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Impact of COVID-19 fiscal measures on Non-Performing Loans

Bachelor's thesis

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Declaration of Authorship

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Prague, May 3, 2022

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Abstract

We study to which extent fiscal measures related to COVID-19 have mitigated credit risk proxied by non-performing loans (NPLs) in selected European countries. In this respect, we control for the macroeconomic and bank-specific determinants of non-performing loans. We limit our empirical analysis to NPLs and fiscal measures that aimed at non-financial corporations. We utilize a quarterly panel dataset covering the period from 2019 to 2021. We further employ split according to sectors of economic activity and cover 423 sectors in 23 European countries. The difference GMM estimation for dynamic panel data is utilized. Our empirical analysis suggests that the following variables significantly affect NPL ratios: economic growth, employment, nominal effective exchange rate and return on equity. In the case of the fiscal measures, public guarantees and tax reliefs were found to have a statistically significant and negative effect on NPLs. This finding supports the notion that during the COVID-19 pandemic, loan guarantees and lower tax burdens helped businesses maintain liquidity and solvency, which resulted in reduction of NPL ratios. Contrary, loan moratoria were found to positively affect NPL ratios. There is mixed evidence regarding direct grants and no empirical evidence was found in the case of public loans, tax deferrals and other measures of fiscal nature.

JEL Classification	G21, G28, G32, F34
Keywords	non-performing loans, credit risk, fiscal measures, COVID-19 pandemic

Title	Impact of COVID-19 fiscal measures on Non-Performing Loans

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Abstrakt

Skúmame do akej miery fiškálne opatrenia súvisiace s COVID-19 zmiernili úverové riziko vyjadrené nesplácanými úvermi vo vybraných európskych krajinách. V tomto zmysle zohľadňujeme makroekonomické a bankové determinanty nesplácaných úverov. Našu empirickú analýzu obmedzujeme na podiel nesplácaných úverov a fiškálne opatrenia, ktoré sú zamerané na nefinančné podniky. Využívame štvrťročný panelový súbor dát pokrývajúci obdobie rokov

2019 až 2021 a rozdelenie podľa sektorov ekonomickej činnosti pokrývajúc 423 sektorov v 23 európskych krajinách. Ďalej využívame diferenčný GMM odhad pre dynamické panelové dáta. Z našej empirickej analýzy vyplýva, že na podiel nesplácaných úverov majú významný vplyv tieto premenné: hospodársky rast, zamestnanosť, nominálny efektívny výmenný kurz a návratnosť vlastného kapitálu. V prípade fiškálnych opatrení sa zistilo, že štátom garantované úvery a daňové úľavy majú štatisticky významný a negatívny vplyv na podiel nesplácaných úverov. Toto zistenie podporuje tvrdenie, že počas pandémie COVID-19 štátom garantované úvery a nižšie daňové zaťaženie pomohli podnikom udržať likviditu a platobnú schopnosť, čo viedlo k zníženiu podielu nesplácaných úverov. Naopak, zistilo sa, že moratóriá na úvery mali pozitívny vplyv na podiel nesplácaných úverov. Pokiaľ ide o priame granty, existujú zmiešané dôkazy a v prípade verejných pôžičiek, odkladov platenia daní a iných opatrení fiškálnej povahy sa nezistili žiadne empirické dôkazy.

Klasifikace JEL	G21, G28, G32, F34
Klíčová slova	nesplácené úvěry, kreditní riziko, fiskální opatření, pandemie COVID-19

Název práce	Dopad fiskálních opatření COVID-19 na nesplácené úvěry

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Acronyms

BIS Bank for International Settlements

CAP Capital adequacy ratio

EBA European Banking Authority

ECB European Central Bank

ECON The Committee on Economic and Monetary Affairs

EEA European Economic Area

EG Economic growth

EMP Employment

ESRB European Systemic Risk Board

ESS European Statistical System

EU European Union

FE Fixed Effects

GDP Gross Domestic Product

GMM Generalised Method of Moments

GVA Gross Value Added

HH Household

NACE Statistical Classification of Economic Activities in the European Community

NEER Nominal Effective Exchange Rate

NFC Non-Financial Corporation

NPE Non-Performing Exposure

NPL Non-Performing Loan

OECD Organisation for Economic Co-operation and Development

R Interest rate

RE Random Effects

ROA Return on Assets

ROE Return on Equity

Chapter 1

Introduction

Non-Performing Loans (NPLs) are loans that are overdue or are unlikely to be repaid by the borrower. Among other indicators, the level of NPLs can be used to approximate and measure credit risk in the banking sector. When credit risk rises, banks' capacity to provide new loans is jeopardized, posing a potential threat to the banking sector and the real economy in the form of a credit crunch and increased expenses. Many studies have looked into the link between credit risk and the real economy, concluding that there is a negative relationship (Baboucek & Jancar 2005; Espinoza & Prasad 2010; Klein 2013; Petkovski et al. 2018; Huljak et al. 2020). Hence, credit risk must be closely monitored because it is a critical component of financial stability and the economy as a whole. Research studies often focus on the evolution of NPLs using macroeconomic and/or bank-specific variables, e.g. Espinoza & Prasad (2010), Nkusu (2011), Louzis et al. (2012), Klein (2013), Makri et al. (2014), Beck et al. (2015), Petkovski et al. (2018) or Jakubik & Kadioglu (2021). In terms of macroeconomic factors, economic growth appears to be the key driver of non-performing loans. Furthermore, unemployment, inflation, interest rates, exchange rates, sovereign debt, and other factors, have an impact on the level of NPLs as well. While the evidence for unemployment is more consistent, the evidence for other variables is mixed. Regarding bank-specific determinants, such as profitability, moral hazard, bank size and capital adequacy, all have been considered and proven to have an impact on NPLs. The majority of the studies use aggregated data per country employing either annual or quarterly frequency. There are a few exceptions. For instance, Louzis et al. (2012) utilize split based on mortgages, consumer and business loans. Alternatively, data on NPLs are also available as per Households (HHs) or Non-Financial Corporations (NFCs). We contribute to the literature by analyzing NFC loans categorized according to Statistical Classification of Economic Activities in the European Community (NACE), which is mandated in the European Union (EU).

Since 2015, NPLs have decreased on average in the EU (ECB 2022). The past crises were responsible for the high initial values and since then the ratio of non-performing loans to total loans has stabilized at 2% in 2021. During the COVID-19 outbreak, the NPL levels were expected to increase, but such scenario did not occur. Nevertheless, some sectors of economic activity were negatively affected in their performance by COVID-19 (see Figures A.1, A.2, A.3, A.4, A.5, A.6 in the Appendix). To support the economy, governments implemented a variety of fiscal measures. The measures are tracked by European Systemic Risk Board (ESRB) and despite many types, they can be broken down to seven categories: direct grants, public guarantees, public loans, loan moratoria, tax reliefs, tax deferrals and other measures of fiscal nature. This thesis contributes to the existing literature by investigating to which extent fiscal measures related to COVID-19 have mitigated credit risk in the selected European countries. By controlling for the macroeconomic and bank-specific factors, we can also find out how those variables behave if analyzed in the context of the COVID-19 pandemic and NACE classification. Moreover, NPLs could potentially increase when the introduced measures phase out. Hence, the aim is to assess also this risk. For this purpose, we gathered data for 23 countries and 19 sectors in quarterly frequency since 2019 to 2021 and applied several estimation techniques. Since NPLs are persistent (Louzis et al. 2012; Beck et al. 2015; Us 2017; Jakubik & Kadioglu 2021), we prefer the difference Generalised Method of Moments (GMM) estimation for dynamic panel data developed by Arrelano and Bond. By this approach, we account for country-sector heterogeneity and endogeneity introduced by inclusion of the dependent variable as a regressor. The ratio of non-performing loans to total loans is utilized as dependent variable, while the lagged NPL ratio, economic growth, employment, exchange rate, interest rate, return on equity, capital adequacy and the fiscal measures as independent variables.

This thesis is structured as follows. The next section provides an overview of academic literature relevant to this thesis. In Chapter 3, we elaborate on NACE classification, non-performing loans and the fiscal measures implemented in response to COVID-19. The fourth chapter describes the data structure and econometric framework. Chapter 5 delves into empirical methodology we followed in our models. In Chapter 6, we provide the results of our analysis together with a robustness check. Finally, the overall conclusion is presented in Chapter 7.

Chapter 2

Literature review

This chapter aims to discuss different factors that might contribute to explain variations and developments of NPLs. First, it introduces relationship between credit risk and the real economy. Second, it focuses on macroeconomic and bank-specific determinants of NPLs. Such review provide us with the variables to employ in our empirical analysis. Finally, we briefly introduce literature regarding tools to mitigate NPL problems and discuss economic effects of various fiscal measures implemented in response to the COVID-19 outbreak.

2.1 Credit risk and real economy

Credit risk is the most important risk in the banking sector amounting to more than 80% of all risks (EBA 2021). It arises when a counterparty fails to meet its obligations and such materialization of credit risk worsens banking assets which has impact beyond the field of finance. There are numerous studies examining the link between credit risk and the real economy paying a special attention to the feedback effect, i.e., how credit risk influences the economy. As one might expect, most of the authors find negative relationship between credit risk and economic growth. This implies that when credit risk rises, the economy is expected to slow down (Baboucek & Jancar 2005; Espinoza & Prasad 2010; Klein 2013; Petkovski et al. 2018; Huljak et al. 2020). One of the possible channels is through adjustments in credit supply which reduces lending to the economy. Such credit supply contractions happen in times of insurgence of credit risk as banks have limited lending resources (Chiesa & Mansilla-Fernandez 2018; Casabianca 2020) and experience widening of lending spreads (Huljak et al. 2020). Supply of credit also contracts due to lower cost efficiency of banks.

This happens because banks incur additional costs resulting from management of bad loans (Karim et al. 2010). Apart from credit risk affecting real Gross Domestic Product (GDP) growth, the studies above also confirmed significant feedback effect on credit, inflation, unemployment, cost of capital or real estate prices.

Credit risk itself can be approximated by several different measures, for instance by probability of default, loan loss provisions, loss given default or non-performing loans, each being used in academic literature (Jakubik & Kadioglu 2021). According to Espinoza & Prasad (2010), NPL levels increase as a result of lower economic growth and higher interest rates. Glen & Mondragon-Velez (2011) studied developments of loan loss provisions (that is, recognized income statement expenses related to expected losses) confirming that loan portfolio performance is mainly driven by economic growth, interest rates, banking system penetration and capitalization, private sector leverage and loan portfolio quality.

In general, the determinants of NPLs and hence of credit risk could be divided into following categories: macroeconomic, bank-specific and regulatory (Saba et al. 2012). These categories have been vastly studied in past years and various combinations of them and of individual factors have been considered. While some attention is paid to the regulatory framework, to our best knowledge, macroeconomic and bank-specific variables dominate the literature. Beck et al. (2015) found significant links between macroeconomic variables and NPLs when analyzing a sample of 75 countries from 2000 to 2010. According to Louzis et al. (2012), Tanaskovic & Jandric (2015), and Jakubik & Kadioglu (2021), who employed both macroeconomic and bank-specific factors in their research, variables in each category seem to significantly affect NPLs. Some of the variables are used more frequently, and others are being introduced as novelties and tested. However, the literature does not always yield the same results and therefore the following section tries to summarise the available findings. We target 6 macroeconomic and 6 bank-specific variables. Jakubik & Kadioglu (2021) provide an excellent summary regarding the NPL determinants which serves as an important inspiration for the following section.

2.2 Macroeconomic determinants of non-performing loans

Economic growth and Unemployment The literature is to a large extent coherent when it comes to establishing effects of economic growth or unemployment on NPLs (Jakubik & Kadioglu 2021). The negative relationship for economic growth is empirically shown by Klein (2013), Makri et al. (2014), Skarica (2014), Beck et al. (2015), Tanaskovic & Jandric (2015), Radivojevic & Jovovic (2017), Karadima & Louri (2020), and Jakubik & Kadioglu (2021), who all focused on a group of several countries. Furthermore, the same conclusion was reached when focus was shifted to individual countries shown by Salas & Saurina (2002), Louzis et al. (2012), Ha & Hang (2016), Us (2017), and Zheng et al. (2019). According to Jakubik & Kadioglu (2021), higher economic growth results in lower incidence of NPLs and vice versa. They suggest that higher economic growth increases income of households and companies which positively affects their abilities to meet their obligations and hence decrease NPLs. Analogical observations can be made when discussing unemployment being one of the possible determinants of NPLs. The literature generally supports positive relationship implying that higher unemployment rate leads to higher NPLs through the income channel (Jakubik & Kadioglu 2021).

Inflation The relationship between NPLs and inflation might be ambiguous. On one hand, it can be argued that inflation reduces the real value of outstanding loans and hence it may be easier for debtors to service their debt. On the other hand, inflation also reduces the real income of the debtors. Assuming sticky wages this decreases their ability to repay their debt, in other words making debt servicing more difficult (Klein 2013). Positive relationship was empirically shown by Nkusu (2011), Klein (2013) and Radivojevic & Jovovic (2017) for NPLs in a selection of countries, but also when focusing on individual countries by Ha & Hang (2016) and Us (2017). On the contrary Shu (2002), Mensah & Adjei (2015) and Petkovski et al. (2018) found evidence supporting negative relationship. Makri et al. (2014) did not find a significant link and some even did not consider inflation as an explanatory variable, e.g., Louzis et al. (2012) or Messai & Jouini (2013).

Interest rates To some extent, developments of NPLs could be also explained by interest rates. Theoretically, when interest rates rise, debt servicing capacity of borrowers should decrease in the sense that fulfilling their obligations might be more challenging. According to Jakubik & Kadioglu (2021), NPLs increase in times of high interest rates partially because borrowers with already low credit scores are still prone to take up loans despite high interest rates. Beck et al. (2015) point to another fact that when central banks set new policy rates, they might not be fully reflected in the lending rates. Hence, evolution of NPLs might be explained by policy rates to a relatively small extent yet still significant. Certain attention should be given to loans which have floating interest rates as they are more sensitive to changes in the lending rates. For instance, Louzis et al. (2012) found positive relationship between NPLs and interest rates for all categories of loans (consumer, business, and mortgages) but attribute lower sensitivity of mortgage NPLs to prevailing fixed interest rates. Positive relationship between interest rates and NPLs was also confirmed by other studies (Espinoza & Prasad 2010; Messai & Jouini 2013; Beck et al. 2015; Jakubik & Kadioglu 2021). On the contrary, Us (2017) found a negative relationship suggesting that contractionary monetary policy leads to responsible lending practices and thus reduction of NPLs.

Exchange rates According to Jakubik & Kadioglu (2021), the literature is uncertain regarding the connection between exchange rates and NPLs. On one side, we should consider exporting capacity of countries because depreciation of domestic currency could be beneficial for heavy exporters. In such case, currency depreciation would lead to higher competitiveness and income of companies through increased exports and hence decrease NPLs. But of course this transmission channel would yield opposite results for importing economies as domestic currency depreciation would decrease their competitiveness by increased costs and reduce business income. On the other side, we should also consider to what extent borrowers have loans in foreign currencies, to whom depreciation of local currency might not be so favourable since their income is most probably in the local one. Lastly, it is also necessary to understand the variable itself. Depreciation can be represented by either increase or decrease in exchange rates depending on notation or computation (Tanaskovic & Jandric (2015) vs Radivojevic & Jovovic (2017)). Beck et al. (2015) and Tanaskovic & Jandric (2015) found empirical evidence that exchange rate depreciation leads to increase of NPLs in countries with high levels of foreign currency loans, which is in line with Radivojevic & Jovovic (2017). But when focus is shifted to a single country that does not have many loans in foreign currency, the effect of exchange rates might not be significant as it is in the case of Turkey (Us 2017).

