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By

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CHAPTER 1

Introduction

1.1.General Introduction

Over the last few years, the global economy and financial system have faced several challenges due to financial and non-financial crises, among them the global financial crisis (GFC) in 2008, followed immediately by the financial and sovereign debt crisis in Europe. As a result, a widely discussed question is whether the major players in the global financial system, including the banking sector, can continue to keep the economy afloat. More recently, the non-financial shock of the coronavirus pandemic affected the international financial system. Notwithstanding, those financial institutions that were more highly regulated faced the pandemic with significantly higher solvency and liquidity than in previous crises. Several lessons have emerged in these times of distress. It has been noted that some of the traditional debt-like capital instruments failed in providing stability to the overall financial system (Van Rixtel and Gasperini, 2013). Also, the business model employed in the financial services market has played a major role shoring up the financial stability during financial distress. Furthermore, in addition to the traditional methods used by academics that aim to support policymakers in decision-making, advanced analytics paradigms for solving financial issues have gained ground.

This doctoral thesis contains three research papers that cover some emerging topics in the areas of capital market and corporate finance aimed to provide useful financial information, as well as to better understand the aforementioned issues related to times of crisis. These topics include the use of contingent convertible instruments (CoCos), the emerging segment of the Islamic banking financial sector, advanced analytics paradigms (Artificial Intelligence tools), and the financial implications from the recent non-financial crisis–coronavirus pandemic.

1.2. Determinants of CoCo issuance: liquidity and risk incentives

The Contingent convertible bonds (CoCos) also known as enhanced capital notes (ECN) are hybrid fixed-income securities that aim at increasing the loss-absorbing capacity of financial institutions. They have a specific strike price that, once breached, can either convert them into new equity or provoke a full/partial write-down in principle. Flannery (2005) was the first to propose the use of these instruments by suggesting the distinctive features of this type of bond could potentially absorb losses through automatic recapitalizing while reducing bankruptcy risk for shareholders. As previously mentioned, since the failure of other debt-like equity instruments during the GFC, CoCos have been gaining more ground. The first CoCo issuance was at the end of 2009. More recently, there have been differing views regarding the main drivers behind issuing CoCos by financial institutions, in particular when it comes to banks, as well as their potential implications on the overall banking sector. Some financial experts argue that they reduce the insolvency risk for banks and provide additional cash flow because their coupon payments are tax deductible (Flannery, 2005, 2014; Calomiris and Herring, 2013). Others argue that CoCos, compared to traditional debt-like equity instruments, are complex to design because their conversion price can be manipulated when they are triggered (Admati et al.,2013).

This paper aims to explore empirically the underlying forces behind CoCo issuance and their implications on the banking industry. In particular, the paper analyses whether (regulatory and nonregulatory) liquidity is related to CoCo issuance and measures the impact of CoCo issuance on bank risk. Only Additional Tier 1 (AT1) CoCos have been analysed since Tier 2 CoCos do not receive equity-like treatment by supervision. A sample of 413 European banks have been selected between years 2011 and 2018. The study focuses on European markets as they contain the highest concentration of CoCo issuances. Out of a total of 413 banks, 92 banks issued CoCos. There were 158 issuances of AT1 CoCos used in the analysis. Of the 158 issuances, 112 were with a write-down loss absorption mechanism, either temporary or permanent, and 46 issuances with a conversion-to equity loss absorption mechanism. As for the type of trigger mechanism level, there were 99 issuances with a trigger level equal to 5.125% and 59 issuances with a trigger level above 5.125%.

Methodologically, this paper uses different approaches to provide empirical evidence regarding the underlying forces behind CoCos issuance and their implications on bank risk. Firstly, a logit model has been applied to analyse whether banks with riskier assets, lower solvency, and liquidity (regulatory and nonregulatory) are more inclined to issue AT1 CoCos. In this stage, both the marginal effect at the mean (MEM) and the average marginal effects (AME) have been computed to assess the economic impact. Secondly, both panel fixed effects regression and univariate analysis have been used to measure the impact of AT1 CoCos on bank risk.

Overall, the results suggest that liquidity regulation is regarded as one of the main drivers behind CoCos issuance. The results show that regulatory liquidity ratios are negatively related to CoCo issuance while nonregularity liquidity ratios do not have a significant impact on their issuance. The results also show that the likelihood of issuing a CoCo is higher in less risky banks as well as those needing recapitalization and additional loss absorption capacity. Furthermore, the findings show that profitable, larger, and more capitalized banks hold lower regulatory liquidity and are therefore more likely to issue CoCos. Additionally, bank risk-taking is found to not change significantly after the AT1 CoCos being issued. Regarding the type of loss absorption mechanism (write-down CoCos and conversion-to-equity CoCos), the analysis shows that they have no significant impact on risk-taking.

The contribution of this paper is twofold. Primarily, this is the first study examining how liquidity regulation could impact contingent convertible issuance (CoCos). Secondarily, although previous empirical studies have analysed the impact of CoCo issue announcements on bank credit default swap (CDS) spreads, this paper examines how the AT1 CoCos and the type of loss absorption mechanism (write-down CoCos and conversion-to-equity CoCos) could impact the issuer asset quality.

1.3. Global Banking Performance in the Time of COVID-19: Impact on Commercial and Islamic Banks

The non-financial shock of the COVID-19 pandemic brought the world´s economy to an unexpected halt, presenting several challenges in order to overcome its implications. While it’s too early to make a clear prediction about the long-term economic effects of the COVID-19 pandemic on the overall financial system, it has caused significant financial hardship. Demand and income were significantly reduced in the banking industry market and generated worries regarding the credit risk segment. In late 2020, the global economy shrank by 3.5%. Additionally, the average decline in international stock markets was 30% by the end of March 2020 (Lyócsa et al.2020). Notably, some previous studies have documented that the type of bank business model plays an important role during times of crisis. For instance, Islamic banks outperformed conventional banks during the GFC (e.g., Beck et al.,2013; Hasan and Dridi,2010), the theory being that the Islamic banking sector has some features that provide flexibility to financial stability during times of crisis.

This study examines these issues during the COVID-19 crisis. In particular, the paper explores the impact of this non-financial shock on global banking performance and financial stability and identifies their determinants. Also, the differential impact on alternate banking systems (commercial and Islamic) is analyzed in the periods both before and during the pandemic. Additionally, we examine whether or not there are signs of recovery in the early post-pandemic period. The empirical analysis relies on a sample of 583 banks across 59 markets. Out of a total of 583 banks, 520 banks are commercial, and the reaming 63 are Islamic. To provide as much information as possible, both yearly and quarterly data have been employed using ordinary least squares regression (OLS) and univariate statistics analysis (t-test P-value).

The results reveal that the COVID-19 pandemic caused a significant reduction in global stock market performance, bank assets quality and profitability. More specifically, the results show that while Islamic and commercial banks experienced a significant reduction in stock market returns during the first quarter of 2020, the returns for Islamic banks were higher than those of commercial banks. However, commercial banks performed better during the pre- and post-pandemic periods. The findings also show that bank capital and liquidity were not affected by the pandemic. Furthermore, banks that relied more on a mix of revenue, exhibited higher liquidity with lower insolvency and market risks, low stock volatility and experienced better stock market performance during the first quarter of 2020. Additionally, it has been observed that commercial banks performed better than their Islamic counterparts in terms of efficiency and had a lower risk of insolvency accompanied by higher asset quality. As for Islamic banks, they were better capitalized, relied more on long-term funding, were more involved in mixed revenue and were more profitable.

This study contributes to the literature related to the performance and financial stability of alternative banking system (commercial and Islamic) during both normal and crisis times. In addition, it investigates the immediate effects of the COVID-19 pandemic on stock market performance and its determinants during the early post-pandemic period. It also contributes by exploring the differences between these two bank groups in terms of mixed revenue, funding structures, profitability, assets quality, market risk and insolvency risk, both before and during the COVID-19 pandemic, as well as in the early post-pandemic period.

1.4. A Machine Learning Approach for Identifying the Drivers of Global Banking Profitability

Lacklustre bank profitability, especially after the GFC, is one of the main challenges for policymakers. It has been noted that the negative effects on bank profitability resulting from the GFC, sovereign debt crisis, and coronavirus pandemic, coupled with a low interest rate environment, have all influenced the level of concern regarding the banking industry´s ability to continue financing the global economy (IMF, 2022). While the underling forces behind this weaker profitability are not clear cut-off, through the use of an advanced analytics paradigm, this study attempts to delve further into the reasons behind this issue.

More precisely, the study uses an advanced machine learning technique applied to a large number of banks across the world in order to discover the drivers of global banking profitability in different time periods and in alternative banking systems. The empirical analysis of this study follows a series of approaches. Firstly, it examines the drivers of bank profitability across all samples during the pre-pandemic, pandemic, and early recovery periods. Secondly, the study explores whether the drivers of bank profitability are distinct during the pandemic period as compared to the period leading up the pandemic. Thirdly, we analyse whether the determinants of bank profitability are unique to alternative banking systems (comparing both commercial and Islamic banks). Several potential factors that might influence bank profitability have been utilized, keeping in mind the time periods in question and individual characteristics of the banking systems being examined. The machine learning algorithm was fed a series of industrial, bank and macroeconomic factors. These factors included soundness indicators, non-traditional banking activities, stock market indicators, market and credit risks, funding and liquidity structures, market power, capital adequacy, efficiency, bank size and opportunity costs.

The machine learning algorithm produced over 93% accuracy in its prediction of bank profitability in all above-mentioned approaches. We find that indicators related to a bank´s liquidity/capital structures, efficiency, size, soundness and total amount of loans issued are the strongest predictors of its profitability during the pandemic period. The algorithm also discovered that the determinates of bank profitability in the period leading up the pandemic are similar to the drivers observed during the pandemic period, with the only exception being the total amount of loans issued. Furthermore, the algorithm indicates that the profitability of alternative banking systems is determined by a different set of dynamics. Specifically, a bank´s market power, liquidity and funding structures, revenue mix, efficiency, size and soundness were all determining factors in profitability for the Islamic bank sector. As for commercial banks, the algorithm reveals that bank soundness, efficiency, liquidity and capital structure and size are the strongest profitability predictors. Additionally, there are indications that the macroeconomic, stock market and credit risk indicators contribute less to bank profitability to in all markets, both commercial and Islamic.

This is the first study to identify the main determinates of global banking profitability in the pre-pandemic and pandemic periods in alternative banking systems (commercial and Islamic) using a novel machine learning technique. Previous studies regarding the drivers of bank profitability were merely based on linear regression models. It is our hope that this research will spawn further investigation into the determining factors of bank profitability as it relates to the COVID-19 pandemic and its influence in both commercial and Islamic banking systems.

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CHAPTER 2

Determinants of CoCo issuance: liquidity and risk incentives[1]

Abstract

This paper aims to study the impact of (regulatory and nonregulatory) liquidity on contingent convertible (CoCo) issuance and the relationship between CoCos and asset quality. The analysis of this study comprises two stages. In the first stage, we used a logit model to test whether banks with riskier assets as well as lower solvency and (regulatory and nonregulatory) liquidity are more likely to issue CoCos. In the second stage, we employ univariate analysis and fixed effects regression to measure the impact of Additional Tier 1 (AT1) CoCos on the quality of the issuer's assets. The study shows that regulatory liquidity ratios are negatively related to CoCo issuance. This study also finds that the likelihood to issue CoCo is higher when banks have lower regulatory capital or are less risky. Asset quality is found to not change significantly after the issuance. All in all, these results suggest that while solvency regulation is primarily regarded as the main motivation for CoCo issuance, liquidity regulation also matters. Despite the fact that CoCos have been emerging as an alternative way to help banks meet regulatory capital requirements, we argue that the relation between liquidity regulation and CoCos should be considered.

Keywords: CoCos, Contingent capital, Liquidity, Risk incentives

JEL Classification: G20, G21

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[1] Abdallah, B. and Rodríguez Fernandez, F. (2022), "Determinants of CoCo issuance: liquidity and risk incentives", *Journal of Financial Regulation and Compliance*, Vol. 30 No. 4, pp. 412-438. https://doi.org/10.1108/JFRC-09-2021-0080.

