December 2017: € 32.7 billion).

On 21 August 2018, following the successful completion of the Third Financial Adjustment Program, banks lost the privilege of a "waiver" that allowed them to access cheap ECB funding. The "waiver" would theoretically allow Greece to participate in the ECB's quantitative easing program before its completion. In order to address this issue, Greek banks maintained funding lines by replacing Greek government bonds and

22 Specifically, ELA has been eliminated since March 2019 for Alpha Bank (0.3 billion euros in December 2018) and for Eurobank (0.5 billion euros in December 2018). It had already been eliminated for the National Bank of Greece since November 2017 (3.8 billion euros in June 2017) and for Piraeus Bank since July 2018 (0.3 billion euros in June 2018).

treasury bills with other ECB-eligible assets. In addition, banks have increased reverse repos with international counterparties pledging high-grade government bonds that serve, inter alia, as eligible collateral from the ECB.

TABLE 3.9

Evolution of funding from the Eurosystem for the four systemic banks

(in bn €)	2015	2016	2017	2018	2019	2020	Q2 2021
National Bank of Greece							
ECB	12.5	6.7	2.8	2.3	2.2	10.5	11.6
ELA	11.5	5.6	0	0	0	0	0
Alpha Bank							
ECB	4.8	5.2	3.2	3.1	3.1	11.9	12.9
ELA	19.6	13.2	7.0	0.3	0	0	0
Bank of Piraeus							
ECB	16.0	9.0	4.0	3.2	0.4	11.0	13.5
ELA	16.7	11.9	5.7	0	0	0	0
Eurobank							
ECB	5.3	2.1	2.1	1.5	1.9	8.0	8.8
ELA	20.0	11.9	7.9	0.5	0	0	0

Source: Bank of Greece (BoG) - Monthly Balance Sheet of the Bank of Greece for ELA funding and Bulletins of Conjunctural Indicators for Eurosystem funding and customer deposits [62]

As liquidity conditions during the first quarter of 2020 deteriorated due to the impact of the COVID-19 pandemic, ECB on 7 April 2020 adopted unprecedented measures to increase eligible collateral for the financing of credit institutions in the euro area. Specifically, the ECB reinstated the “waiver” for the acceptance of Greek government bonds as collateral in the Eurosystem monetary policy operations.

The increase in Eurosystem funding during the first half of 2020 took place simultaneously with the decrease in interbank repo transactions, as the banks are proceeding to the termination of the repurchase agreements of Greek government bonds, which are now eligible as collateral from the ECB. In addition, the cost of interbank repos for banks’ funding has increased temporarily, due to the widening of credit margins due to the COVID-19 pandemic. Nevertheless, repos remain an important source of funding with collateral being securities held by banks, covered bonds and bonds of the Greek State and other eurozone governments.

3.4.3 Political Risk

Political risk has significantly decreased. Following its increase in the first half of 2015 due to the tense negotiations and increased controversy between the Greek government and international creditors, the Greek authorities have substantially increased their compliance thereafter with the creditor instructions resulting in the successful completion of the third economic adjustment program in August 2018. During the post-memorandum period, the Greek authorities are taking into account and in a number of cases applying the creditors' advice in the context of the post-Memorandum enhanced surveillance program.

3.4.4 Country Risk

Greek government debt has been significantly upgraded by international rating agencies. The upgrading of Greece's credit rating by Moody's on March 13, 2019 on the B1 scale from B3 was a positive message to the markets and helped the implementation of the issuance of the 10-year benchmark on 06.03.2019. The lifting of capital restrictions, combined with the easing of fiscal risks, led Standard & Poor's (S&P) on October 25, 2019 to upgrade Greece's debt to "BB-" from "B +" with positive outlook. Positive outlook suggests S&P could upgrade Greece within the next 12 months if the government continues to implement structural reforms that boost the country's economic growth and sustainability of public finances.

The upgrading of Greece's creditworthiness reflects the positive expectations of international rating agencies with regard to the medium-term prospects for the country's public finances and the ability to manage its very high debt. These positive expectations are also reflected in the spreads between the yields of the German and Greek Bonds having fallen significantly in relation to their high levels in the past. Whenever uncertainty prevails, investment funds find a way out of the safest German bonds, pushing German yields down. On the contrary, when investment funds have positive indications of the prospects of a country with a higher risk than Germany, it is prepared to take the extra risk by placing it on the bonds of that country, since it can earn from the highest returns. The spreads between Greek and German bonds have fallen significantly, making it possible to exit to the markets but not yet at an autonomous level, that is to say, through the exclusive support of the country's financing needs for external borrowing.

It should be stated that the reduction of Greek 10-year bond yields to historically low levels is not in itself a trigger for further upgrades of the country's debt, given the very low - even negative - interest rates that have been prevailing in other countries of the eurozone for a long time. However, since low interest rates signal greater potential for public debt management, debt sustainability, combined with the dynamics of reforms, could lead to further upgrades to the Greek sovereign debt rating. Furthermore, despite the expected large deterioration of the fiscal result due to COVID-19, the annual cost of servicing the public debt for Greece in terms of GDP remains low due to the favorable structure of repayments and its composition, as most debt consists of eurozone loans with very low interest rates.

Moreover, Greece maintains certain idiosyncrasies regarding both the country itself and its banking system: Geographical idiosyncrasies. Despite the significant penetration of internet banking in a growing number of corporates and households, the necessity of preserving a large network of branches is maintained, leading to an increase in the operating costs of Greek banks, in those areas that are remote or have relatively low economic activity (e.g. small islands, mountainous areas, etc.). Financial intermediation. The relatively low level of financial intermediation and the small size of Greek banks in relation to the corresponding European ones, do not allow them to adequately exploit the economies of scale, therefore they face higher operating costs than the European ones.

3.5 Analysis of the resilience of the Greek banking system

3.5.1 Profitability and efficiency of the Greek banking system

This section presents the key performance and efficiency indicators, i.e. the Return on Assets (after taxes), the net interest margin, the Return on Equity (after taxes) and the cost to income ratio [Ref. Table 3.10].

During 2018, Greek banks on a consolidated basis recorded profits after taxes but before discontinued operations of € 361.4 million compared to € 96.6 million in 2017 and they increased to € 682.9 million in 2019. In particular, the increase in operating income during 2019 reflects the fact that the decrease in net interest income was offset by an increase in non-interest income. In terms of net interest income, the decrease in interest income was greater in absolute terms than the corresponding decrease in interest expenses. Interest income was negatively affected by the continuing deleveraging of the banks' loan portfolio. The decline in interest expenses is due to the complete disengagement from the Emergency Liquidity Assistance (ELA) in March 2019 and the reduction in the cost of deposits.

During 2020, the profitability of the Greek banking system was adversely affected both by the pandemic and the implementation banks' strategies regarding the reduction of non-performing loans. The main developments were the recording of losses after taxes and discontinued operations, mainly due to the formation of increased provisions for credit risk, as well as the reduction of banks' supervisory own funds. During the first half of 2021, Greek banks recorded high losses after taxes and discontinued operations amounting to 4 billion euros, compared to losses of 1.7 billion euros in the corresponding period of 2020, mainly due to losses from the sale of non-performing loan portfolios. Consequently, in a period of recovery of economic activity from the effects of the Covid-19 pandemic, the Greek banks took the opportunities to restructure their loan portfolios at the cost of being the only loss making sector amongst the banks of the European Union.

TABLE 3.10

Key Income Statement Indicators (%)

All banks	Period									
	2015:Q4	2016:Q4	2017:Q4	2018:Q2	2018:Q4	2019:Q2	2019:Q4	2020:Q2	2020:Q4	2021:Q2
Return on Assets (%) (after taxes)	-0.23	0.08	0.04	0.03	0.14	0.22	0.26	-0.65	-0.57	-2.64
Net Interest Margin (%)	2.35	2.69	3.04	2.79	2.70	2.61	2.52	1.99	1.92	1.88
Return on Equity (%) (after taxes)	-20.48	0.74	0.29	0.27	1.33	1.97	2.37	-6.65	-6.39	-33.6
Cost to Income (excluding provisions for loan losses) (%)	61.28	52.58	50.02	52.91	54.46	50.45	51.31	40.2	43.63	43.85

Source: Bank of Greece (BoG) for the aggregate figures.

In terms of Return on Assets for Greek banks, this ratio increased to 0.14% in 2018 and 0.26% in 2019, compared with 0.04% in 2017 and 0.08% in 2016. While profitability before taxes has been positive since 2016, it has accelerated in 2018 and 2019 despite the continued deleveraging in the lending portfolio due to the increase in the non-interest income.

The acceleration of the repair of Greek banks' balance sheets through the sale of non-performing loan portfolios has resulted in an increase in the cost of credit risk. Specifically, in the first half of 2021, the formation of loan loss impairment amounted at € 6.4 billion compared to € 3.5 billion in the corresponding period of 2020. Of these, € 5.4 billion are attributed to the sale of non-performing loans by two systemic banks.

The net interest margin fell to 2.5% in 2019 compared to 2.7% in 2018 and 3.04% in 2017 due to a decline in the net interest income, reversing the upward trend observed in 2015-2017. However, during 2019-2020 the net interest margin dropped further despite the increase in net interest income due to the increase in total assets at a faster rate. It should be stated that the net interest margin of Greek banks remains significantly higher than that of medium-sized banking groups in the European Union (EU). In particular, the increase in the net interest margin during the periods 2015, 2016 and 2017, is attributed to the faster rate of decline in total assets (denominator of the ratio) in relation to the rate of decrease in net interest income. However, during 2018, a decline in total assets slowed and there has been an increase in total assets from the third quarter of 2018 onwards. Furthermore, during 2019-2021Q2 total assets of Greek banks increased.

Similarly, Return on Equity for Greek banks increased to 1.33% in 2018 and 2.37% in 2019, compared with 0.29% in 2017 and 0.74% in 2016. These performances reflect that the pressures on profitability eased as operating income increased, while loan impairment losses (provisions) decreased. However, during 2020-201Q2 loan impairment losses increased resulting in losses for the Greek banking sector. As a result, Return on Equity for Greek banks went to negative territory and amounted to -6.39% in 2020 and -33.6% in 2021Q2. It should be noted that loan impairment losses declined by 16.8% in 2019 (the total decrease in provisions was 16.4%), while total assets increased despite the decrease in loans due to deleveraging. As a result, the cost of credit risk decreased to 1.8% in 2019 (2018Q4: 2.1%; 2018Q1: 2.1%; 2017: 2.8%). Respectively, the cost of credit risk increased to 3.7% in 2020.

Finally, due to the increase in operating income and to a lesser extent to cost-cutting efforts, the Cost to Income Ratio decreased to 51.3% in 2019 from 54.5% in 2018 (2018: Q2 55.6%; 2018Q1: 56.4%’ 2017Q4: 52.9%; 2016Q4 : 52.6%). During the first half of 2021 operating income as well as operating expenses increased. The latter was due to provisions for voluntary retirement plans, corporate transformation costs, and impairment of goodwill and intangible assets. It should also be noted though that the downward trend in personnel and branch network continued. In addition, depreciation increased mainly as a result of the increase in intangible assets due to investments in IT infrastructure in the context of accelerating digital transformation. As a result, the Cost to Income Ratio reversed the downward trend and stood at 43.9% in the first half of 2021 compared to 40.2% during the same period of 2020.

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3.5.2 Capital adequacy: To what extent to coverage of the capital ensures a more resilient Greek Banking System

The Capital Adequacy Ratio (C.A.R.) of the Greek banking groups increased in 2019 and stood at 17% in 2019 compared to 16% in 2018 and 17.0% in 2017 and 2016. Similarly, Tier 1 ratio increased to 15.92% in 2019 compared to 15.31% in 2018, 16.97% in 2017 and 16.89% in 2016. Finally, the CET1 ratio stood at 15.9% in 2019. On a solo basis, the C.A.R. of Greek banks stood at 17.51% in 2019 compared to 16.31% in 2018and 17.58% in 2017. However during 2020 and 2021Q2 the capital adequacy ratios of Greek banking groups decreased (Table 3.11).

TABLE 3.11

Capital adequacy indicators (%)

	Greek banks						
On a consolidated basis	**Greece**						**EU domestic banks**
	2016	2017	2018	2019	2020	2021H1	2021H1
C.A.R.	17.0	17.02	15.98	17.02	16.65	14.98	18.70
Tier I ratio	16.89	16.97	15.31	15.92	14.99	12.85	17.10
Common Equity Tier I ratio	16.88	16.96	15.29	15.91	14.98	12.47	16.67
On a solo basis	**Greece**						**EU domestic banks**
	2016	2017	2018	2019	2020	2021Q2	2021Q2
C.A.R.	17.47	17.58	16.31	17.51	15.37	15.09	-
Tier I ratio	17.36	17.54	15.60	16.33	13.67	12.94	-
Common Equity Tier I ratio	17.35	17.53	15.58	16.32	13.66	12.54	-

Source: Published Financial Statements and banks' presentations.

It is noted that the application of International Financial Reporting Standard 9 (IFRS 9) as of 1 January 2018 has adversely affected the regulatory equity by 5% in 2018. Greek banks have chosen to use the transition period to absorb the impact in their own funds from the application of the new standard. During 2019, the increase in regulatory equity is attributed to the issuance of subordinated bonds which is regarded as Tier 2, the recording of profits after taxes and the highest stock of securities measured as Fair Value Through Other Comprehensive Income (FVTOCI) which is recorded as equity.

During 2020, supervisory own funds of Greek banks decreased by 7.5%, having been negatively affected by the application of the transitional provisions of IFRS 9 and the recording of losses. An additional factor is that the deferred tax credits (DTCs) amounted to € 15.1 billion and represented 53% of total supervisory own funds.

The capital adequacy declined further in 2021H1, mainly due to the losses arising from the sale of non-performing loan portfolios. Specifically, the Common Equity Tier 1 ratio - CET1 ratio on a consolidated basis decreased to 12.5% in June 2021 from 15% in December 2020.

For this reason, the strengthening of the capital base of Greek banks is necessary; it will result in the creation of a capital buffer, which in turn will support them in order to withstand the effects of the high (albeit declining) level of delinquencies. In any case, GDP growth has allowed banks to restructure their loan portfolios by selling or transferring (securitization) many of the non-performing loans. It is well known that the high percentage of bad debts is a restriction on their ability to finance the real economy, not least when profitability remains ineffective in part due to the need to maintain a high inventory of provisions to cover non-performing exposures. On the other hand, credit institutions increased their liquidity from deposits, while the issuance of subordinated bonds since 2019 essentially marked the banks' return to international financial markets.

Of course, this will also depend on exogenous and geopolitical factors, as the Covid-19 episode in the markets in 2020Q1 highlights that vulnerabilities could lead to capital outflows. Therefore, maintaining a significantly higher capital buffer in Greek banks (through share capital increases and Tier 1/ Tier 2 bond issuances) that should track the average of euro area banks is the only way to ensure their long-term resilience and support their intermediation role for the financing of the real economy.

CHAPTER 4 Evolution of funding conditions and liquidity in the Greek banking sector: Sources and uses of funding and credit risk determinants

Liquidity conditions are a very important component for investigation when designing a short-term monitoring system. According to Bandt O., Chahad M. [26], Duijm P.and Wierts P. [99], liquidity constraints in banks are affecting their lending decisions and limiting their supply capability. Banks' intermediation capacity in channelling funds to entities that need funds is affected by bank liquidity. Based on the characteristics of the maturities of a bank's loans and its third party funding, banks will require liquidity to conduct their business activities. Hence, the role of liquid assets in banking plays an important role because the main business of a bank is managing liquidity to meet the needs of depositors and borrowers according to Diamond & Dybvig [100]. In that case, the European Central Bank (ECB) is empowered with the de-facto task of the lender of last resort (LOLR) and provides emergency liquidity to the banking system. This can, in turn, have an impact on the functioning of the interbank market in countries in case of a systemic liquidity crisis.

This Chapter investigates the liquidity conditions in the Greek banking sector. It addresses both the drawing of liquidity from deposits as well as drawing it from the markets. The deposit base is the most important parameter for maintaining adequate banking liquidity that would enable banks to channel funds to the Greek economy. The results of the analysis demonstrate that Eurosystem funding to Greek banks has continued to decrease up to 2019 given the fact that a sustainable inflow of deposits has been witnessed. It should be noted that the maintenance of deposits at a satisfactory level is of paramount importance, as they enable banks to play their intermediatory role and channel them in the real economy.

4.1 Liquidity provision to the Greek economy

It should be noted that the progress of the liquidity restoration in the Greek economy is directly linked to the health of the banking system. Until recently, the channels for providing liquidity in the real economy were restricted as banks are not able to draw liquidity from the markets and subsequently to "pass" this liquidity to the real economy[23]. On the other hand, households and enterprises were stagnated due to the effects of the prolonged recession. The Greek authorities have been decisive in supporting the financial stability of the system, resulting in the protection of depositors. In addition, according to the recapitalization framework of the banking system through the HFSF, jointly agreed by the Greek authorities and the international lenders, coupled with injection of capital from the private sector (see Bank of Greece: Report on the Recapitalization and Restructuring of the Greek Banking Sector [61]), a wide range of mergers and acquisitions was facilitated in 2013, while the recapitalizations of 2013, 2014 and 2015 enhanced capital adequacy levels. According to the Bank of Greece's Governor's Report for the year 2015 [58], Greek banks completed successfully in December 2015 their recapitalization with increased private sector participation. The four systemic banks covered the required funds resulting from the ECB adverse stress test scenario. The aforementioned development restored confidence in the longer-term viability of Greek banks despite the pessimistic economic climate.

During June 2016, market volatility increased immensely, encompassing both positive and negative news: on the one hand, the positive impact of ECB's Governing Council reinstating the waiver of minimum credit rating requirements for marketable instruments issued or guaranteed by the Hellenic Republic[24] while on the other , the impact of investors' surprise at the outcome of the Brexit referendum which led to an overshooting.

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23 It should be noted that during the period of austerity the banks' deposit base came under a severe strain and it was not possible for the banks to maintain sufficient liquidity, so they reverted to external funding sources. The primary alternative funding source was Eurosystem funding which involves both direct funding from the ECB as well as funding from the emergency liquidity mechanism ELA (Emergency Liquidity Assistance). ECB funding takes place in cases where (a) the collateral held by banks are high quality, low risk and thus high credit rating (for example, bonds issued by the European Financial Stability Facility - EFSF); and (b) collateral held by banks which is of a high credit rating, but still falling short of the aforementioned category (for example, covered bonds, government bonds, loan receivables, securitizations). ELA funding is extraordinary and takes place with the aim to substitute ECB funding in case ECB does not recognize securities as eligible with those of a high credit rating and in other exceptional cases, where a sudden and large-scale outflow of deposits occurs.

24 ECB's Governing Council reinstates waiver of minimum credit rating requirements for marketable instruments issued or guaranteed by the Hellenic Republic, subject to special haircuts https://www.ecb.europa.eu/press/pr/date/2016/html/pr160622_1.en.html

By October 2016, risk decreased as ESM authorized the disbursement of €2.8 billion to Greece, which is the remaining amount of the second tranche of ESM financial assistance, while ESM's Managing Director stated that "if the government continues to implement the reforms agreed, it may be able to start issuing bonds again next year[25]".

Political risks increased on November 2016, in the aftermath of US election results, while debt relief prospects were tied to further implementation efforts by the Greek administration. On December 2016, jitters between the Greek administration and creditors regarding unilateral budget spending measures on pensioners increased risks.

In 2017, political and implementation risks resurfaced again during the first 3 months of 2017, reflecting market sentiment from the stumbling blocks in bailout talks amid deterioration of certain market and economic indicators. Nevertheless, in April 2017 the institutions and the Greek authorities finally reached an agreement on the main elements of the policy reforms[26] required to move ahead with the second review of the current macroeconomic adjustment program. During the fourth quarter of 2017 and the first quarter of 2018, the upward trend in the deposit base of the banks continued (March 2018: € 126 billion; September 2017: € 122.6 billion), as the third review of the third economic adjustment program was concluded at the Eurogroup meeting on 12 March 2018 and the European Stability Mechanism on 27 March 2018 approved the immediate disbursement of the first sub-tranche of € 5.7 billion euros. The overall pattern of deposits continued its upward trend reaching € 130.2 billion euros in July 2018. The return of deposits by households is to the decline in the uncertainty and the gradual recovery of confidence in the stability of the banking system as a whole.

On August 21st 2018, after the successful finalization of the Third Economic Adjustment Program[27], banks lost the "waiver"[28] that allowed them to have access to

25 The Board of Directors of the European Stability Mechanism (ESM) authorized on 25.10.2016 the disbursement of €2.8 billion to Greece https://www.esm.europa.eu/press-releases/esm-board-directors-approves-%E2%82%AC28-bn-disbursement-greece

26 Remarks by J.Dijsselbloem following the Eurogroup meeting of 7 April 2017 https://www.consilium.europa.eu/en/press/press-releases/2017/04/07/eurogroup-jd-remarks/

27 Greece: the third economic adjustment programme https://www.consilium.europa.eu/en/policies/financial-assistance-eurozone-members/greece-programme/

28 The "waiver" was the abolition of the rule that normally prohibited ECB from accepting Greece's sovereign bonds (non-investment grade) as collateral for its liquidity operations. The "waiver" enabled

cheap funding from the ECB. In addition, banks had increased their reverse repo transactions with international counterparties by borrowing high-quality government bonds that serve, among other things, as eligible collateral from the ECB.

However, in order to tackle for deteriorating liquidity conditions in the first quarter of 2020 due to the COVID-19 pandemic, ECB adopted unprecedented measures to increase eligible collateral for the financing of credit institutions in the euro area. Specifically, the ECB reinstated the "waiver" on 7 April 2020 for the acceptance of Greek government bonds as collateral in the Eurosystem monetary policy operations[29]. The increase in Eurosystem funding during the first half of 2020 took place simultaneously with the decrease in interbank repo transactions, as the banks proceed to the termination of the repurchase agreements of Greek government bonds, which are now eligible as collateral from the ECB.

Since the fourth quarter of 2017, the upward trend in the bank deposit base continued uninterrupted. Therefore, banks were able to operate on the interbank repos market by carrying out transactions with longer maturities (i.e. over one month) while maintaining high-quality liquid assets (i.e. cash and high-quality government bonds) even during the acute crisis from Covid-19 in the first quarter of 2020.

4.2. Market funding possibilities

The analysis of the interrelationship between the stock index and the banking indices during the period of the financial crisis indicates the importance of the banking system and its intermediating role for the effective channeling of liquidity from investors and depositors to the real economy, in cases where direct drawing of capital from the markets is difficult. Despite the fact that the funding of the Greek economy – in particular the Small and Medium enterprises – is only to a limited extent dependent on the Greek Stock market, the level of such interrelationship is strong, as the listed banks in the Athens Exchange maintain a large share of the overall market capitalization of all listed companies.

ECB to support Greek banks with the required liquidity during the prolonged period of the application of the memoranda, while its extension could enable Greece to participate in the ECB's quantitative easing program.

29 ECB announces package of temporary collateral easing measures.https://www.ecb.europa.eu/press/pr/date/2020/html/ecb.pr200407~2472a8ccda.en.html

The prospects of the General ATHEX Index and the Banking Indices FTSE/ATHEX-CSE are closely connected to the developments of the Greek economy overall. According to Georgikopoulos [135], the analysis of the interrelationship between the stock index and the banking index during the period of the financial crisis in Greece is important as the banking system plays a vital role in the effective channeling of liquidity from investors and depositors to the real economy, in cases where direct drawing of capital from the markets is difficult. This is evidenced by the fact that any increase/decrease in the values of the stocks is going hand by hand with the developments in the economic outlook and sentiment. The decrease in the stock values experienced over the last years creates an opportunity for a significant profit potential, to the extent that the Greek economy will undergo a sustained growth process. As long as the message of stability is conceived by the investor's community, the stock exchange will be able to quickly act as an effective capital raising mechanism, banks will be able to comply fully with their intermediating role in transferring the desired liquidity to the real economy, and hence liquidity will be more effectively raised from private companies in many sectors of the economy that are growing, such as renewable energy sources, real estate development, tourism, processing of agricultural products, waste management, IT, etc.

Since there is a strong correlation between the market capitalization of the ATHEX Composite Share Price Index and the market capitalization of quoted Greek banks, it is significant to analyze the capitalization of quoted banks and the events that have shaped its course.

4.2.1 The impact on the Greek systemic banks' market capitalization

The analysis on the impact of market capitalization is segregated into 5 periods: (a) the first period from 31.12.2012 until 21.12.2014 is related to the restructuring of the banking sector including the two successful recapitalizations; (b) the period from 31.12.2014 until 12.02.2016 is related to the third Memorandum of Understanding, after the initial stand-off between the Greek administration and the creditors, as well as the successful recapitalization of the banking sector by December 2015; (c) the period from 01.03.2016 to 04.04.2017, which is related to the implementation of the third Memorandum of Understanding and the review process; (d) the period from 05.04.2018 up to 28.03.2019, which entails the period of implementation of Memoranda and the post-Memoranda era; (e) the period from 01.04.2019 up to 30.06.2020, whereby a positive investment climate was reinstated only to be temporarily halted by the implications of the COVID-19 crisis to the Greek economy; and (f) the period from 01.07.2020 up to 14.12.2021, whereby there has been a significant rebound in the Greek economy, the improved ability to tap the international markets, the upgrade in the ratings of Greek systemic banks as well as an international environment that learned its way of operating despite the persistence of the pandemic.

In order to study the impact during the first period, Greek banks have been classified into two market capitalization categories: the high market capitalization banks and the small market capitalization banks[30]. The first category contains banks with a market capitalization above €7 billion as at 31.12.2013, while the second one contains banks with a market cap below the threshold of €1 billion. Again, the average high market capitalization banks constituted of the BIG-3 internationalized banks (National Bank of Greece, Alpha Bank and Piraeus Bank).

Since the end of April 2013, it appeared that the 3 systemic banks – which carried a significant weight on the total market capitalization of banks – were successful in drawing a minimum of 10% of the total recapitalization from the private sector, which was a precondition both for maintaining their private characteristics and for the completion of the recapitalization procedure from the Hellenic Financial Stability Fund (HFSF). As a result, average market capitalization increased substantially to € 5.4 bn in 31.07.2013 compared to only € 512 million in 30.04.2013. Since then, market capitalization reached € 6.6 bn in 30.09.2013 and € 7.9 bn in 31.12.2013 due to the recapitalization from the private sector.

During the first half of 2014, the 4 systemically important banking groups have proceeded to new share capital increases due to the need for redemption of the banks' preference shares and the coverage of their capital needs according to the results of the stress tests exercise (see European Banking Authority (EBA) Results of the 2014 EU-wide stress test, 26 October 2014 [112]). As a result, the average market capitalization

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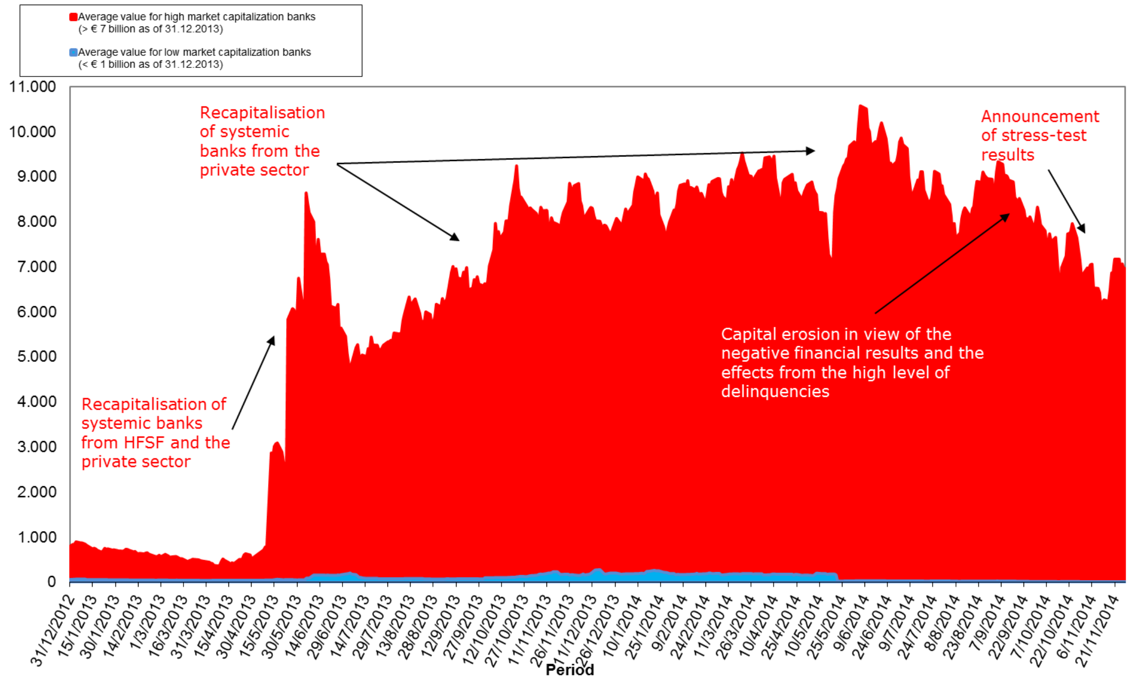
30 The classification of banks according to market capitalization for analysis purposes is a standard practice in financial institutions. https://www.statista.com/statistics/264905/top-10-banks-by-market-capitalization/ In addition, the MSCI Europe Banks Index is composed of large and mid cap stocks across 15 Developed Markets countries* in Europe https://www.msci.com/documents/10199/e72ea9be-ae79-4bb5-8ce0-054d4f371549

increased substantially to € 9.3 bn in 30.06.2014 compared to € 8.0 bn in 31.12.2013. Nevertheless, in the second half of 2014, the appetite for further reforms relaxed, the political climate was reversed and the population started to show preference to anti-austerity policies. In addition, the capital of the 4 systemically important banks had started to erode due to the effect from the negative financial results and the high level of delinquencies. As a result, average market capitalization decreased substantially to € 7.0 bn in 28.11.2014 compared to € 9.3 bn in 30.06.2014.

FIGURE 4.1 Average market capitalization per category (in billion €) for Greek quoted banks



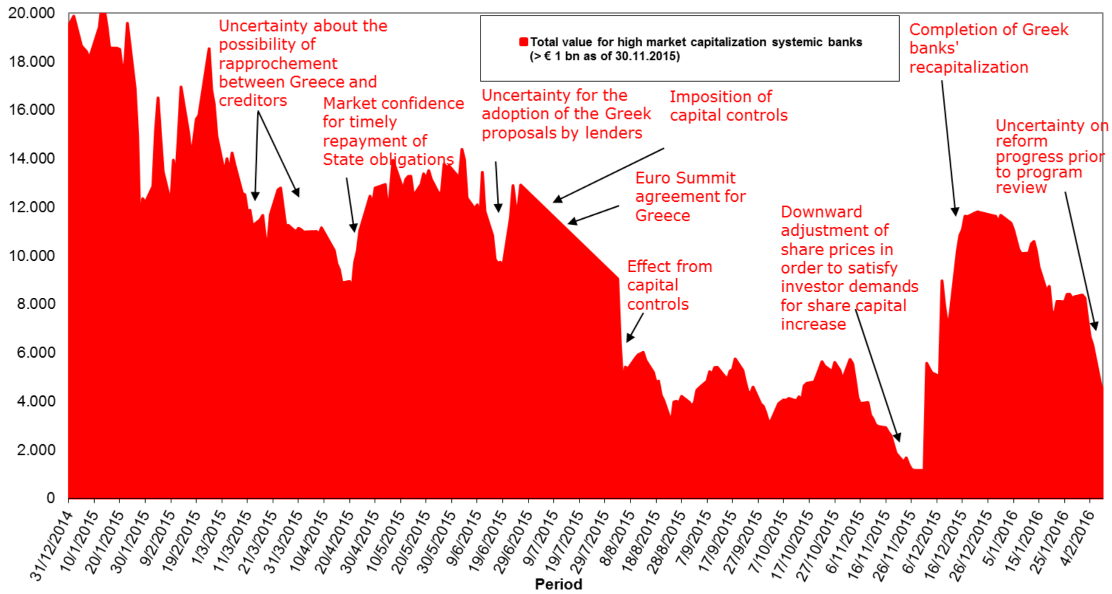
Sources: (a) Bloomberg for data

(b) Bank of Greece, ECB, IMF, ESM, Moody's, S&P, Fitch press releases for information on events

Note: compilation of data and events to produce the graph is the author's responsibility

In order to study the impact during the second period, the four Greek systemic banks have been included into one high market capitalization category, while there isn't any other classification for other banks due to their very small size and market capitalization values. Therefore, this category contains the systemic banks with a market capitalization above €1 billion as at 30.11.2015. Initially, an early general election was triggered in 25.01.2015, and the new governing party was elected on a new platform of abolishing all austerity measures. Since then, the Greek administration started to negotiate with the creditors on an entirely different basis in relation to the previous government. Instead of continuing the existing framework, it stated the need of an entirely new anti-austerity framework that would be recommended by the Greek administration and approved by the international lenders. As a result, negotiations were very complicated in nature and it appeared to be very difficult to come to a mutual agreement soon. Initially, total market capitalization for the systemic banks increased from € 12.2 bn in 30.01.2015 to € 18.5 bn in 24.02.2015 due to the approval of the Greek economic reform proposals as a "sufficiently comprehensive" starting point[31], for the purposes of bailout extension by Eurogroup finance ministers. Thereafter, it decreased to € 9.4 bn in 16.04.2015, as the delay for striking a deal between Greece and international creditors was attributed to the resistance to undertake further austerity measures related to social security that would be against the electorate results. Nevertheless, such a delay created market anxiety.

FIGURE 4.2 Evolution of the total value of capitalization (in billion €) for the Greek systemic banks



Sources: (a) Bloomberg for data

(b) Bank of Greece, ECB, IMF, ESM, Moody's, S&P, Fitch press releases for information on events

Note: compilation of data and events to produce the graph is the author's responsibility

Finally, as pressures mounted and liquidity was quickly abolishing the Greek banking system, the government proceeded to the imposition of capital controls on 28.06.2015 and the closure of the stock market in July, which led to a significant drop in the market

31 Moody's – ECB's Draghi gives guarded welcome to Greek reforms. https://www.reuters.com/article/uk-eurozone-greece-draghi-idUKKBN0LS1TM20150224

capitalization value. As sovereign liquidity was also under stress, the Greek administration on 13.07.2015 succumbed to another 3 year austerity program with international creditors.

Market volatility was reinforced in September 2015, due to early elections that caused a delay in the first assessment of the program by international creditors. Furthermore, in September and October 2015, the volatility in the market capitalization value was influenced by the perception of investors on the outcome of the recapitalization of systemic banks. In November 2015 the capitalization value was influenced by the results of stress tests of the ECB[32] and the uncertainty in the trading price of banking shares in order to attract investors for the share capital increase, which pushed stock prices downwards. In December 2015, the market capitalization increased markedly to €11.8bn in 22.12.2015 due to the successful implementation of the share capital increases of the 4 systemic banks, mainly by institutional investors (hedge funds), while HFSF participated only to a lesser extent (see also Bank of Greece's Governor's Report for the year 2015) [58].

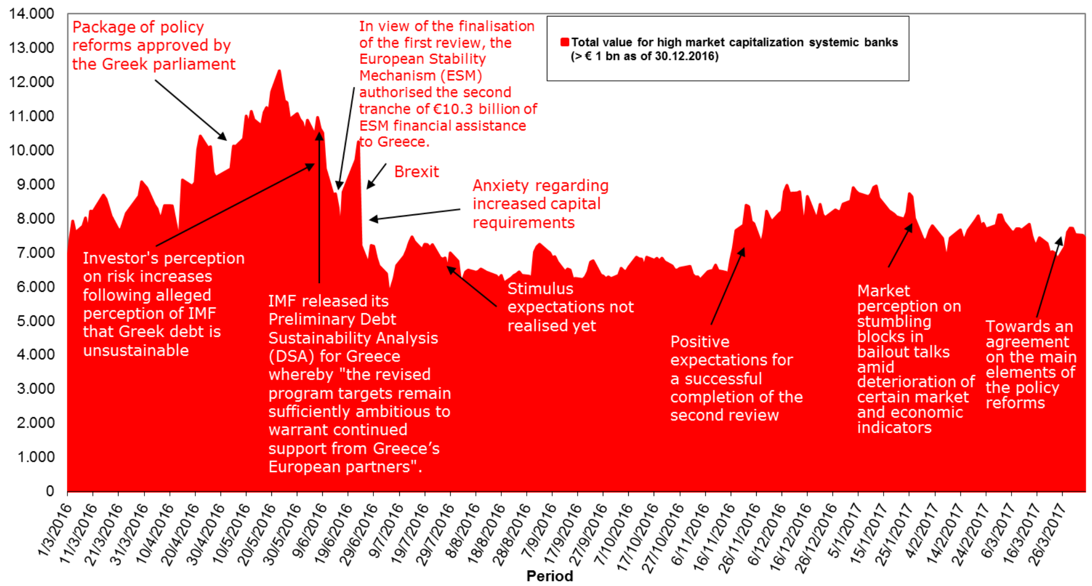
In January 2016, the market capitalization value decreased, as the progress on the bailout program, which is linked to the improvement in pension reform proposals slowed down, postponing the discussions on easing the debt burden. Only some positive reports regarding industrial production and employment were able to somehow mediate this decreasing trend. In February 2016, market capitalization decreased significantly to €4.2bn in 11.02.2016 due to heightened uncertainty over the program assessment process regarding pension reforms and budgetary measures, which is a prerequisite for a successful completion of the first review of the program by international creditors. According to the Bank of Greece's Governor's Report for the year 2016 [58], if the negotiations drag on with no agreement in sight, then Greece will enter a new cycle of uncertainty, deteriorating relations with our partners and creditors, and a backslide of the economy into stagnation.

During the third period, I continue to include the four Greek systemic banks into one

32 ECB finds total capital shortfall of €14.4 billion for four significant Greek banks. https://www.bankingsupervision.europa.eu/press/pr/date/2015/html/sr151031.en.html

high market capitalization category, with a market capitalization above €1 billion per bank as at 30.12.2016. Initially, market capitalization increased to €10.4 bn on 09.05.2016 as Eurogroup welcomed a package of policy reforms approved by the Greek Parliament, i.e. pension system, income tax, VAT, public sector reforms and NPL's[33]. It was decided that after the first review and the disbursement of further financial assistance, possible additional measures to ensure the sustainability of Greece's refinancing needs would be discussed. However, debt sustainability concern brought the market cap down from 12.3 bn as at 23.05.2016 to 10.9 bn as at 31.05.2016, as IMF released its Preliminary Debt Sustainability Analysis (DSA) for Greece stating that "the revised program targets remain sufficiently ambitious to warrant continued support from Greece's European partners"[34]. Then in June 2016 volatility increased as the positive effect of the disbursement of the second tranche of €10.3 financial assistance from the European Stability Mechanism (ESM) was counterbalanced by Brexit fears and the market anxiety regarding capital requirements for European banks.

FIGURE 4.3 Evolution of the total value of capitalization (in billion €) for the Greek systemic banks



Sources: (a) Bloomberg for data

(b) Bank of Greece, ECB, IMF, ESM, Moody's, S&P, Fitch press releases for information on events

Note: compilation of data and events to produce the graph is the author's responsibility

33 Eurogroup statement on Greece. https://www.consilium.europa.eu/en/press/press-releases/2016/05/09/eg-statement-greece/

34 Greece : Preliminary Debt Sustainability Analysis-Updated Estimates and Further Considerations https://www.imf.org/en/Publications/CR/Issues/2016/12/31/Greece-Preliminary-Debt-Sustainability-Analysis-Updated-Estimates-and-Further-Considerations-43915

On November 2016 market capitalization increased due to positive funding and debt relief expectations, while during the first 3 months of 2017 it decreased, reflecting market sentiment from the stumbling blocks in bailout talks amid deterioration of certain market and economic indicators. Finally, in April 2017 the institutions and the Greek authorities reached an agreement on the main elements of the policy reforms required to move ahead with the second review of the current macroeconomic adjustment program.

The fourth period includes the four Greek systemic banks into one high market capitalization category, with a market capitalization per bank above €350 million as at 31.12.2018. On 22.06.2018, market capitalization increased as Eurogroup's agreement on Greece[35] improved its debt sustainability prospects while the medium-and long-term debt measures consist of (a) the abolition of the step-up interest rate margin of the 2nd Greek programme as of 2018; (b) the use of 2014 SMP profits from the ESM segregated account; and (c) a further deferral of EFSF interest and amortization by 10 years. Thereafter, the index fell due to domestic political jitters. During the first half of August 2018, market capitalization decreased significantly reflecting primarily investors' anxiety over contagion risk from Turkey to emerging markets and neighboring countries. Nevertheless, the index thereafter increased as Greece concluded successfully its Third Economic Adjustment program on August 21st. By the beginning of October 2018, market capitalization declined significantly as turmoil in Italy unfolded and accelerated investors' anxiety for perceived challenges in the Greek banking sector. During November 2018, market capitalization declined as according to reports, the three Greek system banks (Eurobank, Piraeus Bank and National Bank) will remain out of the MSCI Index (emerging markets index) during the restructuring of the indices to be held on 13.11.2018 with effect from 30.11.2018. Uncertainty from Italy's budget plans being rejected by the EC has driven the index further down.

Nevertheless, by the end of November 2018, the market capitalization index rebounded strongly. More specifically, on 29.11.2018 Moody's [229] released a report according to which the published Bank of Greece's plan for a reduction of NPEs is viewed as

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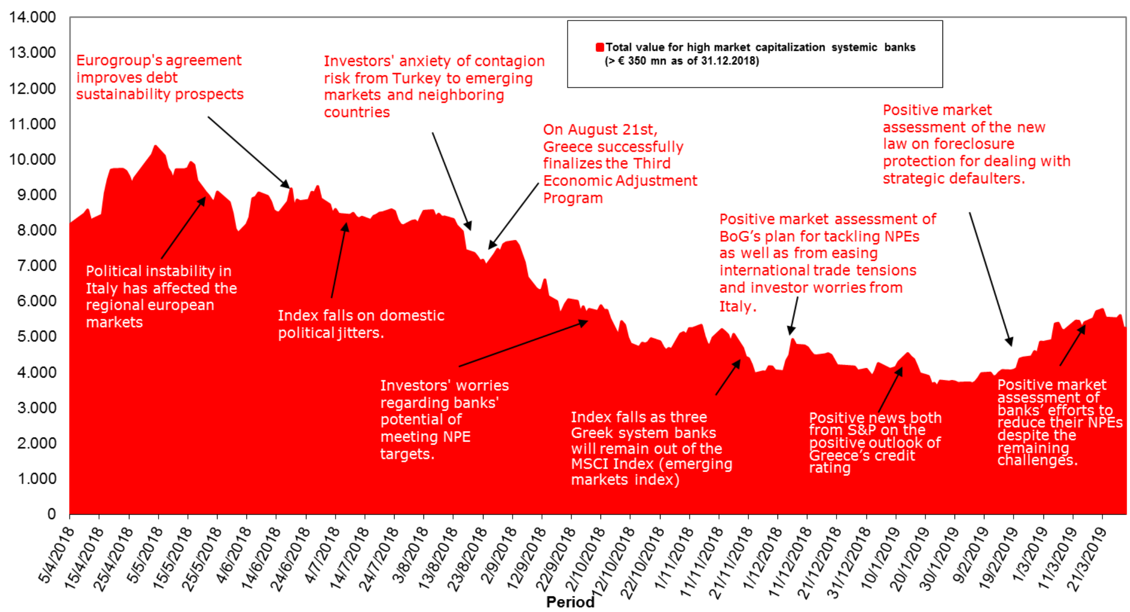
35 Eurogroup statement on Greece of 22 June 2018 https://www.consilium.europa.eu/en/press/press-releases/2018/06/22/eurogroup-statement-on-greece-22-june-2018/

"credit positive" as the plan will improve the quality of assets and the capital base of Greek banks. Thereafter, on 30.11.2018, the positive market mood continued in view of the 2018Q3 results for Greek systemic banks. Finally, in February 2018 market capitalization increased mainly as a result of markets' positive assessment (i.e. Deutsche Bank report) that the changes envisaged by the new law on foreclosure protection for the primary residence are positive for dealing with strategic defaulters. Also, markets rallied prior to the announcement by Moody's on the upgrade of Greece's sovereign credit rating by two notches to B1 from B3.

FIGURE 4.4 Evolution of the total value of capitalization (in billion €) for the Greek systemic banks



Sources: (a) Bloomberg for data

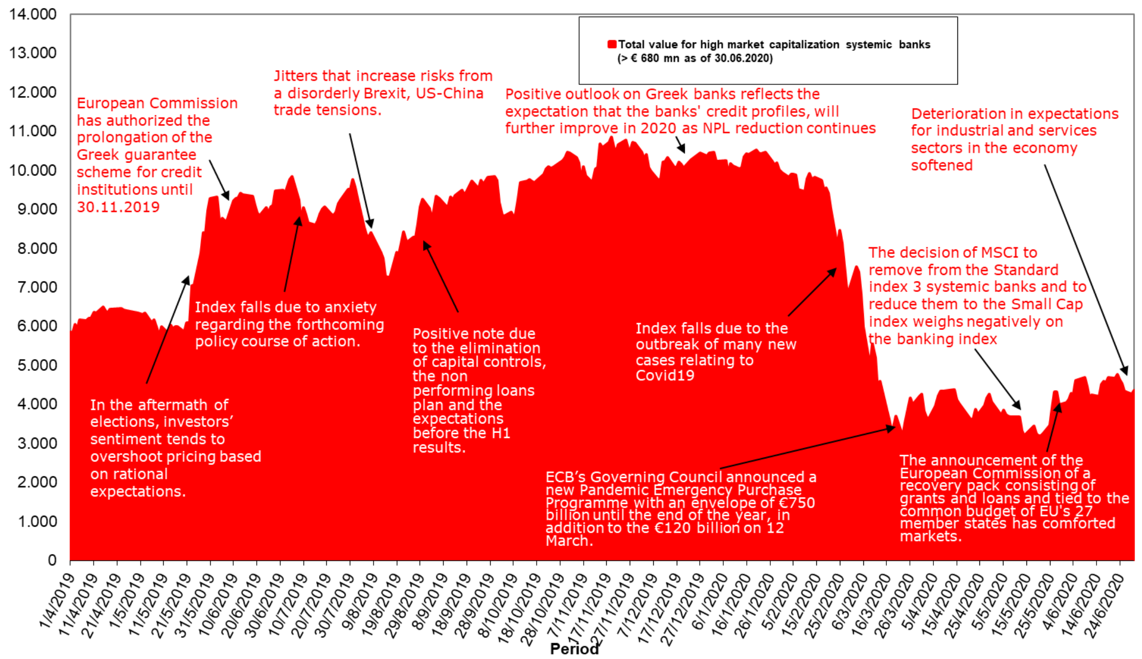
(b) Bank of Greece, ECB, IMF, ESM, Moody's, S&P, Fitch press releases for information on events

Note: compilation of data and events to produce the graph is the author's responsibility

The fifth period includes the four Greek systemic banks into one high market capitalization category, with a market capitalization per bank above €680 million as at 30.06.2020. On 27.05.2019 and 28.05.2019 market capitalization spiked, as in the aftermath of European elections, investors' sentiment tends to overshoot pricing based on rational expectations. Moreover, Fitch upgraded Eurobank from CCC to CCC+, with positive outlook, citing recent accelerated reduction of its non performing exposures, improved funding and liquidity profile and expectations for a recovering asset quality over the next 12 to 24 months. On 11.06.2019, the European Commission has authorized the prolongation of the Greek guarantee scheme for credit institutions until

30 November 2019 under EU State aid rules, citing that although the liquidity situation of the Greek banks is gradually improving, challenges remain. However, the upward course was rapidly reversed as investors' anxiety increased over the forthcoming policy course of action regarding the banking sector. During the first half of August 2019, the FTSE/ATHEX Banks Index recorded a significant decrease due to investors' increased anxiety in the international markets, following jitters that increase risks from a disorderly Brexit, while US-China trade tensions are being maintained. During the next half of August 2019 however, banking stocks rebounded as the non-performing loans plan to be applied in the coming weeks and the expectations before the announcements of banks' financial statements gave a positive tone to banking stocks performance. In addition, Citigroup reported that the Greek government decision to lift capital controls could boost confidence in Greek assets and likely have a positive impact on subsequent credit ratings decisions.

FIGURE 4.5 Evolution of the total value of capitalization (in billion €) for the Greek systemic banks



Sources: (a) Bloomberg for data

(b) Bank of Greece, ECB, IMF, ESM, Moody's, S&P, Fitch press releases for information on events

Note: compilation of data and events to produce the graph is the author's responsibility

For a long period from October 2019 to February 2020, market capitalization remained elevated as the positive outlook on Greek banks reflects the expectation that the banks' credit profiles, will further improve in 2020 as NPL reduction continues. Between 04.03.2020 and 09.03.2020, the banking index plummeted as the coronavirus pandemic

COVID-19 with increasing cases each day spread alarm to the markets with a severe negative impact on the markets. However, the descending course of the banking index was ended as on March 19th 2020 the ECB's Governing Council announced a new Pandemic Emergency Purchase Program with an envelope of €750 billion until the end of the year[36], in addition to the €120 billion on 12 March. The two programs amount to 7.3% of euro area GDP. Thereafter, the Greek PM announced his country's readiness to inject 10 billion euros to support its economy in the coming months.

On 13.05.2020 the market capitalization decreased as the decision of MSCI to remove from the Standard index 3 systemic banks and to reduce them to the Small Cap index weighed negatively on the banking index. During 22-27.05.2020 banking markets rebounded sharply as the EC's announcement on the recovery pack consisting of grants and loans and tied to the common budget of EU's 27 member states has comforted markets[37]. Finally, the volatility in the banking index seems to be eased by June 2020 as the deterioration in expectations for industrial and services sectors in the economy softened. It should be noted however, that the risk of another correction in asset prices remains acute.

Finally, the sixth period includes the four Greek systemic banks into one high market capitalization category, with a market capitalization per bank above €1.7 billion as at 15.11.2021. On 21.07.2021, EU agreed a deal on the €750bn recovery fund aimed at funding post-pandemic relief efforts across the EU consisting of a €390bn program of grants to economically weakened member states. There was also agreement on the €1074.3 billion EU budget for 2021-2027. However, during September-October 2020 markets started a downfall as a reaction from a fall in the international markets due to concerns over the second wave of the COVID-19 pandemic. However, this trend was reversed during November-December 2020. First of all, Moody's [229] on 06.11.2020 upgraded Greece to Ba3 from B1 citing a sustainable improvement in institutional strength from reforms and the positive growth prospects despite the negative impact from the pandemic. Secondly, on 09.11.2020 Pfizer and BioNTech announced that vaccine candidate against COVID-19 achieved success (90% effective) in their first

36 ECB announces €750 billion Pandemic Emergency Purchase Programme (PEPP). https://www.ecb.europa.eu/press/pr/date/2020/html/ecb.pr200318_1~3949d6f266.en.html

37https://ec.europa.eu/info/sites/default/files/about_the_european_commission/eu_budget/recovery_and_resilience_facility_.pdf interim analysis. [38] Thirdly, on 17.11.2020 Greece received 2 billion euros out of a total of about €2.7 billion that will be granted to Greece as a loan from European instrument for temporary Support to mitigate Unemployment Risks in an Emergency (SURE program) [39]. On top of that on 10.03.2021, the Finance Ministry announced new support measures for enterprises (i.e. tax reductions/ tax relief measures) for the transport and hospitality sectors, along with other measures, such as "Gefyra 2" (subsidizing loan payments).