Sovereign debt One of the possible determinants of NPLs, that to our knowledge is included only in a limited number of studies, is sovereign debt. According to Louzis et al. (2012), there are two ways that sovereign debt can affect credit risk. First, it is through cuts in lending in times of high public debt so debtors cannot refinance their personal debt which increases NPLs. Second, the transmission channel might be via fiscal measures. These measures are especially cuts in social expenditure and the wage component of government consumption which causes negative income shock to households followed by decrease in demand for goods and services provided by firms. Positive link between sovereign debt and NPLs is also supported by Makri et al. (2014) and Us (2017). However, there are not many other studies including such macroeconomic variable.

These indicators that we just mentioned are not all that could potentially explain developments of NPLs. We could also consider for instance the stock market index or the indebtedness of non-financial sector among others. The results are mixed. While Nkusu (2011) or Petkovski et al. (2018) argue that high indebtedness (measured as credit to the private sector in percent of GDP) would make debtors vulnerable to shocks and hence affect their debt servicing capacity, others suggest that credit prevalence might dilute the NPL ratio. Us (2017) confirmed negative effect of lending in both pre-crisis and post-crisis periods. However, some authors do not find any relationship (Jakubik 2007; Nkusu 2011; Petkovski et al. 2018) or confirm a positive one (Espinoza & Prasad 2010). Theory regarding the effect of share prices is more unified. It is expected that upward trends in stock markets help borrowers face adverse shocks and ease access to credit (Nkusu 2011). Therefore, credit risk should decrease. Nevertheless, Skarica (2014) and Beck et al. (2015) emphasize the importance of the stock market size. As Beck et al. (2015) confirmed, share prices negatively affect credit risk but mostly in countries with relatively large stock markets. Then, it should not be surprising that no effect is found in countries with small market capitalization or where financial markets are underdeveloped.

2.3 Bank-specific determinants of non-performing loans

Profitability According to Godlewski (2005), Louzis et al. (2012), Klein (2013) and Radivojevic & Jovovic (2017), the quality of bank management approximated by profitability, that is, Return on Assets (ROA) or Return on Equity (ROE), has significant impact on NPLs. It seems that higher quality of bank management results in lower NPLs (Godlewski 2005; Klein 2013; Radivojevic & Jovovic 2017). Similar conclusion was reached by Messai & Jouini (2013) suggesting that profitable banks are less engaged in granting risky loans. While this is in line with Louzis et al. (2012) regarding mortgages and consumer NPLs, the link between management quality and business NPLs was insignificant. No connection was also found by Jakubik & Kadioglu (2021) despite their expectations. Other papers suggest positive significant relationship between profitability and NPLs (Marco & Fernandez 2008; Us 2017). Their proposition is such that profit-maximizing policies are generally accompanied by higher levels of risk.

Moral hazard In 1997, Berger & DeYoung (1997) formulated moral hazard hypothesis saying that banks with relatively low equity-to-assets ratios engage in moral hazard activities increasing their portfolio risk and causing NPLs to increase in the future. This hypothesis was later confirmed by Salas & Saurina (2002) and Klein (2013) saying that low ratio of owners' equity results in higher NPLs incidence. Fiordelisi et al. (2011) also argue that moral hazard incentives are less frequent when bank capital increases but find no relationship between equity-to-assets ratio and risk. In 2021, Jakubik & Kadioglu (2021) used different proxy to capture moral hazard – the ratio of net open position in foreign exchange to the banking capital. They suggest that moral hazard in banks increases due to lower credit standards as banks receive funds from abroad in foreign currency. Positive link between the ratio of net foreign exchange position to capital on NPLs was confirmed.

Diversification Another explanatory variable frequently considered is diversification proxied either by bank size or non-interest income. Louzis et al. (2012) tested the hypothesis that diversification measured by both the bank size and non-interest income ratio negatively impacts NPLs. This stems from the expectation that banks' diversification opportunities go hand in hand with bank size and contribute to lower credit risk. Bank size was also used as a proxy for diversification by Salas & Saurina (2002). While negative relationship was confirmed by Salas & Saurina (2002) and Us (2017), the results were unclear according to Louzis et al. (2012) and Ha & Hang (2016). Louzis et al. (2012) even doubted using bank size as diversification proxy referring to the influence of the "dark side" of diversification forwarded by Stiroh (2004) saying that when banks enter unknown sectors when diversifying, the risk increases. Lastly, Ranjan & Dhal (2003) also found significant empirical evidence albeit different, i.e., opposite signs depending on different measures of bank size.

Cost efficiency Berger & DeYoung (1997) formulated two hypotheses related to cost efficiency, risk behaviour and loan quality – bad management hypothesis and skimping hypothesis. The first one claims that banks with lower cost efficiency experience higher NPLs. Low cost efficiency could be considered as a signal of poor management practices including loan monitoring, underwriting and control. Hence, if efficiency is low, we can expect an increase in problem loans. Second hypothesis suggested the reverse relationship, that managers like to trade short run expense reductions (higher efficiency) for long run reductions in loan quality (higher NPLs). When tested, the bad management hypothesis was confirmed for the whole industry, but the second one only for a subset of efficient banks. These hypotheses have been tested again. Podpiera & Weill (2008) confirmed bad management hypothesis but rejected skimping hypothesis when studying Czech banks over 1994-2005 period. Louzis et al. (2012) did the same, employing expense-to-income ratio to measure cost efficiency, and found empirical evidence in favor of the bad management hypothesis but no evidence regarding the skimping hypothesis. Alternatively, Espinoza & Prasad (2010) measured efficiency in a slightly different way (non-interest expenses to assets ratio) and confirmed their hypothesis of positive relationship between efficiency and risk. They suggest that when banks' risk averse management incurs high monitoring costs, which decreases cost efficiency, the level of NPLs decreases too.

Capital adequacy Another variable capturing risky behaviour could be capital adequacy. However, according to Fiordelisi et al. (2011) the question whether capital ratios reduce risk remains unanswered as literature yields contradictory results. Jakubik & Kadioglu (2021) confirmed negative relationship between regulatory capital to risk-weighted-assets ratio and NPLs. Capital adequacy was found to positively affect loan quality (and negatively NPLs) also by Makri et al. (2014) and Us (2017). But according to Radivojevic & Jovovic (2017) the link between capital adequacy ratio and NPLs is positive suggesting that banks with high capital adequacy ratio engage in high-risk activities, the idea also proposed by Rime (2001).

NPL persistence Finally, according to the literature summaries by Us (2017) and Jakubik & Kadioglu (2021), many studies assume persistence in NPLs. The rationale is such that NPLs are not directly written off immediately and hence affect current levels of NPLs. Positive link between lagged values of NPLs and current values of NPLs was confirmed with exception of Louzis et al. (2012) studying Greek banks over 2003-2009. Because of such persistence, Beck et al. (2015) suggest using dynamic model specification when analyzing determinants of NPLs.

2.4 Non-performing loans and fiscal measures during COVID-19 pandemic

Evidence from the past crises worldwide shows that NPLs tend to rise during banking crises (Ari et al. 2021), which is consistent with above literature. Similar expectations were formed when COVID-19 pandemic seemed to be inevitable. In addition, the build-up of NPLs during crises seems to follow a common pattern (Ari et al. 2021). However, the expected "tsunami" of pandemic NPLs in the EU has not occurred yet (Martin et al. 2021). According to them, the low incidence of NPLs is mainly prevailing due to implemented fiscal measures. Even though the impact of COVID-19 fiscal measures on NPLs is weakly covered in academic literature, there are numerous studies, working papers and articles assessing ways how to deal with NPLs efficiently (Balgova et al. 2016; 2017; Beck 2017; Laeven & Valencia 2018; Brei et al. 2020). Ari et al. (2021) argue that sound ex-ante macroeconomic, financial, and institutional policies, early identification of problem loans and timely actions mitigate NPL problems. Despite the suggestion by Balgova et al. (2016) that credit expansion is the most effective way to solve the NPL problem, active participation on reduction of NPLs is still better than laissez-faire approach. Possible active measures could contain various tax and financial incentives, creation of asset management companies, government guarantees, legal framework for corporate restructuring, provision of bailouts (e.g., public funds for bank recapitalization) and regulatory guidance (Balgova et al. 2016; 2017).

In the recent paper by Deb et al. (2021), authors analyse effects of fiscal measures related to COVID-19 on economic activity. They use database of daily announcements of fiscal measures across 52 countries (27 advanced and 25 emerging economies) throughout 2020 and find evidence that fiscal policy measures were effective in stimulating economic activity and associated with increases of stock market indicators and domestic currency appreciation. Various indicators of economic activity were used, unemployment rates among others, which were significantly affected. The paper goes into more depth analysing different types of measures, employing unique country characteristics and addressing cyclicality of the pandemic. Gourinchas et al. (2021) study effects of fiscal policies at the firm, sector, country, and global level trying to find answers to 8 important questions ranging from whether the fiscal measures prevented business failures to possible financial vulnerabilities due to risk premia. They consider three types of policies – tax waivers, cash grants and pandemic loans. They find evidence that without the support programs, business failures would have increased by 9%, on average, compared to 4,3% with active policies. However, despite fiscal measures saving many businesses, they were generally poorly targeted and reached companies that did not actually need them.

2.5 Contribution of this thesis

So far, vast knowledge about NPLs and their determinants has been gathered in the academic literature over the past years. However, current situation initiated by the COVID-19 pandemic brought unusual consequences and novelties. We contribute to the literature in several ways. First, we add our piece of literature to the one inspecting classical determinants of NPLs capturing different time period. The added value lies in the fact that we look at the determinants in the time of COVID-19 and a short period beforehand. Second, we try to create an overview of newly implemented fiscal measures and assess their impact on NPL ratios. As mentioned before, various policy packages were effective in resolving NPLs and now we would like to find empirical evidence for the recent ones. Third, we further contribute by inspecting data in higher granularity as most papers study NPLs on aggregated level. In contrast, we employ split according to NACE sectors and quarterly frequency. To our best knowledge, this has never been done before. Therefore, this thesis could help decide which factors and fiscal policy measures are effective in diluting NPLs in time of a crisis while taking into account sectoral specifics. Moreover, this study could asses a potential future negative effect on credit risk once the introduced fiscal measures phase out.

Chapter 3

Theoretical background

Before we construct the dataset and perform panel data regressions, we lay down some definitions, theory and historical background of the most important aspects of this thesis. Understanding the meaning of NACE is necessary because it gives our panel its structure and therefore it is our starting point.

3.1 NACE

NACE is a French abbreviation for Statistical classification of economic activities in the European Community, which was implemented in 1970. After a few modifications, version NACE Rev.2 is used as of 2008 and also in this thesis. In fact its usage is mandatory within the European Statistical System (ESS) which contributes to consistency. The ESS works together with Eurostat connecting national bodies of the EU member states and harmonizing statistics. International organizations with which the ESS coordinates its work are on the other side of the spectrum. Hence, statistics produced on the basis of NACE are comparable globally. Nevertheless, we restrict our dataset to the EU countries.

The purpose of NACE is to provide a unified framework for collecting and presenting data based on economic activity. Classification is based on a hierarchical structure with extra level introducing further details: sections –> divisions –> groups –> classes. For our purposes, classification according to the first level expressed by an alphabetical code is sufficient. We exclude last two economic activities as they are not applicable to our analysis: T – Activities of households as employers; undifferentiated goods- and services- producing activities of households for own use and U – Activities of extraterritorial organisations and bodies. The first-level codes are following:

Table 3.1: List of NACE codes

NACE code	Detail
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity; gas, steam and air conditioning supply
E	Water supply, sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities

An exhaustive list of NACE codes to the fourth level can be found on the Eurostat website.

According to Eurostat, statistical classifications are characterized by:

(i) partitioning the universe of statistical observations into meaningful units,

(ii) creating mutually exclusive categories,

(iii) adhering to methodological principles and ensuring consistency.

The NACE categorization is no different, and the NACE code can be used to map any economic activity. In general, an economic activity is defined as a process in which input resources (including intermediary products) are used to produce an output (goods or services). An economic activity can consist of one relatively simple process, e.g. weaving, but it can also cover several minor processes. For instance, when a car is constructed, processes such as welding, assembling or painting take place. Now, if the production is organized as one integrated series within the same statistical unit, the whole procedure is classified as one activity. If not, each process is recognized individually in different categories (Eurostat 2020).

3.2 Non-performing loans

The lack of a consistent definition of NPLs is an important caveat in global research (Nkusu 2011; Klein 2013; Beck et al. 2015). Basel framework itself does not refer to NPLs but to "problem assets", "defaulted exposures" or "past-due exposures" (BCBS 2017). To further support confusion, terms Non-Performing Loans and Non-Performing Exposures (NPEs) are sometimes used interchangeably. The BCBS (2017) guideline tries to overcome these gaps in definition by understanding its differences across jurisdictions. Since this would not help this thesis much, we refer the reader to the guideline itself.

As per the definition of NPEs in the Basel guideline, exposures are classified as non-performing if:

- are "defaulted" according to the Basel framework (e.g. paragraph 452 of the Basel II framework); or
- are "impaired" according to the applicable accounting framework (e.g. IFRS 9 or US GAAP). In layman's terms, if the exposure value has been adjusted downwards due to deterioration of creditworthiness; or

- those exposures that are not classified either as defaulted or impaired but:
  - are more than 90 days past due; or
  - there is evidence that full repayment is unlikely without realization of collateral.

Similarly in the European context according to the definition of NPEs by EBA (2014), exposures are classified as non-performing if:

- are more than 90 days past due; or
- the debtor is unlikely to pay its full credit obligations without realization of collateral.

Note that based on this standard, non-performing exposures also include defaulted and impaired exposures and that analogous definition of NPLs exists because NPLs are part of NPEs (EBA 2014). This definition provided by the European Banking Authority (EBA) is used in Guidance to banks on non-performing loans (ECB 2017), its Addendum (ECB 2018) and also in the EBA Report on NPLs (EBA 2019). Therefore, consistency to a large extent is assured, which is underlined by the fact that our data source for NPLs is the European Banking Authority.

However, neither guideline requires banks to provide more granular breakdown for loans or exposures by NACE. Banks were compelled to do so with the introduction of Reporting Framework 2.9 in December 2018. After implementation of the 2.9 framework, the EBA was able to collect such information and therefore include it in the Risk Dashboard from the Q1 2021 release onwards (EBA 2022). The Risk Dashboard provides a quarterly assessment of risks and vulnerabilities in the banking sector in the EU covering 131 banks corresponding to more than 80% of the EU/European Economic Area (EEA) banking sector assets. In the dashboard, we can find information on NPLs categorized by NACE. More importantly, we have access to the ratio of non-performing loans and advances to total gross carrying amount. By using a ratio of NPLs to total outstanding amount, the indicator is comparable. We further restrict ourselves to loans and advances provided to NFCs. The necessity of excluding HHs from our sample should not be a problem. We assume that NFCs and HHs were affected differently by COVID-19 due to lockdowns and various restrictions imposed on firms and households. Talking about determinants of NPLs, Louzis et al.

(2012) showed dis/similarities when analyzing all types of loans – business, consumer and mortgages. Furthermore, we assume that even economic sectors in which NFCs operate where affected differently. So to work with only one set of individual effects, we opted for NPL ratio of NFC loans and advances. There are other reasons as well. First, the EBA provides such information per NACE in the Risk Dashboard and second, it makes the overview of fiscal measures more bearable. Now, let's have a look at the historical development of NPLs to understand the current situation.

3.2.1 Historical development of non-performing loans and current situation

Generally, the NPL ratio in the EU has been on a steady decline since the second quarter of 2015 when the supervisory banking statistics were first released (ECB 2022). In Q4 2021, the ratio stood at the lowest recorded level of 2%. To help explain why the EU has been successful in addressing the NPL ratio we look at the study prepared by Kasinger et al. (2021) for The Committee on Economic and Monetary Affairs (ECON). Their main goal is to discuss policy implications in case of a surge in NPLs drawing lessons from previous crises and utilizing a scenario-based approach. After examination of previous crises, five main legacies about NPLs were formulated:

(i) Timely identification of NPLs is imperative for their resolution (Ari et al. 2021) and to prevent lending to non-viable firms.