2.1. Introduction

Contingent convertible (CoCos) are regulatory hybrid securities that aim at increasing the loss-absorbing capacity of banks. They convert into new equity or suffer a full or partial write-down in principal upon a trigger event. According to Basel III rules, CoCos can be classified as Tier 1 or Tier 2 capital instruments[2]. Unlike bailout instruments, CoCos are designed to contingently convert before financial institutions go bankrupt. Additionally, CoCos operate as a coupon paying bond if no trigger event applies. CoCos have been mainly issued by European banks. The Lloyds Banking Group was the first one in 2009. Shortly after, they received increased attention from Asian banks. However, American banks are not allowed to use CoCos. From 2009 to 2019, banks issued more than $550bn in CoCos globally. European banks allocated around e290bn, where write-down CoCos (full and partial) represented 54% and conversion-to-equity CoCos 46%[3].

By converting CoCos into new equity at a predetermined conversion rate, issuers have additional equity capital to shore up their loss absorption capacity. This rate can be set up on the market share price when the loss absorption mechanism is activated or on a predetermined price (typically the share price at the time of issuance) (Avdjiev et al., 2013). As for the write-down mechanism, it could be partial or full based on the contract design and provide additional equity by reducing the prespecified value from the issuance amount. Overall, the likelihood of occurrence of these mechanisms depends on the trigger definition. CoCo triggers could be discretionary or bank-specific (mechanical trigger). A discretionary trigger (point of nonviability) occurs when the regulatory authorities realize that the issuers will be prone to insolvency, or they are delayed in applying a prespecified trigger. Then, the loss absorption

[2] Under Basel III and CRD (IV), CoCo can be classified as either AT1 – "Going concern" CoCo or Tier 2 – "Gone concern" CoCo. CoCo (AT1) should be perpetual with trigger level equal to or above 5.125% in terms of the CET1 ratio, while CoCo with trigger level below 5.125% and has a defined maturity classified as Tier2. Indeed, in 2009, some CoCos issued with trigger level below 5.125% and they are legible for AT1 status, Basel III and CRD (IV) later set a new condition regarding trigger level.

[3] Avdjiev et al. (2020), Dealogic database, Association for Financial Markets in Europe, and our calculations.

mechanisms either convert the CoCos to equity or write them down partially or fully. A mechanical trigger operates when regulatory capital ratio (CET1) falls below a certain threshold, known as "book value trigger" or if the market value of the bank falls below a certain threshold, known as "market value trigger" (Avdjiev et al., 2013).

There are different views on the underlying forces behind CoCo issuance and their implications on the overall banking sector. It has been argued that they provide flexibility for banks to meet the regulatory capital requirements or to use them as a tax shield (Flannery, 2005, 2014; Pazarbasioglu et al., 2011; Calomiris and Herring, 2013). CoCos, compared to regular equity, are complex securities to design and carry some risk to issuers. The conversion price of CoCos could be manipulated, particularly when the trigger is potentially reached (Admati et al.,2013). In this paper, we examine two issues associated with CoCo issuance in Europe. First, we investigate whether (regulatory and nonregulatory) liquidity is related to CoCo issuance. Second, we examine the impact of CoCo issuance on bank asset quality. The analysis is restricted to Additional Tier 1 (AT1) CoCos since Tier 2 CoCos are considered as regular bonds with defined maturity date, and do not receive an equity-like treatment by supervision. As far as we are aware, there is no empirical study on how regulatory liquidity affects CoCo issuance (either AT1 or T2). Additionally, unlike previous empirical studies that focus on the impact of CoCos issuance on bank funding risk by examining the effect of CoCo issue announcements on bank credit default swap (CDS) spreads, we examine the impact of AT1 CoCos on asset quality.

Our analysis relies on a sample of 413 banks across 16 European markets. Out of a total of 413 banks, 92 banks have issued CoCos from 2011 to 2018. There were 158 issuances of AT1 CoCos used in our analysis. Our findings reveal 112 out of 158 issuances with a write-down loss absorption mechanism, either temporary or permanent and 46 issuances with a conversion-to equity loss absorption mechanism. As for the trigger level, we have 99 issuances with a trigger level equal to 5.125% and 59 issuances with a trigger level above 5.125%. Our empirical analysis comprises two stages. In the first stage, we use a logit model to examine whether banks with riskier assets, and lower solvency and (regulatory and nonregulatory) liquidity are more likely to issue CoCos. We compute the marginal effects at means then average the marginal effects to assess economic impact. In the second stage, we measure the impact of AT1 CoCos on assets quality using univariate analysis and panel fixed effects regression.

Our main findings suggest that banks with lower regulatory capital (Tier 1 and CET1) ratios are more likely to issue CoCos. Although CoCos are not originally designed to deal with liquidity problems, our results show that banks in Europe have not only used CoCos for regulatory capital considerations but also to meet tighter liquidity requirements. We find that banks with lower liquidity regulatory ratios are more likely to issue CoCos. Additionally, we do not find evidence of significant changes in asset quality after CoCo issuance.

The remainder of the paper is as follows: Section 2 surveys the main studies on CoCo issuance and builds the hypotheses. Data and the relevant summary statistics are provided in Section 3. Section 4 explains the empirical methodology. Section 5 discusses the main empirical results. Section 6 presents the robustness checks. Section 7 draws conclusions.

2.2. Literature background and hypotheses

2.2.1. The motivation for contingent convertible issuance

CoCos capital instruments provide additional equity capital for the sake of shore up the loss absorption capacity or reducing debt upon the occurrence of any trigger event. Regulators have progressively allowed financial institutions to use them after the financial crisis (Pennacchi et al., 2014). As regulation and supervision have focused on covering unexpected future losses, contingent capital has gained ground. Basel III sets the conditions that banks must follow to use these instruments and the trigger events that identify the contingency. By the end of 2013, the Capital Requirements Directive (CRD IV) of the European Union set a list of criteria for CoCos to classify as AT1 capital instruments. Four main criteria were established. First, they must be written down or converted to equity when a prespecified trigger occurs. Second, they must be perpetual with a probability of redemption but not before five years after the date of issuance. Third, they must rank below Tier 2 instruments in the event of insolvency. Fourth, the mechanical trigger level must be at least 5.125% of Common Equity Tier 1 (CET1)/risk-weighted assets (RWA). However, a higher trigger level above 5.125% of CET1/RWA also is allowed under CRD IV package[4].

Theoretical literature on contingent capital instruments has covered key issues such as their optimal design, the calibration of trigger events and their implications on wealth transfers between CoCo holders and shareholders. With regard to the potential benefits of CoCos and trigger events, Albul et al. (2015) suggest that contingent capital instruments increase banks' ability to absorb losses during times of financial distress as they provide an additional capital buffer when they are triggered. They also demonstrate that CoCos increase bank value as their coupons are tax-deductible. Zeng (2014) also suggests that CoCos help meeting regulatory capital requirements, which, in turn, improves shareholder value. Jaworski et al. (2021) develop a model to determine the optimal share of write-down CoCos (AT1 CoCos) in banks' capital structure. They show that depending on the CoCos instrument profitability, the further issuance of these instruments may reduce the probability of bank failure. McDonald (2013) develops a model in which CoCos reduce the probability of default when the trigger level follows some specific conditions. In particular, the conversion-to-equity CoCos should have a dual trigger based on a potential fall in issuers share price, and the value of a financial institutions index is below a trigger value. He also shows that the primary benefit occurs when the issuers rely on these triggers over accounting-based indicator triggers, and also suggests that regulators should

[4] Regulation (EU) No 575/2013 of the European Parliament and of the Council of June 26, 2013.

not interfere in the conversion decision. Gupta et al. (2021) show the ability of a conversion-to-equity CoCo to reduce the probability of bank failure, as well as mitigate systemic risk. They also show that the conversion-to-equity CoCo with a dual trigger is more effective than a CoCo with a single trigger to avoid bankruptcy. Pennacchi (2010) added to these benefits the ability of CoCos to reduce the moral hazard problem relative to the other debt instruments. In particular, CoCos mitigate the likelihood of a negative impact of financial distress on taxpayers via bailouts. He also points out CoCos would be a less costly method of reducing financial distress, especially when the trigger is set at a relatively high level of issuer's equity value. Ma and Nguyen (2021) developed a model to analyse the too big to fail and its optimal regulation. They find that issuing CoCos together with further regulation on capital requirements could address the too big to fail inefficiency, as CoCos provide an additional equity capital buffer when they are triggered.

Earlier studies also identify corporate governance problems in contingent capital issuance, including risk shifting and debt overhang. Berg and Kaserer (2015) and Chan and van Wijnbergen (2017) suggest that the design of CoCos creates some risk-shifting incentives[5]. They illustrate that other than dilutive debt to equity conversion, the wealth transfer between CoCos holders and shareholders of nondilutive debt to equity conversion, as well as the CoCos that are written down, result in risk shifting incentives for banks. In addition, they suggest that if the risk level is noncontractible, they can introduce a perverse risk shifting incentive to the issuers, which, in turn, generates financial distress and restrictions to issue simple equity. As for the potential debt overhang, Goncharenko (2022) focuses on the temporary write-down CoCos, unlike most prior studies that focus on conversion-to-equity CoCos. The main

[5] Berg and Kaserer (2015) do not suggest that CoCos should not be a component of a bank's capital structure. They suggest that it is important to set the conversion rate in such a way that does not encourage a redistribution of wealth from CoCo investors to shareholders upon trigger events. Similarly, Koziol and Lawrenz (2012) also show that the risk-shifting incentives from conversion to-equity CoCos always increase relative to regular bonds. They suggest that its highly important to find a mechanism that prevents the risk-taking imposed by CoCo. Once this happens, CoCo will be a sufficient instrument for providing stability to the banks.

conclusion is that the temporary write-down CoCos could benefit shareholders at the trigger event but induce a perverse incentive effect before the write-down and even after the trigger event. He suggests that the status of temporary write-down CoCos as the component of bank capital structure should be revised. Oster (2020) offers a comprehensive review of the literature regarding theoretical and empirical research on CoCos.

While solvency and agency problems have been mostly identified as the main motivations for CoCo issuance, liquidity may also play a relevant role. Bleich (2014) develops a theoretical model that illustrates that loss absorption through partial write-down CoCos creates stress on the issuer's liquidity. In particular, when the trigger is breached, the issuers should pay cash to CoCo investors, and this may put the issuer liquidity under pressure.

Empirical research on CoCos is sparse and relatively recent. Hesse (2018) examines CoCo design and potential risk-taking incentives. His study focuses on CoCos that qualify as AT1 instruments from banks from the European Economic Area (EEA) plus Switzerland. He finds the write-down CoCos incorporate a yield premium relative to the conversion-to-equity CoCos. However, he also shows that this potential premium of the write-down CoCos is highly correlated with existing moral hazard problems of the issuers. Kind et al. (2021) investigate the determinants of AT1 CoCo spreads issued by Eurozone banks. They find that the maximum distributable amount (MDA) is negatively related to CoCos spreads, while CDS spreads positively affect the CoCos spreads[6]. They also find that conversion-to equity CoCos and low trigger CoCos trade at significantly lower spreads than write-down CoCos, as well as those with a high-trigger level. Avdjiev et al. (2020) investigate why banks in the EEA issue CoCos. Their results show that the best-capitalized and larger banks are more likely to issue CoCos. Additionally, they analyse the impact of CoCo issuance on issuers CDS spreads, finding that

[6] For more details about the MDA concept, see CRD V Article 141.

CoCo issuance reduces CDS spreads in the case of AT1 CoCos, conversion-to-equity CoCos and CoCos that have mechanical triggers.

Goncharenko and Rauf (2016) examine CoCo issuance in the EEA and find that larger banks and those with high leverage, and lower risk are more likely to issue CoCos. They argue that capital constrained banks seek to enhance the return-on-equity as well as to meet the regulatory capital by using contingent capital. Goncharenko et al. (2017, 2021) investigate the agency problems associated with AT1 CoCos. They find that banks with lower asset volatility are more likely to issue them. In particular, they find that once the bank risk increases, the likelihood of issuing equity over CoCos also increases. Moreover, they argue that the agency cost would be higher for issuing CoCos over issuing equity. As a result, risker banks prefer to issue equity. Fiordelisi et al. (2020) empirically find that conversion-to-equity CoCos issued by European banks cause a decline in bank risk and stock return volatility. More specifically, their analysis shows that the reduction in stock return variance appears mainly in those banks that issued CoCos with a conversion-to-equity loss absorption mechanism in place. Williams et al. (2018) investigate the determinants of CoCo issuance for largest 150 banks that are issue them globally. They find that systemically risky banks and those with a higher proportion of bad loans are more likely to issue CoCos. They also find that earnings management practices have a secondary role on banks' decision to issue CoCos. Fajardo and Mendes (2020) examine the determinants of CoCos issuance on a global level. They find that larger banks are more likely to issue CoCos in all regions. They also find that highly levered banks in Brazil, Russia, India, China, and South Africa and other emerging markets are more likely to issue CoCos to meet the regulatory capital requirements. Petras (2020) analyses the use of CoCos that qualify as AT1 instruments as a source of bank capital structure. He finds that the ratio of earnings per assets and loan loss provisions increased the issuance of CoCos. Additionally, he examines the impact of the usage of AT1 CoCos on a bank's profitability. He finds that CoCos increase the bank's profitability due to the tax issue advantage on CoCo coupons and the positive risk-shifting incentives.

