THE IMPACT OF COVID-19 ON THE EUROPEAN COMMERCIAL BANKING SECTOR

A CROSS-COUNTRY EMPIRICAL ANALYSIS

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Abstract:

This paper investigates the impact of COVID-19 on the European commercial banking sector. Using panel data, we study the effect of the severity of the pandemic on bank lending, customer depositing behavior, and the provisioning for credit losses. First, our findings indicate a significant decrease in lending activity with higher exposure to COVID-19, which leads us to call the role of banks as *lenders of first resort* during times of crisis into question. Second, we find weak empirical evidence for the *safe haven theory*, a behavioral observation with depositors, that more funds from customer deposits become available during times of economic uncertainty. In theory, this increased deposit inflow from delayed consumption decisions should finance the origination of new loans. In opposition to prior literature, we do not find statistical evidence for this natural hedge in a European setting. Third, we observe a significantly positive relationship between pandemic impact and loan loss provisions indicating that banks on average perceived an increase in their credit risk during 2020.

Keywords:

COVID-19, Pandemic, Bank lending, Depositing, Loan loss provisions

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List of Abbreviations

BCBS	Basel Committee on Banking Supervision
BoE	Bank of England
C&I	Corporate and industrial loans
COVID-19	Coronavirus disease 2019
DEA	Data envelopment analysis
DMU	Decision-making unit
EBA	European Banking Authority
ECB	European Central Bank
ECL	Expected credit loss
ESMA	European Securities and Markets Authority
EU	European Union
Eurostat	European Statistical Office
FSF	Financial Stability Forum
G20	Group of Twenty
GDP	Gross domestic product
GFC	Global financial crisis
$H_1 – H_3$	Hypotheses one to three
IASB	International Accounting Standards Board
IAS	International Accounting Standards
IFRS	International Financial Reporting Standards
ICL	Incurred credit loss
ILM	Incurred loss model
IMF	International Monetary Fund
LLP	Loan loss provision
LLR	Loan loss reserves
NPL	Non-performing loan
OLS	Ordinary least squares (regression)
ROA	Return on assets
S&P	Standard & Poor’s
SICR	Significant increase in credit risk
Q1 – Q4	First to fourth quarter
UK	United Kingdom
US	United States
VIF	Variance Inflation Factors
WHO	World Health Organization

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1. Introduction

"This is not just a public health crisis, it is a crisis that will touch every sector. So, every sector and every individual must be involved in the fights."[1]

– Dr. Tedros Adhanom Ghebreyesus, WHO director-general

In December 2019, the first known case of a new form of coronavirus was identified in the city of Wuhan in the Chinese Hubei province. Officially designated as *COVID-19*, the novel coronavirus disease has proven to be highly infectious and spread heavily worldwide to the extent that the World Health Organization (WHO) declared COVID-19 a global pandemic on March 11th, 2020 (WHO, 2020a). Indeed, upon the initial COVID-19 outbreak, Europe quickly became the new epicenter of the pandemic with more reported cases and deaths than the rest of the world combined, second only to China (WHO, 2020b).

To combat the spread of COVID-19, governments in many European jurisdictions began to impose drastic restrictions, bringing public life and economic activity to a near standstill. As of March 18th, 2020, more than 250 million Europeans found themselves in some form of lockdown (Dursun-de Neef & Schandlbauer, 2020a). The COVID-19 pandemic and its severe repercussions on businesses and financial markets have significantly haltered global economic prospects. In its *Spring 2020 Economic Forecast*, the European Commission predicted the eurozone economy to contract by 7.75% in 2020 with an uncertain recovery in 2021 (European Commission, 2020a). Thereby, the COVID-19 recession would represent the worst global economic crisis in Europe since the *Great Depression* in the 1920s and 1930s (European Commission, 2020a).

The unfolding events of the still ongoing COVID-19 crisis have been estimated to put the liquidity insurance function of banks to an unprecedented stress test (Li et al., 2020). In contrast to the global financial crisis (GFC) 2008-09, the root cause of this present stress on banks' liquidity insurance function did not originate in the banking sector itself but is instead induced externally by a global pandemic. Its initial occurrence, arriving unexpectedly to most main-street firms and banks, is non-financial by nature and will likely affect every sector in the economy (Li et al., 2020). Following the imposed COVID-19 lockdowns, liquidity has quickly evaporated for both small and large businesses, whereas debt repayments and other fixed costs will come due as usual (Acharya & Steffen, 2020). In anticipation of deteriorated funding conditions and further financial disruptions caused by the advent of the pandemic, firms return to their banks as *lenders*

[1]WHO. (2020a). WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020

of first resort and may start drawing down funds from preexisting credit commitments on large scale (Acharya & Steffen, 2020; Li et al., 2020).

According to classic banking theory, liquidity supply is a central function of banks in the economy and represents an imperative for a well-functioning financial system and macroeconomic growth (Davydov et al., 2021; Diamond & Dybvig, 1983). Indeed, the European Central Bank (ECB) strongly emphasized the role of banks as liquidity providers in light of the current COVID-19 pandemic. In an official recommendation, the ECB called upon banks to refrain from dividend distributions and share buy-back programs until September 2021 (ECB, 2020). Thereby, banks should conserve capital and retain their capacity to support the real economy in a time of crisis. More specifically, the ECB stated that it is essential *"that credit institutions continue to fulfill their role of funding households, small and medium-sized businesses and corporations amid the COVID-19-related economic shock"* (ECB, 2020). Referring back to the initial quote by WHO director-general Dr. Tedros Adhanom Ghebreyesus, the European banking sector is hence viewed to take on a crucial part "*in the fights"* against COVID-19.

In close cooperation with the European Banking Authority (EBA), most national financial supervisory institutions loosened their guidelines on responsible lending to support and release pressure from delinquent lenders. These measures included, but were not limited to, the suspension of principal repayments for an agreed-upon time frame, expansion of loan periods, or introducing a simplified application process for new loans (EBA, 2020). At the same time, the European Securities and Markets Authority (ESMA) stressed that the measures taken in the context of the pandemic outbreak which permit, require or encourage suspension or delays in payments, should not be automatically regarded as having a one-to-one impact on the assessment of credit risk (ESMA, 2020). Hence, a moratorium of local institutions under these conditions should not in itself be considered an automatic trigger event of significant increase in credit risk (SICR) (ESMA, 2020).

This thesis aims to provide a holistic view on the impact of the COVID-19 pandemic on the European commercial banking sector. In particular, we aim to investigate whether banks with higher exposure to COVID-19 have responded differently regarding their lending and risk-taking behavior. For our study, Europe provides a compelling research setting as it constitutes a closely connected economic area that is yet expected to experience very uneven COVID-19 recession levels *"conditioned by the speed at which lockdowns can be lifted, the importance of services like tourism in each economy and by each country's financial resources"* (European Commission, 2020b). Moreover, governmentally-induced COVID-19 restrictions differed substantially throughout Europe, leading to favorable cross-country variation in our sample. Both intensity and timing of lockdowns varied in addition to other containment measures imposed on businesses and citizens (Li et al., 2020). Furthermore, we receive valuable information from time variation in our sample. We can refer to a full year of financial and pandemic impact data capturing both the first and second wave of the pandemic in Europe.

In their role as *lenders of first resort* to the general public and the economy, it is to our utmost interest to study the behavior of commercial banks in a European setting. Since we understand their business model of balance sheet lending and depositing as the purest form of providing liquidity to the market, we specifically focus on commercial banks, which constitute a cornerstone to the European economy.

Following prior literature on banks' role as financial intermediaries and liquidity providers during crises, we aim to provide further evidence to a growing research field related to the ongoing COVID-19 pandemic by answering the following research questions:

How did the COVID-19 pandemic impact the European commercial banking sector from a lending and depositing perspective?

Did the impact of the COVID-19 pandemic and related uncertainty in the credit market materialize in a significant increase in loan loss provisions for European commercial banks?

Prior research on the impact of COVID-19 on the banking sector is very limited, given that the pandemic is still ongoing. Most closely related to our study, Dursun-de Neef & Schandlbauer (2020a) examine how European banks responded to the initial COVID-19 outbreak in the first quarter of 2020. Focusing on bank capital, they find that higher exposure to COVID-19 increased lending for worse-capitalized banks, whereas better-capitalized banks decreased their lending. In a second study on US banks, Dursun-de Neef & Schandlbauer (2020b) find evidence that banks with higher exposure to COVID-19 experienced a significant increase in their deposits, suggesting that households accumulated their savings in banks at the onset of the crisis. Moreover, Li et al. (2020) explicitly investigate the role of banks as *lenders of first resort* during the COVID-19 crisis. They find that, in March 2020, the US commercial banking sector faced the largest increase in liquidity demand ever observed, whereby banks were able to accommodate this liquidity shock due to a robust regulatory capital base as well as the Federal Reserve's liquidity injection programs.

In conjunction with the heightened risk environment caused by the *COVID-19 recession* and encouraged lending by supervisory authorities, European banks face an increasing credit risk in their loan portfolios. Albeit ESMA points out that COVID-19 related payment relief measures should not automatically be considered a trigger for SICR, we observe an increased tendency of loan loss provisioning in our sample (ESMA, 2020; Figure 4). Taking the economic cycle into account, Laeven & Majnoni (2003) observe that banks tend to postpone provisioning for credit losses during eras of economic expansion. Consequently, during phases of economic downturn, an insufficient amount of credit provisioning before an unexpected loss event is set aside. Prior studies show that abnormal loan growth is generally accompanied by an increase in loan loss provisions (LLPs) (Foos et al., 2010). Faced with a general sentiment of uncertainty in the market, an assessment of the timing of loan loss provisioning is of our utmost interest. To the best of our knowledge, research targeting LLPs in light of the COVID-19 pandemic is still limited when writing this thesis. It is to be shown if the implementation of IFRS 9 with its forward-looking provisioning nature made a difference in banks' effort to assess the full impact of the pandemic adequately.

This thesis adds to academic research in three distinct areas. First, our findings contribute to a growing strand of literature examining the economic and financial consequences of the COVID-19 pandemic. In particular, empirical studies investigating the impact of COVID-19 on credit institutions are very limited. Second, our paper complements earlier studies discussing the effects of COVID-19 on the banking sector with an extended observation period. Due to a lack of data, the scope of these early studies is limited to the initial reaction of banks to the pandemic during the first quarter of 2020 (Dursun-de Neef & Schandlbauer, 2020a, 2020b; Li et al., 2020). We aim to contribute by incorporating data from four consecutive quarters to show the full-year impact of the pandemic throughout 2020. Third, our study contributes to the literature on bank liquidity creation, specifically regarding the role of banks as liquidity providers to firms and households during times of crisis. Even though liquidity supply is an essential function that banks perform in the economy, it has received relatively little attention in prior research (Davydov et al., 2021). Prior studies on banks' role as liquidity providers mostly concentrate on credit supply during the GFC 2008-09 and the US banking sector (Acharya & Mora, 2015; Cornett et al., 2011; Ivashina & Scharfstein, 2010). As a result, the current COVID-19 crisis and our geographic focus on the European banking sector represent an interesting research setting to complement this stream of literature.

The pursuant chapters are structured as follows. First, we start with relevant background literature on the role of banks as financial intermediaries between lenders and depositors, as well as their responsibility to detect and regulate credit risk. Second, we develop three hypotheses based on prior theory that are subsequently tested in the fourth part of our thesis. The third section aims at explaining the underlying methodology and data. Finally, the study continues with a chapter on our empirical results and a discussion section thereof before closing with some limitations and concluding remarks.

A brief chronology of the COVID-19 pandemic in Europe during 2020

The first active cases of COVID-19 in Europe were confirmed in France on January 24th, 2020, after two individuals returned from the Wuhan region. By mid-March, Italy was considered the epicenter of the pandemic in Europe, accounting for 43.5% of cases and 78.1% of deaths (Johns Hopkins University & Medicine, 2021). Shortly before, eleven municipalities in the northern part of Italy had been identified as the main pandemic clusters and were placed under quarantine. The rest of the country followed suit shortly thereafter, stalling nearly all commercial activities and placing more than 60 million Italians in lockdown.

In the following weeks, the virus spread across the European continent, reaching 465,241 cumulative confirmed cases by the end of the first quarter. To limit the further spreading of the virus, national governments across the continent closed down significant parts of their economies, restricted public gatherings, and enforced infection protection laws. The peak of the first wave was reached in mid-April when on average 39,000 cases were reported each day on a weekly rolling basis. In the following months, the number of new infections decreased significantly compared to the heights of the first wave. Consequently, most European countries undertook an easement process of their restrictions, albeit still exercising caution. By September 11th, new cases per day had surpassed the peek during the first wave earlier in the year. Exponential growth in the number of daily new cases impelled at the beginning of the fourth quarter, driven mainly by a rapid increase in case numbers in countries such as France, Italy, the UK, and Spain.

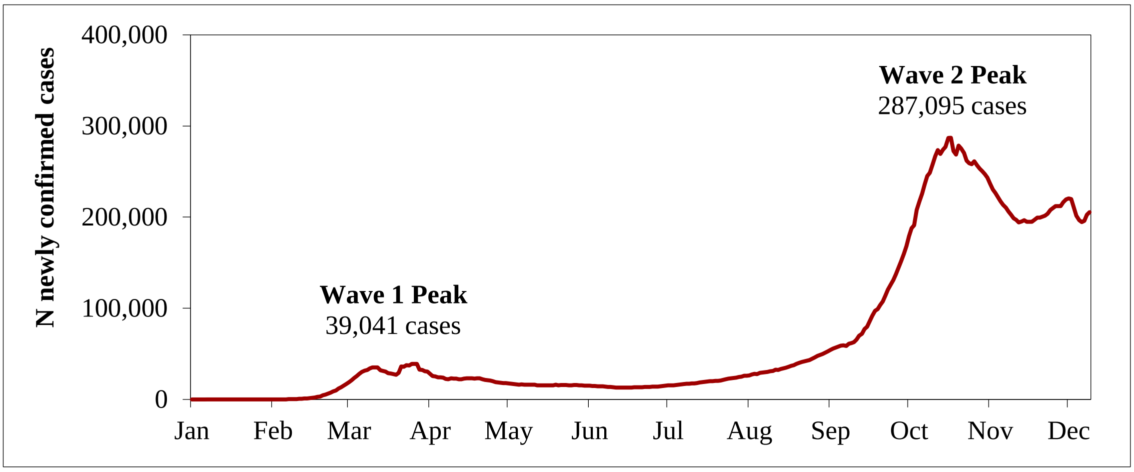


Figure 1. shows the new COVID-19 case numbers on a seven-day rolling average. Source: Johns Hopkins University & Medicine (2021).

Figure 1. Daily new confirmed COVID-19 cases in Europe

Throughout the year, a considerable variation of cases and governmental responses became apparent, not only from a time but also from a geographic perspective. In Sweden, for instance, most businesses have been allowed to keep their operations running while only minor restrictions were introduced to the public to guarantee social distancing. However, the majority of the other European countries followed a more conservative approach, imposing lockdowns on high-incidence regions and restricting social life were deemed necessary.

Initial vaccination programs commenced by the end of December, albeit only accounting for a fractional share of the entire population by the end of the year. At the time of this study, the pandemic is still ongoing with increasing vaccination rates close to 20% of the European population.

2. Literature Review and Theory

2.1. Banking Business Model: Theory and Evidence

In this section, theory and evidence concerning the traditional business model of banks are reviewed. Initially, the theory of financial intermediation is presented, which considers banks as financial intermediaries in providing liquidity to both borrowers and depositors (section 2.1.1). In addition, empirical evidence regarding the role of banks as liquidity providers during crises is discussed (section 2.1.2).

2.1.1. Theory of Financial Intermediation

According to the modern theory of financial intermediation, liquidity creation is a central function that banks perform in the economy (Berger & Bouwman, 2009). The process of liquidity creation represents an imperative to a well-functioning financial system and economic growth (Davydov et al., 2021). Banks supply liquidity on either side of their balance sheets by two distinct types of activities: lending and deposit-taking (Diamond & Rajan, 2001). On the asset side, they provide liquidity to borrowers in the form of term loans and credit lines. On the liability side, they make funds available on-demand to depositors. Thereby, banks create liquidity by financing relatively long-term illiquid assets with more short-term liquid demand deposits (Diamond & Dybvig, 1983). In addition, banks create liquidity through off-balance sheet activities, such as letters of credit and loan commitments (Zheng et al., 2019). Off-balance sheet commitments obligate a bank to provide funds to a borrower on-demand over some specified period (Kashyap et al., 2002). More precisely, an off-balance sheet loan commitment becomes an on-balance sheet loan when a borrower decides to draw down the commitment (Cornett et al., 2011).

Liquidity creation is risky because it leaves banks vulnerable to market-wide liquidity shocks, enhances a bank's exposure to illiquidity, and can therefore be considered a main source of banking fragility (Zheng et al., 2019). Diamond & Rajan (2001) suggest that banks' capital structure can be fragile because banks must provide liquidity to borrowers and depositors on demand while holding illiquid loans. At the extreme, liquidity crunches can quickly propagate from one credit institution to another, trigger bank runs, or force the fire-sale liquidation of illiquid assets, as was seen during the GFC 2008-09 (Davydov et al., 2021; Diamond & Dybvig, 1983). In particular, systematic increases in liquidity demand can occur at inconvenient times, i.e., when loan payments are uncertain due to adverse macroeconomic conditions (Cornett et al., 2011). Besides the withdrawal of funds from wholesale deposits, liquidity risk stems from banks' exposure to undrawn credit commitments (Cornett et al., 2011). Berger & Bouwman (2009) find that approximately half of the liquidity creation at commercial banks occurs through off-balance sheet commitments. Likewise, Gatev & Strahan (2006) provide evidence that borrowers are more inclined to draw down funds from preexisting credit lines during times of economic uncertainty.

Even though the role of banks in providing liquidity insurance to both borrowers and depositors exposes banks to market-wide liquidity shocks, banks can hedge against such liquidity risks by drawing from synergy effects between lending and depositing (Gatev et al., 2009; Gatev & Strahan, 2006; Kashyap et al., 2002). Transaction deposits effectively hedge the liquidity risk inherent in unused loan commitments, whereby this effect is even more pronounced during periods of tight market liquidity (Gatev et al., 2009). Because banks are viewed as *safe havens* by depositors, funding tends to become available to them during periods of market stress, just when borrowers want to draw down funds from their loan commitments (Gatev & Strahan, 2006). In consequence, increased deposit inflows provide financing for loan demand shocks that follow declines in market liquidity. This natural hedge gives banks an advantage in providing liquidity during crises. More specifically, it allows banks to meet loan demands from borrowers without running down on their liquid asset holdings and offer liquidity insurance against systemic declines in liquidity at lower costs than other financial intermediaries (Gatev & Strahan, 2006).

The studies by Gatev & Strahan (2006) and Gatev et al. (2009) on the natural hedge between lending and depositing complement an earlier theoretical model presented by Kashyap et al. (2002), which motivates the coexistence of lending and depositing at commercial banks using a risk-management perspective. Kashyap et al. (2002) provide empirical evidence for diversification synergies between commitment lending and deposits. These diversification benefits exist because both functions require banks to hold large buffers of liquid assets. Provided that deposit withdrawals and loan commitment takedowns are not too highly correlated, lending and depositing can share the overhead costs of the liquid-asset stockpile required. This synergy effect enables banks to provide more commitment-based lending to borrowers in the form of unsecured credit lines than any other type of financial intermediary.

In summary, the theory of financial intermediation states that banks exist because they perform a central role as liquidity providers in the economy. Liquidity is provided both on the balance sheet by financing illiquid loans with liquid deposits and off the balance sheet through loan commitments and similar claims to liquid funds (Berger & Bouwman, 2009). In this respect, the theory of financial intermediation is central to the business model of commercial banks, which will be the main focus of this master thesis.

2.1.2. Evidence on the Role of Banks as Liquidity Providers

The objective of this master thesis is to analyze the lending and depositing behavior of European commercial banks during the COVID-19 pandemic. As indicated by the theory of financial intermediation, deposit inflows provide a natural hedge against loan demand shocks, particularly during times of tight market liquidity. Using the widely accepted notion that banks have a natural advantage in providing liquidity, prior empirical studies have investigated the role of banks as liquidity providers during crisis periods.

Ivashina & Scharfstein (2010) study the effects of the banking panic that occurred after the failure of Lehman Brothers in the fall of 2008 on credit supply to the corporate sector. Using *DealScan* data, the authors find that new credit origination fell by 47% during the peak of the GFC 2008-09. As part of the bank run in the fall of 2008, borrowers drew down preexisting credit commitments on large scales, leading to a spike in commercial and industrial (C&I) loans on banks' balance sheets. These drawdowns were primarily driven by general concerns about the liquidity and solvency of the banking sector. Ivashina & Scharfstein (2010) find that banks characterized by less access to deposit financing and higher exposure to credit line drawdowns were more vulnerable to the bank run and consequently cut their lending to a greater extent than other banks. In particular, banks that co-syndicated a larger proportion of their preexisting credit commitments with Lehman Brothers reduced credit origination to greater extent.

In a similar vein, Cornett et al. (2011) study how US commercial banks managed the liquidity shock during the GFC 2008-09 by adjusting their holdings of liquid assets and how these efforts affected credit supply. In line with Ivashina & Scharfstein (2010), Cornett et al. (2011) highlight that loan commitment drawdowns materialized following the collapse of Lehman Brothers, constraining new credit origination. Specifically, banks with more illiquid assets on their balance sheets expanded their cash buffers, whereby these efforts to build up asset liquidity displaced funding to support new lending. By contrast, banks relying on stable sources of financing, such as core deposits and equity capital, were less adversely affected and continued to lend relative to other banks. Cornett et al. (2011) extend the findings of Ivashina & Scharfstein (2010) by showing that liquidity risk from unused loan commitments was negatively correlated with loan growth and positively correlated with the growth in liquid assets during the GFC 2008-09. Hence, banks' efforts in managing the liquidity crisis led to an overall decline in credit supply.

In this respect, the studies by Ivashina & Scharfstein (2010) and Cornett et al. (2011) find evidence for the natural hedge of lending and depositing in light of the GFC 2008-09. Somewhat contradictory, Acharya & Mora (2015) argue that, at the onset of the GFC 2008-09, the *flight-to-safety* reaction to the banking system broke down, weakening aggregate deposit inflows and forcing banks to cut new credit originations. This effect was particularly pronounced at highly-commitment exposed banks prone to failure, which in turn paid higher deposit rates to attract funding. While banks generally honored credit line drawdowns during the GFC 2008-09, this liquidity supply was possible only because of explicit, large support from the US government and Federal Reserve. Acharya & Mora (2015) conclude that until the government interventions in the fall of 2008, the GFC 2008-09 was, in fact, a crisis of banks as liquidity providers.