(ii) Banks have not been incentivized enough to implement early identification measures, for instance to avoid sending negative signals (Bonfim et al. 2020).

(iii) Regulators and supervisors should put forward using effective asset quality reviews, stress tests, accounting standards (e.g. IFRS 9) and supervisory inspections. Once the NPLs are recognized, banks can resolve them either by internal workout or by engaging in secondary market.

(iv) Forbearance and public bank recapitalization are not effective as they provide adverse incentives to banks.

(v) Modernizing the secondary market for NPLs has the potential to become a more effective tool.

Kasinger et al. (2021) further comment on the Action plan prepared by the European Commission to prevent future build-up of NPLs initiated by the COVID-19 pandemic. They agree with the proposed measures as they are in line with their five main findings. Nevertheless, Kasinger et al. (2021) discuss under which conditions these measures should be used. For instance, they agree on making the secondary market for NPLs more liquid and transparent but stress that even under the extreme scenario of systemic risk, rescue money should be given to viable firms and borrowers rather than banks.

As we have witnessed ourselves, no insurgence of NPLs has materialized yet. This is also observed by Martin et al. (2021), who simultaneously warn against NPL increases in the near future as loans in Stage 2 are on the rise by 2 percentage points compared to early 2020. In a nutshell, Stage 2 loans are loans which are not yet categorized as non-performing but for which the credit risk has risen since loan origination. Martin et al. (2021) also point out to sectors that have been affected the most by the pandemic. In the following figures, we visualize the trends for sectoral NPL ratios using median values.

Figure 3.1: NPL ratios for sectors A - J

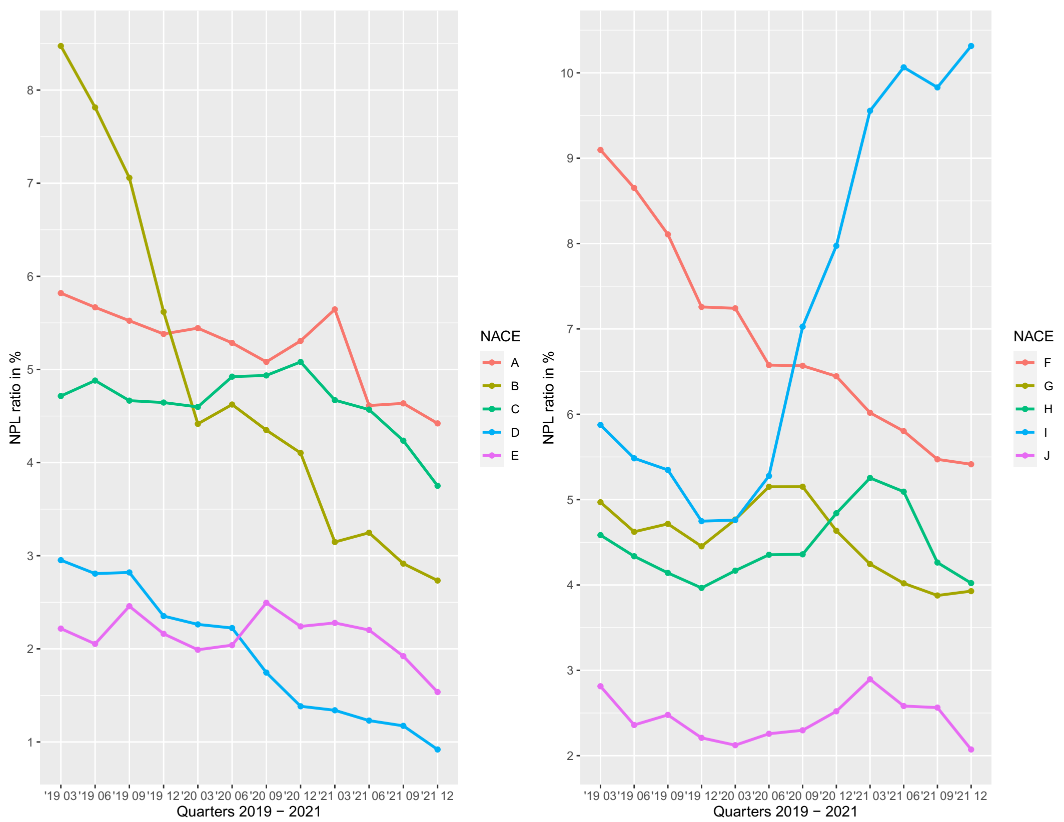
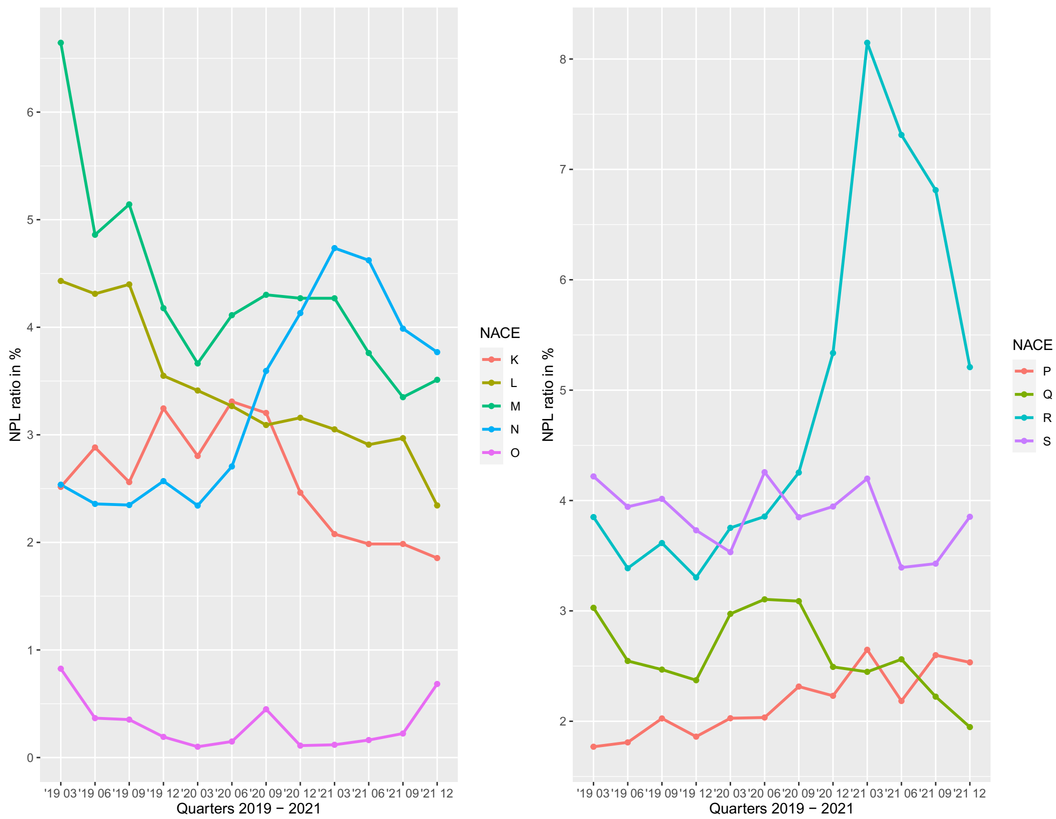


Figure 3.2: NPL ratios for sectors K - S



We see that the NPL ratio declined over time for majority of sectors, but certain heterogeneity is present. Nearly all NPL ratios reached lower level compared to the first reference quarter except for sectors I – Accommodation and food service activities, N – Administrative and support service activities, P – Education and R – Arts, entertainment and recreation. In fact, the NPL ratio for sector I recorded an increase by nearly 4.5 pp. Further, minor yet significant increases throughout 2020 and 2021 were marked in sectors G, H and M. Trends for these sectors might not be surprising as they might have been hit particularly hard by the pandemic.

3.3 Fiscal measures implemented in response to COVID-19

To find empirical evidence behind the trends we have just observed, we need to elaborate on the fiscal measures implemented in response to COVID-19.

The collector of information on policy measures applied in the EU is the ESRB in cooperation with other authorities and data are available on the ESRB website. In relation to COVID-19, the role of ESRB is not limited to data collection. Another function is to provide monitoring, recommendations and establish working groups addressing financial stability and implications of the support measures. In February 2021, the ESRB Working Group released its final report. Despite data covers only up to September 2020, we still deem this report important. The key three findings are following:

(i) The measures were successful in protecting the real economy from the pandemic and ensured functioning of financial services, e.g. 35% of new lending to NFCs was associated with the policy measures.

(ii) Heterogeneity in implemented measures was observed. More precisely, countries with bigger exposure to the pandemic enforced larger and more intense fiscal measures.

(iii) It is necessary to keep monitoring solvency in the corporate and banking sectors.

The ESRB categorizes the fiscal measures by both beneficiaries' sector and NFC economic activity sector. That is, the measures are first classified based on whether they are intended for financial or non-financial sectors with further specification (HHs vs NFCs) and then categorized according to NACE codes. For our purposes, we will discuss measures targeting NFCs. Simultaneously, it is necessary to understand that the same types of measures were targeting other sectors as well and that it is the different perspective from which we interpret these measures. Seven types of measures recognized by ESRB are direct grants, public guarantees, public loans, loan moratoria, tax deferrals, tax reliefs and other measures of fiscal nature (e.g. public support for credit insurance). In the next section, we try to characterize them and illustrate on a few examples.

Direct grants are considered as financial resources provided to entities that need them and often subject to conditions such as assertion that the business was not in financial troubles prior to the pandemic and was affected afterwards. These policies can include partial wage compensations to firms, rent coverage for those that had to close their premises or compensation for loss of turnover or sales among others. In case of kurzarbeit, a short work model, governments could cover the missing wage component when the actual working time was lowered. This should deter employee layoff and wage cuts. To support liquidity of the companies that experienced significant drop in revenue, firms could submit applications and obtain compensation grants based on their previous performance, percentage drop in sales, financial soundness or other conditions.

Public guarantees are programs addressing loans and exposures for which certain banks (typical not commercial ones), ministries or national bodies would take the role of a guarantor in case the debtor should default. Further specification of the guarantees can be based on the principal amount, type of enterprise or industry, credit scoring, interest rate, maturity or possibility to defer installments for certain time period. For instance, National development fund II of Slovakia would guarantee loans with principal up to 2 mil. EUR for SMEs and large corporations with maturity set from 2 to 6 years and interest rate up to 3,9%. Another example is Belgium where a guarantee scheme was implemented on the 15th April 2020 covering credits and credit lines with maximum maturity of 12 months with the exception of refinancing loans. The state and the bank would distribute potential losses based on the portfolio deterioration, e.g. losses above 5% of the guaranteed portfolio value would be borne by 80% by the state and 20% by the bank. The scheme was prolonged in July 2020 and December 2020.

Public loans were given to companies affected by the crisis in the form of repayable and tax free advances. One of the conditions was to not use these loans to settle other debt obligations. Similar measures were applicable in Greece until the end of 2021. Since then the loans or their portions had to be repaid in 60 installments. The loans could also differ in their intention, e.g. loans for operations or investment, loans for projects of national importance or for rural and agricultural sectors as in the case of Estonia or Lithuania. Another country enjoying relatively large portion of public loans was Hungary. Among other programs, SMEs could raise an interest-free loan with 10 year maturity and deferred repayments.

Loan moratoria could be further divided into public and private. The key distinction is whether the loan is provided to the private or the public sector. A typical nature of moratoria is such that the installments of principal and/or interest can be postponed by several months or until a fixed date without any charges or being registered in the credit bureau system. Some conditions can apply, e.g. the entity had no or little payment arrears prior to a specific date or that the entity was financially affected by the pandemic. In Portugal, a public moratorium was in effect since March 2020 applicable to NFCs of all sizes with headquarters or operations in Portugal and loans that were not 90 days or more past due by a certain date. There were further requirements in terms of no insolvency procedure or regarding tax and social security matters.

Tax reliefs refer to policies reducing tax burdens of businesses and helping them to resolve tax-related debt. Among these measures, we could have witnessed cancellation of payments or initial installments of future payments related to taxes or provision of tax credits/deductions equal to percentages of capital losses and expenses related to COVID-19. Another popular measures were adjustments in VAT rates on certain products or services. In Germany, VAT rate for meals in restaurants was reduced from 19% to 7% and the standard and reduced VAT rates were cut from 19% to 16% and 7% to 5% respectively. In the Czech republic, the government introduced a tax relief on social contributions paid by small employers for 3 months and extended the possibility to claim a tax loss as a deductible item from the tax base to 2 preceding tax periods.

Tax deferrals are options to delay tax related payments like employer social contribution, VAT and income tax. In Spain, there was an option to suspend tax payments for 6 months. Similar measures were targeting businesses affected by the pandemic in Greece allowing them to defer VAT payments for one year given retention of the workforce. These measures were repeatedly prolonged and the possibility to restructure the outstanding tax debt was enabled – rearranging the tax debt into 36 or 72 monthly installments.

Other measures which were low in occurrence were equity participation through convertible loans or financing programs and public support for trade credit insurance among others. In Latvia, receiving export credit guarantees was simplified and an alternative investment fund was established. It was estimated that this fund would support 20-30 large enterprises through equity participation. Regarding other measures, there was a possibility of partial reimbursement of expenses incurred due to event cancellations in the Netherlands.

Purpose of the measures we just discussed was mainly to protect liquidity and solvency of firms. The extent to which companies needed support might depend on several factors such as the sector of economic activity or the degree of digitalisation (ESRB 2021a). For instance, we could expect companies in sector I - Accommodation and food service activities to be more exposed than companies in sector J - Information and communication. The transmission channel might be through the physical proximity to do business or decline in demand due to lockdown restrictions. Another factor could be the degree of internationalisation in which potential disruptions of supply chain might have negative consequences. Last but not least, the resilience of firms might also be determined by liquidity reserves and access to credit and capital. In this case, companies with sound financial background would be expected to better cope with potential economic and pandemic turmoil.

Finally, we should consider possible implications once the measures phase out. Foreshadowed by the rise of Stage 2 loans, NPLs might increase when moratoria and guarantees expire. This could be caused by keeping non-viable firms in business which could lead to bankruptcies or solvency problems. The risk of supporting non-viable business is not only subject to moratoria and guarantees but also to other measures (ESRB 2021a). Therefore, as suggested by ESRB (2021b), authorities should use available mechanisms and instruments to differentiate between viable and non-viable companies. The importance of prevention of lending to non-viable firms is highlighted by Laeven & Valencia (2018).

In the first quarter of 2021, the measures generally experienced an increasing uptake compared to the previous quarter with the exception of moratoria as they began to expire (ESRB 2021b). Direct grants and public guarantees were the top two measures with 64.1% and 10% quarterly change respectively. Moreover, direct grants, public guarantees and moratoria were the most popular measures by uptake in % of 2019 GDP. Such consumption of support measures can point to and amplify potential future problems. We mapped usage of individual measures in the Table 3.2 and confirm superiority of direct grants and public guarantees by frequency. If we further look at the Table 3.3 we see that majority of measures expired by the end of 2021 and that some were about to expire in the second quarter of 2022 or had no end-date. The decline in the uptake of moratoria denoted by ESRB (2021b) might be explained by the fact that 73% of moratoria expired by the end of Q2 2021. This could suggest that impact of the fiscal measures might be more easily measurable capturing effects of expiration dates. Moreover, countries with particularly high number of certain measures might be more careful when those measures expire.