The two empirical studies closest to ours are Avdjiev et al. (2020) and Goncharenko et al. (2017, 2021) who focus on European markets. They explore the determinants of CoCo issuance and their impact on risk-taking. While they primarily examine how capital regulations and bank risk affect CoCo issuance, we also look at liquidity regulations as a potential determinant. Pazarbasioglu et al. (2011) and Greene (2016) state that some specific design of CoCos may boost bank liquidity at times of stress. Duffie (2009) suggests that to alleviate the negative impact on the liquidity position upon conversion-to-equity CoCos, the time of trigger should work long before a liquidity crisis starts. As previously shown, other studies show that CoCos provide flexibility and reduce the probability of bankruptcy. However, these positive effects on liquidity may disappear if a CoCo trigger is activated. Duffie (2009) and Maes and Schoutens (2012) argue that regardless of the loss absorption capacity upon the trigger, CoCos do not generate additional cash when a predetermined trigger is downward tripped[7]. They also point out that they are unlikely to stop a liquidity crisis once it has begun. As most of the CoCos issued in EEA have write-down loss absorption mechanisms (either partial or full), this would imply, according to the theoretical analysis of Bleich (2014), that the partial write-down CoCos generate liquidity stress on the issuer upon the occurrence of any trigger. In particular, issuers should pay cash to the CoCo holders, and this may happen at a time when their liquidity is under pressure.

Hence, despite the fact that CoCos are designed with the aim of improving bank capital and not to deal with other issues such as liquidity problems, there are some controversies about the role of liquidity regulations on CoCo issuance and on how are affected by CoCos conversion

[7] Prescott (2012) also demonstrates that even though conversion-to-equity CoCos increases the book value of equity, it does not provide new funds into a bank upon the conversion.

into equity. As this is ultimately an empirical issue, we, therefore, hypothesize that liquidity regulatory requirements will drive to some extent the decision of banks to issue CoCos. We use liquidity regulatory ratios to test this issue. In particular, our focus on some benefits of CoCos that include funded CoCos that provide cash at the time of issuance, net cash flow emerging from the net of tax-deductible on CoCos coupon [8]and the stop of paying interest on CoCos when a predetermined trigger is downward tripped, in which they may motivate banks to issue CoCos to meet liquidity requirements. However, we also use nonregulatory liquidity ratios capturing liquidity needs regardless of the regulatory requirement. Therefore, our first hypothesis is as follows:

H1. Banks with low regulatory liquidity ratios are more inclined to issue CoCos.

Based on the previous discussion, we argue that banks will increase their issuances of CoCos because they are, in theory, less costly than common equity; there is tax-deductibility advantage on the CoCos coupon; and they help meeting capital requirements. Then, to benchmark our analysis with previous research, we will also test whether banks with lower solvency ratios are more inclined to issue CoCos.

As for the impact of CoCo issuance on risk-taking incentives, several issues arise. Martynova and Perotti (2018) show that the reduction in the issuers leverage upon the trigger will reduce risk-taking if the trigger level is set properly. Hilscher and Raviv (2014) argue that with an appropriate conversion price of conversion-to-equity CoCos can lead to a reduction in risk-taking. Avdjiev et al. (2015, 2020) empirically find that depending on the design of CoCos, issuing CoCos generate risk reduction. However, it has been shown that issuing CoCos results in risk shifting incentives for banks in some specific case of CoCos such as nondilutive debt to equity conversion (Koziol and Lawrenz, 2012; Berg and Kaserer, 2015; Chan and van

[8] In most jurisdictions, the coupon on CoCo is tax-deductible. Recently, some governments have canceled this feature. For example, the Netherlands government announced at the end of June 2018 that the coupon on CoCo will not be tax-deductible as from January 2019. However, following theoretical literature, we assume that the coupon on our sample of CoCo is tax-deductible.

Wijnbergen, 2017)[9]. Banks may also prefer to issue CoCos because they are less costly than common equity and the tax issue advantage. Therefore, in light of the above discussions, our second hypothesis is as follows:

H2. Banks with lower asset quality are more inclined to issue CoCos.

2.3. Data

Our sample consists of bank-level data from the EEA plus Switzerland (hereafter, Europe). We focus on this region as it concentrates the majority of CoCo issuances. We collect data from different sources for the period 2011–2018[10]. First, we select the largest 50 banks "ranked by assets" from 16 markets from the Orbis database [11]. We focus on the largest 50 banks in each market, as the bigger banks are more inclined to issue CoCos (Goncharenko and Rauf, 2016; Avdjiev et al., 2020; Williams et al., 2018), and face more pressure from regulatory authorities to rise their capital ratios. In addition, small banks rely more on internal funds and have less access to the capital markets. They also face higher transaction costs when they issue hybrid securities such as CoCo bonds (Titman and Wessels, 1988).

We collect information on all CoCo issuances available in the Dealogic –DCM database. We restrict our attention on CoCos that classify only as AT1 with trigger level equal to and above 5.125%. We eliminate the CoCos that have a defined maturity date. CoCo information includes issue date, trigger level, loss absorption mechanism (write-down CoCos either temporary write-down or permanent write-down and conversion-to-equity CoCos), issue size, coupon, currency (issuer local currency and dollar) and maturity date which is perpetual

[9] It is important to note that the relationship between CoCos and risk is critically depending on their specific design, including the timing of the trigger event.

[10] The issuance of CoCos was rare in 2009 and 2010. According to the Dealogic – Debt Capital Markets (DCM) database, there are three issuances of CoCos. Two of these do not meet our sample conditions (AT1 CoCos with trigger level at least 5.125%). Moreover, even though Fiordelisi et al. (2020) state in their empirical study that the substantial CoCo issuances were from 2011 to 2017, we were not able to retrieve CoCo information after 2018 from the Dealogic database.

[11] Austria, Belgium, Denmark, Estonia, France, Germany, Greece, Ireland, Italy, The Netherland, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. Greece and Estonia do not have any issuance in the Dealogic database

for all CoCos in our sample. As some of this information is missing for some CoCos in the Dealogic database, we extract them from supplementary sources such as the issuer annual reports and from CoCo certificates that are available on the issuer websites. We drop from the sample insurance firms and those banks that have more than two variables with missing values[12]. The final sample consists of 413 banks. Out of 413 banks, 92 banks issued 220 issuances, 158 issuances are used in our study because there are some banks have issued more than one instrument in the same year.

Table 2.1. reports the summary statistics of CoCos and their contract design. Write-down CoCos and conversion-to-equity CoCos represent 70.8% and 28.5%, respectively. As for the trigger level, CoCos with trigger levels equal to 5.125% represent 62.6%, while high-trigger CoCos represent 36.7%. The average coupon on these issues is 6% for write-down CoCos and 6.8% for conversion-to-equity CoCos. Overall, the majority of CoCo issuances in European markets have a write-down loss absorption mechanism (either partial or full) with a trigger level equal to 5.125%[13].

2.4. Methodology

2.4.1. Measuring the determinants of contingent convertible issuance

To test our hypotheses, we use a standard logit model that assesses differences between issuers and non-issuers, including time and country fixed effects and where standard errors are clustered at the bank level[14].

The baseline equation is expressed as follows:

$$P\,(\text{CoCo}_{\,i,\,t} = 1|\text{X}_{\,i,\,t\text{-}1},\text{Z}_{\,i,\,t\text{-}1}) = \Lambda\,(\alpha + \alpha_{f} + \beta\,\text{X}_{\,i,\,t\text{-}1} + \gamma\,\text{Z}_{\,i,\,t\text{-}1}) \qquad (1)$$

where the outcome variable takes the value 1 if banks *(i)* issue at least one CoCo in year *(t)* and 0 otherwise, *Xi* are the explanatory factors capturing regulatory and nonregulatory

[12] There were some exceptions for some variables due to the nature of their data availability.
[13] This is because write-down feature always induces a wealth transfer from CoCos holders to shareholders upon the occurrence of any trigger event
[14] Greene (2002) and Mckenzie (2002) discussed the issue of using fixed logit regression on this type of sample.

indicators, while Zi includes a number of control variables. Λ is a logistic distribution function, α is an intercept and α_f includes the time and country fixed effects. All the explanatory variables are lagged and are winsorized at the 1st and 99th percentiles.

In our empirical analysis, we offer estimation results for several models for both hypotheses. The differences between these models are the measures by which the hypotheses are used in the model, control variables, and the use of the year and country fixed effects. To test the quality of each estimated model, we apply various measures. First, we use the Pseudo R-Squared as a descriptive goodness-of-fit test. It is a useful measure to compare the goodness-of-fit with different models but cannot be used as a measure of goodness-of-fit for the overall model[15]. Second, we apply Hosmer and Lemeshow's goodness-of-fit test. This test assesses the extent to which the predictions of the logit model are calibrated to the data. A well-fitting model should show no significant difference between the model and the data (Hosmer and Lemeshow, 2000). Next, we apply the area under-the-curve [AUC-a receiver operating characteristic curve (ROC)] measure to assess the predictability of each estimated model (DeLong et al., 1988). The effective range of the AUC measure is from 0.5 to 1.0.

We also estimate the model with random effects to control for unobserved bank heterogeneity as a robustness check, as in most of earlier studies (Dinger and Vallascas, 2016; Goncharenko et al., 2021). We use both time and country fixed effects and where standard errors are clustered at the bank level. As for the goodness-of-fit measures, Hosmer and Lemeshow's goodness-of-fit test cannot be used after random effects logit model. Thus, we apply Akaike's Information Criteria (AIC) and Bayesian Information Criteria (BIC).

[15] Pseudo R-Squared measure does not correspond to the R-Squared in linear regression. As there are different types of Pseudo R-Squared that have been used by different researchers, Veall and Zimmermann (1990) show that some Pseudo R-Squared yield values greater than others from the same data. However, based on our statistical package, this study used McFadden's pseudo-R squared. Moreover, some scholars recommend not using Pseudo R-Squared in logistic regression (Hosmer and Lemeshow, 2000; Hoetker, 2007).

We offer alternative definitions of liquidity and solvency to test the hypotheses. As for bank solvency regulatory ratios, we use CET1 and Tier 1 ratios. As for bank liquidity, we use regulatory and nonregulatory measures. First, we use the liquidity coverage ratio (LCR) implemented under the Basel III framework measured as "the value of high-quality liquid assets divided by net cash flows, over a 30-calendar day stress period[16] . Second, we use liquid assets to total assets and liquid assets to total deposits and short-term funding as the nonregulatory liquidity ratios. As for bank asset quality, we use two different indicators. In particular, we use both loan loss reserves over gross loans and impaired loans over gross loans. A loan loss reserve represents a cushion for credit losses, and hence, is a leading indicator of future impairment, while the impaired loans over gross loans ratio reflect the current asset quality.

As for the control variables, we follow Goncharenko and Rauf (2016) and Avdjiev et al. (2020). We use the natural logarithm of total assets to control for bank size, net loans over total assets to control for loan specialization, equity over total assets to control for banks leverage, return on assets and net interest margin (NIM) to control for banks performance and RWA over total assets to control for operational risk.

2.4.2. Contingent convertible issuance and bank risk-taking

The impact of CoCo issuance on bank risk-taking has been controversial due to the distinctive features that distinguish them from other hybrid securities. In this study, we aim to examine the impact of AT1 CoCos only on the asset side of the issuer. AT1 CoCos exhibit a number of conditions that may play an important role regarding bank risk-taking, unlike Tier 2

[16] The main liquidity regulations measure we aimed at investigating is the liquidity coverage ratio. In 2013, LCR – unlike the Net Stable Funding Ratio (NSFR) – was updated in terms of high-quality liquid assets (HQLA). This is happening at the same time when the new conditions on AT1CoCos have been applied as shown in Section 2.1. By using this indicator, we are able to see how these updated affect CoCos issuance that classify as AT1. Additionally, LCR is a short-term buffer and requires banks to hold enough HQLA, which, in turn, may contribute to banks decision to issue CoCos as they provide cash at the time of issuance. In any case, we re-estimate our model using NSFR as a robustness purpose, but during the analysis, we had faced with the problem that we could not use all banks due to the lack of data on this ratio as we have only around 250 observations. However, as shown in appendix B table X, the coefficient on NSFR is negative across model and statistically significant in some model specifications which is matched the results of our main indicator of liquidity regulations.