Thereafter, the upward trend continued and both the Greek State as well as the Greek banking sector demonstrated a lasting ability to tap the local and international markets to obtain liquidity. More specifically, on 17.03.2021, the Hellenic Republic issued a new €2.5bn fixed-rate benchmark due January 2052. The transaction had a coupon of 1.875% and a reoffer yield of 1.956%, and is more than 10 times oversubscribed. The final order book closed in excess of €25bn, with more than 250 investors participating[40]. On 16.04.2021 the Ministry of Development and Investments approved the demerger of Alpha Bank by way of hive-down of its banking business sector with the incorporation of a new entity[41]. Then on 09.06.2021 Greece priced a €2.5bn tap of its outstanding June 2031 Government Bond, taking the total outstanding to €6.0bn. The tap was priced at a re-offer yield of 0.888%, equating to a re-offer price of 98.685%. The offering attracted a final order book in excess of €30.0bn, implying a 12.0x oversubscription and marks the largest order book for any syndicated transaction by the Hellenic Republic[42]. On 07.07.2021 Alpha Bank announced the start of trading on 13.07.2021 of 800 million new common shares, following the successful completion of

38 https://www.pfizer.com/news/press-release/press-release-detail/pfizer-and-biontech-announce-vaccine-candidate-against

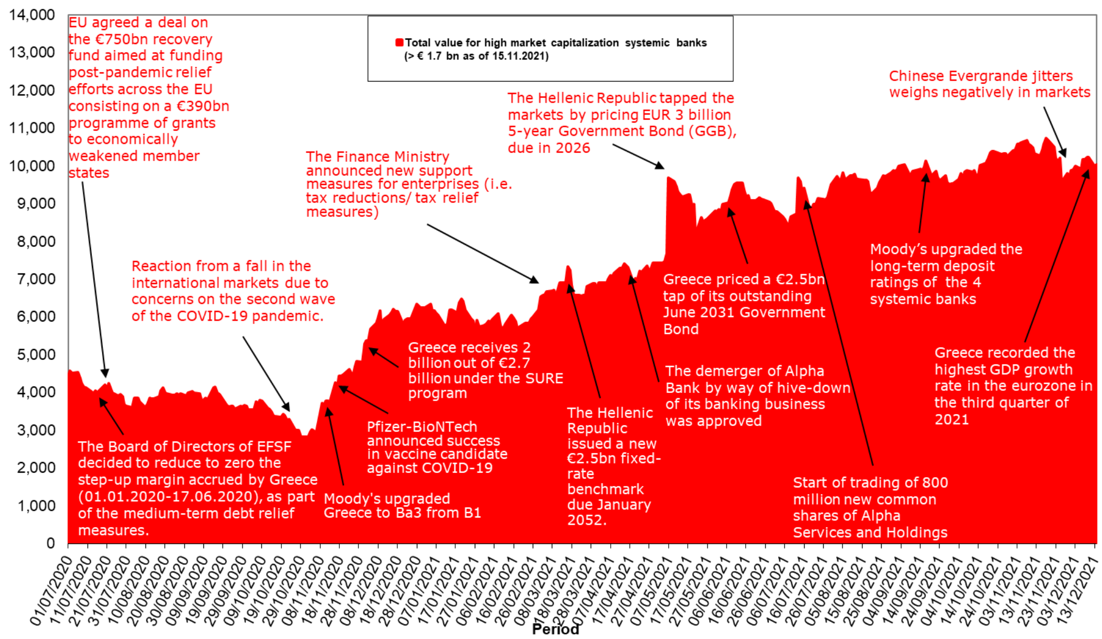
39 https://news.gtp.gr/2020/11/17/greece-gets-access-e2bn-through-eus-sure-support-program/

40 https://www.pdma.gr/en/debt-instruments-greek-government-bonds/announcements/3551-issuance-of-30-year-ggb

41https://www.alpha.gr/-/media/alphagr/pdf-files/enimerosi-ependiton/etairikos-metasximatismos/decision-of-approval-of-hive-down.pdf?la=en&hash=C812DC4CD1A18F3A86CA39AB74EB2FCB3ECD37D0

42https://www.pdma.gr/en/debt-instruments-greek-government-bonds/announcements/3715-issuance-of-10-year-ggb-2 the Company's Share Capital Increase and this has been welcomed by the Athens Stock Exchange[43].

FIGURE 4.6 Evolution of the total value of capitalization (in billion €) for the Greek systemic banks



Sources: (a) Bloomberg for data

(b) Bank of Greece, ECB, IMF, ESM, Moody's, S&P, Fitch press releases for information on events

Note: compilation of data and events to produce the graph is the author's responsibility

There have been certain events thereafter that enabled maintaining this upward trend. More specifically, on 20.09.2021 Moody's [204] upgraded the long-term deposit ratings of National Bank of Greece, Eurobank and Alpha Bank to B2 from Caa1, and Piraeus Bank's long-term deposit rating to B3 from Caa2. Rating action on the four largest Greek banks was primarily driven by their improving asset quality, solvency and good prospects for further enhancing their recurring profitability, according to Moody's. The outlooks remain positive, reflecting Moody's expectation that the four banks will continue to improve their credit profiles. Then on 26.11.2021 market capitalization fell significantly reflecting jitters from the debt crisis by Chinese property giant Evergrande that sent shockwaves to global financial markets. Thereafter, market capitalization increased, reflecting the positive market sentiment as it has been reported

43https://www.alpha.gr/-/media/alphagr/files/group/corporate-announcements/2021/20210707_etairiki_anakoinosi_eng.pdf that Greece recorded the highest GDP growth rate in the eurozone in the third quarter of 2021[44].

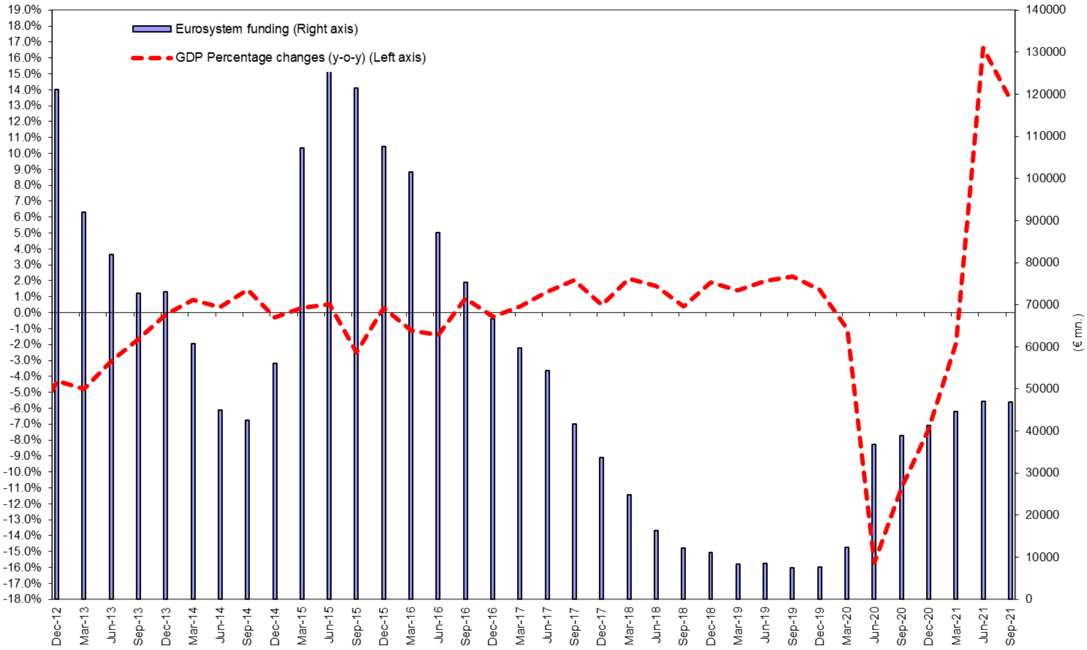
4.2.2 Sources of Liquidity for the Greek banking system

The deposit base is the most important parameter for maintaining adequate banking liquidity that would enable banks to channel funds to the Greek economy. According to Bank of Greece's data (See Bulletin of Conjunctural Indicators [62]), Greek customer deposits decreased by 672mn in February 2017 compared to the previous month, stemming from a decrease in households (-567mn) and to a lesser extent in corporations (-105mn). Since then, the increase in customer deposits continued almost uninterrupted until November 2021. On the other hand, the Emergency Liquidity Assistance (ELA) outstanding balances increased for the first time on February 2017 to 43.1bn, reversing a declining course which was initiated after June 2015 whereby the outstanding balance amounted to € 86.8 billion, as Greek banks tried to compensate for their declining deposits from other sources in order to satisfy their funding needs. ELA evaporated by the end of 2018 terminating a period of liquidity squeeze in the Greek banking system.

In Figure 4.7, Eurosystem funding of the Greek banking system from December 2012 to September 2021, as well as the quarterly GDP rate of change during the same period of the Greek economy on an annual basis is being portrayed. Georgikopoulos [135] found that the funding of banks from the Eurosystem is directly linked to the status of Greek economy, something that is depicted in this graph. More specifically, during 2017 GDP growth had entered a positive territory and accordingly the need for Eurosystem funding decreased, reaching its lowest levels on 30 September 2019 at € 7.5bn. By the end of 2019, the amount from Eurosystem that Greek banks had borrowed fell drastically to € 7.7bn compared to € 11bn in December 2019, €66.6 in December 2016 and €126.7 in June 2015.

44 Source: Hellenic Statistical Authority

FIGURE 4.7 Relationship between the GDP percentage change on an annual basis (left axis) and the funding of banks (in € mn.) from ECB on an aggregate basis (right axis).



Sources: (a) Bank of Greece (BoG) - Bulletins of Conjunctural Indicators [62] for Eurosystem funding and (b) Hellenic Statistical Authority for GDP

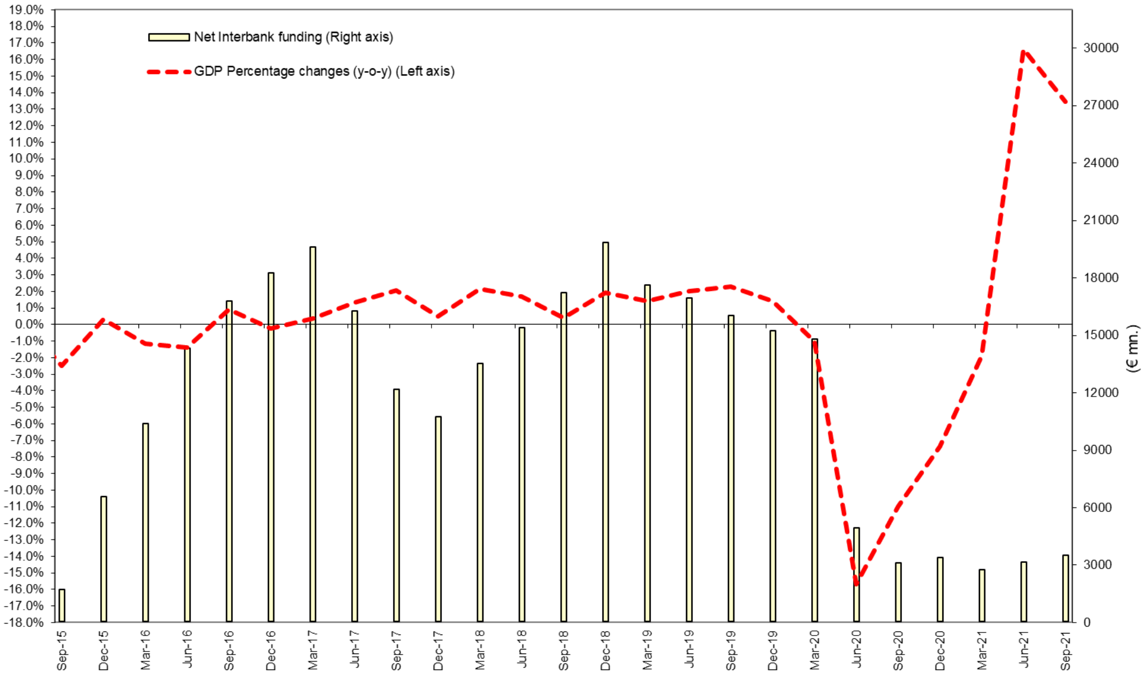
However, as GDP fell substantially in 2020 due to the Covid pandemic, Eurosystem funding increased although it hasn't reached the levels observed during the previous financial crisis. More specifically, in March and June 2020 Eurosystem funding increased to €12.4bn and €36.8bn respectively due to the efforts of the ECB to provide funding to the banking system as a result of deteriorating liquidity conditions. Thereafter, as liquidity conditions improved the rate of growth of Eurosystem, funding decreased significantly, maintaining though its upward trend, and it amounted to €46.9bn in September 2021.

In Figure 4.8, the relationship between the net interbank borrowing of the Greek banking system and the developments in Greek economy is being portrayed on an aggregate basis. Georgikopoulos [135] found that whenever the Greek economy is facing problems, the borrowing of banks from the interbank market decreases significantly. This is confirmed by the data depicted in the graph that demonstrate that the ability of Greek banks to tap the interbank market deteriorated significantly in 2015 due to the increase in uncertainty caused by political jitters while at the same time the improvement in the economic conditions stalled. Indeed, in 30.09.2015, Greek banks had borrowed the amount of €1.7 bn through the interbank market after the imposition of capital controls. Since then however, interbank access improved and Greek banks had borrowed the amount of €19.6 bn as at 31.03.2017 through the interbank market. It should be noted that the increase in deposits observed in the third quarter of 2017 may have helped reduce the demand for short-term interbank borrowing amid a global decline in interbank trade volumes. As a result, the amount borrowed from Greek banks was reduced to €10.7 bn as at 31.12.2017.

The volume of transactions in the interbank market increased during 2018 following increased demand. The terms of trade (interest rate, valuation haircut on collateral) are continuously improving, to levels well below the corresponding ELA levels. As a result, the amount borrowed from Greek banks was increased to €19.8 bn as at 31.12.2018.

Interbank market transactions continued to be a significant source of funding, following the resumption of access of Greece to the international money and capital markets. In this instance, securities held, including the bond portfolio of the Greek State and other euro area countries are used as collateral for repos. This is confirmed again by Figure 4.8, as the amount borrowed from Greek banks increased to €15.2 bn as at 31.12.2019. At the same time, Greek banks continued to expand their positions, improving the composition of their portfolios with high-liquid securities and free of any charges (unencumbered). The goal is the continuous improvement of their supervisory ratios, including the liquidity coverage ratio (LCR).

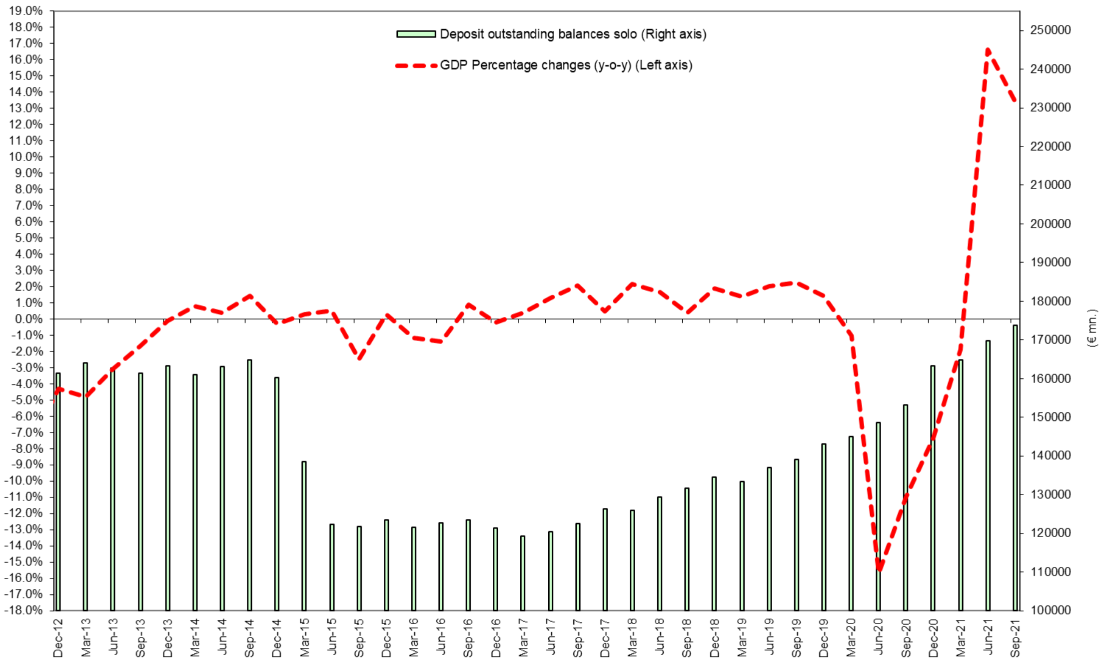
FIGURE 4.8 Relationship between the GDP percentage change on an annual basis (left axis) and net interbank funding of the Greek banking system (in € mn.) on an aggregate basis (right axis).



Sources: (a) Bank of Greece (BoG) - Prudential database on interbank borrowing for Net Interbank funding and (b) Hellenic Statistical Authority for GDP

However, in April and May 2020, interbank market transactions were reduced even further and this decrease took part simultaneously with the increase in the funding of Greek banks by the Eurosystem. Banks proceeded to the termination of the repurchase agreements of Greek government bonds, as they were eligible as collateral from the ECB after the reinstatement of the “waiver” since April 7 2020. Net interbank funding remained to very low levels during 2020 at the same time whereby GDP growth figures became substantially negative. By September 2021, the amount borrowed from Greek banks amounted to €3.5 bn.

FIGURE 4.9 Relationship between the GDP percentage change on an annual basis (left axis) and the deposit outstanding balances of Greek commercial banks (in € mn.) on a solo basis (right axis).

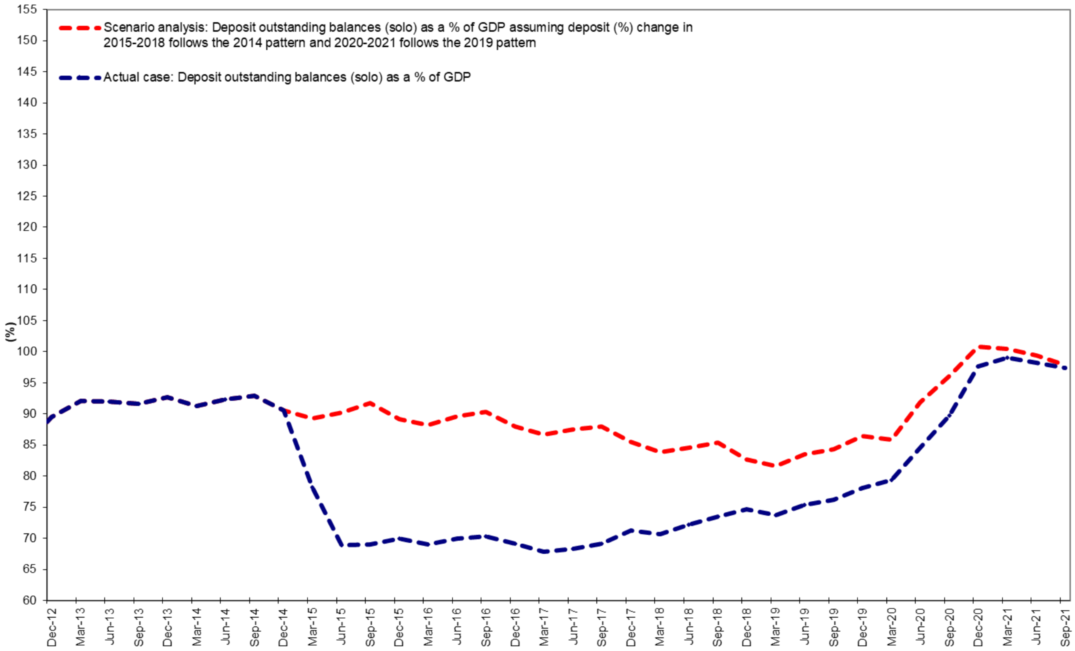


Sources: (a) Bank of Greece (BoG) - Bulletins of Conjunctural Indicators [62] for Deposit outstanding balances and (b) Hellenic Statistical Authority for GDP.

In Figure 4.9, the evolution of deposits of the Greek banking system on an aggregate basis in relation to the GDP rate of change is being examined. Georgikopoulos [135] found that the deposits of Greek households and enterprises are directly linked to the GDP and the fiscal situation of the Greek economy, something that is confirmed by the above graph. It should be noted that Greece underwent a stressed period of a prolonged fiscal and financial system crisis until December 2015. During 2016 deposit growth remained stagnant, as GDP growth was in the negative territory. However, since 2017Q4, the deposit growth of the Greek banking system is uninterrupted and unrelated to the GDP growth. Deposits amounted to around €173.7 bn in June 2021, compared to

€163.2 bn in December 2020, €143.1 bn in December 2019, €134.5 bn in December 2018, €121.4 bn in December 2016 and €138.6 bn in March 2015.

FIGURE 4.10 Analysis of a hypothetical scenario for the deposit outstanding balances of the Greek banking system on an aggregate basis as a percentage of GDP.



Sources: (a) Bank of Greece (BoG) - Bulletins of Conjunctural Indicators [62] for Deposit outstanding balances and (b) Hellenic Statistical Authority for GDP.

Note: Author's calculations for scenario analysis.

Finally, in Figure 4.10 the results of a hypothetical scenario for the outstanding amounts of deposits of Greek commercial banks on a solo basis are being portrayed. The dotted red line portrays the outstanding amount of deposits as a percentage of GDP, on the assumption that the rate of change of deposits in the period 2015-2018 would continue at the same rate as in 2014, while the rate of change of deposits in the period 2020-2021Q2 would continue at the same rate as in 2019. The choices of 2014 and 2019 are relevant as "relatively stable" periods compared to prolonged periods of stress. According to the aforementioned scenario the last quarter of 2019 deposits would have amounted to 86.4% of GDP instead of the actual 78% in the end of 2019, while by the end of the second quarter of 2021 deposits would have amounted to 97.9% of GDP instead of the actual 97.4%. This development signals that the adverse macroeconomic effects of 2015 as well as the manifestation of the 202Q1 stress episode throughout 2020 have been completely absorbed.

4.3 Structure of Bank Credit to the Sectors of the Greek Economy

This section examines to which extent the Greek banking system was able to divert its liquidity to the sectors of the Greek economy by analyzing the development of the 4 most important sectors, i.e. tourism, industry, construction and trade and all sectors as well. Before the expansion of the financial crisis in Europe, Greek banks had played an important role in the increase of economic activity, through the rapid credit growth, by supporting the most significant sectors of the Greek economy. During the period 2007 – 2008, a credit growth at the level of 19% y-o-y has been reported. Nevertheless, during the last period, Greek banks are finding it difficult to be able to divert their liquidity to the funding of the real economy. Since 2011-2012, a deleveraging to the most significant economic sectors has become evident. Georgikopoulos [136] found that the aforementioned trend is due both to the limited demand for loans - given the recession that has slowed down economic activity in important sectors - and to the limited supply - given the continued adoption by credit institutions of strict criteria for all lending categories. At the same time, the limited supply of credit by credit institutions is due both to the difficulty of credit institutions to raise liquidity due to the closure of the capital markets and financial markets and to the reduction of deposits. Despite the fact that the deleveraging trend continued during the period 2013-2014, the rate of deleveraging in 2013 eased somehow, while in 2014 the rate decreased even more. However, in 2015 uncertainty prevailed and the deleveraging trend rebounded again and continued up to the end of 2018. The deleveraging rate for enterprises according to their outstanding credit balances, which is not corrected for loan write-offs, exchange rate valuations and reclassifications, amounted to -18.4% during the period 2015-2018.

Although real GDP growth rate turned positive during 2017-2019, this development could not level-off the prolonged recession during the period 2008-2015, which in conjunction with the implementation of fiscal adjustment measures has maintained a large stock of non-performing exposures. To address this problem, operational targets were set for banks by the Bank of Greece and the Institutions [59] with the aim to reduce the specific volume by the end of 2021. Greek banks have already exceeded the targets and the overall stock is at around 20% by June 2021. In addition, the exodus from the Third Economic Adjustment Program for Greece[45] in 2018 has contributed to a positive

[45] *Greece has already implemented three adjustment programs in the period 2010-2018. The first adjustment program was provided on the basis of bilateral loans from euro-area member states. It was announced by the Eurogroup on 2 May 2010. Greece received the total of €52.9 billion in financial*

shift in the investment climate and enhanced economic confidence indicators. Finally, some banks have already made use of the Hellenic Asset Protection Scheme (HAPS) during the issuance of guarantees by the Greek Government. Despite the fact that the successful completion of NPL sales transactions, through loan securitization with the simultaneous use of the Greek State Guarantee Scheme (HAPS) which has led to a further reduction in the existing stock of NPLs, the stock is higher compared to the European average. Alternative proposals have been submitted by the Bank of Greece [56] (see Bank of Greece Financial Stability Review, Special Feature I) and more specifically, a proposal for the implementation of a scheme for the overall management of non-performing loans (Asset Management Company - AMC) of Greek banks. In particular, through this proposal, the existing sub-structures of the banks are efficiently utilized, and the participation of third parties in the areas of management of NPLs is ensured. Nevertheless, until now there is a political will to continue with and extend the HAPS program as a vehicle to offload the burden of NPLs by banks.

4.3.1 Analysis of funding to sectors

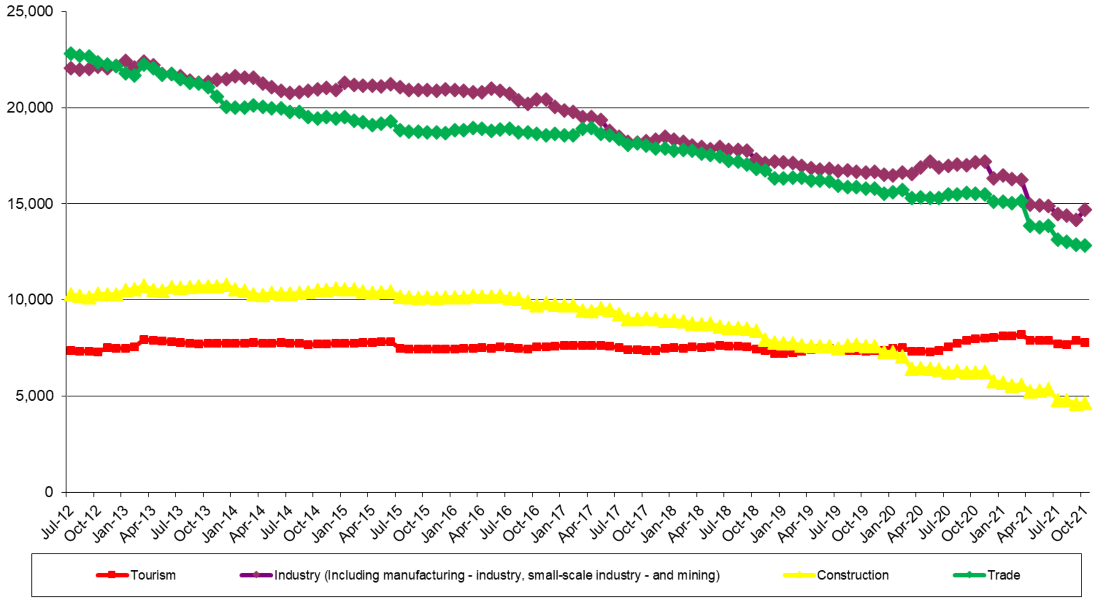
The provision of credit over time (from July 2012 up to October 2021) to the four most significant sectors of the Greek economy is portrayed in Figure 4.11[46]. From the graph below, deleveraging of the most important sectors in the Greek economy during the period July 2012-October 2021 is being confirmed, albeit there were certain differentiations for certain sectors of the economy (i.e. the Tourism sector has overall retained its credit balances and even increased them in the latest period). The deleveraging trend showed a significant slowdown in 2013 and 2014, but increased again after 2015 due to the uncertainty regarding the economic course of Greece. However, deleveraging slowed down gain in 2019, due to the reinstatement of investors' confidence and the prospects of economic growth. During 2020-2021 the pandemic led to a decrease in demand for lending. This in conjunction with supply

assistance while IMF disbursed an additional amount of about €20 billion. The second adjustment program, replaced the first and was endorsed by the Eurogroup on 9 March 2012 and ran until June 2015. In this period, EFSF disbursed €141.8 billion and the IMF approximately €12 billion. The third (and final) adjustment program ran from 19 August 2015 and until 20 August 2018. In total, Greece received €61.9 billion of financial assistance by the European Stability Mechanism (ESM), out of a total program envelope of up to €86 billion.

[46] *According to the official data, as of March 2019, loans to shipping companies, which have their registered office abroad, are no longer included in credit to the domestic economy. However, for the purposes of my study, and in order to ensure comparability over time we retain them.*

problems and energy prices going up on a global scale has resulted in an increase in the deleveraging trend.

FIGURE 4.11 Domestic credit to the 4 most important sectors of the Greek economy
(monthly balances in € million)



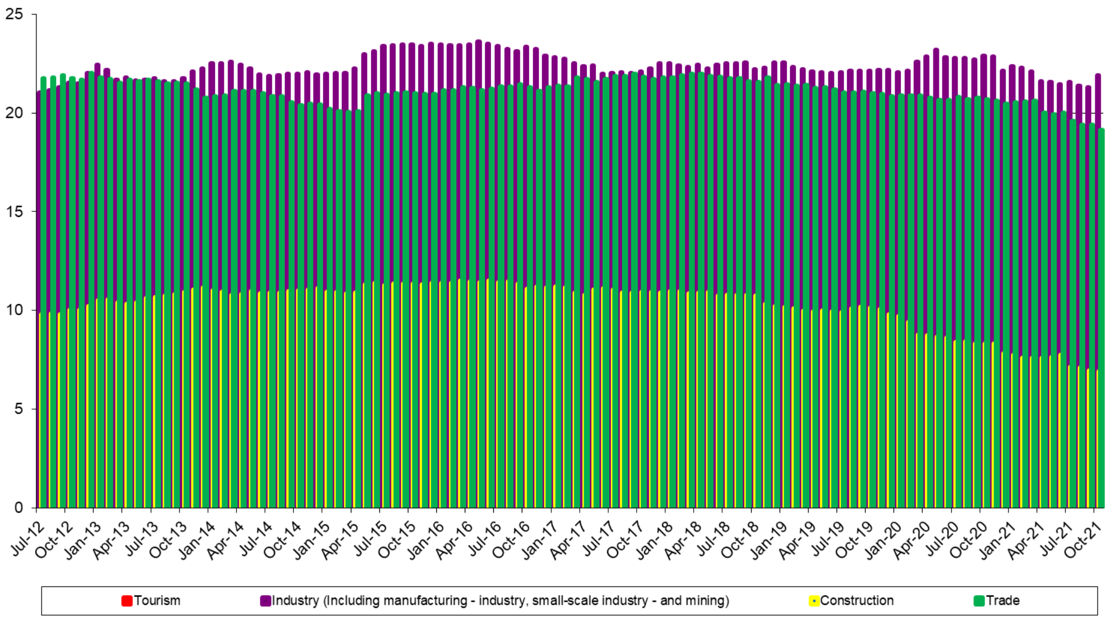
Source: Bank of Greece (BoG) - Bulletins of Conjunctural Indicators [62].

By analyzing Bank of Greece's data [62] and regarding the particular sector breakdown of the Greek economy, a slowdown has been observed in energy during 2013 and 2014 (2014: -11.9%; 2013: -7.9%) being affected from the recession. However, the sector appears to gradually recover in 2015 and 2016 (2016: -0.9%; 2015: -2.3%). The recovery was continued as positive growth rates were observed in 2018-2020, signaling the fact that economic growth fueled credit demand for energy (2020: +8.3%; 2019: +4.0%; 2018: +5.6%; 2017: -0.3%). However, during 2021 supply problems in conjunction with rising energy prices led to a slight drop in October 2021 by 1.9% y-o-y.

Bank of Greece's data [62] also confirm that a positive sign has been maintained in tourism (2014: 0.0%; 2013: 3.1%) where prospects continued to be promising during 2016 (2016: +2.0%). During 2017-2018, the sector showed a remarkable growth from self-finance sources, reducing the need for credit from banks (2018: -3.5%; 2017: -1.4%). As 2019 was an exceptional year beyond expectations, credit demand had to supplement – to an extent – other self-finance sources (2019: +1.8%). Lending demand resumed during 2020 as the industry proceeded to certain renovations during the pandemic (2020: +9.2%) However, 2021 was an exceptional year that reduced the need for lending (October 2021: -2.3% y-o-y). On the other hand, industry (2020: -1.2%; 2019: -4.0%; 2018: -6.9%; 2017: -7.7%; 2016: -4.4%; 2015: 0.2%; 2014: -2.7%; 2013: -3.1%) and trade (2020: -2.7%; 2019: -5.1%; 2018: -8.7%; 2017: -4.0%; 2016: -0.3%; 2015: -3.8%; 2014: -3.0%; 2013: -9.6%; 2012: -10.2%) did not manage to recover. The consequences from the recession up to 2016, continued to weigh their effect on the periods 2017-2019 for these sectors. During 2020-2021 credit to the industry continued its declining course as enterprises struggled to get additional funding for investments due to the pandemic coupled with supply problems. In addition, credit to trade decreased more significantly during 2020-2021 as this sector is impacted by additional external factors, i.e. increase in trade barriers and international trade tensions. The construction sector was severely hit in 2014-2016 (2016: -3.8%; 2015: -4.1%; 2014: -2.0%) after a very good year in 2013 (2013: +5.0%). The deterioration of this sector continued apace during 2017-2019 (2019: -6.4%; 2018: -12.7%; 2017: -8.3%), while the pandemic exacerbated this decline (December 2020: -21.0%). Regarding shipping, and despite its very good performance shown in 2014 (2014: +14.1%; 2013: -4.9%), the sector has deleveraged thereafter (2020: +0.5%; 2019: -0.5%; 2018: +0.8%; 2017: -15.8%; 2016: +0.1%; 2015: -31%). Nevertheless, one cannot draw safe conclusions in determining a longer trend due to significant seasonality effects in the sector. In addition, the shipping industry is increasingly being financed by sources that reside outside the Greek banking system.

Moreover, from the quarterly analysis during the last quarters of 2018-2020 (see Bank of Greece Bulletins of Conjunctural Indicators [62]), there has been an increase in the deleveraging process during the 4th quarter of 2018 (-3.2%), while during the 4th quarter of 2020 this process continued. This is attributed primarily to the deleveraging in the specific sectors of construction (2020Q4-Q3: -7.4%; 2019Q4-Q3: -4.7%; 2018Q4-Q3: -8.3%), trade (2020Q4-Q3: -3.1%; 2019Q4-Q3: -2.2%; 2018Q4-Q3: -4.2%) and industry (2019Q4-Q3: -4.1%; 2019Q4-Q3: -0.9%; 2018Q4-Q3: -3.2%) with a reduction in the outstanding balances, while on the other hand the increase in the energy sector (2020Q4-Q3: +1.0%; 2019Q4-Q3: +2.1%; 2018Q4-Q3: +12.1%), could not act as a counterbalancing factor. The only other positive growth rates occurred in the sector of agriculture (2020Q4-Q3: +2.8%; 2019Q4-Q3: +4.8%; 2018Q4-Q3: +4.6%), while for the shipping sector (2020Q4-Q3: +0.3%; 2019Q4-Q3: -1.0%; 2018Q4-Q3: +2.6%) no safe conclusions can be drawn due to the fact that this sector portrays significant seasonality.

FIGURE 4.12 Domestic credit to the 4 most important sectors of the Greek economy
(as a percentage of total credit to all sectors in the economy)



Source: Bank of Greece (BoG) - Bulletins of Conjunctural Indicators [62].

It should be noted that since 2015 the deleveraging of the Greek banking sector continued unabated. After a small easing during 2016 (-1.8%), deleveraging increased its magnitude during 2017 (-6.2%) and 2018 (-7.0%), while it was eased again during 2019 (-2.5%) and 2020 (-1.0%), reflecting the positive expectations for the Greek economy, albeit the pandemic in 2020 made some enterprises to postpone their investments.

From all sectors that are examined, according to the data as of October 2021 [62], the largest amount of credit is directed to industry which constitutes 21.9% of the total credit to enterprises and to trade which constitutes 19.1% of the total credit to all sectors. A significant amount of credit is directed to the sectors of tourism with 11.6% of the total credit while regarding construction (6.9%) and energy (8.1%) smaller amounts are being granted, although for the latter its relative importance is increasing. Despite the fact that the energy sector has already picked up during 2015-2020 with increasing outstanding amounts, the potential for further growth remains substantial. The potential for granting credit to the energy sector is very significant for the future, after the gradual liberalization of the energy market, being one of the prerequisites of the reviews that the lenders have been conducting prior to the disbursement of the loan amounts. The market shares of credit by sector have been maintained at similar levels over time during the reference period from July 2012 – October 2021 in most of the sectors. Nevertheless, there is a small reduction in the market share of trade in relation to the total credit of sectors, a significant recovery in the market share of energy and tourism, while the relevant importance of the construction sector is consistently declining.

Figure 4.13 portrays the Domestic credit to the 4 most traditionally important sectors of the Greek economy (i.e. Tourism, industry, construction, trade) as a percentage of G.D.P. Based on the analysis of quarterly data by the Bank of Greece and the Hellenic Statistical Agency, it appears that credit to the Greek economy (i.e. credit to all sectors of the Greek economy) as a percentage of the Gross Domestic Product (G.D.P.)[47] has decreased from 61.5% in June 2012 to 40.8% in September 2021. This is signaling significant deleveraging as G.D.P. in 2019 has surpassed 2012 levels. During the period from June 2012 up to December 2015, a smaller reduction of this ratio was observed (December 2015: 54.6%; June 2012: 61.5%) as G.D.P. during this period continued to decline. On the other hand, during the period from December 2015 to December 2019 a larger reduction of this ratio was observed (December 2019: 44.2%; December 2015: 54.6%) as G.D.P. during this period increased. In December 2020, the ratio increased to 47.9% despite the continuation of deleveraging, as GDP contraction was more severe.

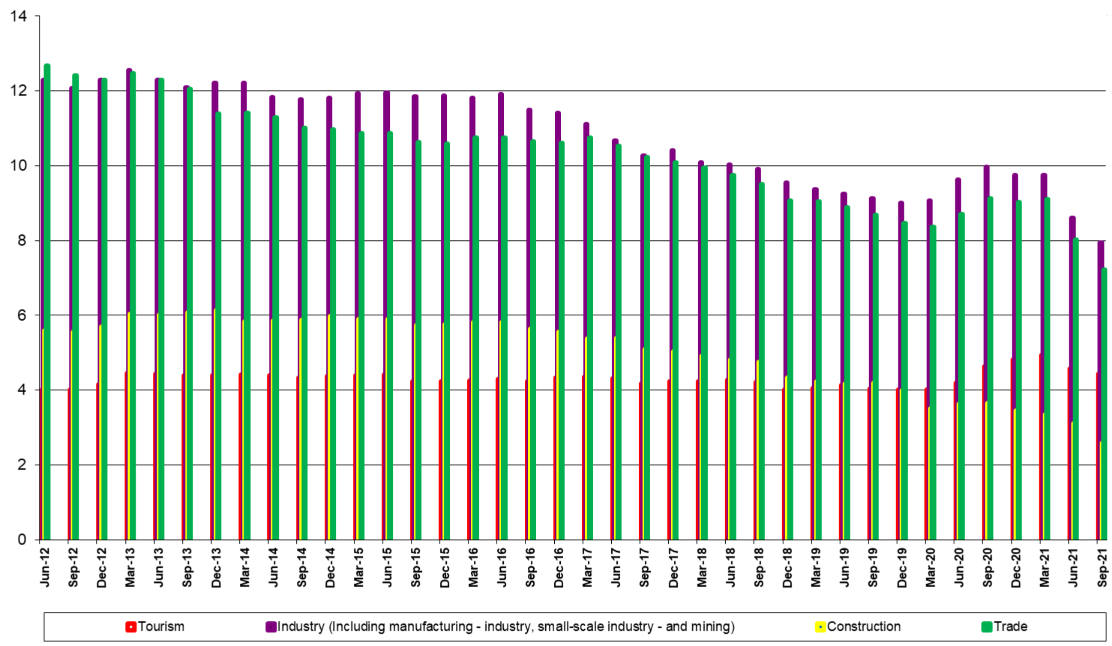
It should be noted that this general trend is portrayed to certain sectors of the economy under examination, with the exception of trade (December 2020: 9.0%; December 2015: 10.6%; June 2012: 12.7%), industry (December 2010 9.8%; December 2015: 11.9%; June 2012: 12.3%) and agriculture (December 2020: 0.7%; December 2015: 0.8%; June 2012: 1.0%). The sectors of tourism and construction exhibited an increase in credit as a percentage of G.D.P. during the period from June 2012 to December 2015, and then subsequently decreased during the period from December 2015 to December 2018. Finally, the energy sector exhibited a decrease in credit as a percentage of G.D.P. during the period from June 2012 to September 2018, but showed a significant rebound during 2018Q4-2021Q3.

From the analysis of the aforementioned sectors, it becomes evident that the sector of agriculture has lost a small market share of credit as a percentage of G.D.P. while more substantial decreases are being observed in the sectors of trade and industry.

[47] G.D.P. is available on a quarterly and not on a monthly basis. However, for the calculation of the ratio credit as a percentage of G.D.P. annualization of G.D.P. took place based on the aggregation of the last 4 quarterly data up to the last reporting period.

On the other hand, regarding the sectors of tourism and energy, the market shares have showed a noteworthy endurance. But especially in the energy sector, after a sharp deterioration until 2014Q2, the sector has maintained its market share from 2014Q3 up to 2018Q4, while the market share even increased during 2019-2021. It appears that the need to maintain a sufficient funding level is more important in this sector after the liberation of markets and the positive growth rates of the real economy during the period 2017-2019.

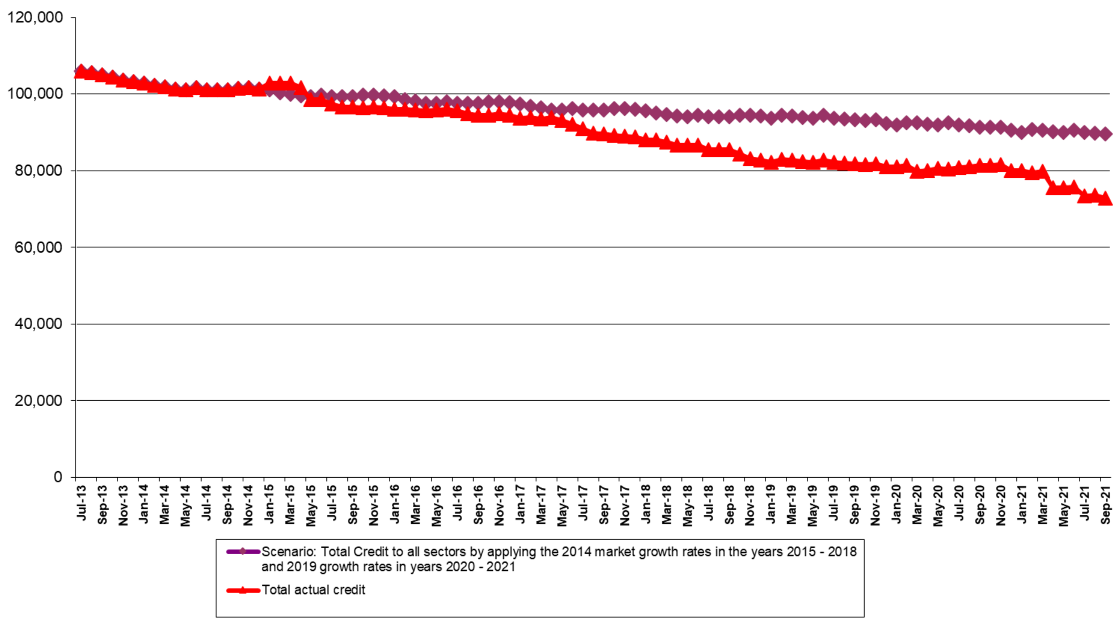
FIGURE 4.13 Domestic credit to the 4 most traditionally important sectors of the Greek economy (as a percentage of G.D.P.)



Source: Bank of Greece (BoG) - Bulletins of Conjunctural Indicators [62]

In order to determine the "dynamics" of the impact of the prolonged financial and fiscal crisis, in the provision of credit to the sectors of the Greek economy, a comparison took place between the actual outstanding amounts of credit to all sectors and the outstanding amounts of credit under a scenario analysis. The assumption was that credit growth rates in the years 2015-2018 will be sustained and follow that of the 2014 year, i.e. by eliminating the credit deleveraging impact from the uncertainty that led to the recession during 2015-2016 that required the signing of the Third Economic Adjustment Program in August 2015. In addition, a further assumption took place that credit growth rates in the period 2020-2021Q2 will be sustained and follow that of the year 2019 (being a year of stability), by eliminating the effects from credit deleveraging impact due to the sharp GDP contraction in 2020. The results are portrayed in Figure 4.14. The divergence in the two lines is now attributed both to macro-economic uncertainties during 2015-2018 and to the Covid pandemic effects from 2020.

FIGURE 4.14 Analysis of credit growth to all sectors (monthly balances in € million)



Source: Bank of Greece (BoG) - Bulletins of Conjunctural Indicators [62] for Credit to all sectors

Note: author's calculations for scenario analysis.

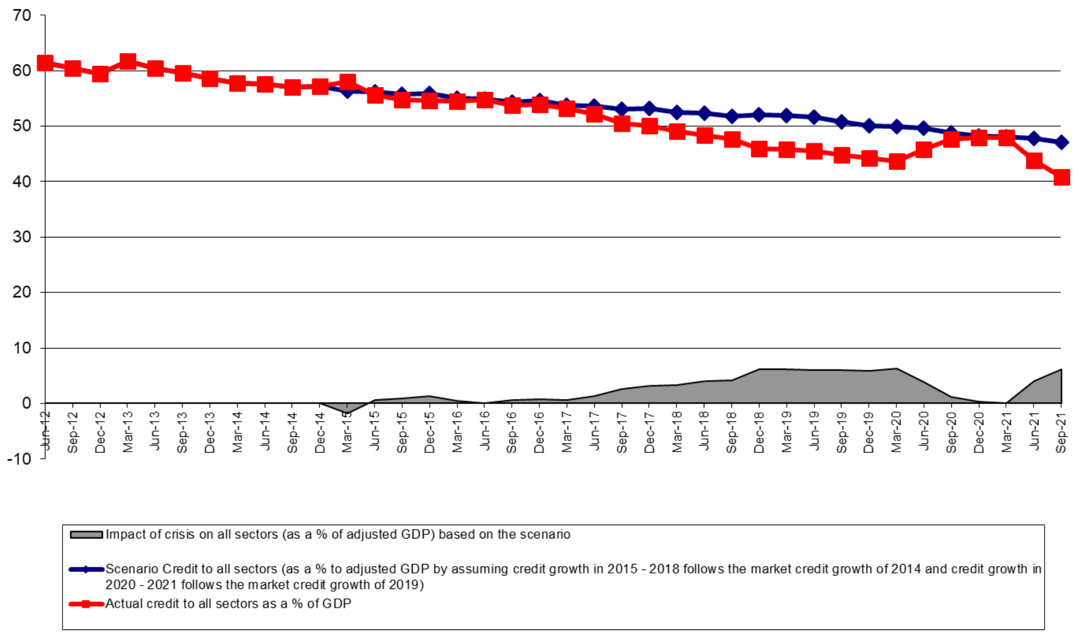
Koopman et. all [189] have studied the relation between the credit cycle and macro-economic fundamentals in an intensity-based framework. Their results in this paper show that out of a number of possible macro fundamentals, many appear to describe rating and default behavior. If they account for a single unobserved common risk factor, however, most of the variables become statistically insignificant. At first sight, it appears that downgrades, up-grades, and defaults are all driven by different sets of macro fundamentals. If they further refine the model to allow for three unobserved risk factors, however, the only relevant macros turn out to be GDP growth, and to some extent stock market returns and return volatilities.

In this vein, the effect from Covid-19 and the subsequent recovery were accommodated. In order to accomplish that, an additional assumption took place that credit growth rates in the years 2020-2021Q2 will follow that of the 2019 year, because this is the year after the first crisis and before the pandemic. This analysis depicted from Figure 4.14 shows that there is a widening of the gap between the two time series throughout the period 2015Q2 – 2020Q1 thus reaching the amount of € 12.6 billion in March 2020. However, the maximum amount of divergence is recorded in September 2021 at €16.7

billion, incorporating the pandemic effects as well. This signifies the fact that there is a relationship between the economic and credit growth although with a time lag.

In addition, the impact of the crisis, the subsequent recovery and the effect from Covid-19 is depicted in Figure 4.15 by portraying the widening of the gap between the actual credit as a percentage of the actual G.D.P. and the scenario analysis credit as a percentage of the adjusted G.D.P. The difference between the 2 time series in percentage points shows the “funding deficit” through credit in the sectors in the Greek economy. The funding deficit amounted to 130 basis points by December 2015, 320 basis points by December 2017 and reached 610 basis points by December 2018. Thereafter the funding gap has been bridged as it amounted to 10 basis points in March 2021. The widening of the gap in September 2021 is due to continued deleveraging and a rebound of the economy at the same time.

FIGURE 4.15 Domestic credit on all sectors as a % of G.D.P. (incorporating scenario analysis)



Sources: (a) Bank of Greece (BoG) - Bulletins of Conjunctural Indicators [62] for Credit to all sectors, (b) Hellenic Statistical Authority for GDP

Note: author’s calculations for scenario analysis.

This gap up to March 2020 has been created entirely by the recession during the period 2015-2016 and has prevented banks from channeling funds to the real economy. As GDP has been increasing during 2017-2018, banks needed to adapt to new business models and support more the small and medium enterprises. In order to manage the funding gap, banks have addressed the issue decisively. They have increased their cooperation with the European Investment Bank (EIB) in order to support enterprises in strategic sectors, raise investment in research and development, and boost infrastructure. However, the pandemic has led to a widening of the gap anew and therefore more needs to be done in order to bridge the funding gap. Banks should make use of all the toolkits that are available[48] and authorities should encourage banks to lend to companies that want to expand into new business sectors through credit guidance. The environment of low interest rates should not act as a deterrent but rather banks should use effective levers to generate and direct investment at scale into the productive economy.

4.3.2 From funding to credit risk: Impact from extrernal and internal factors

The macroeconomic outlook, bank lending behavior and market factors affect credit risk levels at the Greek banking system. Nevertheless, the macroeconomic outlook itself is significantly influenced by international and domestic events. The risks and vulnerabilities from the international economy and financial markets have increased due to the geopolitical tensions (Brexit trade uncertainty, concerns about the debt issues of Chinese construction magnet Evergrande, Italian budget concerns), the slowing growth of emerging economies, while their decreasing equities and pressure on exchange rates could increase risks on foreign-currency denominated debt, resulting in negative spillovers in the Euro area countries. The rising geopolitical risks could deter international investment spending not only to areas nearby the conflict zones but to a wider region, which is burdened by migration flows, perplexing the preconditions for a sustainable growth pattern. Domestic challenges still remain, in many ways as a legacy of the sovereign debt crisis. The banking system, albeit reverting to profitability since 2016, continues to be challenged by a large stock of non-performing loans, which is constraining banks’ lending capacity and the ability to build up further capital buffers. In addition, the continuing – albeit necessary – cleaning of banks’ balance sheets may impact their solvency positions ; therefore banks need to further adjust their business models to cope with persistently weak economic conditions and an environment of historically low interest rates.

Regarding the limited credit creation ability, caused by the still large stock of NPLs, the lack of demand for new lending from households and enterprises and supply issues,

[48] Some of these recommendations are embedded in the OECD toolkit for financing sustainable development.

this maintains interest rates at low levels obstructing profitability prospects for banks. To the extent that the stock of non performing exposures is not hammered out more quickly, the ability of banks to extend credit to the real economy would be severely impacted, exacerbating the preconditions for low interest rate and growth.

Credit institutions have made good progress in improving the quality of their portfolio, having taken initiatives to actively manage NPLs. However, the NPL stock remains particularly high. Achieving sustained growth rates and improving the country's macroeconomic aggregates require active support for the credit system, which, with the existing NPL stock, is unable to make a decisive contribution to this. Credit risk has subsided but a quicker than expected withdrawal of support measures may put pressure on households and enterprises by severely affecting the borrowers’ debt servicing capacity, thus leading to a formation of new NPLs in the medium term. However, such a risk may not materialize as new Covid 19 mutations may put measures on hold for the foreseeable future.

In any case, credit institutions will need to step up their efforts to accelerate the restructuring of viable businesses, tackling multiple debtors with multiple creditors, identifying strategic defaulters, and implementing a definitive solution for non-viable businesses.

However, such initiatives should also be complemented by ensuring proper functioning of private debt clearing mechanisms, which would in turn contribute to the effort to reduce the NPLs stock. In particular, the use of electronic auctions helps to improve the pricing of collateralized collaterals, which inevitably lose their value as long as their sale is postponed.

Improving the infrastructure and enhancing the specialized know-how of the judicial system should be a direct priority of the state, since a significant part of the NPLs has been subject to legal protection. It is noted that at the end of the first half of 2018, an amount of € 12.9 billion is in the line of Law 3869/2010. Consequently, it is a matter of particular importance that these exposures are quickly settled and liquidated.

In conclusion, resolving the problem requires a much faster rate of decline in NPLs since the country has completed its recession cycle and the recovery period requires the full exploitation of the banking system's potential.

4.4 Alternative sources of funding for the Greek economy

The sovereign crisis coupled with the ongoing deleveraging by banks has exacerbated the economic contraction and curtailed access to credit for non-financial corporates, especially for Small and Medium-sized Enterprises (SMEs). This, in turn, has serious implications for the ability of firms to withstand the crisis, pursue profitable investment opportunities and restore growth. As a result, the emergence and strengthening of alternative financing channels for non-financial corporates and infrastructure projects – will support the rebalancing towards the export-oriented tradable sector and the development of a sustainable growth model.

4.4.1 Trade finance and infrastructure projects' insurance

Trade finance and infrastructure projects' insurance, which suffered during the sovereign crisis, facilitates growth enhancing capital expenditure and exports.

The European Investment Bank (EIB) and the European Bank for Reconstruction and Development (EBRD) have activated financing initiatives, either in the form of direct financing to eligible Greek companies, or indirectly through the utilization of ancillary financial instruments.

The European Investment Bank (EIB) has launched a number of initiatives regarding the financing of non-financial corporates in Greece.