Table 3.2: Types of measures per country

Country	Direct grants	Public guarantees	Public loans	Moratoria	Tax reliefs	Tax deferrals	Other	Number of measures
AT	4	1	0	2	0	1	2	10
BE	9	3	0	2	2	4	2	22
BG	5	2	0	0	3	1	2	13
CY	15	4	1	2	4	2	3	31
CZ	24	4	0	2	6	1	2	39
DE	10	4	5	3	5	15	3	45
DK	7	5	0	0	0	2	5	19
EE	10	6	7	1	1	0	1	26
ES	4	12	0	6	17	8	7	54
FI	14	2	1	0	0	1	2	20
FR	2	4	0	1	0	1	3	11
GR	25	3	6	6	1	12	0	53
HR	1	2	2	4	8	7	11	35
HU	19	7	9	5	16	1	6	63
IE	27	3	5	1	3	1	3	43
IS	6	3	0	1	4	3	1	18
IT	1	8	1	3	3	1	4	21
LI	2	1	0	0	0	1	0	4
LT	10	4	6	1	0	2	1	24
LU	2	3	2	2	0	0	0	9
LV	10	4	3	1	0	2	3	23
MT	7	2	0	2	0	3	3	17
NL	7	4	1	2	0	1	1	16
NO	4	3	0	0	4	6	1	18
PL	5	5	3	2	6	4	4	29
PT	5	1	3	4	1	3	7	24
RO	6	4	0	4	2	4	0	20
SE	10	2	1	0	2	3	0	18
SI	1	3	1	1	0	9	0	15
SK	0	6	0	1	0	3	1	11
Number of measures	252	115	57	59	88	102	78	751

Notes: We applied certain filters, which we explain later, to capture measures applicable to NFCs.

Table 3.3: Termination of measures

Types of measures	Q1 2020	Q2 2020	Q3 2020	Q4 2020	Q1 2021	Q2 2021	Q3 2021	Q4 2021	Q1 2022	Q2 2022	Q3 2022	Q4 2022	Other or no end-date
Direct grants		6%	9%	16%	6%	17%	9%	11%	7%	2%		2%	13%
Public guarantees	2%	1%	3%	16%	2%	8%	4%	24%	3%	17%		3%	17%
Public loans			5%	18%	4%	12%	7%	26%		14%		2%	12%
Moratoria		7%	12%	15%	22%	17%	12%	5%	3%	2%			5%
Tax reliefs		7%	7%	13%	7%	9%	3%	15%	2%	5%	2%	6%	25%
Tax deferrals		13%	12%	19%	1%	12%	2%	18%	4%	9%			12%
Other		3%	1%	14%	6%	12%	4%	19%	4%	4%		3%	31%

Notes: We applied certain filters, which we explain later, to capture measures applicable to NFCs.

Chapter 4

Data

This thesis utilizes data on quarterly frequency regarding 23 European countries and 19 sectors of economic activity. We refer to a combination of a country code and a NACE code from Tables 4.2 and 3.1, respectively, as a country-sector. In Austria, for example, ATA is an indicator for sector A – Agriculture, forestry and fishing. The time horizon is from Q1 2019 to Q4 2021 constrained by the Reporting framework 2.9 which enabled EBA to collect desired information with first reference date Q1 2019. Our dependent variable is the ratio of non-performing NFC loans and advances to total NFC loans and advances collected by the European Banking Authority. The NPL ratios are calculated for each country-sector. We further employ other macroeconomic and bank-specific indicators typically used in similar studies. Our uniqueness lies in inclusion of COVID-19 fiscal measures as independent variables. For an overview of all variables, formulas and sources, see Table 4.1. Our panel dataset is balanced, capturing $T = 12$ quarters, $N = 423$ country-sectors amounting to $N{*}T = 5076$ observations. The 23 countries out of 29 potential candidates are chosen from Table 4.2. Because of the lack of data availability we had to exclude Belgium, Bulgaria, Denmark, Iceland, Malta and Norway from our dataset.

Table 4.1: Summary of variables

Variable	Symbol	Description	Source
Bank-specific			
NPL ratio by NACE	NPL	Ratio of non-performing NFC loans and advances to total NFC loans and advances	EBA Risk Dashboard Q4 2021
Capital adequacy ratio	CAP	Difference of the ratio of Tier 1 capital to total risk exposure amount	EBA Risk Dashboard Q4 2021
Return on equity	ROE	Difference of the ratio of profit or loss to total equity	EBA Risk Dashboard Q4 2021
Macroeconomic			
Economic growth	EG	Percentage change Q/Q_{-1} in GVA	Eurostat
Employment	EMP	Percentage change Q/Q_{-1} in hours worked	Eurostat
Interest rate	R	Difference of short-term interest rate per annum	OECD/national central banks
Nominal effective exchange rate	NEER	Logarithmic difference of NEER index; $2010 = 100$	Eurostat
Fiscal measures			
Direct grants	DIRGRA	1 if active, 0 if inactive	ESRB
Public guarantees	PUBGAR	1 if active, 0 if inactive	ESRB
Public loans	PUBLOA	1 if active, 0 if inactive	ESRB
Moratoria	MOR	1 if active, 0 if inactive	ESRB
Tax reliefs	TAXREL	1 if active, 0 if inactive	ESRB
Tax deferrals	TAXDEF	1 if active, 0 if inactive	ESRB
Other	OTHER	1 if active, 0 if inactive	ESRB

Table 4.2: List of countries

Austria (AT)	Iceland (IS)
Belgium (BE)	Italy (IT)
Bulgaria (BG)	Lithuania (LT)
Cyprus (CY)	Luxembourg (LU)
Czech Republic (CZ)	Latvia (LV)
Germany (DE)	Malta (MT)
Denmark (DK)	Netherlands (NL)
Estonia (EE)	Norway (NO)
Spain (ES)	Poland (PL)
Finland (FI)	Portugal (PT)
France (FR)	Romania (RO)
Greece (GR)	Sweden (SE)
Croatia (HR)	Slovenia (SI)
Hungary (HU)	Slovakia (SK)
Ireland (IE)	

4.1 Data on the ratio of non-performing loans

We use data collected for the EBA Risk Dashboard Q4 2021 as our data source. Some data points on NPL ratios were missing from the dashboard – mostly for Iceland and Norway and sectors K and O. However, in certain cases it might have been expected as particular industries may be underdeveloped or absent in some countries. For instance, sector B – Mining and quarrying in Malta. If one data point was missing from a time series, we interpolated the missing part from two nearest values given they were relatively close to each other in absolute values. This procedure was applicable to only 2 data points. The remaining 17 country-sector occurrences were excluded from our sample. Tables 4.3 and 4.4 provide summary statistics for NPL ratios per country and sector respectively. The summaries were calculated prior to exclusion of Belgium, Denmark and Malta from our dataset to capture bigger picture.

As seen in the tables, Greece, Cyprus, Portugal and Croatia on average experienced higher levels of NPL ratio reaching as much as 40% or higher. Sectoral ratios also exhibit wide range of values. Therefore, to account for potential outliers, choice of medians in Figures 3.1 and 3.2 in Subsection 3.2.1 is justified.

Table 4.3: Summary statistics for NPL ratios per country

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
AT	228	3.952	2.658	0.003	2.165	3.513	4.700	13.072
BE	228	3.370	1.484	0.998	2.286	3.101	4.298	9.174
CY	204	20.645	15.758	0.329	6.643	18.299	29.758	70.231
CZ	204	3.380	2.868	0.213	1.305	2.647	4.945	15.080
DE	228	3.009	2.269	0.002	1.234	2.586	4.106	13.711
DK	228	4.727	4.531	0.008	1.768	3.062	5.875	21.492
EE	204	2.703	3.115	0.007	0.918	1.677	3.418	19.030
ES	228	4.504	2.427	0.295	2.982	4.118	5.480	14.894
FI	216	3.846	6.122	0.107	0.831	2.343	3.399	42.850
FR	228	3.987	1.773	0.855	2.859	3.582	4.664	9.384
GR	228	32.250	16.477	0.983	20.217	32.261	44.197	66.494
HR	228	10.798	14.172	0.00003	3.948	7.744	13.549	93.706
HU	228	4.034	3.379	0.001	2.100	2.931	5.097	21.451
IE	216	4.388	3.819	0.001	1.480	3.588	5.756	22.465
IT	228	8.069	5.842	0.016	4.515	6.680	10.009	34.695
LT	192	2.713	3.451	0.028	0.282	1.596	3.225	16.323
LU	228	4.075	5.942	0.100	2.387	3.328	4.299	40.589
LV	216	2.598	3.338	0.0002	0.508	1.327	3.096	17.591
MT	192	8.623	8.955	0.004	2.567	6.224	11.063	39.790
NL	216	4.619	2.363	0.905	2.965	4.376	5.918	12.715
PL	228	6.044	4.609	0.007	2.740	5.374	7.642	21.800
PT	228	12.521	9.218	0.035	6.610	10.450	15.060	45.389
RO	228	8.607	10.240	0.160	3.362	5.283	10.184	64.908
SE	228	1.991	4.514	0.0003	0.221	0.681	1.445	27.632
SI	228	7.381	7.210	0.066	2.479	4.372	11.584	38.359
SK	216	1.849	1.590	0.009	0.506	1.461	3.049	7.368

Table 4.4: Summary statistics for NPL ratios per sector

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
A	312	7.730	8.602	0.356	3.350	5.225	7.748	56.755
B	288	10.508	14.555	0.0005	1.880	4.812	12.538	70.231
C	312	7.002	7.202	1.256	3.207	4.628	7.989	45.508
D	312	2.357	2.202	0.004	0.730	1.652	3.223	12.471
E	312	3.238	4.170	0.001	0.800	2.145	4.130	31.817
F	312	11.993	12.302	0.648	4.582	6.937	14.226	61.301
G	312	6.994	8.787	0.310	3.153	4.440	6.621	52.983
H	312	5.527	4.085	0.302	3.051	4.483	6.332	25.259
I	312	9.515	7.398	0.207	4.324	7.568	13.154	40.589
J	312	4.475	8.614	0.028	1.078	2.373	3.485	66.397
K	240	7.735	16.354	0.009	0.685	2.604	5.323	93.706
L	312	6.375	7.892	0.088	1.567	3.384	8.133	45.762
M	312	7.405	9.202	0.120	2.580	4.139	8.902	58.837
N	312	6.131	7.551	0.280	2.014	3.413	6.936	38.624
O	204	4.317	11.957	0.00003	0.011	0.286	2.002	66.494
P	312	5.996	10.501	0.040	1.100	2.126	6.191	65.593
Q	312	3.836	5.664	0.046	1.030	2.651	3.812	41.499
R	312	8.210	10.655	0.047	2.594	4.330	8.106	49.094
S	312	8.369	10.899	0.059	2.312	3.853	11.048	57.944

4.2 Data on fiscal measures

Data on fiscal measures were obtained from the ESRB database, which is publicly available. We used the measures listed in Table 4.1 and specified in which quarters the individual measures were active for particular country-sectors. The last update on the policies is from 3rd February 2022 and contains 992 fiscal measures. We further applied filters to access only those relevant for NFCs, which provided us with 751 unique measures. We also excluded those measures that lasted only a couple of days (approximately 20 in total) and assumed that those without a specified end-date were active until Q4 2021. To decide on allocation of quarters, we made several assumptions:

(i) There were two possible initial dates – adoption date vs implementation date – and we considered the later one as the starting point.

(ii) If a measure was initiated after the 15th day of March, June, September or December, we allocated the following quarter as the beginning period. We suspect that those measures would hardly impact NPL ratios in the actual time period they were activated.

(iii) If a measure was terminated before the 15th day of January, April, July or October, we allocated the preceding quarter as the termination period. Analogous reasoning as before applies.

Next, to designate correct NACE codes, we followed specification by the data source. Majority of the measures were applicable across all economic activities and about 13% targeted single sectors. Measures intended for multiple but not all sectors (less than 25% of all measures), were considered as for all sectors to avoid text mining.

Finally, we faced a trade-off between variability and types of measures. Figure 4.1 visualizes frequency of each measure type. We proceed by merging groups that are relatively small and/or contain measures with similar nature. Adhering to the following legend, Figure 4.2 provides an overview of the final set of measures that were considered.

(i) Moratoria contain Public moratoria, Private moratoria and Moratoria on other claims.

(ii) Other contains Equity participation, Public support for trade credit insurance and Other measures of fiscal nature.

(iii) Remaining categories are without change.

Figure 4.1: Frequency of measures by type before adjustment

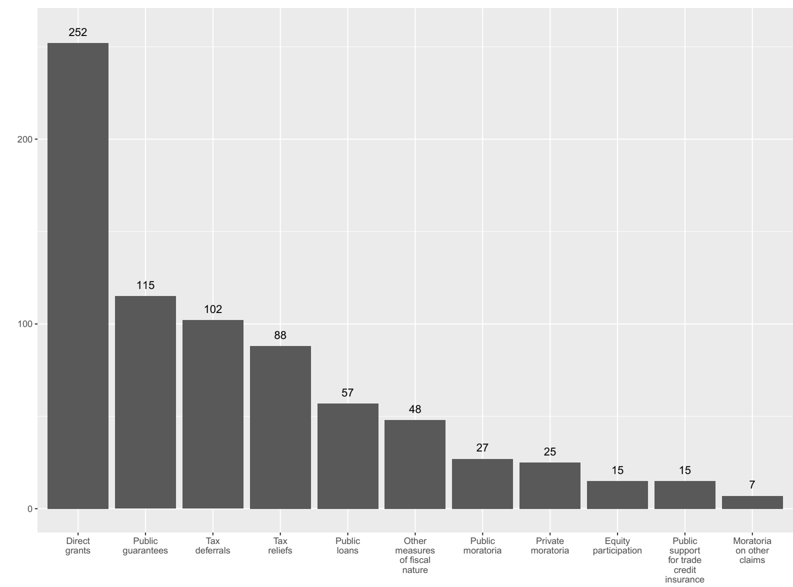
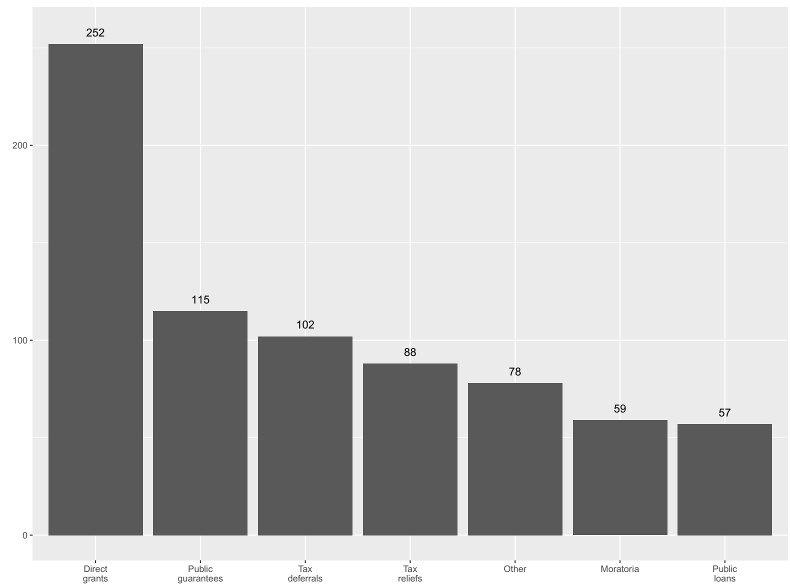


Figure 4.2: Frequency of measures by type after adjustment



Ideally, we would prefer quarterly data on uptake of measures per country-sector in percent of GDP but it might not be possible to collect such data. Having an actual number of active measures as opposed to dummies or percentage uptake would not benefit much as it would lower explanatory value of the fiscal measures. It might be possible that countries with efficiently allocated measures and volumes would not implement additional measures and therefore would be discriminated. Hence, to make our analysis fair and just, we observe whether the measures were active or inactive in respective quarters as a group irrespective of their number. One can argue that this would lower variability in our panel, which is true to some extent. However, according to our opinion sufficient variability is preserved, but an overview could not be provided due to space constraint.