Building on the empirical model of Cornett et al. (2011), Li et al. (2020) examine whether US banks' financial condition has affected their liquidity supply in response to COVID-

19. Drawing from the Federal Reserve's weekly FR 2644 data, the authors highlight that the outbreak of the COVID-19 pandemic constituted an unprecedented stress test on banks' ability to supply liquidity to the market. More precisely, the last three weeks of March 2020 represented the largest increase in liquidity demand for US banks ever observed, exceeding weekly lending growth during the GFC 2008-09 to a great extent. Li et al. (2020) find that the sharp increase in liquidity demand was concentrated at the largest banks and significantly driven by drawdowns of unused loan commitments. In contrast to the GFC 2008-09, the authors conclude that banks' financial condition did not constrain their liquidity insurance function in light of COVID-19. Compared to Cornett et al. (2011), Li et al. (2020) do not find robust evidence that loan growth was more pronounced at banks financed with stable deposits. In addition, Li et al. (2020) argue that pre-crisis measures of capital and asset liquidity did not covary with bank lending. In particular, funding inflows from both the Federal Reserve and depositors enabled banks to accommodate the liquidity demand shock at the onset of the COVID-19 crisis.

In a similar vein, Dursun-de Neef & Schandlbauer (2020a) examine how European banks responded to the initial COVID-19 outbreak, focusing on bank capital. Using a sample of 144 European banks and an individual bank-level COVID-19 exposure measure weighted by bank branches, the authors provide evidence that higher exposure to COVID-19 increased worse-capitalized banks' lending, whereas better-capitalized banks decreased their loan supply. The authors explain this empirical finding by worse-capitalized banks issuing new loans to help their struggling borrowers pay back their existing loans, thereby avoiding the realization of write-downs on their capital. Exploring how the observed differences in loan supply impacted banks' risk-taking behavior, Dursun-de Neef & Schandlbauer (2020a) find that worse-capitalized banks with higher exposure to COVID-19 experienced a significant increase in their risk-weighted assets, leading to an expansion in their balance sheet size. To finance this expansion in size, worse-capitalized banks did not use deposits but rather non-depository debt, cash, and equity as a funding source. This finding appears contradictory to the theory on the natural hedge between lending and depositing, according to which banks use deposit inflows to finance increases in loan supply (Gatev & Strahan, 2006).

In a second study on the US commercial banking sector, Dursun-de Neef & Schandlbauer (2020b) examine whether households accumulated more savings in their deposit accounts in a *flight-to-safety* reaction to COVID-19. They find that banks with higher exposure to COVID-19 experienced a significant increase in their deposits, thereby providing evidence for the *safe haven theory*. The authors argue that this deposit increase can mainly be attributed to decreased consumer spending due to reduced mobility during COVID-19. However, this result only holds for banks located in counties with overall lower increases in unemployment, implying that households experiencing employment layoffs did not save significantly more money in their deposit accounts. Dursun-de Neef & Schandlbauer (2020b) further document that, in response to the increased deposit funding, banks with higher exposure to COVID-19 increased their total credit supply significantly more, both by honoring existing credit commitments and issuing new term loans. Consequently, their study provides evidence on the theory that the natural hedge between lending and depositing gives banks a natural advantage in providing liquidity during crises (Gatev & Strahan, 2006).

Building on the finding of Cornett et al. (2011) that banks increased their cash holdings to manage liquidity risk before supplying credit during the GFC 2008-09, Dursun-de Neef & Schandlbauer (2020b), in a subsequent step study whether banks with higher exposure to COVID-19 saw an increase in their cash holdings. In congruence with Cornett et al. (2011), the authors find that banks with higher exposure to COVID-19 and lower pre-crisis cash holdings increased their cash position significantly more. Dursun-de Neef & Schandlbauer (2020b) conclude that higher pre-crisis cash levels enabled banks to provide significantly more liquidity to the market at the onset of COVID-19.

In conclusion, empirical studies examining the role of banks as liquidity providers during the current COVID-19 pandemic and GFC 2008-09 find varying support for the natural hedge between lending and depositing, as implied by the theory of financial intermediation. Moreover, there seem to be divergent results on the role of bank financial condition for lending during COVID-19 compared to prior crises.

2.2. Bank Credit Risk Assessment

The theory of financial intermediation implies that the process of liquidity creation is inherently risky, as it exposes banks to liquidity crunches and bank runs and may influence the financial fragility of individual banks (Berger & Bouwman, 2009; Diamond & Dybvig, 1983; Kashyap et al., 2002). Prior empirical studies suggest that liquidity risk and credit risk are closely related (Foos et al., 2010). It can be expected that the adverse economic impact of COVID-19 might have increased the credit risk exposure of banks' loan portfolios. Before presenting prior research on the main determinants of LLPs (section 2.2.2), as well as discussing regulators' response on the accounting implications of COVID-19 (section 2.2.3), an overview of the accounting framework for LLPs will be provided (section 2.2.1).

2.2.1. Transition from IAS 39 to IFRS 9

As of 1 January 2018, *IFRS 9 Financial Instruments* effectively replaced *IAS 39 Financial Instruments: Recognition and Measurement* and was mandatorily adopted by all IFRS compliant entities (IASB, 2019). In the aftermath of the GFC 2008-09, the leaders of the G-20 called upon standard setters to strengthen the accounting recognition of LLPs (G20, 2009). The prior standard, IAS 39, was criticized for recognizing impairment losses on financial assets "*too little, too late*" (Pucci & Skærbæk, 2020). Regulators raised significant concern that an "e*arlier recognition of loan losses could have dampened cyclical moves in the current crisis"* (FSF, 2009). Under IAS 39, provisions for credit losses were measured under the incurred loss model (ILM), which stipulated that credit losses be grounded on the occurrence of a triggering loss event (IASB, 2017). Moreover, IAS 39 explicitly prohibited the recognition of credit losses to be based on anticipated future events, but instead required credit losses to be incurred *"if, and only if, there is objective evidence of impairment [...] after the initial recognition of the assets"* (IASB, 2017). In practice, the ILM implied that financial institutions generally deferred the recognition of LLPs until the borrower had actually defaulted (Pucci & Skærbæk, 2020).

In response to the call for a more forward-looking approach to LLPs, IFRS 9 introduced the expected credit loss (ECL) model, incorporating a broader range of credit information (Pucci & Skærbæk, 2020). Under IFRS 9, ECLs are measured on a probability-weighted basis as *"the difference between the cash flows that are due to an entity in accordance with the contract and the cash flows that the entity expects to receive"* (IASB, 2019). For banks to determine an appropriate amount of LLPs, IFRS 9 outlines a three-stage model (general model) for impairment based on changes in credit quality since initial recognition, which must continuously be tracked (IASB, 2019). Thereby, the ECL model relies on a relative assessment of credit risk.

← Change in credit quality since initial recognition →		
Stage 1 Performing Initial Recognition	**Stage 2** Underperforming Assets with significant increase in credit risk	**Stage 3** Non-performing Credit-impaired assets
Recognition of expected credit losses		
12-month expected credit losses	Lifetime expected credit losses	Lifetime expected credit losses
Interest revenue		
Effective interest on gross carrying amount	Effective interest on gross carrying amount	Effective interest on amortized cost (net of loss allowance)

Figure 2. Three-stage model under IFRS 9

Stage 1 includes financial assets that have not had a SICR since initial recognition. For these assets, entities are required to provide for ECLs resulting from default events that are possible within the next 12 months (12-month ECLs). For credit exposures where there has been a SICR since initial recognition (Stages 2 and 3), entities are required to make a loss allowance for ECLs resulting from all possible default events over the expected life of the financial asset (lifetime ECLs). The difference between Stages 2 and 3 is that financial assets classified in Stage 3 have shown objective evidence of impairment. Appendix A of IFRS 9 provides examples of multiple events that may provide evidence of impairment, such as the breach of contract due to default or a past due event (IASB, 2019). If a financial asset becomes credit-impaired (Stage 3), interest revenue is calculated based on its net carrying amount.

The forward-looking, principles-based nature of the ECL model requires banks to apply subjective judgment to estimate changes in credit risk and exercise more managerial discretion in making assumptions about expected future conditions (Gomaa et al., 2019). IFRS 9 does not explicitly define what constitutes a SICR. Instead, *"Credit risk analysis is a multifactor and holistic analysis,"* whereby *"An entity shall consider reasonable and supportable information available"* (IASB, 2019). Relevant information in assessing changes in credit risk may include but is not limited to credit ratings, borrower-specific behavior, external market indicators, or forecast adverse changes in the business environment (IASB, 2019). Furthermore, IFRS 9 neither dictates an exact basis on which banks can determine forward-looking scenarios to measure their ECLs nor does it provide an explicit definition for 'default'. Even though there is a presumption that default does not occur later than when a financial asset is 90 days past due (Picker et al., 2019), IFRS 9 leaves it up to each bank to determine an adequate definition of default. As a result, ECL measurement very much reflects the *"entity's <u>own</u> expectations of credit losses"* (IASB, 2019), which gives the potential for significant diversity in terms of how LLPs for ECLs are applied in practice by preparers of financial statements. During the COVID-19 crisis, banking supervisors repeatedly appealed to banks to not send signals that could suggest market shocks, in order to protect the stability of the global financial sector: "*[...] the flexibility embedded in the accounting and regulatory framework is to be fully used* by *institutions to help maintain soundness through the crisis [...]"* (EBA, 2020).

2.2.2. The Role of Loan Loss Provisions

As the ECL model is grounded on a relative credit risk assessment (IASB, 2019), banks must regularly estimate changes in the credit quality of their loans and build up provisions accordingly. LLPs constitute expenses on banks' income statements to incorporate changing projections for ECLs from banks' lending activities, such as bankruptcies, non-performing loans (NPLs), or renegotiated loans that incur lower payments than previously estimated (Caporale et al., 2018; Norden & Stoian, 2013).

Prior research has identified at least three components that can have a significant influence on LLPs: non-discretionary factors related to expected credit risk, discretionary factors associated with income-smoothing behavior, and general risks associated with the economic cycle or other types of uncertainty (Aristei & Gallo, 2019; Bouvatier & Lepetit, 2008; Caporale et al., 2018). These components have so far been assessed in different geographic and time settings.

As an essential accounting accrual, LLPs play a prominent role in disclosing information on the loan portfolio quality of banks affecting both regulatory capital and earnings (Curcio & Hasan, 2015). Consequently, LLPs are commonly subject to managerial discretion, opening the possibility for earnings management behavior (Hasan & Wall, 2004). To minimize the instability of reported earnings, management can record higher LLPs during favorable economic expansion eras while smoothing earnings in declining periods when increased risks in the credit market become apparent (Leventis et al., 2011). Proponents of the earnings management hypothesis argue that LLPs are used as a signaling device for the credit strength of an institution (Aristei & Gallo, 2019), thereby improving risk perception for regulators and investors (Fonseca & González, 2008).

By contrast, the non-discretionary component of LLPs is specifically related to problem loans and default risk (Aristei & Gallo, 2019), thereby reflecting the main objective of LLPs in providing a realistic credit risk assessment of a bank's outstanding loan portfolio. However, the non-discretionary component also determines the cyclicality of LLPs, potentially leading to a misevaluation of ECLs and fluctuations in credit supply. This situation may result in under-provisioning during expansion eras, whereas provisioning becomes less timely during periods of economic decline when loan default rates tend to increase (Bouvatier & Lepetit, 2008; Gambacorta & Mistrulli, 2004; Laeven & Majnoni, 2003). As a result, an insufficient amount of credit provisioning before an unexpected loss event could seriously harm banks' capital (Bushman & Williams, 2015).

Closely related to our research setting, prior empirical studies investigate banks' loan loss provisioning behavior during times of financial distress (Aristei & Gallo, 2019; Caporale et al., 2018). Contradicting the *cyclicality theory* on LLPs, Caporale et al. (2018) find countercyclical tendencies in their sample of Italian banks from 2001-15. Notably, the ratio of earnings before interest and LLPs has a significantly negative impact on LLPs, lending evidence that Italian banks tend not to use discretionary provisions to smooth income neither in normal times nor during times of crisis. In a similar vein, Aristei & Gallo (2019) identify non-discretionary LLPs as the main determinant of the provisioning behavior of Italian banks during crises. Furthermore, policy uncertainty and risk in international lending lead to an increased build-up of LLPs. Prudent banks with higher loan loss reserves (LLRs) are less likely to be affected by policy uncertainty (Ng et al., 2020; Wetmore & Brick, 1994). On the backdrop of the first pandemic quarter in 2020, Li et al. (2020) find increases in LLPs due to an expansion in lending through drawdowns from preexisting credit commitments as well as a looming uncertainty about the heightened risk environment.

While earlier studies on LLPs focus to a large extent on the discretionary and non-discretionary factors affecting provisioning, research on the topic of LLPs during the COVID-19 pandemic is still limited. It can be expected that a deterioration in credit quality due to COVID-19 will have a significant impact on banks' ECL measurement as the first 'real stress test' since the inception of IFRS 9.

2.2.3. Regulators' Response to COVID-19

Since IFRS 9 requires the exercise of substantial judgment in determining the extent of ECLs, LLPs represent one of the main areas where banks' own judgment can play a significant role in terms of how they deal with the ongoing COVID-19 crisis. The following section addresses the challenges banks may face when applying the ECL model during the current COVID-19 crisis.

Since *"a measure of ECL should be an unbiased probability-weighted amount that is determined by evaluating a range of possible outcomes"* (IASB, 2019), banks may find it even more demanding to incorporate forward-looking information and probability estimations in their ECL models given the high uncertainty related to the magnitude of the current COVID-19 pandemic (el Barnoussi et al., 2020). The Basel Committee on Banking Supervision has acknowledged that the ongoing COVID-19 pandemic imposes *"high levels of uncertainty surrounding the forward-looking information relevant to estimating ECLs"* and that *"At present, information available that is both reasonable and supportable on which to assess SICR and measure ECL is limited"* (BCBS, 2020).

Banking supervisory bodies, standard setters, and other regulators have published guidance on the accounting implications of COVID-19 on IFRS 9, following the initial outbreak of the pandemic in March 2020 (BCBS, 2020; EBA, 2020; ESMA, 2020; IASB, 2020). Generally, banks are advised to be prudent when adopting the ECL and SICR requirements with respect to the effects of COVID-19 on their loan portfolios. The EBA states that "*the flexibility embedded in the accounting (…) frameworks is to be fully used by institutions to help maintain soundness through the crisis and provide critical functions to the economy"* (EBA, 2020). In particular, an *"overstatement of ECL could prompt behavior that leads to unnecessary tightening in credit conditions"* (BoE, 2020). Instead, banks *should "give greater weight to the long-term stable outlook"* (ESMA, 2020) and reflect the mitigating effect of the support efforts by governments and central banks in their ECL measures (BCBS, 2020; EBA, 2020; ESMA, 2020). Moreover, banks are advised to be careful about distinguishing temporary COVID-19 relief measures from long-term effects in assessing changes in the lifetime credit risk of a loan (EBA, 2020; ESMA, 2020). For instance, payment moratoriums granted in the context of COVID-19 should not be *"considered as an automatic trigger of SICR"* (ESMA, 2020) and can be *"excluded by banks from the counting of days past due"* (BCBS, 2020).

In conclusion, whether or not a bank expected the pandemic to be temporary or permanent may have significantly impacted its evaluation of credit risk over the expected life of a loan and hence the recognition of LLPs in light of COVID-19.

2.3. Hypotheses

As stated by the modern theory of financial intermediation, the process of liquidity production by transforming liquid deposits into illiquid assets is a central function that banks perform in the economy (Berger & Bouwman, 2009; Diamond & Rajan, 2001). Banks have a natural advantage in providing liquidity over other financial institutions due to a natural hedge between lending and depositing, the two fundamental activities of commercial banks. This natural hedge is more pronounced during periods of tight market liquidity (Gatev et al., 2009), enabling banks to increase their loan supply during crises. In light of the general economic downturn caused by COVID-19, many businesses and private individuals are faced with difficulties to service their short-term debt obligations. Seeing themselves in need of additional capital, they may turn to their banks as *lenders of first resort*. In particular, the ECB strongly called upon European banks to fulfil their role as liquidity providers to mitigate the adverse economic impact of COVID-19 (ECB, 2020). Based on the financial intermediation theory, we formulate our initial hypothesis related to the lending behavior of credit institutions as follows:

H_1: *In their role as liquidity providers and "lenders of first resort", credit institutions show a significant, positive relationship between the impact of COVID-19 and quarter-on-quarter loan growth.*

At times of economic uncertainty and distress, households consider banks as a *safe haven* for their money and, in turn, accumulate their savings in bank deposits, also referred to as *flight-to-safety* (Dursun-de Neef & Schandlbauer, 2020b; Gatev & Strahan, 2006). Customer deposits constitute the primary funding source for banks to grant new loans during times of crisis. Related to H_1, we are therefore also interested in investigating whether customer deposits increase with the severity of the pandemic's impact.

H_2: *Following the "flight-to-safety" theory during times of uncertainty, there is a significant, positive relationship between the impact of COVID-19 and quarter-on-quarter deposit growth.*

In the first half of 2020, the pandemic saw Europe tumble in its first technical recession since the GFC 2008-09. Business disruptions caused by COVID-19 are assumed to result in liquidity problems for many companies and potential deteriorations in the credit quality of banks' loan portfolios (EY, 2020). Prior literature finds evidence that banks build-up lower LLPs than necessary in times of economic expansion and are consequently forced to increase their LLPs during times of economic downturn, magnifying losses and extending negative capital shocks (Laeven & Majnoni, 2003). Moreover, prior literature indicates a positive relationship of LLPs with loan growth and a negative relationship with GDP growth, respectively, further amplifying credit fluctuations (Bouvatier & Lepetit, 2008; Laeven & Majnoni, 2003). Lending evidence to the *cyclicality theory*, Li et al. (2020) find an increase in LLPs as shock absorbers in conjunction with an increased loan supply during the first quarter of 2020. Hence, our third hypothesis aims to test if banks increase their LLPs with a higher impact of COVID-19 and associated economic implications.

H_3: *Building on the theory that banks increase their LLPs during times of uncertainty and economic downturns, we expect a positive relationship between the COVID-19 impact and an increase in LLPs.*

3. Research Design and Methodology

The research focus of this thesis concerns the impact of COVID-19 on bank lending, depositing as well as the loan loss provisioning behavior of European commercial banks. We design a quantitative study using regression analysis to identify the correlational associations between our bank-specific dependent variables and country-specific exposure to COVID-19. The sample used to test our hypotheses is presented in the first section, followed by the regression models' empirical specifications.

3.1. Data Collection and Sample Selection

We analyze quarterly financial statement data from S&P Capital IQ and hand-collected interim reports of 117 credit institutions from 16 countries from Q1 2016 to Q4 2020. Our dataset focuses on commercial banks operating in the EU, the UK, and the European Free Trade Association countries to obtain a geographically diverse picture of the pandemic's impact on the European banking sector. We further motivate our geographic setting with the similarity in regulatory regimes under the umbrella of EU and EBA, and the compliance to the Basel III criteria.

H_1 and H_2 are tested using the same initial panel data set of 117 banks over the period from Q1 2016 to Q4 2020, arriving at a total sample size of 2,340 observations. However, the sample used to test H_3 differs in terms of the scope of research objects and time-dimension, encompassing a total sample size of 1,332 observations. First, we had to reduce our initial sample from 117 to 111 banks due an insufficient reporting on NPL for some banks. Second, to avoid a potential bias in our sample due to changes in accounting regime for LLPs, this reduced sample covers only the period after the implementation of IFRS 9 (i.e., Q1 2018 – Q4 2020).

As a proxy for the pandemic's impact, we decided against a variable solely based on infection cases on the local level as governmental restrictions varied significantly over the year within countries and across borders. Instead, we consulted the *COVID-19 Government Response Tracker* by *Our World in Data*, an online scientific publication initiated by researchers of the University of Oxford. This stringency index functions as a daily composite measure, based on nine weighted response indicators that measure a country's impact by the pandemic on a scale from 0 to 100. For our models, we use the average daily information on an aggregated quarterly basis through which we are able to capture the first wave in quarters one and two, the easing of restrictions during the third quarter, as well as the inception of the second wave in the fourth quarter of 2020.

To capture the quarterly pandemic development and match the findings to our bank dataset, we have to make concessions in the number of banks to include in our sample. As most privately- and state-held banks in Europe are only required to report their financial reports on a biannual basis, we have to forego a substantial number of European small- to medium-sized banks. Our dataset is further restricted to those credit institutions that report all financial statement variables on a consistent quarterly basis for our observation period. The only notable exception to this limitation is Norway, where most financial institutions, regardless of size, publish their financial data every quarter. As a result, our sample shows a bias towards Norwegian credit institutions that we aim to equalize through a country fixed-effects dummy variable.

In this study, we focus on the role of European commercial banks as liquidity providers and financial intermediaries between lenders and depositors in light of COVID-19. Further, as one of our contributions is the segmentation by bank efficiency, we seek to create a homogenous group classified by business model. Hence, our panel dataset further requires that banks have a clear focus on lending and deposit-taking activities, which we understand as the "traditional banking business model". Banks with substantial revenue streams originating from non-interest income activities, such as wealth and asset management, capital markets advisory, or insurance-related business, were disregarded. Over the observation period, if a credit institution, on average, did not derive more than half of its revenue from interest income, it was excluded from the sample.

Information on COVID-19 cases originates from the Johns Hopkins University. The data for our two economic variables, GDP growth and change in unemployment rate, was derived from the OECD's database. Furthermore, information on household consumption expenditures and population numbers was extracted from Eurostat. Lastly, data on governmental COVID-19 support measures originates from the IMF's database.

Table 1. Sample collection

Criteria	**Adjustment**	**Number of Banks**
Industry Classification "Bank"		10,496
Geographic Scope (EU, EFTA, UK)	8,527	1,969
Reporting since 2016	250	1,719
Initial Sample from S&P Capital IQ		**1,719**
Reporting on Quarterly Basis	1,079	640
Majority of Revenues from Interest Income	340	300
Gap-less Reporting	182	118
Discontinued Operation in Obs. Period	1	117
Final Main Sample		**117**

3.2. Measuring a Bank's COVID-19 Impact

The explaining variable *CovidIndex* constitutes our primary variable of interest in all regression models. As previously elaborated, it represents a proxy for the daily governmental reaction to the pandemic on a scale from 0 to 100, averaged by quarter. The dataset is derived from the *COVID-19 Government Response Tracker* by *Our World in*

Data. It aggregates the following factors on a weighted basis: school closures, workplace closures, cancelation of public events, restrictions on gatherings, closure of public transportation, public information campaigns, stay at home policies, restrictions on internal movement, international travel controls, testing policies, contact tracing, face coverings, and vaccination policy (Hale et al., 2021). Macroeconomic variables like GDP and unemployment rate are not included in their index. Appendix C depicts the variation of the *COVID-19 Government Response Tracker* throughout the year.

$$Index = \frac{1}{k} \times \sum_{j=1}^{k} I_j$$

Where:

- **Index** = Daily value of *COVID-19 Government Response Tracker*
- **k** = Number of factors / subindices 'I'
- **I** = Subindex score for any given indicator 'j'

Unlike other COVID-19-related control variables of prior research, the index neither constitutes the development of case numbers nor the death toll per capita in a given country. Instead, it purely focuses on the governmental response on any given day throughout the year. In their study on the pandemic's impact on bank lending behavior, Dursun-de Neef & Schandlbauer (2020a) use the average COVID-19 case numbers per capita weighted by the number of bank branches in different countries for each observation. In a similar research setting of US-based credit institutions, Li et al. (2020) use two strategies to approximate the magnitude of local outbreaks. First, the regional employment decline in small firms, and second, the ex-post death rates related to cases of COVID-19.