- The initiative "Joint European Resources for Micro to Medium Enterprises" ("JEREMIE")

This initiative has been jointly developed by the European Commission and the European Investment Fund (EIF), the EIB subsidiary dedicated to SMEs support. Its objective is to support financial engineering instruments, such as venture capital funds, guarantee funds and loan funds, primarily, to SMEs.

The JEREMIE Holding Fund currently deploys two instruments:

i. Funded Risk Sharing, with six agreements signed with three banks: These funds aim to support microfinance as well as investments in the Information and Communication Technology (ICT) sector.

ii. Risk Capital, with venture capital funds undertaking early and seed stage ICT sector investments in SMEs.

- The JESSICA initiative

JESSICA stands for Joint European Support for Sustainable Investment in City Areas. This initiative is being developed by the European Commission and the European Investment Bank (EIB), in collaboration with the Council of Europe Development Bank (CEB). Aiming to create more competitive, socially inclusive and sustainable urban areas in Greece, investments will be made. Their investment portfolio may include urban projects such as rehabilitation of deprived urban areas, basic infrastructure works, development of high-technology clusters and added value infrastructure, water and waste management, energy networks, and energy efficiency.

- The ELENA initiative

ELENA is a joint initiative by the EIB and the European Commission under the Horizon 2020 program. ELENA provides grants for technical assistance focused on the implementation of energy efficiency, distributed renewable energy and urban transport projects and programs. The grant can be used to finance costs related to feasibility and market studies, program structuring, business plans, energy audits and financial structuring, as well as to the preparation of tendering procedures, contractual arrangements and project implementation units.

- The EIB supports infrastructure projects in education, energy and transport.

The "Hellenic Guarantee Fund of EIB for Small and Medium-sized Enterprises" was established in the course of 2012 by using €500 mn from unabsorbed Structural Funds for Greece. The Fund is a joint initiative of the Hellenic Republic, the European Commission and the EIB, specifically designed to cater to the financing needs of SMEs in Greece. The stakeholders acknowledge that SME financing is pivotal for re-launching growth and strengthening the competitiveness of the Greek economy.

- State Guarantee Facility

An additional funding instrument for SMEs and Midcaps is the State Guarantee Facility, whereby EIB provides funding via partner banks for loans that are backed by an explicit Greek government guarantee. The State Guarantee Facility supports investments in tangible assets and working capital by SMEs and Midcaps in the fields of manufacturing, tourism and services. SMEs can benefit from these funds for projects with total costs below €25 mn each.

The EIB signed agreements with all systemic banks.

- Trade Finance Enhancement Program

In December 2012 the EIB Board approved a new financing instrument in support of international trade with a first pilot project designed for Greece. The "Trade Finance

Enhancement Program" is a short-term credit support instrument to address the gap left by retreating commercial banks. Under this facility, the EIB provides guarantees to selected major international banks in favor of Greek commercial banks for SMEs' trade financing for an amount up to €500 mn, and as these guarantees are utilized on a revolving basis, they are expected to support a multiple volume of transactions per year.

Through the Trade Finance facility, the EIB is providing its guarantee on a portfolio of Letters of Credit (LCs), Letters of Guarantee (LGs) and other trade finance instruments issued by Greek banks and confirmed by international banks. This alleviates cash collateral constraints otherwise imposed on most SMEs and increases access to international trade instruments, at a time when Greece needs it in order to pursue export-led growth for its economic recovery.

- Greek Local Authorities Framework

In January 2014, EIB approved the second and final tranche of a €100 mn framework facility that will provide financing to local authorities in Greece through the Consignment Deposits & Loan Fund (CDLF). The first tranche of €50 mn was agreed in November 2013. The facility enables the local authorities to invest in the fields of transport, educational infrastructure, cultural and historic heritage, rehabilitation of public buildings, environmental protection, energy efficiency and tourism infrastructure.

- European Bank for Reconstruction and Development (EBRD)

The European Bank for Reconstruction and Development has been underpinning international coordination regarding financing conditions in Central and Eastern Europe since the outbreak of the financial crisis. In the past it has provided credit lines to the subsidiaries of Greek banks in South Eastern Europe to facilitate lending to local companies.

Furthermore, EBRD also engages directly with Greek non-financial corporates. The proceeds will be used for working capital as well as for capital investment in energy efficiency and production shift towards higher value-added products.

4.4.2 Initiatives supported by European Union Structural Funds

Another source of non-bank financing for the private sector are the EU Structural Funds, namely the Cohesion Fund, the European Social Fund (ESF) and the European Regional Development Fund (ERDF).

Administrative efficiency in this field will be growth-enhancing in the medium-term, especially taking into account that Greece anticipates €15.3 billion of Structural Funds for the period 2014-2020 (incorporating the newly established Connecting Europe Facility).

Structural Funds support a multitude of projects. Three initiatives of particular interest, analyzed in more detail, are the Entrepreneurship Fund, the motorway concessions and the Institution for Growth in Greece (IfG).

- Entrepreneurship Fund (ΤΕΠΙΧ)

The Entrepreneurship Fund was established in October 2010, with the objective of improving the competitiveness of Greek enterprises.

SMEs are defined as businesses with a maximum of 250 employees, €50 mn turnover, or €43 mn assets irrespective of their legal form and time of establishment (startup or mature), that abide by the De Minimis Rule.

The Entrepreneurship Fund consists of four sub-funds:

i. Business Restarting Fund;

ii. Island Tourism Entrepreneurship Fund;

iii. Guarantee Fund;

iv. Targeted Actions Fund.

The objective of the Business Restarting Fund is to provide business loans at favorable terms. The ETEAN, as the manager of the Entrepreneurship Fund, will contribute €275 mn and the associated banks a matching amount. The funds are provided in the form of subsidized loans (50% interest free), for:

- working capital needs (size: €10,000-€300,000; duration: up to 48 months) or
- investment projects (size: €10,000-€800,000; duration: 5-12 years, including a 2-year grace period).

All major commercial banks (namely, in alphabetical order, Alpha Bank, Attica Bank, Eurobank, NBG and Piraeus Bank) as well as five cooperative banks (Chania, Epirus, Karditsa, Pancretan and Thessaly) are participating.

The Island Tourism Entrepreneurship Fund aims at supporting tourism enterprises on Greek islands.

The Guarantee Fund aims at facilitating access of SMEs to bank funding through providing a (partial) guarantee. The Guarantee Fund supports:

i. working capital loans (size: €10,000- 500,000; duration: 2-3 years; 80% guarantee);

ii. fixed assets investment (size: €10,000- 800,000; duration: 5-10 years; 70% guarantee; grace period: 6-24 months);

iii. business development loan (as for fixed assets but with a 2-10 year duration).

The Guarantee Fund receives a commission of 0.8% for the guarantee, while the bank interest rate is negotiated freely.

The Targeted Actions Fund aims at facilitating medium term financing for SMEs in specific sectors and activities. The Targeted Actions Fund provides fixed interest rate loans with an 5-10 year duration and has been allocated €133 mn.

- Motorway concessions

The economic crisis caused serious problems in funding for four out of five major motorway concessions, namely the Aegean, the Olympia Odos, the Ionian Odos and the Central Greece motorways. The sudden drop in traffic and the expected toll income as well as withdrawal of support from a part of the banking sector, effectively stopped the projects due to lack of funds in 2010.

The government, concessionaires, lenders and the European Commission worked hard to restart all four motorway concession projects throughout 2013. In December 2013 the European Commission provided its clearance of the “Reset Agreements” on competition and state aid issues and confirmation of the Structural Funds’ contribution to the financing of the four motorways, as well as compatibility with the public procurement rules.

The EU co-financing of up to €3 billion for the four projects is part of a total investment cost of €4.6bn. The four investments come through the EU Regional Policy programme "Reinforcing Accessibility", funded through the European Regional Development Fund (€1.7 billion) and the Cohesion Fund in Greece (€1.3 billion). Greek banks will be providing €1.1 bn of loans.

The concessioners are Greek constructors as well as European companies from several member states, and have recently signed the recast of the project. In addition to the EIB, around 40 Greek and international banks are financially involved.

These investments – among the most important infrastructure projects in Greece – will be central to the country's economic recovery, creating circa 6,000 jobs during the building of the motorways (until 2015) and connecting its regions with fast and safe motorways.

- Institution for Growth (IfG)

The government established the Institution for Growth (IfG), a non-bank financial institution, to support innovation and growth in Greece by catalyzing private sector financing, especially for SMEs, while minimizing fiscal risks.

In particular, the IfG to help address credit constraints will provide:

i. debt or equity financing and guarantees for SMEs;

ii. debt or equity financing and guarantees for infrastructure projects;

iii. equity capital to private equity and venture funds.

The first of three planned sub-funds was established on 7 May 2014 in Luxembourg. Greece and KfW are to each provide financing of EUR 100 million. IfG will distribute the funds to small and medium-sized enterprises (SMEs) in Greece with the help of accredited Greek banks. The key objective is to provide Greek SMEs with improved access to investment loans and working capital to help foster economic growth.

4.4.3 The Recovery Plan for investing in a green, digital and resilient Europe

- The Recovery and Resilience Facility

The € 672.5 billion European Recovery and Resilience Facility (RRF) is at the heart of the Next Generation EU program, and consists of grants and loans in the form of forward-looking financial support for the critical first years of recovery following the effects of COVID -19. To receive support from this Facility, national recovery and resilience plans are required from Member States by 2026. It is noted that the distribution of funds for Greece is 17.5 billion euros in the form of grants and 13.6 billion euros in the form of loans at current prices.

The Greek government has begun preparing the National Recovery and Resilience Plan in line with its reform and investment program. The whole program of the government can be included in the European Mechanism and includes the National Development Plan (Pissaridis Commission), the tax relief program, the saving of fiscal space by enabling financing for public investments and other reforms, the clean production and use of energy, the digitization of public administration and the strengthening of the National Health System.

- REACT-EU (Recovery Assistance for Cohesion and the Territories of Europe)

A new initiative in the proposal aims to extend the crisis response and repair measures that cohesion policy has started, while enlarging the scope to cover green, digital and growth-enhancing investments. It includes a 55 billion top-up of the current cohesion policy programs in the short-term; it notably increases the European Social Fund, which focuses on upskilling and reskilling, education, youth employment and mobility. REACT-EU as a whole focuses on issues of just transition and fair recovery amongst European regions.

- A larger Just Transition Fund

To assist Member States in accelerating the transition towards climate neutrality, the Commission had put forward the Just Transition Mechanism, compensating regions, businesses and workers who will have to adjust the most to the transition needs. The Mechanism included a fund of €7 billion, which was proposed to be increased five-fold, and strengthened up to €40 billion, to ensure that the recovery includes a just transition towards climate neutrality. The significant top-up shows the focus of recovery towards the twin transitions occurring in a fair fashion.

- InvestEU and strategic investments

This InvestEU proposal further strengthens Europe's investment programs in this area, by focusing more on key value chain investments, which are crucial for Europe's future resilience and strategic autonomy, such as sustainable infrastructure and digitization. InvestEU is the expansion of the successful Juncker Plan model of using an EU budget guarantee to crowd-in other investors, and is expected to mobilize at least €650 billion in additional investment between 2021 and 2027.

- Solvency Support Instrument

At the same time, this new instrument aimed to provide urgent equity support to sound companies put at risk by their crisis, while supporting their green and digital transformation. It aspired to mobilize €300 billion for the real economy.

- New Health Programme and rescEU

The third pillar of the Next Generation EU instrument is dedicated to learning lessons from the pandemic, and reaffirms the social and resilience focus of the recovery plan. The new Health program aimed to distribute grants to EU healthcare systems with a focus on health security and capacity to react to crisis, as well as long-term disease prevention and surveillance. RescEU will reinforce the civil protection support capacity to respond to large-scale emergencies, such as health emergencies infrastructure for response.

- New budget revenue streams

To finance the higher proposed EU budget, the Commission has proposed new and diversified sources of revenue that contribute to EU priorities, and in particular climate change, circular economy, digitalization and fair taxation. Those include an extension of the Emissions-Trading System and a digital levy on tech giants. Proposing revenue sources (and taxation streams) that are linked to the green, digital and social agendas is a new concept for the EU budget, which has traditionally been financed by custom duties and Member State contributions, and reinforces the European commitment to its priorities.

4.5 Investment Opportunities in Greece – The way forward

During 2013, the Greek banking system underwent a major consolidation process through a number of mergers and acquisitions that took place. During 2014 and 2015 most of the recapitalization of the Greek banking system was completed. In the current conjuncture, valuations of both financial and physical assets have been diminished. Foreign investors should grab this unique opportunity and be part of this transformation process either with the form of share ownership or by signing other strategic cooperation agreements. Foreign investors should take into account that Greece is situated in one of the most important geopolitical locations in the wider European region, being both part of the Balkan region and of South Eastern Europe. As already known, the larger Greek banking groups already possess a significant network of branches and subsidiaries in the aforementioned area as they offer high-quality financial products and services. As a result, for someone who wants to invest in Greece, access is automatically gained to a wider investment region and to a qualified network of human resources with all the subsequent advantages.

Georgikopoulos [135] has found that there are a number of initiatives that should be implemented in order to make sure that the investment opportunities have viable chances to materialize. First of all, a simplified system of incentives and tax concessions for investments should be put in place in order to improve the tax collection procedure, limit the tax evasion and allocate more fairly the taxation burden to the society. Increased taxation, which was initially useful for reversing the budget deficit into a primary surplus, should be relaxed progressively if a primary surplus is witnessed after more than 2 consecutive periods in order to increase incentives for investments. The administration has already transformed the taxation system, partly as a requirement to its international lenders, but more rationalization of the system aligned towards the aforementioned goals should be warranted.

In addition, the bureaucracy has been addressed by enacting new bills with that aim to simplify the process of a direct investment in Greece with the provision of 'one-stop shop', the more extensive and user-friendly technology (i.e. TAXISNET) and the increase of transparency on the investment proposals (for example on infrastructure and energy), especially for those funded through EU programs.

Furthermore, the regional economic cooperation in the Balkan Region should be promoted despite the geopolitical risks by using Greece's comparative locational advantage. Instead of viewing, for instance, the agreement on planned pipelines only as the "solution" for attracting investments, Greek authorities should undertake a more active stance by exploiting this fact both as a vehicle and as an opportunity to promote closer economic ties on various industrial segments between the countries neighboring the pipeline route. Such cooperation increases production efficiency and increases economies of scale. The country should go on and exploit the natural resources such as petroleum or natural gas: R&D has indicated that there are significant possibilities both in the Ionian and in the Aegean Sea. Any indication of potential oil or gas would stimulate further investment in the region.

A very important parameter is the promotion of young intellectual minds with a specialization in technological innovations (investments, patents.) Funding (with an assistance of EU) of entrepreneurial activity should be a top priority, relating to the creation or expansion of their business and distribution of technologies in Greece or abroad. Such enterprises can then be acquired from foreign established groups, increasing immensely their valuation.

Finally, new investments should target not only the specific "traditional" sectors (i.e. shipping, tourism) but should also involve new sectors which invest in human capital where the potential of growth is enormous in the next 5-10 years (i.e. technological innovations). Once the "priority" sectors are identified, investor fora, seminars and presentations to investors could be hosted around Greece.

CHAPTER 5 An examination of the NPL determinants using GAMLSS models on databases with aggregate data

This Chapter will examine the determinants that contribute to the NPLs formation. For this purpose, I will use variables formed from aggregate datasets on macroeconomic variables and ratios, banks' financial statements variables and ratios and prudential variables and ratios, and then investigate whether macroeconomic, bank specific and market factors play a significant role in affecting credit risk levels, thus prescribing with more accuracy the drivers that affect credit risk levels.

5.1 Data and variables

A selection from 14 credit risk variables, 8 macroeconomic variables (GDP-unemployment), 14 banking capital variables, 16 Resilience-profitability banking variables, 14 Resilience-capital adequacy variables were collected (see Metadata table 5.1 and Annex 1a). Such variables are quarterly variables, and in particular they start from 2007Q4 and end in 2018Q4[49]. The categories of the independent variables are the following: 1) credit risk variables including NPLs, loans and provisions; and 2) macroeconomic variables, such as GDP and unemployment. GDP variables are taken both at an annual and at a quarterly level, as well as their yearly changes on annual and quarterly figures. Unemployment variables are taken in terms of their actual figures as well as their unemployment rate; 3) Book value equity and components including share capital and reserves; 4) Resilience-Profitability variables, such as operating income and costs, impairment charges and profits before/after taxes; 5) Resilience-capital adequacy ratios including risk components. Such ratios include the components of solvency, risk weighted assets both on a solo and on a consolidated basis.

The response variable is the total non-performing loans (NPLs_total). As discussed in the Literature Review Chapter, it is expected that macroeconomic variables will be negatively associated with NPLs because a deterioration in the economy affects income ,hence the borrower's ability to repay the loan obligations on time. Bank specific variables that affect lending behavior are also expected to affect NPLs due to the "procyclical" policy of granting loans. Usually, during a period of booms, banks adopt

[49] It should be noted that the number of observations (42) provide certain limitations on modelling discussed below. Data are collected on a quarterly basis and have been used since the end of 2007, which marks the beginning of the financial crisis.

a more expansionary credit policy, followed by a substantive tightening in the recessionary period. Non-discretionary loan loss provisions exacerbate a procyclical effect because higher non-discretionary provisions reduce bank loan growth. In contrast, discretionary loan loss provisions – particularly related to income smoothing behavior – have no significant impact on bank loan growth. Finally, leverage and solvency-related variables may have an effect on NPLs. Solvency ratios associate the level of supervisory own funds with the risk-weighted assets. The risk weighting depends on the probability of default for each asset item and the losses that would likely incur when a default takes place – in the case of market, risk derivative investments for instance are riskier than investments in government bonds.

TABLE 5.1 Metadata table for variables used for the GAMLSS models

Cat	Metadata name	Cat	Metadata name	Cat	Metadata name
CREDIT RISK	NPLs_consum	MACROECONOMIC	GDP_quarterly_volumes	BANKING CAPITAL consolidated/solo	Share_capital_con
	NPLs_mortgages		GDP_yearly_volumes		Share_premium_con
	NPLs_Corp		GDP_change_quartervolumes		Reserves_con
	NPLs_total		GDP_change_yearvolumes		Treas_shares_con
	Consum_loans		Employed_number		Min_interest_con
	Mortgages		Unemployed_number		Hybrid_capital_con
	Corporates		Inactive_number		Total_equity_con
	Total_loans		Unemployment_rate		Share_capital_solo
	Total_provisions				Share_premium_solo
	NPLs_ratio_consum				Reserves_solo
	NPLs_ratio_mortgage				Treas_shares_solo
	NPLs_ratio_corp				Min_interest_solo
	Total_nplratio				Hybrid_capital_solo
	Total_coverage_ratio				Total_equity_solo
RESILIENCE- Profitability consolidated/solo	Operating_income_con	RESILIENCE- capital adequacy consolidated	CET1_capital_con	RESILIENCE- capital adequacy solo	CET1_capital_solo
	Operating_costs_con		Add_T1_capital_con		Add_T1_capital_solo
	Profit_bef_prov_con		Total_Tier1_con		Total_Tier1_solo
	Flow of provisions_con		Tier2_capital_con		Tier2_capital_solo
	Non_recurr_results_con		Total_own_funds_con		Total_own_funds_solo
	Profit_bef_tax_con		Riskassets_creditrisk_con		Riskassets_creditrisk_solo
	Tax_con		Riskassets_settlementrisk_con		Riskassets_settlementrisk_solo
	Profit_aft_tax_con		Riskassets_marketrisk_con		Riskassets_marketrisk_solo
	Operating_income_solo		Riskassets_operationalrisk_con		Riskassets_operationalrisk_solo
	Operating_costs_solo		Riskassets_otherrisk_con		Riskassets_otherrisk_solo
	Profit_bef_prov_solo		Total_riskassets_con		Total_riskassets_solo
	Flow of provisions_solo		C.A.R_ratio_ con		C.A.R_ratio_solo
	Non_recurr_results_solo		Tier1_ratio_con		Tier1_ratio_solo
	Profit_bef_tax_solo		CET1_ratio_con		CET1_ratio_solo
	Tax_solo				
	Profit_aft_tax_solo				

5.2. Modeling the impact of macroeconomic, bank-specific and market factors on credit risk using the GAMLSS R programming

To estimate the norms properly, it is important that the distributional parameters are estimated properly. A criterion-based method for the selection of variables has been used, i.e. the generalized Akaike information criterion (GAIC; [232]). The GAIC tries to prevent overfitting of the data, which increases generality of the model. The prevention of overfitting is done indirectly by the GAIC, where the number of parameters is penalized, enabling one to accurately estimate the norms for the reference population.

Some of the explanatory variables included in the model formulation of the parameters were not significant and a variable selection procedure had to be carried out. In particular, the variable selection was performed using step-wise elimination based on an Akaike Information Criterion (AIC). More specifically, a forward stepwise procedure has been used which allows adding a variable at each step. All variables were taken into consideration and then were individually considered for adding at each step. The variable to add that gives the minimum value of AIC of the model selection was chosen at every step.

My framework employed two models for fitting the data: The first one is a linear model whereby the response variable is a linear function of the selected variables. The second model is an nonlinear semi-parametric GAMLSS smoothing model (P-spline model) that captures potential nonlinear relationships between the explanatory variables to model the parameters favorably. To estimate the functions, a method for automatic selection of the smoothing parameters is used, which is specially developed for GAMLSS objects, as stated in Rigby R. A. and Stasinopoulos D. M. [262] (2014). P-splines (i.e. non-parametric penalized smoothers) are the most important smoothers within the GAMLSS family because they can be applied in a variety of different cases.

The GAMLSS R package that was used is available from CRAN [35], [73], [126], [142], [147], [245], [280], [281], [304], [305], which is the comprehensive R Archive Network. This comprises of a collection of sites which carry identical material, consisting of the R distribution(s), the contributed extensions, documentation for R, and binaries.

5.2.1. Functions in GAMLSS R programming for the linear model

Initially the null model was fitted containing only the constant and then each variable was added one at a time:

```
m0 <- gamlss(NPLs_total~1, data=da1)
```

For the linear GAMLSS model, a formula was created, containing all the linear main effects and second-order interactions of the explanatory variables:

```
FORM<-as.formula(paste("~",paste(paste(paste("(",names(da1)[-1],
sep=""),")",sep=""), collapse="+")))
```

The "FORM" function is being used as an upper argument for scope. The "scope" function defines the set of models searched, including its lower and upper components. The scope is a list containing components upper and lower, both formulae. While the terms defined by the formula in lower are always included in the model, the formula in upper is the most complicated model that the procedure would consider. The stepwise procedure "stepGAIC()" provides a mechanism for stepwise selection of appropriate linear terms for any of the parameters of the distribution (μ, σ skewness, kurtosis).

All variables not currently in the model are considered for adding. The variable to add that gives the minimum value of the model selection criterion is chosen at that step, provided it reduces the criterion. There are functions which are the building blocks for stepGAIC(), which is suitable for stepwise selection of terms for one of the distribution parameters. It is important to start from m0 (all linear terms) so that all interactions are considered at the first step. Hence in stepGAIC(), interactions involving the linear component of smoothing terms never enter into consideration. This is a limitation of stepGAIC(), of which the user has to be aware, and is the reason for starting from m0 (all linear terms) above.

Finally, in order to define a normal random intercept in the predictor for μ, the user has to set the argument K for the number of Gaussian quadrature points. It is recommended at least K=10 for reasonable accuracy:

```
mf <- stepGAIC(m0, scope=list(lower=~1, upper=FORM), k=10)
```

5.2.2. Functions in GAMLSS R programming for the non-linear P spline model

For the non-linear P spline GAMLSS model, a formula was created, containing all the linear main effects and second-order interactions of the explanatory variables plus smooth functions of the explanatory variables:

```
FORM1<-as.formula(paste("~",paste(paste(paste("pb(", names(da1)[-1],
sep=""),")",sep=""), collapse="+")))
```

The “pb()” function is a GAMLSS implementation of the Eilers and Marx [110] (1996) B-spline approach. In the smoothing function pb() the smoothing parameter (and therefore the effective degrees of freedom) are estimated automatically, using the default local maximum likelihood method described in Section 3.4.2.1 by Rigby, Stasinopoulos et al. [268] (2013).

As the number of knots in a spline becomes relatively large, a fitted spline function will show more variation than justified by the data. To limit overfitting, O’Sullivan [90] (1990) introduced a smoothness penalty by integrating the square of the second derivative of the fitted spline function. Later, Eilers et al. [95] (1996) showed that this penalty could also be based on higher-order finite differences of adjacent B-splines. Penalized splines or “P-splines” use the latter method to estimate spline functions.

Rigby, Stasinopoulos et al. [268] (2017) note that one of the important things to remember when fitting a smooth nonparametric term in gamlss() is that the displayed coefficient of the smoothing term and its standard error (s.e.) refer only to the linear component of the term. This is because the linear part of the smoothing is fitted together with all other linear terms (in the above case only the intercept). One should try to interpret the whole smoothing function, which can be obtained using term.plot().

Again, in order to define a normal random intercept in the predictor for μ, the user has to set the argument K for the number of Gaussian quadrature points. It is recommended at least K=10 for reasonable accuracy:

```
mfpb <- stepGAIC(m0, scope=list(lower=~1, upper=FORM1), k=10)
```

5.3 Estimation results

5.3.1 A GAMLSS fitted linear model

This section will analyze the results from the linear model that has been fitted using the stepwise procedure outlined above. The results of this process are illustrated in Table 5.2.

TABLE 5.2 Model 1: Linear Model: A Gamlss Fit of macroeconomic (unemployed number), bank lending behavior (Total provisions) and leverage and solvency (Total Tier1 solo), (Share capital solo) to credit risk levels (NPL_total) in the Greek banking system

```
******************************************************************
Family:  c("NO", "Normal")
```

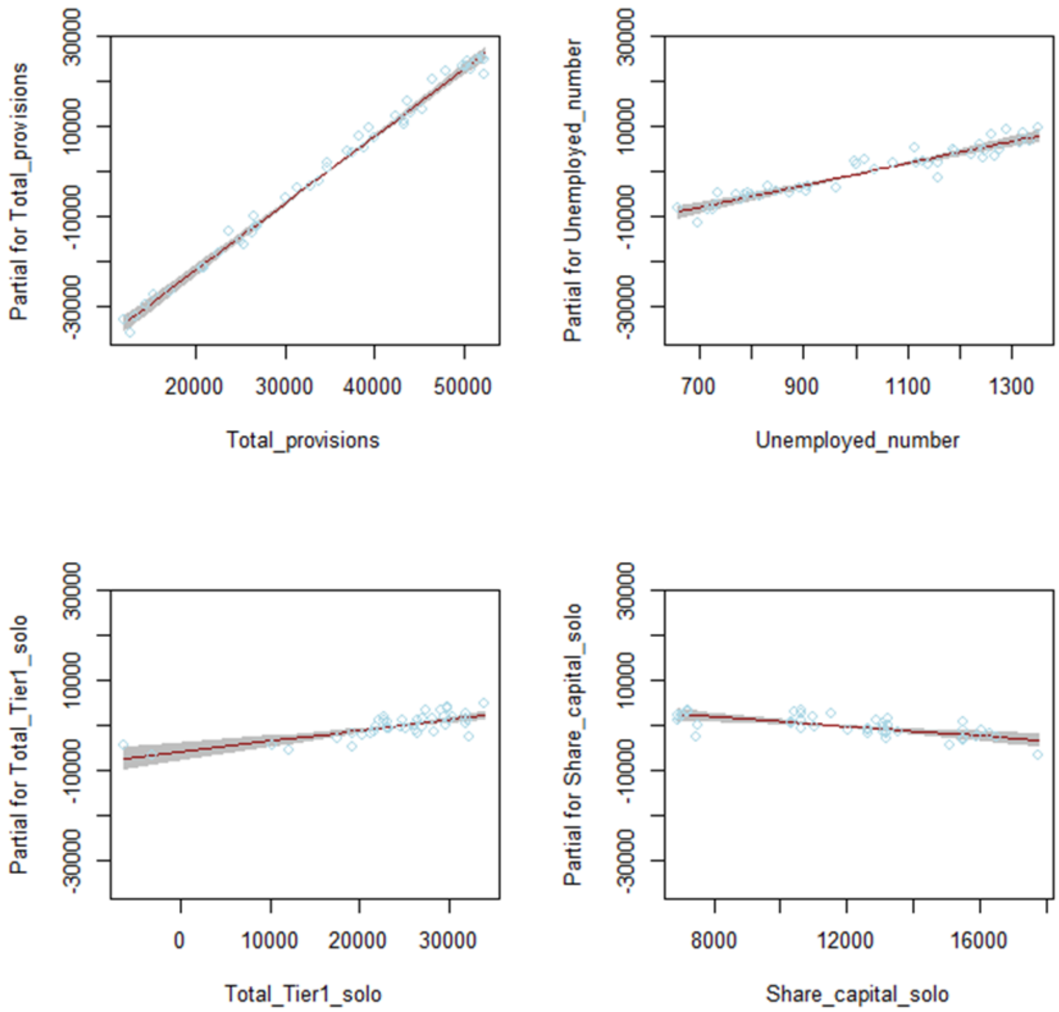
```
Call:  gamlss(formula = NPLs_total ~ Total_provisions + Unemployed_number +
   Total_Tier1_solo + Share_capital_solo, data = da1,      trace = FALSE)

Fitting method: RS()
-------------------------------------------------------------------
Mu link function:  identity
Mu Coefficients:
                            Estimate        Std. Error       t value       Pr(>|t|)
(Intercept)                 1325.59634      2008.63220       0.660          0.513
Total_provisions            1.48927           0.03665        40.640       < 2e-16 ***
Unemployed_number           24.41782          1.75765        13.892       < 2e-16 ***
Total_Tier1_solo             0.23495          0.03791         6.198      3.05e-07 ***
Share_capital_solo          -0.51625          0.11520        -4.481      6.61e-05 ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
-------------------------------------------------------------------
Sigma link function:  log
Sigma Coefficients:
              Estimate    Std. Error      t value       Pr(>|t|)
(Intercept)   7.4127        0.1066         69.54      <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
-------------------------------------------------------------------
No. of observations in the fit:  44
Degrees of Freedom for the fit:  6
     Residual Deg. of Freedom:  38
                  at cycle:  2

Global Deviance:     777.1808
          AIC:     789.1808
          SBC:     799.886
**********************************************************************
```

Table 5.2. provides coefficients and standard errors. The t test checks whether the linear part in x is significant. The summary function shows the standard errors and t-tests of the estimated coefficients. The fitted model is given by $Y \dashleftarrow N(\hat{\mu}, \sigma^2)$ where $\hat{\mu}$ = 1325.59634+ 1.48927 Total Provisions 24.41782 Unemployed Number 0.23495 Total Tier I solo -0.51625 Share capital solo while log($\hat{\sigma}$) = 7.4127.

Figure 5.1. shows the fitted terms of the linear model, i.e. the contribution to the predictor of a specific term in the model. It is used for plotting the additive contribution of a specific predictor of a distribution parameter. It appears that by using the NPLs ratio (Total_nplratio) as the response variable, the linear model provides evidence that the variables (a) provisions and (b) unemployment number are playing a very important role in explaining the course of non-performing loans, while the (c) Total_Tier1_solo and (d) Share_capital_solo play a less important role. However, given that there is a

relationship between variables (c) and (d) (supervisory risk-weighted capital adequacy and accounting equity variables), variable (d) has to be excluded from the selection process. The exclusion is based on the fact that the supervisory capital adequacy variables may understate the risk in certain cases.

FIGURE 5.1: A plot for the fitted terms for the linear model



The Greek banks' resilience can be increased via the build-up of good quality capital levels ahead of Basel III implementation. Resilience through a good quality capital may be a more useful measure compared to accounting capital measures. In certain cases, banks could appear with higher risk-weighted capital ratios, if their holdings are concentrated on less risk weighted asset items, for instance sovereign debt, which does not carry any risk component. Given that the sovereign-bank nexus may be reemerging, such risks may not be understated. In general, more importance should be given to "underestimated" risk-weighted assets and this can be achieved only by increasing the buildup of good quality capital.

Therefore, the factors that should be considered as more relevant by the linear model comprise of (a) unemployment (macroeconomic variable), (b) provisions (lending behavior variable) and (d) Total_Tier1_solo (leverage indicator and mitigant for risk).

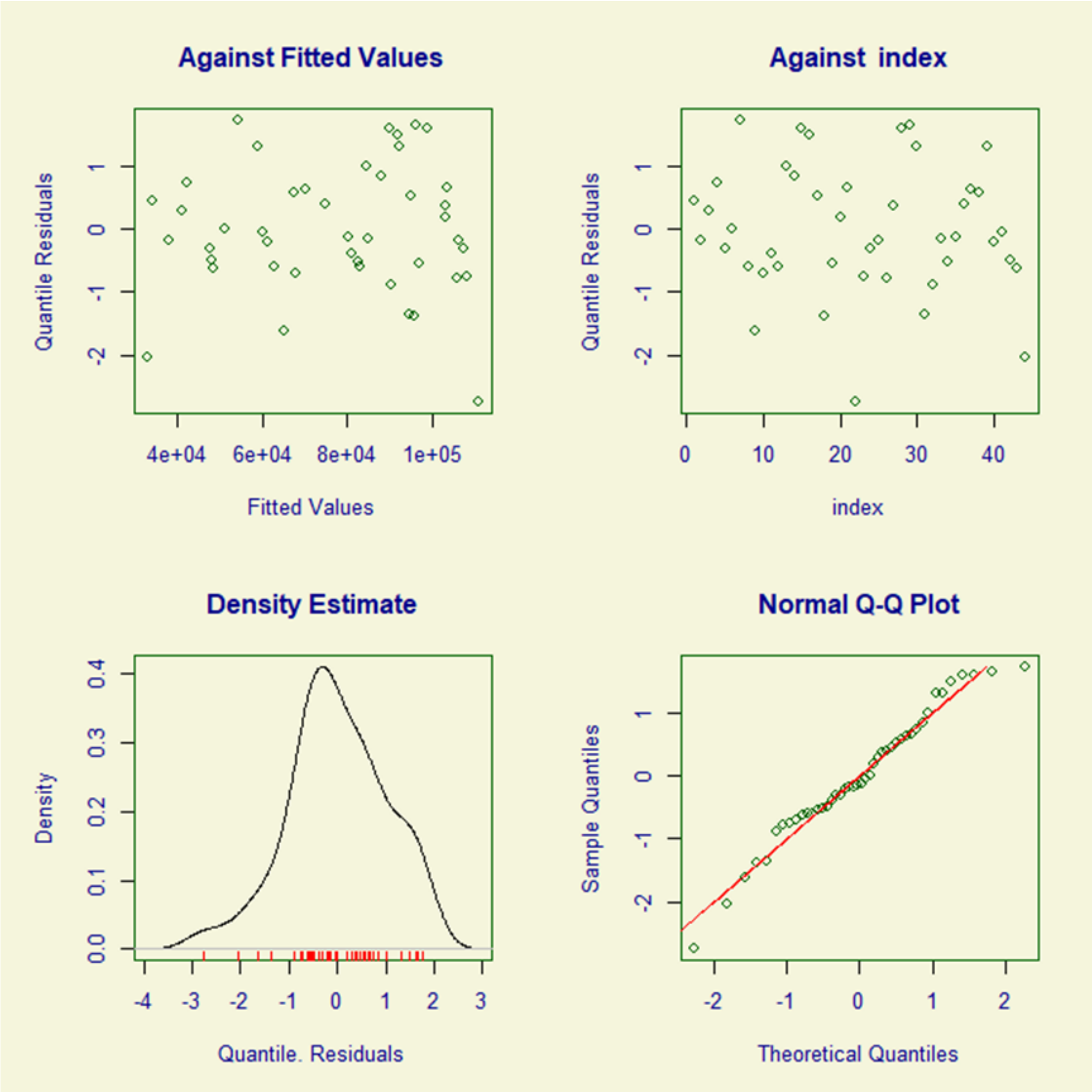
More specifically, the linear GAMLSS model for the overall Greek banking system suggests that macroeconomic, bank lending behavior and market factors influence credit risk levels in Greece in a significant way. The model finds that total provisions and unemployment are the most significant factors with $p\_p < 2e\text{-}16 < 0.001$, $p\_unemployment < 2e\text{-}16 < 0.001$ while the capital-related variables are to a lesser extent significant.

After the linear model has been fitted, it is important to assess the adequacy of the fitted model using the model residuals.

In this case, the R GAMLSS function "plot()" is being used, which produces four plots for checking the normalized (randomized) quantile residuals of a fitted gamlss object. According to Rigby, Stasinopoulos et al. [268] (2017), randomization is performed for discrete and mixed response variables and also for interval or censored data. The four plots are (a) residuals against the fitted values of the μ parameter; (b) residuals against an index or a specified covariate; (c) a kernel density estimate of the residuals; and (d) a QQ-normal plot of the residuals.

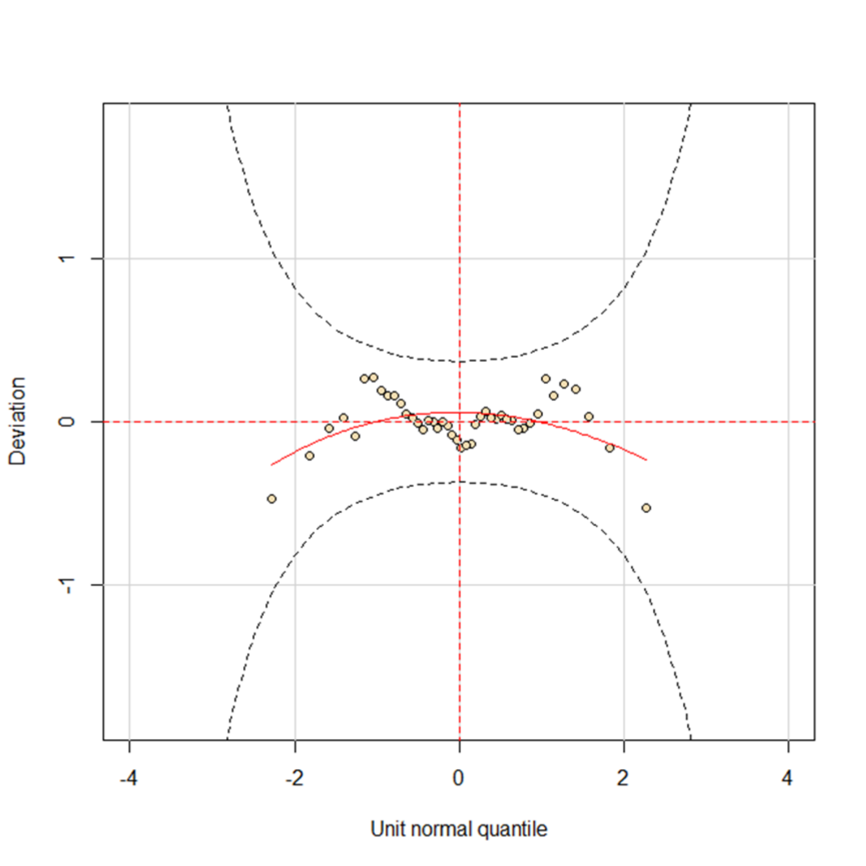
The resulting plot is shown in Figure 5.2. It is shown that the residuals behave well, since the top two plots of the residuals against the fitted values of μ and against the index show a random scatter around the horizontal line at 0, while the kernel density estimate of the residuals is approximately normal and the normal Q-Q plot is approximately linear.

FIGURE 5.2: Residual plots from the fitted linear model



Finally, analysis will be performed on the “worm” plots of the residuals. Worm plots of the residuals were introduced by van Buuren and Fredriks [72] (2001) in order to identify regions (intervals) of an explanatory variable within which the model does not adequately fit the data (which they called ‘model violation’). The R function wp(), based on the original S-PLUS function given in van Buuren and Fredriks [72]), provides single or multiple worm plots for gamlss fitted objects. This is a diagnostic tool for checking the residuals for different ranges (by default not overlapping) of one or two explanatory variables. The worm plot is a detrended QQ-plot and the name comes from the worm-like appearance of the plotted points.

FIGURE 5.3: Worm plot of the fitted linear model



My model is assessed according to the following criteria of the worm plot (Figure 5.3) addressed by Rigby, Stasinopoulos et al. [268] (2017):

- The points of the plot (the worm): These points show how far the ordered residuals are from their (approximate) expected values represented in the figure by the horizontal dotted line. The closer the points are to the horizontal line, the closer the distribution of the residuals is to a standard normal distribution. It appears that the points in my model are fairly close to the horizontal line.
- The approximate point-wise 95% confidence intervals given by the two elliptic curves in the figure. The accuracy of my model is indicated by the fact that approximately 95% of the points lie between the two elliptic curves and 5% outside. If there was a higher percentage of the points outside the two elliptic curves (or a clear systematic departure from the horizontal line) that would indicate that the fitted distribution (or the fitted terms) of the model are inadequate to explain the response variable.
- The fitted curve to the points of the worm: This curve is a cubic fit to the worm plot points. The shape of this cubic fit reflects different inadequacies in the model, i.e. if the level of plotting points in the worm plot is above a horizontal

line at the origin or if the level of the worm plot is below a horizontal line at the origin. Furthermore a linear, quadratic or cubic shape could indicate a problem with the variance, skewness or kurtosis of the residuals, respectively.

As far as my model is concerned, all the observations fall in the "acceptance" region inside the two elliptic curves and no specific shape is detected in the points. Therefore, my model appears to fit well overall.

5.3.2 A GAMLSS fitted P spline model

An additional model that has been used is a nonparametric penalized smoothing spline. After the selection of the significant variables using the Akaike criterion, a P spline model has been fitted. The results of this process are illustrated in Table 5.3.

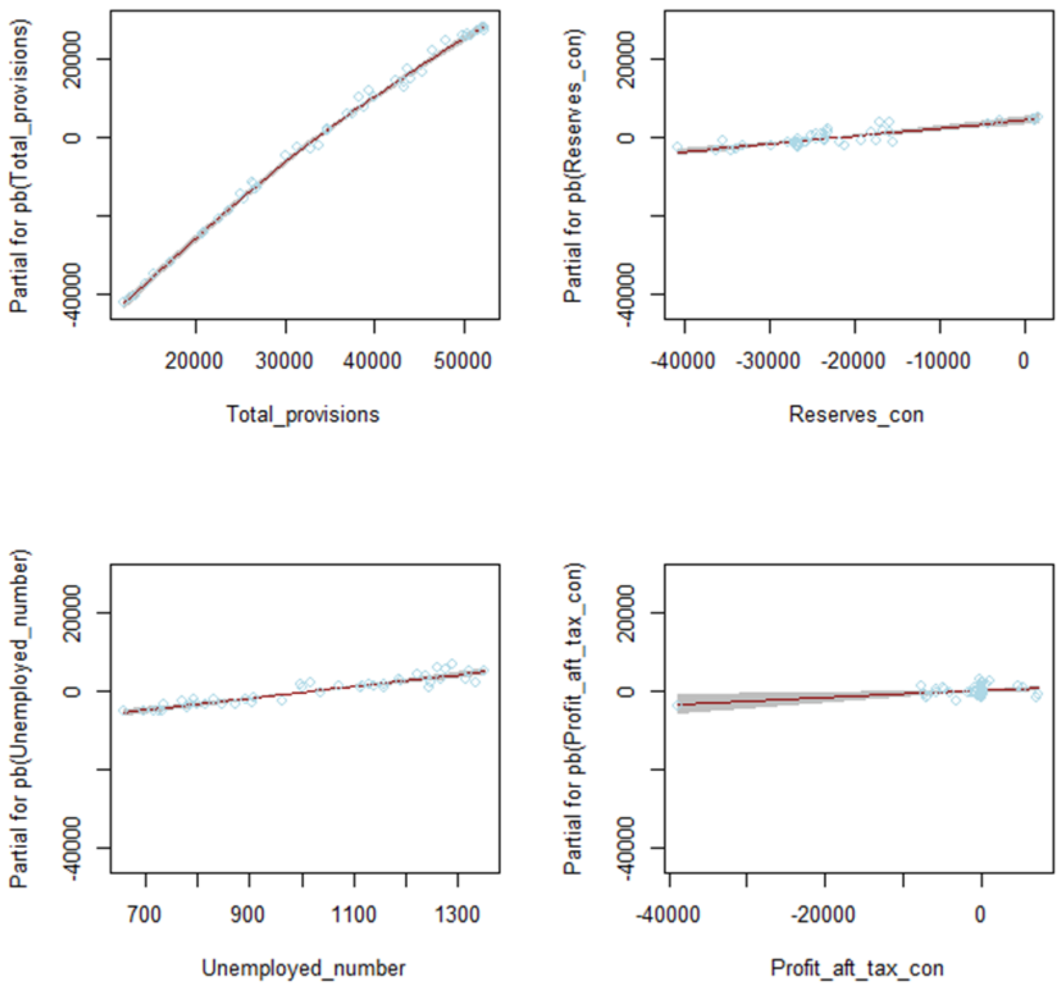
Table 5.3. provides coefficients and standard errors. Figure 5.4. shows the fitted terms of the non-parametric P spline model, i.e. the contribution to the predictor of a specific term in the model is selected. One of the properties of the fitted nonparametric smooth functions is that they cannot be described simply in a mathematical form. However, they can be displayed. One should try to interpret the whole smoothing function, which can be obtained using term.plot(). However, in this case, we should not interpret the linear coefficients or the standard errors of the smoothing terms.

It appears that by using the NPLs ratio (Total_nplratio) as the response variable, the P spline model provides evidence that the variables (a) provisions and (b) unemployment number are playing the most important role in explaining the course of non-performing loans while the variables Reserves and Profit after taxes play a lesser role as a risk mitigant. However, given the fact that both profits and capital may understate the risk in certain cases, Reserves and Profit after taxes have to be excluded. Overall, the P spline GAMLSS model for the overall Greek banking system suggests that basically the macroeconomic and bank lending behavior variables influence credit risk levels in Greece in a significant way. The model finds that total provisions and unemployment are the most significant factors with $p\_p < 2e\text{-}16 < 0.001$, $p\_unemployment < 2e\text{-}16 < 0.001$, while the profit and capital-related variables are to a lesser extent significant in adequately explaining the course of NPLs in Greece.

TABLE 5.3 Model 2: P spline Model: A Gamlss Fit of macroeconomic (GDP yearly volumes), bank lending behavior (Total provisions) and mitigant for risk (Total Tier2 capital) to credit risk levels (NPL total) in the Greek banking system

```
Family:  c("NO", "Normal")

Call:  gamlss(formula = NPLs_total ~ pb(Total_provisions) +
    pb(Reserves_con) + pb(Unemployed_number) + pb(Profit_aft_tax_con),
    data = da1, trace = FALSE)

Fitting method: RS()
------------------------------------------------------------------
Mu link function:  identity
Mu Coefficients:
                          Estimate    Std. Error    t value      Pr(>|t|)
(Intercept)               4.193e+03   9.314e+02     4.502    6.96e-05 ***
pb(Total_provisions)      1.734e+00   1.808e-02    95.924     < 2e-16 ***
pb(Reserves_con)          1.395e-01   2.057e-02     6.781    6.83e-08 ***
pb(Unemployed_number)     1.611e+01   9.902e-01    16.272     < 2e-16 ***
pb(Profit_aft_tax_con)    1.457e-01   2.972e-02     4.901    2.10e-05 ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
------------------------------------------------------------------
Sigma link function:  log
Sigma Coefficients:
                         Estimate       Std. Error     t value     Pr(>|t|)
(Intercept)              7.0854         0.1066         66.47     <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
------------------------------------------------------------------
NOTE: Additive smoothing terms exist in the formulas:
 i) Std. Error for smoothers are for the linear effect only.
ii) Std. Error for the linear terms maybe are not accurate.
------------------------------------------------------------------
No. of observations in the fit:  44
Degrees of Freedom for the fit:  8.496494
Residual Deg. of Freedom:  35.50351
                 at cycle:  4

Global Deviance:     748.3857
         AIC:     765.3787
         SBC:     780.5381
******************************************************************
```

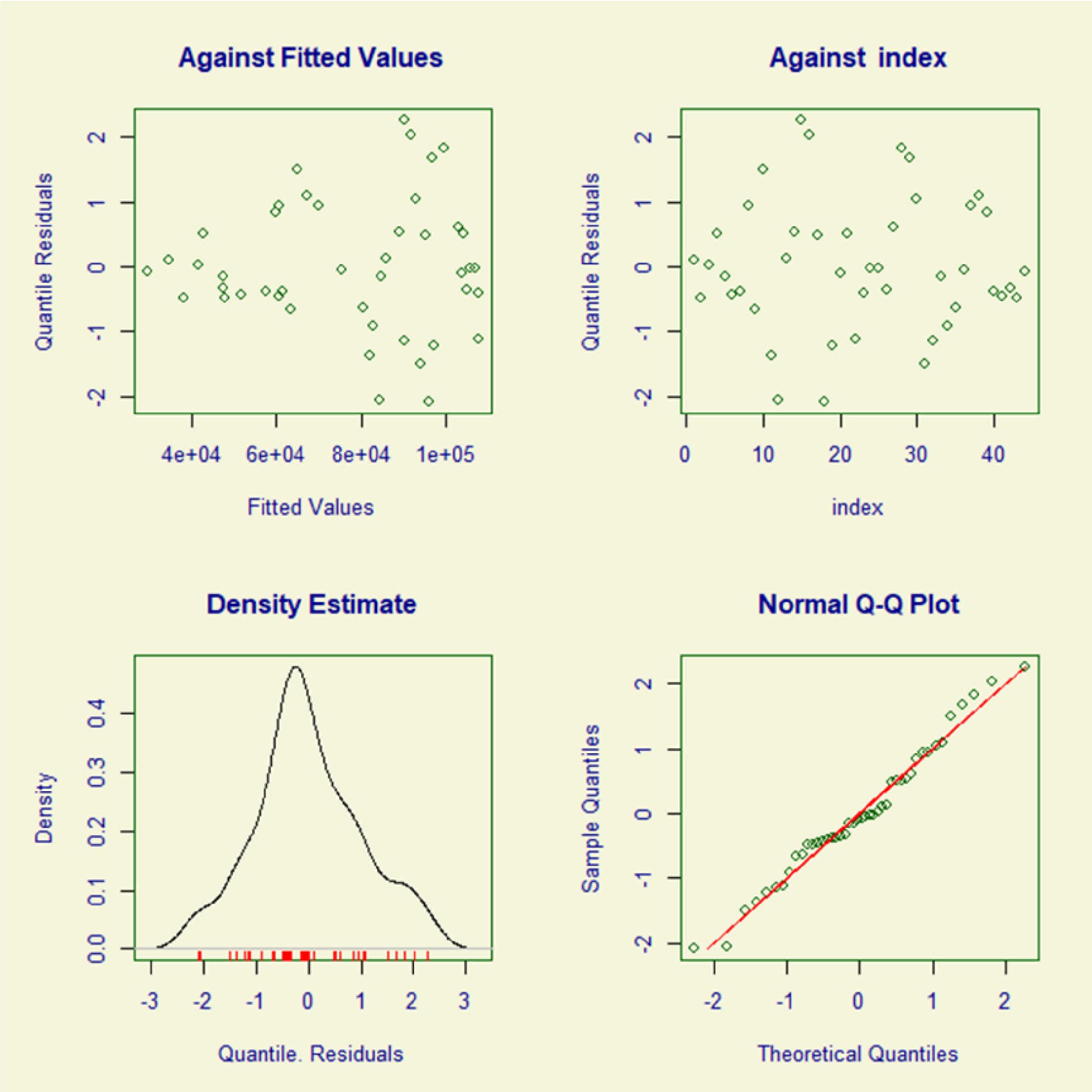
FIGURE 5.4: A plot for the fitted terms for the P spline model



After the P spline model has been fitted, it is important to assess the adequacy of the fitted model using the model residuals.

The resulting plot is shown in Figure 5.5. Again, this shows that the residuals behave well, since the top two plots of the residuals against the fitted values of μ and against the index show a random scatter around the horizontal line at 0, while the kernel density estimate of the residuals is approximately normal, while the normal Q-Q plot is approximately linear.

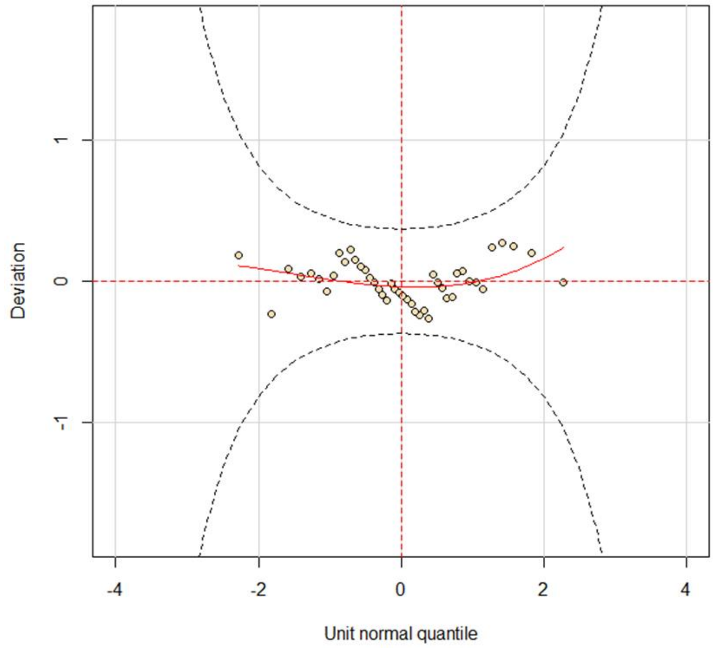
FIGURE 5.5: Residual plots from the fitted P spline model



Finally, my P spline model is assessed according to the following criteria of the worm plot (Figure 5.6) addressed by Rigby, Stasinopoulos et all [268] (2017).