4.3 Macroeconomic and bank-specific variables

We utilize macroeconomic and bank-specific variables which tend to affect asset quality and are consistent with the literature. To capture the impact of the growth rate, we applied logarithmic difference to variables expressed in levels (NEER) and simple difference to variables reported in percentages (R, ROE, CAP). The rest of the variables remained unchanged because they either already represented the growth rate (EG, EMP) or such transformation was not necessary (NPL ratio), which is in line with the literature. Economic growth (EG) is expressed as percentage change in Gross Value Added (GVA) which is conceptually close to GDP and is available in NACE breakdown. Percentage change is with respect to the previous quarter and figures used for calculation are calendar and seasonally adjusted. Similarly to EG, data for Employment (EMP) are also obtained from the Eurostat and available in NACE Rev.2. EMP is calculated as percentage change in hours worked and serves as an alternative to unemployment rate. Data on hours worked are calendar and seasonally adjusted as well. Unfortunately, EG and EMP had values merged for certain NACE: B–E (without C), G–I, M–N, O–Q and R–S. To resolve this issue, we used aggregated values for individual codes within each group. Lastly, data on EMP were unavailable for Belgium, Denmark and Malta. After testing various specifications, we decided to include EMP in our analysis which simultaneously meant exclusion of the aforementioned countries from our dataset.

For other explanatory variables, data were not available in sectoral division according to economic activity. Hence, we applied data for countries to corresponding individual sectors. Among bank-specific variables, ROE and Capital adequacy ratio (CAP) were included in our analysis to capture impact of bank profitability and capital adequacy on the NPL ratio. Both indicators were obtained from the Risk Dashboard Q4 2021. In the literature, Nominal Effective Exchange Rate (NEER) is used as a proxy for exchange rate. NEER is obtained from Eurostat and is calculated using 27 EU trading partners and constructed in such way that its increase indicates an appreciation of the domestic currency against the weighted basket of currencies of the trading partners. 3 months Euribor rate was chosen as an indicator of interest rates for eurozone countries. For non-eurozone countries, rates of the closest resemblance were selected. Source for the data on interest rates is the Organisation for Economic Co-operation and Development (OECD) database to ensure consistency. Nevertheless, a few countries were not included, so we supplemented the data from national central banks, e.g. 3 months Robor rate for Romania. In case of Croatia, we also prefer 3 months Euribor rate since the Zibor rate was abandoned by the end of 2019 and 3 months Euribor rate accounted for the largest proportion of loans (42.9%).

Lastly, indebtedness of NFC sector measured as credit to the private sector in percent of GDP and government debt as percentage of GDP were also considered.

Similarly, we also considered inflation and share price indices as explanatory variables. Data for them were taken from the European Central Bank (ECB), Bank for International Settlements (BIS), Eurostat and OECD databases, respectively. However, the first two variables were missing observations for Q4 2021 and altogether did not improve our model significantly. Therefore, we excluded them.

Table 4.5 provides summary statistics for utilized variables. NPL ratio varies between near zero and 93.7 and both EG and EMP take negative values indicating decreases in their performance as expected.

Table 4.5: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Median	Max
NPL	5,076	6.909	9.972	0.00003	3.712	93.706
EG	5,076	0.568	8.271	−49.300	0.600	138.400
EMP	5,076	0.245	7.851	−45.100	0.200	62.200
NEER	4,653	−0.001	0.007	−0.051	0.0004	0.027
R	4,653	−0.006	0.252	−1.567	−0.009	1.917
ROE	4,653	−0.193	4.067	−31.666	0.064	20.127
CAP	4,653	0.139	0.877	−3.320	0.116	5.834
DIRGRA	5,076	0.556	0.497	0	1	1
PUBGAR	5,076	0.585	0.493	0	1	1
PUBLOA	5,076	0.350	0.477	0	0	1
MOR	5,076	0.375	0.484	0	0	1
TAXREL	5,076	0.287	0.452	0	0	1
TAXDEF	5,076	0.453	0.498	0	0	1
OTHER	5,076	0.383	0.486	0	0	1

4.4 Econometric framework

Academic literature on non-performing loans suggests persistency in NPLs (Louzis et al. 2012; Klein 2013; Beck et al. 2015). In order to capture this phenomenon, we estimate our model in two specifications – static and dynamic – with appropriate panel data techniques. First, static Equation 4.1 is estimated. Afterwards, we include lagged dependent variable as a regressor and estimate Equation 4.2. We test various specifications including lags of EG, EMP and fiscal measures to account for potential delayed impact of explanatory variables.

Static model is given by the equation:

$$\begin{aligned} NPL_{i,t} = \beta_1 EG_{i,t} + \beta_2 EMP_{i,t} + \beta_3 NEER_{i,t} + \beta_4 R_{i,t} \\ + \beta_5 ROE_{i,t} + \beta_6 CAP_{i,t} + \gamma FISCAL_{i,t} + a_i + u_{i,t} \end{aligned} \tag{4.1}$$

where NPL, EG, EMP, $NEER$, R, ROE and CAP refer to variables specified in Table 4.1. $FISCAL$ denotes the fiscal measures specified in the same table. a_i refers to the time-invariant individual effect for every i, $u_{i,t}$ is the error term and βs and γ are the parameters representing the effect of the independent variables on NPL. i denotes a country-sector and t stands for quarters where $i = 1, ..., N$ and $t = 1, ..., T$.

Dynamic model is given by the equation:

$$\begin{aligned} NPL_{i,t} = \rho NPL_{i,t-1} + \beta_1 EG_{i,t} + \beta_2 EMP_{i,t} + \beta_3 NEER_{i,t} + \beta_4 R_{i,t} \\ + \beta_5 ROE_{i,t} + \beta_6 CAP_{i,t} + \gamma FISCAL_{i,t} + a_i + u_{i,t} \end{aligned} \tag{4.2}$$

with similar specification as Equation 4.1 except for ρ being a parameter capturing the effect of lagged dependent variable on NPL and $t = 2, ..., T$.

Table 4.7 displays the correlation matrix. The coefficients are generally higher for fiscal measures, the highest equal to 0.766 for Direct grants and Public guarantees. Nonetheless, no strong correlation is present between the variables. Kennedy (2008) suggests that multicollinearity should be addressed if the correlation exceeds 0.8 which is not the case for any instance. Following Beck et al. (2015), who operated with a panel dataset covering 75 countries at an annual frequency over 10 years period, we test our variables for stationarity. According to Maddala & Wu (1999), performance of the Fisher unit root test for panel data shows superiority to other panel data unit root tests. Therefore, in line with Beck et al. (2015) we apply the Fisher test using an augmented version of the Dickey-Fuller test to test for panel stationarity. Except for three fiscal measures (Direct grants, Public loans and Tax reliefs), we were able to reject the null hypothesis of non-stationarity. However, this result may not be unanticipated as our time horizon is relatively short and that variables on fiscal measures take values of 0 and 1 depending on their continuity. Thus, certain level of non-stationarity may not necessarily be a problem in this case. In our set-up we treat all explanatory variables as exogenous. We acknowledge that the causality between economic growth and non-performing loans might run in both directions. Despite this simultaneity we suggest that NPLs were minor factors affecting economic situation during the COVID-19 outbreak. Endogeneity of other regressors is also possible albeit marginal so we assume exogeneity in our specifications. The choice of these options is also motivated by literature.

In Table 4.6 we outline our expectations regarding the impact of explanatory variables on the NPL ratio. We expect that EG and EMP decrease the level of NPLs. Other macroeconomic and bank-specific variables might yield mixed results as could be seen in the literature review. For the fiscal measures, we expect negative signs indicating the intended influence on the NPL ratio and credit risk as such.

The next chapter delves into the methods we applied in our estimations.

Table 4.6: Expected effects on NPL ratio

Variable	**Expectation**	**Variable**	**Expectation**
EG	(-)	DIRGRA	(-)
EMP	(-)	PUBGAR	(-)
NEER	(+/-)	PUBLOA	(-)
R	(+/-)	MOR	(-)
ROE	(+/-)	TAXREL	(-)
CAP	(+/-)	TAXDEF	(-)
		OTHER	(-)

Table 4.7: Correlation matrix

	NPL	EG	EMP	NEER	R	ROE	CAP	DIRGRA	PUBGAR	PUBLOA	MOR	TAXREL	TAXDEF	OTHER
NPL	1	0.0004	0.001	0.010	-0.027	-0.073	-0.024	-0.076	-0.093	-0.011	0.032	-0.046	-0.024	-0.165
EG	0.0004	1	0.578	0.046	-0.084	0.128	-0.046	0.030	0.032	0.027	-0.015	-0.018	-0.005	0.033
EMP	0.001	0.578	1	-0.010	-0.091	0.127	-0.023	0.047	0.045	0.029	0.009	-0.005	0.005	0.056
NEER	0.010	0.046	-0.010	1	0.099	0.031	-0.063	-0.005	0.0001	-0.027	-0.062	-0.085	-0.007	-0.063
R	-0.027	-0.084	-0.091	0.099	1	-0.039	-0.145	-0.022	-0.048	0.049	-0.081	0.055	-0.097	0.066
ROE	-0.073	0.128	0.127	0.031	-0.039	1	-0.132	0.181	0.168	0.040	0.017	0.143	0.100	0.196
CAP	-0.024	-0.046	-0.023	-0.063	-0.145	-0.132	1	-0.009	0.038	-0.010	0.045	0.087	-0.016	0.057
DIRGRA	-0.076	0.030	0.047	-0.005	-0.022	0.181	-0.009	1	0.766	0.550	0.477	0.501	0.611	0.494
PUBGAR	-0.093	0.032	0.045	0.0001	-0.048	0.168	0.038	0.766	1	0.619	0.528	0.488	0.678	0.619
PUBLOA	-0.011	0.027	0.029	-0.027	0.049	0.040	-0.010	0.550	0.619	1	0.427	0.408	0.371	0.288
MOR	0.032	-0.015	0.009	-0.062	-0.081	0.017	0.045	0.477	0.528	0.427	1	0.346	0.380	0.228
TAXREL	-0.046	-0.018	-0.005	-0.085	0.055	0.143	0.087	0.501	0.488	0.408	0.346	1	0.397	0.569
TAXDEF	-0.024	-0.005	0.005	-0.007	-0.097	0.100	-0.016	0.611	0.678	0.371	0.380	0.397	1	0.452
OTHER	-0.165	0.033	0.056	-0.063	0.066	0.196	0.057	0.494	0.619	0.288	0.228	0.569	0.452	1

Chapter 5

Methodology

5.1 Static panel estimation

We start our estimations using static panel with Fixed Effects (FE) and Random Effects (RE) to account for unobserved time-invariant and country-sector specifics. Choice of these methods is in line with the relevant literature where static estimations are sometimes used as robustness checks or to uncover any preliminary effects. Since we work with a set of country-sectors and do not include any time-constant variables in our regressions, FE and RE methods seem to be appropriate estimation techniques. Situations where one or the other method is preferred are described in the following subsection.

5.1.1 Fixed effects and Random effects

First, let's start with a simple static equation:

$$y_{i,t} = \alpha \boldsymbol{x}_{i,t} + a_i + u_{i,t} \tag{5.1}$$

where a_i is the time-invariant individual effect for every i and u_{it} is the error term for $i = 1, ..., N$ and $t = 1, ..., T$. If the individual effects are truly present in our sample, FE and RE can produce unbiased and consistent estimators in contrast to pooled OLS. Let's imagine, that individual effects are present, they are unobserved, constant over time and $Cor(\boldsymbol{x}, a_i) \neq 0$, i.e. are correlated with some independent variables. Then fixed effects are present in our panel which causes the omitted variable problem. To address this, the FE transformation eliminates the unobserved effects. However, such transformation also eliminates other time-invariant variables. Since, we do not include any of those in our models, this does not pose a problem to us. The FE method time-demeans all variables and hence gets rid of all time-invariant regressors and the fixed effects:

$$y_{i,t} - \bar{y}_i = \alpha(\boldsymbol{x}_{i,t} - \bar{\boldsymbol{x}}_i) + u_{i,t} - \bar{u}_i \tag{5.2}$$

On the other hand, if we impose stricter condition that $Cor(\boldsymbol{x}, a_i) = 0$, RE method is more suitable. It weighs FE and pooled OLS based on the variance of the error term and the individual effect. In the presence of no correlation between the unobserved effects and explanatory variables, pooled OLS is consistent. Nevertheless, standard errors are not trustworthy due to the serial correlation of the error term arising because of the present a_i:

$$y_{i,t} - \theta\bar{y}_i = \alpha(\boldsymbol{x}_{i,t} - \theta\bar{\boldsymbol{x}}_i) + (1-\theta)a_i + u_{i,t} - \theta\bar{u}_i \tag{5.3}$$

where $\theta = 1 - (\frac{\sigma_u^2}{\sigma_u^2 + T\sigma_a^2})^{\frac{1}{2}}$.

For instance, if the variance of a_i is close to 0, the pooled OLS is estimated. If the variance is relatively large compared to the variance of the error term, FE model is estimated.

To choose whether FE or RE fits our specification better, Hausman test is performed. Under the null hypothesis, RE is consistent and efficient. The alternative hypothesis is in favor of FE model as RE is inconsistent.

The next section concentrates on the dynamic panel estimation.

5.2 Dynamic panel estimation

In order to comply with the literature, we assume persistence in NPLs. This assumption seems to be logical as it takes some time to write off NPLs from balance sheets. Therefore, current levels of NPLs might be influenced by their past values and so we need to include some lags of the dependent variable in our equations. However, by including lags of the dependent variable we would introduce endogeneity into our model and the estimators would become biased (Nickell 1981; Judson & Owen 1997). Therefore, we use the difference GMM estimation for dynamic panel data proposed by Arellano & Bond (1991). Our motivation is such that this modeling approach is frequently employed in the papers on the determinants of NPLs. The method relies on first differences and is suitable for panels with individual fixed effects, endogeneity and autocorrelation. Suitability can also be illustrated by the data choice itself – Arellano and Bond used data on 140 companies with 7 to 9 continuous observations. Note that T < N, where T stands for the number of time periods and N for the number of entities. We work with a bit larger sample of 423 country-sectors with 12 observations but the dimensional comparison still holds. Arellano-Bond estimation is appropriate for samples with large N and small T, typical for macroeconomic studies.

Now, let's explore the difference GMM estimation in more detail.

5.2.1 Difference GMM

Let's begin by outlining the problem and then we will look at how it is solved. Dynamic model contains lagged values of the dependent variable as regressors. Hence we modify the equation (5.1) such that

$$y_{i,t} = \rho y_{i,t-1} + \boldsymbol{x}_{i,t}\alpha + a_i + u_{i,t} \tag{5.4}$$

for $t = 2, ..., T$.

For simplicity, let's assume that the regressors in $\boldsymbol{x}$ are exogenous.

Arellano and Bond begin solving the equation (5.4) by first differencing it, which eliminates the individual fixed effects.

$$\Delta y_{i,t} = \rho \Delta y_{i,t-1} + \Delta \boldsymbol{x}_{i,t}\alpha + \Delta u_{i,t} \tag{5.5}$$

for $t = 3, ..., T$.

This, however, introduces endogeneity problem when we have lagged dependent variable as a predictor. The endogeneity is embodied by the fact that $\Delta y_{i,t-1}$ is correlated with $\Delta u_{i,t}$. Note here, that the GMM estimation itself does not deal with endogeneity, but it is rather the approach proposed by Arellano and Bond that does. To help solve endogeneity problem, instrumental variables are used. It turns out that deeper lags of the dependent variable are suitable as "GMM" instruments. This seems rational for two reasons:

(i) Relevance – deeper lags affect the differenced recent lags and are part of the difference by definition,

(ii) Exclusion – past values are not correlated with future error terms, e.g. $y_{i,t-2}$ is not correlated with $u_{i,t}$ and $u_{i,t-1}$.

Furthermore, the Arellano-Bond estimation also uses the exogenous variables as "normal" instruments with the same lag structure. In the case that some elements of $\boldsymbol{x}$ are considered endogenous, "GMM" instruments are created in similar fashion for them too (Roodman 2009).