As previously stated, we deem our measure more adequate. Regardless of the severity of the pandemic (measured in cases and deaths per capita), government responses varied drastically across countries not adhering to a joint legislative directive on the European level. Furthermore, we see an issue with the differences in testing infrastructure capacities between the first and second half of the year. By applying the *COVID-19 Government Response Tracker*, we can evade a potential distortion due to unrecorded cases. Given the case of a bank with operations in multiple geographies, we weigh the variable by the total revenue exposure in 2020 to each geography:

$$CovidIndex = \sum_{i=1}^{I} Index_{avg.,t} \times RevenueShare_{c,2020}$$

Where:

- **CovidIndex** = Main variable of interest in regression models to determine the impact of pandemic restrictions on our dependent variables
- **Index$_{avg.,t}$** = Average value of Government Response Tracker for quarter ’t’
- **RevenueShare** = Share of total revenues in 2020 by country ’c’

3.3. Empirical Model Specification

To analyze the impact of COVID-19 on bank lending, customer depositing, and the loan loss provisioning behavior of European commercial banks, we perform pooled ordinary least square (OLS) regressions. Pooled OLS regressions allow us to capture causal relationships between our primary variable of interest, *CovidIndex*, and our dependent bank-specific variables (*ΔLoans*, *ΔDeposits*, and *LLR*). Moreover, regression analysis allows us to control for other bank-specific explanatory variables as identified in prior literature. To account for unobserved heteroscedasticity, all our regression models incorporate robust standard errors (Wooldridge, 2019). Heteroscedasticity can lead to incorrect interpretations of the significance level of the coefficients due to biased estimates of standard errors.

Regression (1) – Bank Lending

Regression model (1) is used to test the role of banks as *lenders of first resort* in light of COVID-19. Specifically, we are interested in investigating the relationship between pandemic exposure and bank lending (H_1), captured by the β_1 coefficient. A strain of literature has investigated bank liquidity creation in a crisis setting (Cornett et al., 2011; Dursun-de Neef & Schandlbauer, 2020a; Li et al., 2020). Closely related to their empirical models, we regress the change in on-balance sheet lending on a crisis exposure measure while controlling for other factors affecting bank liquidity creation. For instance, the empirical model by (Cornett et al., 2011) uses the *TED spread*[2] as a variable for banks’ exposure to the GFC 2008-09, whereas COVID-19 related studies use reported COVID-19 cases or death tolls to quantify crisis exposure (Li et al., 2020; Dursun-de Neef & Schandlbauer, 2020a). As explained in the previous section, we use a variable (*CovidIndex*) based on government restrictions to measure banks’ exposure to the pandemic.

$$\begin{aligned}\Delta Loans_{i,t} = \beta_0 + \beta_1 * CovidIndex_{i,t} + \beta_2 * Tier1Cap_{i,t-1} + \beta_3 * LiquidAssets_{i,t-1} \\ + \beta_4 * Deposits_{i,t-1} + \beta_5 * LLR_{i,t-1} + \beta_6 * ROA_{i,t} + \beta_7 \\ * Log(Assets)_{i,t-1} + \beta_8 * \Delta GDP_{j,t} + \beta_9 * \Delta UR_{j,t} + \varepsilon_{i,t}\end{aligned}$$

H_0: $\beta_1 = 0$; **H_1:** $\beta_1 > 0$

[2] Difference between three-month LIBOR rate and three-month Treasury rate

Where:

- $\mathbf{\Delta Loans_{i,t}}$ = Change in gross loans to lagged total assets
- $\mathbf{CovidIndex_{i,t}}$ = Quarterly pandemic response weighted by country exposure
- $\mathbf{Tier1Cap_{i,t-1}}$ = Tier 1 capital ratio, lagged by one quarter
- $\mathbf{LiquidAssets_{i,t-1}}$ = Cash, deposits with central banks and receivables from other credit institutions to total assets, lagged by one quarter
- $\mathbf{Deposits_{i,t-1}}$ = Customer deposits to total assets, lagged by one quarter
- $\mathbf{LLR_{i,t-1}}$ = Loan loss reserves to gross loans, lagged by one quarter
- $\mathbf{ROA_{i,t}}$ = Net income to lagged total assets
- $\mathbf{Log(Assets)_{i,t-1}}$ = Natural logarithm of lagged total assets, denominated in Euro
- $\mathbf{\Delta GDP_{j,t}}$ = Quarter-on-quarter GDP growth
- $\mathbf{\Delta UR_{j,t}}$ = Quarter-on-quarter change in unemployment rate

The dependent variable *ΔLoans* represents the quarterly change in gross loans, normalized by lagged total assets (Berger & Bouwman, 2009; Cornett et al., 2011; Dursun-de Neef & Schandlbauer, 2020a; Li et al., 2020). Normalization by total assets is necessary to make the dependent variable *ΔLoans* comparable across banks and avoid giving undue weight to the largest banks in our sample (Berger & Bouwman, 2009). *ΔLoans* equals the sum of new loan originations plus net drawdowns on existing credit commitments (Cornett et al., 2011; Li et al., 2020). Gross loans on a bank's balance sheet adjust both when a bank originates a new loan and when a borrower decides to draw down funds from preexisting credit lines (reported off-balance sheet as long as still undrawn).

According to the theory of financial intermediation, liquidity creation is risky because it exposes banks to different types of risk, including bank runs and liquidity crunches (Diamond & Dybvig, 1983; Zheng et al., 2019). Prior studies have argued that liquidity risk exposure is negatively correlated with lending (Cornett et al., 2011; Ivashina & Scharfstein, 2010). In line with prior empirical models, we include a set of bank characteristics that capture both a bank's liquidity risk exposure and financial condition (Cornett et al., 2011; Li et al., 2020; Dursun-de Neef & Schandlbauer, 2020a).

First, the control variable *LiquidAssets* captures the composition and market liquidity of a bank's asset portfolio at the beginning of the quarter (Cornett et al., 2011; Li et al., 2020). For the banks included in our sample, we define liquid assets as cash, deposits with central banks, and receivables from other credit institutions. Banking theory suggests that banks hold cash and other liquid assets as part of their strategy to manage liquidity risk (Cornett et al., 2011; Kashyap et al., 2002). A higher proportion of liquid assets reduces a bank's liquidity risk exposure, thereby enabling higher loan growth. For instance, Cornett et al. (2011) find that banks with lower liquid asset holdings reduced new credit origination relative to other banks during the GFC 2008-09. The coefficient of *LiquidAssets* is hence expected to be positive.

Second, the control variable *Deposits* represents the fraction of a bank's balance sheet financed with deposits at the beginning of the quarter. Deposits are considered a more stable funding source than short-term debt (Cornett et al., 2011; Ivashina & Scharfstein, 2010) and effectively hedge the liquidity risk inherent in liquidity creation (Gatev et al., 2009). Prior studies find that banks relying more on deposit financing are more willing to run down their liquidity buffers and increase lending (Cornett et al., 2011; Li et al., 2020). We, therefore, expect the coefficient of *Deposits* to be positive.

Third, the control variable *Tier1Cap* describes the fraction of a bank's risk-weighted assets covered by Tier 1 capital at the beginning of the quarter, thereby accounting for capital adequacy (Cornett et al., 2011). Generally, there are two theories regarding how bank capital affects liquidity creation (Berger & Bouwman, 2009; Distinguin et al., 2013). On the one hand, the "*financial fragility-crowding out"* hypothesis states that bank capital negatively affects liquidity creation because it crowds out the liquidity hedging effect of deposits (Gorton & Winton, 2017) and makes a bank's capital structure less fragile (Diamond & Rajan, 2001). By monitoring the profitability of their borrowers, banks have an informational advantage over depositors, which creates an agency problem. A fragile capital structure increases the credibility of a bank's commitment to its depositors, enabling a bank to collect more deposits and grant more loans. On the other hand, the *"risk absorption"* hypothesis implies that bank capital positively affects liquidity creation because it absorbs the illiquidity risk associated with liquidity creation while expanding a bank's risk-bearing capacity (Berger & Bouwman, 2009). Specifically, banks may strengthen their capital buffers in response to mitigating illiquidity risk (Distinguin et al., 2013). Moreover, Cornett et al. (2011) find evidence that banks relying more on equity capital continued to lend relative to other banks during the GFC 2008-09. For our study, the "*risk absorption"* hypothesis seems more intuitive. We, therefore, expect the coefficient of *Tier1Cap* to be positive.

Fourth, the control variable *LLR* accounts for the asset quality and perceived credit risk of a bank's loan portfolio, measured by the fraction of LLRs to gross loans at the beginning of the quarter (Berger & Bouwman, 2009; Dursun-de Neef & Schandlbauer, 2020a). The financial intermediation literature suggests that liquidity creation and credit risk are closely related (Diamond & Dybvig, 1983; Diamond & Rajan, 2001). We expect the coefficient on *LLR* to be negative, implying that banks with a higher loan default risk are less willing to expand lending. Fifth, we include *ROA* as a control variable for bank profitability (Dursun-de Neef & Schandlbauer, 2020a). Prior studies find that bank risk is negatively correlated with profitability (Davydov et al., 2021). Based on the hypothesis that risk exposure negatively affects loan growth, we expect the coefficient of *ROA* to be positive.

To control for bank size, we include the natural logarithm of total assets, *Log(Assets)*, in every regression (Berger & Bouwman, 2009; Cornett et al., 2011; Li et al., 2020). Bank size likely relates to liquidity risk management but controls for many other sources of heterogeneity (Cornett et al., 2011). Prior empirical studies find that liquidity creation is generally concentrated at larger banks (Berger & Bouwman, 2009; Li et al., 2020). Hence, we expect a positive relationship between *Log(Assets)* and *ΔLoans*. Lastly, to control for local market economic conditions, we include the quarterly changes in GDP (*ΔGDP*) and unemployment rate (*ΔUR*), respectively (Berger & Bouwman, 2009; Dursun-de Neef & Schandlbauer, 2020a).

Regression Model (2) – Customer Depositing

Regression model (2) attempts to test whether banks see a heightened inflow of deposits with an increase in pandemic impact. As a stable financing source, customer deposits usually constitute the largest source of funds used by banks to provide liquidity.

$$\begin{aligned}\Delta Deposits_{i,t} = \beta_0 + \beta_1 * CovidIndex_{i,t} + \beta_2 * Tier1Cap_{i,t-1} + \beta_3 \\ * LiquidAssets_{i,t-1} + \beta_4 * Deposits_{i,t-1} + \beta_5 * LLR_{i,t-1} + \beta_6 * ROA_{i,t} \\ + \beta_7 * Log(Assets)_{i,t-1} + \beta_8 * \Delta GDP_{j,t} + \beta_9 * \Delta UR_{j,t} + \varepsilon_{i,t}\end{aligned}$$

H_0: $\beta_1 = 0$; **H_2:** $\beta_1 > 0$

Where:

- **$\Delta Deposits_{i,t}$** = Change in customer deposits to lagged total assets
- All other variables equal to regression model (1)

The dependent variable *ΔDeposits* describes the quarterly change in customer deposits to lagged total assets (Dursun-de Neef & Schandlbauer, 2020b; Li et al., 2020). In their function as financial intermediaries, credit institutions create liquidity by transforming liquid customer deposits into credit lines for lenders (Diamond & Dybvig, 1983). This transformation function makes banks inherently vulnerable to systemic risk that can materialize in the form of bank runs if depositors lose trust in their banks, as was the case during the GFC 2008-09 (Cornett et al., 2011). On the other hand, banks can also be seen as *safe havens* during times of economic uncertainty when depositors accumulate their 'savings for rainy days' in their bank accounts (Gatev & Strahan, 2006). In contrast to the dependent variables used in regressions (1) and (3), *ΔDeposits* does not depend on bank behavior in the first place but rather on depositors' sentiment. Indeed, a bank can set a favorable environment with attractive interest rates for its customers to accumulate more deposits. Nevertheless, in the end, it is up to the individual depositor how much funding is available for the bank to transform into credit. In line with prior literature (Dursun-de Neef & Schandlbauer, 2020b; Li et al., 2020), we keep the structure of regression (2) similar to regression (1), replacing only the dependent variable, ceteris paribus. Once again, *CovidIndex* is our main variable of interest, as it establishes the relationship to test our H_2 if depositing increases with higher exposure to COVID-19.

Regression Model (3) – Loan Loss Provisions

Regression model (3) tests H_3 on the loan loss provisioning behavior by European commercial banks in light of COVID-19. Closely related to the empirical models used in prior studies, our regression analysis is based on a dynamic specification that controls for the main discretionary and non-discretionary determinants of LLPs (Aristei & Gallo, 2019; Bouvatier et al., 2014; Caporale et al., 2018; Leventis et al., 2011). To avoid a potential bias in our sample due to changes in accounting regime, regression (3) excludes observations before 2018.

$$
\begin{aligned}
LLP_{i,t} = \beta_0 + \beta_1 * CovidIndex_{i,t} + \beta_2 * \Delta LOANS_{i,t} + \beta_3 * \Delta NPL_{i,t} + \beta_4 * NPL_{i,t-1} \\
+ \beta_5 * Tier1Cap_{i,t-1} + \beta_6 * RevLLP_{i,t} + \beta_7 * Log(Assets)_{i,t-1} + \beta_8 \\
* \Delta GDP_{j,t} + \beta_9 * \Delta UR_{j,t} + \varepsilon_{i,t}
\end{aligned}
$$

H_0: $\beta_1 = 0$; **H_3:** $\beta_1 > 0$

Where:

- **$LLP_{i,t}$** = Loan loss provisions to lagged total assets
- **$CovidIndex_{i,t}$** = Quarterly pandemic response weighted by country exposure
- **$\Delta Loans_{i,t}$** = Change in gross loans to lagged total assets
- **$\Delta NPL_{i,t}$** = Change in non-performing loans to lagged gross loans
- **$NPL_{i,t-1}$** = Non-performing loans to gross loans, lagged by one quarter
- **$Tier1Cap_{i,t-1}$** = Tier 1 capital ratio, lagged by one quarter
- **$RevLLP_{i,t}$** = Revenues before loan loss provisions to lagged total assets
- **$Log(Assets)_{i,t-1}$** = Lagged natural logarithm of total assets, denominated in Euro
- **$\Delta GDP_{j,t}$** = Quarter-on-quarter GDP growth
- **$\Delta UR_{j,t}$** = Quarter-on-quarter change in unemployment rate

The dependent variable *LLP* is defined as the period's LLPs expense to lagged total assets. In line with prior literature's *cyclicality theory* on LLPs (Laeven & Majnoni, 2003) and the general notion that the adverse economic impact of COVID-19 may cause a significant deterioration in the credit quality of banks' loan portfolios, we expect a positive relationship between our main explanatory variable *CovidIndex* and *LLP*.

Although the main function of LLPs is to provide a realistic assessment of the credit risk associated with a bank's outstanding loan portfolio, prior studies find evidence for discretionary behavior, such as capital management or income smoothing (Bouvatier et al., 2014; Leventis et al., 2011). Closely related to prior empirical models, regression (3) therefore further controls for the main discretionary and non-discretionary determinants of LLPs (Aristei & Gallo, 2019; Bouvatier & Lepetit, 2008). The non-discretionary factors include the control variables *ΔLoans*, *NPL*, *ΔNPL*, and *Log(Assets)*. The coefficient on *ΔLoans* is expected to be positive since loan expansions require banks to make general LLPs for ECLs under IFRS 9 (Bouvatier et al., 2014). Moreover, prior empirical studies identify abnormal loan growth as a major source for increased credit risk (Foos et al., 2010), particularly when banks extend credit to customers with lower levels of creditworthiness (Caporale et al., 2018). In a similar vein, the control variables *NPL* and *ΔNPL* represent measures of expected loan default risk (Aristei & Gallo, 2019; Caporale et al., 2018). In particular, a higher proportion of NPLs implies an inferior asset quality of a bank's loan portfolio, increasing the need to account for ECLs. Hence, the coefficients on *NPL* and *ΔNPL* are estimated to be positive. In general, NPLs constitute credit obligations for which borrowers are in default (Stage 3). This interpretation is intentionally kept vague as countries frequently have different regulatory definitions for NPLs. For our analysis, we follow the rationale of the IMF, which classifies a financial asset as non-performing if interest or principal payments have not been serviced in at least 90 days or if future payments come with high levels of uncertainty (IMF, 2019). We include the natural logarithm of total assets, *Log(Assets)*, as prior literature has identified banks size to be an important dimension of bank credit risk management (Aristei & Gallo, 2019), albeit with contradictory results. The expected coefficient on *Log(Assets)* is therefore non-directional. On the one hand, a more diversified credit portfolio for larger banks is hypothesized to reduce credit risk and the need for LLPs (Leventis et al., 2011). In addition, larger banks may be more prone to the "*too big to fail*" phenomena, creating incentives to take on riskier credit commitments while adopting a less cautious provisioning policy (Aristei & Gallo, 2019). On the other hand, larger banks generally face higher levels of regulatory scrutiny, implying a more prudent accounting for ECLs.

To control for the discretionary component of LLPs, regression (3) includes the variables *Tier1Cap* and *RevLLP*, whereby the latter is defined as the ratio of earnings before interest, taxes, and LLPs to lagged total assets (Caporale et al., 2018). In line with prior literature, we include the variables *Tier1Cap* and *RevLLP* to account for the capital management and income smoothing hypothesis of LLPs (Aristei & Gallo, 2019; Bouvatier et al., 2014; Leventis et al., 2011) but refrain from interpreting their effects given that discretionary provisioning is not the main focus of our analysis.

In addition to controlling for the main discretionary and non-discretionary LLPs, regression model (3) incorporates the macroeconomic variables *ΔGDP* and ΔUR to control for changes in the general economic environment across countries. Prior studies have argued that *ΔGDP* captures the creditworthiness of a bank's customers and should negatively affect LLPs (Bouvatier et al., 2014). Moreover, previous empirical models have included GDP growth as a control variable for the cyclical pattern of LLPs (Laeven & Majnoni, 2003). Given that improved economic conditions should lower the need for LLPs and in conjunction with the *cyclicality theory,* we expect a negative relationship between *ΔGDP* and *LLP* and a positive relationship between *ΔUR* and *LLP*, respectively (Laeven & Majnoni, 2003).

4. Results

4.1. Descriptive Statistics

Table 2. Descriptive statistics regression models (1) and (2)

	N	Mean	St.Dev	Min	25th Pct.	Median	75th Pct.	Max
Panel A: All Periods								
(1) ΔLoans	2340	0.015	0.034	-0.083	0.001	0.012	0.026	0.194
(2) ΔDeposits	2340	0.014	0.039	-0.098	-0.004	0.008	0.026	0.223
(3) Loans	2340	0.780	0.104	0.416	0.735	0.814	0.848	0.933
(4) Tier1Cap	2340	0.184	0.036	0.108	0.162	0.182	0.203	0.312
(5) LiquidAssets	2340	0.070	0.068	0.002	0.029	0.050	0.086	0.391
(6) Deposits	2340	0.655	0.160	0.121	0.599	0.693	0.756	0.894
(7) LLR	2340	0.023	0.036	0.000	0.005	0.008	0.024	0.212
(8) ROA	2340	0.002	0.002	-0.005	0.001	0.002	0.003	0.011
(9) Log(Assets)	2340	7.950	2.296	4.761	5.963	7.334	9.690	13.683
(10) ΔGDP	2340	0.003	0.024	-0.190	-0.001	0.005	0.009	0.164
(11) ΔUR	2340	0.001	0.079	-0.222	-0.046	-0.010	0.026	0.377
Panel B: Pre-COVID-19 (Q1 2016 – Q4 2019)								
(1) ΔLoans	1872	0.017	0.034	-0.083	0.003	0.013	0.027	0.194
(2) ΔDeposits	1872	0.014	0.040	-0.098	-0.004	0.008	0.026	0.223
(3) ΔGDP	1872	0.005	0.008	-0.040	0.001	0.005	0.009	0.070
(4) ΔUR	1872	-0.016	0.050	-0.222	-0.050	-0.017	0.016	0.245
Panel C: COVID-19 (Q1 2020 – Q4 2020)								
(1) ΔLoans	468	0.010	0.030	-0.083	-0.003	0.008	0.018	0.194
(2) ΔDeposits	468	0.016	0.039	-0.098	-0.003	0.010	0.029	0.223
(3) CovidIndex	468	0.440	0.177	0.095	0.299	0.470	0.602	0.762
(4) ΔGDP	468	-0.004	0.050	-0.190	-0.046	-0.003	0.027	0.164
(5) ΔUR	468	0.070	0.125	-0.137	-0.030	0.024	0.122	0.377

Table 2. shows the descriptive statistics for regression models (1) and (2). We analyze panel data over the period between Q1 2016 – Q4 2020 with a sample of 117 banks. *ΔLoans* is the change in gross loans to lagged total assets. *ΔDeposits* is the change in customer deposits to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *Loans* is the ratio of gross loans to lagged total assets, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *LiquidAssets* is the ratio of cash, deposits with central banks, and receivables from other credit institutions to total assets, lagged by one quarter. *Deposits* is the ratio of customer deposits to total assets, lagged by one quarter. *LLR* is the ratio of loan loss reserves to gross loans, lagged by one quarter. *ROA* is the ratio of net income to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate.