The model's accuracy is indicated by the fact that the points are fairly close to the horizontal line, approximately 95% of the points lie between the two elliptic curves and 5% outside, while all the observations fall in the "acceptance" region inside the two elliptic curves and no specific shape is detected in the points.

FIGURE 5.6: Worm plot of the fitted P spline model



5.4. Comparison of the two fitted models: Which one is the best for the data?

This section will provide a comparison of the two models and determine which one is the optimal. To compare the 2 models, one can use the generalized Akaike information criterion (GAIC) given by GAIC(k) = −2 log ˆL c + (k x df), where df denotes the total effective degrees of freedom (i.e. the effective number of parameters) of the model and k is the penalty for each degree of freedom used. Hence GAIC(k = 2) gives the Akaike information criterion (AIC).

The results of this comparison between the linear model (mf) and the P spline model (mfpb) are outlined in Table 5.4. The table presents all AIC and effective degrees of freedom values for the two models considered to fit such data. The idea here is to show how much reduction in AIC is caused by the addition of a smoother in the GAMLSS framework. The P spline GAMLSS model, that included additive smoothing terms, outperformed the linear GAMLSS fitted model, granting a relatively better fit.

Notwithstanding the criterion of AIC, the models should also be assessed based on their properties, by noting the association between their location parameter and other important characteristics, such as mean, percentiles, standard deviation, skewness, and kurtosis. This means that, in the modeling stage of the location parameter, we are implicitly modeling these characteristics, as well. The advantage of the GAMLSS structure, is that we can explicitly model any and all parameters directly, i.e., different regression structures can be considered to explain all the parameters of the response variable distribution. Thus, apart from producing better goodness-of-fit measures, we can still identify which characteristics affect each of the parameters.

TABLE 5.4 Comparison between the 2 models using the GAIC criterion

	df	AIC
mfpb	8.496494	765.3787
mf	6.000000	789.1808

TABLE 5.5 Comparison between the residuals between the 2 models

```
*****************************************************************
           Summary of the Quantile Residuals – linear model
                     mean   =  -6.129093e-16
                 variance   =  1.023256
         coef. of skewness  =  -0.2749346
         coef. of kurtosis  =  2.919092
Filliben correlation coefficient  =  0.9870883
*****************************************************************
           Summary of the Quantile Residuals – P spline model
                     mean   =  2.082371e-10
                 variance   =  1.023256
         coef. of skewness  =  0.2004709
         coef. of kurtosis  =  2.724058
Filliben correlation coefficient  =  0.9902738
```

Table 5.5 provides a comparison of the residuals of the 2 models: the results presented indicate that the means of the residuals for the linear GAMLSS model and the P spline GAMLSS model are close to zero. The variances of the residuals under both models are above but close to one. In terms of skewness, the linear model residual is slightly left-skewed relative to a normal distribution, but the P spline model is slightly right-skewed. In terms of kurtosis, both models are heavy-tailed relative to a normal distribution. Finally, the Filliben correlation coefficient is close to one for both models.

The residuals of the P spline model behave better compared to the residuals of the linear model in the sense that the 2 plots in Figure 5.5 of the residuals against the fitted value μ and against the index appear to be randomly selected. In addition, the kernel density estimate of the residuals in Figure 5.5 (P spline) follows more closely the normal distribution compared to the kernel density estimate of the residuals in Figure 5.2 (linear model). Finally, the normal Q-Q plot in Figure 5.5 appears to be closely aligned with the line, at least more in comparison with the relevant normal Q-Q plot in Figure 5.2.

CHAPTER 6 Moving beyond to granular data: Analysis of the database on Large Exposures

Since the advent of the financial crisis in 2008, it has become obvious that despite the fact that a wide range of data on credit are already available, more granular, frequent and flexible credit and credit risk data are considered of high relevance for monetary policy, financial stability and research analyses. Such granular credit and credit risk data are critical both for macro-prudential and for micro-prudential supervisory purposes. This Chapter will analyze the granular database for corporate borrowers that will be used for modeling purposes, and the process of transforming it into a panel dataset which will provide a more accurate information on credit and credit risk levels.

6.1 A description of the database

Credit institutions are submitting quarterly data of debtors of natural or legal persons at the level of a group of connected clients, as defined in Regulation 575/2013, Article 4, where the total balance of the debts for each natural or legal person exceeds one million euro. If the credit institution is not consolidated or consolidated using the equity method, the credit institution submits data on an individual basis. The Large Corporate's database excludes certain categories of debtors, such as central government, credit institutions, natural persons, residents of abroad and legal entities with headquarters abroad and exclusive activity abroad if they do not carry out any economic activity in Greece and do not belong to a group of companies based in Greece. The database provides the most up-to-date granular breakthrough in the study of the behavior of NPLs, because not only does it provide information at the most disaggregate possible level, i.e. amounts per borrower and per credit institution and their respective NPLs, it also provides the ranking of the corporation and to which extent this ranking has been changed, i.e. being able to analyze the change in the credit conditions that affect the decisions of the lenders to grant a loan. In addition, borrowers' behavior is also being monitored. Another advantage of this database is that it can go back in time, i.e. since the advent of the financial crisis. However, although availability exists, there is the issue of confidentiality, i.e. such data can only be provided on an anonymized basis. In no way could the name of the creditor (i.e. bank) or the borrower be disclosed.

The Large corporate Borrowers Database includes as variables, the unique ID Tax identifier for the lender and for the borrower, the sector in which the borrower operates, all kinds of loans and advances, including debts of individuals by means of credit cards, debentures issued by the debtor and other exposures in debt securities, derivative financial instruments with a counterparty the same legal or natural person, letters of guarantee issued in the same legal or natural form and other off-balance sheet items. It also includes the total NPLs,

the value of collateral, and the ranking of the organization for the current and the previous period. For example, for quarterly data with reference as of 31.03.2017 the current period for ranking is [31.12.2016-31.03.2017], while the previous period for ranking is [30.09.2016-31.12.2016].

The sectoral classification is according to the NACE Rev2, and it is provided by the Hellenic Statistical Authority. In addition, the Hellenic Statistical Authority has received from the First Court of Instance the corporate defaults for the period 2013-2020 broken down by sectors. This is illustrated in Table 6.1.

It should be noted that if the total exposure of at least one of the affiliated clients to the credit institution on a consolidated basis is equal to or above EUR 1 million, the exposures to the credit institution of all legal and natural persons are explicitly provided for this group of connected customers. It is clarified that there will be no reference when the total of the debts of the group of connected clients exceeds € 1 million, but the amount of the debt of each group of companies is less than the above mentioned reference limit.

Finally, an extra column with the definition of non-performing exposures has been inserted. Subsequently, the raw data from the Large Borrowers' database has been converted into panel data. The conversion of the Large Corporates Database into Panel Data took into consideration the same number (27,088) of corporate borrowers with an observation point of 31.12.2013, reference year of 31.12.2014 and examined them for the periods 31.12.2014, 31.03.2015, 30.06.2015, 30.09.2015, 31.12.2015, 31.03.2016, 30.06.2016, 30.09.2016, 31.12.2016 and 31.03.2017. The Panel Data includes all the variables from the Large Corporates Database. However, the variables DATE, BANK, Lender Name, Tax ID creditor, Tax ID borrower, Sector, remain the same during the whole period of analysis , hence each borrower is observed for the defined characteristics of these variables that remain stable over time. Nevertheless, the value of a variable from a borrower may not appear in subsequent years, because either a borrower may have repaid the loan in full or a special arrangement may have occurred between the borrower and the bank, i.e. payment of the loan outstanding through the provision of a new loan at a lower interest rate. In order to merge data from the initial Large Corporate's Database, a unique ID identifier has been used, being the ID Tax identifier of the borrower, followed by the ID Tax identifier of the creditor if 1 borrower has more than one loans in different banks.

Although a full conversion of the Large Corporate's Database was completed for all the 27,088 outstanding amounts of loans borrowed with reference date as of 31.12.2013 and for all the variables they remain stable over time, it is not possible to present in this report the full conversion and the whole length of the database ; therefore, 2 extracts have been portrayed (Table 6.2) regarding the Loans, Exposures, Non-Performing Loans and Non-Performing Exposures and for 18 rows. However, the relevance between Table 6.1 and Table 6.2 is evident because one can, for example, track the same number of loans and exposures in both Tables for the reference year 2014.

Finally, it should be noted that this panel is unbalanced in the sense that one borrower may appear initially, then not appear in the next periods but then reappear in the subsequent periods. However, this can be explained as one borrower may have repaid one loan and granted another one, or even the same loan could be refinanced at a later period under better terms and conditions.

Table 6.1: Percentage (%) distribution of bankruptcies, by sector of economic activity (NACE Rev.2), 2010-2017

Sectors of economic activity	2013	2014	2015	2016	2017	2018	2019	2020
Total	100	100	100	100	100	100	100	100
Agriculture, forestry and fishing	0.7	0.9	0.5	1.8	0.0	1.2	1.6	3.5
Mining and quarrying	0.0	0.0	0.0	0.0	0.0	1.2	0.0	0.0
Manufacturing	17.6	22.1	18.9	18.9	19.3	24.4	23.8	24.6
Electricity, gas, steam and air-conditioning supply	0.0	0.0	0.0	0.9	1.8	0.0	0.0	0.0
Water supply, sewerage, waste management and remediation	0.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Construction	5.3	4.5	3.4	7.2	8.8	4.9	6.3	7.0
Wholesale and retail trade, repair of motor vehicles and motorcycles	48.3	41.2	41.7	30.6	32.5	46.3	38.1	28.1
Transportation and storage	3.0	1.5	3.9	3.6	4.4	0.0	1.6	7.0
Accommodation and food service activities	12.4	14.6	11.2	16.2	18.4	13.4	15.9	12.3
Information and communication	3.7	3.0	5.8	1.8	1.8	1.2	3.2	5.3
Financial and insurance activities	0.2	0.3	1.0	0.9	1.8	1.2	3.2	0.0
Real estate activities	0.0	0.3	0.5	0.9	0.0	1.2	0.0	1.8
Professional, scientific and technical activities	3.0	3.9	4.4	5.4	2.6	2.4	1.6	3.5
Administrative and support service activities	2.7	4.2	3.9	4.5	3.5	1.2	1.6	3.5
Public administration and defence, compulsory social security	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Education	0.2	0.6	0.5	0.0	0.0	1.2	0.0	1.8
Human health services and social work activities	1.4	0.9	1.9	5.4	1.8	0.0	0.0	0.0
Arts, entertainment and recreation	0.2	0.9	0.5	1.8	0.9	0.0	1.6	1.8
Other services	0.7	1.2	1.9	0.0	2.6	0.0	1.6	0.0
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Activities of extra-territorial organisations and bodies	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Source: Hellenic Statistical Authority

Table 6.2: Extract from the Bank of Greece's Large Corporate's Database (sample of 18 rows from a total of 27,088 rows)

		Amounts owed from corporate borrowers above 1 million euros (on a loan to loan basis), quarterly data, amounts in thousand euros															
		Information of the creditor		Information of the borrower		Debt categories					Totals					Ranking of corporation	
		Lender Name	Tax Identification Number	Tax Identification Number	Sector	Loans	Debt Securities	Derivative Financial Instruments	Guarantees	Other contingent liabilities	Loans and advances	Exposures	NPLs over 90 days	NPEs	Value of collateral	Current period	Previous period
DATE	BANK	1	2	3	5	1	2	3	4	5			6		7	8	9
31/12/2014	011	ETE	094014201	800578900						3.981	0	3.981		3.981		11	99
31/12/2014	011	ETE	094014201	094005751	41	13.406			7.883	7.117	13.406	28.406				13	99
31/12/2014	011	ETE	094014201	999644205	35	2.567					2.567	2.567				11	11
31/12/2014	011	ETE	094014201	094420461	41					100.000	0	100.000		100.000		10	99
31/12/2014	011	ETE	094014201	094027509	46	56.313			10.090	333.598	56.313	400.001		400.001		11	11
31/12/2014	011	ETE	094014201	S00007186	06		2.284				2.284	2.284				99	99
31/12/2014	011	ETE	094014201	094207780	41	5.861			40.824	449	5.861	47.134		47.134	5.861	14	14
31/12/2014	011	ETE	094014201	S00000797	63	1			11.892	5.112	1	17.005		17.005	1	15	15
31/12/2014	011	ETE	094014201	S00006057	62				550	2.450	0	3.000		3.000		99	99
31/12/2014	011	ETE	094014201	094025610	25	51.071		1.726	9.701	61.165	51.071	123.663		123.663	42.025	12	12
31/12/2014	011	ETE	094014201	094039428	27	45.674		2	3.017	1.495	45.674	50.188			36.772	13	99
31/12/2014	011	ETE	094014201	094061318	25	125.844		9	792	3.323	125.844	129.968			71.143	12	12
31/12/2014	011	ETE	094014201	094100416	25	97.242		726	1.855	29.668	97.242	129.491			75.297	15	10
31/12/2014	011	ETE	094014201	094130920	25	40.111				8.025	40.111	48.136			30.768	14	16
31/12/2014	011	ETE	094014201	094280379	25	52.827			3.040	3.324	52.827	59.191			34.145	12	12
31/12/2014	011	ETE	094014201	094322547	46	5.051			94	2.556	5.051	7.701				11	03
31/12/2014	011	ETE	094014201	094010146	20	2.007			253	7.747	2.007	10.007		10.007		13	13
31/12/2014	011	ETE	094014201	094049864	20	344.006		20.695	317.095	315.038	344.006	996.834				03	03
31/12/2014	011	ETE	094014201	094006030	41	19			73.562	6.408	19	79.989		79.989	19	10	99
31/12/2014	011	ETE	094014201	094451683	41	6.170			3.828	3.591	6.170	13.589				16	16
31/12/2014	011	ETE	094014201	094206769		5			2.751		5	2.756		2.756		13	13
31/12/2014	011	ETE	094014201	099810415	35	8.043			3.440	205	8.043	11.688				11	11
31/12/2014	011	ETE	094014201	999503170	42	23.434			211.336	58.171	23.434	292.941		292.941	8.077	12	12
31/12/2014	011	ETE	094014201	800625630	43					9.975	0	9.975		9.975		99	99
31/12/2014	011	ETE	094014201	094004914	43	48.930				15.500	48.930	64.430			15.000	14	14
31/12/2014	011	ETE	094014201	094149722	43	19.618			339.018	157.248	19.618	515.884		515.884		12	12
31/12/2014	011	ETE	094014201	094508956	35	78.275			24.583	84.406	78.275	187.264		187.264		12	12
31/12/2014	011	ETE	094014201	099352983	35					21.685	0	21.685		21.685		99	99
31/12/2014	011	ETE	094014201	999933224	42				8.490		0	8.490		8.490		99	99
31/12/2014	011	ETE	094014201	090000045	35	373.678	1.523	1.351	141.798	153.200	375.201	671.550				12	12
31/12/2014	011	ETE	094014201	S00007187	35		5.587				5.587	5.587				99	99
31/12/2014	011	ETE	094014201	S00002668	20		1.951				1.951	1.951				99	99
31/12/2014	011	ETE	094014201	021587618	74	1.765					1.765	1.765	118	1.765	1.068	99	99
31/12/2014	011	ETE	094014201	021863906		1.018					1.018	1.018	27	1.018	483	99	99
31/12/2014	011	ETE	094014201	022047439	47	969			2.965		969	3.934	531	3.934	353	20	99
31/12/2014	011	ETE	094014201	023137142		884				120	884	1.004			631	99	99
31/12/2014	011	ETE	094014201	023195460	46	1.055					1.055	1.055	84	1.055	659	99	99
31/12/2014	011	ETE	094014201	023323100	74	1.277					1.277	1.277	1.277	1.277	1.277	20	99
31/12/2014	011	ETE	094014201	023361336	46	1.125					1.125	1.125			670	99	99
31/12/2014	011	ETE	094014201	023501417	74	2.897					2.897	2.897	2.673	2.897	2.218	20	99
31/12/2014	011	ETE	094014201	023679300	96	1.117					1.117	1.117			657	99	99
31/12/2014	011	ETE	094014201	023740190		1.206					1.206	1.206			567	99	99
31/12/2014	011	ETE	094014201	024117165		1.017				1	1.017	1.018			667	99	99
31/12/2014	011	ETE	094014201	024424952		3.213					3.213	3.213			1.715	99	99
31/12/2014	011	ETE	094014201	024560913	96	2.446			5		2.446	2.451	288	2.451	1.302	99	99
31/12/2014	011	ETE	094014201	024831637	74	1.188					1.188	1.188	1.104	1.188	760	99	99
31/12/2014	011	ETE	094014201	025113152		1.841					1.841	1.841			1.275	99	99
31/12/2014	011	ETE	094014201	025229738	58	1.111					1.111	1.111	18	1.111	821	99	99

Table 6.3: Reorganization of the Large Corporate’s Database into Panel Data (sample of 18 rows from a total of 27,088 rows)

DATE	BANK	Lender Name	Tax ID creditor	Tax ID borrower	Sector	Loans12.2014	Loans03.2015	Loans06.2015	Loans09.2015	Loans12.2015	Loans03.2016	Loans06.2016	Loans09.2016	Loans12.2016	Loans03.2017	NPLs12.2014	NPLs03.2015	NPLs06.2015	NPLs09.2015	NPLs12.2015	NPLs03.2016	NPLs06.2016	NPLs09.2016	NPLs12.2016	NPLs03.2017
31/12/2014	011	ETE	094014201	800578900	00	0	0	0	1.472	2.332	2.323	0	3.948	3.189	2.671	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094005751	41	13.406	13.034	13.034	13.254	10.549	10.532	13.034	10.240	16.065	16.317	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	999644205	35	2.567	2.580	2.580	1.970	1.917	1.936	2.580	1.912	1.868	1.887	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094420461	41	0	8	8	10	10	7	8	12	6	3	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094027509	46	56.313	142.811	142.811	154.303	153.477	153.089	142.811	152.186	144.629	60.241	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	S00007186	06	0	35.870	35.870	40.870	41.008	43.536	35.870	0	0	0	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094207780	41	5.861	3.900	3.900	11.275	10.767	10.104	3.900	10.289	9.944	9.234	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	S00000797	63	1	0	0	15	6	59	0	1.621	2.070	3.562	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	S00006057	62	0										0									
31/12/2014	011	ETE	094014201	094025610	25	51.071	101.557	101.557	102.428	56.185	56.612	101.557	0	0	0	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094039428	27	45.674	46.494	46.494	46.521	46.025	46.896	46.494	44.715	42.414	48.982	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094061318	25	125.844	126.251	126.251	127.860	118.681	124.594	126.251	118.335	113.536	117.047	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094100416	25	97.242	121.050	121.050	121.058	0	16.054	121.050	3	0	0	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094130920	25	40.111	41.147	41.147	41.391	41.123	41.527	41.147	41.465	41.147	41.461	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094280379	25	52.827	52.771	52.771	53.266	56.395	57.796	52.771	62.547	62.237	62.572	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094322547	46	5.051	6.689	6.689	6.694	6.795	7.675	6.689	7.694	7.798	7.689	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094010146	20	2.007	2.009	2.009	2.001	2.012	2.006	2.009	17.994	17.980	31.843	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094049864	20	344.006	541.939	541.939	588.058	624.386	643.349	541.939	703.299	608.560	613.108	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094006030	41	19	35.580	35.580	40.564	36.552	34.999	35.580	1	82	1	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094451683	41	6.170	6.166	6.166	8.565	8.401	8.434	6.166	8.503	8.518	8.400	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094206769	00	5	0	0	7	7	11	0	17	0	0	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	099810415	35	8.043	7.477	7.477	7.097	7.006	6.549	7.477	5.947	6.034	5.704	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	999503170	42	23.434	24.392	24.392	24.336	22.990	24.435	24.392	23.086	22.863	23.193	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	800625630	43	0				0	2.526		2.525	5.439	5.450	0				0	0		0	0	0
31/12/2014	011	ETE	094014201	094004914	43	48.930	47.999	47.999	47.933	48.597	47.909	47.999	46.852	47.439	46.806	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094149722	43	19.618	22.112	22.112	22.138	22.800	22.522	22.112	22.361	31.312	30.338	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	094508956	35	78.275	120.787	120.787	120.068	114.352	115.510	120.787	122.252	119.488	106.588	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	099352983	35	0										0									
31/12/2014	011	ETE	094014201	999933224	42	0										0									
31/12/2014	011	ETE	094014201	090000045	35	373.678	422.784	422.784	506.643	392.841	493.621	422.784	387.237	29	891.283	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	S00007187	35	0	54.143	54.143	67.270	67.139	64.499	54.143	70.939	0	69.814	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	S00002668	20	0	1.879	1.879	7.985	7.939	8.283	1.879	8.617	8.342	22.072	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	021587618	74	1.765	1.792	1.792	1.794	1.766	1.795	1.792	1.798	1.765	1.799	118	124	124	163	200	210	124	258	296	296
31/12/2014	011	ETE	094014201	021863906	00	1.018	1.022	1.022	1.026	1.026	1.026	1.022	1.033	1.030	1.003	27	27	27	27	27	27	27	27	27	27
31/12/2014	011	ETE	094014201	022047439	47	969	984	984	986	1.011	1.008	984	993	996	996	531	523	523	524	0	0	523	0	0	0
31/12/2014	011	ETE	094014201	023137142	00	884										0									
31/12/2014	011	ETE	094014201	023195460	46	1.055	1.055	1.055	1.193	1.200	1.203	1.055	1.206	1.204	1.204	84	84	84	84	84	84	84	84	84	84
31/12/2014	011	ETE	094014201	023323100	74	1.277	1.277	1.277	1.277	1.279	1.279	1.277	1.339	1.281	1.281	1.277	1.277	1.277	1.277	1.279	1.279	1.277	1.279	1.281	1.281
31/12/2014	011	ETE	094014201	023361336	46	1.125	1.130	1.130	1.123	1.117	1.106	1.130	1.093	1.087	1.088	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	023501417	74	2.897	2.898	2.898	2.899	2.902	2.905	2.898	2.918	2.907	1.910	2.673	2.673	2.673	2.673	2.673	2.675	2.673	2.676	2.676	1.910
31/12/2014	011	ETE	094014201	023679300	96	1.117	1.095	1.095	1.106	1.119	1.121	1.095	1.123	1.121	1.124	0	0	0	305	319	321	0	328	330	330
31/12/2014	011	ETE	094014201	023740190	00	1.206	1.382	1.382	1.327	1.336	1.325	1.382	1.332	1.351	1.353	0	0	0	0	0	0	0	0	0	0
31/12/2014	011	ETE	094014201	024117165	00	1.017			1.004							0			0						
31/12/2014	011	ETE	094014201	024424952	00	3.213	3.213	3.213	3.218	3.219	3.227	3.213	3.230	3.946	3.232	0	0	0	0	0	0	0	0	374	0
31/12/2014	011	ETE	094014201	024560913	96	2.446	2.447	2.447	2.447	2.449	2.459	2.447	2.471	2.469	2.469	288	289	289	289	289	289	289	289	289	289
31/12/2014	011	ETE	094014201	024831637	74	1.188	1.186	1.186	1.186	1.185	1.184	1.186	1.188	1.184	1.183	1.104	1.104	1.104	1.103	1.103	1.101	1.104	1.100	1.099	1.099
31/12/2014	011	ETE	094014201	025113152	00	1.841	2.009	2.009	1.954	1.952	1.937	2.009	1.949	2.113	1.980	0	0	0	0	0	0	0	0	4	0
31/12/2014	011	ETE	094014201	025229738	58	1.111	1.263	1.263	1.215	1.223	1.213	1.263	1.220	1.235	1.238	18	18	18	18	18	18	18	18	18	18

DATE	BANK	Lender Name	Tax ID creditor	Tax ID borrower	Sector	Exposures 12.2014	Exposures 03.2015	Exposures 06.2015	Exposures 09.2015	Exposures 12.2015	Exposures 03.2016	Exposures 06.2016	Exposures 09.2016	Exposures 12.2016	Exposures 03.2017	NPEs12.2014	NPEs03.2015	NPEs06.2015	NPEs09.2015	NPEs12.2015	NPEs03.2016	NPEs06.2016	NPEs09.2016	NPEs12.2016	NPEs03.2017
31/12/2014	011	ETE	094014201	800578900	00	3.981	3.981	3.981	1.472	4.989	3.587	3.981	4.158	3.189	2.671	3.981	3.981	3.981		4.989		3.981			
31/12/2014	011	ETE	094014201	094005751	41	28.406	28.034	28.034	28.254	25.549	25.532	28.034	32.740	31.065	31.317								32.740		
31/12/2014	011	ETE	094014201	999644205	35	2.567	2.580	2.580	1.970	1.917	1.936	2.580	2.773	1.868	1.887										
31/12/2014	011	ETE	094014201	094420461	41	100.000	5.008	5.008	5.010	5.010	5.007	5.008	5.012	5.006	5.003	100.000	5.008	5.008	5.010	5.010	5.007	5.008	5.012	5.006	5.003
31/12/2014	011	ETE	094014201	094027509	46	400.001	415.536	415.536	234.576	236.075	232.050	415.536	365.518	229.718	231.527	400.001	415.536	415.536				415.536	365.518		231.527
31/12/2014	011	ETE	094014201	S00007186	06	2.284	35.870	35.870	40.870	41.008	43.536	35.870	2.823	623	14.632										
31/12/2014	011	ETE	094014201	094207780	41	47.134	4.550	4.550	52.935	52.274	51.701	4.550	50.070	15.561	50.429	47.134			52.935	52.274	51.701		50.070		50.429
31/12/2014	011	ETE	094014201	S00000797	63	17.005	17.028	17.028	41.038	43.458	43.417	17.028	20.235	42.817	42.780	17.005	17.028	17.028	41.038	43.458	43.417	17.028	20.235	42.817	42.780
31/12/2014	011	ETE	094014201	S00006057	62	3.000										3.000									
31/12/2014	011	ETE	094014201	094025610	25	123.663	131.768	131.768	118.582	61.375	62.763	131.768	304	0	0	123.663									
31/12/2014	011	ETE	094014201	094039428	27	50.188	50.560	50.560	49.598	50.193	51.223	50.560	51.197	42.642	60.269										
31/12/2014	011	ETE	094014201	094061318	25	129.968	129.869	129.869	129.424	127.910	129.300	129.869	126.862	118.686	119.491										
31/12/2014	011	ETE	094014201	094100416	25	129.491	134.307	134.307	122.627	3.424	16.054	134.307	12.916	22.090	11.500					3.424			12.916	22.090	11.500
31/12/2014	011	ETE	094014201	094130920	25	48.136	53.173	53.173	41.600	41.174	41.578	53.173	49.516	41.301	41.512										
31/12/2014	011	ETE	094014201	094280379	25	59.191	63.266	63.266	57.830	58.985	59.880	63.266	70.007	63.735	64.065										
31/12/2014	011	ETE	094014201	094322547	46	7.701	7.793	7.793	6.794	6.895	8.275	7.793	9.293	8.398	8.290										
31/12/2014	011	ETE	094014201	094010146	20	10.007	10.009	10.009	20.001	12.387	20.006	10.009	37.891	60.158	60.021	10.007	10.009	10.009	20.001	12.387	20.006	10.009		60.158	
31/12/2014	011	ETE	094014201	094049864	20	996.834	1.039.323	1.039.323	945.530	898.063	937.380	1.039.323	1.007.843	985.220	1.102.306										
31/12/2014	011	ETE	094014201	094006030	41	79.989	86.407	86.407	83.433	79.395	81.030	86.407	1	82	1	79.989	86.407	86.407	83.433	79.395	81.030	86.407			
31/12/2014	011	ETE	094014201	094451683	41	13.589	13.946	13.946	8.565	8.401	8.434	13.946	14.013	8.518	8.400										
31/12/2014	011	ETE	094014201	094206769	00	2.756	2.742	2.742	8.007	8.007	8.011	2.742	1.013	8.000	8.000	2.756	2.742	2.742	8.007	8.007	8.011	2.742	1.013	8.000	8.000
31/12/2014	011	ETE	094014201	099810415	35	11.688	11.107	11.107	10.537	10.446	9.989	11.107	9.387	9.474	9.144										
31/12/2014	011	ETE	094014201	999503170	42	292.941	91.416	91.416	93.941	417.521	428.966	91.416	477.873	486.369	486.699	292.941	91.416	91.416	93.941	417.521	428.966	91.416	477.873	486.369	486.699
31/12/2014	011	ETE	094014201	800625630	43	9.975				9.975	9.985		9.984	9.986	17.420	9.975				9.975	9.985		9.984		17.420
31/12/2014	011	ETE	094014201	094004914	43	64.430	51.362	51.362	50.933	51.597	50.909	51.362	50.111	50.439	49.806										
31/12/2014	011	ETE	094014201	094149722	43	515.884	514.598	514.598	521.590	533.603	532.872	514.598	468.062	503.842	502.646	515.884	514.598	514.598	521.590	533.603	532.872	514.598	468.062	503.842	502.646
31/12/2014	011	ETE	094014201	094508956	35	187.264	189.480	189.480	144.665	150.181	151.338	189.480	164.816	152.485	133.266	187.264									
31/12/2014	011	ETE	094014201	099352983	35	21.685										21.685									
31/12/2014	011	ETE	094014201	999933224	42	8.490										8.490									
31/12/2014	011	ETE	094014201	090000045	35	671.550	667.684	667.684	705.733	583.746	683.123	667.684	635.571	29	1.236.525										
31/12/2014	011	ETE	094014201	S00007187	35	5.587	54.143	54.143	67.270	67.139	64.499	54.143	70.939	0	69.814										
31/12/2014	011	ETE	094014201	S00002668	20	1.951	1.879	1.879	7.985	7.939	8.283	1.879	8.617	8.342	22.072										
31/12/2014	011	ETE	094014201	021587618	74	1.765	1.792	1.792	1.794	1.766	1.795	1.792	1.798	1.765	1.799	1.765	1.792	1.792	1.794	1.766	1.795	1.792	1.798	1.765	1.799
31/12/2014	011	ETE	094014201	021863906	00	1.018	1.022	1.022	1.026	1.026	1.026	1.022	1.033	1.030	1.003	1.018	1.022	1.022	1.026	1.026	1.026	1.022	1.033	1.030	1.003
31/12/2014	011	ETE	094014201	022047439	47	3.934	3.949	3.949	4.193	4.076	4.073	3.949	3.958	3.961	3.961	3.934	3.949	3.949	4.193	4.076	4.073	3.949	3.958	3.961	3.961
31/12/2014	011	ETE	094014201	023137142	00	1.004																			
31/12/2014	011	ETE	094014201	023195460	46	1.055	1.055	1.055	1.193	1.200	1.203	1.055	1.206	1.204	1.204	1.055	1.055	1.055	1.193	1.200	1.203	1.055	1.206	1.204	1.204
31/12/2014	011	ETE	094014201	023323100	74	1.277	1.277	1.277	1.277	1.279	1.279	1.277	1.339	1.281	1.281	1.277	1.277	1.277	1.277	1.279	1.279	1.277	1.339	1.281	1.281
31/12/2014	011	ETE	094014201	023361336	46	1.125	1.130	1.130	1.123	1.117	1.106	1.130	1.093	1.087	1.088										
31/12/2014	011	ETE	094014201	023501417	74	2.897	2.898	2.898	2.899	2.902	2.905	2.898	2.918	2.907	1.910	2.897	2.898	2.898	2.899	2.902	2.905	2.898	2.918	2.907	1.910
31/12/2014	011	ETE	094014201	023679300	96	1.117	1.095	1.095	1.106	1.119	1.121	1.095	1.123	1.121	1.124				1.106	1.119	1.121		1.123	1.121	1.124
31/12/2014	011	ETE	094014201	023740190	00	1.206	1.382	1.382	1.327	1.336	1.325	1.382	1.332	1.351	1.353										
31/12/2014	011	ETE	094014201	024117165	00	1.018			1.005																
31/12/2014	011	ETE	094014201	024424952	00	3.213	3.213	3.213	3.218	3.219	3.227	3.213	3.230	3.946	3.232									3.946	
31/12/2014	011	ETE	094014201	024560913	96	2.451	2.452	2.452	2.452	2.454	2.464	2.452	2.476	2.474	2.474	2.451	2.452	2.452	2.452	2.454	2.464	2.452	2.476	2.474	2.474
31/12/2014	011	ETE	094014201	024831637	74	1.188	1.186	1.186	1.186	1.185	1.184	1.186	1.188	1.184	1.183	1.188	1.186	1.186	1.186	1.185	1.184	1.186	1.188	1.184	1.183
31/12/2014	011	ETE	094014201	025113152	00	1.841	2.009	2.009	1.954	1.952	1.937	2.009	1.949	2.113	1.980									2.113	
31/12/2014	011	ETE	094014201	025229738	58	1.111	1.263	1.263	1.215	1.223	1.213	1.263	1.220	1.235	1.238	1.111	1.263	1.263	1.215	1.223	1.213	1.263	1.220	1.235	1.238

6.2 Addressing the response variables

I have included a new response variable in the database, apart from the non-performing loans, i.e. the non-performing exposures. I have clarified the definition of non-performing exposures and its difference with non-performing loans and its relevance to credit risk.

Non-performing exposures comprise of the following cases[50]:

(i) Material exposures that are (a) more than 90 days past due (this means that the borrower is unable to repay the bank his obligations for more than 90 days) and (b) all exposures "defaulted" under the Basel framework

(ii) all exposures impaired, i.e. having experienced a downward adjustment to their valuation due to deterioration of their creditworthiness

(iii) all exposures where there is evidence that full repayment of principal and interest without realization of collateral is unlikely, even if the number of days past due is less than 90 days.

The traditional definition of non-performing loans involved only category (i). Case (iii) involves the situation whereby the bank judges that even though a loan is not classified as non-performing in the traditional sense, there is increasing difficulty of the borrower to repay it.

It should be noted that exposures comprise of (i) on-balance sheet loans, debt securities and other amounts due and (ii) off-balance sheet items, i.e. loan commitments and financial guarantees. This categorization was available in the large corporates database, hence I was able to extract the non-performing exposures in a separate column.

Non-performing loans and exposures are principally a regulatory term used for credit risk monitoring. The importance of identification of non-performing loans and exposures is very important from a credit risk management perspective, as it can lead to the bank's directing greater attention to reduce the risk of further loss arising from non-recoverability of amounts due from the borrower or from the liquidation of the collateral securing the credit risk and improving their credit risk appraisal standards.

[50] Source: paragraph 145 of Annex V of the EBA (European Banking Authority) ITS on Supervisory Reporting

6.3 Addressing the issue of data gaps

The implementation of credit risk assessment raises two main types of challenges. First, on the large corporate borrower's database, there are shortcomings in granularity for some types of borrowers and sectors. In addition, there are limitations in the coverage of some types of sectors, most notably with respect to the "sectors without identification" category. Second, there is a lack of granular information on cross-border activities between EU and non-EU countries. While recognizing this importance, a more "domestic" perspective could be taken as regards the Greek banking system and its dynamics, by not including the cross-border activity. After all, credit risk is mostly locally domiciled in Greece, while risk stemming from banking activities abroad is considered less important.

My research challenges motivated me to proceed to an investigation of whether additional data may not be available from other public data providers. While missing information on credit data could be complemented from surveys, the coverage of such information is incomplete. On the other hand, credit and credit risk data collected in this database is according to binding Bank of Greece regulations providing a consistent approach to data collection. Furthermore, this database goes back in time. Of course, there are data gaps with respect to unidentified sectors i.e. sectors whereby credit data are available but the sector identification is missing. For sectors below the 1 million threshold, data collection is not binding, and data are not provided for this database, so a significant part of small corporations is not covered. Given their relative size, these non-covered entities represent a key data gap where further information is necessary in order to determine which parts are relevant from a banking perspective. Still, from a systemic risk viewpoint, only entities with large exposures have the potential to induce significant risk, which are adequately covered from this database.

In general, my data gap investigation has provided the following specific insights:

(i) Certain borrowers may be classified as belonging to a particular sector although in reality they may belong to another sector. The dividing line in certain cases is not clear-cut, particularly given the diversity of the population.

(ii) A large amount of certain entities (corporations) are consolidated into another entity. However, as the data feeding into credit risk monitoring are on a non-consolidated basis, risks could be overestimated (i.e. to the extent that this is seen as double counting). Furthermore, credit risks may ultimately reside in other sectors and jurisdictions.

(iii) There is no clear definition of certain activities within sectors. A pragmatic approach may be undertaken to define these activities, confining the reporting population to certain entities.

6.4 The Large Borrower's Corporate Database: The process of reorganization into a form of Panel Data

The Large corporate Borrowers Database includes as variables the unique ID Tax identifier for the lender and for the borrower, the sector in which the borrower operates, all kinds of loans and advances, including debts of individuals by means of credit cards, debentures issued by the debtor and other exposures in debt securities, derivative financial instruments with a counterparty the same legal or natural person, letters of guarantee issued in the same legal or natural form and other off-balance sheet items. It also includes the total NPLs, the value of collateral, and the ranking of the organization for the current and the previous period. For example, for quarterly data with reference as of 31.03.2017, the current period for ranking is [31.12.2016-31.03.2017] while the previous period for ranking is [30.09.2016-31.12.2016]. An extra column with the definition of non-performing exposures has been inserted.

It should be noted that if the total exposure of at least one of the affiliated clients to the credit institution on a consolidated basis is equal to or above EUR 1 million, the exposures to the credit institution of all legal and natural persons are explicitly provided for this group of connected customers. It is clarified that there will be no reference when the total of the debts of the group of connected clients exceeds € 1 million, but the amount of the debt of each group of companies is less than the above mentioned reference limit.

The column "Current Period" portrays the ranking of the corporation (borrower) in the rating system applied by the credit institution itself concerning changes in the internal credit rating of the borrower for the respective quarter. Typically, the lowest numerical value for the ranking of the corporation, the better it is. If there is no ranking for the corporation (borrower) which forms part of a group, the parent company's ranking of the group is recorded as it is the most significant amongst the group companies. In case of no ranking for any corporation (borrower) in the Group or for unclassified borrowers, the entry "99" is entered. However, there is no direct link in the database between the rating and its creditworthiness.

Credit models are increasingly being adjusted not only in calculating the probability of default but also in what happens to credit on its way to default. Attention is being focused on the probability of moving from one credit level, or rating, to another. Greek credit institutions maintain migration matrices, assessing the quality of the business portfolio of borrowers via their internal rating system. However, this is for their internal system and not widely available or accessible.

It was also assumed that if there is collateral in the database, then the loans are secured, otherwise unsecured. This can be confirmed as the column "Value of collateral" may be deriving from one (or multiple) of the following collateral categories:

(i) cash and cash equivalents;

(ii) collateral from registered property in Residential Properties;

(iii) collateral from registered real estate, industrial property and other property;

(iv) guarantees by the Greek State,

(v) other collateral, excluding the guarantees of natural and legal persons.

The level of collateral is strong as it does not include the guarantees of natural and legal persons (this would not constitute a strong form of collateral).

The value of collateral refers to the reference Date (last day of the submission quarter, for example for 31.03.2017 the value refers to the 31.03.2017 itself). The value of collateral is determined based on the credit institution's estimates at the reporting date.

The collateral categories included are those described in BoG's Executive Act 42/2014 as applicable. If the collateral value exceeds the amount of the exposure, the total value will be reported without any adjustments (uncapped value).

A disadvantage is that there are not any further covariates in the database. This database is considered the most detailed one. More granular information about the company would be inherently difficult to be found, as most of the companies are non-listed companies. Probably the "sector" column could provide some hints regarding the "type of the company". The Large Borrower's Corporate Database provides the more granular information to date. Although I could theoretically be able to find more granular information and ratios from some of the companies (debtors) that are listed in the Athens Stock Exchange (or are obliged by the Law to provide quarterly data), this information could not fit the length and depth of the Large Corporate Database

There have been some occasions where manual interpretation is warranted. For instance, a diminishing NPL observation value means that the customer could be repaying. On the other hand, the same customer may have a lower amount outstanding in the previous periods. This would mean that the customer repaid the loan and then took a new loan for the new period onwards, or has partly used the new loan to refinance the old loan on better terms.

An NPL value could appear only once and then disappear and if this did not appear again in the next quarter, it has to be the case that this is written off completely. This is a large sum amount to be repaid at once, especially if the whole amount of the loan is non-performing. In other cases, the same amount is reported on another company both on the loan amount outstanding and in the NPL column more than twice, which means that the entire loan amount is non-performing for multiple periods. Typically, the bank should have written off a loan when it reappears in multiple periods as NPL and the fact that it remains there may be attributed to other reasons (loans to sensitive sectors whereby a write-off could provoke reactions).

An NPL value could be growing because of interest rate being added. In general, loans do not include (i) interest calculated on a non-recurring basis, based on article 150 of Law 4261/2014, as in place; (ii) shares; and (iii) the debt resulting from debentures, which is shown on a separate column under "Debt securities". Loans shall include (i) accrued interest on part of loans in arrears; and (ii) obligations arising from leasing contracts for the entire duration of the contract. Obviously, the accrued interest on the part of the loan that has become NPL (in arrears) is included in the NPL column. No other penalty (if any) is included. The value of NPL may also be increasing due to the inability of the borrower to repay the loan, so the segment “in arrears” is increased.

As the database cannot clearly provide information on whether the NPLs are appearing for the new loans or earlier ones, I proceed to the following assumptions: Typically most of NPLs that are reported in a respective period (i.e. 31.03.2017) have originated from earlier loans, i.e. loans that have been granted in earlier periods. The amount of NPLs on new loans (NPL formation) for this particular period is fairly small and it is constantly declining. In any case, the Greek problem is the amount of NPLs outstanding, i.e. the stock of NPLs that have originated from earlier loans (this is the biggest amount). Theoretically, I could check which part of the NPLs is derived from new loans if I had a column on NPL formation, but this is not available in this dataset, which contains granular information. NPL formation is available in the “typical” NPL analysis we do at an aggregate level, i.e. from consumer, corporate and mortgage loans. However, it would not be possible from the aggregated source to link this information on NPL formation to this disaggregated database (by borrower). However, we may assume that the current stock of NPLs (which is most of the NPLs amount appearing in the column) is deriving from old loans, i.e. loans that were granted more than 5 years ago, unless for a recent borrower (i.e. loan that has been granted after 2016) this specific loan becomes quickly non-performing (this is a rare case).

Finally, I need to mention that when we report metrics (such as NPL ratio) we take the outstanding positions only into account, i.e. the outstanding amount of NPLs as at 31.03.2017 over the outstanding amount of gross loans as at 31.03.2017, hence it does not really matter in my analysis the origination of NPLs.

Subsequently, the raw data from the Large Borrowers' database has been converted into panel data. The conversion of the Large Corporates Database into Panel Data took into consideration the same number (27,088) of corporate borrowers with a reference date as of 31.12.2014 and examined them for the periods 31.12.2014, 31.03.2015, 30.06.2015, 30.09.2015, 31.12.2015, 31.03.2016, 30.06.2016, 30.09.2016, 31.12.2016 and 31.03.2017. The Panel Data includes all the variables from the Large Corporates Database. However, the variables DATE, BANK, Lender Name, Tax ID creditor, Tax ID borrower, Sector, remain the same during the whole period of analysis , hence each borrower is observed for the defined characteristics of these variables that remain stable over time. Nevertheless, the value of a variable from a borrower may not appear in subsequent years, because either a borrower may have repaid the loan in full or a special arrangement may occur between the borrower and the bank, i.e. payment of the loan outstanding through the provision of a new loan at a lower interest rate. In order to merge data from the initial Large Corporate's Database, a unique ID identifier has been used, being the ID Tax identifier of the borrower, followed by the ID Tax identifier of the creditor if 1 borrower has more than one loans in different banks.

The Panel Data is organized in a form whereby the initial Borrower ID & Lender ID are taken as of 31.12.2014 and do not change for the period (i.e. from 31.12.2014 to 31.03.2017). I use the same borrowers over the period, i.e. the same number of loans. However, if a new loan suddenly appears say at 31.03.2015, I have kept them separately as two different cases (two rows). It is true that there will not be any other variable as a criterion, as Borrower ID and Lender ID would be the same but NPL's amount and date of the loan would be different..

I have also treated separately the cases whereby a loan amount (from the same borrower and lender ID) may have the value of either 0 or non-existent for 2-3 consecutive periods and then reappear again with a similar value. I took the same approach in my sample in cases where the same borrower had taken a loan from a bank, but then this bank was sold to another lender, hence in the meantime the lender ID had changed. In other words, the loan had been transferred because the lender had changed his name or it had merged with another lender/ proceeded to a new merger.

6.5 Managing separation of borrowers with different origination dates: Truncated loans and restructured loans

Given the aforementioned assumptions, there were some issues that required further clarification. From the 27093 cases of borrowers, there were 3620 cases where Origination date for Loans is the same as the Origination date for NPLs, 109 cases where the difference between Origination date for Loans and Origination date for NPLs is equal to 2 months, and 190 cases where the difference between Origination date for Loans and Origination date for NPLs is equal to 3 months, and 95 cases where Origination date for NPLs is EARLIER THAN Origination date for Loans.

However, this can be explained by the following: Firstly, up to 30.12.2013, the frequency of reporting was 6 months. This means that although a loan and an NPL may have been classified as the same date of origination, actually the NPL actual date is later than the loan origination date. The second justification is that a loan may have been granted by Bank A, it continues to be serviced by Bank B and this Bank B has acquired Bank A. In such cases, we will continue to consider the loan that has been serviced by Bank B as a new loan, because it may have been restructured in the first place. Since Bank B is acquiring a new loan, it will also acquire its respective NPL, and this explains (in these particular cases) why Loan origination and NPL have the same date. A third reason is that in some cases, an NPL value could have been originated not by a loan (in the strict sense) but by a convertible bond or another contingent liability. In only few (extreme) cases, the origination date for NPLs is EARLIER THAN Origination date for Loans. In such a case, the NPL may have been originated by a convertible, meaning that a debt instrument had a particular clause, i.e. some loan characteristics. In some other cases, there are small loan values but large debt values, so an NPL could even have been initiated from a debenture bond, not a loan. Also, for older dates, this loan may have been originated by a different lender, but serviced by another lender in which case it becomes an NPL.

A specialized category of origination refers to truncated loans, defined as loans that have been originated form the initial data set, having more than two consecutive non-existent values. Origination_date_for_NPLs is a useful variable to determine if a loan had/did not have an NPL component from the beginning. However, the NPL component is not exclusively determined by this variable, because a loan with an NPL component that originated earlier may have ceased to exist before 2014, so there may not be any NPL component when the loan has terminated. With the origination date of NPLs, I am suggesting which of the loans have an NPL component. The origination date for an NPL in this column may go earlier than the period 2014-2017, so the number of events from this column may not necessarily coincide with the events if we were solely restricted in the 2014-2017 period.

Truncated loans are the loans that I have separated into two or 3 rows because the values in certain periods did not come close to the values of the initial period. An initial loan (Row 1) has been separated into 2 or 3 (maximum) rows. For instance, a loan with an identifier L has been separated into L1, L2 and (in rare cases) L3.

In addition , restructuring is the rationale that had enabled us to split the loan into different rows. As such the initial part of the loan (L1) is truncated (because it has been actually detached) but not restructured. Obviously, the next rows (new Loans L2 and L3) that have emerged from the original Loan L are truncated following the decision for a restructuring. A restructuring can occur due to borrower inability to service its loan (or debt) or due to the decision of the bank to restructure the loan anyway, following business considerations.

This distinction created the need for the addition of more information in the panel dataset, i.e. the following columns have been added in Table 6.4:

Table 6.4: Separation of borrowers due to different origination dates

Non-truncated loans (categories 0=no separation and 1=initial loan original before separation) and truncated loans (categories 2=second loan from original and 3=third loan from original)	Restructured (R) and Not restructured (NR)	Origination date for restructured loans and Non-restructured (NR)

Restructured refers to the category whereby the loan has already been separated into a different row (i.e. truncated loans categories 2 and 3). Then the origination date was given ONLY for restructured (R) loans, otherwise the symbol NR (non-restructured) was retained.

Restructured with an NPL (category 1) or without an NPL (category 0) or not restructured (NR)	Loan origination value of restructured loans with an NPL or non-applicable (n/a/)	NPL origination value of restructured loans with an NPL or non-applicable (n/a/)

I have included one further column on whether restructured loans have an NPL (1) or not (0). The remaining loans were left with the symbol NR. Finally, the loan origination value and the NPL origination value for Restructured loans was provided in 2 separate columns, otherwise the loan was labelled as non-applicable. The latter information is very important, as there could be a distinction on whether this was a forced restructuring (because of the NPL) or a restructuring based on business considerations (0 value without an NPL). Also, the fact that the Loan and the NPL value for restructured loans is provided is very important as a sensitivity analysis could take place regarding the different thresholds of NPLs values in relation to the loan values, which could be linked to the decision for restructuring.

6.6 Handling the issue of the ratings classification

A common practice is to collect historical frequencies for a given horizon in a transition matrix. This approach associates the transition probabilities, including default probabilities (PD), with internal ratings or credit ratings published by agencies, such as Moody's Investor Service. However, ratings are not intended to capture a particular default probability over a particular time horizon. How to translate the ordinal content of credit ratings into cardinal default probabilities has always been of interest to fixed income investors and risk managers.

In practice, I decided to bypass this obstacle by employing standard bank approaches to the extent that they publish the classification of its corporate borrowers (i.e. Piraeus Bank). I have seen many similarities between the approach of Piraeus Bank and the approach in the Large Borrower's Database regarding the link between the rating and its creditworthiness and the numbering "ranking" of borrowers. There are 23 scales which is compatible with the Large Borrower's Database, which goes between 1-99, but most of the borrowers are within the 1-24 scales. I therefore assume that the 99 scale is non-identifiable. More specifically, the categorization that was followed is portrayed in Table 6.5:

Table 6.5: Matching of different scales of ratings by employing standard classification approaches

11 scale	16 scale	23 scale	99 scale
1-3	1-4	1-7	1-20
4-6	5-7	8-12	21-33
7-9	8-10	13-17	34-55
10	11-13	18-19	56-74
11	14-16	20-23	75-99

As there are many lenders in the sample (not only the 4 systemic banks), all lenders were classified to the 23-scale rating categorization. The classification by lender was deemed as necessary because even lenders that belong to the same category (i.e. branches of foreign banks) do not follow the same categorization, so there had to be a separate grouping even between them.

6.7 Creating the credit events from lending behaviour

The loans database was then further split into four categories to denote the credit events from the end status of the loan which was categorized as a write-off, securitized loan, repaid early or matured. The criteria for categorization were the following (I also used the concept of quartiles in order to classify them):

a) Write-offs: They are designated as such if the end NPL value of the loan is more than 75% of the value of the gross loan. This is in the last quartile (the long-end) of the distribution. The underlying logic is that banks cannot do anything else but write-off such loans. It is not a coincidence that such loans have a very bad credit rating (category of restructuring and below). Of course, a significant write-off could come at a cost for banks, but the issue here is that banks did not have any alternative to recover some part of the loan due to the inability of the borrower.

b) Securitization: They are designated as such if the end NPL value of the loan is less than 75% and more than 25% of the loan, i.e. in the intermediate 2 quartiles. In this case, the write-off can be avoided. It makes full sense that banks have the opportunity to transfer such loans to a third counterparty. They can split it in different tranches, i.e. one tranche may have the more “green” part of the loan, the second tranche may have equal “green” and “red”, the third tranche more “red” than “green”. The higher the risk (more red than green), the higher the return of the relevant tranche.

c) Matured: This is the physical closure of the loan if no NPL is attached to it. They are designated as such if the early termination value for NPLs is zero and the loan is not truncated.

d) Early repayment: All the remaining loans that terminate earlier than 03.2017 and do not fall in the 3 aforementioned categories. Such loans could either have an NPL or not.

In order to derive the credit events I took all the loans from category a (write -offs) and combined them with the NPLs from categories b (securitization) and d (early repayment). This contained the set of loans experiencing the main credit risk of being NPLs. The remaining non-NPLs from categories b and d were combined to form the competing risk of loans that experienced early non-NPLS termination. The loans that matured (category c) were treated as right censored.

Of course, I should emphasize that the origination date for an NPL is the date where the first value appears as non-performing. Non-performing may mean that part of the payment is not received. If all the payment had not been received, i.e. the whole loan would have become non-performing, it would have been written off. However, in such cases, the loan continues to exist. The 4 categorizations (matured, write-off, securitized, early terminated) were based on the concept of the early termination of a loan, not an early termination of an NPL. Obviously, if the whole loan is terminated, its NPL part is terminated as well. In the cases where the loan continues to exist until 31.03.2017, it is normal to suggest that no option (matured, write-off, securitized, early terminated) is being selected. The 1 of the 4 options is only selected if there is an early termination of a loan, i.e. the loan seizes to exist before the end of the reference period, i.e. 31.03.2017.