Now, let's rewrite the equation (5.5) as:

$$\Delta y = \Delta R\beta + \Delta u \tag{5.6}$$

Then we construct the instrumental matrix Z:

$$Z = \begin{pmatrix} Z_1 \\ Z_2 \\ \vdots \\ Z_N \end{pmatrix}$$

where for each individual $i \in \{1, ..., N\}$ holds

$$Z_i = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \dots \\ y_{i1} & 0 & 0 & 0 & 0 & 0 & \dots \\ 0 & y_{i2} & y_{i1} & 0 & 0 & 0 & \dots \\ 0 & 0 & 0 & y_{i3} & y_{i2} & y_{i1} & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

This matrix illustrates several properties. The number of instruments increases with time dimension – there is one instrument available at $T = 3$, two at $T = 4$, three at $T = 5$ etc. Then, it addresses the trade-off between the lag distance and the sample size as opposed to traditional construction of instrumental variables by Anderson & Hsiao (1982). For example, in their case, when $y_{i,t-2}$ is used as an instrument for $\Delta y_{i,t-1}$, all observations for $T = 2$ must be dropped because $y_{i,t-2}$ is unavailable at that time period. By adding extra instrument $y_{i,t-3}$, observations from $T = 3$ must be dropped and sample size decreases. This trade-off is avoided by the Arellano-Bond approach by zeroing out dropped observations. Furthermore, different instruments are used for different time periods. For instance, no instruments are used for $\Delta y_{i,2}$ (referring to the zeros in the first row of the matrix), and one instrument $y_{i,1}$ is used for $\Delta y_{i,3}$, but is 0 for all other time periods. Then two instruments $y_{i,1}$ and $y_{i,2}$ are used for $\Delta y_{i,4}$, but are 0 outside $T = 4$ etc.

Now, let's define the moment condition as:

$$\mathbb{E}(Z^T \Delta u) = \mathbb{E}(Z^T(\Delta y - \Delta R\beta)) = 0 \tag{5.7}$$

After the two-step difference GMM estimation, we need to obtain the result in the following form:

$$\widehat{\beta} = [\Delta R^T Z(Z^T\widehat{\Omega}Z)^{-1}Z^T\Delta R]^{-1}\Delta R^T Z(Z^T\widehat{\Omega}Z)^{-1}Z^T\Delta y \tag{5.8}$$

To arrive at the first-step estimator, we need to minimize the GMM criterion function:

$$F(\beta) = NT\left[\frac{1}{NT}(\Delta y - \Delta R\beta)^T Z\right](Z^T\Omega Z)^{-1}\left[\frac{1}{NT}Z^T(\Delta y - \Delta R\beta)\right] \tag{5.9}$$

where the middle factor is the weighting matrix of the moments with:

$$\Omega = \begin{pmatrix} 2 & -1 & 0 & \dots & 0 \\ -1 & 2 & -1 & \dots & 0 \\ 0 & -1 & 2 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & -1 & 2 \end{pmatrix}$$

This would bring us the first step estimator in the desired form. Then, we use the residuals $\Delta\hat{u}$ from the first step to arrive at the second-step estimator, which accounts for the presence of heteroskedasticity. For more details, please, refer to Arellano & Bond (1991), Roodman (2009) or Croissant & Millo (2008).

5.2.2 Tests

To make inference valid, we need to check validity of several tests once the Arellano-Bond procedure is finished. Firstly, the Wald test of joint significance of coefficients (sometimes also time dummies) must hold. The null hypothesis is that there is no joint significance hence the goal is to reject it at least at 10% significance level.

Furthermore, we have to be careful about autocorrelation and over-identification restrictions. Arellano and Bond devised a test for first and second order autocorrelation of the GMM residuals, referred to as AR(1) and AR(2). Their null hypotheses are such that there is no serial autocorrelation of given order. For AR(1) test, the null hypothesis is rejected, which seems to be intuitive because of inclusion of the lagged dependent variable. According to Arellano & Bond (1991), the estimation heavily relies on lack of second order serial correlation since presence of such autocorrelation would yield inconsistent results. Therefore, the goal is to not reject the AR(2) hypothesis at least at 5% significance level. If one fails in this task, further lag of the dependent variable should be included and then test for higher order serial correlation conducted (Roodman 2009).

Finally, Sargan-Hansen test is used to assess whether the model is not overidentified with many (invalid) instruments. This is a crucial assumption for the validity of the GMM estimation. Sargan-Hansen test builds upon Wald test to verify joint validity of identifying restrictions. The null hypothesis is the opposite to the one in the original Wald test mentioned above. Hence, we aim to not reject this null hypothesis at least at 10% significance level. In such case, it would be suggested that the set of used instruments is appropriate.

5.2.3 Implementation

We performed the regressions using the plm package in R software. For main estimations we chose Arellano-Bond two-step difference GMM estimation. Standard errors in Arellano-Bond estimation are robust, implementing correction by Windmeijer (2005). He also showed that two-step difference GMM estimation performs better than one-step GMM estimation, which further justifies our choice (Windmeijer 2005; Roodman 2009).

Chapter 6

Empirical results

The results, including coefficients with standard errors and appropriate statistics, are presented in this chapter. First, we start with static estimation and proceed with dynamic estimation. We finish with a robustness check, which includes a division based on the level of exposure to COVID-19, as well as the presence of lockdowns in the case of moratoria. We were able to adhere to the proposed p-values in all specifications and tried a variety of them. We have included models we think are important since they convey the main message of our regressions. Despite the fact that p-values of AR(2) in Arellano-Bond estimations and Adjusted R^2 in fixed effects/random effects are not ideal, possibly due to the short time period, we believe our findings have explanatory value.

6.1 Static panel estimation

In Tables 6.1, 6.2 and 6.3 we report results for static regressions with all estimated coefficients displayed with robust standard errors. The Hausman test favored RE most of the time, although in some circumstances, such as when analyzing effects of moratoria, other measures and all measures simultaneously, FE were preferred despite the negative values of Adjusted R^2. These findings are included in the appendix (see Tables A.1, A.2, A.3, A.4 and A.5). The choice of the FE/RE option is stated either in the title or in the column heading, along with the fiscal measure included in that regression. Table 6.1 depicts the situation without fiscal measures, Table 6.2 evaluates effects of direct grants, public guarantees and public loans. Finally, in Table 6.3 focus is on tax reliefs and tax deferrals. When assessed individually, all measures were found to significantly affect the NPL ratio. When we added one measure to another, the significance of some estimates changed slightly. Economic growth and employment were found to be significant in all specifications. The sign is expected for EMP, which indicates that with more hours worked, the NPL ratio declines. Contrary to the literature, we found positive relationship between economic growth and the NPL ratio. This possibly unanticipated discovery can also be seen in dynamic estimations. Nonetheless, we believe economic growth reduces NPLs, but we were unable to empirically capture it. Other parameter estimates are more mixed. Since NPLs are persistent, we do not further discuss the results of static estimation and proceed with the dynamic estimation.

Table 6.1: Static estimation RE: without fiscal measures

	Dependent variable: NPL
EG	0.022*** (0.008)
EMP	−0.035*** (0.011)
NEER	7.801 (5.026)
R	−0.220 (0.152)
ROE	−0.019 (0.015)
CAP	0.116* (0.063)
Constant	6.688*** (0.414)
Observations	4,653
R^2	0.004
Adjusted R^2	0.002
F Statistic	17.101***
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 6.2: Static estimation RE: Direct grants – Public loans

	Dependent variable: NPL		
	(1) – DIRGRA	(2) – PUBGAR	(3) – PUBLOA
EG	0.022*** (0.008)	0.023*** (0.008)	0.023*** (0.008)
EMP	−0.032*** (0.010)	−0.032*** (0.010)	−0.034*** (0.011)
NEER	4.936 (4.912)	9.086* (5.256)	8.955* (5.092)
R	−0.228 (0.159)	−0.305** (0.152)	−0.133 (0.149)
ROE	0.018 (0.013)	0.015 (0.013)	−0.011 (0.013)
CAP	0.140** (0.068)	0.173** (0.069)	0.120* (0.063)
DIRGRA	−1.648*** (0.317)		
PUBGAR		−1.694*** (0.320)	
PUBLOA			−1.130*** (0.309)
Constant	7.682*** (0.558)	7.760*** (0.566)	7.122*** (0.470)
Observations	4,653	4,653	4,653
R^2	0.031	0.034	0.014
Adjusted R^2	0.029	0.032	0.012
F Statistic	146.343***	162.249***	65.218***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6.3: Static estimation RE: Tax reliefs – Tax deferrals

	Dependent variable: NPL	
	(1) – TAXREL	(2) – TAXDEF
EG	0.021*** (0.008)	0.022*** (0.008)
EMP	−0.035*** (0.011)	−0.035*** (0.011)
NEER	7.360 (5.077)	4.226 (5.309)
R	−0.165 (0.151)	−0.346** (0.156)
ROE	−0.004 (0.014)	−0.004 (0.015)
CAP	0.157** (0.068)	0.108* (0.063)
TAXREL	−0.909*** (0.241)	
TAXDEF		−1.160*** (0.258)
Constant	6.971*** (0.445)	7.264*** (0.503)
Observations	4,653	4,653
R^2	0.009	0.017
Adjusted R^2	0.007	0.015
F Statistic	41.025***	78.042***
Note:		*p<0.1; **p<0.05; ***p<0.01

6.2 Dynamic panel estimation

Due to the high persistency in NPLs, we prefer the dynamic estimations. We begin by examining the effects of explanatory variables other than fiscal measures in Table 6.4. Table 6.4 compares regressions with and without fiscal measures followed by Tables 6.5 and 6.6 that include direct grants, public guarantees, public loans and moratoria in the first and tax reliefs, tax deferrals and other measures in the latter. We focus on lagged NPLs, contemporaneous and lagged economic growth and employment and the rest of the macroeconomic and bank-specific variables at contemporaneous levels. The lagged NPL estimate is positive and significant, indicating persistence. It supports the notion that NPLs are on balance sheets for at least a quarter and so influence the NPL ratio in the future. The contemporaneous economic growth is found to positively affect NPLs. When Beck et al. (2015) studied 75 countries over ten-year period, the overall impact of the real GDP growth was negative, i.e. with high economic growth, NPLs were expected to decline. But the lagged real GDP growth was found to have a positive impact. They argued that loose credit standards in boom periods worsen bank asset quality with a lag. We might question applicability of such statement in our case because of the quarterly frequency and related business cyclicality. Rather, we believe that there was an additional factor that influenced the effect of economic growth. For example, while goods were being manufactured, they may have been left in warehouses and not purchased. Therefore, while the production was on, potentially supported through the fiscal measures, the final goods may not have reached the ultimate customers, depriving companies of income and hence distorting the impact of EG. Alternatively, the growth might not have been sufficient enough due to the capacity restrictions in services, workplace restrictions in the case of products manufacture or increased costs related to hygienic expenses. This could deprive firms of their income and decrease their debt servicing capacity. As a result, while enterprises produced more, their income may not have increased proportionally, and NPLs may have increased. Second, contemporaneous and lagged employment proves to have a significant negative impact on NPLs. Let us recall that employment is defined as a change in the number of hours worked on a quarterly basis. Rather than using the actual number of individuals employed, this method accounts for possible distortions caused by employees who were not working but whose contracts could not be terminated due to legislation and COVID-19 constraints. For this reason, changes in hours worked may better represent the (un)employment rate. This appears to be similar to EG at first glance. However, these two variables are not correlated and EMP captures the state of the labor market. Our finding suggests that the level of employee income shapes the demand for goods and services provided by businesses, potentially leading to a reduction of NPLs. This result is also consistent with the literature. The negative sign of the EMP estimate and its lagged value is present in all specifications. Third, the effect of NEER and ROE is another finding that is consistent across all specifications. The appreciation of the domestic currency is associated with a reduction of NPLs. This finding suggests that importing economies or sectors within economies may have improved their competitiveness and cut costs, resulting in a decrease in NPLs. Alternatively, if the businesses had loans in foreign currencies, the appreciation of the domestic currency could have aided their debt servicing capacity. When it comes to profitability measured by ROE, our findings support the minority of the literature that suggests that profit-maximizing activities are associated with higher risk (Marco & Fernandez 2008; Us 2017). However, in our situation, banks may not have been chasing risky projects, but rather the risk itself increased for some sectors as a result of the pandemic (see Figures 3.1 and 3.2) and became ingrained in otherwise sound loans. Consequently, banks with rising profitability may have faced increased credit risk. Lastly, NPLs appear to be unaffected by interest rates and capital adequacy as no effect was found in any specification.

Once we have established the effects of macroeconomic and bank-specific variables, let's assess the impact of fiscal measures. To begin, we look at direct grants. The estimate of the contemporaneous level of direct grants is insignificant when tested individually but becomes significant and negative when all measures are tested simultaneously. However, the significance of the estimate varied across specifications suggesting that the empirical evidence may not have been fully captured or is ambiguous. Second, the results are more robust in the case of public guarantees. In both specifications, the estimated coefficients are negative and significant at the highest level. This finding supports the idea that guarantees provided to businesses helped with liquidity difficulties, resulting in reduction of NPLs. Similarly to direct grants, the lags are not significant. Table 3.3 shows that approximately a quarter of public guarantees was about to expire by the end of Q4 2021, and 37% afterwards. Hence, authorities may be more careful when public guarantees expire to minimize rises in NPLs, as noted by ESRB (2021a). This could be further emphasized by the strong significant effect, expiration after considered time horizon, and the fact that public guarantees were popular in uptake (ESRB 2021b). Possible ways to mitigate insurgence of NPLs are suggested by Kasinger et al. (2021), e.g. timely identification of non-performing loans, implementation of asset quality reviews and stress tests and modernization of the secondary market for NPLs. Third, on a contemporaneous or lagged level, no empirical evidence for public loans was discovered. Fourth, lagged moratoria were found to positively affect the NPL ratio. This evidence may appear counter-intuitive because moratoria allowed borrowers to defer loan payments, implying that moratoria could reduce NPL levels. Given that 73% of loan moratoria expired by Q2 2021, their popular uptake in % of 2019 GDP and due to the fact that it is the lagged estimate which is significant, it could imply that loans become non-performing once moratoria expire, and that this evidence could be demonstrated empirically. We further investigate the impact of loan moratoria in Section 6.3, where we interact moratoria with a dummy for sectors with high exposure to COVID-19 and the presence of lockdowns. Fifth, in the first column of Table 6.6, we considered tax reliefs as one of the explanatory variables. We discovered that the contemporaneous indicator of tax reliefs is both significant and negative. When all measures were assessed at the same time, the effect was likewise detected, albeit smaller and less significant. Our findings suggest that by lowering tax burdens, enterprises' liquidity and solvency would be successfully supported, resulting in a decrease in NPLs. Finally, the effects of tax deferrals and other measures on the NPL ratio could not be captured.