CoCos. To do so, we specify a panel fixed effects regression. The estimated equation is as follows:

$$\text{Asset Risk}_{i,t} = \alpha_i + \gamma^* \text{ AT1COCOS}_{i,t} + \beta \, {}^*X_{i,t} + \epsilon_{i,t} \qquad (2)$$

The dependent variable is the ratio of loan loss reserves to gross loans and impaired loans to gross loans of the issuer *i* in year *t*. AT1 CoCos is a dummy variable that takes the value 1 if the bank *i* issue at least one issuance in a year *t* and 0 otherwise, *X* is a vector of control variables, and α_i and ϵ denote constant and error terms, respectively. All variables are winsorized at the 1st and 99th percentiles. As for the control variables, we use the natural logarithm of total assets to control for bank size, net loan over assets to control for loan specialization, equity over total asset ratio to control for banks leverage, total customer deposit over total asset to control for liquid liabilities, NIM to control for bank performance and the Tier 1 ratio to control for capital adequacy. Table 2.2. provides the summary statistics of the main variables including control variables[17].

2.5. Results

2.5.1. Baseline model: the impact of solvency on contingent convertible issuance

Table 2.3. shows the results of the analysis of the determinants of CoCo issuance as a benchmark to previous studies focusing on the impact of solvency. Columns (1)– (2) report the findings using Tier 1 as a broad measure of capitalization. The coefficient of the Tier 1 ratio is 6.912 and it is statistically significant at the 5% level. The negative sign suggests that banks with lower capital are more likely to issue CoCos. Columns (3)– (4) report the results using the CET1 ratio as a solvency indicator. The coefficient is 10.142 and is statistically significant at the 5% level. This supports the idea that banks with lower regulatory capital ratios are more likely to issue CoCos. To assess the economic significance of these estimates, we compute their marginal effects at means and average marginal effects. As shown in Columns (6)– (7), the

[17] All the variables are described in Table 2.13.

marginal effect of Tier 1 ratio on the decision to issue CoCos is statistically significant and is equal to 0.178. This implies that 1%-point increase in Tier 1 ratio is associated with a decrease of 0.178% points in the probability of CoCos issuance with the mean values for all the other variables. As for the CET1, we find that a 1%-point increase in the CET1 decreases the probability of CoCo issuance by 0.356% points.

Overall, the results indicate, in line with the findings of Goncharenko and Rauf (2016) and Fajardo and Mendes (2020), that banks with lower regulatory capital ratios are more inclined to issue CoCo. This could imply that these banks attempt to meet capital requirements by issuing CoCos and substitute other debt instruments with them in their capital structure. These findings also correspond with the extant theory on why banks issue CoCos and which banks use CoCos as effective instruments for recapitalization in addition to boosting loss absorption capacity Basel III, Basel Committee on Banking Supervision (2010). As for the control variables, bank size is positively related to CoCo issuance, and it is statistically significant at 1% across all models. This appears to suggest that larger banks are more likely to issue CoCos. The marginal effect shows that an increase of one unit in the logarithm of total assets in millions of euros is associated with an increase of 0.034% points in the probability of CoCos issuance. The finding concurs with prior studies (Goncharenko and Rauf, 2016; Avdjiev et al., 2020; Williams et al., 2018) that reveal larger banks are more inclined to issue CoCos. As shown in Column 3, the coefficient on return on average assets (ROAA) is positive and statistically significant at 1%. The marginal effect shows that the probability of issuing CoCos increases by 2.190% points per 1%-point increase in ROAA. Overall, the evidence suggests more profitable banks are more likely to issue CoCos. The coefficient on RWA is negative and statistically significant at 1%, and this is consistent with the findings by Fajardo and Mendes (2020). We find that the probability of issuing CoCos decreases by 0.116% points per 1%-point increase in RWA. However, the significant effect on the coefficients of ROAA and RWA is not found across all specifications.

2.5.2. Liquidity and contingent convertible issuance

Table 2.4. reports the results that test H1. This incorporates liquidity to the baseline model to check whether regulatory and nonregulatory liquidity have an impact on CoCo issuance. Columns (1)– (4) show the results when bank liquidity is measured by the LCR. The coefficient is negative and statistically significant. The marginal effect shows that the probability of issuing CoCos decreases by 0.028% points per each percentage point increase in LCR. This indicates that banks with lower regulatory liquidity are more likely to issue CoCos, which supports H1. Columns (5)– (7) report the findings using liquid assets over total assets and liquid assets over total deposits and short-term funding as nonregulatory liquidity ratios. We do not find a significant effect of these variables on CoCo issuance. This would suggest that only regulatory liquidity plays a role in CoCo issuance. As for the control variables, we include bank solvency indicator to this model. By using this indicator, we are able to separate out the effect of bank capital on the impact of bank liquidity on CoCos issuance. The finding is consistent with the previous result on the impact of banks solvency on CoCos issuance. The coefficients on total assets and ROAA are still positive and statistically significant. In line with the data from Goncharenko and Rauf (2016), we find that the coefficient on the ratio of total equity over total assets is negative and statistically significant in most specifications. The marginal effect shows that the probability of issuing CoCos decreases by 0.709% points per each percentage point increase in the total equity over total assets ratio.

Additionally, we measure the impact of liquidity regulations on CoCo issuance breaking down banks into two groups: more capitalized and less capitalized banks as suggested by the median of the CET1 ratio. Results are provided in Table 2.5. Columns (1)– (3) refer to more capitalized banks, while Columns (4)– (6) correspond to the findings for less capitalized banks. The coefficient on LCR is negative and statistically significant at 1% in all the specifications for Group 1. The marginal effect shows that the probability of issuing CoCos decreases by 0.017% points per each percentage point increase in LCR. This implies that more capitalized banks holding lower regulatory liquidity are more likely to issue CoCos. The negative sign on LCR coefficient for Group 2 is constant for all models, but the coefficient loses its significance when we control for bank size. All in all, these results lend further support to H1 that banks with less regulatory liquidity change their debt funding structure by issuing CoCo bonds to meet liquidity requirements. In line with this theory, it appears that CoCos provide cash at the time of issuance. The net cash flow emerging from the tax-deductibles on CoCo coupons, and the stopping of interest payments on CoCos when a predetermined trigger is downward tripped seem to contribute to the decision to issue CoCos.

2.5.3. Contingent convertible issuance and asset quality

As for the tests of H2, the findings are reported in Table 2.6. Columns (1)– (2) show the results of the bank risk and CoCos issuance using impaired loans ratio, while Columns (3)– (4) report the results using loan loss reserve ratio. The estimated coefficients are 4.464 and 8.855, respectively, and statistically significant at the 5% level in most specifications. The marginal effect shows that the probability of issuing CoCos decreases by 0.128% points per each percentage point increase in impaired loans ratio and decreases by 0.244% points per each percentage point increase in loan loss reserve ratio. These estimates appear to suggest that riskier banks are less likely to issue CoCos, a finding that would lead us to reject H2. However, these results contradict the findings of Petras (2020) and Fajardo and Mendes (2020), but they are in line with the data from Goncharenko et al. (2017, 2021). One possible explanation is that before any trigger event occurs, CoCos operate as coupon paying bonds, which, in turn, may make riskier banks bear more costs, in addition to the existing risk related to issuing CoCos, such as debt overhang or agency problems. As for the control variables, the coefficient on bank size measure is again positive and statistically significant across all models. As for bank's profitability, the coefficient on NIM is positive and statistically significant. The marginal effect shows that the probability of issuing CoCos increases by 0.848% points per each percentage point increase in NIM[18].

We also examine the changes in bank risk-taking before and after CoCo issuance. Table 2.7. shows that the average impaired loan ratio is 4.90% before issuance and declines to 3.80% after the issuance. As for the loan loss reserves ratio, it is 2.63% before issuance and decreases to 1.94% after the issuance. The mean difference is statistically significant in all cases at 1%.

Table 2.8. examines the change in risk after CoCo issuance alongside with a set of control variables. Columns (1)– (3) show the results when bank risk is measured by loans loss reserve ratio. The coefficient on CoCo is statistically significant at 1% in all the specifications that include both banks and time fixed effects, and standard errors clustered at bank level. The results show a negative relationship between CoCo and the risk measures. This suggests that issuing CoCos reduce risk-taking. On the other side, Columns (4)– (6) show the results when bank risk is measured by impaired loans ratio. Overall, we do not find evidence of an ex-post increase in bank risk-taking after CoCo issuance. The results show that issuing CoCos has no significant impact in reducing risk-taking incentives.

There are three possible interpretations of these results. First, risker banks in Europe are not inclined to hold CoCos in their capital structure. Intuitively, when less risky banks issue CoCos they seem to have more flexibility to control the potential risks. Second, although speculative in our empirical framework, the tax advantage of CoCos' coupon may play a role in reducing risk-taking. Third, CoCos have been emerging as an alternative way to helping banks meeting regulatory requirements. As noted previously, banks in Europe issuing CoCos

[18] We report the results of the goodness-of-fit tests, together with the Log pseudo likelihood, p-value (chi2) and Pseudo R-Squared for each estimated model in the above Tables (A3–A6). The results show that the models fit the data well as indicated by the insignificant values of Hosmer– Lemeshow test. The predictive power in all models is excellent as indicated by the area under the ROC curve measure.

for regulatory considerations, which, in turn, lead to use CoCos only for the sake of shore up the loss absorption capacity.

2.6. Robustness check

Our baseline estimations are based on a logit model with both time and country fixed effects and where standard errors are clustered at the bank level. However, to test the robustness of the logit regression results, we also estimate the model with random effects to control for unobserved bank heterogeneity adding also both time and country fixed effects. Overall, the main findings remain very similar. Table 2.9. reports the results of the impact of banks solvency on CoCos issuance. The coefficients on Tier 1 and CET1 remain negative and statistically significant at the 5% level. Table 2.10. reports the test of H1. The coefficient on LCR is negative and statistically significant at 5% level across all models, while the coefficients on nonregulatory liquidity ratios are negative but still not significant. In fact, the random effect model shows a larger impact of liquidity regulations on the odds of issuing CoCos. As for the tests of H2, we include country fixed effect to the loan loss reserve model, unlike standard logit regression and the coefficients are still found to be negative and statistically significant at the 5% level in most model specifications as reported in Table 2.11. However, the coefficients on the control variables are similar to the previous regressions. Bank profitability and size indicators are found to have a positive effect coefficient and are statistically significant, while the coefficient on banks leverage is negative and statistically significant in most model specifications.

We also examine how CoCo design (write-down CoCos and conversion-to-equity CoCos) affect banks risk-taking, as suggested by some theoretical studies. Hence, we examine the impact of loss absorption mechanisms of CoCos on the risk-taking incentives of issuers at the time of issuance. To do so, we create dummy variables identifying each trigger mechanism. The first dummy equals 1 when the CoCos are issued as a write-down mechanism and 0 otherwise. The second dummy equals 1 when the CoCos are issued as equity conversion and 0 otherwise. The results are reported in Table 2.12. Overall, we do not find a statistically significant effect of these mechanisms on the risk-taking at the time of issuance. This suggests that the type of loss absorption mechanism have no impact on risk taking.

2.7. Conclusion

CoCos capital instruments are hybrid securities that convert into common share or suffer a partial or full write-down in principal when a predetermined trigger is downward tripped. Precisely because CoCos are an innovative instrument that have gained ground since they were first issued in 2009, there are differing views on the underlying forces behind their issuance and their impact on bank risk. This study aims to investigate two issues associated with CoCo issuance. First, we explore if banks with riskier assets and lower regulatory liquidity and solvency are more likely to issue CoCos that qualify as AT1 instruments. To the best of our knowledge, this paper is the first to study how regulatory liquidity affects CoCo issuance (either AT1 or T2). Our analysis relies on a data set from the Dealogic and Orbis databases. This data set contains information on CoCos instrument and banks' characteristics. We rely on a sample of 413 banks across 16 European markets. Out of a total of 413 banks, 92 banks have issued CoCos. Using logit regression, we find that banks with lower regulatory requirements for capital and liquidity are more likely to issue CoCos, while nonregulatory liquidity ratios do not seem to affect CoCo issuance, providing support for H1. Contrary to our H2, our results show that less risky banks are more likely to issue CoCos.