Additionally, in cases where a loan had previously an NPL (i.e. before 2014) while it does not have it anymore (2014-2017) and the loan continues to exist until 31.03.2017, this automatically constituted another category, but not one of the 4 aforementioned. Caution was guaranteed, in naming this extra category. After all, before 2014, and more specifically during 2011-2013 there was a significant wave of mergers and acquisitions and this may have played a role in loan termination (although not in all cases).

Regarding the survival of loans: only cases that survived until 2014 are included but they did not survive during the period 2014-2017. The reason is that before 2014, and more specifically during 2011-2013, as I have also mentioned, there was a significant wave of mergers and acquisitions. In such cases it is difficult to track when a specific loan that was granted for example in 2006, ceased to exist as it does not belong to one of the 4 cases simply because it ceased to exist in my database due to mergers and acquisitions. To explain this further, this effectively means that there can be a number of cases whereby a loan could have been terminated before 2014 simply because this loan was transferred to another bank with different codes and not because it belongs to the 4 cases.

One level of analysis could be to focus only on the early terminations, i.e. a loan terminating before the end of the period that is examined. One can still distinguish between a termination due to an event (securitization, write-off, early repayment) and a termination (matured) which is not due to an event. When the analysis is focused on the early termination, this is when one wants to observe whether there has been some change on behalf of the borrower or lender (i.e. borrower's choice (or inability) not to repay or creditor's (bank's) choice to retain) and see how this is associated with the probability of a loan becoming an NPL. Of course, by excluding the remaining cases, I am not considering cases that are still being repaid. In this case, the reason for "excluding" the remaining cases is that they do not "fit in" in the early termination schedule, because they continue to exist.

6.8 Final refurbishing of the data sample

After the modifications, the value of NPLs was ~38% of the total loans. This was the case when all observations were taken into consideration (i.e. 26654 cases). Some cases from the overall initial 27093 were eliminated due to inconsistencies. When only the early terminations are taken into account, i.e. 11635 cases, the amount of NPLs drops to 13% of total loans for the categories of write-offs, securitization, early repayment and matured. It is normal that for the loans that continue to exist, they still carry a significant portion of NPLs with them. As these loans have not been restructured anyhow, one would expect to see a significant level of NPLs inside them. Two reasons may have resulted in the "reduction" of NPLs for early terminations. First of all, I took a smaller sample because I wanted to capture only the early terminations, and additionally, I took a sample with specific characteristics, which is not representative of the population.

TABLE 6.6. Metadata table for variables to be used for Cox and Survival tree models

	Metadata name	Definition
IDENTIIFICATION	Date	The date when the panel data start is 2014, and for the period 2014-2017 the sequence of lender and borrower does not change.
	Bank	Bank's own classification code
	Bank_size	1 if the lender is one of the 4 systemic banks (National Bank of Greece, Alpha Bank, Bank of Piraeus, Eurobank), otherwise 0.
	Loan_ID	Unique loan identifier
LOANS CLASSIFICATION	Origination_date_for_Loans	Date whereby the first value of the loan appears in the database
	obs_point	This is set to 31.12.2013
	Loan_value	Origination value for loans, i.e. the first value of the loan that appears in my database
	Origination_date_NPLs	Date where the first value appears as non-performing
	Early_termination_for_loans	Binary variable which shows whether a loan ended before 31.03.2017 (1) or not (0)
	Early_Termination_date_for_loans	This is the last period whereby the loan value was last observed **before** 31.03.2017.
	Early_Termination_value	Value observed in the early termination date
CREDIT EVENTS	Write_off	Designated as (1) write-off if the end NPL value of the loan is more than 75% of the gross loan value (last quartile of distribution), otherwise (0).
	Write_off_dates	Date whereby the loan value appeared before it was written-off
	Securitization	Designated as (1) securitization if the end NPL value of the loan is more than 25% and less than 75% of the gross loan value (intermediate quartile of distribution), otherwise (0).
	Securitization_dates	Date whereby the loan value appeared before it was securitized
	Early_repayment	Designated as (1) early repayment if they do not fall under categories "write-offs, securitization and matured", otherwise (0).
	Early_repayment_dates_with_NPLs	Date whereby the loan value appeared before it was early repaid while it was also carrying an NPL component.
	Early_repayment_dates_without_NPLs	Date whereby the loan value appeared before it was early repaid while it was NOT carrying an NPL component.
	Matured	Physical "closure" of the loan if no NPL is attached to it. They are designated as such if the early termination value for NPLs is zero and the loan is not truncated.
	Matured_dates	Date whereby the loan value appeared before it matured.
SEPARATION OF BORROWERS/RESTRUCTURING	Non_truncated_loans	Loans that are not truncated; these loans have originated from the initial data set having less than two consecutive non-existent values.
	Restructured _R_and_Not_restructured _NR	Restructured and non-restructured loans
	Origination_date_for_restructured_loans_and_Non_restructured	Origination date is given ONLY for restructured (R) loans, otherwise the symbol NR (non-restructured) is retained
	Restructured_with_an_NPL_category 1_or_without an NPL_category_0_ or_not_restructured_NR	3 results: If restructured loans have an NPL, the response is 1. If restructured loans do not have an NPL, the response is 0. For the remaining loans, the symbol NR is retained.
	Loan_origination_value_of_restructured_loans_with _an_NPL_or_non_applicable	Loan origination value for Restructured loans is provided, otherwise the loan was labelled as non-applicable.
	NPL_origination_value_of _restructured_loans_with_ an_NPL_or_non_applicable	NPL origination value for Restructured loans is provided, otherwise the loan was labelled as non-applicable.
TIME TO EVENT ID REFURBISHMENT	final_date	Final date of observations
	time1	Time-to-event: Time period from the origination until the "death" of the loan incorporating an "in between" observation point, i.e. 31.12.2013; event is when the loan is initially being "infected", i.e. become NPL.
	time2	
	NPL	

<table>
<tr><td rowspan="6">ID after SAMPLE REFURBISHMENT</td><td>Origination date</td><td>Date where the first value appears as non-performing within the period 2006-2017</td></tr>
<tr><td>Lender_Name</td><td>Lender name from whom the loan has been originated.</td></tr>
<tr><td>Tax_ID_creditor</td><td>Unique ID number for the creditor</td></tr>
<tr><td>Tax_ID_borrower</td><td>Unique ID number for the borrower</td></tr>
<tr><td>Sector</td><td>Two-digit code of the borrower’s economic activity, based on the classification of the Hellenic Statistical Authority</td></tr>
<tr><td>Sector_broader_group</td><td>Full name of the principal activity denoted in “Sector”</td></tr>
<tr><td rowspan="14">CREDIT EVENTS PER SECTOR</td><td>ACCOMODATION</td><td rowspan="14">Binary variable for the 14 sectors. If a loan becoming an NPL is classified in a specific sector, then the value 1 appears, otherwise the value 0 appears.</td></tr>
<tr><td>AGRICULTURE</td></tr>
<tr><td>COMMERCIAL_REAL_ESTATE</td></tr>
<tr><td>CONSTRUCTION</td></tr>
<tr><td>ENERGY</td></tr>
<tr><td>TRADE</td></tr>
<tr><td>FINANCIAL_SERVICES</td></tr>
<tr><td>FOOD_SERVICE</td></tr>
<tr><td>HEALTH_SERVICES</td></tr>
<tr><td>MANUFACTURING</td></tr>
<tr><td>PUBLIC_ADMINISTRATION</td></tr>
<tr><td>SHIPPING</td></tr>
<tr><td>TELECOMS_IT_MEDIA</td></tr>
<tr><td>TRANSPORT_OTHER_THAN_SHIPPING</td></tr>
</table>

6.9. Addressing the question of data modelling or developing alternative models to address credit risk

Up to now, there has already been research on the impact on credit risk from external factors. According to the extensive literature, a strong relationship between NPLs and economic variables such as gross domestic product (GDP) and unemployment rates has been evidenced, as well as NPLs and bank characteristics such as size, profitability, effectiveness, degree of risk, quality of corporate governance, etc. On this basis, a recent empirical analysis has been carried out [58] (see Bank of Greece 2018 [48] Box VII.I page 204) which attempts, through alternative econometric techniques, to assess whether the estimated positive economic conditions for the forthcoming years can bring about a reduction in the stock of NPLs as provided by the operational objectives of Greek banks. In particular, the effect of macroeconomic variables (rate of change in economic activity, unemployment, property prices, exports, private consumption, price level) on the default rate of a loan portfolio (corporate, housing, consumer) of Greek banks was examined, using alternative econometric approaches (regression of alternating conditions, Bayesian regression). The results suggest that the default rate is negatively related to the rate of change in economic activity (within a time lag), the change in the real estate price index and the rate of change in private consumption, and positively to inflation and unemployment.

Research on the impact on credit risk has already been conducted by the use of macro-random models (Wieland, V. et all [301]). Constraints on bank credit due to liquidity and solvency concerns and counterparty risks in the interbank market played a key role in amplifying the problems in lending during the global financial crisis. Banking sector models deal with the supply side of credit creation. Thus, shocks can originate from the banking sector and this sector plays an important role in the transmission of standard macroeconomic shocks.

Finally, more conceptual issues were taken into consideration on credit risk data modeling. Inactivity of credit creation was exacerbated by low interest rates and declining asset prices, which led to collective failures in the banking sector, hence priority has been given to the development of recovery and resolution frameworks. Other potential channels include risks from so-called non-traditional and non-banking activities and procyclicality. The procyclicality channel stems from an increased reliance on more provisioning and collateral requirements during hard times and relaxation of standards during the upside of the economic cycle. This is conceptually similar to the procyclical behaviour linked to market valuations at other financial institutions. However, it should be stressed that the new regulation includes several measures aimed at reducing artificial volatility, avoiding fire sales and reducing procyclical behaviour in periods of stress. For example, the Financial Stability Board (FSB) already highlights risks from systemically important financial institutions. Recovery and resolution plans have already been developed for banks, but they are consistently being developed for insurers and CCPs, whereby banks may have important exposures. Both the European Systemic Risk Board (ESRB) and FSB have converged to conceptually similar approaches that stress the need to address similar systemic risks in a similar manner across sectors, entities and activities.

CHAPTER 7 An application of survival trees and Cox models for forecasting NPLs on granular data

This Chapter will investigate the use of survival analysis techniques that analyze the time until a certain event occurs. Such statistical models for prediction may be used to serve as the basis of projecting credit risk portfolio dynamics for various sectors of economic activity. The models were fed with the panel data set which was formed from the granular database on corporate borrowers analyzed in the previous Chapter. The Chapter provides information on credit and credit risk levels and will equip policy makers with significant insight and policy tools for the supervision of the financial system in order to enhance financial stability monitoring and support decision making.

7.1 Model environment

I use a discrete-time version of the Cox hazard model with time-dependent business sector specific covariates and with a failure outcome being default of loan. The output of this analysis would be the covariate dependent hazard rate function for a loan becoming non-performing. Compared to the existing credit risk literature, the approach is novel in that it uses time dependent covariates. In addition, a survival analysis prediction methodology is used, based on a discrete time version of Random Survival Forest with time dependent covariates. The output of this analysis would be the survival probability of a loan as a function of its covariates.

7.1.1 Cox model - Hazard functions and Model definition

Survival analysis techniques analyze the time until a certain event occurs. The use of this approach to business failure is fundamentally different from other approaches because it models a timeline instead of a classification problem. This timeline is most commonly described by the survival or hazard function (each is derivable from the other). The survival function S(t) indicates the probability that an individual survives until time t. When applied to financial distress prediction, an individual can be a business and survival represents the absence of financial distress. Contrastingly, the hazard function h(t) indicates the instantaneous rate of death or financial distress at a certain time t. In this case, this denotes the probability of a loan becoming an NPL. The semi-parametric proportional hazards (PH) model is proposed by Cox [95] in 1972 and it is defined as $\mathbf{h(t) = h0(t)e^{BX}}$, where h0(t) is the non-parametric baseline function that describes the change in the hazard function over time and e^{BX} describes how the hazard function relates to the explanatory variables (X) and is the parametric part of the model, where β is a vector of variable coefficients. The survival function is then computed as S(t) = e−H(t), where H(t) is the cumulative hazard function from time 0.

7.1.2 Survival tree models - Model definition

Survival trees, or classification trees, are a non-parametric data – mining technique. The trees are built by a recursive process of splitting data when moving from higher-to-lower levels. In this research I am utilizing trees for predicting NPLs whereby each sector is classified as either succeeding (surviving) or failing. In addition, every tree illustrates that every non-classification node contains a splitting rule (usually univariate) that describes how data are split.

Survival trees use multiple algorithms to decide to split a node in two or more sub-nodes. The creation of sub-nodes increases the homogeneity of resultant sub-nodes. In other words, we can say that purity of the node increases with respect to the target variable. Decision tree splits the nodes on all available variables and then selects the split which results in most homogeneous sub-nodes.

Finally, the terminal nodes are created. The number of loans in each terminal node is in parenthesis. Each terminal node contains a corresponding survival function estimated using Kaplan-Meier (KM) method. The Kaplan-Meier estimator or the product limit estimator is a nonparametric statistic. It involves the calculation of the probability of each event at the time it occurs. The denominator for this calculation is the population at risk at the time of each event's occurrence.

7.2. Empirical analysis of NPL predictability

7.2.1 Measurement issues

The hazard function in the Cox model is an unspecified baseline, time dependent hazard function. Traditional methods of logistic and linear regression are not suited to be able to include both the event and time aspects as the outcome in the model. Traditional regression methods are also not equipped to handle censoring, a special type of missing data that occurs in time-to-event analyses when subjects do not experience the event of interest during the follow-up time.

The Cox model applies both to the whole sample and to the sample of the early terminated loans. It consists of two time frames, the initial origination of the loan and the observation date. The origination date for loans means the initial date on which the proceeds of the loan or other extension of credit is granted .. As data are on a six-monthly or quarterly basis, it is not possible to know the exact day on which the credit has been granted. However, the following assumption may apply: The database does not have any earlier data than from 31.12.2006. Therefore, if a loan has values already as of 31.12.2006 then I assume that the loan was granted at 31.12.2006 even if it was granted earlier. If a loan was granted for instance on 21.02.2010 (which I do not know), the next available value will be taken into consideration, i.e. in my case 30.06.2010. So, in this particular instance, I assume that the loan was granted on 30.06.2010. The second time frame is 31.12.2013, which is the observation time for the panel data analysis.

One of the challenges specific to survival analysis is that only some loans will have experienced the event by the end of the panel data period, therefore survival times will be unknown for a subset of the panel group data. This phenomenon is called censoring and may arise in the following ways: the study participant has not yet experienced the relevant outcome, such as the end of the loan by the end of the panel data period; or, the study participant experiences a different event that makes further follow-up impossible. Such censored interval times underestimate the true but unknown time to event.

There are three main types of censoring, right, left, and interval. If the events occur beyond the end of the study, then the data is right-censored. Left-censored data occurs when the event is observed, but exact event time is unknown. Interval-censored data occurs when the event is observed, but participants come in and out of observation, so the exact event time is unknown. In this case, it is right-censored as the sample may survive beyond December 2016. In practice, most survival analytic methods are designed for right-censored observations.

Censoring rate has an obvious impact on the trees as we can see that heavy censoring reduces the recovery rate in all cases. The impact of heavy censoring is large when the sample size is smaller, presumably because larger samples bring stability to the trees, which partially offsets the effects caused by information lost due to censoring.

In my case, the data sample is left truncated because most of the loans were issued before December 2013 and right censored because loans survive after 2017. Left truncation and right censoring (LTRC) presents a unique challenge for nonparametric estimation of the hazard rate, however the impact is less profound. Unconditional logistic regression, commonly used in such studies, ignores left truncation, whereas survival analysis can accommodate left truncation and is therefore more appropriate. Since left-truncation causes information loss in the “head” while the right-censoring causes information loss in the “tail,” censoring has more impact than left-truncation.

7.2.2 Empirical facts

The main empirical question is whether these techniques of survival analysis and decision trees can predict financial distress. As such models are addressed to tackle real – world applications, many authors, including Agarwal and Taffler [16], provide criticism against focusing entirely on the theoretic aspects of such models and instead advise that models be first subjected to thorough empirical testing. While a model’s ability to correctly classify the data from which it is developed is important, it also needs to be tested for predictive accuracy on data separate from the model building stage as this is a much better guide for future performance.

It is clearly important for financial distress models to minimize both types of misclassification errors:

• Missing financially distressed businesses (Type I Error) will result in financial losses, including those to debtors, investors, suppliers and customers. It will also damage economic stability; and,

• Falsely classifying businesses without financial distress (Type II Error) produces opportunity costs, such as missed gains from an investment or business association. It can also result in difficulties for the misclassified business tasks such as raising capital, purchasing on credit and receiving payment before delivery.

While it is fairly safe to assume that a Type I Error is more critical than a Type II Error, a quantifiable difference in misclassification costs has not been agreed upon in the literature as it seems to be subjective and will vary depending on the situation and point of view of the user. Consequently, testing a model over a range of misclassification costs is beneficial.

In addition to accuracy, such models need to produce predictions early enough to be useful. In some cases one year ahead might be long enough, but in other cases an earlier prediction might be needed such as when considering long – term business decisions. Hence, as with misclassification costs, testing models over various prediction intervals would be beneficial.

Overall, the results presented provide empirical evidence to support the use of survival analysis and decision tree techniques in financial distress warning systems that are useful to most entities in the financial markets.

7.3 Strategy

7.3.1 Data formulation

A large panel data set has been used by the granular database on Large Exposures, presented in Chapter 6, whereby the formulation of this database into panel data has been thoroughly explained. The original sample for the period December 2014-March 2017 consisted of 26655 cases. For this analysis, I took into consideration both the whole sample and a subsample concentrated only on early terminated loans, i.e. 11635 cases for this period.

The sub-sample of the early terminated loans is described in Chapter 6 and includes all 4 categorizations, i.e. write-offs (they may carry an NPL component or not), securitization (they may carry an NPL component or not), matured (no NPL component) and early repayment (they may carry an NPL component or not). The remaining cases (15020) are those that still exist (right censored).

The reason that early terminated loans were used as well in the analysis is linked to the fact that analysis on early terminations (and especially the first 2 categories of write-offs or securitization as segregated in the data file) will enable matching the repayment capacity and repayment plans of borrowers as closely as possible including follow-up action by banks. That is, to examine borrower's choice (or inability) not to repay or creditor's (bank's) choice to restructure loans and see how this is associated with the probability of a loan becoming an NPL.

The start of the observation period of the panel data has been moved to December 2013 instead of December 2014 as there were many early terminations (411) in the year Dec 2013-Dec 2014. During the cleaning of the data for the period Dec 2013-Dec 2016, some of the loans had to be deleted due to the inconsistencies with the dates (loans that have the same termination and origination date, case where duration = 1 month). After the data cleaning has been completed, I have been left with 11217 cases of early terminations for the analysis. For these cases, origination dates and values of the loan are from December 2006 till September 2016 and Early termination date is from December 2013 to December 2016. That is why I did not encounter cases until March 2017.

In this specific research, financially distressed corporate borrowers are defined on the basis of debt default criteria, hence avoiding many of the problems related to using a legal definition of bankruptcy. The "distress" is the probability of a loan becoming an NPL. Of course, I took into account that some financially distressed companies never file for bankruptcy because of an acquisition or for legal reasons other than financial distress.

The data set is comprised of fixed covariates, such as bank size, industry sector and loan value (amount). Bank size is coded as 1 for a systemic bank and 0 for a non-systemic one. Industry sector has 15 categories, i.e. Accommodation, Agriculture, Commercial Real Estate, Construction, Energy, Financial Services, Food Service, Health Services, Manufacturing, Other, Public Administration, Shipping, Telecoms, Transport other than Shipping and Trade. This is compliant with the borrower's economic activity, based on the most recent classification of the Hellenic Statistical Authority (STAKOD), which indicates the debtor's principal activity. In case of parallel activities, the main activity (with the largest contribution to the turnover) of the business or individual is selected. This is coded with 14 dummy variables. For example: Energy=1 if loan was in Energy sector, 0 if not. The value of the loan refers to the origination value of the loan. The loan value is expressed in millions of Euros in case of Cox model and in 10,000 of Euros in case of the decision tree models.

Survival analysis techniques analyze the time until a certain event occurs. In this case, there are two time-dependent variables measured in 3-month periods. For example, 5 means 5 quarters. T1 is the time from the origination date of the loan until the observation point (31.12.2013), while T2 is the time from the origination date of the loan until the early termination date (event) of the loan.

The model is designed to predict the probability that borrowers that were "alive" at time T1 will fail at T2, allowing it to forecast not only which corporates are likely to fail, but to provide an estimate of the probable time to failure. The probability of failure an instant after time t given the state of the explanatory variables is indeed the survival function. The sample includes only firms that at a specific point in time are likely to fail. The Survival function is based on the time variables but also on the NPL. The NPL is coded as 1 if an NPL value has been originated during the period under consideration and 0 if there was no origination during the period under consideration.

7.3.2 Estimation procedure

This semiparametric model does not require distributional assumptions for the estimation of the baseline hazard function or probability that an average bank will fail. It does require a multiplicative relationship between the underlying hazard function and the log-linear function of the covariates (the proportionality assumption), but Lane et al. [190] demonstrate that this is not a binding constraint even if violated.

The Cox and survival tree models were estimated using a forward stepwise procedure. However, as the Cox model incorporates time, only one Cox model is needed. For example, the one and three – year prediction intervals with the Cox model could be obtained by using S(1) and S(3) respectively.

7.3.3 Parameters and model fit

One of the main advantages of semi-parametric models is that the baseline hazard does not need to be specified in order to estimate hazard ratios that describe differences in the relative hazard between groups. It may be, however, that the estimation of the baseline hazard itself is of interest. In this case, a parametric approach is necessary. In parametric approaches, both the hazard function and the effect of the covariates are specified. The hazard function is estimated based on an assumed distribution in the underlying population.

Advantages of using a parametric approach to survival analysis are:

- Parametric approaches are more informative than non- and semi-parametric approaches. In addition to calculating relative effect estimates, they can also be used to predict survival time, hazard rates and mean and median survival times. They can also be used to make absolute risk predictions over time and to plot covariate-adjusted survival curves.

- When the parametric form is correctly specified, parametric models have more power than semi-parametric models. They are also more efficient, leading to smaller standard errors and more precise estimates.

- Parametric approaches rely on full maximum likelihood to estimate parameters.

- Residuals of parametric models take the familiar form of the difference in the observed versus expected.

Nevertheless, the main disadvantage of using a parametric approach is that is relies on the assumption that the underlying population distribution has been correctly specified.

Parametric models are not robust to misspecification, which is why semi-parametric models are more common in the literature and are less risky to use when there is uncertainty about the underlying population distribution.

Non-parametric approaches do not rely on assumptions about the shape or form of parameters in the underlying population. In survival analysis, non-parametric approaches are used to describe the data by estimating the survival function, $S(t)$, along with the median and quartiles of survival time. These descriptive statistics cannot be calculated directly from the data due to censoring, which underestimates the true survival time in censored subjects, leading to skewed estimates of the mean, median and other descriptives. Non-parametric approaches are often used as the first step in an analysis to generate unbiased descriptive statistics, and are often used in conjunction with semi-parametric or parametric approaches.

As to the Cox Models, I have fitted the following models:

Model A: A model for survival time, using all industrial sectors as predictors and for the whole sample.

Model B: A model for survival time, using the main effects of 4 predictors, specifically, construction, shipping, energy and commercial real estate and for the whole sample

Model C: A model for survival time, using all industrial sectors as predictors and for early terminated loans.

Model D: A model for survival time, using the main effects of 4 predictors, specifically, construction, shipping, energy and commercial real estate and for early terminated loans.

Models B+ and D+: Models B and D respectively that take into account interaction variables.

7.4 Estimation results

7.4.1 Cox Model A: Using all explanatory variables for the Cox Model for all the sample

The results of the Cox regression for survival analysis will be presented next. As aforementioned, the method is not truly nonparametric because it does assume that the effects of the predictor variables upon survival are constant over time and are additive in one scale. The hazard function in Cox model is defined as $h(t) = h_0(t)\exp(BX')$, where h_0(t) is an unspecified baseline, time-dependent hazard function, B= (B_1,…,B_n) is the row vector of the coefficients and X=(X_1, X_2, …,X_n) the row vector of covariates. One can estimate the coefficients in B without knowing h_0(t). h_0(t) can also be estimated for the purpose of estimating the survival function associated with Cox model. The first numeric column shows the coefficients in B. The second numeric column gives the exponent of the coefficient exp(coef)=hazard ratio, where in the numerator we have the hazard when a value of a given variable is increased by one unit compared to its value in the hazard in the denominator keeping other variables constant. Hazard ratio greater than 1 indicates an increased hazard of a loan becoming NPL, and less than 1 indicates a decreased hazard.

TABLE 7.1: Results of the Cox model A fit and the probability of a loan becoming non-performing for the whole sample (Total of 26,654 rows)

Call:

coxph(formula = Surv(time1, time2, NPL) ~ ACCOMODATION + AGRICULTURE +COMMERCIAL_REAL_ESTATE + CONSTRUCTION + ENERGY + TRADE +SHIPPING + FINANCIAL_SERVICES + FOOD_SERVICE + HEALTH_SERVICES + MANUFACTURING + PUBLIC_ADMINISTRATION + TELECOMS_IT_MEDIA + TRANSPORT_OTHER_THAN_SHIPPING + bank_size + Loan_value, data = greekmacro, x = TRUE)

	coef	exp(coef)	se(coef)	z	p
ACCOMODATION	3.586e-02	1.037e+00	4.097e-02	0.875	0.381450
AGRICULTURE	1.420e-01	1.153e+00	6.134e-02	2.315	0.020610
COMMERCIAL_REAL_ESTATE	1.498e-01	1.162e+00	4.772e-02	3.140	0.001688
CONSTRUCTION	2.554e-01	1.291e+00	2.982e-02	8.566	< 2e-16
ENERGY	-1.099e+00	3.331e-01	1.075e-01	-10.228	< 2e-16
TRADE	6.686e-02	1.069e+00	2.665e-02	2.509	0.012103
SHIPPING	-2.840e-01	7.528e-01	5.538e-02	-5.129	2.92e-07
FINANCIAL_SERVICES	2.142e-01	1.239e+00	1.010e-01	2.120	0.034018
FOOD_SERVICE	5.991e-02	1.062e+00	1.122e-01	0.534	0.593367
HEALTH_SERVICES	1.310e-01	1.140e+00	7.458e-02	1.757	0.079000
MANUFACTURING	5.973e-02	1.062e+00	2.860e-02	2.088	0.036765

PUBLIC_ADMINISTRATION -4.929e-01 6.108e-01 1.808e-01 -2.726 0.006417

TELECOMS_IT_MEDIA 9.940e-02 1.105e+00 5.336e-02 1.863 0.062473

TRAN_OTHER_THAN_SHIPPING 5.668e-02 1.058e+00 6.828e-02 0.830 0.406494

bank_size -9.284e-02 9.113e-01 2.654e-02 -3.498 0.000469

Loan_value -3.994e-06 1.000e+00 1.173e-06 -3.404 0.000663

Likelihood ratio test=370.8 on 16 df, p=< 2.2e-16 n= 25866, number of events= 13319

ACCOMODATION

AGRICULTURE *

COMMERCIAL_REAL_ESTATE **

CONSTRUCTION ***

ENERGY ***

TRADE *

SHIPPING ***

FINANCIAL_SERVICES *

FOOD_SERVICE

HEALTH_SERVICES .

MANUFACTURING *

PUBLIC_ADMINISTRATION **

TELECOMS_IT_MEDIA .

TRANSPORT_OTHER_THAN_SHIPPING

bank_size ***

Loan_value ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Concordance= 0.541 (se = 0.003)

Likelihood ratio test= 370.8 on 16 df, p=<2e-16

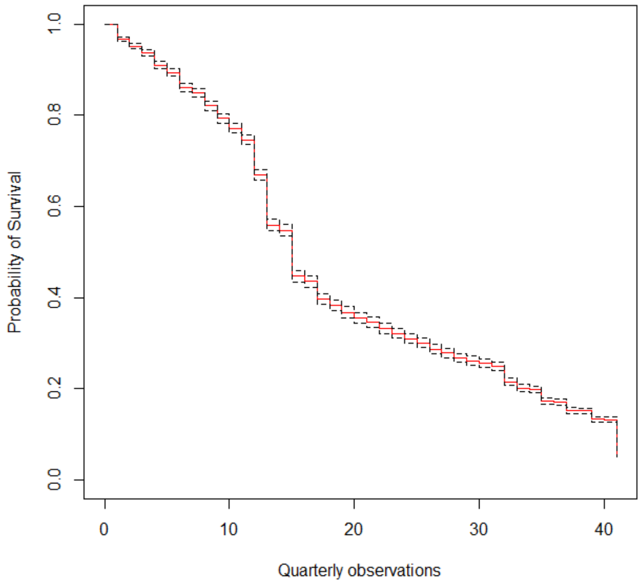
Wald test = 302.4 on 16 df, p=<2e-16

Score (logrank) test = 318.6 on 16 df, p=<2e-16

The concordance as a measure of fit quality is only appropriate when we have at least one continuous predictor in my Cox model, in which case it assesses the probability of agreement between the survival time and the risk score generated by the predictor (or set of predictors). A value of 1 indicates perfect agreement and 0.5 is an agreement that is no better than chance. Finally a significance test, such as the Wald test (shown next to the coefficient estimates in the position of a t test in linear regression), for an individual predictor compares the coefficient to its standard error, just like a t test in linear regression.

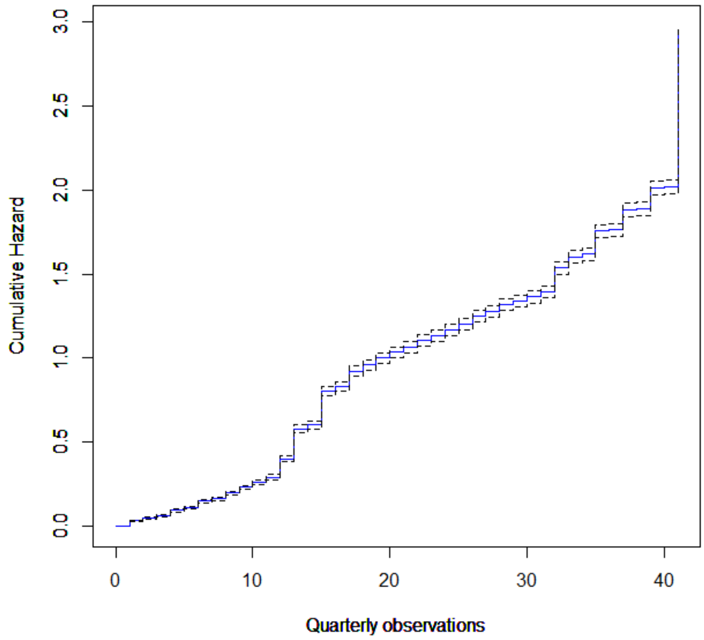
Then, both the implied survival curve for loans and the cumulative survival curve are being portrayed:

FIGURE 7.1: Survival Curve for loans implied from the Cox Model A for the whole sample



The crosses in the plot indicate censoring points, while the drops indicate loans that nolonger exist and are thus no longer at risk of becoming NPLs.

FIGURE 7.2: Cumulative Hazard implied from the Cox Model A for the whole sample



From the above analysis it can be derived that the construction sector has an increased hazard of its loans becoming NPLs, by keeping all the other variables constant. On the other hand, each one of the shipping, the public administration and the energy sectors have a decreased hazard of becoming NPLs by keeping all the other variables constant. The individual variables of the Cox model that predict a loan becoming an NPL with statistical significance ($p<0.000$) were the construction and energy sectors with a high probability of occurrence and the shipping sector with a very low probability of occurrence.

Finally, the hazard of a loan becoming NPL decreases as the value of a loan increases by a million Euros. But the coefficient of a loan value is very small resulting in the hazard ratio close to 1, which means that if one compares two loans with loan values differing by a million Euros, their hazards of becoming NPLS will be essentially the same. One needs a much larger than unit increase to see the effect of a loan value on the hazard function.

7.4.1.1 Evaluation of the proportional Hazards Assumption of the Cox Model A

Even though assessment of fit of the regression part of the Cox proportional hazards assumption model corresponds with other regression models such as the logistic model, the Cox model has its own distributional assumption in need of validation. Here, of course, the distributional assumption is not as stringent as with other survival models, but we do need to validate how the survival or hazard functions for various subjects are connected.

TABLE 7.2: Checking the Proportional Hazards Assumption for the whole sample (Total of 26,654 rows)

> #Checking Proportional Hazards Assumption

> cox.zph(Cox.fit)

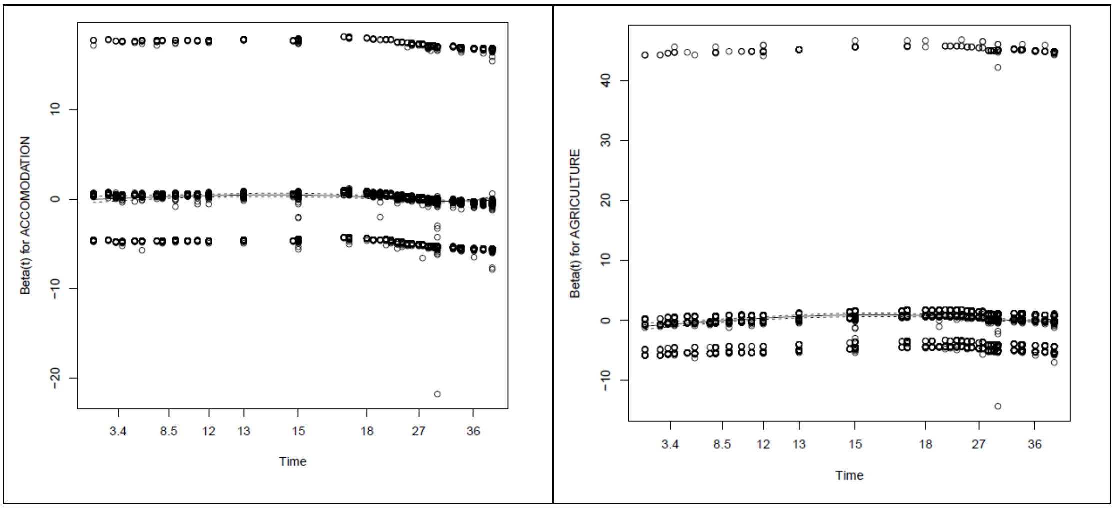
	chisq	df	p
ACCOMODATION	9.93e-03	1	0.921
AGRICULTURE	2.52e+00	1	0.112
COMMERCIAL_REAL_ESTATE	9.55e-01	1	0.328
CONSTRUCTION	3.90e-01	1	0.532
ENERGY	1.59e+01	1	6.8e-05
TRADE	3.08e+01	1	2.8e-08
SHIPPING	9.68e-02	1	0.756
FINANCIAL_SERVICES	3.00e-02	1	0.862
FOOD_SERVICE	8.69e-01	1	0.351
HEALTH_SERVICES	3.58e-02	1	0.850
MANUFACTURING	1.99e+01	1	8.1e-06
PUBLIC_ADMINISTRATION	3.31e+00	1	0.069
TELECOMS_IT_MEDIA	4.31e-01	1	0.512
TRANSPORT_OTHER_THAN_SHIPPING	8.86e-01	1	0.347
bank_size	4.76e+01	1	5.2e-12
Loan_value	2.94e-01	1	0.588
GLOBAL	1.57e+02	16	< 2e-16

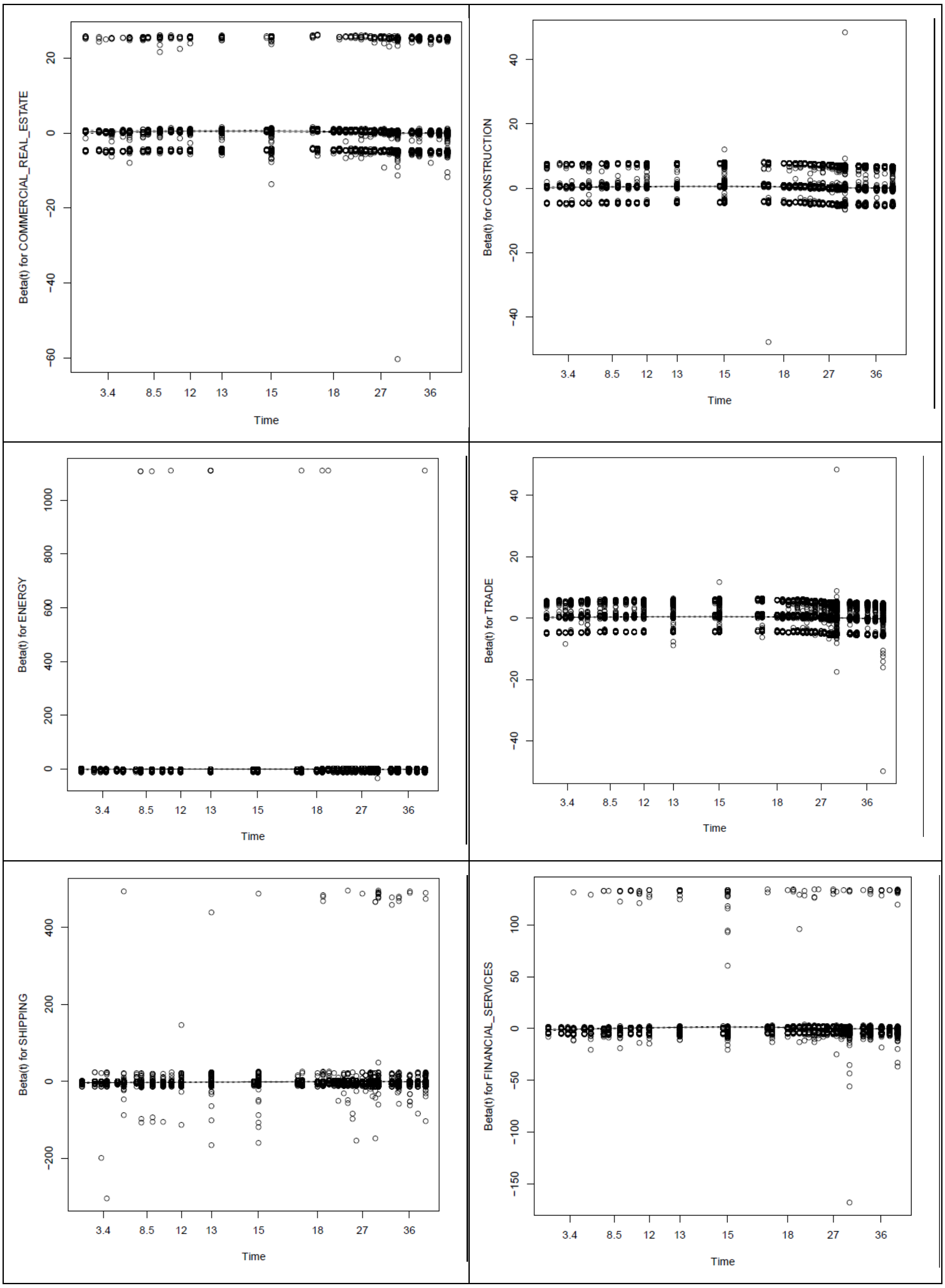
Perhaps Energy, Trade and Manufacturing significantly change over time (P = 0.05 for testing the correlation rho between the scaled Schoenfeld residual and time), while the global test of PH is done penalizing for 16 d.f., and the P value is <2e-16. The graphical examination of the trends is performed by using the Schoenfeld residuals. Pettitt and Bin Daud proposed a score test for proportional hazards assumption based on the Schoenfeld residuals. However, this has its disadvantages. Grambsch and Therneau [279], [280], [281], [282] found that the Pettitt–Bin Daud standardization is sometimes misleading in that non-proportional hazard in one variable may cause the residual plot for another variable to display non-proportional hazards. Therneau discussed four types of residuals from the Cox model: martingale, score, Schoenfeld, and deviance. The first three have been proven to be very useful. The Grambsch–Therneau weighted residual solves this problem and also yields a residual that is on the same scale as the log relative hazard ratio. Their residual is $\hat{\beta} + dR\hat{V}$, where d is the total number of events, R is the n × p matrix of Schoenfeld residuals, and $\hat{V}$ is the estimated covariance matrix for $\hat{\beta}$.

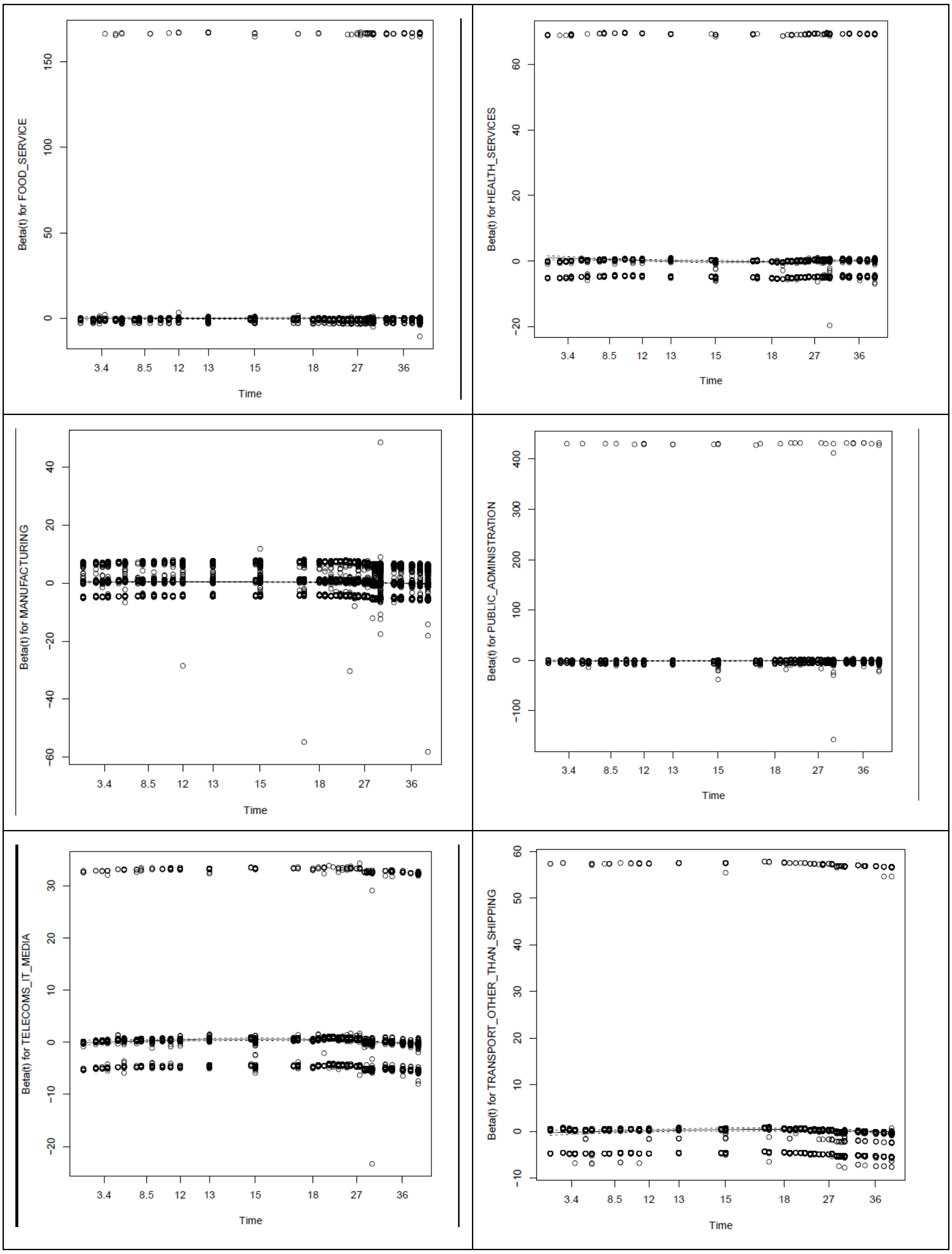
The computation and plotting of scaled Schoenfeld residuals could have been done automatically by using the single command plot(cox.zph(cox)). In this particular case, the use of Therneau's cox.zph function implements Harrell's Schoenfeld residual correlation test for proportional hazards. This function also stores results that can easily be passed to a plotting method for cox.zph to automatically plot smoothed residuals.

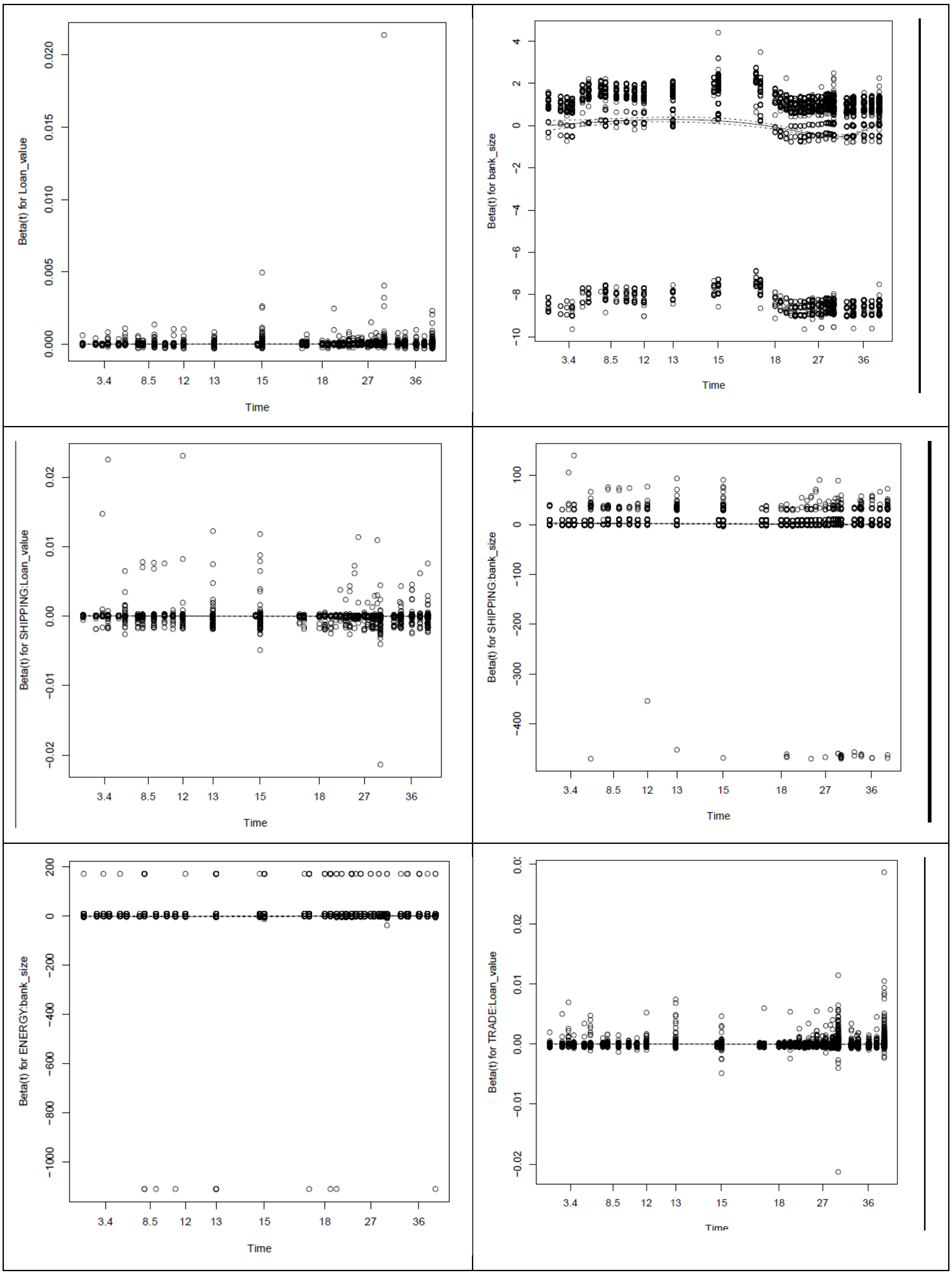
Next, I compute scaled Schoenfeld residuals separately for each predictor and test the PH assumption using the "correlation with time" test. Also, I plot the smoothed trends in the residuals. The plot method for cox.zph objects uses cubic splines to smooth the relationship.

FIGURE 7.3: Raw and spline-smoothed scaled Schoenfeld residuals for all the predictors coded from the Cox model fit, with ± 2 standard errors.




Beta(t) for COMMERCIAL_REAL_ESTATE
Time
Beta(t) for CONSTRUCTION
Time
Beta(t) for ENERGY
Time
Beta(t) for TRADE
Time
Beta(t) for SHIPPING
Time
Beta(t) for FINANCIAL_SERVICES
Time


Beta(t) for FOOD_SERVICE
Time
Beta(t) for HEALTH_SERVICES
Time
Beta(t) for MANUFACTURING
Time
Beta(t) for PUBLIC_ADMINISTRATION
Time
Beta(t) for TELECOMS_IT_MEDIA
Time
Beta(t) for TRANSPORT_OTHER_THAN_SHIPPING
Time
3.4
8.5
12
13
15
18
27
36


Beta(t) for Loan_value
0.000
0.005
0.010
0.015
0.020
3.4 8.5 12 13 15 18 27 36
Time
Beta(t) for bank_size
−10 −8 −6 −4 −2 0 2 4
3.4 8.5 12 13 15 18 27 36
Time
Beta(t) for SHIPPING:Loan_value
−0.02 −0.01 0.00 0.01 0.02
3.4 8.5 12 13 15 18 27 36
Time
Beta(t) for SHIPPING:bank_size
−400 −300 −200 −100 0 100
3.4 8.5 12 13 15 18 27 36
Time
Beta(t) for ENERGY:bank_size
−1000 −800 −600 −400 −200 0 200
3.4 8.5 12 13 15 18 27 36
Time
Beta(t) for TRADE:Loan_value
−0.02 −0.01 0.00 0.01 0.02
3.4 8.5 12 13 15 18 27 36
Time

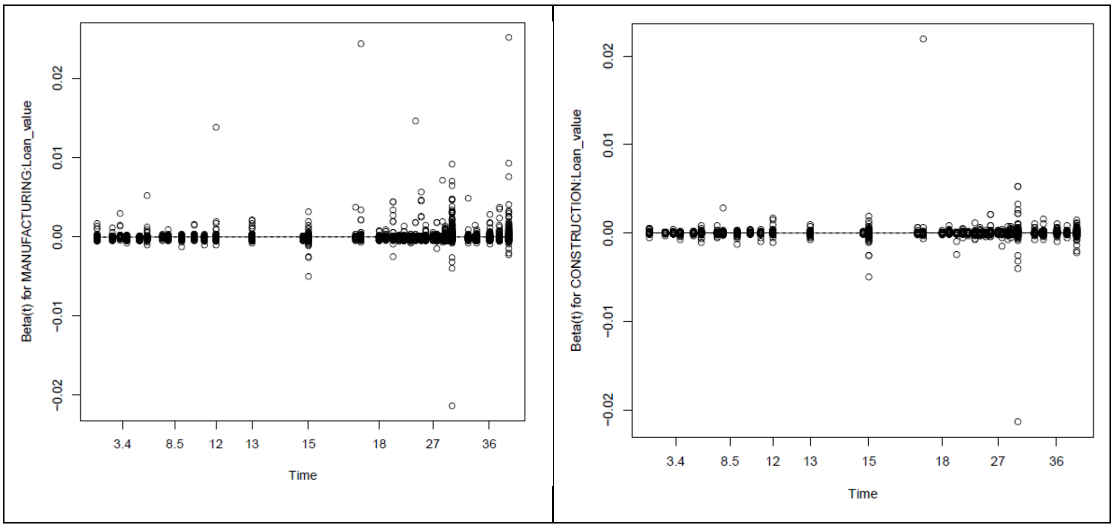


Figure 7.3 computes scaled Schoenfeld residuals separately for each predictor and tests the proportional hazards assumption using the "correlation with time" test. The smoothed trends in the residuals is plotted in this respect. The plot method for cox.zph objects uses cubic splines to smooth the relationship. The graphical examination of the trends shows that there are systematic departures from the horizontal line for the 3 predictors mentioned above. The solid line is a smoothing spline fit to the plot, with the dashed lines representing a +-2 standard error band around the fit. There are systematic departures for Energy, Trade and Manufacturing from a horizontal line, therefore we can conclude that there are strong indications of non-proportional hazards for these 3 predictors. Note that proportional hazards assume that estimates β1, β2 and β3 do not vary much over time.

The residual plot is computationally very attractive since the score residual components are byproducts of Cox maximum likelihood estimation. Another attractive feature is the lack of the need to categorize the time axis. Unless approximate confidence intervals are derived from smoothing techniques, a lack of confidence intervals from most software is one disadvantage of the method. The systematic departure of certain variables is is crucial in order for the method to able to fit another Cox model with fewer predictors that respect the proportional Hazards Assumption.