Table 6.4: Arellano–Bond estimation: without measures vs with all measures

	Dependent variable: NPL	
	(1)	(2)
NPL (-1)	0.926*** (0.034)	0.927*** (0.035)
EG	0.012** (0.006)	0.011* (0.006)
EG (-1)	0.003 (0.005)	0.002 (0.005)
EMP	−0.016** (0.008)	−0.015** (0.008)
EMP (-1)	−0.012** (0.006)	−0.011* (0.006)
NEER	−10.666** (4.566)	−10.406** (4.666)
R	−0.024 (0.115)	−0.074 (0.121)
ROE	0.054*** (0.013)	0.059*** (0.014)
CAP	0.058 (0.050)	0.052 (0.049)
DIRGRA		−0.227* (0.126)
PUBGAR		−0.996*** (0.364)
PUBLOA		0.256 (0.239)
MOR (-1)		0.225* (0.131)
TAXREL		−0.441** (0.225)
TAXDEF		−0.102 (0.160)
OTHER		0.267 (0.165)
Observations used	4,230	4,230
AR(1), p-value	0.004	0.005
AR(2), p-value	0.097	0.104
Sargan test, p-value	0.292	0.290
Wald test, p-value	<0.001	<0.001
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6.5: Arellano–Bond estimation: Direct grants – Moratoria

	Dependent variable: NPL			
	(1) – DIRGRA	(2) – PUBGAR	(3) – PUBLOA	(4) – MOR
NPL (-1)	0.927*** (0.034)	0.923*** (0.034)	0.926*** (0.034)	0.933*** (0.035)
EG	0.013** (0.006)	0.012* (0.006)	0.012** (0.006)	0.013** (0.006)
EG (-1)	0.004 (0.005)	0.002 (0.005)	0.003 (0.005)	0.004 (0.005)
EMP	−0.015** (0.008)	−0.016** (0.008)	−0.016** (0.008)	−0.016** (0.008)
EMP (-1)	−0.012** (0.006)	−0.012** (0.006)	−0.012** (0.006)	−0.012** (0.006)
NEER	−9.695** (4.674)	−10.948** (4.641)	−10.641** (4.606)	−10.929** (4.597)
R	−0.016 (0.117)	−0.034 (0.120)	−0.017 (0.118)	0.004 (0.116)
ROE	0.057*** (0.013)	0.055*** (0.014)	0.055*** (0.013)	0.054*** (0.013)
CAP	0.062 (0.050)	0.047 (0.050)	0.057 (0.050)	0.057 (0.052)
DIRGRA	−0.208 (0.127)			
DIRGRA (-1)	0.174 (0.160)			
PUBGAR		−0.973*** (0.284)		
PUBGAR (-1)		−0.040 (0.391)		
PUBLOA			−0.040 (0.205)	
PUBLOA (-1)			0.001 (0.212)	
MOR				0.030 (0.105)
MOR (-1)				0.290** (0.127)
Observations used	4,230	4,230	4,230	4,230
AR(1), p-value	0.004	0.004	0.004	0.004
AR(2), p-value	0.098	0.097	0.097	0.099
Sargan test, p-value	0.307	0.297	0.292	0.262
Wald test, p-value	<0.001	<0.001	<0.001	<0.001

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6.6: Arellano–Bond estimation: Tax reliefs – Other

	Dependent variable: NPL		
	(1) – TAXREL	(2) – TAXDEF	(3) – OTHER
NPL (-1)	0.932*** (0.034)	0.927*** (0.035)	0.928*** (0.034)
EG	0.012* (0.006)	0.013** (0.006)	0.013** (0.006)
EG (-1)	0.002 (0.005)	0.003 (0.005)	0.003 (0.005)
EMP	−0.016** (0.008)	−0.015** (0.008)	−0.015** (0.008)
EMP (-1)	−0.011* (0.006)	−0.011* (0.006)	−0.011* (0.006)
NEER	−12.148** (4.863)	−10.455** (4.516)	−9.527** (4.603)
R	−0.041 (0.118)	−0.073 (0.122)	−0.022 (0.119)
ROE	0.058*** (0.013)	0.055*** (0.013)	0.053*** (0.013)
CAP	0.058 (0.048)	0.062 (0.051)	0.062 (0.050)
TAXREL	−0.589*** (0.223)		
TAXREL (-1)	0.039 (0.260)		
TAXDEF		−0.105 (0.144)	
TAXDEF (-1)		0.285 (0.228)	
OTHER			0.247 (0.165)
OTHER (-1)			−0.215 (0.207)
Observations used	4,230	4,230	4,230
AR(1), p-value	0.005	0.004	0.004
AR(2), p-value	0.102	0.096	0.099
Sargan test, p-value	0.255	0.300	0.291
Wald, p-value	<0.001	<0.001	<0.001

Note: *p<0.1; **p<0.05; ***p<0.01

6.3 Robustness check

We tested robustness of our results using FE, RE, and several Arellano-Bond estimations, some of which are included in this thesis. As an additional robustness check, we interact individual fiscal measures with dummy for exposure to COVID-19. This dummy takes value of one for country-sectors with exposure above the median and zero otherwise. To assess exposure to the COVID-19 pandemic, ESRB (2021a) recommends looking at the decline in economic growth and employment. When we look at Figures A.1, A.2, A.3, A.4, A.5, A.6, we can see that there were significant drops in multiple sectors in Q2 2020. Therefore, we ordered the country-sectors according to drops in economic growth and employment in Q2 2020, and identified those with the largest declines and formed a union. Unlike ESRB (2021a), which suggests that sectors G to I and R to U were hit the hardest, our technique allows us to account for country-sector peculiarities. We agree with ESRB (2021a) to a considerable extent, but we also include additional sectors that would otherwise be ignored.

Tables 6.7 and 6.8 summarize the findings. There is no evidence that direct grants have any effect. In terms of public guarantees, there seems to be no difference between high and low exposure either. However, when we do not control for country-sectors with low exposure, the estimate is significant and negative for public guarantees in country-sectors with high exposure (see Table A.6). In the case of public loans, the contemporaneous values are not significant, but the lagged values are significant for country-sectors with low exposure. Nonetheless, the impact of public loans on the NPL ratio is mixed. In terms of the lagged moratoria, we are able to confirm that moratoria in country-sectors with high-exposure have a statistically significant and positive impact on NPLs. In terms of tax reliefs, the interaction of contemporaneous TAXREL and exposure provides no additional benefits. Despite this, a pattern emerged when lags were included in a regression (see Table A.7). The lagged and contemporaneous estimates offset each other in specifications with exposures. This confirms our previous finding that contemporaneous tax reliefs are associated with a decrease in the NPL ratio. The remaining fiscal measures – tax deferrals and other measures – do not prove to be statistically significant. An exception applies to lagged other measures for country-sectors with low exposure to COVID-19, but overall results remain mixed.

Since moratoria were found to increase the NPL ratio we wanted to confirm this finding in another way. It might be possible that there was an explanatory variable that we omitted from our regressions. The presence of lockdowns, which could distort the effect of loan moratoria, could be one of the possible factors. Therefore, we gathered the data on country responses to COVID-19 from European Centre for Disease Prevention and Control. "Stay-at-home" orders related to lockdowns were filtered, and dummies were made in the same way as for the fiscal measures. We assume that lockdowns applied to all sectors in a country. In Table 6.9, neither contemporaneous nor lagged lockdowns alone have any influence on the NPL ratio. When we include loan moratoria in column 2 while controlling for lockdowns, a significant and positive effect of lagged moratoria is observed. Similarly, when we interact lockdowns with moratoria, the positive impact of the lagged variable remains. Hence, our evidence suggests that loan moratoria delayed the rise of the risk associated with non-performing loans.

Table 6.7: Arellano–Bond estimation: Direct grants – Moratoria (COVID-19 exposure)

	Dependent variable: NPL			
	(1) – DIRGRA	(2) – PUBGAR	(3) – PUBLOA	(4) – MOR
NPL (-1)	0.949*** (0.145)	0.933*** (0.146)	0.933*** (0.034)	0.935*** (0.035)
EG	0.011 (0.007)	0.010 (0.008)	0.011* (0.006)	0.011* (0.006)
EG (-1)	0.003 (0.005)	0.001 (0.006)	0.003 (0.005)	0.003 (0.005)
EMP	−0.012 (0.018)	−0.014 (0.019)	−0.018** (0.008)	−0.017** (0.008)
EMP (-1)	−0.013* (0.007)	−0.013* (0.007)	−0.012** (0.006)	−0.012** (0.006)
NEER	36.029 (196.301)	18.722 (204.539)	−10.768** (4.598)	−10.906** (4.650)
R	−0.512 (2.042)	−0.348 (2.136)	−0.034 (0.117)	−0.004 (0.117)
ROE	0.062** (0.025)	0.058** (0.024)	0.055*** (0.013)	0.054*** (0.013)
CAP	0.077 (0.085)	0.054 (0.085)	0.059 (0.051)	0.057 (0.052)
DIRGRA*EXPOSUREHIGH	−0.439 (0.490)			
DIRGRA*EXPOSURELOW	−0.329 (0.519)			
PUBGAR*EXPOSUREHIGH		−1.193 (0.929)		
PUBGAR*EXPOSURELOW		−0.823 (0.922)		
PUBLOA*EXPOSUREHIGH (-1)			0.236 (0.297)	
PUBLOA*EXPOSURELOW (-1)			−0.454** (0.219)	
MOR*EXPOSUREHIGH (-1)				0.444** (0.176)
MOR*EXPOSURELOW (-1)				−0.029 (0.163)
Observations used	4,230	4,230	4,230	4,230
AR(1), p-value	0.003	0.004	0.004	0.004
AR(2), p-value	0.089	0.091	0.098	0.099
Sargan test, p-value	0.573	0.552	0.284	0.279
Wald test, p-value	<0.001	<0.001	<0.001	<0.001

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6.8: Arellano–Bond estimation: Tax reliefs – Other (COVID-19 exposure)

	Dependent variable: NPL		
	(1) – TAXREL	(2) – TAXDEF	(3) – OTHER
NPL (-1)	0.929*** (0.035)	0.939*** (0.161)	0.935*** (0.035)
EG	0.011 (0.007)	0.011 (0.008)	0.012* (0.006)
EG (-1)	0.002 (0.005)	0.003 (0.006)	0.003 (0.005)
EMP	−0.019 (0.020)	−0.014 (0.020)	−0.017** (0.008)
EMP (-1)	−0.011 (0.008)	−0.012 (0.007)	−0.011** (0.006)
NEER	−32.952 (220.177)	5.426 (220.179)	−10.332** (4.622)
R	0.167 (2.247)	−0.207 (2.331)	−0.012 (0.120)
ROE	0.056*** (0.020)	0.056** (0.025)	0.054*** (0.013)
CAP	0.051 (0.084)	0.063 (0.090)	0.064 (0.050)
TAXREL*EXPOSUREHIGH	−0.840 (0.709)		
TAXREL*EXPOSURELOW	−0.253 (0.620)		
TAXDEF*EXPOSUREHIGH		−0.199 (0.576)	
TAXDEF*EXPOSURELOW		−0.248 (0.536)	
OTHER*EXPOSUREHIGH (-1)			−0.041 (0.213)
OTHER*EXPOSURELOW (-1)			−0.662** (0.322)
Observations used	4,230	4,230	4,230
AR(1), p-value	0.005	0.004	0.004
AR(2), p-value	0.106	0.091	0.099
Sargan test, p-value	0.551	0.550	0.303
Wald test, p-value	<0.001	<0.001	<0.001

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6.9: Arellano–Bond estimation: Moratoria and Lockdown

	Dependent variable: NPL		
	(1)	(2)	(3)
NPL (-1)	0.930*** (0.034)	0.934*** (0.035)	0.932*** (0.034)
EG	0.012** (0.006)	0.013** (0.006)	0.011* (0.006)
EG (-1)	0.004 (0.005)	0.004 (0.005)	0.004 (0.005)
EMP	−0.015* (0.008)	−0.016** (0.008)	−0.014* (0.008)
EMP (-1)	−0.011* (0.006)	−0.012** (0.006)	−0.011* (0.006)
NEER	−11.490** (4.641)	−10.971** (4.626)	−12.900*** (4.764)
R	−0.023 (0.115)	0.003 (0.116)	−0.003 (0.114)
ROE	0.054*** (0.013)	0.054*** (0.014)	0.053*** (0.013)
CAP	0.058 (0.052)	0.059 (0.052)	0.079 (0.049)
LOCKDOWN	0.045 (0.091)		
LOCKDOWN (-1)	0.131 (0.129)		
MOR		0.032 (0.104)	
MOR (-1)		0.296** (0.131)	
LOCKDOWN		−0.007 (0.106)	
MOR*LOCKDOWN			−0.040 (0.096)
MOR*LOCKDOWN (-1)			0.201* (0.114)
Observations used	4,230	4,230	4,230
AR(1), p-value	0.004	0.004	0.004
AR(2), p-value	0.097	0.099	0.099
Sargan test, p-value	0.302	0.258	0.396
Wald test, p-value	<0.001	<0.001	<0.001

Note: *p<0.1; **p<0.05; ***p<0.01

Chapter 7

Conclusion

Credit risk must be closely monitored in order to ensure financial stability and economic growth. The NPL ratio, which measures the ratio of loans that are either past due or unlikely to be repaid to the total outstanding amount, is one possible measure of credit risk. When credit risk materializes, the quality of banking assets worsens, and financial institutions' lending ability deteriorates. The financial system and national economies will be impacted as a result. Hence, monitoring NPL ratios is critical for both banking industry representatives and economic policymakers. Credit risk and the real economy have a two-way interaction in which one aids in the explanation of the other's variations and changes, and vice versa. What affected economic growth is the COVID-19 pandemic hitting the EU in early 2020. Different effects in terms of economic growth and employment could be seen in different areas of the economy. The credit risk, on the other hand, has not materialized yet. Because the COVID-19 crisis is still relatively new phenomenon, in this thesis, we attempted to examine the evolution of credit risk during the pandemic outbreak while taking sectoral peculiarities into consideration. An essential part of our analysis is inclusion of fiscal measures implemented in response to COVID-19 as their aim was to support liquidity and solvency of companies and the economy in general. To our best knowledge, there are no studies that simultaneously used macroeconomic and bank-specific factors together with fiscal policy measures to examine determinants of NPL ratios. This thesis tries to fill this gap in the literature. Another aim is to assess potential future implications once the measures phase out. We acquired data on a quarterly basis for this purpose, encompassing the fullest possible period between Q1 2019 and Q4 2021 that was subject to reporting concerns. We further employed split according to sectors of economic activity – the NACE classification. By this approach, we cover 423 economic sectors across 23 European countries for the given time period. The ratio of non-performing loans to total loans was used as the dependent variable, while economic growth, employment, nominal effective exchange rate, interest rates, return on equity, capital adequacy ratio and 7 fiscal measures were used as independent variables. The NPL ratio, economic growth, employment and fiscal measures were available in the breakdown according to NACE codes. The remaining factors were only reported at the country level. We used Arellano and Bond's difference GMM dynamic panel estimation as our estimation technique.

Our results confirm the persistence in NPLs and support the idea that macroeconomic and bank-specific factors and fiscal measures influence the level of non-performing loans. Precisely, in the context of the COVID-19 outbreak, economic growth appears to positively affect the NPL levels and negatively affect the banking assets quality. This finding is in contrast to the literature implying potential limitations in our research. Contrary, employment and exchange rates have a negative impact on the NPL ratio. Lower NPLs are associated with more hours worked. Similarly, appreciation of the domestic currency tends to reduce NPLs. In terms of bank-specific variables, higher return on equity is associated with deterioration of the asset quality. Other regressors – interest rates and capital adequacy ratio – did not prove to significantly affect the NPL ratio. Regarding the fiscal measures, there is no empirical evidence that public loans, tax deferrals and other miscellaneous measures have an impact on the asset quality. When it comes to direct grants, the evidence is ambiguous because the significance of particular estimates differed across specifications. Nevertheless, the estimated coefficients had negative signs most of the times, but these results should be treated with caution. The findings are more robust in the case of public guarantees and tax reliefs, which were found to have a statistically significant and negative influence on NPLs. This implies that by supporting liquidity and solvency of businesses via loan guarantees and reduction of tax burdens, non-performing loans are reduced. However, as these measures phase out, the authorities may be more cautious about credit risk in the future. Public guarantees should be given special attention because they were relatively popular in terms of uptake and frequency, and their expiration could result in a rise in NPLs. Finally, loan moratoria were found to positively affect the NPL ratio with a lag. The estimate remained statistically significant when controlling for lockdowns and sectors with high exposure to COVID-19. This could indicate that loans became non-performing once moratoria expired and the rise of credit risk has been delayed.

Lastly, our analysis has implications for policymakers and future researchers. First, due to relevance of some fiscal measures, certain policies seem to be more preferable to be used in potential future crises as they appear to better mitigate credit risk. Second, policymakers should be cautious when existing policies, such as public guarantees, loan moratoria, and tax reliefs, expire. Third, appropriate mechanisms, such as timely identification of NPLs, adequate asset quality reviews, stress tests and secondary markets for NPLs should be considered when addressing credit risk. Regarding future research, more granular breakdown of variables and inclusion of policies as regressors should be considered when analyzing determinants of non-performing loans. Our current work could be further extended when data capturing longer time horizon become available or when new statistical data regarding COVID-19 emerge in the future. Potential researchers could also utilize different mixture of explanatory variables and try various interactions. In our context, the data are currently limited in their time span and granularity. However, we believe that a foundation for future research regarding determinants of NPLs in more granular breakdown and in times of a crisis has been established.