Table 2 depicts summary statistics for the panel data set used in regressions (1) and (2) to investigate the change in lending and depositing in relation to banks' exposure to the COVID-19 pandemic. The dependent variable *ΔLoans* for regression (1) shows that loan growth constitutes on average 1.5% of lagged total assets with a standard deviation of

3.4% (Panel A). The largest increase in lending represents 19.4% of lagged total assets, whereas the most considerable reduction in lending amounts to -8.3% of lagged total assets. Hence, we observe substantial amounts of variation in the change of loan growth over time. To better depict the variation in our variables of interest, specifically regarding the COVID-19 quarters, we split Panel A into *Pre-COVID-19* (Panel B) and *COVID-19* (Panel C). Given that the first governmentally-imposed COVID-19 restrictions in Europe occurred during Q1 2020, we define the period Q1 2020 – Q4 2020 as COVID-19 quarters regarding our observation period. Comparing Panels B and C, we observe a reduction in average lending growth to lagged total assets from 1.7% to 1.0%, indicating that the overall growth in bank lending decreased during the pandemic compared to prior quarters. Given that our variables are winsorized on the 1st and 99th percentiles, there is no observable difference in the minimum and maximum values for *ΔLoans* between Panel B and Panel C. However, comparing the mean and median values between the two panels demonstrates the relative reduction in loan growth during the pandemic.

The dependent variable *ΔDeposits* for regression (2) shows a mean of 1.4% (Panel B) and 1.6% (Panel C) of lagged total assets, indicating that deposit inflows slightly increased during COVID-19. We include the variable *Loans*, defined as the ratio of gross loans to lagged total assets, in Table 2, albeit not tested in regressions (1) and (2), in order to highlight further that the banks in our sample generally have a strong focus on the traditional lending business. The variable *Loans* demonstrates a relatively high gross loans to assets ratio with a mean and median of 78.0% and 81.4%, respectively. Likewise, the control variable *Deposits* shows a comparatively high mean of 65.5%, further providing evidence to our intention to only include credit institutions with a clear focus on the traditional commercial banking business model of lending and depositing.

The control variable *Tier1Cap* has a mean of 18.4%, indicating that the banks in our sample show a high capitalization compared to the regulatory minimum Tier 1 capital ratio of 10.5% as implemented in light of Basel III (BCBS, 2016). The minimum observation shows a Tier 1 capital ratio of 10.8%, further proving that banks in our sample are generally not constrained by their Tier 1 capital. We want to stress that our control variable for profitability, *ROA*, exhibits relatively low values in Table 2, given that this variable constitutes quarterly return data divided by lagged total assets. Overall, the standard deviations for our control variables *Tier1Cap*, *LiquidAssets*, *LLR*, and *ROA* are relatively low, ranging from 0.2% to 6.8%. Hence, the financial condition of banks included in our sample, as measured by these variables, did not significantly vary over the sample period.

Considering our macroeconomic variables *ΔGDP* and *ΔUR*, a comparison between the descriptive statistics in Panels B and C further implies an impact of COVID-19 on the broader economic environment. While the quarterly GDP growth decreased from 0.5% to -0.4%, the quarterly change in the unemployment rate increased from -1.6% to 7.0%. The minimum value for *ΔGDP* (-19.0%) occurred in the UK in Q2 2020, whereas the maximum value of *ΔUR* (37.7%) prevailed in Estonia likewise in Q2 2020. Finally, our main variable of interest, *CovidIndex*, which we show separately in Panel C (no observations before Q1 2020), takes on an average value of 44.0%. As previously stated, this variable is based on the underlying dataset from the *COVID-19 Government Response Tracker*. The relatively high standard deviation of 17.7% indicates cross-country variation in governmentally-imposed COVID-19 restrictions and time variation in the course of the pandemic itself. The spread in observations ranges from a minimum *CovidIndex* of 9.5% (Q1 2020, Sweden) to a maximum of 76.2% (Q2 2020, Portugal).

Table 3. Pearson's correlation matrix regression models (1) and (2)

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
(1) ΔLoans	1										
(2) ΔDeposits	0.484***	1									
(3) CovidIndex	-0.107***	0.032	1								
(4) Tier1Cap	0.058***	-0.008	0.085***	1							
(5) LiquidAssets	0.042**	0.075***	0.036*	-0.039*	1						
(6) Deposits	0.0601***	0.090***	-0.015	-0.193***	0.341***	1					
(7) LLR	-0.129***	-0.018	-0.006	-0.302***	0.131***	0.190***	1				
(8) ROA	0.286***	0.238***	-0.088***	0.087***	0.112***	0.153***	-0.064***	1			
(9) Log(Assets)	-0.135***	-0.068***	0.0534***	-0.282***	0.033	-0.410***	0.288***	-0.231***	1		
(10) ΔGDP	0.037*	-0.081***	-0.249***	-0.011	0.015	0.020	0.013	0.029	0.002	1	
(11) ΔUR	-0.036*	0.025	0.539***	0.137***	0.044**	-0.061***	-0.107***	0.029	-0.083***	-0.205***	1

Table 3. shows Pearson's correlation matrix for regression models (1) and (2). *ΔLoans* is the change in gross loans to lagged total assets. *ΔDeposits* is the change in customer deposits to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *Loans* is the ratio of gross loans to lagged total assets, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *LiquidAssets* is the ratio of cash, deposits with central banks, and receivables from other credit institutions to total assets, lagged by one quarter. *Deposits* is the ratio of customer deposits to total assets, lagged by one quarter. *LLR* is the ratio of loan loss reserves to gross loans, lagged by one quarter. *ROA* is the ratio of lagged income to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Table 3 depicts the correlations among variables used in regressions (1) and (2). The dependent variable *ΔLoans* shows high correlations with all independent variables, not accounting for macroeconomic control variables. The explaining variable *CovidIndex* exhibits a significantly negative correlation with *ΔLoans*, hinting at a rejection of our first hypothesis. A significantly positive correlation between *Tier1Cap*, *Liquid Assets*, and *Deposits* with the dependent variable *ΔLoans* further adds to prior studies that credit institutions relying on stable sources of financing are less significantly affected by economic downturns and can continue providing liquidity to the market (Cornett et al., 2011). Indeed, the significantly positive correlation between *Deposits* and *ΔLoans* can be referred to the theory that deposit inflows provide an essential source of financing for loan demand shocks that typically follow declines in market liquidity (Gatev et al., 2009). The negative correlation between *LLR* and *ΔLoans* seems to follow our hypothesis that banks with lower quality in their loan portfolios, hence higher loan loss reserves on their balance sheets, granted fewer loans during our observation period. Likewise, *ROA* is positively correlated with *ΔLoans*, signaling that profitable banks have an increased ability to originate loans.

As previously explained, the dependent variable *ΔDeposits* primarily relies on the behavior of bank customers. In particular, the negative correlation between *ΔGDP* and *ΔDeposits* can be explained by the *safe haven theory* stating that funding through customer deposits becomes more feasible to banks during periods of market stress (Gatev & Strahan, 2006). However, our correlation matrix does not show a significantly positive relationship between *CovidIndex* and *ΔDeposits*, which appears to be slightly contradictory to the *safe haven theory*. We notice the positive correlations between *ΔDeposits* and several other bank explanatory variables but choose not to comment on the relationship further. Although some of the independent variables show significant correlations, we deem these correlations not to be disproportionate. The highest correlation can be observed between *ΔUR* and *CovidIndex* at 53.9%. This relationship comes to no surprise as the underlying data for *CovidIndex* incorporates, among others, workplace closures that have led to an increase in unemployment throughout the year and across Europe.

Table 4. Descriptive statistics regression model (3)

Variable	N	Mean	St.Dev	Min	25th Pct.	Median	75th Pct.	Max
Panel A: All Periods								
(1) LLP	1332	0.0009	0.0017	-0.0011	0.0000	0.0003	0.0009	0.0083
(2) ΔLoans	1332	0.0142	0.0288	-0.0703	0.0012	0.0114	0.0245	0.1537
(3) ΔNPL	1332	0.0004	0.0053	-0.0224	-0.0012	0.0001	0.0017	0.0191
(4) NPL	1332	0.0333	0.0584	0.0008	0.0071	0.0147	0.0302	0.3605
(5) Tier1Cap	1332	0.1877	0.0318	0.1200	0.1675	0.1866	0.2068	0.3000
(6) RevLLP	1332	0.0076	0.0051	0.0018	0.0052	0.0063	0.0081	0.0304
(7) Log(Assets)	1332	7.9306	2.2408	4.9137	5.9916	7.2766	9.5059	13.2188
(8) ΔGDP	1332	0.0017	0.0282	-0.1788	-0.0013	0.0025	0.0069	0.1641
(9) ΔUR	1332	0.0193	0.0923	-0.2217	-0.0427	-0.0072	0.0400	0.3775
Panel B: Pre-COVID-19 (Q1 2016 – Q4 2019)								
(1) LLP	888	0.0007	0.0016	-0.0011	0.000	0.0002	0.0007	0.0083
(2) ΔGDP	888	0.0047	0.0061	-0.0149	0.0008	0.0037	0.0069	0.0474
(3) ΔUR	888	-0.0068	0.0546	-0.2217	-0.0504	-0.0088	0.0259	0.2454
Panel C: COVID-19 (Q1 2020 – Q4 2020)								
(1) LLP	444	0.0011	0.0018	-0.0011	0.0001	0.0005	0.0014	0.0083
(2) CovidIndex	444	0.4370	0.1741	0.0950	0.2992	0.4701	0.6020	0.7620
(3) ΔGDP	444	-0.0042	0.0476	-0.1788	-0.0460	-0.0030	0.0267	0.1641
(4) ΔUR	444	0.0716	0.1247	-0.1373	-0.0297	0.0238	0.1223	0.3775

Table 4. shows the descriptive statistics for regression model (3). We analyze panel data over the period between Q1 2018 – Q4 2020 with a sample of 111 banks. Constricted reporting practices for NPLs, lead to sample reduction of six banks for regression model (3) compared to our main sample. *LLP* is the ratio of s to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *ΔLoans* is the change in gross loans to lagged total assets. *ΔNPL* is the change in non-performing loans to lagged gross loans. *NPL* is the ratio of non-performing loans to gross loans, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *RevLLP* is the ratio of Revenues before loan loss provisions to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. To highlight the fractional differences in LLPs to total assets before and during the COVID-19 pandemic (Panel B and C) values are rounded to the fourth decimal.

Table 4 shows the descriptive statistics for the panel data set used in regression (3), which investigates the impact of COVID-19 on the loan loss provisioning behavior of European commercial banks. The dependent variable *LLP* indicates that the average LLP expense constitutes 0.09% of lagged total assets over the entire observation period (Panel A). Furthermore, the winsorized extreme values demonstrate a high variation in our panel dataset from negative 0.11% (indicating a LLP reversion) to positive 0.83%. Comparing LLPs before and during the pandemic (Panels B and C), it turns out that mean and median provisioning for ECLs was higher during the pandemic quarters than the prior two years of our observation period.

The average value of 3.33% for *NPL* (denominated by total gross loans) indicates that the banks in our sample, on average, hold high-quality loan portfolios. However, we still find a considerable variation in *NPL* given the discrepancy between our minimum and maximum values (from 0.08% to 36.05%). Overall, the descriptive statistics for regression (3) yield slightly different values as compared to the descriptive statistics for regressions (1) and (2) due to the reduction in sample size and change in observation period.

Table 5. Pearson's correlation matrix regression model (3)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) LLP	1									
(2) CovidIndex	0.087***	1								
(3) ΔLoans	0.130***	-0.138***	1							
(4) ΔNPL	0.242***	-0.035	0.168***	1						
(5) NPL	0.514***	0.032	-0.081***	-0.118***	1					
(6) Tier1Cap	-0.086***	0.095***	0.004	0.080***	-0.234***	1				
(7) RevLLP	0.778***	-0.044	0.237***	0.272***	0.359***	-0.078***	1			
(8) Log(Assets)	0.068**	0.054**	-0.075***	-0.124***	0.215***	-0.340***	-0.126***	1		
(9) ΔGDP	-0.083***	-0.249***	0.072***	0.004	-0.016	-0.010	0.002	-0.012	1	
(10) ΔUR	0.022	0.535***	-0.053*	0.031	-0.067**	0.135***	-0.010	-0.096***	-0.220***	1

Table 5. shows Pearson's correlation matrix for regression model (3). *LLP* is the ratio of loan loss provisions to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *ΔLoans* is the change in gross loans to lagged total assets. *ΔNPL* is the change in non-performing loans to lagged gross loans. *NPL* is the ratio of non-performing loans to gross loans, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter.

Table 5. (cont.) *RevLLP* is the ratio of Revenues before loan loss provisions to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Table 5 illustrates the correlations among variables used in regression (3). Overall, the independent variables show significant correlations with our dependent variable *LLP*, albeit we do not find evidence for multicollinearity in a subsequent robustness test. The non-discretionary control variables *ΔLoans, ΔNPL*, and *NPL* exhibit a significantly positive correlation with *LLP* at the 0.01-level. This finding supports prior literature on the non-discretionary components on LLPs. It indicates that faster growth in total loans and NPLs, as well as the overall fraction of NPLs represent important drivers for the credit risk of a bank's loan portfolio (Aristei & Gallo, 2019). Moreover, *ΔGDP* shows a significantly negative correlation with our dependent variable *LLP* following the *cyclicality theory* of LLPs (Laeven & Majnoni, 2003). Finally, our main variable of interest, *CovidIndex*, exhibits a significantly positive correlation with *LLP*, supporting the predicted relationship developed in H_3.

4.2. Regression Results

4.2.1. Regression (1) – Bank Lending

Table 6 depicts the results of regression (1) investigating the relationship between quarterly loan growth and the COVID-19 impact on European commercial banks. Column (1) presents the findings of our baseline model as defined previously in the methodology section, whereas columns (2) to (4) illustrate further model specifications, including time and country fixed effects. Our primary variable of interest, *CovidIndex*, displays a negative coefficient, significant at the 0.01-level. Hence, we reject H_1 and determine a negative relationship between loan growth and European commercial banks' exposure to COVID-19. This result does not support prior literature on the role of banks as liquidity providers and contradicts the notion that banks have a natural advantage in providing liquidity during times of crisis (Gatev et al., 2009).

Table 6. Regression model (1) – Lending

	(1)	(2)	(3)	(4)
Dependent Variable: ΔLoans	Baseline Model Regression (1)	Extended Model Specifications		
CovidIndex	-0.013***	-0.044*	-0.013***	
	(-3.40)	(-1.86)	(-3.56)	
Log(Assets)	-0.000	-0.000	0.001*	-0.001
	(-1.10)	(-0.70)	(1.90)	(-1.47)
Tier1Cap	0.006	0.000	0.003	0.000
	(0.25)	(0.01)	(0.12)	(0.02)
LLR	-0.103***	-0.104***	-0.111**	-0.103***
	(-4.96)	(-5.08)	(-2.36)	(-4.99)
LiquidAssets	0.013	0.012	0.013	0.013
	(0.99)	(0.92)	(0.74)	(1.04)
Deposits	0.004	0.005	0.017**	0.002
	(0.71)	(0.93)	(2.05)	(0.41)
ROA	3.946***	3.911***	3.455***	4.042***
	(8.39)	(8.05)	(6.36)	(8.71)
Δ GDP	0.012	-0.068	0.011	0.027
	(0.44)	(-1.19)	(0.39)	(0.99)
Δ UR	-0.007	0.009	-0.008	-0.024***
	(-0.72)	(0.55)	(-0.85)	(-2.60)
Constant	0.009	0.008	-0.027*	0.011
	(1.12)	(0.99)	(-1.80)	(1.36)
N Observations	2340	2340	2340	2340
Country Fixed Effects	NO	NO	YES	NO
Time Fixed Effects	NO	YES	NO	NO
Adj. R^2	0.100	0.108	0.120	0.097

Table 6. presents our results for regression model (1). *ΔLoans* is the change in gross loans to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *Loans* is the ratio of gross loans to lagged total assets, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *LiquidAssets* is the ratio of cash, deposits with central banks, and receivables from other credit institutions to total assets, lagged by one quarter. *Deposits* is the ratio of customer deposits to total assets, lagged by one quarter. *LLR* is the ratio of loan loss reserves to gross loans, lagged by one quarter. *ROA* is the ratio of lagged income to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

When introducing time fixed effects to our baseline model (column 2), *CovidIndex* loses in statistical significance, albeit still showing a negative sign. This absorbing effect can be explained by the nature of time fixed effects that account for unobserved endogenous effects that are constant across the banks in our sample but vary over time. In comparison to time fixed effects, adding country fixed effects alters neither the statistical significance nor the negative sign of *CovidIndex* (column 3). We conclude that the negative relationship between *ΔLoans* and *CovidIndex* is predominantly induced by the time variation in governmental responses associated with the course of the pandemic throughout 2020 as compared to cross-sectional variation.

To test for economic significance of our primary variable of interest, *CovidIndex,* we derive the beta factor for regression (1), norming the impact of the explaining variables on the explained variable *ΔLoans* on a standard deviation basis. A one standard deviation increase in *CovidIndex* leads to a 7.3% standard deviation decrease of loan growth (Appendix D). Albeit only taking the third position in the magnitude of economic significance (after *ROA* and *LLR*), we still deem the impact of COVID-19 on bank lending relatively high. Specifically, we find a higher economic significance of *CovidIndex* than the other explanatory variables on bank financial condition (*LiquidAssets, Tier1Cap, and Deposits*).

We find that both *LLR* and *ROA* show statistically significant relationships with our dependent variable *ΔLoans* at the 0.01-level across all model specifications concerning bank financial control variables. The variable *LLR*, controlling for credit risk, has a negative coefficient, indicating that banks with a higher fraction of loan loss reserves as part of their loan portfolio generally support new lending to a lesser extent. In addition, the coefficient for *ROA* follows the predicted sign. By contrast, the control variables *Tier1Cap*, *LiquidAssets,* and *Deposits* do not yield a significant relationship with *ΔLoans*. This finding contradicts prior empirical evidence and theory, stating that deposits, equity capital, and liquid assets reduce the liquidity risk exposure of banks, thereby enhancing their lending capacity (Cornett et al., 2011; Gatev & Strahan, 2006). However, this finding reflects Li et al. (2020), who find no robust evidence that bank financial condition (measured by liquid assets, deposits, and Tier 1 capital) constrained banks' ability to supply liquidity during COVID-19. Regression model (1) returns an adjusted R-squared ranking on the lower side of the range exhibited by prior research, ranging from 10.8% (Dursun-de Neef & Schandlbauer, 2020a) to 38.1% (Cornett et al., 2011). One possible explanation for our lower adjusted R-squared could be the limited access to off-balance data on unused loan commitments that the aforementioned studies were able to include as an additional control variable in their regression models.

Segmentation results

Appendix (E) segments the findings of regression (1) based on balance sheet size. To determine if a bank is placed in Panel A (*Small Banks*) or Panel B (*Large Banks*), we took the total assets of all banks headquartered in Europe, available on *S&P Capital IQ,* as reported in their latest annual report. Thereafter, we calculated the median total assets value of our sample obtained, which we use as a cut-off value and external classification tool. Consequently, our banks are split into two roughly even control groups. Our findings indicate that bank lending significantly reduced with higher governmental restrictions across both panels. Hence, the effect does not originate exclusively from one of the two control groups but is instead a phenomenon observed among all banks regardless of balance sheet size. A similar picture can be observed when dividing our sample by company type as a privately held or publicly listed bank. Both types yield significant reductions in bank lending on the 0.01-level (private) and 0.05-level (public) (Appendix F). Moreover, a paired difference test of the two coefficients for private and public credit institutions returns no statistically significant results.

Following the financial intermediation theory, stating that banks supply liquidity on either side of their balance sheets to lenders and depositors, the efficiency of this intermediation process can be tested by applying a data envelopment analysis (DEA) approach (for a detailed explanation, see: Appendix G). Ranking the credit institutions in our sample relative to each other based on their efficiency to transform liquid customer deposits into illiquid loans, we derive three control groups over a five-year observation period. Banks in the highest percentile were generally able to convert customer deposits, interest expenses, and non-interest expenses (input factors) into loans, interest income, and non-interest income (output factors) in a more efficient way relative to their peers. We observe that banks in the low-efficiency panel experience a significant decline in loan origination with higher exposure to COVID-19 on the 0.01-level while the other two control groups yield no statistically significant findings (Appendix H). Hence, we conclude that those banks in our sample drive the negative relationship between *ΔLoans* and *CovidIndex* in regression (1) which we classified having a less efficient financial intermediation process. However, these results have to be interpreted with caution. As the DEA only ranks credit institutions relative to each other based on their financials, the classification could change significantly with the respective underlying sample.

4.2.2. Regression (2) – Customer Depositing

Prior literature finds empirical evidence that bank lending increased significantly at the onset of the COVID-19 pandemic and subsequently turn their attention towards where the source of funds for the observed loan growth stemmed from (Dursun-de Neef & Schandlbauer, 2020b; Li et al., 2020). Regression (1), in contrast, exhibits the contrarian effect of COVID-19 on the change in lending for the banks in our panel data set. Hence, regression (2) aims not to analyze the change in deposits as a means of financing source for bank lending. Instead, we investigate the change in deposits to test the *safe haven theory* in light of COVID-19 (Gatev & Strahan, 2006).

Appendix I displays the results of regression (2) scrutinizing our second hypothesis whether European commercial banks saw an increased inflow of customer deposits with stricter governmental regulation on the backdrop of the COVID-19 pandemic. *CovidIndex* returns a positive relationship with *ΔDeposits*, albeit at a low statistical significance level of 0.1. Hence, we find some support for H_2 and determine a positive relationship between the inflow of customer deposits and banks' exposure to COVID-19. Although these findings lend some empirical evidence to the *safe haven theory* that customers tend to accumulate savings in their bank accounts during times of uncertainty (Gatev & Strahan, 2006), these results have to be interpreted with caution as the statistical significance of *CovidIndex* in our models is relatively low. Interestingly, in our baseline model and model specifications (3) and (4), *ΔGDP* shows a negative high-significance relationship with the dependent variable *ΔDeposits*, hinting at an increase in customer deposits during the *COVID-19 recession*. When introducing time fixed effects (column 2), neither *CovidIndex* nor *ΔGDP* show a statistically significant coefficient, providing further evidence on the absorbing effect of time fixed effects on the statistical significance of *CovidIndex* and *ΔGDP*. Since we only find results of low significance in our main variable of interest, we decided to forego additional segmentations by size, company type, or there like.

4.2.3. Regression (3) – Loan Loss Provisions

Table 7 presents the results from regression (3), testing if European commercial banks reported significantly more LLPs in their financial statements with higher exposure to COVID-19 (H_3). *CovidIndex* shows a significantly positive relationship with *LLP* at the 0.01-level. Thus, our regression results find support for H_3 and generally validate the view that European commercial banks account for the adverse economic shock of COVID-19 and corresponding implications on the perceived credit risk of their loan portfolios with regards to their loan loss provisioning behavior. Adding time fixed effects to our baseline model yields no significant result in our primary variable of interest, *CovidIndex*. As previously mentioned, time fixed effects cause an absorbing effect in the statistical significance of *CovidIndex*. By contrast, the inclusion of country fixed effects does not change the statistical significance of *CovidIndex*, further implying that the positive relationship between *LLP* and *CovidIndex* is driven by time variation rather than cross-country variation.