Second, we measure the impact of AT1 CoCo issuance on bank risk-taking. We contribute to the literature regarding the relationship between CoCos and bank risk by examining the impact of AT1 CoCos on the issuer's asset quality. We use the ratio of loan loss reserves and impaired loans to gross loans as measures of asset risk. Using univariate analysis and panel fixed effect regression, the findings suggest there is no evidence that bank risk-taking increases after issuing CoCos. They also seem to indicate that issuing CoCos has no significant impact in reducing risk-taking. We also examine the impact of the loss absorption mechanisms of CoCos on issuers risk-taking. The results are not statistically significant, indicating that the type of loss absorption mechanisms of CoCos does not play a role in assessing the effect size on banks risk-taking.

Overall, these findings seem to have policy implications. At a time when regulators are focusing on increasing the availability of loss-absorption mechanisms for banks – when CoCos are being largely used – the relations between solvency, liquidity regulation and CoCos should be taken into account. While our approach is general in scope, we believe more in-depth analyses studying these relationships in times of stress, such as the period encompassing the COVID-19 pandemic, and with more granular information on risk and liquidity exposures, may provide further insight into these matters.

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Appendix 2.1. CoCos issuance results

Table 2.1. Summary statistics of CoCos (and their contract design) issued in Europe during 2011–2018

This table provides the summary statistics of the CoCos issued in Europe. Panel A lists the summary statistics of all the CoCos issued. Panel B provides the summary statistics of only Write Down -CoCos, Panel C refers only to Conversion-to-Equity CoCos, Panel D provides information on CoCo issues with High-Trigger level, and Panel E covers CoCo issues with trigger level equal to5.125%.

Panel A: All CoCos

Variable	Obs	Mean	Std. Dev.	Min	Max
Amount Issued(Million$)	158	862.462	905.603	1.063	4742.844
Trigger Level	157	0.058	0.009	0.051	0.08
Coupon%	130	6.352	1.802	1.7	11.875

Panel B: Only Write Down -CoCos

Variable	Obs	Mean	Std. Dev.	Min	Max
Amount Issued(Million$)	111	671.459	765.877	1.063	4742.844
Trigger Level	112	0.056	0.008	0.051	0.08
Coupon%	85	6.085	1.765	1.7	9.5

Panel C: Only Conversion-to-Equity CoCos

Variable	Obs	Mean	Std. Dev.	Min	Max
Amount Issued(Million$)	45	1331.853	1052.824	60.497	4000
Trigger Level	45	0.063	0.009	0.051	0.07
Coupon%	44	6.888	1.791	2	11.875

Panel D: Only Higher - Trigger CoCos Above 5.125%

Variable	Obs	Mean	Std. Dev.	Min	Max
Amount Issued(Million$)	58	1207.313	1007.323	51.39	4000
Trigger Level	58	0.07	0.001	0.07	0.08
Coupon%	56	6.522	1.977	1.7	11.875

Panel E: Only CoCos with a Trigger Level Equal to 5.125%

Variable	Obs	Mean	Std. Dev.	Min	Max
Amount Issued(Million$)	98	657.563	775.981	1.063	4742.844
Trigger Level	99	0.051	0	0.051	0.051
Coupon%	73	6.234	1.67	2	10.75

Table 2.2. Summary Statistics

This table provides the summary statistics of the variables considered in our analysis from 2011 to 2018. All variables are winsorized at the 1st and 99th percentile.
Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Tier 1	2654	0.165	0.068	0.071	0.477
CET1	2467	0.159	0.065	0.068	0.441
Liquid Asset	2910	0.273	0.171	0.01	0.869
Liquid A/Dep	2889	0.408	0.625	-0.079	9.245
LCR	1002	2.017	1.239	0.82	7.327
Loan Loss Res	2820	0.035	0.044	0	0.238
Impaired Loan	2751	0.064	0.088	0	0.501
Net Loans	2905	0.6	0.217	0.035	0.962
ROAA	2910	0.005	0.009	-0.03	0.035
RWAs	2539	0.454	0.196	0.07	0.958
Customer Depo	2743	0.532	0.232	0.004	0.907
Total Assets (Million)	2910	141872.48	322929.69	7.91	2253094.6
Equity/Assets	2910	0.083	0.052	0.016	0.368
NIM	2900	0.018	0.016	-0.001	0.106
NSFR	341	1.245	0.188	0.91	1.907

Table 2.3. Logit regression on the impact of bank solvency on the decision to issue CoCos (baseline model)

This table shows the coefficients and the marginal effects of the baseline logit regressions examining the impact of bank solvency on the issuance of the AT1CoCos in Europe between 2011 and 2018. The dependent variable is a dummy which is equal to 1 when a bank issue CoCos in a given year and 0 otherwise. The variables of interest are the ratio of total Tier 1 capital to risk-weighted assets and the ratio of bank common equity tier 1 (CET1) to risk-weighted assets. Control variables are the proportion of bank net loans to its total assets, the return on average assets (ROAA), the ratio of risk-weighted assets to total assets (RWA), and the natural logarithm of bank total assets. All explanatory variables are winsorized at the 1st and 99th percentile and lagged one year. Standard errors are clustered at the bank level. Columns 1-4 report the coefficients for the logit regressions, column 6 reports the results of marginal effects at means, and column 7 reports the results of average marginal effects.

Dependent variable	CoCos (AT1)					
	(1)	(2)	(3)	(4)	(6)	(7)
Independent variables						
Tier 1_{t-1}	-8.042***	-6.912**			-0.178**	-0.376**
	(2.287)	(3.502)			(0.086)	(0.188)
CET1 $_{t-1}$			-6.194**	-10.142**	-0.356***	-0.627**
			(2.716)	(3.938)	(0.130)	(0.245)
Control variables						
Net Loans $_{t-1}$	-0.333	-0.776	0.552	-0.730	0.022	0.035
	(0.557)	(0.658)	(0.63)	(0.685)	(0.025)	(0.039)
ROAA $_{t-1}$	23.688	26.679	53.039***	28.616	2.190***	3.386***
	(15.297)	(22.727)	(17.75)	(23.131)	(0.711)	(1.159)
RWAs $_{t-1}$	-2.71***	0.853	0.286	0.608	-0.116***	-0.163***
	(0.653)	(0.942)	(0.856)	(0.964)	(0.032)	(0.044)
Total Assets $_{t-1}$		0.642***	0.543***	0.63***	0.022***	0.034***
		(0.101)	(0.086)	(0.102)	(0.003)	(0.006)
_cons	-2.958***	-12.487***	-7.878***	-8.016***		
	(1.137)	(2.147)	(1.396)	(1.611)		
Observations	2115	2043	1821	1765		
Pseudo R^2	0.081	0.227	0.154	0.21		
H-L	0.831	0.682	0.174	0.460		
ROC	0.727	0.845	0.792	0.832		
Log pseudolikelihood	-478.51501	-398.33952	-417.36018	-386.39255		
p-value (chi2)	0.000	0.000	0.000	0.000		
Time Fixed Effect	YES	YES	YES	YES		
Country Fixed Effect	NO	YES	NO	YES		

Cluster-robust standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1

Table 2.4. Logit regression on the impact of bank regulatory and nonregulatory liquidity on the decision to Issue CoCos -Testing hypothesis 1

This table reports the coefficients and the marginal effects of the logit regressions explaining the impact of bank liquidity on the issuance of AT1CoCos in Europe between 2011 and 2018. The dependent variable is a dummy which is equal to 1 when a bank issue CoCo in a given year and 0 otherwise. The variables of interest are the regulatory liquidity coverage ratio (LCR) measured as high-quality liquid assets divided by net cash flows, over a 30-calendar day stress period, and two non-regulatory liquidity ratios: Liquid Assets over total assets and Liquid assets over total deposits and short-term funding. Control variables are total equity over total assets, the ratio of bank common equity tier 1 to risk-weighted assets (CET1), the natural logarithm of bank total assets, the return on average assets (ROAA), and Net Loans as the proportion of bank net loans to total assets. All explanatory variables are winsorized at the 1st and 99th percentile and one year lagged. Standard errors are clustered at the bank level. Columns (1-7) report the coefficients for the logit regressions, column (8) reports the results of marginal effects at means, and column (9) reports the results of average marginal effects.

Dependent variable	CoCos (AT1)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Independent variable									
LCR $_{t-1}$	-0.466**	-0.295*	-0.472**	-0.314*				-0.028**	-0.039**
	(0.209)	(0.154)	(0.206)	(0.182)				(0.011)	(0.017)
Liquid Asset $_{t-1}$					-0.421	-0.368		-0.014	-0.022
					(0.758)	(0.758)		(0.029)	(0.046)
Liquid A/Dep $_{t-1}$							-0.119	-0.003	-0.007
							(0.144)	(0.004)	(0.008)
Control variables									
Equity/Assets $_{t-1}$	-11.348*	-4.522	-11.919*					-0.709*	-0.998*
	(6.408)	(5.343)	(6.28)					(0.377)	(0.535)
CET1 $_{t-1}$				-11.63**	-5.406**	-6.343**	-10.61***	-0.252***	-0.390**
				(4.68)	(2.259)	(2.466)	(3.557)	(0.095)	(0.152)
Total Assets $_{t-1}$	0.523***	0.513***	0.501***	0.543***	0.449***	0.508***	0.618***	0.298***	0.042***
	(0.137)	(0.128)	(0.135)	(0.122)	(0.074)	(0.075)	(0.093)	(0.007)	(0.011)
ROAA $_{t-1}$	62.727	73.413**	63.538	38.03		53.869***	29.986	2.141***	3.313***
	(39.67)	(31.597)	(39.106)	(25.028)		(15.917)	(20.027)	(0.608)	(1.004)
Net Loans $_{t-1}$		0.51	-0.552	-0.643				-0.032	-0.046
		(0.658)	(0.771)	(0.942)				(0.046)	(0.064)
_cons	-6.551***	-7.549***	-5.958***	-5.603***	-6.04***	-6.877***	-7.863***		
	(1.763)	(1.873)	(1.755)	(1.712)	(1.021)	(1.037)	(1.198)		
Observations	728	748	728	707	1931	1931	1853		
Pseudo R^2	0.183	0.138	0.184	0.19	0.138	0.152	0.207		
H-L	0.737	0.428	0.139	0.463	0.374	0.850	0.835		
ROC	0.803	0.804	0.768	0.808	0.774	0.791	0.834		
Log pseudolikelihood	-207.73711	-207.47829	-221.19477	-203.90527	-437.22495	-429.94602	-397.45115		
p-value (chi2)	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
Time Fixed Effect	YES	YES	YES	YES	YES	YES	YES		
Country Fixed Effect	YES	NO	YES	YES	NO	NO	YES		

Cluster-robust standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1

Table 2.5. Logit regression on the impact of bank liquidity regulations on the decision to issue CoCos at more capitalized and less capitalized banks

This table shows the coefficients and the marginal effects of the logit regressions exploring the impact of bank liquidity on the issuance of AT1CoCos offering a breakdown for more capitalized and less capitalized banks in Europe between 2011 and 2018. The dependent variable is a dummy which is equal to 1 when a bank issue CoCo in a given year and 0 otherwise. The variable of interest is regulatory liquidity coverage ratio (LCR) measured as "high quality liquid assets divided by net cash flows, over a 30-calendar day stress period." Control variables are total equity over total assets, the natural logarithm of bank total assets, the return on average assets (ROAA), and the proportion of bank net loans to total assets. All explanatory variables are winsorized at the 1st and 99th percentile and are lagged one year. Standard errors are clustered at the bank level. Columns 1, 2 and 3 report the coefficients for more capitalized banks; columns 4-5-6 report the coefficients for the logit regressions for less capitalized banks, and column 7 reports the marginal effects.