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Appendix A

Appendix

A.1 Static panel estimation

Table A.1: Static estimation FE: without fiscal measures

	Dependent variable: NPL
EG	0.023*** (0.008)
EMP	−0.037*** (0.011)
NEER	6.954 (4.999)
R	−0.159 (0.150)
ROE	−0.011 (0.015)
CAP	0.142** (0.062)
Observations	4,653
R^2	0.004
Adjusted R^2	-0.096
F Statistic	3.178*** (df = 6; 4224)
Note: Back to Section 6.1.	*p<0.1; **p<0.05; ***p<0.01

Table A.2: Static estimation FE & RE: with fiscal measures

	Dependent variable: NPL	
	(1) – FE	(2) – RE
EG	0.022*** (0.008)	0.022*** (0.008)
EMP	−0.034*** (0.011)	−0.032*** (0.010)
NEER	11.944* (6.154)	12.043** (6.094)
R	−0.623*** (0.216)	−0.614*** (0.208)
ROE	0.016 (0.014)	0.012 (0.014)
CAP	0.202*** (0.070)	0.173** (0.069)
DIRGRA	−1.107*** (0.389)	−1.007*** (0.355)
PUBGAR	−2.465*** (0.570)	−2.423*** (0.542)
PUBLOA	0.959** (0.442)	0.978** (0.411)
MOR	−0.448** (0.204)	−0.335* (0.194)
TAXREL	0.329 (0.312)	0.398 (0.284)
TAXDEF	0.224 (0.314)	0.320 (0.296)
OTHER	1.560*** (0.514)	1.098** (0.450)
Constant		7.847*** (0.579)
Observations	4,653	4,653
R^2	0.060	0.045
Adjusted R^2	-0.037	0.042
F Statistic	20.781*** (df = 13; 4217)	218.988***

Note: Back to Section 6.1. *p<0.1; **p<0.05; ***p<0.01

Table A.3: Static estimation FE: Direct grants – Public loans

	Dependent variable: NPL		
	(1) – DIRGRA	(2) – PUBGAR	(3) – PUBLOA
EG	0.023*** (0.008)	0.024*** (0.008)	0.024*** (0.008)
EMP	−0.033*** (0.011)	−0.033*** (0.010)	−0.035*** (0.011)
NEER	3.935 (4.870)	8.339 (5.271)	8.445* (5.085)
R	−0.169 (0.158)	−0.247* (0.150)	−0.069 (0.148)
ROE	0.027** (0.013)	0.023* (0.013)	−0.003 (0.013)
CAP	0.166** (0.068)	0.199*** (0.069)	0.146** (0.062)
DIRGRA	−1.686*** (0.321)		
PUBGAR		−1.710*** (0.321)	
PUBLOA			−1.216*** (0.322)
Observations	4,653	4,653	4,653
R^2	0.037	0.041	0.018
Adjusted R^2	-0.060	-0.057	-0.082
F Statistic (df = 7; 4223)	23.465***	25.474***	11.166***

Note: Back to Section 6.1. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A.4: Static estimation FE: Tax reliefs – Tax deferrals

	Dependent variable: NPL	
	(1) – TAXREL	(2) – TAXDEF
EG	0.022*** (0.008)	0.022*** (0.008)
EMP	−0.037*** (0.011)	−0.037*** (0.011)
NEER	6.778 (4.986)	2.965 (5.422)
R	−0.105 (0.150)	−0.288* (0.153)
ROE	0.005 (0.014)	0.005 (0.015)
CAP	0.186*** (0.068)	0.134** (0.062)
TAXREL	−0.942*** (0.257)	
TAXDEF		−1.224*** (0.269)
Observations	4,653	4,653
R^2	0.011	0.021
Adjusted R^2	-0.090	-0.078
F Statistic (df = 7; 4223)	6.637***	13.072***

Note: Back to Section 6.1. *p<0.1; **p<0.05; ***p<0.01

Table A.5: Static estimation FE & RE: Moratoria – Other

	Dependent variable: NPL			
	(1) – MOR (FE)	(2) – MOR (RE)	(3) – OTHER (FE)	(4) – OTHER (RE)
EG	0.020** (0.008)	0.019** (0.008)	0.023*** (0.008)	0.023*** (0.008)
EMP	−0.034*** (0.011)	−0.033*** (0.011)	−0.035*** (0.011)	−0.033*** (0.010)
NEER	9.524* (5.148)	9.704* (5.166)	4.966 (5.236)	5.248 (5.256)
R	−0.468*** (0.176)	−0.494*** (0.176)	−0.084 (0.148)	−0.123 (0.148)
ROE	−0.005 (0.014)	−0.014 (0.014)	0.004 (0.015)	−0.001 (0.015)
CAP	0.186*** (0.069)	0.156** (0.069)	0.156** (0.065)	0.135** (0.066)
MOR	−1.567*** (0.304)	−1.420*** (0.289)		
OTHER			−0.671*** (0.247)	−0.824*** (0.243)
Constant		7.258*** (0.501)		7.032*** (0.458)
Observations	4,653	4,653	4,653	4,653
R^2	0.031	0.022	0.008	0.009
Adjusted R^2	-0.068	0.021	-0.092	0.007
F Statistic (df = 7; 4223)	19.108***	104.807***	5.149***	41.417***

Note: Back to Section 6.1. *p<0.1; **p<0.05; ***p<0.01

A.2 Dynamic panel estimation

Table A.6: Arellano–Bond estimation: detail on Public guarantees

	Dependent variable: NPL	
	(1)	(2)
NPL (-1)	0.842*** (0.062)	0.811*** (0.072)
EG	0.013* (0.007)	0.013* (0.007)
EG (-1)	0.003 (0.005)	0.004 (0.005)
EMP	−0.016 (0.019)	−0.017 (0.019)
EMP (-1)	−0.014** (0.007)	−0.014* (0.007)
NEER	13.294 (207.954)	6.848 (214.365)
R	−0.272 (2.165)	−0.192 (2.230)
ROE	0.050** (0.021)	0.047** (0.022)
CAP	0.058 (0.087)	0.057 (0.089)
PUBGAR*EXPOSUREHIGH	−0.410** (0.200)	
PUBGAR*EXPOSURELOW		0.320 (0.197)
Observations used	4,230	4,230
AR(1), p-value	0.006	0.007
AR(2), p-value	0.096	0.097
Sargan test, p-value	0.363	0.269
Wald test, p-value	<0.001	<0.001
Note: Back to Section 6.3.		*p<0.1; **p<0.05; ***p<0.01

Table A.7: Arellano–Bond estimation: detail on Tax reliefs

	Dependent variable: NPL
NPL (-1)	0.890*** (0.134)
EG	0.015** (0.007)
EG (-1)	0.006 (0.005)
EMP	−0.040*** (0.013)
EMP (-1)	−0.004 (0.007)
NEER	−296.908** (151.147)
R	2.737* (1.481)
ROE	0.035* (0.020)
CAP	−0.035 (0.074)
TAXREL*EXPOSUREHIGH	−1.393*** (0.470)
TAXREL*EXPOSUREHIGH (-1)	1.824** (0.889)
TAXREL*EXPOSURELOW	−0.778* (0.456)
TAXREL*EXPOSURELOW (-1)	1.568 (1.019)
Observations used	4,230
AR(1), p-value	<0.001
AR(2), p-value	0.209
Sargan test, p-value	0.877
Wald test, p-value	<0.001
Note: Back to Section 6.3.	*p<0.1; **p<0.05; ***p<0.01

A.3 Miscellaneous

Figure A.1: Quarterly percentage change in EG for sectors A - F

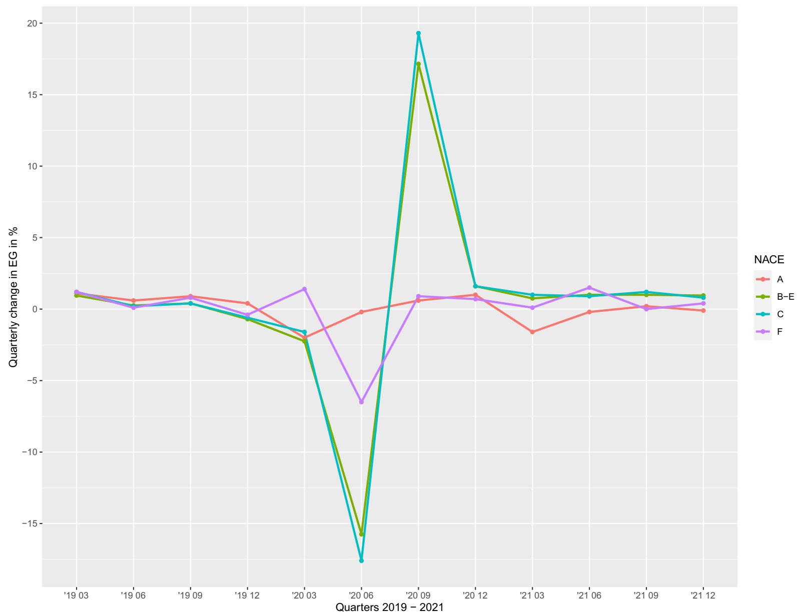

Figure A.2: Quarterly percentage change in EG for sectors G - L

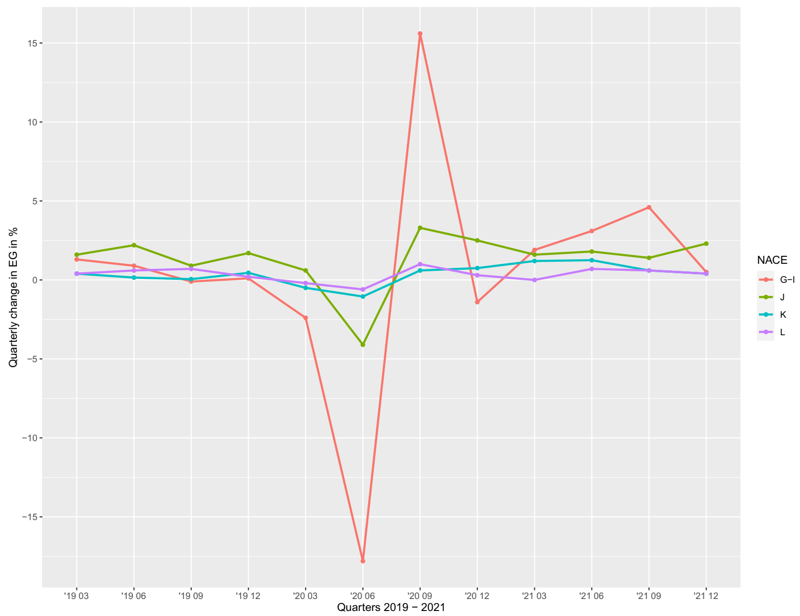

Figure A.3: Quarterly percentage change in EG for sectors M - S

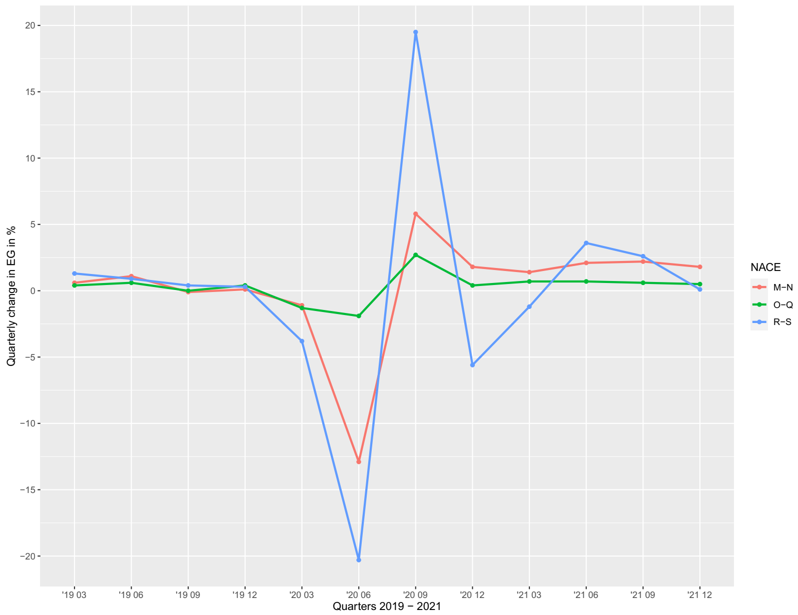

Figure A.4: Quarterly percentage change in EMP for sectors A - F

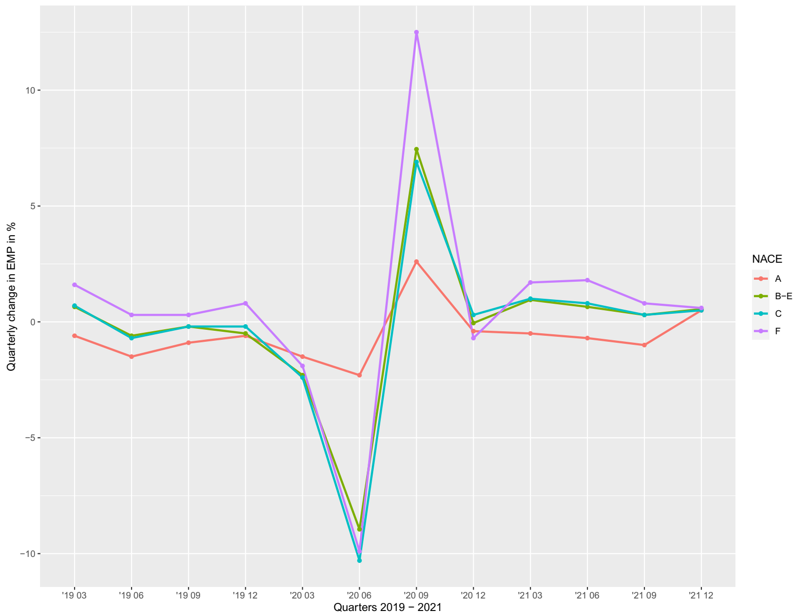

Figure A.5: Quarterly percentage change in EMP for sectors G - L

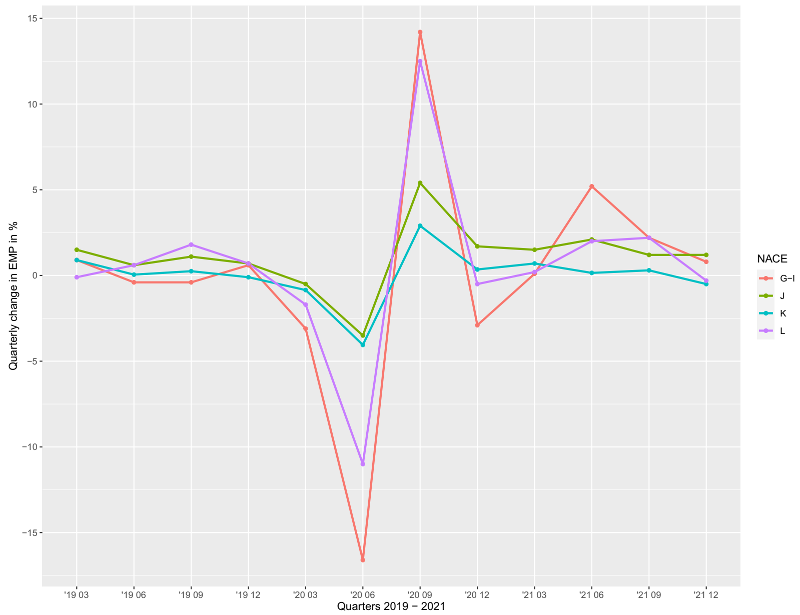

Figure A.6: Quarterly percentage change in EMP for sectors M - S