7.4.1.2 Evaluation of collinearity of the Cox Model A

We now need to investigate whether there is a case when at least one of the predictors can be predicted well from the other predictors. In this case, the standard errors of the regression coefficient estimates can be inflated and corresponding tests have reduced power. In stepwise variable selection, collinearity can cause predictors to compete and make the selection of "important" variables arbitrary. One way to quantify collinearity is with variance inflation factors or VIF, which in ordinary least squares are diagonals of the inverse of the X′X matrix scaled to have unit variance.

TABLE 7.3: Checking Collinearity for the whole sample (Total of 26,654 rows)

```
#Checking Collinearity
> vif(Cox.fit)
        ACCOMODATION                 AGRICULTURE
            1.227204                    1.089993
COMMERCIAL_REAL_ESTATE               CONSTRUCTION
            1.157880                    1.506887
              ENERGY                       TRADE
            1.024300                    1.711722
            SHIPPING          FINANCIAL_SERVICES
            1.145103                    1.041319
        FOOD_SERVICE             HEALTH_SERVICES
            1.000905                    1.055843
       MANUFACTURING       PUBLIC_ADMINISTRATION
            1.594849                    1.009741
    TELECOMS_IT_MEDIA  TRANSPORT_OTHER_THAN_SHIPPING
            1.122868                    1.071817
           bank_size                  Loan_value
            1.009861                    1.051617
```

The variance inflation factors don't look enormous - it may be that removing one of these variables will help make the others look more significant.

7.4.2 Cox Model B: Using the explanatory variables CONSTRUCTION, ENERGY, COMMERCIAL_REAL_ESTATE and SHIPPING for the Cox Model for all the sample

Model B takes into account the whole dataset but it is restricted to the following explanatory variables, Construction, Energy, Commercial Real Estate and Shipping.

TABLE 7.4: Results of the Cox model B fit and the probability of a loan becoming non-performing for the whole sample (Total of 26,654 rows)

> Cox.fit1 <- coxph(Surv(time1, time2, NPL) ~ CONSTRUCTION +ENERGY + COMMERCIAL_REAL_ESTATE + SHIPPING, data= greekmacro, x=TRUE)

> Cox.fit1

Call:

coxph(formula = Surv(time1, time2, NPL) ~ CONSTRUCTION + ENERGY +

COMMERCIAL_REAL_ESTATE + SHIPPING, data = greekmacro, x = TRUE)

	coef	exp(coef)	se(coef)	z	p
CONSTRUCTION	0.16990	1.18519	0.02442	6.959	3.43e-12
ENERGY	-1.27212	0.28024	0.10619	-11.980	< 2e-16
COMMERCIAL_REAL_ESTATE	.08479	1.08848	0.04444	1.908	0.0564
SHIPPING	-0.55166	0.57599	0.05168	-10.674	< 2e-16

Likelihood ratio test=425.9 on 4 df, p=< 2.2e-16 n= 26654, number of events= 13371

Concordance= 0.528 (se = 0.002)

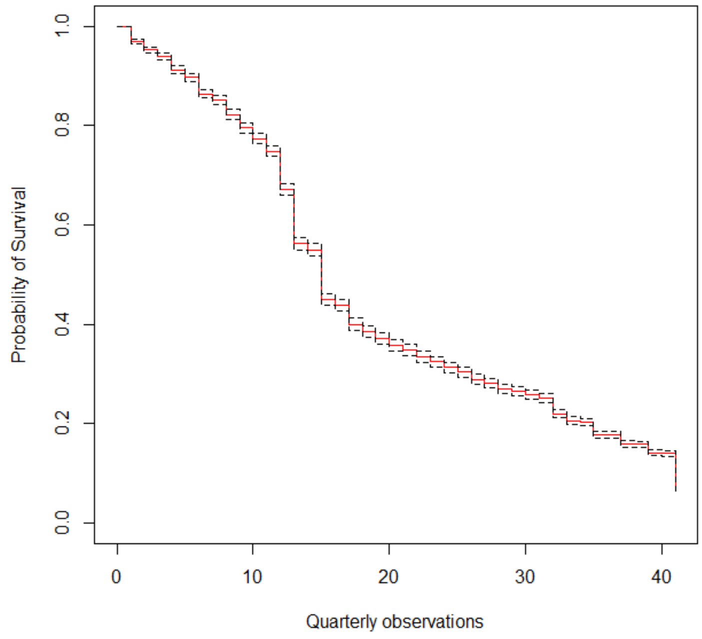
Likelihood ratio test= 425.9 on 4 df, p=<2e-16

Wald test = 322.8 on 4 df, p=<2e-16

Score (logrank) test = 348.6 on 4 df, p=<2e-16

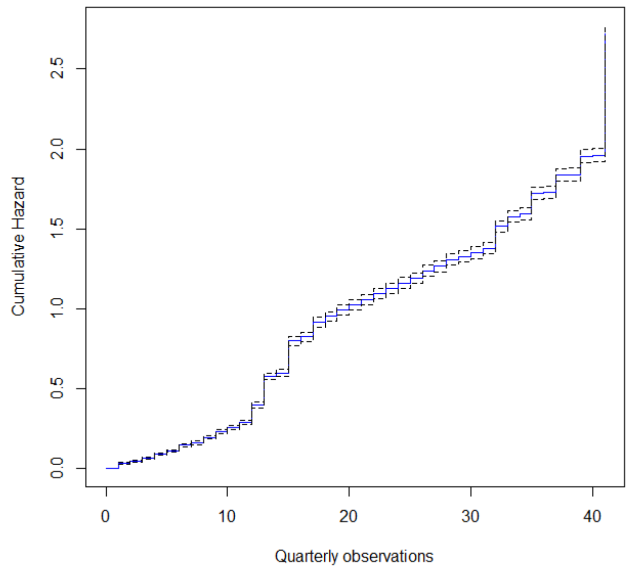
Again, both the implied survival curve for loans and the cumulative survival curve are being portrayed:

FIGURE 7.4: Survival Curve for loans implied from the Cox Model B for the whole sample



The crosses in the plot indicate censoring points, while the drops indicate loans that no longer exist and are thus no longer at risk of becoming NPLs.

FIGURE 7.5: Cumulative Hazard implied from the Cox Model B for the whole sample



From the above analysis it can be derived that the construction and the commercial real estate sector have an increased hazard of its loans becoming NPLs, by keeping all the other variables constant. On the other hand, the shipping and the energy sectors have a decreased hazard of becoming NPLs by keeping all the other variables constant. The individual variables of the Cox model that predict a loan becoming an NPL with statistical significance ($p<0.000$) are the construction, energy and shipping sectors with a high probability of occurrence, while the commercial real estate sector has a very low probability of occurrence.

7.4.2.1 Evaluation of the proportional Hazards Assumption of the Cox Model B

Also, for this model, it is important to validate how the survival or hazard functions for various subjects are connected.

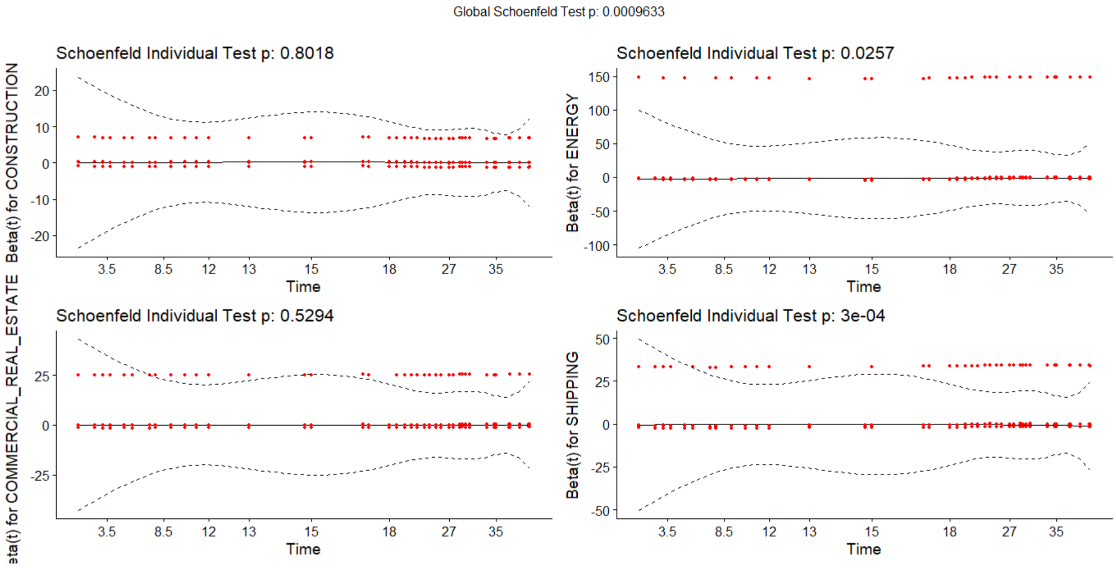
TABLE 7.5: Checking the Proportional Hazards Assumption for the whole sample for Cox Model B (Total of 26,654 rows)

> #Checking Proportional Hazards Assumption

	chisq	df	p
CONSTRUCTION	0.063	1	0.80179
ENERGY	4.974	1	0.02573
COMMERCIAL_REAL_ESTATE	0.396	1	0.52944
SHIPPING	13.012	1	0.00031
GLOBAL	18.550	4	0.00096

In this case, the Energy and Shipping Sector significantly changes over time (P = 0.05 for testing the correlation rho between the scaled Schoenfeld residual and time), while the global test of PH is done penalizing for 4 d.f., and the P value is 0.00096. The graphical examination of the trends is performed by using the Schoenfeld residuals. I have computed scaled Schoenfeld residuals separately for each of the 4 predictors and tested the PH assumption using the “correlation with time” test. Also, I plot the smoothed trends in the residuals.

FIGURE 7.6: Raw and spline-smoothed scaled Schoenfeld residuals for the 4 predictors, Construction, Energy, Shipping and Commercial Real estate coded from the Cox model fit, with ± 2 standard errors.



Although the shipping sector (and marginally the energy sector) does not pass the test, I do not observe any systematic departures from a horizontal line, hence I can conclude that I do not have any strong indication of non-proportional hazards for these 4 predictors. I am looking for the smooth curve to be fairly level across the time horizon here, as opposed to substantially increasing or decreasing in level as time passes. This is the case in Figure 7.6. Note that proportional hazards assume that estimates β1, β2 and β3 do not vary much over time. In a nutshell, Model B passes the proportional Hazards assumption.

7.4.2.2 Evaluation of collinearity of the Cox Model B

TABLE 7.6: Checking Collinearity for the whole sample (Total of 26,654 rows)

```
#Checking Collinearity
> vif(Cox.fit1)
CONSTRUCTION        ENERGY        COMMERCIAL_REAL_ESTATE
    1.014257       1.001985                 1.009672
    SHIPPING
    1.007441
```

The variance inflation factors look negligible, so any sign of collinearity has already been removed on Model B.

7.4.3 Cox model C: Using all explanatory variables for the Cox Model for early terminated loans

In addition, the Cox model was also run for the sample of early terminated loans, i.e. loans that terminate before the end of the period we examine. As explained in the previous Chapter, a termination considered all the 4 cases whereby a loan is terminated due to an event (securitization, write-off, early repayment cases) or not due to an event (matured cases). This level of analysis is focused only on the early terminations, because we want to observe whether there has been some change on behalf of the borrower or lender (i.e. borrower's choice (or inability) not to repay or creditor's (bank's) choice to retain) and see how this is associated with the probability of a loan becoming an NPL.

Of course, the probability of a loan becoming NPL is derived not only for the early termination category. Early termination is the result, not the cause for a loan that has already become an NPL. Just because a loan became an NPL, the bank could for example take some action, by write-offs etc. leading to an early termination. As I have mentioned previously, this restructuring process does not always come from the borrower's side, but it could be the lender's strategic decision. In general, the probability of a loan becoming an NPL could need the whole population.

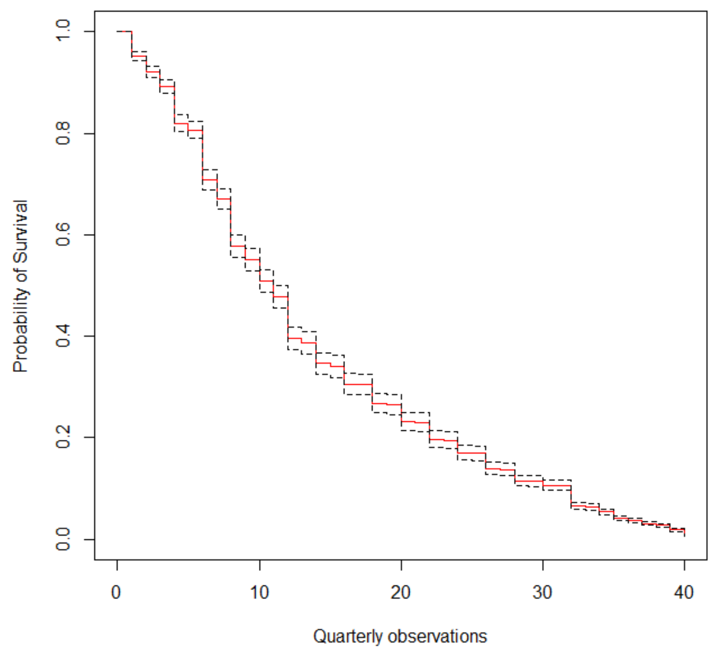
The results of the Cox model with early terminated loans are illustrated in table 7.7.

Likewise in the previous case, the construction sector has an increased hazard of its loans becoming NPLs, therefore the Cox model predicts a loan becoming an NPL with statistical significance ($p<0.000$) in this sector, while the energy and the shipping sectors have a reduced hazard of its loans becoming NPLs with a statistical significance ($p<0.000$) in the relevant sectors. However, in the construction and shipping sectors the magnitude of the effect of a loan becoming NPL is more profound. This is because in the first case both surviving and non-surviving (early terminated) loans were taken into consideration while in the second case only non-surviving loans were taken into consideration.

TABLE 7.7: Results of the Cox model fit and the probability of a loan becoming non-performing for early terminated loans (Total of 11,635 rows)

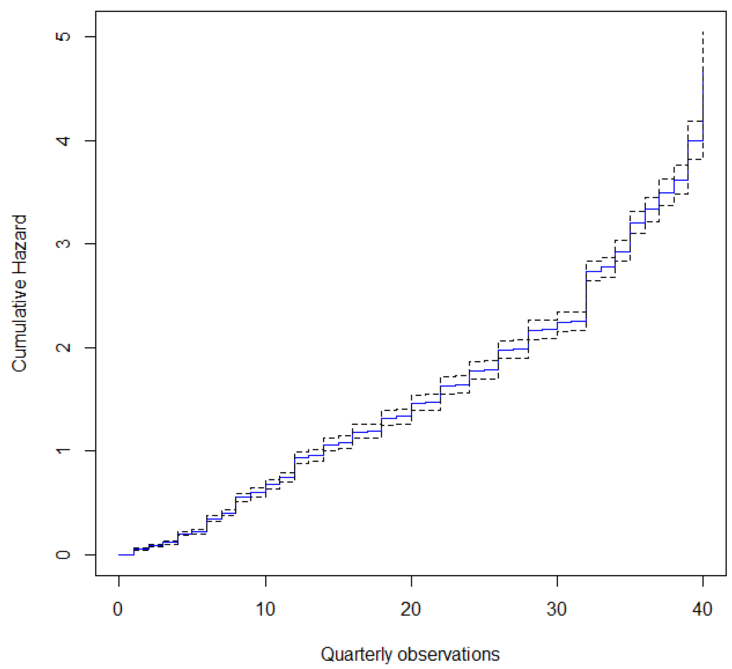
```
Call:
coxph(formula = Surv(time1, time2, NPL) ~ ACCOMODATION + AGRICULTURE +
   COMMERCIAL_REAL_ESTATE + CONSTRUCTION + ENERGY + TRADE +
   SHIPPING + FINANCIAL_SERVICES + FOOD_SERVICE + HEALTH_SERVICES +
   MANUFACTURING + PUBLIC_ADMINISTRATION + TELECOMS_IT_MEDIA +
   TRANSPORT_OTHER_THAN_SHIPPING + bank_size + Loan_value, data = greekmacro)
                                    Coef      exp(coef)  se(coef)    z      p
ACCOMODATION                       1.46e-01  1.16e+00  7.92e-02  1.85   0.065
AGRICULTURE                       -3.99e-02  9.61e-01  1.11e-01 -0.36   0.718
COMMERCIAL_REAL_ESTATE             1.51e-01  1.16e+00  8.45e-02  1.79   0.074
CONSTRUCTION                       4.78e-01  1.61e+00  5.30e-02  9.00 < 2e-16
ENERGY                            -1.08e+00  3.38e-01  1.82e-01 -5.98 2.3e-09
TRADE                              5.14e-02  1.05e+00  4.78e-02  1.08   0.282
SHIPPING                          -5.58e-01  5.72e-01  9.13e-02 -6.12 9.7e-10
FINANCIAL_SERVICES                 4.76e-02  1.05e+00  1.80e-01  0.27   0.791
FOOD_SERVICE                      -1.68e-01  8.45e-01  1.97e-01 -0.86   0.392
HEALTH_SERVICES                    1.54e-01  1.17e+00  1.15e-01  1.34   0.180
MANUFACTURING                      3.27e-02  1.03e+00  4.92e-02  0.66   0.507
PUBLIC_ADMINISTRATION             -2.83e-01  7.54e-01  2.80e-01 -1.01   0.312
TELECOMS_IT_MEDIA                  8.18e-02  1.09e+00  8.32e-02  0.98   0.325
TRANSPORT_OTHER_THAN_SHIPPING      1.48e-01  1.16e+00  1.04e-01  1.43   0.153
bank_size                         -6.38e-02  9.38e-01  3.91e-02 -1.63   0.103
Loan_value                        -3.46e-07  1.00e+00  1.29e-06 -0.27   0.788
Likelihood ratio test=258  on 16 df, p=0 n= 11504, number of events= 4919

ACCOMODATION            .

AGRICULTURE

COMMERCIAL_REAL_ESTATE       .

CONSTRUCTION    *** ENERGY     ***        SHIPPING       ***

TRADE               FINANCIAL_SERVICES                  FOOD_SERVICE

HEALTH_SERVICES        MANUFACTURING        PUBLIC_ADMINISTRATION

TELECOMS_IT_MEDIA

TRANSPORT_OTHER_THAN_SHIPPING

bank_size

Loan_value

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Concordance= 0.566  (se = 0.005 )

Likelihood ratio test= 257.6  on 16 df,   p=<2e-16

Wald test            = 237.9  on 16 df,   p=<2e-16

Score (logrank) test = 249.4  on 16 df,   p=<2e-16
```

FIGURE 7.7: Survival Curve for loans implied from the Cox Model C for the sample of early terminations



The crosses in the plot indicate censoring points, while the drops indicate loans that no longer exist and are thus no longer at risk of becoming NPLs.

FIGURE 7.8: Cumulative Hazard implied from the Cox Model C for the sample of early terminations



It appears that in the construction sector the hazard ratio for a loan becoming NPL is greater when the loans in this sector have been terminated at a particular point in time, indicating indeed that the borrower has increased difficulties to repay the loan. Also, in the shipping sector, the hazard ratio is even lower when there is an early termination of loans indicating that in this category the borrower was able to repay the loans faster, hence the non-survival of the loans in this category is due to the fact that the borrower was indeed in a better position to repay the loan. In this case, it could also be the lender's decision to restructure the loan due to certain macroeconomic developments irrespective of the inability of the borrower. Let us not forget that the shipping sector is a highly seasonal business , hence the decision for restructuring may be affected from macroeconomic factors.

7.4.3.1 Evaluation of the proportional Hazards Assumption of the Cox Model C

Even though assessment of fit of the regression part of the Cox proportional hazards assumption model corresponds with other regression models such as the logistic model, the Cox model has its own distributional assumption in need of validation. Here, of course, the distributional assumption is not as stringent as with other survival models, but we do need to validate how the survival or hazard functions for various subjects are connected.

TABLE 7.8: Checking the Proportional Hazards Assumption for the sample of early terminations (Total of Total of 11,635 rows)

```
> #Checking Proportional Hazards Assumption
> cox.zph(Cox.fit)
```

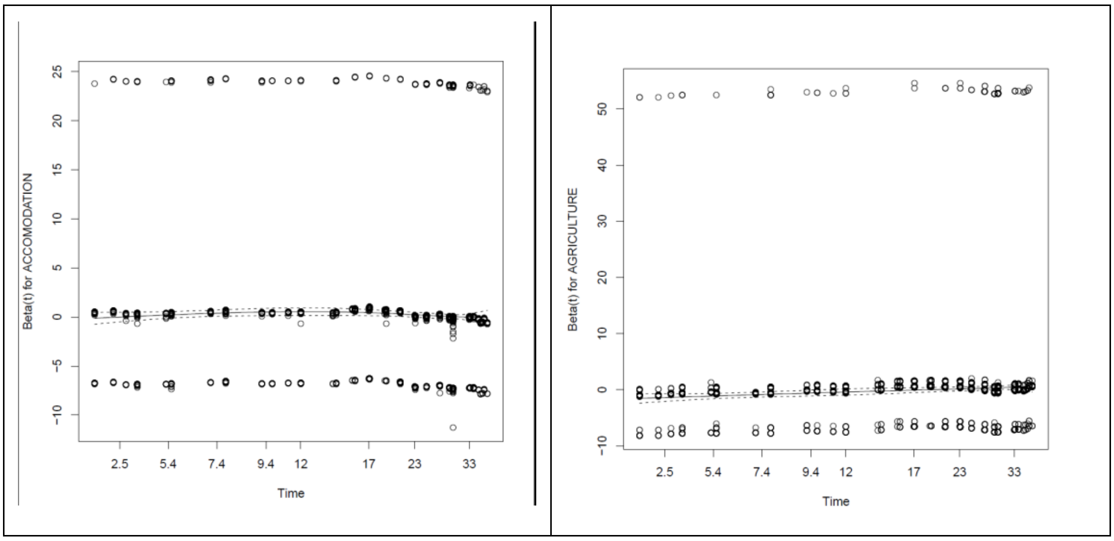
	chisq	df	p
ACCOMODATION	2.9264	1	0.087
AGRICULTURE	16.6566	1	4.5e-05
COMMERCIAL_REAL_ESTATE	1.2386	1	0.266
CONSTRUCTION	4.1469	1	0.042
ENERGY	6.5147	1	0.011
TRADE	0.2288	1	0.632
SHIPPING	6.2479	1	0.012
FINANCIAL_SERVICES	0.8196	1	0.365

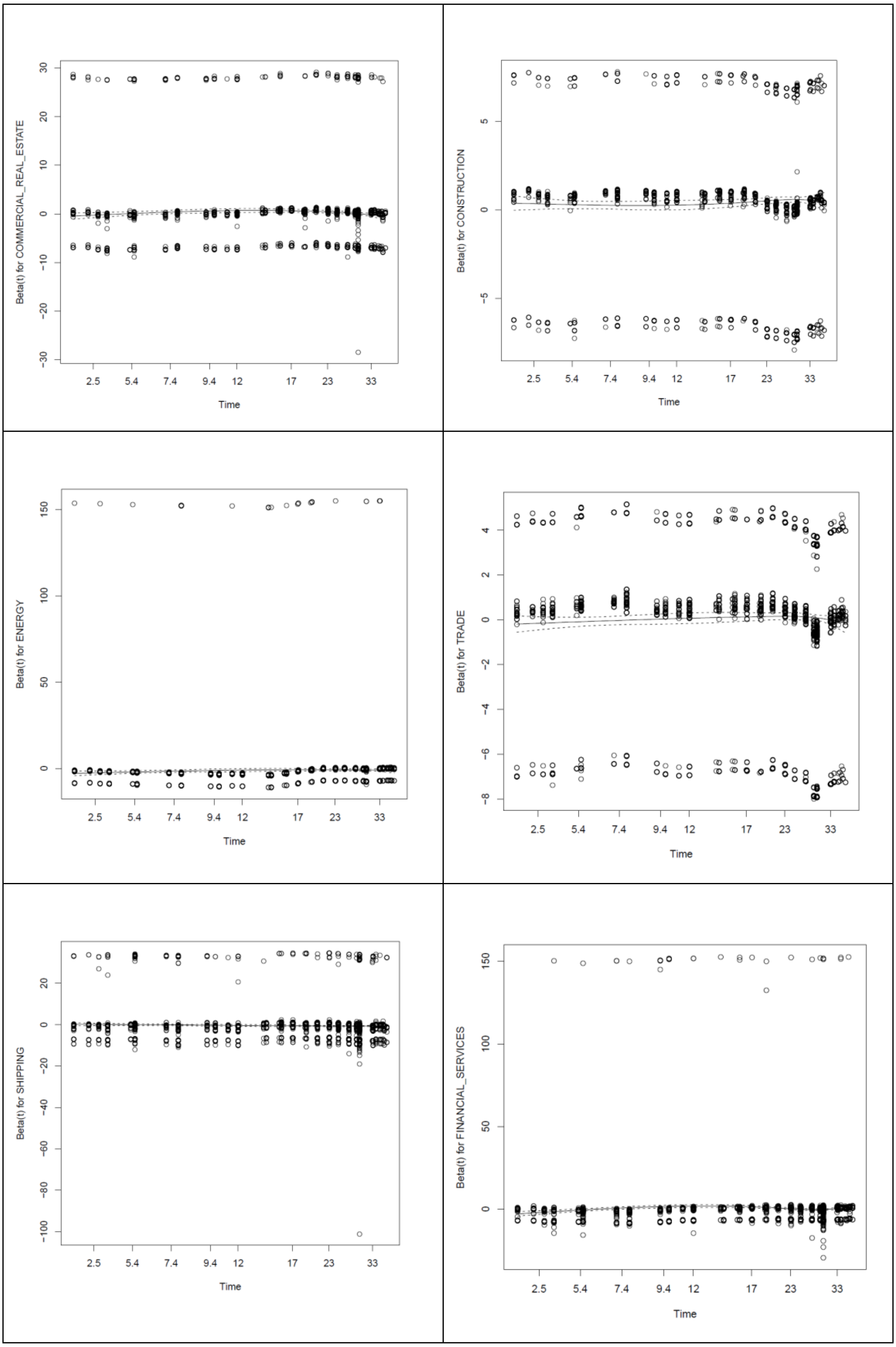
FOOD_SERVICE	0.9127	1	0.339
HEALTH_SERVICES	3.2606	1	0.071
MANUFACTURING	0.0262	1	0.871
PUBLIC_ADMINISTRATION	0.0167	1	0.897
TELECOMS_IT_MEDIA	1.8530	1	0.173
TRANSPORT_OTHER_THAN_SHIPPING	2.9066	1	0.088
bank_size	53.2455	1	2.9e-13
Loan_value	1.6494	1	0.199
GLOBAL	109.1179	16	6.6e-16

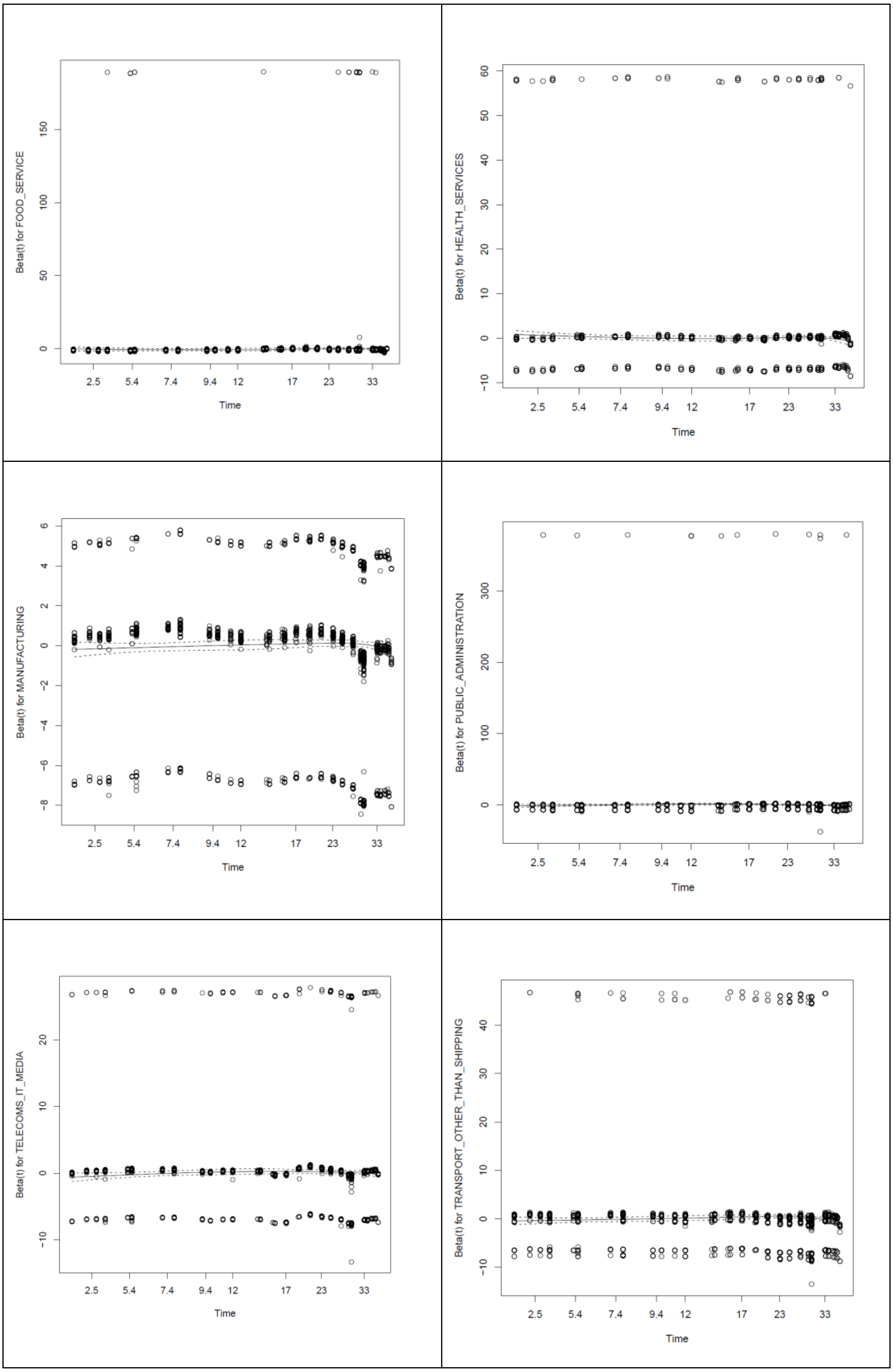
In this case, Agriculture, Shipping and Energy significantly change over time (P = 0.05 for testing the correlation rho between the scaled Schoenfeld residual and time), while the global test of PH is done penalizing for 16 d.f., and the P value is 6.6e-16.

The graphical examination of the trends is performed by using the Schoenfeld residuals. Again, we compute scaled Schoenfeld residuals separately for each predictor and test the PH assumption using the "correlation with time" test. Also, I plot the smoothed trends in the residuals. The plot method for cox.zph objects uses cubic splines to smooth the relationship.

FIGURE 7.9: Raw and spline-smoothed scaled Schoenfeld residuals for all the predictors coded from the Cox model C fit, with ± 2 standard errors.




Beta(t) for COMMERCIAL_REAL_ESTATE
Beta(t) for CONSTRUCTION
Beta(t) for ENERGY
Beta(t) for TRADE
Beta(t) for SHIPPING
Beta(t) for FINANCIAL_SERVICES
Time
2.5 5.4 7.4 9.4 12 17 23 33


Beta(t) for FOOD_SERVICE
Time
Beta(t) for HEALTH_SERVICES
Time
Beta(t) for MANUFACTURING
Time
Beta(t) for PUBLIC_ADMINISTRATION
Time
Beta(t) for TELECOMS_IT_MEDIA
Time
Beta(t) for TRANSPORT_OTHER_THAN_SHIPPING
Time

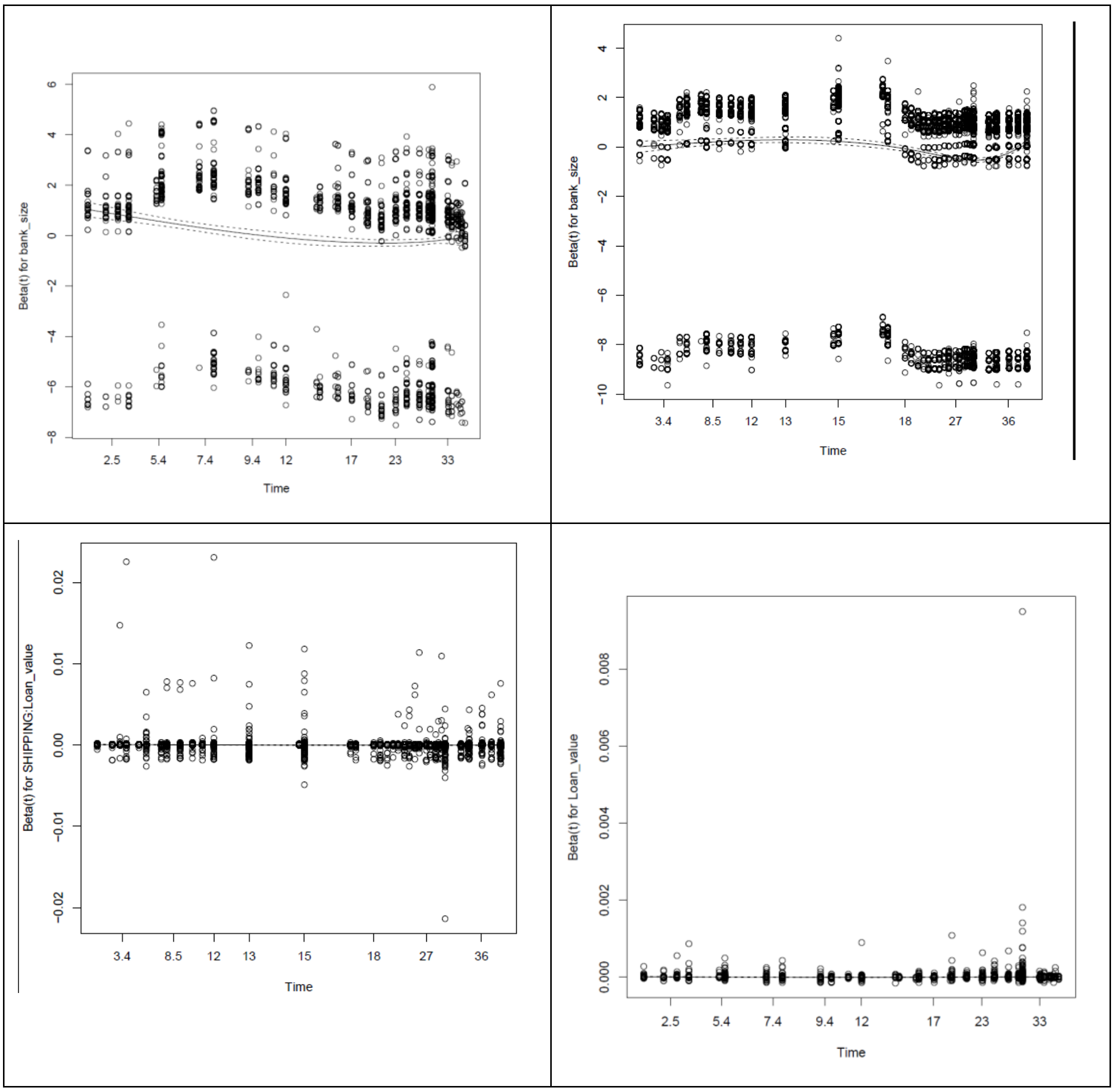


Figure 7.9 computes scaled Schoenfeld residuals separately for each predictor and tests the proportional hazards assumption using the "correlation with time" test. The graphical examination of the trends shows that there are systematic departures from the horizontal line for a number of predictors; therefore, I can conclude that there are strong indications of non-proportional hazards for these predictors.

7.4.3.2 Evaluation of collinearity of the Cox Model C

Next, we need to investigate whether there is a case when at least one of the predictors can be predicted well from the other predictors. In this case, the standard errors of the regression coefficient estimates can be inflated and corresponding tests have reduced power. In stepwise variable selection, collinearity can cause predictors to compete and make the selection of "important" variables arbitrary. One way to quantify collinearity is with variance inflation factors or VIF, which in ordinary least squares are diagonals of the inverse of the $X'X$ matrix scaled to have unit variance.

TABLE 7.9: Checking Collinearity for the sample of early terminations (Total of 11,635 rows)

```
#Checking Collinearity
> vif(Cox.fit)
          ACCOMODATION                    AGRICULTURE
              1.248068                       1.115073
COMMERCIAL_REAL_ESTATE                   CONSTRUCTION
              1.211127                       1.769252
                ENERGY                          TRADE
              1.036224                       2.146280
              SHIPPING             FINANCIAL_SERVICES
              1.224879                       1.054209
          FOOD_SERVICE                HEALTH_SERVICES
              1.000729                       1.102351
         MANUFACTURING          PUBLIC_ADMINISTRATION
              2.038412                       1.016316
      TELECOMS_IT_MEDIA  TRANSPORT_OTHER_THAN_SHIPPING
              1.223839                       1.137298
             bank_size                     Loan_value
              1.039756                       1.046763
```

Again, the variance inflation factors don’t look enormous - it may be that removing one of these variables will help make the others look more significant.

7.4.4 Cox Model D: Using the explanatory variables CONSTRUCTION, ENERGY, COMMERCIAL_REAL_ESTATE and SHIPPING for the Cox Model and for early terminations

Model D takes into account the dataset of early terminations and it is restricted to the following explanatory variables, Construction, Energy, Commercial Real Estate and Shipping.

TABLE 7.10: Results of the Cox model D fit and the probability of a loan becoming non-performing for the whole sample (Total of 11,635 rows)

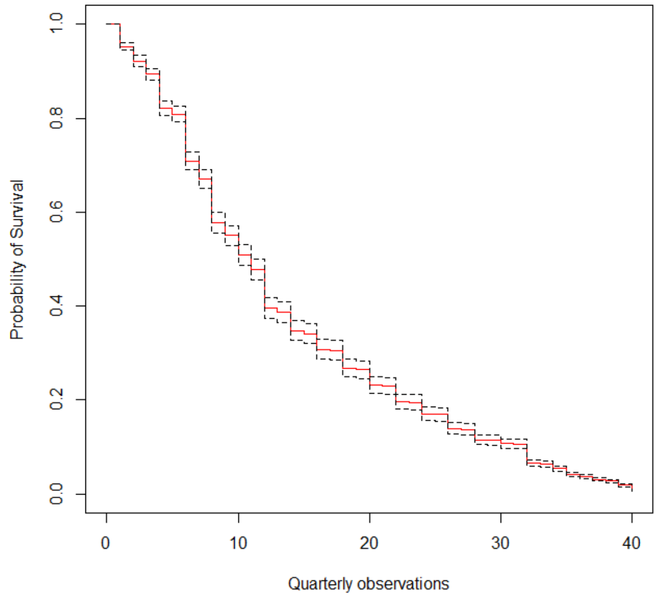
```
>

> Cox.fit1 <- coxph(Surv(time1, time2, NPL) ~ CONSTRUCTION +ENERGY + COMMERCIAL_REAL_ESTATE + SHIPPING, data= greekmacro, x=TRUE)

> Cox.fit1

Call:

coxph(formula = Surv(time1, time2, NPL) ~ CONSTRUCTION + ENERGY +
    COMMERCIAL_REAL_ESTATE + SHIPPING, data = greekmacro, x = TRUE)
```

	coef	exp(coef)	se(coef)	z	p
CONSTRUCTION	0.42886	1.53551	0.04011	10.693	< 2e-16
ENERGY	-1.12844	0.32354	0.17853	-6.321	2.60e-10
COMMERCIAL_REAL_ESTATE	0.09506	1.09973	0.07689	1.236	0.216
SHIPPING	-0.58296	0.55824	0.08258	-7.059	1.67e-12

```
Likelihood ratio test=241  on 4 df, p=< 2.2e-16 n= 11635, number of events= 4948

Concordance= 0.553  (se = 0.004 )

Likelihood ratio test= 241  on 4 df,   p=<2e-16

Wald test            = 220.8  on 4 df,   p=<2e-16

Score (logrank) test = 231.8  on 4 df,   p=<2e-16
```

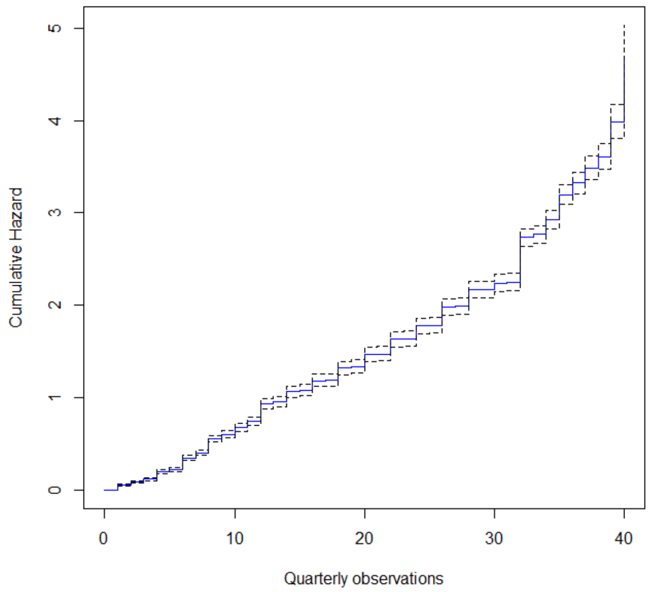
Both the implied survival curve for loans and the cumulative survival curve are being portrayed:

FIGURE 7.10: Survival Curve for loans implied from the Cox Model D for the sample of early terminations



The crosses in the plot indicate censoring points, while the drops indicate loans that nolonger exist and are thus no longer at risk of becoming NPLs.

FIGURE 7.11: Cumulative Hazard implied from the Cox Model D for the sample of early terminations



From the above analysis it can be derived that the construction sector has an increased hazard of its loans becoming NPLs, by keeping all the other variables constant. On the other hand, the shipping and the energy sectors have a decreased hazard of becoming

NPLs by keeping all the other variables constant. The commercial real estate does not seem to indicate a specific hazard of loans becoming NPLs. The individual variables of the Cox model that predict a loan becoming an NPL with statistical significance ($p<0.000$) were the construction, energy and shipping sectors with a high probability of occurrence.

7.4.4.1 Evaluation of the proportional Hazards Assumption of the Cox Model D

Also, for this model, it is important to validate how the survival or hazard functions for various subjects are connected.

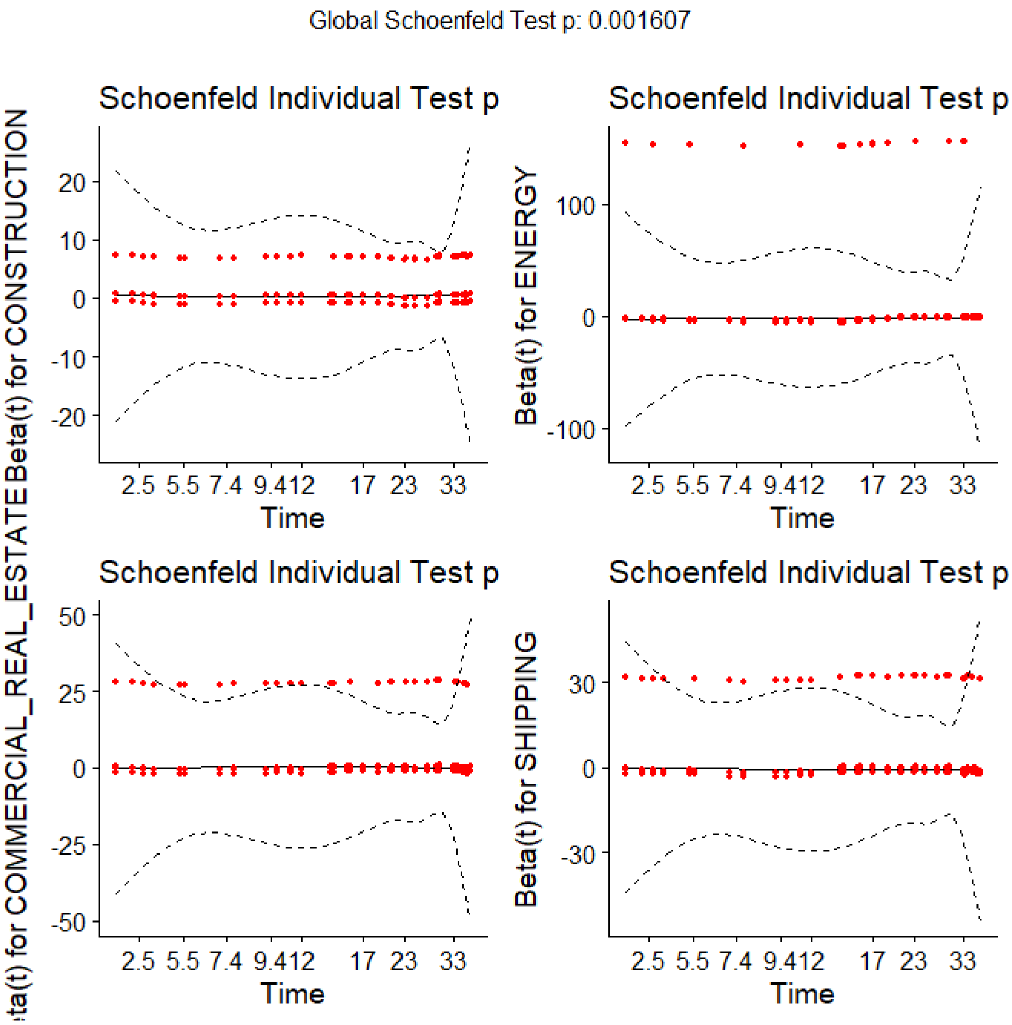
TABLE 7.11: Checking the Proportional Hazards Assumption for the whole sample for Cox Model B (Total of 11,635 rows)

```
> #Checking Proportional Hazards Assumption
> cox.zph(Cox.fit1)
```

	chisq	df	p
CONSTRUCTION	4.04	1	0.0443
ENERGY	6.56	1	0.0105
COMMERCIAL_REAL_ESTATE	1.19	1	0.2752
SHIPPING	6.54	1	0.0105
GLOBAL	17.41	4	0.0016

In this case, a couple of variables significantly change over time (P = 0.05 for testing the correlation rho between the scaled Schoenfeld residual and time), while the global test of PH is done penalizing for 4 d.f., and the P value is 0.0016. The graphical examination of the trends is performed by using the Schoenfeld residuals. I have computed scaled Schoenfeld residuals separately for each of the 4 predictors and tested the PH assumption using the “correlation with time” test. Also I plot the smoothed trends in the residuals.

FIGURE 7.12: Raw and spline-smoothed scaled Schoenfeld residuals for the 4 predictors, Construction, Energy, Shipping and Commercial Real estate coded from the Cox D model fit, with ± 2 standard errors.



Through the graphs, we do observe certain systematic departures from a horizontal line; therefore, we can conclude that there are certain indications of non-proportional hazards for these 4 predictors.

7.4.4.2 Evaluation of collinearity of the Cox Model D

TABLE 7.13: Checking Collinearity for the sample of early terminations (Total of 11,635 rows)

```
> #Checking Collinearity
> vif(Cox.fit1)
CONSTRUCTION    ENERGY    COMMERCIAL_REAL_ESTATE
1.014684        1.002408  1.009745
SHIPPING
1.008522
```

The variance inflation factors look negligible, so any sign of collinearity has been removed on Model D.

7.4.5 LTRCIT Decision tree model

7.4.5.1 Evaluation of the model with the whole sample

The first split is based on the Energy sector. Loans with an energy sector value>0 go to the right node and those with value less or equal to zero (with value of 0) go to the left node. The second split involves the Shipping sector; loans not in Shipping go to the left node and those in the Shipping sector go to the right node. The third split involves the Transport Other than the Shipping sector. Loans not in a Transport Other than the Shipping sector go to the left node and those in the construction sector go to the right node. The next splits involve bank size. In both cases, loans from a non-systemic bank go to the left node and those from a systemic bank go to the right node.

It appears that the loans in the Energy sector (node 10) demonstrate the best performance in terms of survival, meaning that they have the smallest probability of becoming NPLs. The loans in the Shipping sector obtained from small banks exhibit peculiar survival behaviour. Finally, the loans in the Construction sector seem to have the lowest survival probability.

FIGURE 7.13:LTRCIC fitted tree model for the whole sample

#LTRCIT tree

> LTRCIT.fit <- LTRCIT(Surv(time1, time2, NPL) ~ ACCOMODATION+AGRICULTURE +COMMERCIAL_REAL_ESTATE +CONSTRUCTION +ENERGY +TRADE+ FINANCIAL_SERVICES +

+ FOOD_SERVICE+ HEALTH_SERVICES +MANUFACTURING + PUBLIC_ADMINISTRATION +SHIPPING +

+ TELECOMS_IT_MEDIA +TRANSPORT_OTHER_THAN_SHIPPING+ bank_size+ Loan_value, data= greekmacro)

> LTRCIT.fit

Fitted party:

```
[1] root
|   [2] ENERGY <= 0
|   |   [3] SHIPPING <= 0
|   |   |   [4] bank_size <= 0
|   |   |   |   [5] TRANSPORT_OTHER_THAN_SHIPPING <= 0
|   |   |   |   |   [6] MANUFACTURING <= 0
|   |   |   |   |   |   [7] TRADE <= 0: 17.000 (n = 3873)
|   |   |   |   |   |   [8] TRADE > 0: 17.000 (n = 1444)
|   |   |   |   |   [9] MANUFACTURING > 0: 17.000 (n = 1301)
|   |   |   |   [10] TRANSPORT_OTHER_THAN_SHIPPING > 0: 13.000 (n = 238)
|   |   |   [11] bank_size > 0
|   |   |   |   [12] CONSTRUCTION <= 0
|   |   |   |   |   [13] MANUFACTURING <= 0
|   |   |   |   |   |   [14] TRADE <= 0
|   |   |   |   |   |   |   [15] PUBLIC_ADMINISTRATION <= 0: 15.000 (n = 18391)
|   |   |   |   |   |   |   [16] PUBLIC_ADMINISTRATION > 0: 22.000 (n = 209)
|   |   |   |   |   |   [17] TRADE > 0
|   |   |   |   |   |   |   [18] Loan_value <= 19960: 13.000 (n = 11697)
|   |   |   |   |   |   |   [19] Loan_value > 19960
|   |   |   |   |   |   |   |   [20] Loan_value <= 41767: 32.000 (n = 109)
|   |   |   |   |   |   |   |   [21] Loan_value > 41767: Inf (n = 15)
|   |   |   |   |   [22] MANUFACTURING > 0
|   |   |   |   |   |   [23] Loan_value <= 32102: 13.000 (n = 8991)
|   |   |   |   |   |   [24] Loan_value > 32102: 41.000 (n = 106)
|   |   |   |   [25] CONSTRUCTION > 0: 14.000 (n = 5608)
|   |   [26] SHIPPING > 0: 19.000 (n = 2642)
|   [27] ENERGY > 0
|   |   [28] bank_size <= 0: 41.000 (n = 140)
|   |   [29] bank_size > 0: 37.000 (n = 1078)
```

Number of inner nodes: 14, Number of terminal nodes: 15

7.4.5.2 Evaluation of the model with the sample of early terminations

The first split is based on the Shipping sector. Loans with a shipping sector value>0 go to the right node and those with value less or equal to zero (with value of 0) go to the left node. The second split involves the energy sector; loans not in Energy go to the left node and those in the Energy sector go to the right node. The third split involves the Construction sector. Loans not in a construction sector go to the left node and those in a construction sector go to the right node. The next splits involve bank size. In both cases, loans from a non-systemic bank go to the left node and those from a systemic bank go to the right node.

It appears that the loans in the Energy sector (node 16) have the best performance in terms of survival, meaning that they have the smallest probability of becoming NPLs. The loans in the Shipping sector obtained from small banks exhibit peculiar survival behavior. Finally, the loans in the Construction sector seem to have the lowest survival probability.