Figure (3) depicts the cumulative growth in LLP expenses reported on banks' income statements over our observation period. The chart highlights that the increase in banks' provisioning for ECLs was particularly pronounced during Q1 2020, implying that European commercial banks adjusted their LLPs promptly to reflect the high uncertainty related to the COVID-19 pandemic in their financial reporting. For Q2 and Q3 2020, we observe an average reversion in European commercial banks' accounting for LLPs, reflecting the declining number of newly reported cases and gradual easing of the imposed COVID-19 restrictions during the summer period in 2020. With rising case numbers and a renewed tightening of COVID-19 restrictions on the backdrop of the second wave of the pandemic, we observe an increase in banks' LLPs during Q4 2020.

To test for economic significance of *CovidIndex*, we once again derive the beta factor for regression (3), norming the impact of the explaining variables on the explained variable *LLP* on a standard deviation basis. A one standard deviation increase in *CovidIndex* leads to a 9.4% standard deviation increase in LLPs (Appendix J). We observe that other discretionary (*RevLLP*) and non-discretionary variables (*ΔNPL, NPL*) yield higher beta factors compared to the other independent variables. Assuming that the pandemic also has a strong impact on the other non-discretionary variables in our analysis and given that *CovidIndex* only displays governmental responses, this effect comes to no surprise. In particular, we observe a higher economic significance for *ΔNPL* and *NPL* as compared to *CovidIndex*, whereby these non-discretionary variables capture deteriorations in credit quality and increased credit risk as a result of COVID-19.

Table 7. Regression Model (3) – Loan loss provisions

	(1)	(2)	(3)	(4)
Dependent Variable: LLP	Baseline Model Regression (3)	Extended Model Specifications		
CovidIndex	0.070***	0.155	0.070***	
	(4.99)	(1.53)	(5.16)	
ΔLoans	-0.011	-0.011	0.023	-0.058
	(-0.09)	(-0.08)	(0.17)	(-0.45)
ΔNPL	3.299***	3.008***	3.241***	3.241***
	(4.02)	(3.78)	(4.21)	(3.88)
NPL	0.771***	0.761***	0.636***	0.786***
	(8.57)	(8.59)	(5.04)	(8.60)
Tier1Cap	0.287***	0.232**	0.262***	0.325***
	(3.05)	(2.51)	(2.71)	(3.48)
RevLLP	22.73***	23.04***	24.36***	22.69***
	(21.60)	(21.92)	(22.00)	(21.34)
Log(Assets)	0.009***	0.009***	0.015***	0.010***
	(8.85)	(8.57)	(7.91)	(9.38)
ΔGDP	-0.354***	-0.323	-0.337***	-0.427***
	(-3.15)	(-1.37)	(-3.00)	(-3.70)
ΔUR	-0.030	0.088	-0.025	0.058*
	(-0.85)	(1.42)	(-0.70)	(1.82)
Constant	-0.248***	-0.254***	-0.391***	-0.252***
	(-10.66)	(-10.68)	(-11.37)	(-10.81)
N Observations	1332	2340	2340	2340
Country Fixed Effects	NO	NO	YES	NO
Time Fixed Effects	NO	YES	NO	NO
Adj. R^2	0.703	0.720	0.715	0.698

Table 7. presents our results for regression model (3). *LLP* is the ratio of loan loss provisions to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *ΔLoans* is the change in gross loans to lagged total assets. *ΔNPL* is the change in non-performing loans to lagged gross loans. *NPL* is the ratio of non-performing loans to gross loans, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *RevLLP* is the ratio of Revenues before loan loss provisions to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

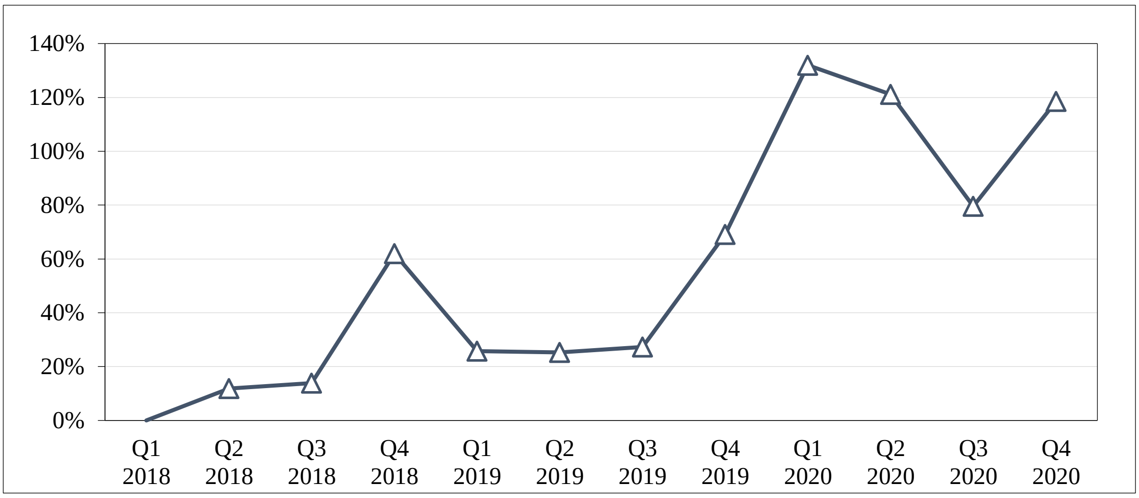


Figure 3. shows the average cumulative growth in LLPs to lagged total assets of our reduced sample (regression 3) over the observation period from Q1 2018 to Q4 2020.

Figure 3. Cumulative growth in LLPs from Q1 2018 – Q4 2020

As previously stated, empirical literature commonly distinguishes LLPs for bank credit risk into discretionary and non-discretionary components, whereby non-discretionary LLPs are related explicitly to problem loans and the default risk of a bank's loan portfolio (Aristei & Gallo, 2019; Bouvatier & Lepetit, 2008). Given that we are interested in investigating the LLPs accounting for expected credit risks concerning COVID-19, we choose to only comment on the regression results for the non-discretionary control variables in regression (3). Across all regression specifications, the variables *ΔNPL* and *NPL* show a statistically significant result, whereby the coefficients follow their predicted sign. This finding is in line with prior literature, indicating that the ratio of NPLs on a bank's loan portfolio and the growth in NPLs represent important measures of banks' credit risk. However, we do not find a statistically significant coefficient with regards to our third non-discretionary variable *ΔLoans*. *Log(Assets)*, controlling for bank size, exhibits a significantly positive coefficient, indicating that larger banks account for higher LLP expenses. Regression (3) returns a relatively high adjusted R-squared of 70.3% in our baseline model when compared to previous studies (Aristei & Gallo, 2019; Caporale et al., 2018) who find values in the range of 50.4% to 85.4%. Hence, we deem our regression model to hold high explanatory power.

Similar to regression (1), we have segmented the findings of regression (3) based on balance sheet size, using the same methodology to split our sample into two control groups. The findings indicate that both small and big banks significantly increased the level of LLPs on their financial statements with higher exposure to COVID-19 (Appendix K). Hence, the statistically significant result of *CovidIndex* is independent of bank balance sheet size. A segmentation by company type as a privately held or publicly listed bank yields a similar result. Both company types significantly increase their accounting for LLPs with higher governmental COVID-19 restrictions (Appendix L). Hence, we assume that the COVID-19 pandemic impacted the European banking sector as a whole, not differentiating between company types.

4.3. Sensitivity Analysis and Robustness Tests

To ensure the statistical integrity of our results, several sensitivity tests and additional robustness tests are performed, which are described below in further detail.

4.3.1. Alternative Specification of COVID-19 Variable

To investigate whether our results are robust for the specification of our main variable of interest, *CovidIndex*, we run regression models (1) – (3) using an alternative definition for measuring the impact of the COVID-19 pandemic on European commercial banks. As mentioned before, prior studies use different approaches to quantify bank-specific variation in the pandemic exposure. Dursun-de Neef & Schandlbauer (2020a) calculate their bank-specific COVID-19 variable by weighting the cases per capita with the proportion of bank branches in each country, while Li et al. (2020) incorporate two variables in their regression model to measure a bank's exposure to COVID-19. First, Li et al. (2020) control for total hours worked at small firms located in the same state as the bank's headquarters, and second, they account for state-level COVID-19 deaths per capita. To perform a sensitivity test with an alternative definition of our main variable of interest, we use a similar approach as Dursun-de Neef & Schandlbauer (2020a) by weighting the seven-day rolling average of new COVID-19, averaged by quarter and normalized for country population, with the banks' total revenue exposure in 2020 to each geography. Besides governmentally-imposed restrictions, the pandemic severity as measured by reported cases varied significantly across European jurisdictions over time.

Nevertheless, these two COVID-19 impact measures are not perfectly correlated with each other, as legislators responded quite differently both in the intensity and timing of lockdowns, often regardless of reported COVID-19 case numbers (compare Figure 1 with Appendix C). Our results may therefore be driven by the specific definition of our bank-level COVID-19 impact variable. While the highest values of *CovidIndex* were obtained during Q2 2020, our new variable *Cases* shifts the severity of pandemic impact to Q4 2020 when the daily new infection cases skyrocketed with the outbreak of the second COVID-19 wave. Accordingly, our results change slightly but do not vary a lot in the grand scope of things. We still observe the same results in regression models (1) and (3), i.e., a significant decrease in bank lending and significant increase in LLPs with higher exposure to COVID-19, albeit losing significance in regression (2). This comes to no surprise, given the emphasis of our *Cases* variable on Q4 2020 (Appendices M, N, O). When analyzing these findings with the help of Appendix T, we acknowledge that consumer spending did not decrease to the same extent as previously seen in Q1 and Q2 2020.

We still deem the *COVID-19 Government Response Tracker* a more adequate tool to assess the impact of the pandemic. First, it offers an unobstructed view on the actual impact of the pandemic on businesses and civil life that is not distorted by (at the least questionable) case counting practice of some countries. Second, during the inception of the pandemic, in the first two quarters, adequate testing infrastructure was not as pronounced compared to the second half of the year, leading to a potential distortion of a variable like C*ases* that is solely based on case numbers. Third, we are convinced that our variable *CovidIndex* further yields superior results as it captures the actual governmentally imposed restrictions on private and business life that in turn had a serious impact on the liquidity demand by borrowers that banks faced in 2020.

4.3.2. Regression Results excluding Norwegian Banks

To test for changes in our bottom-line results when excluding the country bias towards Norway in our sample, we repeat regression models (1) – (3) accordingly. As initially elaborated in section 3.1, Norwegian banks constitute 56.4% of our sample in regressions (1) and (2) as well as 59.5% in regression (3) (Appendix A). This bias originates from the very pronounced reporting requirements for small- and medium-sized banks in Norway. When excluding Norwegian banks in regressions (1) and (3), the reduced sample size yields no loss in statistical significance for *CovidIndex*, confirming that our findings are robust to country biases. The result of this robustness check is further reflected in column (3) of the output tables for regressions (1) and (3), showing that the addition of country fixed effects neither affects the statistical significance nor the coefficient for *CovidIndex*. However, when performing the robustness test for regression (2), *CovidIndex* loses its statistical significance on the already low 0.1-level (Appendices P, Q, R). This effect could be driven in large parts by the reduced sample variation.

4.3.3. Multicollinearity

Multicollinearity exists when two or more independent variables in a multiple regression equation are highly correlated with each other, which may cause misleading results when determining the independent contribution of individual variables (Wooldridge, 2019). The two Pearson's correlation matrices presented in section 4.1 show no excessively high correlations among the independent variables. To further test for multicollinearity in our regression models, a *Variance Inflation Factors* test (VIF) is conducted. VIFs and tolerance measures for regressions (1) – (3) are presented in Appendix S. Setting a good cut-off value for VIF above which we conclude multicollinearity is debated, but generally, a VIF above ten is considered to be an indication for collinearity (Wooldridge, 2019). Given that the independent variables used in our regression models have VIFs below 10, with the mean VIF ranging from 1.29 – 1.39 for regression models (1) – (3), we conclude that our findings are not affected by multicollinearity.

5. Analysis

5.1. Discussion of Findings

The following section contains a thorough discussion about the results presented in this study in light of prior empirical research and theory. In addition, limitations of the generalizability of our findings are addressed before concluding with the main contributions of our study and corresponding implications for future research.

The purpose of this thesis is to investigate the impact of the COVID-19 pandemic on the traditional commercial banking business model of lending and depositing. While our results are somewhat contradictory to prior theory on the role of banks as liquidity providers during times of market distress (H_1), we find evidence for the *safe haven theory*, indicating that depositors increased their savings in bank accounts in relation to COVID-19 (H_2).

Lending behavior of banks during COVID-19

To analyze the lending behavior of European commercial banks during the pandemic, we developed our first hypothesis based on the modern theory of financial intermediation. According to this theory, banks have a natural advantage in providing liquidity during times of adverse economic and financial market conditions, given that deposit inflows effectively hedge the liquidity risk inherent in systematic loan demand shocks (Gatev & Strahan, 2006). The results of regression (1) suggest that European banks significantly decrease their loan supply with higher exposure to COVID-19, which leads us to reject H_1 and call the role of banks as liquidity providers during the pandemic into question.

Thereby, this thesis contrasts previous studies which have provided empirical evidence that banks indeed fulfilled their role as *lenders of first resort* at the onset of the current COVID-19 crisis (Dursun-de Neef & Schandlbauer, 2020b; Li et al., 2020). In particular, Li et al. (2020) highlight that the immediate liquidity crisis of March 2020 represented the most considerable liquidity shock to the banking sector ever observed, whereby banks were able to accommodate this liquidity demand due to a robust capital base and the Federal Reserve's liquidity injection programs. However, it has to be noted that Li et al. (2020) solely investigate the change in C&I loans, while they acknowledge no unusual growth in other types of loans during the first quarter of 2020. Our thesis, by contrast, considers the change in total on-balance sheet lending while being able to fall back on four consecutive quarters of pandemic data. Moreover, the studies mentioned above focus on the US banking sector, whereas our thesis is based on European commercial banks. Over the year 2020, fiscal, monetary, and political decision-making varied drastically between these two geographies, potentially explaining the discrepancy in the obtained results.

Focusing on European banks in light of COVID-19, Dursun-de Neef & Schandlbauer's (2020a) study therefore provides a more comparable research setting to our thesis. They find that overall lending decreased at the onset of the pandemic, verifying the results of regression (1) which also displays a decrease in loan growth in conjunction with the COVID-19 pandemic in Europe. Somewhat contradictory to the negative relationship between *ΔLoans* and *CovidIndex* developed in regression (1), Dursun-de Neef & Schandlbauer (2020a) indicate that banks with higher exposure to COVID-19 decreased their loan supply relatively less. However, they conduct further segmentations by bank capital and geographic location, whereby these segmentations show a more coherent picture to our study results.

When segmenting by bank capital, Dursun-de Neef & Schandlbauer (2020a) find that higher exposure to COVID-19 results in an increase in lending for worse-capitalized banks, whereas better-capitalized banks tend to decrease their loan supply. In particular, the authors argue that worse-capitalized banks have an incentive to issue more loans during contraction times to help their weaker borrowers and avoid loan write-offs. The banks included in our sample are generally very well-capitalized, with a mean equity-to-assets ratio of 10.5%. The negative relationship between *ΔLoans* and *CovidIndex* in our sample is therefore congruent with the finding by Dursun-de Neef & Schandlbauer (2020a) that better-capitalized banks decreased their loans significantly more during COVID-19. Compared to our sample, the banks included in their study generally yield a lower capitalization with a mean equity-to-assets ratio of 9.3%. This difference in sample composition regarding bank capitalization might explain why Dursun-de Neef & Schandlbauer (2020a) identify an increase in bank lending with a higher COVID-19 exposure, while regression model (1) in our study yields a negative relationship.

In addition, when segmenting the European banks in their sample into three geographic regions (Nordics, Central, and Western European countries, Southern and Southeastern European countries), Dursun-de Neef & Schandlbauer (2020a) infer that banks located in the Nordics, as well as Southern and Southeastern European countries, decrease their loan supply significantly with higher exposure to COVID-19. In contrast, the opposite result holds for banks located in Central and Western European countries. Given that the Central and Western European banks in their sample are characterized by a lower capital ratio than the Nordic as well as Southern and Southeastern European banks, the authors suggest that this result is in line with their main discussion that worse-capitalized (better-capitalized) banks increased (decreased) lending. As our panel data set has a strong bias towards Nordic banks (with the on average highest capitalizations in our sample), we observe further parallels between the negative relationship of *ΔLoans* and *CovidIndex* developed in regression (1) and their study.

So far, we have established that research on bank lending in the context of the COVID-19 pandemic is still a novel strand of literature and hence limited in its extent. While Li et al.'s (2020) study focuses on a US research setting, accompanied with contrarian findings to our study, Dursun-de Neef & Schandlbauer (2020a) investigate the pandemic impact on the European banking sector. Their results yield similar findings to our study, which generally opens up room for discussion on the divergence of the results when assessed in a US versus a European research setting. One possible explanation for why US banks seem to fulfill their role as *lender of first resort* during COVID-19 to a greater extent than their European counterparts could be the difference in government spending for pandemic relief (Figure 4). The closest comparison in terms of economic strength represent the European members of the G20: Germany, France, Italy, the UK, and Spain. While the five European G20 members on average spent 29.4% of their GDP on pandemic aids related to liquidity support for businesses and non-health-related actions directed at their citizens (plus additional grants by the EU adding up to 10.6% of total EU GDP) in 2020, the US only contributed 16.8% measured against its total economic output (IMF, 2021).

Furthermore, the governmental support measures in the US also include two economic impact payments (stimulus checks) for its citizens, while in Europe, nothing similar occurred, further complicating a direct comparison. We conclude that businesses in the US could have been more reliant on bank lending during times of economic instability, whereas businesses in the EU received pandemic-related state support to a greater extent. This trend could explain the findings of Li et al. (2020) from a fiscal policy perspective.

Figure 4. Governmental COVID-19 support measures as percentage of GDP

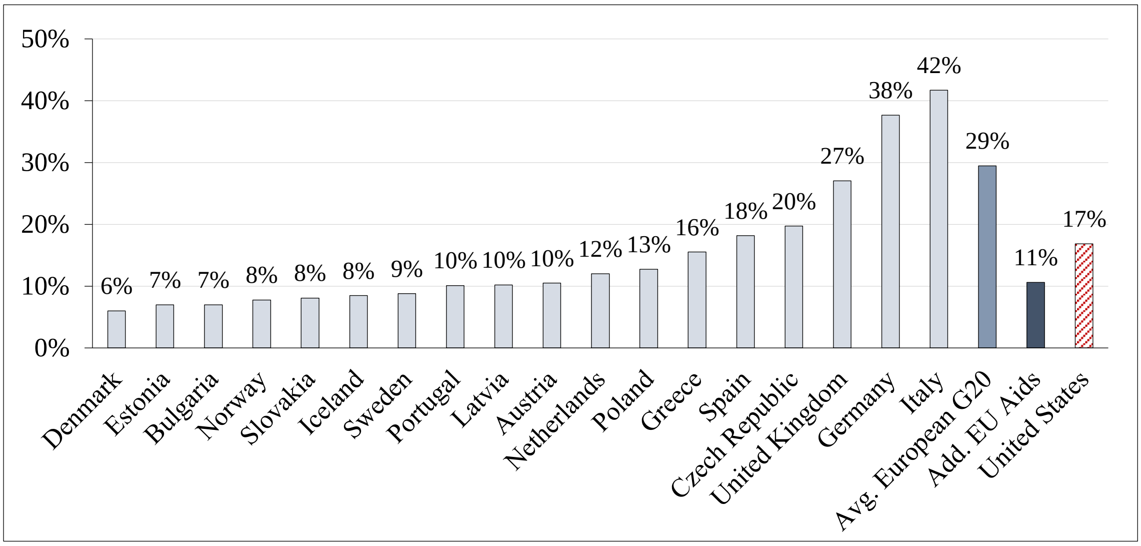


Figure 4. shows governmental support measures as of year-end 2020 including liquidity support for businesses (equity injections, loans, asset purchases, and debt assumptions) and additional spending or foregone revenues for the non-health sector (additional governmental legislature targeting citizens and businesses). The chart includes all countries from our sample expanded to additional aids granted by the European Union and the United States as a comparable. 'European G20 Countries' constitutes the average spending relative to GDP of Germany, France, Italy, the United Kingdom, and Spain. Source: IMF (2021).

Returning to the rejection of our first hypothesis, it can be inferred that the role of lender of first resort during times of financial distress was covered to a larger extent by governmental institutions in Europe than it was the case in the US. This finding provides an opportunity for future research to investigate further the interplay of states and higher, cross-national authorities with regional credit institutions to provide liquidity to businesses and individuals during the COVID-19 pandemic. Besides testing for the role of banks as liquidity providers in light of COVID-19 (H_1), regression (1) included the additional control variables *Tier1Cap*, *LiquidAssets*, and *Deposits* to account for banks' financial condition. We do not find statistically significant coefficients for these variables, indicating that banks' financial condition does not affect their lending behavior. This result is in line with Li et al. (2020), who equally do not find robust evidence that banks' financial condition constrained their ability to meet the liquidity demand shock that occurred in March 2020. However, it contradicts earlier empirical studies suggesting that changes in credit supply covary with bank's financial condition (Cornett et al., 2011; Ivashina & Scharfstein, 2010). In particular, these studies highlight that banks relying more on stable sources of financing, such as deposits and equity capital, as well as banks holding more liquid assets curtailed new credit origination to a lesser extent during the GFC 2008-09. Hence, our results support the notion that, unlike in 2008, bank financial conditions did not significantly affect bank lending in response to the COVID-19 crisis. After the GFC 2008-09, regulatory changes initiated through the Basel Accords, and stress tests implemented by banking supervisory authorities, increased regulatory capital well above minimum requirements, and improved banks' internal risk management processes. In addition, interventions by policymakers generally occurred at a much faster pace, as compared to the GFC 2008-09. This additional liquidity supply to the banking sector by central banks leads to a situation where banks are not constrained by their financial condition to meet the liquidity demands caused by the pandemic.

Bank depositing and the safe haven theory during the pandemic

As depositors tend to seek a *safe haven* for their savings in times of economic uncertainty, we decided to subsequently turn our attention to the depositing behavior of bank customers during the pandemic. We tested whether we find statistical evidence to prove the *safe haven theory* in light of COVID-19 (H_2). In theory, additional funds should become available to credit institutions to finance the loan demand shocks that follow declines in market liquidity through the increased inflow of deposits. This natural hedge gives banks an advantage to provide liquidity during crises and meet loan demands from borrowers without running down on their liquid asset holdings (Gatev & Strahan, 2006). The results of regression (2) find support for H_2, implying that deposits increase with more substantial governmental COVID-19 restrictions, albeit at a weak statistical significance. In connection to the rejection of H_1, however, it appears that our banks did not fully use the increased deposit inflows to originate new loans. Thereby, our results show limited support for the natural hedge in Europe, as implied by the theory of intermediation, in the context of COVID-19.