Dependent variable	CoCos (AT1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent variable							
LCR $_{t-1}$	-1.179***	-0.475***	-1.138***	-0.638*	-0.051	-0.163	-0.017**
	(0.346)	(0.18)	(0.33)	(0.375)	(0.251)	(0.247)	(0.009)
Control variables							
Equity/Assets $_{t-1}$	-57.99***	-19.383***	-55.951***	-7.827	8.315	-1.621	-0.861***
	(19.292)	(6.132)	(18.93)	(9.291)	(9.254)	(12.276)	(0.316)
Total Assets $_{t-1}$	0.429***	0.338*	0.419***		0.627***	0.574***	0.006*
	(0.15)	(0.201)	(0.152)		(0.181)	(0.212)	(0.003)
ROAA $_{t-1}$	170.055**	137.083***	154.17**	34.732	39.225	55.864	2.374***
	(61.901)	(36.69)	(59.853)	(34.953)	(38.09)	(56.247)	(1.030)
Net Loans $_{t-1}$		0.933	-0.989		0.916	0.325	-0.015
		(0.854)	(1.256)		(1.27)	(1.74)	(0.022)
_cons	-2.927	-5.116*	-2.021	-0.673	-10.144***	-8.314**	
	(1.984)	(2.637)	(2.32)	(1.024)	(2.956)	(3.476)	
Observations	324	390	324	342	348	342	
Pseudo R^2	0.312	0.14	0.315	0.103	0.131	0.164	
H-L	0.387	0.186	0.152	0.746	0.209	0.879	
ROC	0.880	0.781	0.880	0.730	0.757	0.780	
Log pseudolikelihood	-67.146173	88.814448	-66.907885	-130.82831	-127.60377	-121.85303	
p-value (chi2)	0.000	0.000	0.000	0.000	0.016	0.000	
Time Fixed Effect	YES	YES	YES	YES	YES	YES	
Country Fixed Effect	YES	NO	YES	YES	NO	YES	

Cluster-robust standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1

Table 2.6. Logit regression on the impact of bank asset quality on the decision to issue CoCos -Testing hypothesis 2

This table reports the coefficients and marginal effects of the logit regressions explaining the issuance of AT1CoCos and banks assets quality in Europe between 2011 and 2018. The dependent variable is a dummy which is equal to 1 when a bank issues a CoCo in a given year and 0 otherwise. The variables of interest are Loan loss reserves to gross loans and Impaired loans to gross loans. Control variables are the proportion of bank net loans to total assets, the natural logarithm of bank total assets, total equity over total assets, and the net interest margin (NIM). All explanatory variables are winsorized at the 1st and 99th percentile and are lagged one year. Standard errors are clustered at the bank level. Columns 1-4 report the coefficients for the logit regressions, column 5 reports the results of marginal effects at means, and column 6 reports the marginal effects.

Dependent variable	CoCos (AT1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Independent variables						
Impaired Loan $_{t-1}$	-4.464**	-1. 199			-0.128**	-0.226**
	(1.804)	(1.382)			(0.056)	(0.095)
Loan Loss Res $_{t-1}$			-6.822**	-8.855**	-0.244**	-0.443**
			(3.176)	(3.871)	(0.116)	(0.200)
Control variables						
Net Loans $_{t-1}$	0.316	-0.697	0.793	0.454	0.009	0.016
	(0.604)	(0.636)	(0.537)	(0.575)	(0.017)	(0.304)
Total Assets $_{t-1}$	0.522***	0.6***	0.518***	0.525***	0.015***	0.026***
	(0.084)	(0.099)	(0.086)	(0.084)	(0.002)	(0.005)
Equity/Assets $_{t-1}$	-2.254	-6.736	2.812	-2.82	-0.064	-0.114
	(3.413)	(4.154)	(2.439)	(3.385)	(0.098)	(0.173)
NIM $_{t-1}$	29.523***	29.113***		29.195***	0.848***	1.497***
	(8.028)	(8.109)		(7.999)	(0.233)	(0.420)
_cons	-10.629***	-11.149***	-10.76***	-10.711***		
	(1.512)	(1.533)	(1.498)	(1.493)		
Observations	2362	2273	2429	2425		
Pseudo R^2	0.168	0.213	0.159	0.171		
H-L	0.901	0.768	0.628	0.455		
ROC	0.808	0.841	0.812	0.801		
Log pseudolikelihood	-444.25941	-416.15319	-450.37204	-457.41197		
p-value (chi2)	0.000	0.000	0.000	0.000		
Time Fixed Effect	YES	YES	YES	YES		
Country Fixed Effect	NO	YES	NO	NO		

Cluster-robust standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1

Table 2.7. Univariate statistics on the impact of CoCo issuance on bank risk before and after issuance (Issuers only sample)

This table reports a univariate analysis on how bank risk-taking is affected before and after CoCo issuance. We focus only on the issuers sample.

	(1) Before Issuance	(2) After Issuance	(3) Differences
Loan Loss Res	0.0263	0.0194	-0.006***
	(0.0007)	(0.0008)	(0.001)
Impaired Loans	0.049	0.038	-0.011***
	(0.0013)	(0.0016)	(0.002)

*** p<.01, ** p<.05, * p<.1

Table 2.8. Fixed effects regression on the impact of CoCo issuance on bank risk (Equation 2)

This table provides the results of a panel regression with bank and time fixed effects explaining the impact of CoCo issuance on risk-taking incentives of issuers during 2011 to 2018. The dependent variables are Loan loss reserves to gross loans (columns 1, 2 and 3) and Impaired loans to gross loans (Columns 4, 5 and 6). The variable of interest is CoCo issuance, a dummy that takes the value 1 when a bank issue CoCos in a given year and 0 otherwise. Control variables are the natural logarithm of bank total assets, the proportion of bank net loans to total assets, total customer deposits to total assets, the net interest margin (NIM), total equity over total assets, and bank Tier1 to risk-weighted assets. All variables are winsorized at the 1st and 99th percentile.

Dependent variable	Loan Loss Res			Impaired Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
Independent variable						
CoCos	-0.003***	-0.003***	-0.002*	-0.004*	-0.003	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Control variables						
Total Assets		0.003	-0.008	-0.003	0.007	-0.007
		(0.004)	(0.005)	(0.006)	(0.007)	(0.006)
Net Loans		-0.036**	-0.045**	-0.051	-0.031	-0.057
		(0.016)	(0.018)	(0.036)	(0.037)	(0.044)
Customer Depo		-0.005	-0.009	-0.031	-0.024	-0.026
		(0.013)	(0.015)	(0.025)	(0.025)	(0.024)
NIM		0.174	0.132	0.207	-0.272	-0.049
		(0.245)	(0.241)	(0.435)	(0.466)	(0.539)
Equity /Assets		0.149**		0.13	0.237*	
		(0.075)		(0.124)	(0.135)	
Tier1			-0.039			-0.044
			(0.029)			(0.057)
_cons	0.028***	0.009	0.141**	0.125*	0.008	0.18**
	(0.001)	(0.046)	(0.057)	(0.073)	(0.084)	(0.075)
Observations	2820	2665	2458	2608	2608	2409
R-squared	0.062	0.096	0.097	0.017	0.069	0.077
Time Fixed Effect	YES	YES	YES	NO	YES	YES
Cluster	Bank	Bank	Bank	Bank	Bank	Bank

Cluster-robust standard errors are in parentheses.
*** p<.01, ** p<.05, * p<.1

Appendix 2.2. Robustness checks

Table 2.9. The impact of bank solvency on the decision to issue CoCos. A Logit Random Effects Model

This table reports the results of the random effects logistic regression explaining the issuance of the AT1CoCos and bank solvency in Europe between 2011 and 2018. The dependent variable is a dummy which is equal to 1 when a bank issue CoCo in a given year and 0 otherwise. The variables of interest are the ratio of total Tier 1 capital to risk-weighted assets and the ratio of bank common equity tier 1 (CET1) to risk-weighted assets. Control variables are the proportion of bank net loans to its total assets, the return on average assets, (ROAA), risk-weighted assets to total assets (RWA), and the natural logarithm of bank total assets. All explanatory variables are winsorized at the 1st and 99th percentile and are lagged one year. Standard errors are clustered at the bank level.

Dependent variable	CoCos (AT1)			
	(1)	(2)	(3)	(4)
Independent variables				
Tier 1 $_{t-1}$	-11.535***	-9.11**		
	(3.883)	(4.595)		
CET1 $_{t-1}$			-8.502**	-11.713**
			(3.629)	(4.759)
Control variables				
Net Loans $_{t-1}$	0.189	-0.742	1.064	-0.669
	(0.777)	(0.789)	(0.74)	(0.8)
ROAA $_{t-1}$	27.134	17.971	50.438**	20.162
	(22.781)	(25.705)	(22.88)	(27.064)
RWAs $_{t-1}$	-3.372***	0.98	0.089	0.786
	(1.092)	(1.157)	(1.092)	(1.227)
Total Assets $_{t-1}$		0.695***	0.559***	0.685***
		(0.112)	(0.1)	(0.114)
_cons	-4.725***	-14.322***	-8.579***	-9.28***
	(1.429)	(2.383)	(1.664)	(1.939)
/lnsig2u	1.359***	0.559**	0.78***	0.515*
	(0.218)	(0.269)	(0.262)	(0.286)
AIC	879.285	816.374	815.805	792.972
BIC	934.368	962.551	881.890	929.869
Observations	2115	2043	1821	1765
Time Fixed Effect	YES	YES	YES	YES
Country Fixed Effect	NO	YES	NO	YES

Cluster-robust standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1

Table 2.10. The impact of bank liquidity on the decision to Issue CoCos. A Logit Random Effects Model. Alternative measures of liquidity regulations, and extra Controls (alternative test of hypothesis 1)

This table reports the results of the random effects logistic regression explaining the impact of bank liquidity on the issuance of the regulatory hybrid securities (AT1CoCos) in Europe between 2011 and 2018. The dependent variable is a dummy which is equal to 1 when a bank issue CoCo in a given year and 0 otherwise. The variables of interest are regulatory liquidity coverage ratio (LCR) measured by "high quality liquid assets divided by net cash flows, over a 30-calendar day stress period", Net Stable Funding Ratio, and two non-regulatory liquidity ratios: Liquid Assets over total assets and Liquid assets over total deposits and short-term funding. Control variables are total equity over total assets, the natural logarithm of bank total assets, the return on average assets (ROAA), the proportion of bank net loans to total assets, the ratio of bank common equity tier 1 (CET1) to risk-weighted assets, and the risk-weighted assets (RWA) to total assets. All explanatory variables are winsorized at the 1st and 99th percentile and are lagged one year. Standard errors are clustered at the bank level.

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				AT1 CoCos				
Independent variables								
LCR $_{t-1}$	-0.489**	-0.376**	-0.500**					
	(0.217)	(0.18)	(0.218)					
NSFR $_{t-1}$				-3.257**	-2.616*			
				(1.584)	(1.581)			
Liquid Asset $_{t-1}$						-1.285	-1.204	
						(0.848)	(0.829)	
Liquid A/Dep $_{t-1}$								-0.293
								(0.192)
Control variables								
Equity/Assets $_{t-1}$	-17.196**	-9.315	-17.71**	-43.483*		-1.133	-4.34	-2.688
	(7.586)	(6.348)	(7.528)	(22.562)		(3.179)	(4.709)	(5.064)
Total Assets $_{t-1}$	0.548***	0.48***	0.521***			0.468***	0.495***	0.638***
	(0.147)	(0.144)	(0.146)			(0.093)	(0.092)	(0.112)
ROAA $_{t-1}$	79.143*	84.417**	78.826*	8.426	14.538		48.161**	22.026
	(45.196)	(37.579)	(44.418)	(41.772)	(39.101)		(24.303)	(27.427)
Net Loans $_{t-1}$		0.669	-0.746	-2.686*	-1.202			
		(0.788)	(0.915)	(1.493)	(1.196)			
CET1 $_{t-1}$					-20.692*			
					(12.308)			
RWAs $_{t-1}$				6.31	-2.991			
				(3.875)	(2.16)			
_cons	-7.042***	-7.344***	-6.269***	4.985**	7.307**	-10.761***	-10.933***	-13.003***
	(1.91)	(2.109)	(1.938)	(2.423)	(2.995)	(1.549)	(1.561)	(1.76)
/lnsig2u	0.275	0.489	0.276	-0.626	-2.854	1.013***	0.908***	0.706***
	(0.488)	(0.467)	(0.487)	(1.506)	(9.531)	(0.224)	(0.233)	(0.246)
AIC	451.38	453.94	452.85	184.87	184.71	922.58	918.56	897.07
BIC	556.95	509.35	563.02	254.65	254.39	986.69	988.49	1041.63
Observations	728	748	728	205	204	2510	2510	2,398
Time Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Country Fixed Effect	YES	NO	YES	YES	YES	NO	NO	YES

Cluster-robust standard errors are in parentheses

*** p<.01, ** p<.05, * p<.1

Table 2.11. The Impact of banks asset quality on the decision to issue CoCos. A Logit Random Effects Model (alternative test of Hypothesis 2)

This table reports the results of a random effects logistic regression explaining the impact of the issuance of the regulatory hybrid securities (AT1CoCos) on bank asset quality in Europe between 2011 and 2018. The dependent variable is a dummy which is equal to 1 when a bank issue CoCo in a given year and 0 otherwise. The variables of interest are Loan loss reserves to gross loans and Impaired loans to gross loans. The control variables are the proportion of bank net loans to its total assets, the natural logarithm of bank total assets, total equity over total assets, and the net interest margin (NIM). All explanatory variables are winsorized at the 1st and 99th percentile and are lagged one year. Standard errors are clustered at the bank level.