FIGURE 7.14:LTRCIC fitted tree model for the sample of early terminations

```
> LTRCIT.fit

LTRCIT.fit <- LTRCIT(Surv(time1, time2, NPL) ~
ACCOMODATION+AGRICULTURE +COMMERCIAL_REAL_ESTATE +CONSTRUCTION +ENERGY +TRADE+ FINANCIAL_SERVICES  +

FOOD_SERVICE+  HEALTH_SERVICES +MANUFACTURING  + PUBLIC_ADMINISTRATION
 +SHIPPING +

TELECOMS_IT_MEDIA +TRANSPORT_OTHER_THAN_SHIPPING+ bank_size+  Loan_value,
data= greekmacro)
LTRCIT.fit


Fitted party:

[1] root

|   [2] SHIPPING <= 0

|   |   [3] ENERGY <= 0

|   |   |   [4] CONSTRUCTION <= 0

|   |   |   |   [5] bank_size <= 0
```

| | | | | [6] TRANSPORT_OTHER_THAN_SHIPPING <= 0: 12.000 (n = 5221)

| | | | | [7] TRANSPORT_OTHER_THAN_SHIPPING > 0: 11.000 (n = 309)

| | | | [8] bank_size > 0

| | | | | [9] TRADE <= 0

| | | | | | [10] MANUFACTURING <= 0: 10.000 (n = 10637)

| | | | | | [11] MANUFACTURING > 0

| | | | | | | [12] Loan_value <= 20488: 10.000 (n = 7802)

| | | | | | | [13] Loan_value > 20488: 20.000 (n = 206)

| | | | | [14] TRADE > 0: 11.000 (n = 9594)

| | | [15] CONSTRUCTION > 0: 8.000 (n = 4312)

| | [16] ENERGY > 0: 24.000 (n = 870)

| [17] SHIPPING > 0

| | [18] bank_size <= 0

| | | [19] Loan_value <= 11276: 24.000 (n = 359)

| | | [20] Loan_value > 11276: Inf (n = 453)

| | [21] bank_size > 0: 8.000 (n = 1060)

Number of inner nodes: 10, Number of terminal nodes: 11

Compared to Cox model, the LTRCIT tree model accounts for the interaction between variables and this is one of their main advantages compared to the Cox model. In this case, there appears to be an interaction between the Shipping and Energy Sectors with the Bank size and an interaction in the Trade and Manufacturing Sectors with the Loan Value.

7.4.6 LTRCART Decision tree model: Analyzing the vulnerabilities of specific sectors

The LTRCART Decision tree model is similar to the LTRCIT, but it uses the Loan Value. It has 9 terminal nodes. The model was run both for the whole sample and the sample of early terminations.

FIGURE 7.15:LTRCART fitted tree model with the whole sample

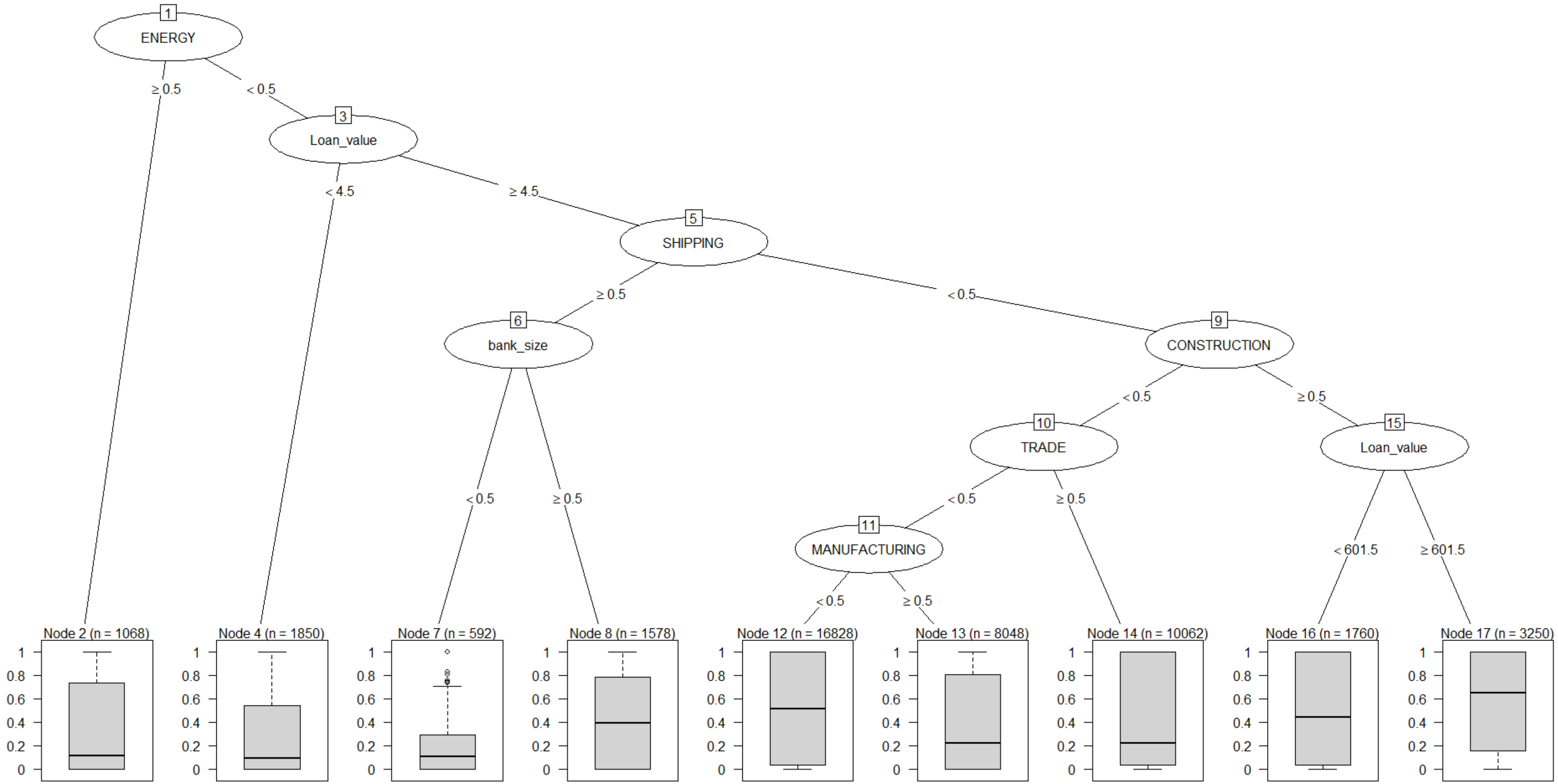
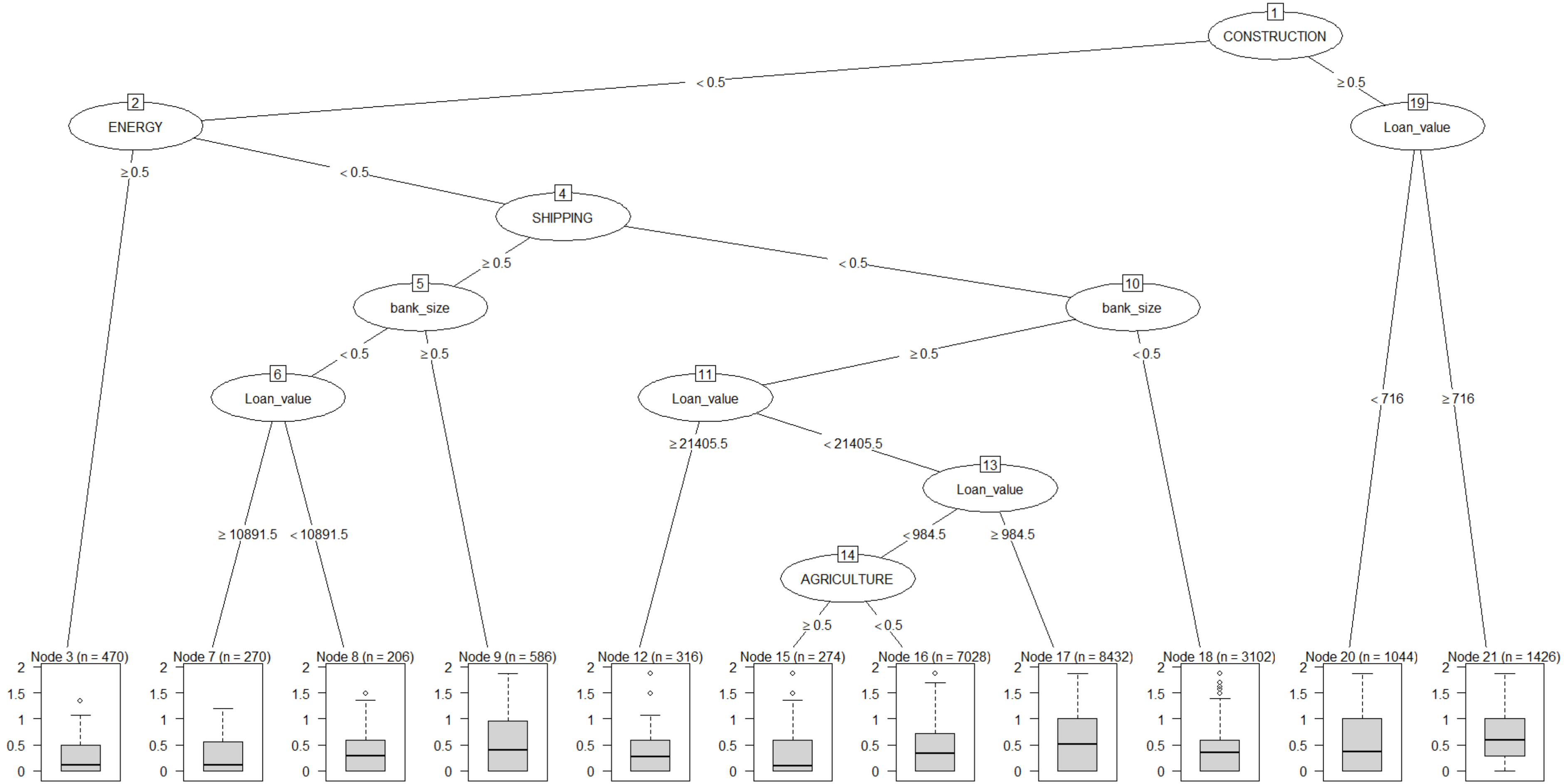


FIGURE 7.16:LTRCART fitted tree model with the sample of early terminations



In Figure 7.15, the first split is based on the Energy sector and the second on the Loan value. Loans with the Loan value>4.5 go to the right node and those with the Loan amount <4.5 to the left one. The third split involves the Shipping sector whereby loans with the Loan value>0.5 go to the left node and those with the Loan amount <0.5 to the right one. For the big loans, the bank size plays a role, i.e. loans from a non-systemic bank go to the left, while loans from a systemic bank go to the right. The next split is the Construction sector, whereby loans <0.5 go to the left node while loans >=0.5 go to the right node. Finally, the Construction Sector is also split to the Trade and Manufacturing Sectors on the left, while the Loan Value plays a role.

The ten terminal nodes are nodes 2,4, 7, 8, 12, 13, 14, 16 and 17. The number of loans in each terminal node is in parenthesis. Each terminal node contains a corresponding survival function estimated by using the Kaplan-Meier (KM) method. More precisely:

Node 2 shows survival function for loans in the Energy sector.

Node 4 shows survival function for loans with the loan values less than 4.5 in sectors other than Energy.

Node 7 shows survival function for loans in the Shipping sector other than Energy with the loan values less than 0.5 obtained from non-systemic banks.

Node 8 shows survival function for loans in the Shipping sector other than Energy with the loan values more than 0.5 obtained from systemic banks.

Node 12 shows survival function for loans in the manufacturing sector obtained from non-systemic banks.

Node 13 shows survival function for loans in the Manufacturing sector obtained from systemic banks.

Node 14 shows survival function for loans in the Trade sector obtained from systemic banks.

Node 16 shows survival function for loans with the loan values less than 601.5 obtained from sectors other than Energy, Shipping, Construction, Trade and Manufacturing.

Node 17 shows survival function for loans with the loan values more than 601.5 obtained from sectors other than Energy, Shipping, Construction, Trade and Manufacturing.

As we see from the plots of KM survival functions in Figure 7.15, the loans in the Energy sector (node 2) demonstrate the best performance in terms of survival, meaning that they have the smallest probability of becoming NPLs. The loans with the loan values less than 4.5 in sectors other than Energy (node 4) and the loans in the Shipping sector other than Energy with the loan values less than 0.5 obtained from non-systemic banks (node 7) exhibit similar behavior. However, the loans in the Shipping sector with the loan values greater than 0.5 obtained from large banks (node 8) have a greater probability of becoming NPLs. The loans in the construction sector have the worst survival compared to all loans. Finally, Figure 6.16 portrays the LTRCART fitted tree model with the sample of early terminations.

The comparison between the LTRCIT and LTRCART shows that LTRCART uses additional variable, namely, Loan value. This makes the two trees somewhat different. But both trees agree that the loans in the Energy sector have the smallest probability of becoming NPLs and that the loans in the Construction sector have the highest probability of becoming NPLs among all loans.

Compared to Cox model, the LTRCART tree model accounts for the interaction between variables and this is one of their main advantages compared to the Cox model. In this case, there appears to be an interaction between Shipping with Bank size and an interaction in Construction with Loan Value. In this sense, it is important to add interaction terms to the Cox model.

7.4.7 Revisiting the Cox model: Adding interaction variables to Cox models B and D

Based on the results obtained by the decision tree models, I have revisited the Cox model and I have added the following interaction variable:

Loan_value

The results of the Cox model with all the sample and with interaction variables is illustrated in table 7.14:

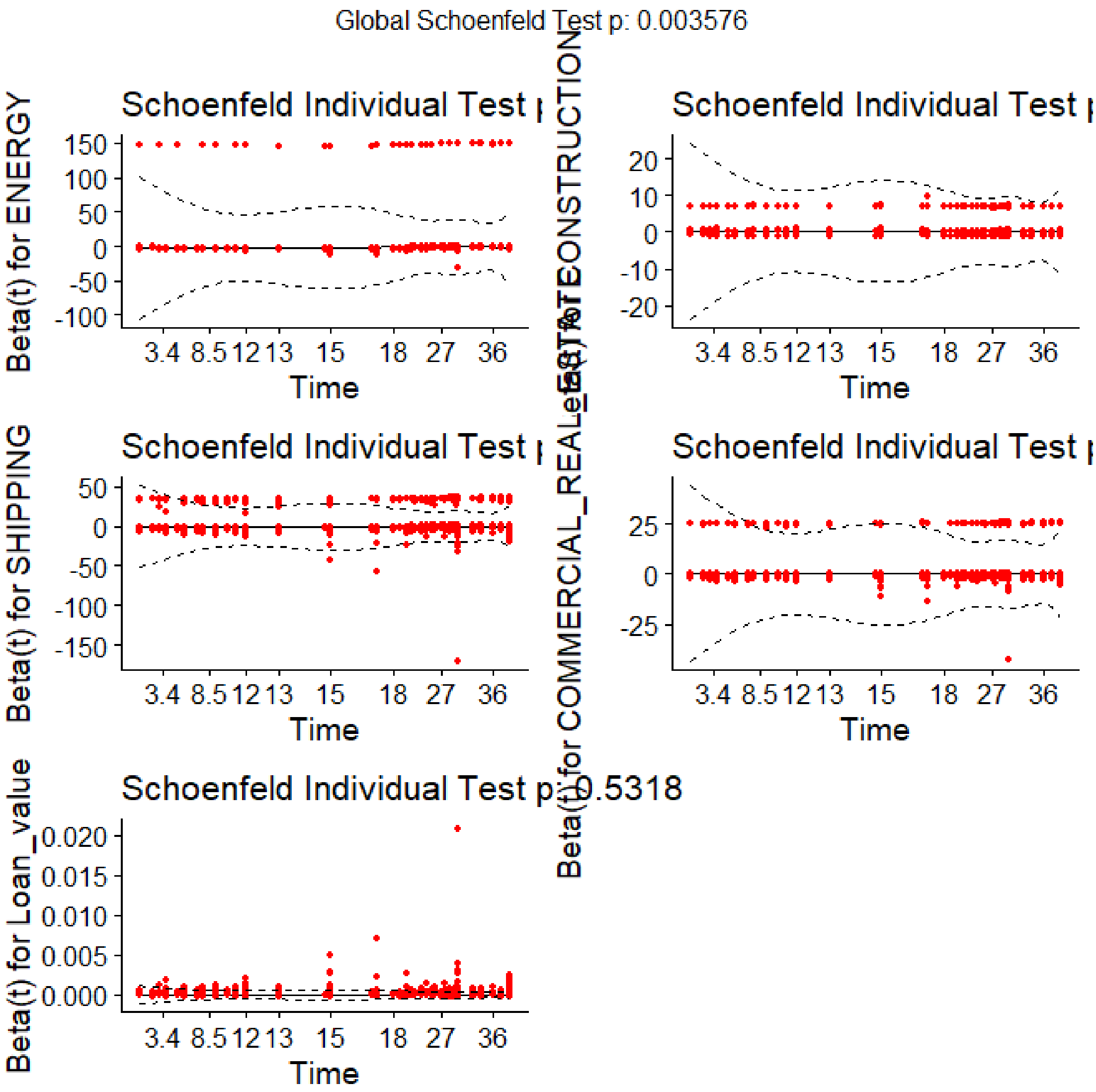
TABLE 7.14: Results of the Cox model B+ fit and the probability of a loan becoming non-performing for the whole sample with interaction variables (Total of 26,654 rows)

```
Call:
coxph(formula = Surv(time1, time2, NPL) ~ ENERGY + CONSTRUCTION +
    SHIPPING + COMMERCIAL_REAL_ESTATE + Loan_value, data = greekmacro)

  n= 25866, number of events= 13319
   (29976 observations deleted due to missingness)

                              coef      exp(coef)  se(coef)       z Pr(>|z|)
ENERGY                     -1.147e+00  3.175e-01  1.063e-01    -10.790  < 2e-16 ***
CONSTRUCTION                2.117e-01  1.236e+00  2.447e-02      8.650  < 2e-16 ***
SHIPPING                   -3.257e-01  7.221e-01  5.278e-02     -6.170 6.82e-10 ***
COMMERCIAL_REAL_ESTATE      1.001e-01  1.105e+00  4.462e-02      2.243   0.0249 *
Loan_value                 -3.752e-06  1.000e+00  1.150e-06     -3.263   0.0011 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Concordance= 0.533  (se = 0.003 )
Likelihood ratio test= 333.5  on 5 df,   p=<2e-16
Wald test            = 267.4  on 5 df,   p=<2e-16
Score (logrank) test = 283.1  on 5 df,   p=<2e-16
```

From the above analysis it can be derived that the construction and the commercial real estate sectors have an increased hazard of its loans becoming NPLs, by keeping all the other variables constant, with a statistical significance ($p<0.000$) in the relevant sectors. On the other hand, each one of the shipping and energy sectors have a decreased hazard of becoming NPLs by keeping all the other variables constant with a statistical significance ($p<0.000$) in the relevant sectors.

It can be seen that the *Loan value" has highly statistically significant coefficient, decreased hazard of becoming NPL. Loan size - albeit important – is not associated with increased hazard of loans becoming NPLs. That means that funding of significant projects through loans do not get "infected" and do not "die" easily.

FIGURE 7.17: Raw and spline-smoothed scaled Schoenfeld residuals for the 5 predictors, Construction, Energy, Shipping, Commercial Real estate and Loan_value coded from the Cox B+ model fit, with ± 2 standard errors.



Finally, the results of the Cox model D+ with the sample early terminated loans and with interaction variables is illustrated in table 7.15:

TABLE 7.15: Results of the Cox model fit D+ and the probability of a loan becoming non-performing for the sample of the early terminated loans with interaction variables (Total of 11,635 rows)

	coef	exp(coef)	se(coef)	z	Pr(>|z|)	
ENERGY	-1.123e+00	3.252e-01	1.785e-01	-6.291	3.16e-10	***
CONSTRUCTION	4.390e-01	1.551e+00	4.018e-02	10.926	< 2e-16	***
SHIPPING	-5.830e-01	5.582e-01	8.381e-02	-6.955	3.51e-12	***
COMMERCIAL_REAL_ESTATE	1.057e-01	1.111e+00	7.718e-02	1.370	0.171	
Loan_value	-2.091e-07	1.000e+00	1.238e-06	-0.169	0.866	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Concordance= 0.545 (se = 0.005)

Likelihood ratio test= 245.6 on 5 df, p=<2e-16

Wald test = 226.3 on 5 df, p=<2e-16

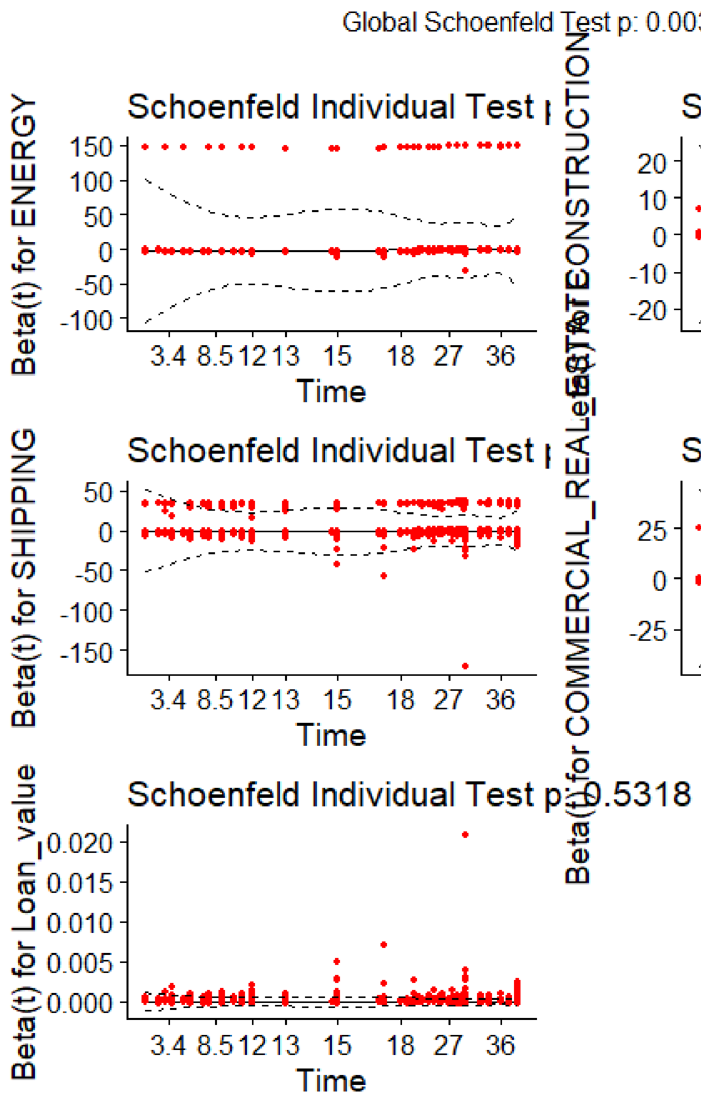
Score (logrank) test = 237.5 on 5 df, p=2e-16

In this case, it can be derived that the construction sector has an increased hazard of its loans becoming NPLs, by keeping all the other variables constant, with a statistical significance ($p<0.000$). On the other hand, the shipping and energy sectors have a decreased hazard of becoming NPLs by keeping all the other variables constant with a statistical significance ($p<0.000$). However, it appears that for the sample of early terminated loans the model cannot predict with a statistical significance that there is an increased hazard of the loans in the commercial real estate sector becoming NPLs.

Having said that, loans related to Greek commercial real estate had a very serious impact on banks during the previous crises. Although the potential impact on real estate loans in the coming years will be smaller compared to the crisis of 2008, the most serious changes brought by the pandemic crisis may mean greater in depth and longer in time horizon falls in some sectors of commercial real estate. Of course, banks are more adequately capitalized compared to ten years ago, which means that they have more room to absorb any losses. In addition, banks are less exposed to commercial real estate compared to 2008, but in some cases risk has been transferred to other investors such as hedge funds that moved aggressively in the Greek market in 2016-2019. Many of these foreign funds expected that this year or next year they would leave the Greek market with significant profits, but they counted without the pandemic.

Finally, this model can predict with a statistical significance whether a loan can become an NPL, by taking the Loan Value parameter into consideration. As only the sample of early terminations is considered, there are more loans associated with the lender's decision to restructure them due to certain macroeconomic developments irrespective of the inability of the borrower.

FIGURE 7.18: Raw and spline-smoothed scaled Schoenfeld residuals for the 5 predictors, Construction, Energy, Shipping, Commercial Real estate and Loan_value coded from the Cox D+ model fit, with ± 2 standard errors.



It appears that there is no problem with the proportional hazards assumption and the smooth curve is fairly leveled across the time horizon here, as opposed to substantially increasing or decreasing in level as time passes.

Overall, B+ model is better, because it assigns significance to the interaction variable "Loan value". Loan size - albeit important – is associated with decreased hazard of loans becoming NPLs. This could be interpreted by the fact that a significant loan size is associated with a project from a significant counterparty that has a lower probability of default. It is the smaller loans to SMEs that warrant attention because they are suffering from being "infected" and "dying" to a greater extent.

CHAPTER 8 Discussion on model performance and further research

This is the first study to examine simultaneously the effects of the macroeconomic factors on credit risk based on aggregate databases using GAMLSS and the factors related to borrowers' behavior based on the most available granular databases (loan data) using Cox and Decision tree models. In the latter case, the number of observations in the sample were increased by the granular data on large exposures in addition to the aggregate data on loans and NPLs. In this respect, the granular database on Large Exposures has been assessed on a borrower-per-borrower base that would provide information about credit events in the full population of Greek corporates with loans above 1million euros over a long time period. Finally, the credit events have been reduced after taking into account data gaps, different origination dates and ratings classification. The approach in both databases is consistent as the data provided both in an aggregate and in a granular form is stemming from the same credit providers, i.e. banks.

8.1 Evaluation of model performance

This broad look at the problem suggests several insights. Overall, it was confirmed that while the incorporation of macroeconomic variables, bank specific and market specific variables, can be the explanatory variables for the course of NPLs, other loan variables relating to the sectors of the economy which are linked at the borrower level lead to a highly statistically significant increase in explanatory power.

My estimates of the effects of sector-specific factors of the economy to the prediction and forecasting of NPLs provides a new impetus which hasn't been researched in previous studies. More specifically, when taking into consideration all the explanatory variables relating to business sectors it can be derived that the construction sector has an increased hazard of its loans becoming NPLs, by keeping all the other variables constant. On the other hand, each one of the shipping, public administration and energy sectors have a decreased hazard of becoming NPLs by keeping all the other variables constant. However, when the explanatory variables were reduced to Construction, Energy, Commercial Real Estate and Shipping, it was made evident that the construction and the commercial real estate sector have an increased hazard of its loans becoming NPLs, by keeping all the other variables constant. On the other hand, the shipping and the energy sectors have a decreased hazard of becoming NPLs by keeping all the other variables constant.

Despite the fact that there wasn't any significant evidence of collinearity, this research has shown that a reduced Cox model in terms of its explanatory variables and for the same sample would not lose from each predictive power.

In addition, the explanatory variables for all the sectors of the economy were examined by reducing the sample to early terminated loans, i.e. loans that terminate before the end of the period. In this vein, termination considered the 4 possible cases whereby a loan is terminated due to an event (securitization, write-off, early repayment cases). Likewise in the case when the whole sample is being considered, i.e. not only the early terminated loans, the construction sector has an increased hazard of its loans becoming NPLs while the energy and the shipping sectors have a reduced hazard of its loans becoming NPLs. Similarly, the reduced explanatory variables Construction, Energy, Commercial Real Estate and Shipping of the economy were examined by reducing the sample to early terminated loans. In this case, it was found that the construction sector has an increased hazard of its loans becoming NPLs, by keeping all the other variables constant. On the other hand, the shipping and the energy sectors have a decreased hazard of becoming NPLs by keeping all the other variables constant. The commercial real estate does not seem to indicate a specific hazard of loans becoming NPLs.

However, it was only when the survival tree models were applied that it became evident that only a reduced set of explanatory variables are needed. More specifically, the decision trees have demonstrated that energy shipping and construction sectors appear as important nodes in the specification. At the same time, decision trees also revealed another fact that they account for the interaction between variables and this was not evident in the Cox models that have already been used. Tree models have the advantage of not requiring any functional form for the predictors and of not assuming additivity of predictors (i.e., recursive partitioning can identify complex interactions). More specifically, bank size and in particular loan value seem to play an important role. In order to utilize this information, the Cox model was revisited both for the whole sample and for the early terminations but with the reduced set of explanatory variables and the interaction term loan value was added. This appeared in many nodes both in the LCTRIT tree and in the LCART tree. Then the Cox model was revisited again with 4 predictors, i.e. energy, construction, shipping, commercial real estate and the interaction term loan value. It has finally been derived that the construction and the commercial real estate sectors have an increased hazard of its loans becoming NPLs, while each one of the shipping and the energy sectors have a decreased hazard of becoming NPLs. No other predictors, such as accommodation, food services, and manufacturing were eligible to predict loans becoming NPLs.

8.2 Suggestions for further research

8.2.1 Applicability of the models should be further tested against independent datasets across different countries and markets

The deliverables lead to the general conclusion that macroeconomic, bank lending behavior and market factors influence credit risk levels in Greece in a significant way. In addition, there are specific sectors in the economy that play a more significant role in loans becoming NPLs than others. For example, the primary sectors of the economy (i.e. construction/ energy) play a more significant role in loans becoming/not becoming NPLs with more explanatory power. On the other hand, the services sectors (i.e. accommodation and food service) did not provide any explanatory power.

In a nutshell, this research represents a broad first impetus at incorporating a wide range of measures of the macroeconomic environment into Gamlss' models and of specific economic sectors disaggregated at the borrower level into reduced-form Cox models for the hazard rates of several important credit events.

The issue that arises is whether models could still be applied in more complex financial environments, which are not prevalent in Greece, whereby the banking sector plays an active role not only as a credit provider through loans but also through market-based finance. In countries where banks are predominantly under public ownership, such as India or China, the conclusions may not be relevant. Similarly, the macroeconomic environment and market structure in these countries would be different, and this fact needs to be taken into consideration. In addition, research evidence suggests that there is a "bias" towards more advanced countries where data series are available for a long period of time. Liu L. X. et al. (2021) [215] reviewed 24 papers in the artificial intelligence and machine-learning research areas, and 41 papers that used regression models and discriminant analyses to assess bank failures. However, almost half of the machine-learning papers used U.S. bank data.

Therefore, what is imperative to address is whether the application of survival models can be generalized across independent data sets. Zhang W et. al. (2013) [310] propose Net-Cox, a network-based survival model, which to their knowledge is among the first models that directly incorporate network information in survival analysis. They applied this model to identify gene expression signatures associated with the outcomes of death and recurrence in the treatment of ovarian carcinoma. To evaluate the generalization of the models, they first measured the consistency among the signature genes selected from the three independent datasets by each method. The results demonstrate that Net-Cox effectively utilized the network information to improve gene selection and accordingly, the generalization of the model to independent data. Wang J et. al. [296] (2021) proposed a new real-world dataset and a novel multi-task based neural network, SurvNet, to further improve the prognosis prediction for IB-IIA stage lung cancer. The proposed SurvNet outperforms the traditional Cox model and Cox-Net significantly.

Nevertheless, the generalization of survival models that also apply to independent datasets is addressed in medical research but has yet not been properly tested in the banking systems across different countries and financial markets. What has been assessed so far is the importance of the use of macro-networks for the interpretation and prediction of banking crises in Europe, being an emerging domain in financial research with regard to the measurement of systemic risk. As a rule, the use of macro-networks augments existing early warning models and increases their predictive capacity. According to Peltonen T.A. et al. [247], early-warning models increase their predictive capacity in terms of predicting banking crises in relation to other traditional models, when augmented with macro-networks. Overall, it is observed that the driving factors for an increase in the early-warning performance are network measures that quantify the position of each banking sector with respect to all other banking sectors across Europe and non-banking sectors in the domestic economy. Another finding is that the assessment of the role of the banking sector as part of the overall financial and non-financial system is becoming even more important. As a result, macro-networks constitute a more comprehensive characterization of the interconnectedness (or position) of a banking sector, providing a more explicit characterization of the closeness of the banking sector to the real economy.

Finally, a more central position of the banking sector in the macro-network increases the probability of a banking crisis. While vulnerabilities are associated more to credit risk and to a lesser extent to funding and liquidity risk or market risk, a more central position of the banking sector in the macro-network increases the probability of a banking crisis, irrespectively of the instrument.

8.2.2 Model calibration should be further enhanced

Further research along these lines should proceed to assess calibration, i.e. the agreement between predicted probabilities and observed event rates or frequencies of the outcome within a given duration of time. Whereas assessing calibration is an important component of deriving and validating prediction models, in this particular research there are certain limitations.

Weathers B. [297] applied predicted survivor curves and Random Survival Forests to a number of publicly available datasets and compared their fits using prediction error curves and the concordance index. In this process they identified ‘types of data’ in which Random Survival Forests may be expected to outperform the Cox model.

Bertrand F. and Betrand M. M., (2021) [30] extended previous algorithms from Bastien et al. (2015) [29] to enable practitioners to apply new extensions of Partial Least Squares (PLS) models to censored data: group and sparse group PLS regression as well as their kernel counterparts. When applying the commonly used criteria, such as the cross-validated partial loglikelihood or a van Houwelingen scheme, these cross-validation methods failed with all the seven extensions of partial least squares regression to the Cox model, found in Bastien et al. (2015) [29]. In their simulation study, by spotting 23 performance measures of prediction accuracy and the newly found cross-validation, they performed a benchmark reanalysis that showed enhanced performances of these techniques and a much better behavior even against other well-known competitors.

Fang et. al. [128] found that the Kennedy-O'Hagan approach that is widely used for model calibration, cannot be used directly in this case, and they propose a method to incorporate the censoring information when performing model calibration.

Harrell F.E. et. al. [154] evaluated methods for graphically assessing the calibration of survival models. Due to the presence of censoring, they evaluated calibration at the specified quantiles of the observed survival time in the large super-population, rather than at the specified quantiles of event times. Censoring has not been incorporated in the set of simulations with quadratic interrelationships and with interactions as they found no effect of censoring in the previous set of simulations. They found that the calibration curves can perform as intended when the models are correctly specified and identified some forms of model mis-specification, as not all mis-specification factors could be identified. This demonstrates that a model can display adequate calibration despite being mis-specified.

McGough S.F. et al. (2021) [219] applied an approach for estimating penalized Cox proportional hazard model with LTRC survival data and compared it to penalized models designed for survival data that is right-censored but not left-truncated. Using simulation studies and examples from real-world EHR and genomics data, they showed that there is a need for approaches that can both adjust for left truncation and model high-dimensional data. In particular, their simulation showed that predictions from models that fail to adjust for left truncation will overestimate true survival probabilities whereas models that properly adjust can yield well calibrated survival predictions, even with high-dimensional data.

Baek et. al. (2021) [28] proposed a survival time prediction DNN architecture. It is the first paper to predict survival time through an end-to-end deep learning model with censoring data as previous deep learning-based approaches mainly studied classification methods to determine whether patients survive rather than predict their survival time directly.

As calibration models have not been systematically tested to handle simultaneously left truncation and right censoring, it is very challenging to test such models. An analyst could have mistakenly concluded that models which are non-adjusted for truncation could be indicative of good model performance when it could be driven in part by a high correlation between predictors and left truncation. Further research is also needed to construct R functions for models in order to bypass both the left truncation issue as well the censoring issue for calibration. This is very important for validation predictions, as adjustments are needed so that left truncation time is not correlated with survival time. In addition, research should also bypass the computational limitations and constraints in order to ensure comprehensiveness. Thompson N. C. et. al. (2020) [283] have shown that the computational limits of deep learning will soon be constraining for a range of applications, making the achievement of important benchmark milestones impossible if current trajectories hold. They suggest various ways of reducing the computational burden by (a) increasing computing power through Hardware accelerators; (b) reducing computational complexity through Network Compression and Acceleration; and (c) finding high-performing small deep learning architectures through Neural Architecture Search and Meta Learning.

CONCLUSIONS

The first aim of the thesis was to investigate the determinants that contribute to the NPLs formation. The empirical evidence justifies the use of GAMLSS models for such an analysis. In fact, GAMLSS models can be a more powerful way to address the impact of external factors to NPLs. It allows any distribution for the response variable where all the parameters of the distribution can be modelled as a function of explanatory variables, the fitted algorithm is modular, where different components can be added easily and it extends basic statistical models allowing flexible modelling of over-dispersion, excess of zeros, skewness and kurtosis in the data.

Both GAMLSS models found that macroeconomic variables, such as unemployment, appeared to affect credit risk levels. The GAMLSS models also provided evidence that the provisioning variable which describes bank lending behavior can affect credit risk levels. The third determinant that was found to affect credit risk levels (albeit at a lesser extent) is risk variables. Both of the models, i.e. the GAMLSS linear model and the best-fitted P spline model found some evidence that certain capital adequacy variables which perform as risk mitigants may be negatively related to credit risk.

The second research aim was to employ models of prediction and forecasting for NPLs. As noted in the Literature Review, many studies have addressed credit risk and delinquencies through the structural approach, based on market variables, and the statistical approach from the financial statements. In that sense, credit risk models were focused on static modeling using cross-sectional data. Although the logistic regression or discriminant analysis methods have contributed significantly to Loss Given Default (LGD) prediction, they have not considered "time to failure", which is an integral factor in corporate distress analysis. Some recent studies went further to utilize survival models in order to determine the survival time of loans. They have assessed whether the survival time differs by the loan category and studied the influence of predictors on survival of a loan but fell short of employing a monitoring system for NPL prediction and forecasting.

This Thesis extends earlier research by employing a short-term monitoring system with the aim to forecast "failures" i.e. NPL creation. The Cox proportional hazards regression models are incorporating time-to-event, involving a timeline, described by the survival function, indicating the probability that a loan becomes an NPL until time t. The time period of the short-term monitoring system applied in this research counts from the origination of the loan until the “death” of the loan, i.e. its termination, incorporating an “in between” observation point. The event is when the loan is initially being “infected”, i.e. it has become NPL. The creation of such a monitoring system allows the risk of a “failure” to change over time, measuring the likelihood of “failure” given the time it survived and a set of explanatory variables. The application of Cox proportional hazards models and survival trees to forecast NPLs applies in the Greek corporate sectors. Enduring sectors that have a smaller probability of becoming NPLs are the shipping, and the energy sectors, whereas the probability of loans becoming NPLs is magnified by the construction and commercial real estate sectors. Last but not least, this research has demonstrated that the superior proportional hazards model to forecast NPLs included apart from the industry sectors the following fixed variable: loan value (amount).

RECOMMENDATIONS TO THE BANKING INDUSTRY

It should be noted that the recovery of the Greek economy and the achievement of a sustainable economic growth require a healthy, functional and viable banking system. Nowhere in the world could a sustainable growth be observed if the financial system did not function properly, its key role being the provision of liquidity from those who have surpluses (depositors and investors) to the real economy that shows a lack of funds (businesses and households) through the channel of credit growth.

In this vein, banks need to step up their efforts to reduce their non-performing loans. However, the operational measures and the HAPS program are not enough to address the issue of non-performing loans but a more systemic solution should be envisaged in the form of a “bad bank”. In addition to a mechanical “sale” of non-performing loans, the banking sector should adjust to this new environment by addressing the high share of DTCs, avoid undue dilution of existing shareholders, abstain from using government subsidies in order to address the existing NPL stock and ensure transparency regarding the appropriate recognition of current and future losses on the loan book.

The necessity of the banks’ support of the Greek enterprises– with the assistance of alternative sources when and if applicable – is imperative due to the prolonged economic recession. Nevertheless, the sources of funding for the Greek banking groups are not countless and for this reason banks should make optimal use of these sources so that funds can be directed to the Greek economy, contributing thus to the efforts to exit the crisis.

Eurosystem funding to Greek banks has continued to decrease up to 2019 (ELA funding has already been zero) given the fact that a sustainable inflow of deposits is expected as Greece has entered the post-memoranda era. Banks should reduce their dependence on Eurosystem funding only to the extent that inflows of deposits are being observed at the same rate.

It should be noted that the maintenance of deposits at a satisfactory level is of paramount importance, as they constitute the most proper and prudent way of providing credit to existing exposures that banks maintain in the corporate sector. The longer-term objective, however, should be that banks maintain sufficient liquidity not only to reverse the deleveraging process observed today and to maintain existing exposures that banks have in the corporate sector but also to increase the provision of credit to the sectors in the future.

Banks have already tapped into the interbank market. They have drawn liquidity through repos and there is even observed an increasing trend of market utilization without collateral. Despite the fact that the interbank market does not yet offer an adequate source of funding, banks need to strengthen their penetration in these markets. This will facilitate a quick comeback once the conditions fully normalize.

In a period whereby the previous prolonged economic recession has come to its end and a new one has emerged, the reduction of credit risks will depend on a number of interrelated factors. Greek banks should strike the right balance between the management of high risks and the fulfilment of specific funding needs of Greek enterprises that would boost entrepreneurship and support households. Therefore, Greek banks are recommended to fully appraise the risks that are inherent in the new loan applications of their clients, but in such a way as to ensure that they do not put too much pressure on the markets. In addition, they should correctly price such risks and not require higher interest rates in the case of funding innovative products and services for which an immediate demand in the future is anticipated. It is more prudent to require a higher interest rate only in those cases where the degree of the creditworthiness of the borrower is high, according also to the implementation of the new stricter models for credit appraisal. In addition, they could modify the contractual terms of certain older loan agreements in order to relieve their borrowers - clients from the economic recession that had drastically restricted their incomes while at the same time avoid classifying them as non-performing.

Finally, in the new post-memorandum era whereby new risks are emerging due to COVID-19, it is imperative that banks can identify which corporate sectors have a higher probability of becoming NPLs and divert their loans to those sectors that demonstrate durability. Banks should direct their new lending to those small and medium-sized enterprises (SMEs) with a specialization in the field of new technologies, promote growth through the use of specialized staff and not require significant investment in fixed assets, in addition to working capital. This is very important, especially during a financial crisis or any other crisis that could unfold to the real economy. Investors can construct investment strategies to take advantage of corporates that may show deteriorating operations but have a significant growth potential. Financial institution regulators can determine which banks continue to provide lending to sectors that have a higher probability of being distressed and intervene to eliminate failure and disruption of financial markets, borrowers, and depositors. Future research may focus on other statistical techniques within a changing economic and regulatory environment.

ANNEXES

Annex 1a. Definition of variables for inclusion into the GAMLSS models

Variables on a quarterly basis

Variable	Definition	Category	Sample	Source
NPLs_consum	Non-performing loans of the consumer portfolio	NPLs - Provisions (on a solo - parent bank) basis	All Greek Banks (Greek commercial + Greek cooperatives	Bank of Greece - Aggregate supervisory statistics (since H1 2015 figures refer to non-performing exposures)
NPLs_mortgages	Non-performing loans of the mortgage portfolio			
NPLs_Corp	Non-performing loans of the corporate portfolio			
NPLs_total	Total Non-performing loans of all portfolios			
Consum_loans	Consumer loans			
Mortgages	Mortgage loans			
Corporates	Corporate loans			
Total_loans	Total loans			
Total_provisions	Total provisions			
NPLs_ratio_consum	Non-performing loans ratio of the consumer loan portfolio			
NPLs_ratio_mortgage	Non-performing loans ratio of the mortgage loan portfolio			
NPLs_ratio_corp	Non-performing loans ratio of the corporate loan portfolio			
Total_nplratio	Aggregate non-performing loans ratio			
Total_coverage_ratio	Coverage ratio of non-performing loans by provisions			
GDP_quarterly_volumes	GDP quarterly volumes	GDP	applies domestically in Greece	Hellenic Statistical Authority (ELSTAT)
GDP_yearly_volumes	GDP annual volumes (annualised from the quarterly volumes)			
GDP_change_quartervolumes	GDP (y-o-y % change based on quarterly figures)			
GDP_change_yearvolumes	GDP (y-o-y % change based on annualised figures)			

Employed_number	Number of employed people	Unemployment	applies domestically in Greece	Hellenic Statistical Authority (ELSTAT)
Unemployed_number	Number of unemployed people			
Inactive_number	Number of people registered as unemployed			
Unemployment_rate	The official Unemployement rate			
Operating_income_con	Operating Income	Profitability on a group-level (consolidated) basis	All Greek Banks (Greek commercial + Greek cooperatives	Bank of Greece - Financial Accounts (since 31.03.2016 supervisory financial accounts)
Operating_costs_con	Operating costs			
Profit_bef_prov_con	Profits before provisions (operating profitability)			
Flow of provisions_con	Flow of provisions			
Non_recurr_results_con	Non-recurrent results			
Profit_bef_tax_con	Profit before taxes			
Tax_con	Taxes			
Profit_aft_tax_con	Profit after taxes			
Operating_income_solo	Operating Income	Profitability on a parent-level (solo) basis	All Greek Banks (Greek commercial + Greek cooperatives	Bank of Greece - Financial Accounts (since 31.03.2016 supervisory financial accounts)
Operating_costs_solo	Operating costs			
Profit_bef_prov_solo	Profits before provisions (operating profitability)			
Flow of provisions_solo	Flow of provisions			
Non_recurr_results_solo	Non-recurrent results			
Profit_bef_tax_solo	Profit before taxes			
Tax_solo	Taxes			
Profit_aft_tax_solo	Profit after taxes			
CET1_capital_con	Common Equity Tier I capital (Core Tier I capital from 31.12.2010 until 31.12.2012)	Supervisory own funds. Components and ratios on a group-level (consolidated) basis	All Greek Banks (Greek commercial + Greek cooperatives	Bank of Greece - Aggregate supervisory statistics (since H1 2015 figures refer to non-performing exposures)
Add_T1_capital_con	Additional Tier I capital			
Total_Tier1_con	Total Tier I capital			
Tier2_capital_con	Tier II capital			
Total_own_funds_con	Total supervisory own funds			
Riskassets_creditrisk_con	Risk weighted assets for credit risk			
Riskassets_settlementrisk_con	Risk weighted assets for settlement risk			
Riskassets_marketrisk_con	Risk weighted assets for market risk			
Riskassets_operationalrisk_con	Risk weighted assets for operational risk			
Riskassets_otherrisk_con	Risk weighted assets for other risks			

Total_riskassets_con C.A.R_ratio_ con Tier1_ratio_con CET1_ratio_con	Total risk weighted assets Capital Adequacy Ratio Tier I ratio Common Equity Tier I ratio (Core Tier I ratio from 31.12.2010 until 31.12.2012)			
CET1_capital_solo Add_T1_capital_solo Total_Tier1_solo Tier2_capital_solo Total_own_funds_solo Riskassets_creditrisk_solo Riskassets_settlementrisk_solo Riskassets_marketrisk_solo Riskassets_operationalrisk_solo Riskassets_otherrisk_solo Total_riskassets_solo C.A.R_ratio_solo Tier1_ratio_solo CET1_ratio_solo	Common Equity Tier I capital (Core Tier I capital from 31.12.2010 until 31.12.2012) Additional Tier I capital Total Tier I capital Tier II capital Total supervisory own funds Risk weighted assets for credit risk Risk weighted assets for settlement risk Risk weighted assets for market risk Risk weighted assets for operational risk Risk weighted assets for other risks Total risk weighted assets Capital Adequacy Ratio Tier I ratio Common Equity Tier I ratio (Core Tier I ratio from 31.12.2010 until 31.12.2012)	Supervisory own funds. Components and ratios on a parent bank-level (solo) basis	All Greek Banks (Greek commercial + Greek cooperatives	Bank of Greece - Aggregate supervisory statistics (since H1 2015 figures refer to non-performing exposures)
Share_capital_con Share_premium_con Reserves_con Treas_shares_con Min_interest_con Hybrid_capital_con Total_equity_con	Share capital Share premium account Reserves and retained earnings Treasury shares Minority interest Hybrid capital Total equity capital	Accounting (book value) equity components on a group-level (consolidated) basis	All Greek Banks (Greek commercial + Greek cooperatives	Bank of Greece - Financial Accounts (since 31.03.2016 supervisory financial accounts)
Share_capital_solo Share_premium_solo Reserves_solo Treas_shares_solo Min_interest_solo Hybrid_capital_solo Total_equity_solo	Share capital Share premium account Reserves and retained earnings Treasury shares Minority interest Hybrid capital Total equity capital	Accounting (book value) equity components on a parent bank-level (solo) basis	All Greek Banks (Greek commercial + Greek cooperatives	Bank of Greece - Financial Accounts (since 31.03.2016 supervisory financial accounts)

Annex 1b. GAMLSS' MODELS in R

```
# clear everything in the work space
rm(list=ls())
#   Reading the data
da<-read.csv("C:/Users/kkanellopoulos/Dropbox/Kon Kanellopoulos - Prof M.
Stasinopoulos/Quarterly data_all.csv", header=TRUE)
#  the dimension   off the data
dim(da)
#  the names all the variables
names(da)
# read date as R object
da$Date<- as.Date(da$Date, "%d/%m/%Y" )
# clear the explanatory variables with NA's
index <- c(0)
# first find which have NA's
for (i in 2:81)
{
  cat(i, "\n")
 if (any(is.na(da[, i]))) index = c(index,i)
}
# the variables with NA are
index[-1]
# take them off the data
da <- da[,-index[-1]]
dim(da)
# now we reduce to 63 variables all together
# check if any NA
any(is.na(da))
# No fine
names(da)
# we will analyze NPLs_total as response so the
# extra columns are not needed in the analysis

# NPLs_consum          2
# NPLs_mortgages       3
# NPLs_Corp            4
# NPLs_total           5
# NPLs_ratio_consum    11
# NPLs_ratio_mortgage  12
# NPLs_ratio_corp      13
# Total_nplratio       14
# Total_coverage_ratio 15)

names(da[, -c(1,2,3,4,11,12,13,14,15,73)])

da1 <- da[,-c(1,2,3,4,11,12,13,14,15,73)]
dim(da1)
plot(da1[,1:10])
plot(da1[,c(1,11:20)])
```

```
plot(da1[,c(1,21:30)])
plot(da1[,c(1,31:40)])
plot(da1[,c(1,41:50)])
plot(da1[,c(1,51:60)])
plot(da1[,c(1,61:65)])

#plot(da1[,c(1,61,64)])
#------------------------------------------------------------
#Start the analysis
#  Bring GAMLSS
# selecting variables using GAIC
library(gamlss)
#  fit null model to start from
m0 <- gamlss(NPLs_total~1, data=da1)
#  get the formula for model selection
FORM<-as.formula(paste("~",paste(paste(paste("(",
          names(da1)[-1], sep=""),")",sep=""), collapse="+")))
FORM
# select the best variables as linear functions
mf <- stepGAIC(m0, scope=list(lower=~1, upper=FORM), k=10)
#  plot the fitted linear terms
# important this plot in conjunction with the summary
# will give the results from the selection exercise
term.plot(mf, pages=1, partial=T)
# get the coefficients and standard errors
summary(mf)
# residual plot
plot(mf)
plot(mf, ts=T)
wp(mf)
#----------------------------------------------------------
# Using Smoothers rather than linear
FORM1<-as.formula(paste("~",paste(paste(paste("pb(",
        names(da1)[-1], sep=""),")",sep=""), collapse="+")))
# using pb() P-splines
mfpb <- stepGAIC(m0, scope=list(lower=~1, upper=FORM1), k=10)
summary(mfpb)
term.plot(mfpb, pages=1, partial.resid=TRUE)
plot (mfpb)
wp(mfpb)
# using GAIC to compare models
GAIC(mf,mfpb,k=2)
# using worm plots of the residuals
wp(mf, ylim.all=.5)
#######
wp(mfpb, ylim.all=.5)
```

Annex 2a.Data formulation of the Large Exposures Database: Final panel data set

Variable-Column A: Date: The date when the panel data start. For the whole period 2014-2017 the sequence of lender and borrower does not change.
Variable-Column B: Bank: Bank's own classification code.
Variable-Column C: Bank Binary: If the lender is one of the 4 systemic banks (National Bank of Greece, Alpha Bank, Bank of Piraeus, Eurobank), then denote this with 1, otherwise denote this as 0.
Variable-Column D: Loan ID: This is the unique loan identifier. It stems from the unique borrower identifier but in certain cases, the initial borrower identifier was truncated into 2 or 3 categories to reflect the fact that the borrower time series has changed substantially. Therefore, the initial loan has to be split to reflect the fact that it may have been restructured or just to signal that the lender has changed (i.e. due to a merger) or the terms and conditions of the loan has changed so drastically that it has to be classified as a new loan.
Variable-Column E: Origination date for loans: This is the period whereby the first value of the loan appears in the database. This covers the whole period that the database is in existence, i.e. since 2006, not only the period of the panel data (i.e. 2014-2017).
Variable-Column F: Observation point: This is set to 31.12.2013.
Variable-Column G: Origination value for loans (or loan value): This is the first value of the loan that appears in the database. This covers the whole period that the database is in existence, i.e. since 2006, not only the period of the panel data (i.e. 2014-2017).
Variable-Column H: Origination date for NPLs: This is the date where the first value appears as non-performing. Non-performing may mean that part of the payment is not received by the lender. If all the payment had not been received, i.e. the whole loan became non-performing, the whole loan would have been written off.
Variable-Column I: Early termination for loans: This is a binary variable which shows whether a loan ended before 31.03.2017 (1) or not (0).