Closely related to regression (2), US studies find an increase in deposits for banks with a higher COVID-19 exposure at the onset of the pandemic, consistent with the theory that depositors accumulate their savings at banks during crises (Dursun-de Neef & Schandlbauer, 2020b; Li et al., 2020). Dursun-de Neef & Schandlbauer (2020b) further find that especially banks in counties with higher mobility restrictions saw a significant trend of increased depositing among their customers. However, this trend was only observable in counties with higher average household incomes available for consumption and an overall lower increase in unemployment rates. Thereby, the authors suggest that the flight to safety attempt does not hold for households who experienced employment lay-offs and had to use their savings to pay their bills. From their findings, we infer that our investigation of the *safe haven theory* in light of COVID-19 generally requires a more differentiated analysis given that depositors might have been affected by the pandemic very differently regarding their saving behavior. For instance, depositors employed in more affected industries (e.g., hoteling and lodging sector) might have been less able to accumulate significantly more savings in their bank accounts, despite an overall trend of decreased consumer spending. We conclude that further segmentation by depositors' occupation and income would be necessary to assess the *safe haven theory* in light of COVID-19 adequately. The studies by Dursun-de Neef & Schandlbauer (2020b) and Li et al. (2020) tested the *safe haven theory* at the onset of the COVID-19 pandemic.

In the subsequent quarters, the US government handed out economic impact payments (stimulus checks) for its citizens to compensate laid-off workers and prompt the economy. The first stimulus checks over USD 1,200 per capita were put into legislation in April 2020 and arrived within the following two to eight weeks on Americans' deposit accounts or via check in the mail. We assume that these stimulus checks could have influenced the depositing behavior of bank customers past the research horizon of the aforementioned US studies. This opens up room for future research to investigate the savings behavior of US citizens during the pandemic when taking the economic impact payments into account. Turning our attention to Europe again, Appendix T shows that household spending decreased sharply during the first two quarters of 2020, followed by a rebound in the subsequent quarter. Our regression results yield low statistical evidence for the hypothesis that bank deposits increased with a higher pandemic impact. Therefore, we assume that this effect mainly originates from the first half of 2020 when governmental restrictions tightened, and households were less able to spend their income as usual due to business closures and the slowing-down process of public life (Appendices C, T).

In summary, the findings of Li et al. (2020) and Dursun-de Neef & Schandlbauer (2020b) provide evidence for the natural hedge of lending and depositing during the outbreak of the COVID-19 pandemic in the US, as implied by the theory of financial intermediation. For European commercial banks, the results of this thesis and prior empirical studies (Dursun-de Neef & Schandlbauer, 2020a) suggest that the hedging effect was less pronounced. Even though the ECB encouraged European banks to fulfil their role as liquidity providers during the pandemic (ECB, 2020), our assumption is that stronger governmental aids and other COVID-19 relief measures in Europe led to a situation where this role was potentially covered to a greater extent by governmental institutions.

Loan loss provisioning behavior among European commercial banks

At the inception of the pandemic, banking supervisors instructed European credit institutions that *"the flexibility embedded in the accounting and regulatory frameworks [with regards to ECL] is to be fully used by institutions to help maintain soundness through the crisis and provide critical functions to the economy"* (EBA, 2020) in order to avoid *"that a significant overstatement of ECL could prompt behavior that leads to unnecessary tightening in credit conditions"* (BoE, 2020). With the second research question, we aim to scrutinize whether European commercial banks with a higher exposure to COVID-19 perceive an increased credit risk in their loan portfolios. The results of regression (3) provide empirical support for our hypothesis that European credit institutions significantly increased their LLPs with more stringent COVID-19 governmental constraints, thereby lending evidence to the *cyclicality theory* of loan loss provisioning practices.

Following this result, it might appear that European banks once again made their provisions for credit losses "too little, too late" when the pandemic had already resulted in a sharp decrease in GDP and the first lenders had to file for bankruptcy. However, in all fairness, we must also acknowledge that the COVID-19 pandemic constitutes an unprecedented black swan event for the global economy that was foreseeable for the fewest economists and experts associated with the matter. Even though the COVID-19 pandemic caused considerable uncertainty about the potential scale of loan default losses, the positive relationship between *LLP* and *CovidIndex* developed in regression (3) supports the forward-looking nature of the ECL model under IFRS 9. Serving as an example, the ING Groep (2020) states: *"Approximately 30% of the 2020 risk costs were Stage 1 and Stage 2, mainly due to Covid-19, reflecting IFRS 9-related provisioning based on macroeconomic scenarios"*. Thereby, our results indicate that European commercial banks indeed account for potential deteriorations in credit quality caused by the adverse economic impact of the pandemic. However, determining whether the impairment losses for loan defaults due to COVID-19 were reported in a timelier manner with the ECL model than they would have been with the ICL model requires further research.

In addition, our results find support for the results of prior empirical studies investigating the loan loss provisioning behavior of Italian banks in a crisis setting (Aristei & Gallo, 2019; Caporale et al., 2018). In particular, these studies suggest that LLPs during crises are significantly driven by non-discretionary factors related to expected credit risk. Similarly, our results demonstrate a significantly positive relation between the non-discretionary variables, *NPL* and *ΔNPL*, and our dependent variable *LLP*.

5.2. Limitations

The findings of this study are subject to several limitations. First, at the time of writing this thesis, the impacts of COVID-19 are still unfolding without a clear indication about when the pandemic will subside. Based on the availability of financial statement data, the observation period of our sample ceases in Q4 2020. In particular, we observe a high increase in reported COVID-19 cases and governmental restrictions after the observation period of our thesis. As a result, *CovidIndex* does not yet capture the entire variation in governmentally-imposed restrictions related to the second and third wave of the pandemic in Europe. Second, by the end of 2020, substantial uncertainty regarding the actual economic consequences of the COVID-19 crisis and corresponding implications on the banking sector prevailed. This further affects the validity and reliability of our underlying data set and the generalizability of our results. In particular, we cannot say whether banks have correctly estimated the effects of the pandemic for their ECL provisions. Once the COVID-19 period can be appropriately defined, we propose future research to reevaluate our findings with a complete set of pandemic data.

In the data collection process, one of our critical criteria for prospective companies was a gapless financial reporting every quarter from 2016 to 2020 to adequately match bank fundamentals with the quarterly pandemic development. In consideration of the financial intermediation theory, we moreover required credit institutions to have a clear focus on lending and depositing operations, thereby foregoing a large number of sizeable universal banks with substantial revenue streams originating from non-interest income. In combination, these two requirements implied a trade-off situation and caused a significant reduction in our sample size. On the one hand, we had large (often public) credit institutions with reliable quarterly reporting data but diversified business models due to their size. On the other hand, we had smaller (private) banks with a more traditional commercial banking business model accompanied, however, by more irregular disclosure with regulatory authorities only requiring financial reporting on a biannual basis.

As previously mentioned, data access to off-balance sheet loan commitments was limited. Hence, we generally cannot separate new credit origination from drawdowns on preexisting credit lines, implying further limitations for our study. Regression (1) only investigates the impact of COVID-19 on on-balance sheet lending, as measured by our dependent variable *ΔLoans*. Prior studies on bank lending during crises have analyzed the change in total credit production (sum of on-balance sheet lending plus off-balance sheet commitments). This broader measure of credit production is not affected by credit line drawdowns and only reflects new credit origination from both loans and off-balance sheet commitments (credit line drawdowns decrease off-balance sheet commitments by the same level that they increase on-balance sheet lending). For instance, Dursun-de Neef & Schandlbauer (2020b) find that banks with higher exposure to COVID-19 in the US experienced a significantly higher increase in total credit supply, implying that banks did not only honor their existing commitments to borrowers but also issued new credit. By contrast, prior studies on the GFC 2008-09 highlight that off-balance sheet commitments materialized after the failure of Lehman Brothers, which in turn, constrained new credit origination (Cornett et al., 2011; Ivashina & Scharfstein, 2010). Thereby, these studies suggest potential differences in total credit production between the COVID-19 pandemic and the GFC 2008-09. However, with our underlying data set, we cannot draw any conclusions about total credit production in light of COVID-19.

6. Concluding Remarks

The COVID-19 pandemic represents an unprecedented stress test to the role of banks as liquidity providers to the corporate sector and the general public (Li et al., 2020). To contain the spread of the novel coronavirus, European governments imposed drastic restrictions, causing economic activity and public life to nearly grind to halt. As a result, businesses and private individuals found themselves struggling to adequately service their liabilities and pay their debts, putting the liquidity insurance function of banks under pressure. The financial intermediation theory implies that banks have a natural advantage in providing liquidity during times of crisis when depositors seek a *safe haven* for their savings and banks in turn experience an increase in their deposit funding (Gatev & Strahan, 2006).

In light of the financial intermediation theory, this thesis aimed to investigate the impact of COVID-19 on bank lending and customer depositing of European commercial banks. In conjunction with the general economic downturn of COVID-19 and potential long-term business disruptions, our thesis moreover aimed to scrutinize whether European commercial banks perceive an increased credit risk of their loan portfolios, as measured by their LLPs, on the backdrop of the pandemic. Hence, we formulated the following two research questions:

How did the COVID-19 pandemic impact the European commercial banking sector from a lending and depositing perspective?

Did the impact of the COVID-19 pandemic and related uncertainty in the credit market materialize in a significant increase in loan loss provisions for European commercial banks?

To answer these research questions, we conducted a quantitative study on two samples of European credit institutions: First, one sample analyzing quarterly panel data of 117 banks over a period from Q1 2016 to Q4 2020 to investigate the general financial intermediation function of bank lending and depositing. Second, a reduced sample of 111 banks covering only the period after the implementation of IFRS 9 (i.e., Q1 2018 – Q4 2020) to investigate the loan loss provisioning behavior of banks under IFRS 9.

Our results show a significant negative relationship between on-balance sheet lending and the exposure to COVID-19, implying that European commercial banks, on average, decreased lending with stricter governmental COVID-19 restrictions. This result has implications on the characterization of banks as liquidity providers during crises and contrasts earlier US studies that find a significant increase in bank lending in the advent of COVID-19 (Dursun-de Neef & Schandlbauer, 2020b; Li et al., 2020). The difference in results compared to previous research may be attributed to the varying geographical settings. Although our results suggest that European banks did not live up to the expectations regulatory authorities voiced at the inception of the pandemic, we argue that, in Europe, the role of liquidity provider was to a larger extent covered by national governments. Testing the *safe haven theory*, our results indicate an increased *flight to safety* attitude among bank customers with more substantial governmental COVID-19 restrictions, albeit at weak statistical significance. Thereby, our study shows limited support for the natural hedge of lending and depositing, as implied by the financial intermediation theory, in light of COVID-19.

Concerning the provisioning behavior for credit losses, our results imply that European commercial banks indeed account for potential deteriorations in portfolio quality as a result of COVID-19. These results further support the forward-looking nature of the ECL model under IFRS, enabling credit institutions to react to the potential business disruptions caused by the pandemic in a timely manner.

With this paper, we aim to contribute to academic research in three distinct areas. First, our findings contribute by examining the economic and financial consequences of the COVID-19 pandemic, which, to this day, is very limited. Second, our paper complements earlier studies discussing the effects of COVID-19 on the banking sector with an extended observation period. To the best of our knowledge, this paper is the first publication that incorporates quarterly data for the full year 2020 and is hence able to present a more holistic picture of the pandemic impact on the European banking sector. Third, our study contributes to the literature on bank liquidity creation, specifically with regards to the role of banks as liquidity providers to firms and households during times of crisis while also shedding light on bank behavior with regards to credit loss provisioning.

The findings of this study provide ample starting points for future research. First, as the COVID-19 crisis can be regarded as the first 'real stress test' for the ECL model implemented under IFRS 9, future studies could investigate whether impairment losses for loan defaults due to the pandemic were actually reported in a timelier manner than under the reign of the previous ICL model under IAS 39. Second, building on the findings of our study that banks decreased their loan origination with higher pandemic impact, forthcoming research could further assess who (as in banks versus governmental authorities) in fact took over the role as liquidity provider in various geographic settings during the pandemic. Lastly, as we only investigated loan growth on an aggregate basis, it would be of interest if varying results could be obtained when further dissecting loan origination by loan type. Prior studies have already provided evidence that lending levels, in fact, increased when observing C&I loans in particular, however only in a US setting (Li et al., 2020). Addressing these open questions could help research get a better overall understanding of the pandemic as such and its impact on the financial sector.

7. Reference List

Articles

Acharya, V., & Mora, N. (2015). A Crisis of Banks as Liquidity Providers. *The Journal of Finance*, *70*(1), 1–43. https://doi.org/https://doi.org/10.1111/jofi.12182

Acharya, V. V., & Steffen, S. (2020). “Stress Test” for Banks as Liquidity Insurers in a time of COVID. *VOX EU Working Paper*. https://voxeu.org/article/stress-tests-banks-liquidity-insurers-time-covid

Aristei, D., & Gallo, M. (2019). Loan loss provisioning by Italian banks: Managerial discretion, relationship banking, functional distance and bank risk. *International Review of Economics and Finance*, *60*, 238–256. https://doi.org/10.1016/j.iref.2018.10.022

Berger, A. N., & Bouwman, C. H. S. (2009). Bank Liquidity Creation. *Oxford University Press*, *22*(9), 3779–3837. https://doi.org/10.1093/rfs/hhnl04

Bouvatier, V., & Lepetit, L. (2008). Banks’ procyclical behavior: Does provisioning matter? *Journal of International Financial Markets, Institutions and Money*, *18*, 513–526. https://doi.org/10.1016/j.intfin.2007.07.004

Bouvatier, V., Lepetit, L., & Strobel, F. (2014). Bank income smoothing, ownership concentration and the regulatory environment. *Journal of Banking and Finance*, *41*, 253–270. https://doi.org/10.1016/j.jbankfin.2013.12.001

Bushman, R. M., & Williams, C. D. (2015). Delayed Expected Loss Recognition and the Risk Profile of Banks. *Journal of Accounting Research*, *53*(3), 511–553. https://doi.org/10.1111/1475-679X.12079

Caporale, G. M., Alessi, M., Di Colli, S., & Lopez, J. S. (2018). Loan loss provisions and macroeconomic shocks: Some empirical evidence for italian banks during the crisis. *Finance Research Letters*, *25*, 239–243. https://doi.org/10.1016/j.frl.2017.10.031

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*, 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Cho, S., & Kim, J. Y. (2012). Straightness and flatness evaluation using data envelopment analysis. *International Journal of Advanced Manufacturing Technology*, *63*, 731–740. https://doi.org/10.1007/s00170-012-3925-6

Cornett, M. M., McNutt, J. J., Strahan, P. E., & Tehranian, H. (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics*, *101*, 297–312. https://doi.org/10.1016/j.jfineco.2011.03.001

Curcio, D., & Hasan, I. (2015). Earnings and capital management and signaling: the use of loan-loss provisions by European banks. *European Journal of Finance*, *21*(1), 26–50. https://doi.org/10.1080/1351847X.2012.762408

Davydov, D., Vähämaa, S., & Yasar, S. (2021). Bank liquidity creation and systemic risk. *Journal of Banking and Finance*, *123*. https://doi.org/10.1016/j.jbankfin.2020.106031

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, *91*(3), 401–419. https://doi.org/10.1086/261155

Diamond, D. W., & Rajan, R. G. (2001). Liquidity Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking. *Journal of Political Economy*, *109*(2), 147–158. https://doi.org/https://doi.org/10.1086/319552

Distinguin, I., Roulet, C., & Tarazi, A. (2013). Bank regulatory capital and liquidity: Evidence from US and European publicly traded banks. *Journal of Banking and Finance*, *37*, 3295–3317. https://doi.org/10.1016/j.jbankfin.2013.04.027

Dursun-de Neef, H. Ö., & Schandlbauer, A. (2020a). COVID-19 and European Banks. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3681937

Dursun-de Neef, H. Ö., & Schandlbauer, A. (2020b). COVID-19 and Bank Loan Supply. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3642522

el Barnoussi, A., Howieson, B., & van Beest, F. (2020). Prudential Application of IFRS 9: (Un)Fair Reporting in COVID-19 Crisis for Banks Worldwide?! *Australian Accounting Review*, *30*(94), 178–192. https://doi.org/10.1111/auar.12316

Fonseca, A. R., & González, F. (2008). Cross-country determinants of bank income smoothing by managing loan-loss provisions. *Journal of Banking and Finance*, *32*, 217–228. https://doi.org/10.1016/j.jbankfin.2007.02.012

Foos, D., Norden, L., & Weber, M. (2010). Loan growth and riskiness of banks. *Journal of Banking and Finance*, *34*, 2929–2940. https://doi.org/10.1016/j.jbankfin.2010.06.007

Gambacorta, L., & Mistrulli, P. E. (2004). Does bank capital affect lending behavior? *Journal of Financial Intermediation*, *13*, 436–457. https://doi.org/10.1016/j.jfi.2004.06.001

Gatev, E., Schuermann, T., Strahan, P. E., The, S., Studies, F., & Mar, N. (2009). Managing Bank Liquidity Risk : How Deposit-Loan Synergies Vary with Market Conditions. *The Review of Financial Studies*, *22*(3), 995–1020. https://doi.org/https://doi.org/10.1093/rfs/hhm060

Gatev, E., & Strahan, P. E. (2006). Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market. *The Journal of FinanceJournal of Finance*, *61*(2), 867–892. https://doi.org/10.1111/j.1540-6261.2006.00857.x

Gomaa, M., Kanagaretnam, K., Mestelman, S., & Shehata, M. (2019). Testing the Efficacy of Replacing the Incurred Credit Loss Model with the Expected Credit Loss Model. *European Accounting Review*, *28*(2), 309–334. https://doi.org/10.1080/09638180.2018.1449660

Gorton, G., & Winton, A. (2017). Liquidity Provision, Bank Capital, and the Macroeconomy. *Journal of Money, Credit and Banking*, *49*(1), 5–37. https://doi.org/10.1111/jmcb.12367

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, *5*, 529–538. https://doi.org/10.1038/s41562-021-01079-8

Hasan, I., & Wall, L. D. (2004). Determinants of the loan loss allowance: Some cross-country comparisons. *The Financial Review*, *39*, 129–152. https://doi.org/10.1111/j.0732-8516.2004.00070.x

Ivashina, V., & Scharfstein, D. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, *97*, 319–338. https://doi.org/10.1016/j.jfineco.2009.12.001

Kashyap, A. K., Rajan, R., & Stein, J. C. (2002). Banks as Liquidity Providers : An Explanation for the Coexistence of Lending and Deposit- Taking. *The Journal of Finance*, *57*(1), 33–73. https://doi.org/https://doi.org/10.1111/1540-6261.00415

Laeven, L., & Majnoni, G. (2003). Loan loss provisioning and economic slowdowns: Too much, too late? *Journal of Financial Intermediation*, *12*, 178–197. https://doi.org/10.1016/S1042-9573(03)00016-0

Leventis, S., Dimitropoulos, P. E., & Anandarajan, A. (2011). Loan Loss Provisions, Earnings Management and Capital Management under IFRS: The Case of EU Commercial Banks. *Journal of Financial Services Research*, *40*, 103–122. https://doi.org/10.1007/s10693-010-0096-1

Li, L., Strahan, P. E., & Zhang, S. (2020). Banks as lenders of first resort: Evidence from the COVID-19 crisis. *The Review of Corporate Finance Studies*, *9*, 472–500. https://doi.org/10.1093/rcfs/cfaa009

Ng, J., Saffar, W., & Zhang, J. J. (2020). Policy uncertainty and loan loss provisions in the banking industry. *Review of Accounting Studies*, *25*, 726–777. https://doi.org/10.1007/s11142-019-09530-y

Norden, L., & Stoian, A. (2013). Bank Earnings Management Through Loan Loss Provisions: A Double-Edged Sword? *SSRN Electronic Journal*, 1–45. https://doi.org/10.2139/ssrn.2369798

Parman, B. J., Featherstone, A. M., & Coffey, B. K. (2017). Estimating product-specific and multiproduct economies of scale with data envelopment analysis. *Agricultural Economics*, *48*, 523–533. https://doi.org/10.1111/agec.12353

Pucci, R., & Skærbæk, P. (2020). The co-performation of financial economics in accounting standard-setting: A study of the translation of the expected credit loss model in IFRS 9. *Accounting, Organizations and Society*, *81*. https://doi.org/10.1016/j.aos.2019.101076

Wetmore, J. L., & Brick, J. R. (1994). Loan-loss provisions of commercial banks and adequate disclosure: A note. *Journal of Economics and Business*, *46*, 299–305. https://doi.org/10.1016/0148-6195(94)90040-X

Yue, P. (1992). Data Envelopment Analysis and Commercial Bank Performance: A Primer with Applications to Missouri Banks. *Federal Reserve Bank of St. Louis Review*, *74*(1), 31–45. https://doi.org/10.20955/r.74.31-45

Zheng, C., (Wai Kong) Cheung, A., & Cronje, T. (2019). The moderating role of capital on the relationship between bank liquidity creation and failure risk. *Journal of Banking and Finance*, *108*. https://doi.org/10.1016/j.jbankfin.2019.105651

Books

Woolridge, J. (2019). Introductory Econometrics; A Modern Approach. *South-Western College Publishing*.

Picker, R., Clark, K., Dunn, J., Kolitz, D., Livne, G., Loftus, J., van der Tas, L. (2019). Applying IFRS Standrards: 4th Edition. *John Wiley & Sons*.

Reports and government publications

Bank of England. (2020). *Letter from Sam Woods 'Covid-19: IFRS 9, Capital Requirements and Loan Covenants'*. https://www.bankofengland.co.uk/-/media/boe/files/prudential-regulation/letter/2020/covid-19-ifrs-9-capital-requirements-and-loan-covenants.pdf

Basel Committee on Banking Supervision. (2009). *Guiding principles for the replacement of IAS 39*. https://www.bis.org/publ/bcbs161.pdf

Basel Committee on Banking Supervision. (2016). *Basel III Monitoring Report March 2016*. https://www.bis.org/bcbs/publ/d354.pdf

Basel Committee on Banking Supervision. (2020). *Measures to reflect the impact of COVID-19*. https://www.bis.org/bcbs/publ/d498.pdf

Ernst & Young. (2020). *Applying IFRS: Disclosure of Covid-19 impact.* https://www.ey.com/en_gl/ifrs-technical-resources/applying-ifrs-disclosure-of-covid-19-impact

European Banking Authority. (2020). *Statement on the Application of the Prudential Framework Regarding Default, Forbearance and IFRS9 in Light of COVID-19* Measures. https://www.eba.europa.eu/eba-provides-clarity-banks-consumers-application-prudential-framework-light-covid-19-measures

European Central Bank. (2020). *Recommendation of the European Central Bank of 15 December 2020 on dividend distributions during the COVID-19 pandemic and repealing Recommendation*. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020HB0062&from=EN

European Commission. (2020a). *European Economic Forecase – Spring 2020. Institutional Paper, 125.* https://ec.europa.eu/info/publications/european-economic-forecast-spring-2020_en#:~:text=Description,by%20around%206%25%20in%202021.