Dependent variable	CoCos (AT1)			
	(1)	(2)	(3)	(4)
Independent variables				
Impaired Loan $_{t-1}$	-5.809**	-1.263		
	(2.3)	(1.744)		
Loan Loss Res $_{t-1}$			-9.667**	-0.105
			(4.032)	(3.924)
Control variables				
Net Loans $_{t-1}$	0.703	-0.653	1.245*	-0.362
	(0.75)	(0.794)	(0.673)	(0.751)
Total Assets $_{t-1}$	0.576***	0.679***	0.543***	0.708***
	(0.098)	(0.11)	(0.1)	(0.111)
Equity/Assets $_{t-1}$	-3.726	-9.317*	2.056	-9.429*
	(4.326)	(5.488)	(3.501)	(5.421)
NIM $_{t-1}$	36.141***	36.626***		36.796***
	(9.915)	(10.417)		(10.33)
_cons	-12.74***	-13.431***	-12.517***	-13.918***
	(1.685)	(1.778)	(1.689)	(1.789)
/lnsig2u	0.921***	0.696***	0.974***	0.632**
	(0.238)	(0.249)	(0.23)	(0.249)
AIC	857.62	842.02	879.57	854.50
BIC	932.59	990.97	949.12	1004.13
Observations	2362	2273	2429	2333
Time Fixed Effect	YES	YES	YES	YES
Country Fixed Effect	NO	YES	NO	YES

Cluster-robust standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1

Table 2.12. The impact of CoCo issuance on bank risk based on CoCos' contract design (write-down CoCos and conversion-to-equity CoCos)

This table provides the results of a panel regression with bank and time fixed effects checking the impact of the loss absorption mechanisms of CoCos on banks risk-taking during 2011- 2018. The dependent variables are loan loss reserves to gross loans (Columns 1-3) and Impaired loans to gross loans (Columns 2-4). The variables of interest are PWD (write-down CoCos), a dummy which is equal 1 when the issuance is a write-down CoCo and 0 otherwise, and CE (conversion-to-equity CoCos), a dummy which is equal 1 when the CoCo is issued as conversion-to-equity and 0 otherwise. Controls variables are the natural logarithm of bank total assets, the proportion of bank net loans to total assets, total customer deposits to total assets, the net interest margin (NIM) and total equity to total assets. All variables are winsorized at the 1st and 99th percentile.

Dependent variables	(1) Loan Loss Res	(2) Impaired Loans	(3) Loan Loss Res	(4) Impaired Loans
Independent variables				
PWD	-0.001	-0.003		
	(0.001)	(0.003)		
CE			0.001	0.003
			(0.001)	(0.003)
Control variables				
Total Assets	-0.031**	-0.038*	-0.031**	-0.038*
	(0.012)	(0.02)	(0.012)	(0.02)
Net Loans	0.012	0.132**	0.012	0.132**
	(0.023)	(0.058)	(0.023)	(0.058)
Customer Depo	-0.119***	-0.259***	-0.119***	-0.259***
	(0.034)	(0.083)	(0.034)	(0.083)
NIM	-1.522***	-2.342*	-1.522***	-2.342*
	(0.555)	(1.393)	(.555)	(1.393)
Equity/Assets	-0.284	-0.278	-0.284	-0.278
	(0.231)	(0.335)	(0.231)	(0.335)
_cons	0.468***	0.571**	0.467***	0.568**
	(0.158)	(0.253)	(0.158)	(0.253)
Observations	144	142	144	142
R-squared	0.551	0.575	0.551	0.575
Time Fixed Effect	YES	YES	YES	YES
Cluster	Bank	Bank	Bank	Bank

Cluster-robust standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1

Table 2.13. Description of the variables

Variable	Description	Source and Reference
AT1 CoCos	Dummy which is equal to 1 when a bank issue CoCos in a given year (2011-2018) and 0 otherwise.	Dealogic database and our calculations.
PWD	Write-down CoCos, a dummy which is equal 1 when the issuance is a write-down CoCo and 0 otherwise.	Dealogic database and our calculations.
CE	Conversion-to-equity CoCos, a dummy which is equal 1 when the CoCo is issued as conversion-to-equity and 0 otherwise.	Dealogic database and our calculations.
Tier 1	Ratio of total Tier 1 capital to risk-weighted assets.	Orbis database (Bureau van Dijk). Avdjiev et al. (2020) and Fajardo and Mendes (2021).
CET1	Ratio of bank common equity tier 1 to risk-weighted assets.	Orbis database (Bureau van Dijk). Goncharenko et al. (2017, 2021).
LCR	Ratio of high-quality liquid assets to net cash flows over a 30-calendar day stress period.	Orbis database (Bureau van Dijk).
NSFR	Ratio of the available source of stable funding (ASF) to the required source of stable funding (RSF) over a one-year horizon.	Orbis database (Bureau van Dijk).
Liquid Asset	Ratio of total liquid assets to total assets.	Orbis database (Bureau van Dijk). Fajardo and Mendes (2021)
Liquid A/Dep	Ratio of total liquid assets to total deposits and short-term funding.	Orbis database (Bureau van Dijk).
Impaired loans	Ratio of Impaired loans to gross loans.	Orbis database (Bureau van Dijk). Petras (2020) and Williams et al. (2018).
Loan Loss Res	Ratio of loan loss reserves to gross loans.	Orbis database (Bureau van Dijk). Williams et al. (2018)
ROAA	Return on average assets.	Orbis database (Bureau van Dijk). Goncharenko et al. (2017, 2021) and Williams et al. (2018)
Net Loans	Ratio of bank net loans to total assets.	Orbis database (Bureau van Dijk). Goncharenko and Rauf (2016) and Avdjiev et al. (2020)
Equity/Assets	Ratio of total equity to total assets.	Orbis database (Bureau van Dijk). Goncharenko et al. (2017, 2021)
Total Assets	The natural logarithm of bank total assets.	Orbis database (Bureau van Dijk) and our calculations. Avdjiev et al. (2020) and Goncharenko et al. (2017, 2021)
NIM	Ratio of net interest income (expense) to interest earning assets.	Orbis database (Bureau van Dijk). Williams et al. (2018)
Customer Depo	Ratio of total customer deposits to total assets.	Orbis database (Bureau van Dijk) and our calculations. Avdjiev et al. (2020)
RWA	Ratio of total risk-weighted assets to total assets.	Orbis database (Bureau van Dijk) and our calculation Fajardo and Mendes (2021)

CHAPTER 3

Global Banking Performance in the Time of COVID-19: Impact on Commercial and Islamic Banks[19]

Abstract

While some studies have documented differences in the performance of commercial and Islamic banks, we wonder whether these disparities make one banking model more resilient than the other in the face of an unpredicted shock. We examine the impact of the COVID-19 outbreak on banking performance and financial stability in both commercial and Islamic banks, as well as the determinants of their respective differences in performance. We find that while both types of banks experienced a reduction in stock market performance during the pandemic, the returns for Islamic banks were 11%–13% higher than those of commercial banks. In contrast, commercial banks performed better during the pre-COVID-19 period, as well as in the early recovery period. Additionally, banks that relied more heavily on non-traditional banking activities exhibited higher liquidity, lower insolvency and market risk showed better stock market performance during the pandemic. Islamic banks were better capitalized than their commercial counterparts, relied more on long-term funding, were more involved in non-traditional banking loan businesses and were more profitable. Commercial banks performed better in terms of efficiency and had higher asset quality along with a lower risk of insolvency.

Keywords: Bank performance, stock markets, COVID-19, commercial banks, Islamic banks

JEL Classification: G01, G15, G20, G21

[19] Rodríguez Fernandez, F. and Abdallah, B. (2022), " Global Banking Performance in the Time of COVID-19: Impact on Commercial and Islamic Banks " *Emerging Issues in Banking Special Issue, Review of Corporate Finance.*

3.1. Introduction

While the long-term economic repercussions of the COVID-19 crisis are still unclear, the pandemic is estimated to have had a greater short-term economic impact than the 2008 global financial crisis (Glocker and Piribauer,2021; Li et al.,2021; Parker,2020). As reported by the IMF (2020; 2021), the global economy shrank by 3.5% in 2020. International stock markets also suffered sharp declines, particularly in late March 2020 (Lyócsa et al.,2020; Sharif et al., 2020; Zaremba et al., 2020; Zhang et al.,2020). The average decline in global markets was 30% (Paulus, 2020; Zhang et al., 2020). Additionally, banks were affected by the pandemic in multiple ways. Although financial institutions faced COVID-19 with a significantly higher solvency than in the 2008 financial crisis, the lockdown caused an important setback: demand and income were significantly reduced, which in turn also generated concerns about the mid-term impact on credit risk (Baldwin and di Maruro, 2020; Beck et al., 2020).

The policy response to the pandemic was both fiscal and monetary. Central banks intensified the expansionary stance of their policies. Meanwhile, several governments also provided economic support by offering guarantees on bank loans, thereby assuming a share of the potential credit losses. Additionally, supervisory authorities increased the flexibility of some of their solvency requirements (Hill et al., 2021; Beck et al.,2020). Overall, the combined monetary and fiscal support measures were effective, not only for the banking sector but also in terms of speeding up the recovery, at least when compared to the financial crisis of 2008 (Aldasoro et al.,2020; Bellens et al., 2020; Campbell et al.,2021; Vereckey,2021).

In this article, we evaluate the effects of COVID-19 on the performance of the banking industry and on financial stability around the world. We compare commercial and Islamic banks in the pre-pandemic, pandemic and early recovery periods[20].

Some previous studies show that Islamic banks exhibited a greater performance during the 2008 financial crisis than their commercial counterparts (e.g., Beck et al.,2013; Hasan and Dridi,2010). We examine the impact of a non-financial shock, COVID-19, and we analyze whether the pandemic had a differential impact on commercial and Islamic banks. Our analysis relies on a sample of 583 banks across 59 markets. Out of those 583 banks, 520 are commercial and 63 Islamic. In order to compare them over varying time frames and frequencies, we use both yearly data from 2018-2020 and quarterly data from 2019 Q1 to 2021 Q2.

Our study contributes to the growing strand of literature on the performance and resilience of different banking models during crises (Beck et al.,2013; Beltratti and Stulz, 2012; Demirguc-Kunt et al., 2013; Hasan and Dridi,2010; Irresberger et al., 2015; Pelster et al., 2018). Beck et al. (2013) analyze differences in the asset quality, stability and efficiency of Islamic banks versus conventional banks during the financial crisis of 2008. They conclude that Islamic banks were better capitalized, had higher asset quality and exhibited better stock market performance when compared to commercial banks during the crisis. They also found that the superior stock performance of Islamic banks during this period was related to asset quality and capitalization.

Demirguc-Kunt et al. (2020) study bank stock prices around the world in order to measure the impact of COVID-19 on different corporate sectors. They show that the adverse impact of the COVID-19 crisis was significantly greater for banks than for non-bank financial institutions. They also find that larger, better-capitalized banks had a

[20] We consider the first quarter of 2021 as the early recovery period.

greater stock return performance during the pandemic. Elnahass et al. (2021) show that the performance and stability of banks have been negatively impacted by the global health crisis. They conclude that Islamic banks experienced higher profitability and lower operational risk during the pandemic. Mirzae et al. (2022) also suggest that Islamic banks fared significantly better in terms of stock market performance relative to other banks during the COVID-19 crisis. In addition, they show that this higher performance was related to the efficiency of Islamic banks prior to the COVID-19 crisis. Beck and Keil (2021) examine the impact of the pandemic on the U.S. banking system. They find that the health crisis caused a decline in syndicated loans from U.S. banks.

The two empirical studies most closely related to ours are Elnahass et al. (2021) and Mirzae et al. (2022) who focus on a large sample of global banks. While Mirzae et al. (2022) investigate the immediate effects of the COVID-19 pandemic on stock market performance in Islamic and commercial banks, we aim to explore the differences between these two groups in terms of non-traditional banking activities, capital, liquidity and funding structures, profitability, asset quality, and both market and insolvency risk. In addition, we look at the impact of the COVID-19 pandemic on stock market performance and its determinants in the pre-pandemic, pandemic and early recovery post-pandemic periods. Our study also differs from that of Elnahass et al. (2021) in that it explores the impact of the COVID-19 pandemic over a longer time frame, by extending the sample to cover 2020 Q3 to 2021 Q2 (early post-pandemic period). We also use both market and accounting-based performance indicators and analyze the differences between these groups in terms of funding structure and non-traditional banking activities. Some studies have examined the immediate impact of the COVID-19 pandemic on Islamic banks versus conventional banks, but only use a significantly limited sample of banks from a single emerging market or a single region (e.g., El-Chaarani et al., 2022; Fakhri and Darmawan, 2021).