Variable-Column J: Early termination Date for Loans: This is the last period whereby the loan value was last observed before 31.03.2017.
Variable-Column K: Early termination Value for Loans: The early termination value of loans is the value last observed of a loan before 31.03.2017.
Variable-Column L: Early termination Value for NPLs: The early termination value of loans is the value last observed of a loan before 31.03.2017.
Variable-Column M: Write-offs: They are designated as such if the end NPL value of the loan is more than 75% of the value of the gross loan. This is in the last quartile (the long-end) of the distribution. The underlying logic is that banks cannot do anything else but to write-off such loans. It is not a coincidence that such loans have a very bad credit rating (category of restructuring and below). Of course a significant write-off could come at a cost for banks, but the issue here is that banks did not have any alternative to recover some part of the loan due to the inability of the borrower.
Variable-Column N: Write-offs dates: This is the last period whereby the loan value appeared before it was written-off.
Variable-Column O: Securitization: They are designated as such if the end NPL value of the loan is less than 75% and more than 25% of the loan, i.e. in the intermediate 2 quartiles. In this case, the write-off can be avoided. It makes full sense that banks have the opportunity to transfer such loans to a third counterparty. They can split it in different tranches, i.e. one tranche may have the more "green" part of the loan, the second tranche may have equal "green" and "red", the third tranche more "red" than "green". The higher the risk (more red than green), the higher the return of the relevant tranche.
Variable-Column P: Securitization dates: This is the last period whereby the loan value appeared before it was securitized.
Variable-Column Q: Early repayment: All the remaining loans that terminate earlier than the end of the period under examination (03.2017) and do not fall in the categories Write-offs, Securitization or Matured. Such loans could either have an NPL or not.
Variable-Column R: Early repayment dates with NPLs: This is the last period whereby the loan value appeared before it was early repaid while it was also carrying an NPL component.
Variable-Column S: Early repayment dates without NPLs: This is the last period whereby the loan value appeared before it was early repaid while it was NOT carrying an NPL component.

Variable-Column T: Matured: This is the physical "closure" of the loan if no NPL is attached to it. They are designated as such if the early termination value for NPLs is zero and the loan is not truncated.
Variable-Column U: Matured dates: This is the last period whereby the loan value appeared before it matured.
Variable-Column V: This column provides the following 3 categorization of loans:
1. loan is not truncated and not restructured (category= 0)
2. loan is truncated but not restructured (category=1)
3. loan is truncated and restructured (category=2 or 3)

Category	**truncated**	**restructured**
0	**no**	**No**
1	**yes**	**No**
2,3	**yes**	**Yes**

Variable-Column W: Restructured refers to the category whereby the loan has already been separated into a different row (i.e. truncated loans categories 2 and 3).
Variable-Column X: The origination date is given ONLY for restructured (R) loans, otherwise the symbol NR (non-restructured) is retained.
Variable-Column Y: This column provides 3 results: If restructured loans have an NPL then the response is 1. If restructured loans do not have an NPL then the response is 0. For the remaining loans, the symbol NR is retained.
Variables-Columns Z, AA: The loan origination value and the NPL origination value for Restructured loans is provided in 2 separate columns, otherwise the loan was labelled as non-applicable. The latter information is very important, as there could be a distinction on whether this was a forced restructuring (because of the NPL), or a restructuring based on business considerations (0 value without an NPL). Also the fact that the Loan and the NPL value for restructured loans is provided is very important as a sensitivity analysis could take place regarding the different thresholds of NPLs values in relation to the loan values, which could be linked to the decision for restructuring.
Variable-Columns AB: Final date of observations.
Variable-Columns AC, AD:, Duration and status.
Variable-Column AE: Binary variable for the origination of NPLs. It is 1 if a loan becomes an NPL during the reporting period or 0 if it does not become an NPL.
Variable-Column AF: Origination date for NPLs: This is the date where the first value appears as non-performing within the period that the database is in existence 2006-2017.
Variable-Column AG: Lender Name: This is the name of the lender from whom the loan has been originated.
Variable-Column AH: Tax ID Creditor: This is the unique ID number for the creditor.
Variable-Column AI: Tax ID Borrower: This is the unique ID number for the borrower.
Variable-Column AJ: Sector: In the column "Borrower Information: Sector" the two-digit code of the borrower's economic activity is given, based on the most recent classification of the Hellenic Statistical Authority (STAKOD), which indicates the debtor's principal activity. In case of parallel activities, the main activity (with the largest contribution to the turnover) of the business or individual is selected. In case the activity of the company or the individual is not known to the credit institution (lender), the code "00" "LACK OF ACTIVITY" is indicated.
Variable-Column AK: Sector broader group: In this column the full name of the principal activity is indicated, which was denoted by the two-digit code in the previous column AI.
Variables-Columns AL-AY: Binary variable for the 14 sectors. If a loan is classified in a specific sector, then the variable 1 appears, otherwise the variable 0 appears.

Annex 2b. COX and DECISION TREE MODELS in R

```
library(LTRCtrees)
library(partykit)
library(prodlim)
library(survival)
library(survminer,warn.conflicts = FALSE)
library(rms)
library(validate)
library(randomForestSRC)
library(pec)
library(polspline)
greekmacro<- read.table("D:/My Documents/Projects/Research/PHD/Survival Trees Cox
models/test4.csv", header = TRUE,fill = TRUE,sep=",")

#Cox model with all observations and all predictors
Cox.fit <- coxph(Surv(time1, time2, NPL) ~
ACCOMODATION+AGRICULTURE +COMMERCIAL_REAL_ESTATE +CONSTRUCTION
 +ENERGY +TRADE
+SHIPPING+ FINANCIAL_SERVICES  +FOOD_SERVICE+  HEALTH_SERVICES +MANU
FACTURING+ PUBLIC_ADMINISTRATION +
                  TELECOMS_IT_MEDIA  +TRANSPORT_OTHER_THAN_SHIPPING+
bank_size+  Loan_value , data= greekmacro)

Cox.fit
plot(survfit(Cox.fit), ylab="Probability of Survival",
    xlab="Quarterly observations", col=c("red", "black", "black"))
plot(survfit(Cox.fit, type="fleming"), col=c("blue", "black", "black"),
fun="cumhaz", ylab="Cumulative Hazard", xlab="Quarterly observations")
#Checking Proportional Hazards Assumption
cox.zph(Cox.fit)
#ggcoxzph(cox.zph(Cox.fit))
#pdf("D:/My Documents/Projects/Research/PHD/Survival Trees Cox models/lala0.pdf")
#for (i in 1:10){plot(cox.zph(Cox.fit))}
#dev.off()
#Checking Collinearity
vif(Cox.fit)
summary(Cox.fit)

#Cox model with all observations and 4 predictors

Cox.fit1 <- coxph(Surv(time1, time2, NPL) ~  CONSTRUCTION +ENERGY +
COMMERCIAL_REAL_ESTATE + SHIPPING, data= greekmacro, x=TRUE)
Cox.fit1
plot(survfit(Cox.fit1), ylab="Probability of Survival",
    xlab="Quarterly observations", col=c("red", "black", "black"))
plot(survfit(Cox.fit1, type="fleming"), col=c("blue", "black", "black"),
fun="cumhaz", ylab="Cumulative Hazard", xlab="Quarterly observations")
#Checking Proportional Hazards Assumption
cox.zph(Cox.fit1)
```

```
ggcoxzph(cox.zph(Cox.fit1))
#Checking Collinearity
vif(Cox.fit1)
summary(Cox.fit1)

#interactions variable Loan value added to Cox model:
Cox.fit21 <- coxph(Surv(time1, time2, NPL) ~ ENERGY +CONSTRUCTION+
SHIPPING+COMMERCIAL_REAL_ESTATE+Loan_value , data= greekmacro)
plot(survfit(Cox.fit21), ylab="Probability of Survival",
    xlab="Quarterly observations", col=c("red", "black", "black"))
plot(survfit(Cox.fit21, type="fleming"), col=c("blue", "black", "black"),
fun="cumhaz", ylab="Cumulative Hazard", xlab="Quarterly observations")
#Checking Proportional Hazards Assumption
cox.zph(Cox.fit21)
ggcoxzph(cox.zph(Cox.fit21))
#pdf("D:/My Documents/Projects/Research/PHD/Survival Trees Cox models/lala3.pdf")
#for (i in 1:10){plot(cox.zph(Cox.fit21))}
#dev.off()
#Checking Collinearity
vif(Cox.fit21)
summary(Cox.fit21)



#LTRCIT tree
LTRCIT.fit <- LTRCIT(Surv(time1, time2, NPL) ~
ACCOMODATION+AGRICULTURE +COMMERCIAL_REAL_ESTATE +CONSTRUCTION
 +ENERGY +TRADE+ FINANCIAL_SERVICES  +

FOOD_SERVICE+  HEALTH_SERVICES +MANUFACTURING  + PUBLIC_ADMINISTRAT
ION +SHIPPING +

TELECOMS_IT_MEDIA +TRANSPORT_OTHER_THAN_SHIPPING+ bank_size+  Loan_valu
e, data= greekmacro)
LTRCIT.fit
plot(LTRCIT.fit)
#Plot as partykit::party object with survival curves on terminal nodes
#LTRCIT.fit.party <- as.party(LTRCIT.fit)
#LTRCIT.fit.party$fitted[["(response)"]]<- Surv(greekmacro$time1, greekmacro$time2,
greekmacro$NPL)
#plot(LTRCIT.fit.party)

LTRCIT.fit1 <- LTRCIT(Surv(time1, time2, NPL) ~
CONSTRUCTION  +ENERGY +COMMERCIAL_REAL_ESTATE, data= greekmacro)
LTRCIT.fit1
plot(LTRCIT.fit1)
##Plot as partykit::party object with survival curves on terminal nodes
#LTRCIT.fit1.party <- as.party(LTRCIT.fit1)
#LTRCIT.fit1.party$fitted[["(response)"]]<- Surv(greekmacro$time1, greekmacro$time2,
greekmacro$NPL)
```

```
#plot(LTRCIT.fit1.party)

#LTRCART tree
LTRCART.fit <- LTRCART(Surv(time1, time2, NPL) ~
ACCOMODATION+AGRICULTURE +COMMERCIAL_REAL_ESTATE +CONSTRUCTION
 +ENERGY +TRADE+ FINANCIAL_SERVICES  +

FOOD_SERVICE+  HEALTH_SERVICES +MANUFACTURING  + PUBLIC_ADMINISTRAT
ION +SHIPPING +

TELECOMS_IT_MEDIA  +TRANSPORT_OTHER_THAN_SHIPPING+ bank_size+  Loan_val
ue , data= greekmacro)

LTRCART.fit
## Plot as partykit::party object with survival curves on terminal nodes
LTRCART.fit.party <- as.party(LTRCART.fit)
#LTRCART.fit.party$fitted[["(response)"]]<- Surv(greekmacro$time1, greekmacro$time2,
greekmacro$NPL)
plot(LTRCART.fit.party)

LTRCART.fit1 <- LTRCART(Surv(time1, time2, NPL) ~
CONSTRUCTION  +ENERGY+  COMMERCIAL_REAL_ESTATE, data= greekmacro)

LTRCART.fit1
## Plot as partykit::party object with survival curves on terminal nodes
LTRCART.fit1.party <- as.party(LTRCART.fit1)
#LTRCART.fit.party$fitted[["(response)"]]<- Surv(greekmacro$time1, greekmacro$time2,
greekmacro$NPL)
plot(LTRCART.fit1.party)
```

ABBREVIATIONS

ABS

An asset-backed security (ABS) is a type of financial investment that is collateralized by an underlying pool of assets—usually ones that generate a cash flow from debt, such as loans, leases, credit card balances, or receivables.

aggregated MFI balance sheet

A balance sheet comprising the sums total of the data included in the harmonised balance sheets of all MFIs that are resident in the euro area (inter-MFI positions on a gross basis). The legal basis for the collection of harmonised balance sheet statistics is laid down in Regulation ECB/2008/32. This Regulation is complemented by Guideline ECB/2007/9, which sets out the procedures to be followed by NCBs when reporting information relating to money and banking statistics to the ECB.

APRC

The annual percentage rate of charge (APRC) is an effective lending rate that covers the total costs of the credit to the consumer, i.e. the interest payments as well as all other related charges. The concept of "total costs for the consumer" was designed for the purpose of consumer protection. The compilation of the APRC is defined in Directives 2008/48/EC and 2014/17/EU.

asset

A resource controlled by an enterprise as a result of past events and from which future economic benefits are expected to flow to the enterprise.

AT1

Additional Tier 1 (AT1) is a subcomponent of Tier 1 capital (see supervisory own funds) whereby Tier 1 = CET1 + AT1. AT1 is defined as instruments that are not common equity but are eligible for inclusion in this tier. An example of AT1 capital is a contingent convertible or hybrid security, which has a perpetual term and can be converted into equity when a trigger event occurs.

authorisation

The consent given by a participant (or a third party acting on behalf of that participant) in order to transfer funds or securities.

average cost

The continued (or weighted) average method, by which the cost of every purchase is added to the existing book value to produce a new weighted average cost.

bad bank

A bad bank is a bank set up to buy the bad loans and other illiquid holdings of another financial institution. The entity holding significant nonperforming assets will sell these holdings to the bad bank at market price. By transferring such assets to the bad bank, the original institution may clear its balance sheet—although it will still be forced to take write-downs.

Basel Committee on Banking Supervision (BCBS)

The primary global standard-setter for the prudential regulation of banks and a forum for cooperation on banking supervisory matters. Its mandate is to strengthen the regulation, supervision and practices of banks worldwide with the purpose of enhancing financial stability. BCBS members include organizations with direct banking supervisory authority and central banks.

Basel framework (Basel III)

A global regulatory framework for banks and banking systems, developed by the Basel Committee on Banking Supervision in response to the financial crisis of 2008. Basel III builds upon the Basel II rulebook. Its aim is to strengthen the regulation, supervision and risk management of the banking sector. The measures aim to improve the banking sector's ability to absorb shocks arising from financial and economic stress, improve risk management and governance, and strengthen banks' transparency and disclosures.

BIS

The Bank for International Settlements (BIS) is an international organization with a mission to support central banks' pursuit of monetary and financial stability through international cooperation, and to act as a bank for central banks.

bond market

The market for interest-bearing securities (with either a fixed or a floating rate and with a maturity of at least one year) that companies and governments issue to raise capital for investment. Fixed-rate bonds account for the largest share of this market.

capital controls in Greece

Capital controls were introduced in Greece in June 2015, when Greece's government came to the end of its bailout extension period without having come to an agreement on a further extension with its creditors and the European Central Bank decided not to further increase the level of its Emergency Liquidity Assistance for Greek banks.

As a result, the Greek government was forced to immediately close Greek banks for almost 20 days and to implement controls on bank transfers from Greek banks to foreign banks, and limits on cash withdrawals (only €60 per day permitted), to avoid an uncontrolled bank run and a complete collapse of the Greek banking system. The capital controls were gradually minimized until their complete removal on the 1st of September 2019.

capital conservation buffer (CCoB)

A capital buffer of up to 2.5% of a bank’s total exposures to avoid breaches of minimum capital requirements during periods of stress when losses are incurred. The capital buffer has been implemented in Europe via Article 129 CRD IV and must be met with CET1 capital. Phasing-in arrangements apply between 2016 and 2019, but earlier introduction is possible.

Capital Requirements Regulation / Capital Requirements Directive (CRR/CRD IV)

Capital Requirements Regulation and Directive: Regulation (EU) No 575/2013 on prudential requirements for credit institutions and investment firms (CRR) and Directive 2013/36/EU on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms (CRD IV). The CRR/CRD IV package transposes the global standards on bank capital (the Basel III agreement) into EU law.

CDS

A credit default swap (CDS) is a financial derivative that allows an investor to "swap" or offset his or her credit risk with that of another investor. For example, if a lender is worried that a borrower is going to default on a loan, the lender could use a CDS to offset or swap that risk.

central bank

An institution which - by way of a legal act - has been given responsibility for conducting the monetary policy for a specific area.

CET1

Common equity Tier 1 (CET1) is a subcomponent of Tier 1 capital (see supervisory own funds) whereby Tier 1 = CET1 + AT1. CET1 comprises a bank's core capital and includes common shares, stock surpluses resulting from the issue of common shares, retained earnings, common shares issued by subsidiaries and held by third parties, and accumulated other comprehensive income (AOCI).

CMU

The capital markets union (CMU) is a plan to create a single market for capital. The aim is to get money – investments and savings – flowing across the EU so that it can benefit consumers, investors and companies, regardless of where they are located.

collateral

An asset or third-party commitment that is used by a collateral provider to secure an obligation vis-à-vis a collateral taker.

collateral pool

A collateralization technique that enables an institution to make collateral available to a counterparty without allocating it to a specific transaction.

consolidated MFI balance sheet

A balance sheet obtained by netting out inter-MFI positions (e.g. inter-MFI loans and deposits) in the aggregated MFI balance sheet. It provides statistical information on the MFI sector's assets and liabilities vis-à-vis residents of the euro area not belonging to this sector (i.e. the general government and other euro area residents) and vis-à-vis non-euro area residents. It is the main statistical source for the calculation of monetary aggregates, and it provides the basis for the regular analysis of the counterparts of M3.

consumer credit

Loans granted to households for personal use in the consumption of goods and services.

COREP

Common Reporting (COREP) is the standardized reporting framework issued by the European Banking Authority (EBA) for the Capital Requirements Directive reporting. It covers credit risk, market risk, operational risk, own funds and capital adequacy ratios.

countercyclical capital buffer (CCyB)

A capital buffer intended to ensure that credit institutions accumulate sufficient capital during periods of excessive credit growth to be able to absorb losses during periods of stress. It has been implemented in Europe via Article 130, 135-140 CRD IV and it amounts to 0-2.5% of total risk exposure amount and must be met with CET1 capital, but it can be set at a higher level under certain procedures. The buffer is institution-specific and is calculated as a weighted average of the countercyclical buffer rates that apply in the countries where an institution's credit exposures are located.

counterparty

The opposite party in a contract or financial transaction (e.g. any party transacting with a central bank).

counterparty risk

The risk that between the time a transaction is agreed and the time it is actually settled, the counterparty to that transaction will fail to fulfil its obligations.

Cox models

A Cox model is a statistical technique for exploring the relationship between the survival of a patient (i.e. in this case a loan) and several explanatory variables. A Cox model provides an estimate of the treatment effect (restructuring for instance) on survival after adjustment for other explanatory variables.

credit risk

The risk that a counterparty will not settle the full value of an obligation – neither when it becomes due, nor at any time thereafter. Credit risk includes replacement cost risk and principal risk. It also includes the risk of the settlement bank failing.

CRAN

CRAN is a network of ftp and web servers around the world that store identical, up-to-date, versions of code and documentation for R.

debt (in the context of the financial accounts)

Loans, deposit liabilities, debt securities issued and pension fund reserves of non-financial corporations (created through direct pension commitments of employers on behalf of their employees), valued at market value at the end of the period. However, due to data limitations, the debt given in the quarterly financial accounts does not include loans granted by non-financial sectors (e.g., inter-company loans) or by banks outside the euro area, whereas these components are included in the annual financial accounts.

debt ratio

The subject of one of the fiscal criteria used to define the existence of an excessive deficit, as laid down in Article 126(2) TFEU. It is defined as the ratio of government debt to gross domestic product at current market prices, while government debt is defined in Protocol No 12 (on the excessive deficit procedure) as the total gross debt at nominal value outstanding at the end of the year and consolidated between and within the sectors of general government.

debt security

A negotiable financial instrument serving as evidence of a promise on the part of the issuer (the borrower) to make one or more payment(s) to the holder (the lender) on a specified future date or dates. Such securities usually carry a specific rate of interest (the coupon) and/or are sold at a discount to the amount that will be repaid at maturity. Debt securities issued with an original maturity of more than one year are classified as long-term. Money market paper and, in principle, private placements are included in the debt securities statistics of the ECB.

debt sustainability

According to IMF's definition, a country's public debt is considered sustainable if the government is able to meet all its current and future payment obligations without exceptional financial assistance or going into default.

default

An event stipulated in an agreement as constituting a default. Generally, such events relate to a failure to complete a transfer of funds or securities in accordance with the terms and rules of the system in question. A failure to pay or deliver on the due date, a breach of agreement and the opening of insolvency proceedings all constitute such events.

deposit facility rate

The interest rate paid on the surplus liquidity that credit institutions may deposit overnight in an account with a national central bank that is part of the Eurosystem.

derivative

A financial contract whose value depends on the value of one or more underlying reference assets, rates or indices, on a measure of economic value or on factual events.

Deferred tax assets (DTA) and deferred tax credits (DTC)

Deferred Tax Assets (DTAs) are instruments that may be used to reduce the amount of future tax obligations. Normally, DTAs are contingent on profits. However, legislative changes may enable DTAs to be transformed into deferred tax credits (DTCs) – that are not contingent on future profits, and can be counted as capital regardless of whether the bank makes a profit or a loss.

EAD

Exposure at default (EAD) is the total value a bank is exposed to when a loan defaults. Using the internal ratings-based (IRB) approach, financial institutions calculate their risk. Banks often use internal risk management default models to estimate respective EAD systems. Outside of the banking industry, EAD is known as credit exposure.

Economic adjustment program(s)

ELA (Emergency Liquidity Assistance) aims to provide central bank money to solvent The Economic Adjustment Program(s) for Greece are usually referred to as the bailout packages or memoranda are memoranda of understanding on financial assistance to the Hellenic Republic in order to cope with the Greek government-debt crisis.

ELA

ELA (Emergency Liquidity Assistance) aims to provide central bank money to solvent financial institutions that are facing temporary liquidity problems, outside of normal Eurosystem monetary policy operations. The rules and procedures surrounding the provision of ELA are laid down in the ELA agreement, which sets out the Governing Council's role in the provision of ELA by national central banks (NCBs), in particular when assessing, pursuant to Article 14.4 of the Statute of the European System of Central Banks (ESCB) and of the ECB, whether the provision of ELA by Eurosystem NCBs interferes with the objectives and tasks of the ESCB.

equity market

The market in which equities are issued and traded.

ESM

The European Stability Mechanism (ESM) is an intergovernmental organization, which operates under public international law for all eurozone Member States having ratified a special ESM intergovernmental treaty. Its purpose is to safeguard and provide instant access to financial assistance programs for member states of the eurozone in financial difficulty.

Euribor

The Euro Interbank Offered Rate (Euribor) is a daily reference rate, published by the European Money Markets Institute, based on the averaged interest rates at which Eurozone banks offer to lend unsecured funds to other banks in the euro wholesale money market (or interbank market).

euro

The name of the European single currency adopted by the European Council at its meeting in Madrid on 15 and 16 December 1995.

euro area

The area formed by the EU Member States whose currency is the euro and in which a single monetary policy is conducted under the responsibility of the Governing Council of the ECB. The euro area currently comprises Belgium, Germany, Estonia, Ireland, Greece, Spain, France, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Austria, Portugal, Slovenia, Slovakia and Finland.

Eurogroup

An informal gathering of the ministers of economics and finance of the euro area member countries, at which they discuss issues connected with their shared responsibilities in respect of the single currency. The European Commission and the ECB are invited to take part in the meetings. The Eurogroup usually meets immediately before an Ecofin Council meeting.

European Banking Authority (EBA)

An independent EU authority established on 1 January 2011 as part of the European System of Financial Supervision to ensure effective and consistent prudential regulation and supervision across the EU banking sector. Its main task is to contribute to the creation of the European single rulebook in banking, the objective of which is to provide a single set of harmonized prudential rules throughout the EU.

European Central Bank (ECB)

The ECB was established on 1 June 1998 in Frankfurt am Main as the body at the center of the European System of Central Banks (ESCB) and the Eurosystem. Together with the national central banks of the EU Member States whose currency is the euro, the ECB defines and implements the monetary policy for the euro area. Since the entry into force of the Treaty of Lisbon on 1 December 2009, the ECB has been an EU institution.

European Systemic Risk Board (ESRB)

An independent EU body responsible for the macro-prudential oversight of the financial system within the EU. It contributes to the prevention or mitigation of systemic risks to financial stability that arise from developments within the financial system, taking into account macroeconomic developments, so as to avoid periods of widespread financial distress.

Eurosystem funding

Since the latter part of 2014, Eurosystem refinancing operations have been essentially determined by the implementation of the single monetary policy and the need to reinforce the monetary stimulus by means of non-standard measures. In depicting graphs in the case of Greece (i.e. Figure 3.17), Eurosystem funding comprises both of ECB funding and ELA. Though ELA funding is typically granted by national central banks to meet temporary liquidity difficulties at specific solvent banks, in recent years it has been used over a prolonged period in exceptional cases, such as in the case of the Greek banking system up to 2018.

Eurosystem

The central banking system of the euro area. It comprises the ECB and the national central banks of those EU Member States whose currency is the euro.

exposure

The loss that would be incurred if a certain risk materialized.

FDML

First difference maximum likelihood (FDML) is an estimation methodology in dynamic panel data modeling whereby differencing eliminates fixed effects and, in the case of a unit root, differencing transforms the data to stationarity, thereby addressing both incidental parameter problems and the possible effects of nonstationarity.

financial asset

Any asset that is (i) cash; or (ii) a contractual right to receive cash or another financial instrument from another enterprise; or (iii) a contractual right to exchange financial instruments with another enterprise under conditions that are potentially favorable; or (iv) an equity instrument of another enterprise.

financial intermediary

A commercial entity that serves as an interface between lenders and borrowers, e.g. by collecting deposits from the general public and extending loans to households and businesses.

financial liability

Any liability that is a legal obligation to deliver cash or another financial instrument to another enterprise or to exchange financial instruments with another enterprise under conditions that are potentially unfavorable.

financial markets

Markets in which those who have a surplus of funds lend to those who have a shortage.

financial stability

The condition in which the financial system – comprising financial intermediaries, markets and market infrastructures – is capable of withstanding shocks and the unravelling of financial imbalances, thereby mitigating the likelihood of disruptions in the financial intermediation process which are severe enough to significantly impair the allocation of savings to profitable investment opportunities.

Fitch Ratings

Fitch ratings is a credit rating agency that rates the viability of investments relative to the likelihood of default.

fixed rate instrument

A financial instrument for which the coupon is fixed throughout the life of the instrument.

floating rate instrument

A financial instrument for which the coupon is periodically reset relative to a reference index to reflect changes in short or medium-term market interest rates. Floating rate instruments have either pre-fixed coupons or post-fixed coupons.

GAM

The generalized additive model (GAM) is a generalized linear model in which the linear response variable depends linearly on unknown smooth functions of some predictor variables, and interest focuses on inference about these smooth functions.

GAMLSS

The Generalized Additive Models for Location, Scale and Shape (GAMLSS) are univariate distributional regression models, where all the parameters of the assumed distribution for the response can be modelled as additive functions of the explanatory variables

GLM

The term general linear model (GLM) usually refers to conventional linear regression models for a continuous response variable given continuous and/or categorical predictors. It includes multiple linear regression, as well as ANOVA and ANCOVA (with fixed effects only).

GMM

The generalized method of moments (GMM) is a statistical method that combines observed economic data with the information in population moment conditions to produce estimates of the unknown parameters of this economic model.

gross domestic product (GDP)

A measure of economic activity, namely the value of an economy's total output of goods and services, less intermediate consumption, plus net taxes on products and imports, in a specified period. GDP can be broken down by output, expenditure or income components. The main expenditure aggregates that make up GDP are household final consumption, government final consumption, gross fixed capital formation, changes in inventories, and imports and exports of goods and services (including intra-euro area trade).

HAPS

HAPS stands for the Hellenic Asset Protection Scheme. Under the scheme, an individually managed, private securitization vehicle will buy non-performing loans from the bank and sell notes to investors. The State will provide a public guarantee for the senior, less risky notes of the securitization vehicle. In exchange, the State will receive a remuneration at market terms. The objective is to attract a wide range of investors and to support the banks in their ongoing efforts to reduce the amount of non-performing loans on their balance sheets.

HFSF

The Hellenic Financial Stability Fund (HFSF) was established in 2010, with the objective of contributing to maintain the financial stability of the Greek banking system in the public interest (Law 3864/2010). The independence of the fund in decision-making and in the management of its investments is guaranteed by the provisions of the founding law.

haircut

A risk control measure applied to underlying assets whereby the value of those underlying assets is calculated as the market value of the assets reduced by a certain percentage (the “haircut”). Haircuts are applied by a collateral taker in order to protect itself from losses resulting from declines in the market value of a security in the event that it needs to liquidate that collateral.

households

One of the institutional sectors in the European System of Accounts 2010 (ESA 2010). The household sector covers individuals or groups of individuals as consumers, but also as entrepreneurs (i.e. sole proprietorships and partnerships). Non-profit institutions serving households are a separate institutional sector according to the ESA 2010, although they are often reported together with households.

Herfindahl index

It is the sum of the squares of the market shares of banks and has values from 0 to 10,000. A market is defined to be highly concentrated when Herfindahl Index exceeds 1,800, moderate concentrated when the value is between 1,000 and 1,800, and relatively low concentrated when the value is lower than 1.000.

industrial production

The gross value added created by industry at constant prices.

IFRS 9

IFRS 9 is an accounting standard published by the International Accounting Standards Board covering the measurement of financial instruments, asset impairment and hedge accounting.
The new standard introduces the concept of expected credit loss accounting, requiring banks to predict the future loss of all assets at the point of origination or purchase, and set aside provisions for these assets. Under the previous regime, IAS 39, banks provisioned for assets only at the point of impairment.

inflation

An increase in the general price level, e.g. in the consumer price index.

interbank money market

The market for short-term lending between banks, usually involving the trading of funds with a maturity of between one day (overnight or even shorter) and one year.

interest rate

The ratio, usually expressed as a percentage per annum, of the amount that a debtor has to pay to the creditor over a given period of time to the amount of the principal of the loan, deposit or debt security.

interest-growth differential

The difference between the annual change in nominal GDP and the nominal average interest rate paid on outstanding government debt (the “effective” interest rate). It is one of the determinants of changes in the government debt ratio.

internal model

Any risk measurement and management approach applied in the calculation of own funds requirements that is proprietary to a credit institution and requires prior permission by the competent authority in accordance with Part Three of the CRR.

International Monetary Fund (IMF)

An international organization, based in Washington, D.C., with a membership of 189 countries (2017). It was established in 1945 to promote international monetary cooperation and exchange rate stability, to foster economic growth and high levels of employment and to help member countries to correct balance of payments imbalances.

intraday liquidity

Funds which are available or can be borrowed during the business day in order to enable financial institutions to effect payments/settlement. Repayment of the funds borrowed should take place before the end of the business day.

issuer

The entity which is obligated on a security or other financial instrument.

Key ECB interest rates

The interest rates that reflect the stance of the monetary policy of the ECB and that are set by the Governing Council. The key ECB interest rates are: the interest rate on the main refinancing operations (the fixed rate in fixed rate tenders and the minimum bid rate in variable rate tenders); the interest rate on the marginal lending facility; and the interest rate on the deposit facility.

large exposure

An institution's exposure to a client or group of connected clients, the value of which is equal to or exceeds 10% of its eligible capital. Limits to large exposures can be implemented in Europe via Article 458 CRR.

leverage ratio

The Basel III leverage ratio is defined as Tier 1 capital divided by the bank’s total exposure, expressed as a percentage. The prudential use of a leverage ratio limit is intended to restrict the build-up of leverage in the banking sector and to strengthen the risk-based requirements by adding a simple, non-risk-based backstop.

LCR

The liquidity coverage ratio (LCR) refers to the proportion of highly liquid assets held by financial institutions, to ensure their ongoing ability to meet short-term obligations.

liquidity

The ease and speed with which a financial asset can be converted into cash or used to settle a liability. Cash is thus a highly liquid asset. Bank deposits are less liquid, the longer their maturities. The term “liquidity” is also often used as a synonym for money.

liquidity risk

The risk that a counterparty will not settle an obligation in full when it becomes due. Liquidity risk does not imply that a counterparty or participant is insolvent, since it may be able to effect the required settlement at some unspecified time thereafter.

loans for house purchase

Credit extended to households for the purpose of investment in housing, including building and home improvements. Included are loans secured by residential property (i.e. mortgage loans) that are used for house purchase and, where identifiable, other loans for house purchase provided on a personal basis or secured by other types of asset.

longer-term interest rates

The rates of interest or the yield on interest-bearing financial assets with a relatively long period to maturity, for which the yield on government bonds with a maturity of ten years are often used as a benchmark.

M&As

mergers and acquisitions (M&A) is a general term that describes the consolidation of companies or assets through various types of financial transactions, including mergers, acquisitions, consolidations, tender offers, purchase of assets, and management acquisitions.

margin

The difference between average lending and deposit rates

market capitalization

The value of a company that is traded on the stock market, calculated by multiplying the total number of shares by the present share price.

market price

The price that is quoted for a gold, foreign exchange or securities instrument usually excluding accrued or rebate interest either on an organized market e.g. a stock exchange, or a non-organized market, e.g. an over-the-counter market.

market risk (price risk)

The risk of losses (in both on and off-balance sheet positions) arising from movements in market prices. See also
replacement cost risk

marking-to-market

The practice of revaluing securities and financial instruments using current market prices.

maturity date

The date on which a monetary policy operation expires. In the case of a repurchase agreement or swap, the maturity date corresponds to the repurchase date.

mid-market price

The mid-point between the bid price and the offer price for a security based on quotations for transactions of normal market size by recognised market-makers or recognised trading exchanges. The mid-market price is used for the year-end revaluation procedure.

minimum requirement for own funds and eligible liabilities (MREL)

The requirement for all EU credit institutions, with the aim of enabling credit institutions to absorb losses in case of failure. The MREL was issued by the European Commission in the Bank Recovery and Resolution Directive (BRRD). It has the same goal as the total loss-absorbing capacity (TLAC) requirement. However, the specific capital requirements prescribed by the MREL are calculated differently, following criteria set by the EBA.

Moody’s Investors Service

Moody's Investors Service provides investors with credit ratings, risk analysis, and research for stocks, bonds, and government entities.

monetary financial institution (MFI)

Financial institutions which together form the money-issuing sector of the euro area. These include the Eurosystem, resident credit institutions (as defined in EU law) and all other resident financial institutions whose business is to receive deposits and/or close substitutes for deposits from entities other than MFIs and, for their own account (at least in economic terms), to grant credit and/or invest in securities. The latter group consists predominantly of money market funds.

monetary policy

Action undertaken by a central bank using the instruments at its disposal in order to achieve its objectives (e.g. maintaining price stability).

money market

The market in which short-term funds are raised, invested and traded, using instruments which generally have an original maturity of up to one year.

MSCI

The MSCI Emerging Markets Index is a selection of stocks that is designed to track the financial performance of key companies in fast-growing nations. It is one of a number of indexes created by MSCI Inc., formerly Morgan Stanley Capital International.

national competent authority (NCA)

A public authority or body officially recognized by national law, which is empowered by national law to supervise institutions as part of the supervisory system in operation in the Member State concerned.

NFCI

net fee and commission income (NFCI). Fee income is the revenue taken in from account-related charges. Charges that generate fee income include non-sufficient funds fees, overdraft charges, late fees, over-the-limit fees, wire transfer fees, monthly service charges, and account research fees, among others.

NII

Net interest income (NII) reflects the difference between the revenue generated from a bank's interest-bearing assets and the expenses associated with paying its interest-bearing liabilities.

non-financial corporation (NFC)

A corporation or quasi-corporation that is not engaged in financial intermediation but is active primarily in the production of market goods and non-financial services.

non-performing loans (NPLs)

Under paragraph 145 of Annex V of the EBA ITS on Supervisory Reporting, these are loans that satisfy either or both of the following criteria: (a) material exposures which are more than 90 days past due; (b) the debtor is assessed as unlikely to pay its credit obligations in full without realization of collateral, regardless of the existence of any past-due amount or of the number of days past due.

Non-performing exposures (NPEs)

Non-performing exposures comprise of the following cases:

(i) Material exposures that are (a) more than 90 days past due (this means that the borrower is unable to repay the bank for more than 90 days his obligations) and (b) all exposures "defaulted" under the Basel framework

(ii) all exposures impaired, i.e. having experienced a downward adjustment to their valuation due to deterioration of their creditworthiness

(iii) all exposures where there is evidence that full repayment of principal and interest without realization of collateral is unlikely, even if the number of days past due is less than 90 days.

open market operation

An operation executed on the initiative of the central bank in the financial market. With regard to their aims, regularity and procedures, Eurosystem open market operations can be divided into four categories: main refinancing operations; longer-term refinancing operations; fine-tuning operations; and structural operations. As for the instruments used, reverse transactions are the main open market instrument of the Eurosystem and can be employed in all four categories of operations. In addition, the issuance of debt certificates and outright transactions are available for structural operations, while outright transactions, foreign exchange swaps and the collection of fixed-term deposits are available for the conduct of fine-tuning operations.

operational risk

The risk of negative financial, business and/or reputational impacts resulting from inadequate or failed internal governance and business processes, people, systems, or from external events.

opportunity cost

A measure of the costs of holding an asset, typically measured as the spread between its own return and the return on an alternative asset.

Organization for Economic Co-operation and Development (OECD)

The OECD (based in Paris) was founded in 1961 as the successor to the Organization for European Economic Co-operation (OEEC). It brings together 36 member countries (2020) in an organization that, most importantly, provides governments with a setting in which to discuss, develop and perfect economic and social policy.

P&L

The profit and loss statement (P&L) is a financial statement that summarizes the revenues, costs, and expenses incurred during a specified period.

P/E

The price-to-earnings ratio (P/E ratio) is the ratio for valuing a company that measures its current share price relative to its earnings per share (EPS).

payment

In a strict sense, a payment is a transfer of funds which discharges an obligation on the part of a payer vis-à-vis a payee. However, in a technical or statistical sense, it is often used as a synonym for “transfer order”. See also
transfer order

payment system

This term has two meanings. 1) In some cases, it refers to the set of instruments, banking procedures and interbank funds transfer systems which facilitate the circulation of money in a country or currency area. 2) In most cases, it is used as a synonym for “funds transfer system”.

pension fund

A provision or similar funds set aside by non-financial corporations to pay for their employees' pensions.

pledge

The delivery of assets in order to secure the performance of an obligation by one party (the debtor) vis-à-vis another (the secured party). For the secured party, a pledge creates a security interest (a “lien”) in the assets delivered, while ownership of the assets remains with the debtor.

portfolio investment (in a b.o.p. context)

Cross-border transactions and positions involving debt or equity securities, other than those included in direct investment or reserve assets.

premium

The difference between the par value of a security and its price when such price is higher than par.

price stability

The primary objective of the Eurosystem, which has been defined by the Governing Council as a year-on-year increase in consumer prices (as measured by the HICP) for the euro area that is below but close to 2% over the medium term.

principal (in a debt service context)

The face value of a bond or original amount for which it is issued, i.e. excluding interest payable.

principal risk

The risk that the seller of a financial asset (e.g. securities or currency) will deliver, but not receive payment, or the risk that the buyer will pay, but not receive delivery. In such a situation, the full value of the securities or funds transferred is at risk.

private sector debt

Outstanding amounts at the end of the year of securities issued and loans taken out by non-financial corporations and households (including non-profit institutions serving households). The private sector debt-to-GDP ratio is defined as the ratio of private sector debt to GDP at current market prices.

processing

The performance of all of the actions required in accordance with the rules of a system for the handling of a transfer order from the point of acceptance by the system to the point of discharge from the system. Processing may include clearing, sorting, netting, matching and/or settlement.

provisions

Amounts set aside before arriving at the profit and loss figure in order to provide for any known or expected liability or risk, the cost of which cannot be accurately determined.

PSPP

ECB’s Asset Purchase Programme (APP) is part of a package of non-standard monetary policy measures that also includes targeted longer-term refinancing operations, and which was initiated in mid-2014 to support the monetary policy transmission mechanism and provide the amount of policy accommodation needed to ensure price stability. The Eurosystem conducted net purchases of public sector securities under the public sector purchase programme (PSPP) between 9 March 2015 and 19 December 2018. As of January 2019, the Eurosystem continued to reinvest the principal payments from maturing securities held in the PSPP portfolio. As of 1 November 2019 the Eurosystem restarted net purchases under the PSPP.
The securities covered by the PSPP include:

- nominal and inflation-linked central government bonds
- bonds issued by recognised agencies, regional and local governments, international organisations and multilateral development banks located in the euro area

purchasing power parity (PPP)

The rate used for the conversion of one currency into another that equalises the purchasing power of the two currencies by eliminating the differences in the price levels prevailing in the countries concerned. In their simplest form, PPPs show the ratio of the prices in national currency of the same good or service in different countries.

realised gains or losses

Gains/losses arising from the difference between the sale price of a balance sheet item and its (adjusted) cost.

R

R is ‘GNU S’, a freely available language and environment for statistical computing and graphics which provides a wide variety of statistical and graphical techniques: linear and nonlinear modelling, statistical tests, time series analysis, classification, clustering, etc

reclassifications

An aggregate in monetary statistics that comprises changes in the MFI balance sheet that are due to a change in the MFI reporting population, to corporate restructuring, to a reclassification of assets and liabilities and to the correction of reporting errors (whenever the reporting error can be totally removed from the series, no specific reclassification needs to be reported). The occurrence of these factors gives rise to breaks in the series and, hence, affects the comparability of successive end-of-period levels.

reconciliation

A procedure to verify that two sets of records issued by two different entities match.

recovery plan

Banks are required to draft recovery plans to prepare for possible financial difficulties and restore their viability in a timely manner during periods of financial distress. The core of the recovery plan outlines a wide range of credible and feasible recovery options to restore viability, for example to improve the capital or liquidity situation.

refund

In the field of direct debits, a claim made by a debtor for the reimbursement of debits effected from its account (with or without a specific reason being indicated by that debtor).

replacement cost risk

The risk that, owing to a party to a transaction failing to meet its obligation on the settlement date, its counterparty may have to replace the original transaction at current market prices (“replacement cost”). See also
market risk

repurchase agreement

The process of borrowing money by combining the sale of an asset (usually a fixed income security) with the subsequent repurchase of that same asset for a slightly higher price (which reflects the borrowing rate).

reserves

An amount set aside out of distributable profits, which is not intended to meet any specific liability, contingency or expected diminution in value of assets known to exist at the balance sheet date.

residence

The location (dwelling, place of production or other premises) within the economic territory of a country, from which an institutional entity engages and intends to continue engaging (indefinitely or for a finite period of, as a rule, one year or more) in economic activities and transactions on a significant scale. See also
resident

residual maturity

Time remaining until the maturity date of a debt instrument.
A funds transfer system which typically handles a large volume of payments of relatively low value in forms such as cheques, credit transfers and direct debits.

returns

Funds sent back by the payee to the payer following settlement of the original payment instruction. The term “return” is used in connection with both direct debits and credit transfers.

reverse sale and repurchase agreement ("reverse repo")

A contract under which a holder of cash agrees to the purchase of an asset and, simultaneously, agrees to re-sell the asset for an agreed price on demand, or after a stated time, or in the event of a particular contingency. Sometimes a repo transaction is agreed via a third party ("triparty repo").

ROA

The term return on assets (ROA) refers to a financial ratio that indicates how profitable a company is in relation to its total assets.

ROE

Return on equity (ROE) is a measure of financial performance calculated by dividing net income by shareholders' equity.

RORAC

The return on risk-adjusted capital (RORAC) is a rate of return measure commonly used in financial analysis, where various projects, endeavors, and investments are evaluated based on capital at risk.

RRE

Residential real estate (RRE) is any property used for residential purposes. Examples include single-family homes, condos, cooperatives, duplexes, townhouses, and multifamily residences with fewer than five individual units.

S&P

Standard & Poor's (S&P) is a leading index provider and data source of independent credit ratings.

seasonally adjusted (s.a.)

Statistical technique designed to remove the effects of seasonal variations on a time series. Seasonal variations repeat themselves at around the same time every year and have a similar effect on the time series. A series may also be affected by calendar situations such as moving holidays (e.g. Easter). Time series with seasonal and calendar effects are usually adjusted for both.

Securities Markets Programme

In the advent of the sovereign debt crisis in 2010 the European Central Bank (ECB) instituted the Securities Markets Program (SMP) on May 9, 2010. It consisted of interventions by the Eurosystem in public and private debt securities markets in the euro area to ensure depth and liquidity in those market segments that are dysfunctional. The objective is to restore an appropriate monetary policy transmission mechanism, and thus the effective conduct of monetary policy oriented towards price stability in the medium term. The impact of these interventions is sterilized through specific operations to re-absorb the liquidity injected and thereby ensure that the monetary policy stance is not affected. This program enabled Eurosystem central banks to purchase securities from entities in Greece, Ireland, Portugal, Italy, and Spain. The program ended on September 6, 2012.

securitization

The pooling of financial assets, such as residential mortgage loans, and their subsequent sale to a special-purpose vehicle, which then issues fixed income securities for sale to investors. The principal and interest of these securities depend on the cash flows produced by the pool of underlying financial assets.

segregation

A method of protecting a client’s assets by holding them separately from those of the custodian (or other clients, as the case may be).

self selection

Process whereby organizations or firms that choose to take part in an activity, rather than being chosen by someone else

settlement risk

The risk that settlement in a transfer system will not take place as expected, usually owing to a party defaulting on one or more settlement obligations. This risk includes, in particular, operational risks, credit risks and liquidity risks.

significant institution (SI)

The criteria for determining whether banks are considered significant – and therefore under the ECB’s direct supervision – are set out in the SSM Regulation and the SSM Framework Regulation. To qualify as significant, banks must fulfil at least one of these criteria. Notwithstanding the fulfilment of the criteria, the SSM may declare an institution significant to ensure the consistent application of high-quality supervisory standards. Overall, the ECB oversees directly 119 significant banking groups.

significant supervised entity

A supervised entity that fulfils certain criteria regarding size, importance for the economy of the EU or any participating Member State or significance of its cross-border activities. All other supervised entities have to be considered less significant supervised entities.

SIFI

A systemically important financial institution (SIFI) is a bank, insurance company, or other financial institution whose failure might trigger a financial crisis. They are colloquially referred to as "too big to fail".

Single Supervisory Mechanism (SSM)

A mechanism composed of the ECB and national competent authorities in participating Member States for the exercise of the supervisory tasks conferred upon the ECB. The ECB is responsible for the effective and consistent functioning of this mechanism, which forms part of European banking union.

SMEs

According to EU recommendation 2003/361, the category of micro, small and medium-sized enterprises (SMEs) is made up of enterprises which employ fewer than 250 persons and which have an annual turnover not exceeding EUR 50 million, and/or an annual balance sheet total not exceeding EUR 43 million.

solvency risk

The risk of loss owing to the failure (bankruptcy) of an issuer of a financial asset or to the insolvency of the counterparty.

sovereign bond yield

sovereign bond yield is the interest rate paid to the buyer of the bond by the government, or sovereign entity, issuing that debt instrument.

spread

The spread is the gap between the bid and the ask prices of a security or asset, like a stock, bond or commodity. This is known as a bid-ask spread.

SSM Framework Regulation

The regulatory framework setting out the practical arrangements concerning the cooperation between the ECB and the national competent authorities within the Single Supervisory Mechanism: Regulation (EU) No 468/2014.

Stability programmes

These are medium-term government plans and assumptions provided by euro area countries regarding the development of key economic variables with a view to the achievement of the medium-term objective of a budgetary position close to balance or in surplus as referred to in the Stability and Growth Pact. These programmes present measures for the consolidation of fiscal balances as well as the underlying economic scenarios. Stability programmes must be updated annually. They are examined by the European Commission and the Economic and Financial Committee (EFC). Their reports serve as the basis for an assessment by the ECOFIN Council, focusing in particular on whether the medium-term budgetary objective in the programme is in line with a budgetary position close to balance or in surplus, providing for an adequate safety margin to ensure that an excessive deficit is avoided. Countries whose currency is not the euro must submit annual convergence programmes, in accordance with the Stability and Growth Pact.

supervised entity

Any of the following: (a) a credit institution established in a participating Member State; (b) a financial holding company established in a participating Member State; (c) a mixed financial holding company established in a participating Member State, provided that it fulfils the conditions laid down in point (21)(b); (d) a branch established in a participating Member State by a credit institution which is established in a non-participating Member State.

supervisory own funds

According to the Basle framework the components of own funds are as follows:
(a) Tier 1 capital comprises of paid-up share capital, reserves other than revaluation, net minority interests, net consolidation differences, hybrid capital instruments (lower Tier 1) minus own shares at book value held by the credit institution, intangible assets - in accordance with Art. 4 (9) of the Bank Accounts Directive - material negative results of the current financial year.
(b) Tier 2 capital comprises of revaluation reserves, value adjustments, perpetuals, subordinated debt and preferred shares with cumulative dividends irrespective of maturity, hybrid capital not recognized as Tier I.
(c) Tier 3 capital that covers part of market rate vis-à-vis changes in interest rates, exchange rates, equity and commodity prices etc. Moreover, the issuance of subordinated debt subject to lock-in period clause of 2 years and also limited to the extent of 250% of Tier I capital would also form part of Tier III capital.

Survival tree analysis

Survival analysis is a branch of statistical methods for investigating event occurrence— whether events occur and when events occur. Survival tree and survival ensemble methods are statistical learning techniques adapted to right-censored survival data

swap

An agreement to exchange future cash flows according to a prearranged formula.

systemic risk buffer (SyRB)

The systemic risk buffer (SyRB) aims to address systemic risks of a long-term, non-cyclical nature that are not covered by the Capital Requirements Regulation. The buffer level may vary across institutions or sets of institutions. There is no maximum limit for this buffer, but depending on its level and the impact on other Member States, authorization from the European Commission may be required.

systemic risk

The risk that the inability of one participant to meet its obligations in a system will cause other participants to be unable to meet their obligations when they become due, potentially with spillover effects (e.g. significant liquidity or credit problems) threatening the stability of or confidence in the financial system. That inability to meet obligations can be caused by operational or financial problems.

T2

Tier 2. See definition in supervisory own funds.

TLTROs

The targeted longer-term refinancing operations (TLTROs) are Eurosystem operations that provide financing to credit institutions. By offering banks long-term funding at attractive conditions they preserve favorable borrowing conditions for banks and stimulate bank lending to the real economy.

trade confirmation

A document which parties to a derivatives transaction use to specify the commercial terms of the transaction, including pricing terms such as spreads.

trade date

The date on which a trade (i.e. an agreement on a financial transaction between two counterparties) is struck. The trade date might coincide with the settlement date for the transaction (same-day settlement) or precede the settlement date by a specified number of business days (the settlement date is specified as T + the settlement lag).

transaction

An economic flow that reflects the creation, transformation, exchange, transfer or extinction of economic value and involves changes in ownership of goods and/or financial assets, the provision of services, or the provision of labour and capital.

transaction cost

Costs that are identifiable as related to the specific transaction.

transaction price

The price agreed between the parties when a contract is made.

tri-party repo

Repurchase agreement in which a third party (e.g. a custodian bank, a clearing house or a central securities depository (CSD)) is responsible for the management of the collateral during the life of the transaction.

trigger point

A pre-specified level of the value of the liquidity provided at which a margin call is executed.

TRIM

The targeted review of internal models (TRIM) was a multi-year project launched by the ECB at the beginning of 2016 in close cooperation with the national competent authorities (NCAs) that are part of European banking supervision. TRIM aimed to assess whether the Pillar I internal models used by significant institutions (SIs) within the Single Supervisory Mechanism (SSM) are appropriate in the light of the applicable regulatory requirements and whether their results are reliable and comparable. Furthermore, TRIM aimed to harmonize supervisory practices relating to internal models within the SSM.

truncation

A procedure in which a paper-based transfer order or other financial instrument is replaced, in whole or in part, by an electronic record of the content of that instrument for the purposes of further processing and transmission.

truncated loans

Truncated loans are defined as loans that have been originated form the initial data set having more than two consecutive non-existent values.

underlying asset

The asset (i.e. the financial instrument or security) upon which a derivatives contract is based.

unemployed

Any person, according to the EU definition, aged 15 to 74 who is (i) without work during the reference week, (ii) currently available for work and (iii) actively seeking work.

unemployment rate

The number of unemployed persons as a percentage of the labor force.

unit labor costs

Total labor costs per unit of output calculated for the euro area as the ratio of total compensation per employee to GDP at constant prices per person employed.

unrealised gains or losses

Gains/losses arising from the revaluation of assets compared with their (adjusted) cost of acquisition.

valuation date
The date on which the assets underlying credit operations are valued.

value date

The date on which it is agreed to place a payment or transfer at the disposal of the receiving user. The value date is also used as a point of reference for the calculation of interest on the funds held on an account.

VaR

Value at risk (VaR) is a statistic that quantifies the extent of possible financial losses within a firm, portfolio, or position over a specific time frame. This metric is most commonly used by banks to determine the extent and probabilities of potential losses in their institutional portfolios.

variable rate bonds

Debt securities whose nominal coupon payments are linked to an interest rate or some other index.

variable rate tender

A tender procedure whereby the counterparties bid both the amount of money they want to transact with the central bank and the interest rate at which they want to enter into the transaction. See also
tender procedure

write-down

A downward adjustment to the value of loans recorded in the balance sheets of MFIs when it is recognized that the loans have become partly unrecoverable.

write-off

The removal of the value of loans from the balance sheets of MFIs when the loans are considered to be totally unrecoverable.

yield curve
A curve describing the relationship between the interest rate or yield and the maturity at a given point in time for debt securities with the same credit risk but different maturity dates. The slope of the yield curve can be measured as the difference between the interest rates at two selected maturities.

waiver
A “waiver” is the abolition of the rule that normally prohibited ECB from accepting Greece’s sovereign bonds (non-investment grade) as collateral for its liquidity operations. The “waiver” enabled ECB to support Greek banks with the required liquidity during the prolonged period of the application of the memoranda, while its extension could enable Greece to participate in the ECB’s quantitative easing program.

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