European Securities and Markets Authority. (2020). *Accounting Implications of the COVID-19 Outbreak on the Calculation of Expected Credit Lossesin Accordance with IFRS 9*. https://www.esma.europa.eu/sites/default/files/library/esma32-63-951_statement_on_ifrs_9_implications_of_covid-19_related_support_measures.pdf

Financial Stability Forum. (2009). *Financial Stability Forum Issues Recommendation and Principles to Strengthen Financial Systems*. https://www.fsb.org/wp-content/uploads/pr_090402a.pdf

G20. (2009). *Progress Report on the Economic and Financial Actions of the London, Washington and Pittsburgh G20 Summits: Prepared by the UK Chair of the G20*. https://www.iasplus.com/en/binary/crunch/0911g20progressreport.pdf

ING Groep. (2020). *2020 Annual Report ING Groep*. https://www.ing.com/Investor-relations/Financial-performance/Annual-reports.html

International Accounting Standards Board. (2017). *The Annotated IFRS Standards Part A: The Conceptual Framework for Financial Reporting and requirements*. IFRS.

International Accounting Standards Board. (2019). *The Annotated IFRS® Standards Part A: Issued Standards and the Conceptual Framework for Financial Reporting. IFRS*.

International Accounting Standards Board. (2020) *IFRS 9 and COVID-19. International Accounting Standards Board. (2020) IFRS 9 and COVID-19*. https://www.ey.com/en_gl/ifrs-technical-resources/applying-ifrs-disclosure-of-covid-19-impact

International Monetary Fund. (2019*). The Dynamics of Non-Performing Loans during Banking Crises: A New Database*. https://www.imf.org/en/Publications/WP/Issues/2019/12/06/The-Dynamics-of-Non-Performing-Loans-during-Banking-Crises-A-New-Database-48839

Websites

European Commission. (2020b). *Paolo Gentiloni, European Commissioner for the Economy*. https://ec.europa.eu/newsroom/ecfin/items/676321

International Monetary Fund. (2021). *Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic.* https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19

Johns Hopkins University & Medicine. (2021). *Coronavirus Resource Center.* https://coronavirus.jhu.edu/

World Health Organization. (2020a). *WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020*. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020

World Health Organization. (2020b). *WHO Director-General's opening remarks at the media briefing on COVID-19 - 13 March 2020*. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-mission-briefing-on-covid-19---13-march-2020

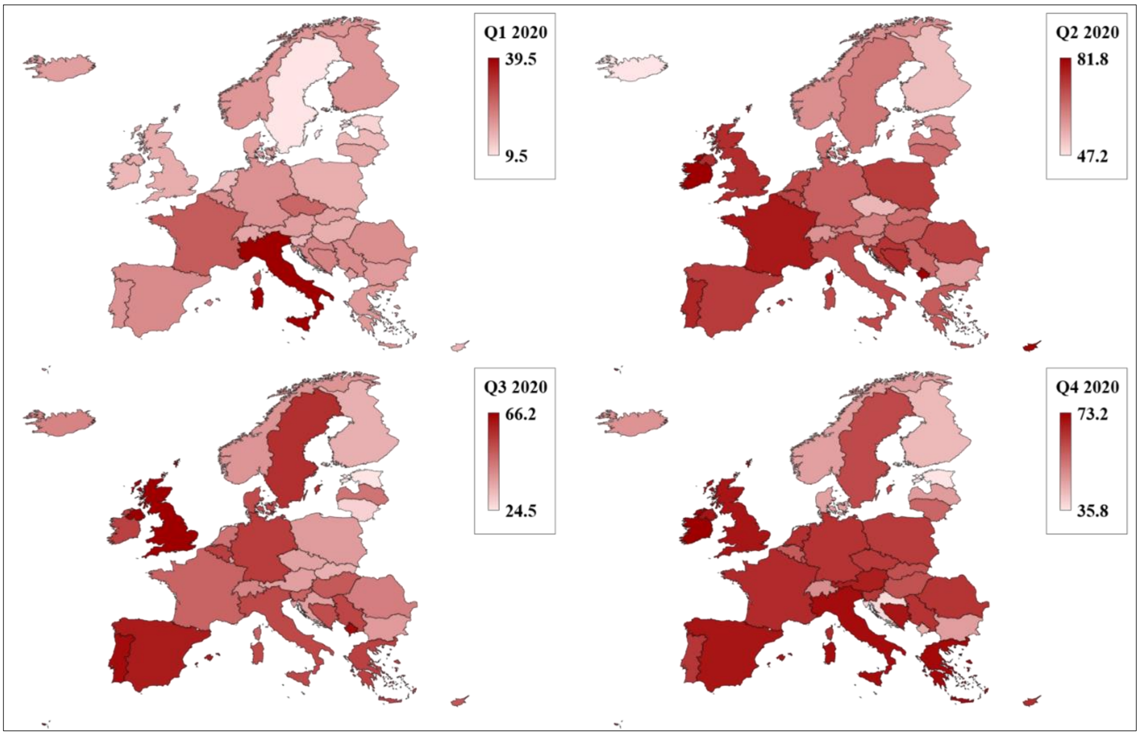
8. Appendices

Appendix A. Sample Distribution by country

Country	**Number of Banks Reg. Models (1) and (2)**	**Percentage**	**Number of Banks Reg. Model (3)**	**Percentage**
Austria	1	0.9%	1	0.9%
Bulgaria	1	0.9%	0	0.0%
Czech Republic	2	1.7%	2	1.8%
Denmark	4	3.4%	4	3.6%
Estonia	3	2.6%	3	2.7%
Germany	1	0.9%	1	0.9%
Greece	2	1.7%	2	1.8%
Iceland	2	1.7%	2	1.8%
Italy	2	1.7%	2	1.8%
Latvia	2	1.7%	1	0.9%
Netherlands	2	1.7%	2	1.8%
Norway	66	56.4%	66	59.5%
Poland	9	7.7%	8	7.2%
Portugal	4	3.4%	2	1.8%
Slovakia	2	1.7%	2	1.8%
Spain	1	0.9%	1	0.9%
Sweden	12	10.3%	12	10.8%
United Kingdom	1	0.9%	0	0.0%
Total	**117**		**111**	

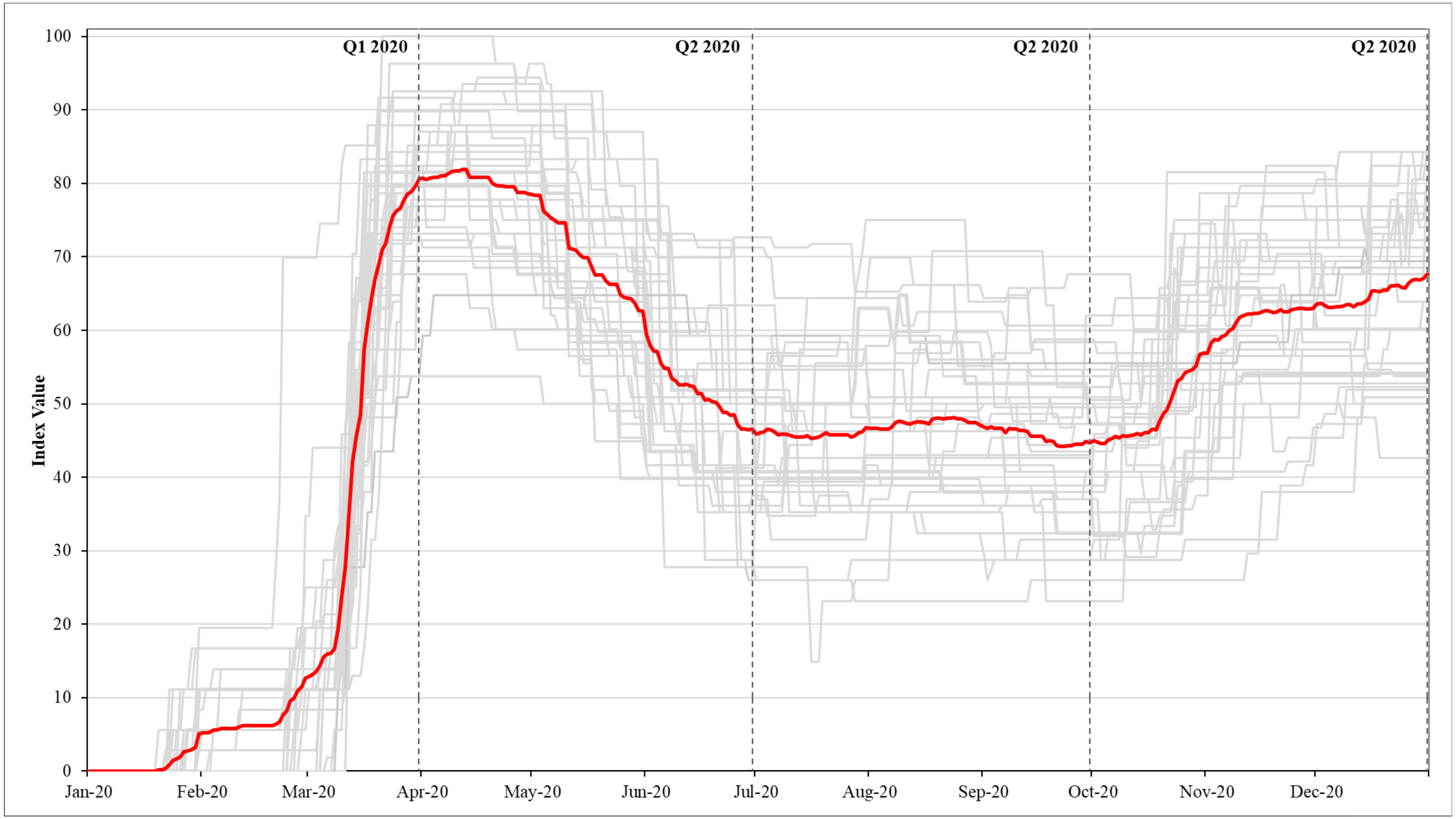
Appendix A. shows our sample distribution by country for all three regression models. Constricted reporting practices for NPLs, lead to sample reduction for regression model (3).

Appendix B. *COVID-19 Government Response Tracker* map overview



Appendix B. shows an overview of the COVID-19 Government Response Tracker by quarter. Country coloring is oriented on a relative quarterly ranking of governmental response severity among European countries. Hence, individual countries coloring must be interpreted on a quarter-by-quarter basis.

Appendix C. *COVID-19 Government Response Tracker* daily variation by country



Appendix C. shows the development over the year. The daily average value is highlighted in red.

Appendix D. Regression model (1) – Lending, economic significance (beta testing)

Dependent Variable: ΔLoans	All Banks	Beta
CovidIndex	-0.013***	[-0.073]
	(-3.40)	
Log(Assets)	-0.000	[-0.032]
	(-1.10)	
Tier1Cap	0.006	[0.007]
	(0.25)	
LLR	-0.103***	[-0.110]
	(-4.96)	
LiquidAssets	0.013	[0.025]
	(0.99)	
Deposits	0.004	[0.019]
	(0.71)	
ROA	3.946***	[0.259]
	(8.39)	
ΔGDP	0.012	[0.009]
	(0.44)	
ΔUR	-0.007	[-0.017]
	(-0.72)	
Constant	0.009	-
	(1.12)	
N Observations	2340	-
Country Fixed Effects	NO	-
Time Fixed Effects	NO	-
Adj. R^2	0.100	-

Appendix D. presents our results for regression model (1) highlighting the economic significance of our independent variables. *ΔLoans* is the change in gross loans to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *Loans* is the ratio of gross loans to lagged total assets, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *LiquidAssets* is the ratio of cash, deposits with central banks, and receivables from other credit institutions to total assets, lagged by one quarter. *Deposits* is the ratio of customer deposits to total assets, lagged by one quarter. *LLR* is the ratio of loan loss reserves to gross loans, lagged by one quarter. *ROA* is the ratio of lagged income to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix E. Regression model (1) – Lending, size segmentation

	(1)	(2)	(3)
Dependent Variable: ΔLoans	All Banks	Small	Large
CovidIndex	-0.013***	-0.015**	-0.014***
	(-3.40)	(-2.43)	(-2.96)
Log(Assets)	-0.000	-0.000	-0.002***
	(-1.10)	(-0.08)	(-2.92)
Tier1Cap	0.006	0.037	0.006
	(0.25)	(0.73)	(0.24)
LLR	-0.103***	-0.042	-0.152***
	(-4.96)	(-0.61)	(-7.75)
LiquidAssets	0.013	0.051**	-0.017
	(0.99)	(2.02)	(-1.13)
Deposits	0.004	0.020	0.010
	(0.71)	(1.31)	(1.63)
ROA	3.946***	4.923***	2.439***
	(8.39)	(5.86)	(4.64)
ΔGDP	0.012	0.055	-0.000
	(0.44)	(0.99)	(-0.01)
ΔUR	-0.007	-0.014	0.007
	(-0.72)	(-1.22)	(0.37)
Constant	0.009	-0.017	0.027***
	(1.12)	(-1.05)	(2.67)
N Observations	2340	1200	1140
Country Fixed Effects	NO	NO	NO
Time Fixed Effects	NO	NO	NO
Adj. R^2	0.100	0.128	0.093

Appendix E. presents our results for regression model (1) segmenting the results by balance sheet size relative to all other banks operating in Europe. *ΔLoans* is the change in gross loans to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *Loans* is the ratio of gross loans to lagged total assets, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *LiquidAssets* is the ratio of cash, deposits with central banks, and receivables from other credit institutions to total assets, lagged by one quarter. *Deposits* is the ratio of customer deposits to total assets, lagged by one quarter. *LLR* is the ratio of loan loss reserves to gross loans, lagged by one quarter. *ROA* is the ratio of lagged income to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix F. Regression model (1) – Lending, private / public segmentation

	(1)	(2)	(3)
Dependent Variable: ΔLoans	All Banks	Private	Public
CovidIndex	-0.013***	-0.015***	-0.013**
	(-3.40)	(-3.51)	(-2.14)
Log(Assets)	-0.000	0.003**	-0.002***
	(-1.10)	(2.17)	(-3.79)
Tier1Cap	0.006	-0.019	0.085
	(0.25)	(-0.80)	(1.41)
LLR	-0.103***	-0.267***	-0.088***
	(-4.96)	(-5.92)	(-3.81)
LiquidAssets	0.013	-0.002	0.047**
	(0.99)	(-0.12)	(2.33)
Deposits	0.004	0.015	0.025***
	(0.71)	(1.33)	(3.04)
ROA	3.946***	2.660***	4.077***
	(8.39)	(5.12)	(5.59)
ΔGDP	0.012	0.008	0.012
	(0.44)	(0.20)	(0.29)
ΔUR	-0.007	-0.003	-0.014
	(-0.72)	(-0.23)	(-0.74)
Constant	0.009	-0.010	-0.004
	(1.12)	(-0.66)	(-0.28)
N Observations	2340	1340	1000
Country Fixed Effects	NO	NO	NO
Time Fixed Effects	NO	NO	NO
Adj. R^2	0.100	0.064	0.197

Appendix F. presents our results for regression model (1) segmenting the results by company type. *ΔLoans* is the change in gross loans to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *Loans* is the ratio of gross loans to lagged total assets, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *LiquidAssets* is the ratio of cash, deposits with central banks, and receivables from other credit institutions to total assets, lagged by one quarter. *Deposits* is the ratio of customer deposits to total assets, lagged by one quarter. *LLR* is the ratio of loan loss reserves to gross loans, lagged by one quarter. *ROA* is the ratio of lagged income to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix G. A brief introduction to data envelopment analysis model (DEA)

Data envelopment analysis is a nonlinear, non-convex programming methodology in academia to estimate the relative efficient production frontier of observed decision-making units (DMU). DMUs constitute producing entities that consume input parameters 'x_i^0' and transform them into outputs 'y_j^0'. The efficiency of this transformation process is subsequently determined by the variable 'θ^0'. The relativity term is of great importance as the DEA can only determine the efficiency of DMUs relative to each other. Hence, the theta of one DMU can vary or even be classified as inefficient compared to different dataset (Charnes et al., 1978).

Simplified model assuming uniform weights of input and output factors:

$$Max\ \theta^0 = \sum_{j=1}^{J} y_j^0 \ / \sum_{i=1}^{I} x_i^0$$

Subject to:

$$\sum_{j=1}^{J} y_j^n \ / \sum_{i=1}^{I} x_i^n \leqq 1; \qquad n = 1, \dots, N$$

Where:

- $\boldsymbol{\theta^0}$ = DEA efficiency score assigned to DMU^0
- $\mathbf{y_j^0}$ = Number of 'j' outputs of DMU^0
- $\mathbf{x_i^0}$ = Number of 'i' inputs of DMU^0

Every DMU can hold an arbitrary number of inputs and outputs. If a DMU is assigned a score of $\theta^0 = 1$, then it satisfies the condition to be efficient according to the DEA. Otherwise, it returns a value $0 \leqq x < 1$ and is thereby deemed inefficient to varying degree.

The DEA has its origin in engineering and economic optimization situations (Charnes et al., 1978; Cho & Kim, 2012; Parman et al., 2017) but has also been successfully adapted to efficiency testing of commercial banks. In order to derive a meaningful, efficient frontier, it is of the utmost importance that the observed DMUs are homogenous. On the topic of credit institutions, the companies in question should provide similar services and use similar inputs and outputs. For this reason (among other factors discussed in section 3.1), we require that banks in our sample have a clear focus on lending and deposit-taking activities. Banks with substantial revenue streams originating from activities other than the traditional commercial banking business model of lending and depositing were disregarded.

To successfully implement the DEA methodology in a banking setting, it is crucial to select adequate input and output factors to determine the relative efficiency of credit institutions. Prior literature has, among others, settled on the notion adopted by Yue (1992) that views credit institutions as financial intermediaries between depositors and lenders. Accordingly, Yue (1992) chose interest expenses, non-interest expenses, and customer deposits as input variables, and interest income, non-interest income, as well as total loans as output variables. We decided to follow this approach, as it is closely related to our first hypothesis and our discussion of banks' financial intermediation role.

Appendix H. Regression model (1) – Lending, efficiency segmentation (DEA)

	(1)	(2)	(3)	(4)
Dependent Variable: ΔLoans	All Banks	Low Efficiency	Medium Efficiency	High Efficiency
CovidIndex	-0.013***	-0.016***	-0.008	-0.011
	(-3.40)	(-2.70)	(-1.10)	(-1.63)
Log(Assets)	-0.000	-0.001	-0.001*	-0.002
	(-1.10)	(-0.74)	(-1.85)	(-1.21)
Tier1Cap	0.006	0.068	-0.097**	0.025
	(0.25)	(1.31)	(-2.34)	(0.69)
LLR	-0.103***	-0.023	-0.084***	-0.277***
	(-4.96)	(-0.45)	(-3.57)	(-3.47)
LiquidAssets	0.013	-0.010	0.053**	-0.014
	(0.99)	(-0.47)	(2.57)	(-0.72)
Deposits	0.004	0.027*	0.002	0.023**
	(0.71)	(1.73)	(0.15)	(2.21)
ROA	3.946***	3.193***	4.314***	3.529***
	(8.39)	(2.81)	(3.92)	(4.07)
ΔGDP	0.012	0.009	0.060	-0.024
	(0.44)	(0.25)	(1.12)	(-0.42)
ΔUR	-0.007	-0.01	0.004	-0.016
	(-0.72)	(-0.76)	(0.28)	(-0.69)
Constant	0.009	-0.019	0.029**	0.016
	(1.12)	(-0.94)	(2.19)	(0.99)
N Observations	2340	780	780	780
Country Fixed Effects	NO	NO	NO	NO
Time Fixed Effects	NO	NO	NO	NO
Adj. R^2	0.100	0.087	0.119	0.099

Appendix H. presents our results for regression model (1) segmenting the results by company efficiency, derived by applying DEA. As previously explained, the credit institutions in our sample are ranked relatively to each other to determine an efficient frontier for each point in time determine by the reported quarterly financials. We use the average value from Q1 2016 to Q4 2020 for each bank to determine their long-term theta and rank them accordingly on a 'best practice' basis. High efficiency credit institutions were able to transform customer deposits, interest expenses, and non-interest expenses into loans, interest income, and non-interest income in a more efficient way than their peers. *ΔLoans* is the change in gross loans to lagged total assets.

Appendix H. (cont.) *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *Loans* is the ratio of gross loans to lagged total assets, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *LiquidAssets* is the ratio of cash, deposits with central banks, and receivables from other credit institutions to total assets, lagged by one quarter. *Deposits* is the ratio of customer deposits to total assets, lagged by one quarter. *LLR* is the ratio of loan loss reserves to gross loans, lagged by one quarter. *ROA* is the ratio of lagged income to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. t statistics in parentheses.t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix I. Regression model (2) – Depositing

	(1)	(2)	(3)	(4)
Dependent Variable: ΔDeposits	Baseline Model Regression (2)	Extended Model Specification		
CovidIndex	0.009*	-0.028	0.008*	
	(1.87)	(-0.93)	(1.67)	
Log(Assets)	-0.000	-0.000	-0.001	0.000
	(-0.13)	(-0.04)	(-0.56)	(0.11)
Tier1Cap	-0.033	-0.039	-0.015	-0.029
	(-1.05)	(-1.21)	(-0.42)	(-0.92)
LLR	-0.027	-0.031	-0.101*	-0.027
	(-1.06)	(-1.19)	(-1.69)	(-1.04)
LiquidAssets	0.022	0.026	0.018	0.021
	(0.91)	(1.06)	(0.57)	(0.89)
Deposits	0.010	0.011	0.001	0.011*
	(1.51)	(1.61)	(0.06)	(1.73)
ROA	4.192***	3.790***	4.180***	4.121***
	(8.00)	(7.06)	(6.76)	(7.96)
ΔGDP	-0.135***	-0.092	-0.139***	-0.145***
	(-3.95)	(-1.32)	(-4.12)	(-4.27)
ΔUR	-0.011	-0.006	-0.009	0.001
	(-0.79)	(-0.23)	(-0.68)	(0.10)
Constant	0.004	0.002	0.019	0.002
	(0.37)	(0.19)	(0.89)	(0.22)
N Observations	2340	2340	2340	2340
Country Fixed Effects	NO	NO	YES	NO
Time Fixed Effects	NO	YES	NO	NO
Adj. R^2	0.067	0.090	0.083	0.066

Appendix I. presents our results for regression model (1). *ΔDeposits* is the change in customer deposits to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *Loans* is the ratio of gross loans to lagged total assets, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *LiquidAssets* is the ratio of cash, deposits with central banks and receivables from other credit institutions to total assets, lagged by one quarter. *Deposits* is the ratio of customer deposits to total assets, lagged by one quarter. *LLR* is the ratio of loan loss reserves to gross loans, lagged by one quarter. *ROA* is the ratio of lagged income to lagged total assets.

Appendix I. (cont.) *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in unemployment rate. t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix J. Regression model (3) – LLP, economic significance (beta testing)

Dependent Variable: LLP	All Banks	Beta
CovidIndex	0.070*** (4.99)	[0.094]
ΔLoans	-0.011 (-0.09)	[-0.002]
ΔNPL	3.299*** (4.02)	[0.103]
NPL	0.771*** (8.57)	[0.264]
Tier1Cap	0.287*** (3.05)	[0.053]
RevLLP	22.73*** (21.60)	[0.680]
Log(Assets)	0.009*** (8.85)	[0.120]
ΔGDP	-0.354*** (-3.15)	[-0.059]
ΔUR	-0.030 (-0.85)	[-0.016]
Constant	-0.248*** (-10.66)	-
N Observations	1332	-
Country Fixed Effects	NO	-
Time Fixed Effects	NO	-
Adj. R^2	0.703	-

Appendix J. presents our results for regression model (3) highlighting the economic significance of our independent variables. *LLP* is the ratio of loan loss provisions to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *ΔLoans* is the change in gross loans to lagged total assets. *ΔNPL* is the change in non-performing loans to lagged gross loans. *NPL* is the ratio of non-performing loans to gross loans, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *RevLLP* is the ratio of Revenues before loan loss provisions to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. *Time FE* indicate the time fixed effects for the quarters from Q1 2020 – Q4 2020. We intentionally do not show time fixed effects prior to 2020 in our table as they are not a prospect of interest for our study. t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix K. Regression model (3) – LLP, size segmentation

Dependent Variable: LLP	(1) All Banks	(2) Small	(3) Large
CovidIndex	0.070***	0.054***	0.081***
	(4.99)	(2.91)	(4.07)
ΔLoans	-0.011	-0.140	0.088
	(-0.09)	(-0.84)	(0.50)
ΔNPL	3.299***	3.819***	2.806**
	(4.02)	(4.04)	(2.23)
NPL	0.771***	2.121***	0.752***
	(8.57)	(6.46)	(8.00)
Tier1Cap	0.287***	-0.315*	0.287**
	(3.05)	(-1.88)	(2.46)
RevLLP	22.73***	21.05***	20.05***
	(21.60)	(12.05)	(13.94)
Log(Assets)	0.009***	0.007	0.012***
	(8.85)	(1.50)	(6.09)
ΔGDP	-0.354***	-0.491***	-0.312**
	(-3.15)	(-3.35)	(-2.32)
ΔUR	-0.030	-0.110***	0.096
	(-0.85)	(-2.68)	(1.61)
Constant	-0.248***	-0.115**	-0.265***
	(-10.66)	(-2.55)	(-7.13)
N Observations	1332	708	624
Country Fixed Effects	NO	NO	NO
Time Fixed Effects	NO	NO	NO
Adj. R^2	0.703	0.783	0.640

Appendix K. presents our results for regression model (3) segmenting the results by balance sheet size relative to all other banks operating in Europe. *LLP* is the ratio of loan loss provisions to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *ΔLoans* is the change in gross loans to lagged total assets. *ΔNPL* is the change in non-performing loans to lagged gross loans. *NPL* is the ratio of non-performing loans to gross loans, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *RevLLP* is the ratio of Revenues before loan loss provisions to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. *Time FE* indicate the time fixed effects for the quarters from Q1 2020 – Q4 2020. We intentionally do not show time fixed effects prior to 2020 in our table as they are not a prospect of interest for our study. t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix L. Regression model (3) – LLP, private / public segmentation

	(1)	(2)	(3)
Dependent Variable: LLP	All Banks	Private	Public
CovidIndex	0.070***	0.050***	0.083***
	(4.99)	(3.60)	(3.56)
ΔLoans	-0.011	-0.272**	0.133
	(-0.09)	(-2.27)	(0.64)
ΔNPL	3.299***	0.596	4.256***
	(4.02)	(0.68)	(3.63)
NPL	0.771***	0.304***	0.918***
	(8.57)	(4.44)	(9.35)
Tier1Cap	0.287***	0.103	0.694***
	(3.05)	(1.27)	(3.88)
RevLLP	22.73***	14.58***	25.26***
	(21.60)	(7.65)	(23.46)
Log(Assets)	0.009***	0.009***	0.006***
	(8.85)	(4.73)	(3.82)
ΔGDP	-0.354***	-0.416***	-0.298*
	(-3.15)	(-2.73)	(-1.83)
ΔUR	-0.030	-0.006	-0.036
	(-0.85)	(-0.14)	(-0.58)
Constant	-0.248***	-0.146***	-0.313***
	(-10.66)	(-5.29)	(-8.92)
N Observations	1332	768	564
Country Fixed Effects	NO	NO	NO
Time Fixed Effects	NO	NO	NO
Adj. R^2	0.703	0.404	0.801

Appendix L. presents our results for regression model (1) segmenting the results by company type. *LLP* is the ratio of loan loss provisions to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *ΔLoans* is the change in gross loans to lagged total assets. *ΔNPL* is the change in non-performing loans to lagged gross loans. *NPL* is the ratio of non-performing loans to gross loans, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *RevLLP* is the ratio of Revenues before loan loss provisions to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. *Time FE* indicate the time fixed effects for the quarters from Q1 2020 – Q4 2020. We intentionally do not show time fixed effects prior to 2020 in our table as they are not a prospect of interest for our study. t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix M. Robustness test – Lending with daily new cases

	(1)	(2)	(3)	(4)
Dependent Variable: ΔLoans	Baseline Model Regression (1)	Extended Model Specifications		
Cases	-0.004***	-0.001	-0.004***	
	(-3.01)	(-0.53)	(-3.84)	
Log(Assets)	-0.001	-0.000	0.001*	-0.001
	(-1.23)	(-0.93)	(1.89)	(-1.51)
Tier1Cap	0.003	0.001	-0.003	-0.000
	(0.10)	(0.03)	(-0.10)	(-0.00)
LLR	-0.105***	-0.103***	-0.107**	-0.103***
	(-5.06)	(-5.07)	(-2.27)	(-4.97)
LiquidAssets	0.014	0.012	0.012	0.013
	(1.09)	(0.95)	(0.68)	(1.03)
Deposits	0.003	0.005	0.017**	0.002
	(0.52)	(0.81)	(2.03)	(0.37)
ROA	3.979***	3.958***	3.423***	4.044***
	(8.52)	(8.17)	(6.28)	(8.71)
ΔGDP	0.023	-0.067	0.021	0.027
	(0.86)	(-1.18)	(0.81)	(0.99)
ΔUR	-0.024***	0.014	-0.025***	-0.023**
	(-2.60)	(0.87)	(-2.90)	(-2.57)
Constant	0.010	0.009	-0.000	0.012
	(1.23)	(1.09)	(-0.01)	(1.40)
N Observations	2340	2340	2340	2340
Country Fixed Effects	NO	NO	YES	NO
Time Fixed Effects	NO	YES	NO	NO
Adj. R^2	0.100	0.107	0.120	0.097

Appendix M. presents our results for regression model (1) with daily case numbers instead of *CovidIndex*. *ΔLoans* is the change in gross loans to lagged total assets. *Cases* is the quarterly average of daily new cases on a seven-day rolling basis weighted by country exposure. *Loans* is the ratio of gross loans to lagged total assets, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *LiquidAssets* is the ratio of cash, deposits with central banks, and receivables from other credit institutions to total assets, lagged by one quarter. *Deposits* is the ratio of customer deposits to total assets, lagged by one quarter. *LLR* is the ratio of loan loss reserves to gross loans, lagged by one quarter. *ROA* is the ratio of lagged income to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix N. Robustness test – Depositing with daily new cases

	(1)	(2)	(3)	(4)
Dependent Variable: ΔDeposits	Baseline Model Regression (2)	Extended Model Specifications		
Cases	0.000	0.000	-0.000	
	(0.24)	(0.20)	(-0.01)	
Log(Assets)	0.000	-0.000	-0.000	0.000
	(0.10)	(-0.19)	(-0.47)	(0.12)
Tier1Cap	-0.029	-0.038	-0.009	-0.028
	(-0.91)	(-1.17)	(-0.26)	(-0.91)
LLR	-0.027	-0.030	-0.103*	-0.027
	(-1.03)	(-1.18)	(-1.73)	(-1.04)
LiquidAssets	0.021	0.026	0.019	0.021
	(0.89)	(1.06)	(0.60)	(0.89)
Deposits	0.011*	0.010	0.001	0.011*
	(1.72)	(1.55)	(0.13)	(1.74)
ROA	4.125***	3.822***	4.130***	4.119***
	(7.91)	(7.13)	(6.67)	(7.95)
ΔGDP	-0.145***	-0.088	-0.148***	-0.145***
	(-4.24)	(-1.26)	(-4.38)	(-4.26)
ΔUR	0.001	-0.003	0.002	0.001
	(0.10)	(-0.12)	(0.14)	(0.09)
Constant	0.002	0.002	0.017	0.002
	(0.21)	(0.23)	(0.81)	(0.20)
N Observations	2340	2340	2340	2340
Country Fixed Effects	NO	NO	YES	NO
Time Fixed Effects	NO	YES	NO	NO
Adj. R^2	0.066	0.089	0.082	0.066

Appendix N. presents our results for regression model (2) with daily case numbers instead of *CovidIndex*. *ΔDeposits* is the change in customer deposits to lagged total assets. *Cases* is the quarterly average of daily new cases on a seven-day rolling basis weighted by country exposure. *Loans* is the ratio of gross loans to lagged total assets, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *LiquidAssets* is the ratio of cash, deposits with central banks, and receivables from other credit institutions to total assets, lagged by one quarter. *Deposits* is the ratio of customer deposits to total assets, lagged by one quarter. *LLR* is the ratio of loan loss reserves to gross loans, lagged by one quarter. *ROA* is the ratio of lagged income to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix O. Robustness test – Loan loss provisions with daily new cases

	(1)	(2)	(3)	(4)
Dependent Variable: LLP	Baseline Model Regression (3)	Extended Model Specifications		
Cases	0.015***	0.015**	0.017***	
	(3.33)	(2.16)	(3.99)	
ΔLoans	-0.030	-0.022	0.016	-0.058
	(-0.23)	(-0.17)	(0.12)	(-0.45)
ΔNPL	3.247***	2.980***	3.194***	3.241***
	(3.90)	(3.72)	(4.09)	(3.88)
NPL	0.791***	0.770***	0.645***	0.786***
	(8.66)	(8.57)	(5.04)	(8.60)
Tier1Cap	0.314***	0.232**	0.307***	0.325***
	(3.39)	(2.49)	(3.27)	(3.48)
RevLLP	22.63***	22.97***	24.31***	22.69***
	(21.29)	(21.84)	(21.75)	(21.34)
Log(Assets)	0.009***	0.009***	0.015***	0.001***
	(9.00)	(8.92)	(7.93)	(9.38)
ΔGDP	-0.415***	-0.307	-0.396***	-0.427***
	(-3.61)	(-1.29)	(-3.44)	(-3.70)
ΔUR	0.064**	0.069	0.073**	0.058*
	(2.00)	(1.14)	(2.26)	(1.82)
Constant	-0.248***	-0.254***	-0.393***	-0.252***
	(-10.71)	(-10.78)	(-11.37)	(-10.81)
N Observations	1332	1332	1332	1332
Country Fixed Effects	NO	NO	YES	NO
Time Fixed Effects	NO	YES	NO	NO
Adj. R^2	0.700	0.720	0.712	0.698

Appendix O. presents our results for regression model (3) with daily case numbers instead of *CovidIndex*. *LLP* is the ratio of loan loss provisions to lagged total assets. *Cases* is the quarterly average of daily new cases on a seven-day rolling basis weighted by country exposure. *ΔLoans* is the change in gross loans to lagged total assets. *ΔNPL* is the change in non-performing loans to lagged gross loans. *NPL* is the ratio of non-performing loans to gross loans, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *RevLLP* is the ratio of Revenues before loan loss provisions to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix P. Robustness test – Lending without Norway

	(1)	(2)	(3)	(4)
Dependent Variable: ΔLoans	Baseline Model Regression (1)	Extended Model Specifications		
CovidIndex	-0.013***	-0.072**	-0.013***	
	(-2.76)	(-2.29)	(-2.98)	
Log(Assets)	-0.003***	-0.003***	0.001	-0.003***
	(-4.35)	(-4.27)	(0.49)	(-4.51)
Tier1Cap	-0.052**	-0.057**	-0.086***	-0.051**
	(-2.27)	(-2.35)	(-3.51)	(-2.25)
LLR	-0.139***	-0.137***	-0.143***	-0.136***
	(-6.75)	(-6.68)	(-3.20)	(-6.64)
LiquidAssets	0.009	0.007	0.007	0.009
	(0.61)	(0.52)	(0.32)	(0.66)
Deposits	-0.005	-0.006	0.010	-0.007
	(-0.88)	(-1.03)	(1.08)	(-1.19)
ROA	2.222***	2.163***	1.635***	2.334***
	(5.37)	(5.17)	(3.55)	(5.66)
Δ GDP	0.016	-0.005	0.017	0.031
	(0.54)	(-0.08)	(0.60)	(1.09)
Δ UR	0.014	0.005	0.005	-0.002
	(0.72)	(0.21)	(0.25)	(-0.14)
Constant	0.052***	0.048***	0.006	0.053***
	(4.71)	(4.07)	(0.32)	(4.72)
N Observations	1020	1020	1020	1020
Country Fixed Effects	NO	NO	YES	NO
Time Fixed Effects	NO	YES	NO	NO
Adj. R^2	0.118	0.125	0.156	0.114

Appendix P. presents our results for regression model (1) without Norwegian banks. *ΔLoans* is the change in gross loans to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *Loans* is the ratio of gross loans to lagged total assets, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *LiquidAssets* is the ratio of cash, deposits with central banks, and receivables from other credit institutions to total assets, lagged by one quarter. *Deposits* is the ratio of customer deposits to total assets, lagged by one quarter. *LLR* is the ratio of loan loss reserves to gross loans, lagged by one quarter. *ROA* is the ratio of lagged income to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix Q. Robustness test – Depositing without Norway

	(1)	(2)	(3)	(4)
Dependent Variable: ΔDeposits	Baseline Model Regression (2)	Extended Model Specifications		
CovidIndex	0.005	-0.065	0.004	
	(0.80)	(-1.45)	(0.63)	
Log(Assets)	-0.001**	-0.001*	0.000	-0.001*
	(-1.98)	(-1.81)	(0.01)	(-1.93)
Tier1Cap	-0.076**	-0.078**	-0.093***	-0.076**
	(-2.45)	(-2.42)	(-2.63)	(-2.46)
LLR	-0.060**	-0.057**	-0.107*	-0.061**
	(-2.36)	(-2.25)	(-1.86)	(-2.40)
LiquidAssets	0.027	0.026	0.028	0.026
	(0.94)	(0.94)	(0.81)	(0.93)
Deposits	0.002	0.001	-0.007	0.003
	(0.35)	(0.18)	(-0.57)	(0.46)
ROA	2.057***	1.976***	1.682***	2.011***
	(3.81)	(3.54)	(2.65)	(3.75)
ΔGDP	-0.110***	0.022	-0.114***	-0.116***
	(-2.78)	(0.27)	(-2.97)	(-2.90)
ΔUR	0.028	0.011	0.028	0.035
	(0.97)	(0.29)	(0.93)	(1.37)
Constant	0.036***	0.032**	0.030	0.036***
	(2.68)	(2.24)	(0.96)	(2.68)
N Observations	1020	1020	1020	1020
Country Fixed Effects	NO	NO	YES	NO
Time Fixed Effects	NO	YES	NO	NO
Adj. R^2	0.047	0.0420	0.0801	0.0472

Appendix Q. presents our results for regression model (2) without Norwegian Banks. *ΔDeposits* is the change in customer deposits to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *Loans* is the ratio of gross loans to lagged total assets, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *LiquidAssets* is the ratio of cash, deposits with central banks, and receivables from other credit institutions to total assets, lagged by one quarter. *Deposits* is the ratio of customer deposits to total assets, lagged by one quarter. *LLR* is the ratio of loan loss reserves to gross loans, lagged by one quarter. *ROA* is the ratio of lagged income to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. t statistics in parentheses. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix R. Robustness test – Loan loss provisions without Norway

	(1)	(2)	(3)	(4)
Dependent Variable: LLP	Baseline Model Regression (3)	Extended Model Specifications		
CovidIndex	0.094***	0.074	0.081***	
	(4.54)	(0.65)	(4.10)	
Δloans	0.353*	0.347**	0.404**	0.260
	(1.96)	(1.98)	(2.17)	(1.44)
ΔNPL	0.931	0.757	1.564	1.006
	(0.79)	(0.67)	(1.36)	(0.82)
NPL	0.653***	0.659***	0.289***	0.652***
	(7.49)	(7.66)	(2.77)	(7.34)
Tier1Cap	0.003	-0.002	-0.013	-0.043
	(0.03)	(-0.02)	(-0.12)	(-0.41)
RevLLP	21.39***	21.35***	23.11***	21.19***
	(16.22)	(16.25)	(16.93)	(15.79)
Log(Assets)	0.013***	0.013***	0.013***	0.013***
	(6.60)	(6.71)	(3.82)	(6.68)
ΔGDP	-0.324**	0.293	-0.308**	-0.427***
	(-2.51)	(0.97)	(-2.32)	(-3.28)
ΔUR	0.182***	0.178**	0.239***	0.299***
	(2.87)	(2.42)	(3.67)	(4.76)
Constant	-0.240***	-0.265***	-0.316***	-0.218***
	(-6.57)	(-6.72)	(-5.97)	(-6.05)
N Observations	540	540	540	540
Country Fixed Effects	NO	NO	YES	NO
Time Fixed Effects	NO	YES	NO	NO
Adj. R^2	0.659	0.673	0.684	0.646

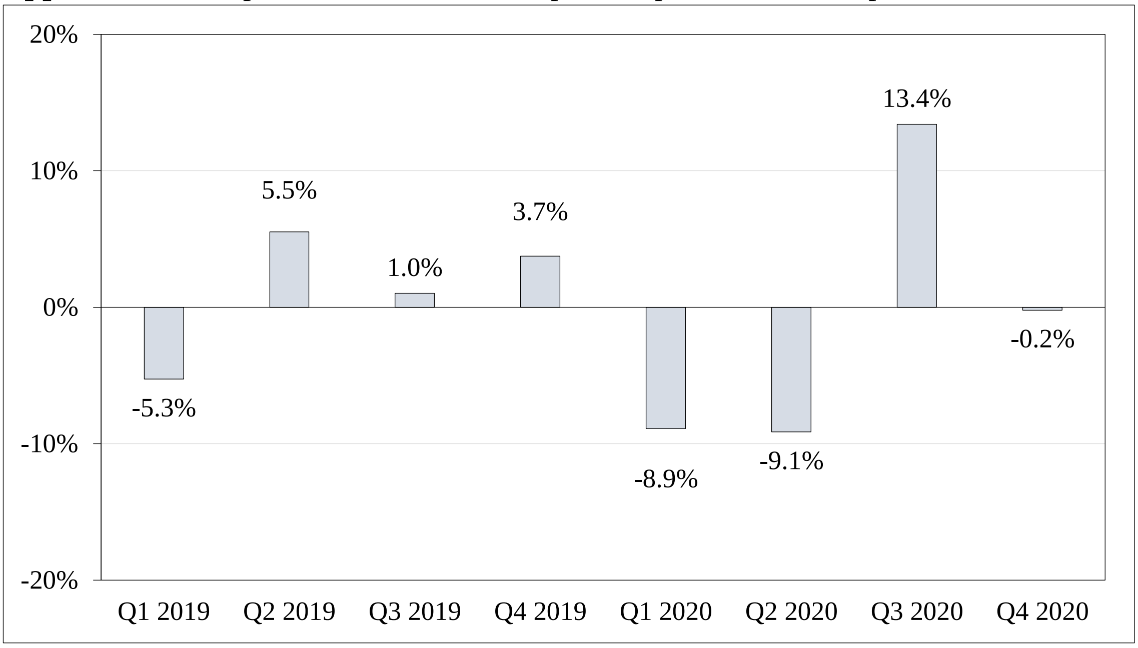
Appendix R. presents our results for regression model (3) without Norwegian banks. *LLP* is the ratio of loan loss provisions to lagged total assets. *CovidIndex* is the quarterly governmental pandemic response weighted by country exposure. *ΔLoans* is the change in gross loans to lagged total assets. *ΔNPL* is the change in non-performing loans to lagged gross loans. *NPL* is the ratio of non-performing loans to gross loans, lagged by one quarter. *Tier1Cap* is the tier 1 capital ratio, lagged by one quarter. *RevLLP* is the ratio of Revenues before loan loss provisions to lagged total assets. *Log(Assets)* is the lagged natural logarithm of total assets, denominated in Euro. *ΔGDP* is the quarter-on-quarter GDP growth. *ΔUR* is the quarter-on-quarter growth in the unemployment rate. The notation *, **, and *** represents significance at the 0.10-, 0.05-, and 0.01-levels, respectively.

Appendix S. Multicollinearity – variance inflation factors test (VIF)

Regression Models (1) and (2)	**VIF**	**Tolerance**
CovidIndex	1.51	0.6641
Log(Assets)	1.79	0.5596
Tier1Cap	1.30	0.7689
LLR	1.27	0.7866
LiquidAssets	1.22	0.8199
Deposits	1.80	0.5548
ROA	1.09	0.9197
ΔGDP	1.08	0.9294
ΔUR	1.49	0.6706
Mean VIF	**1.39**	

Regression Model (3)	**VIF**	**Tolerance**
CovidIndex	1.49	0.6692
ΔLoans	1.12	0.8918
ΔNPL	1.16	0.8648
NPL	1.37	0.7285
Tier1Cap	1.20	0.8364
RevLLP	1.45	0.6910
Log(Assets)	1.24	0.8048
ΔGDP	1.08	0.9249
ΔUR	1.46	0.6839
Mean VIF	**1.29**	

Appendix T. European household consumption expenditure development



Appendix T. shows the quarterly change in household consumption spending in Europe. Source: Eurostat (2021).