By expanding the scope of sample banks studied, our results reveal that the pandemic caused a significant reduction in stock market performance, bank profitability and asset quality. However, we do not observe a significant impact from COVID-19 on either bank capital or liquidity. The results also show that Islamic banks exhibited higher stock market performance during the pandemic period when compared to their commercial banks counterparts. However, commercial banks outperformed Islamic banks during the pre-COVID-19 period, as well as in the first quarter of 2021 (early recovery period). Furthermore, we find that banks with lower stock market volatility and insolvency risk, more liquid assets, and higher reliance on non-traditional banking activities in the pre-COVID-19 period, exhibited a higher stock market performance during the pandemic. Additionally, we observe that Islamic banks were better capitalized, relied more heavily on long-term funding, were more involved in non-traditional banking loans, and were more profitable during the COVID-19 crisis. As for commercial banks, they were more efficient, had higher asset quality and lower risk of insolvency during the pandemic.

The article is organized as follows: Section 2 describes the data and sample, Section 3 explains the empirical methodology and variables, Section 4 discusses the empirical results and Section 5 summarize the conclusions.

3.2. Data

The data set comprises a large number of commercial and Islamic banks that are publicly traded, whose accounting data we obtain from the Orbis database (Bureau van Dijk). We exclude banks with missing stock data in the last two months of 2019 and/or the first quarter of 2020. As such, the resulting sample contains 583 banks from 59 markets, 520 of which are commercial, while the remaining 63 are Islamic. We retrieve stock price data of individual banks from December 31, 2018, to March 31, 2021, which we use to estimate bank stock returns during the pre-COVID-19 period, the COVID-19 crisis, and in the early recovery period.

We rely on a set of financial indicators to explore changes in bank stock prices: funding structure, risk profile, non-traditional banking activities, capital adequacy, liquidity, asset quality, profitability and efficiency. Furthermore, we use additional control variables such as bank size, bank market value, bank opportunity costs and loan specialization. To control for the overall economic conditions in each market, we obtain data from the World Development Indicators (WDI) database. We also employ quarterly balance sheet information from individual banks taken from the Orbis database between the first quarter of 2019 and the second quarter of 2021. The pre-COVID 19 period is defined as the year 2019. The first and second quarters of 2020 define the COVID-19 crisis period, and the early recovery period corresponds to the first two quarters of 2021.

3.3. Methodology

The impact of the COVID-19 outbreak on banking performance and financial stability is examined using two approaches. As a preliminary benchmark, we analyze how the COVID-19 crisis affected stock market performance. We follow previous studies that use OLS on a large cross-section sample of banks (Demirguc-Kunt et al., 2020; Demirguc-Kunt et al., 2013; Elnahass et al., 2021; Mirzae et al., 2022)[21], alongside a set of control variables similar to earlier studies (Aebi et al.,2012; Beck et al., 2013; Beltratti and Stulz, 2012; Berger and Bouwman, 2013; Demirguc-Kunt et al., 2013). As the main

[21] To check for the potential endogeneity issues, the OLS estimations control whether bank performance and financial stability during the COVID-19 crisis are related with pre-COVID-19 crisis levels of bank financial indicators, as well as with the macroeconomic indicators. We also use bank and country fixed effects, as well as clustered standard errors at the bank level in the models.

impact of the COVID-19 pandemic occurred during the first two quarters of 2020 (IMF, 2020; Weiss et al., 2020), we conduct our analysis based on both yearly and quarterly bank financial information.

Our empirical analysis follows various stages. In the first stage, we examine the impact of the COVID-19 outbreak on the stock market value of both commercial and Islamic banks using ordinary least squares. Additionally, we employ univariate t-test statistics to check for differences between the two types of banks within a wide array of financial indicators, along with bank stock market indicators for two periods: pre-COVID-19 and COVID-19 crisis.

The first equation is expressed as follows:

$$\text{Stock returns}_{i,j} = \alpha_0 + \gamma^* \text{ Islamic banks}_{i,j} + \beta {}^*X_{(\text{pre-COVID})\, i,j} + \epsilon_{i,} \qquad (1)$$

Where the dependent variable is the bank stock market measure for bank *i* in market *j*. *Islamic banks* is a dummy variable that takes the value of 1 if bank *i* is Islamic, and 0 otherwise. *X* is a vector of control variables at the end of 2019 (bank and macroeconomic variables). All variables are winsorized at the 1st and 99th percentiles.

In the second stage, we measure the stock market performance of the two types of banks during the early recovery period.

The second equation is expressed as follows:

$$\text{Rec.stock } i, j = \alpha 0 + \gamma^* \text{ commercial banks } i, j + \beta \ {}^*X\ (2020)\ i, j + \epsilon\ i, j \qquad (2)$$

Where the dependent variable is the Early Recovery Stock (*Rec stock*) measure for bank *i* in market *j*. *Commercial banks* is a dummy variable that takes on the value of 1 if bank *i* is commercial, and 0 otherwise. *X* is a vector of control variables at the end of 2020 (bank and macroeconomic variables). All variables are winsorized at the 1st and 99th percentiles.

For robustness purposes, we examine the impact of COVID-19 on global banking performance and financial stability by using OLS regression and univariate statistics comparisons on a quarterly basis for all banks. Additionally, we measure the differences between the two bank types in terms of performance and financial stability in the early recovery period.

For robustness purposes we additionally employ alternative definitions of stock market performance. As for the pre-COVID-19 period, we use the change in log stock returns from Dec 31, 2018, to Dec 31, 2019. As for the COVID-19 period, we employ two indicators. In particular, *Stock returns$_1$* -which is computed as the log returns from Dec 31, 2019, to Mar 31, 2020.- and *Stock returns$_2$* - defined as the log returns from the average closing prices from (Nov 30, 2019-Dec 31, 2019 to Feb 28, 2020-Mar 31, 2020. As for the early recovery period, we use the changes in log stock returns from Dec 31, 2020, to Mar 31, 2021[22]. Regarding bank-specific financial indicators, we employ market-based, risk-based and accounting-based variables. Capital adequacy is measured as Tier 1 capital to total assets, tangible equity-to-total assets and total equity-to-total assets. As for bank liquidity, we use two different indicators: the ratio of total liquid assets-to-total assets and the ratio of total liquid assets-to-total deposits and short-term funding. As for bank asset quality, we use loan losses and non-performing loan (NPL) ratios. We analyze the funding structure of commercial versus Islamic banks using four indicators: funding fragility, customer deposits, long-term funding and short-term funding ratios. We also include the non-interest and income diversity ratios to account for non-traditional banking activities. As for risk, we use the insolvency and market risk ratios. Together with stock market performance indicators, we also use accounting-based profitability ratios, in particular, the ROAA and ROEA ratios. Finally, we employ overhead cost and cost-to-income ratios to account for bank efficiency. The list of variables and their definitions are shown in Table 3.1.

[22] We use closing price to calculate the returns.

3.4. Results

3.4.1.Stock Market Performance and Financial Indicators: Univariate Statistics

In the interest of simplicity, the tables with the univariate statistics are shown in the Appendix. Table 3.5.offer the results for the overall sample group, as well as a comparison between Islamic and commercial banks. As for bank stock market performance, the results show that the average stock return in the pre-COVID-19 period was 4.9% for commercial banks and 0.70% for Islamic banks. The mean difference is not statistically significant. The average stock return$_1$ for commercial banks fell 29.6% during the pandemic period, compared to a decline of 12.9% for Islamic banks. A similar pattern is shown by the change in stock returns$_2$ in the same period (-17.5% for commercial banks, and -5.1%f for Islamic banks). The mean difference is statistically significant in all cases at 1%. As for the early recovery period, we find that stock returns for commercial banks experienced a 6% increase, while for their Islamic counterparts the decline was 2.7%. The mean difference is statistically significant at 1%. These findings indicate a stronger stock market performance for Islamic banks than commercial banks during the COVID-19 crisis. However, the results also suggest that commercial banks exhibited better stock market performance than Islamic banks both prior to the COVID-19 crisis, as well as in the early recovery period. Nevertheless, this difference is not statistically significant during the pre-COVID-19 period. In line with previous studies, Islamic banks have proven to be more resilient than commercial banks during times of crisis. However, commercial banks outperformed Islamic banks during the early recovery period.

Bank solvency is found to be greater for Islamic banks than for commercial banks both before and during the COVID-19 pandemic. We observe that Islamic banks exhibited an average 18.8% total capital ratio pre-crisis, which remains almost unchanged at 18.5% during the crisis. As for commercial banks, this ratio increased from 16.7% in the year leading up the COVID-19 crisis to 17.7% during the COVID-19 period.

As for bank asset quality, Islamic banks had significantly higher non-performing loan and loan-loss reserve ratios than commercial banks both before and during the COVID-19 crisis. As for the non-performing loan ratio, Islamic banks experienced an increase from 8.3% in the pre-COVID-19 period to 8.8% during the pandemic. In the case of commercial banks, this ratio fell from 5.3% pre-crisis to 5% during the crisis. The mean difference is statistically significant in all cases at 1%. These findings seem to suggest that commercial banks had better asset quality than Islamic banks in the pre-COVID-19 period and during the COVID-19 crisis.

As for the liquidity ratios, we do not find statistically significant differences between the two types of banks either before or during the COVID-19 crisis. Islamic banks have a 23.7% liquid assets-to-total-assets ratio as compared to a 24.1% ratio for commercial banks in the pre-COVID-19 period. The results are similar for the ratio of liquid assets-to-total deposits and short-term funding. As for the performance accounting ratios, Islamic banks exhibited a significantly higher return on assets during the COVID-19 crisis, while there are no significant differences between both types of banks during the pre-COVID-19 period.

We also compare the funding structure of both types of banks. Our results show nothing statistically significant for any of the measures employed. We only observe statistically significant differences at 1% in long-term funding during the COVID-19 crisis. In particular, the long-term debt ratio of Islamic banks was 72% compared with 52.9% for commercial banks. Overall, our results show that Islamic banks relied more on long-term funding during the COVID-19 crisis. As for bank efficiency, we find that the overhead cost ratio of Islamic banks was 3.7% in the pre-COVID-19 period compared to

2.5% for commercial banks. This difference persisted during the COVID-19 crisis. The mean difference is statistically significant at 1% in all cases. This result seems to indicate that Islamic banks had a lower level of cost efficiency both before and during the COVID-19 crisis. However, we do not find statistically significant differences between Islamic and commercial banks in the cost-to-income ratio neither before nor during the COVID-19 crisis.

With regard to non-traditional banking activities, the non-interest income ratio of Islamic banks was 48.1% compared to 34.8% for commercial banks in the year leading up to the COVID-19 crisis. During the pandemic, the ratio was 50.1% for Islamic banks and 33.9% for commercial banks. The mean difference is statistically significant at 1% in all cases. In the same vein, the results show that commercial banks had a significantly lower insolvency risk.

All in all, we find that Islamic banks had higher stock market performance, were better capitalized, relied more on long-term funding, were more involved in non-traditional banking loan businesses and were overall more profitable during the COVID-19 crisis. We also find that Islamic banks were better capitalized and more involved in non-traditional banking loan activities in the pre-COVID-19 crisis period. As for commercial banks, they are found to be more efficient, have higher asset quality and lower insolvency risk both before and during the COVID-19 crisis. They also exhibited higher stock market performance in the pre-COVID-19 and early recovery periods.

In order to benchmark our results with previous studies, we re-estimate our analysis utilizing only the markets where both types of banks compete with each other. As shown in Table 3.6., we do not find statistically significant differences in stock market performance between the two in the early recovery period. We observe that commercial banks were better capitalized in these shared markets. In addition, we find that commercial banks had significantly higher liquidity than Islamic banks during the pandemic.

We also wonder to what extent the results are driven by differences in bank size. As shown in the table 3.7., where the comparisons are made for large banks only, we observe a more resilient stock market performance for large Islamic banks than for large commercial banks during the COVID-19 crisis. The average stock $return_1$ was -0.08% for large Islamic banks and -31.2 % for large commercial banks. As for the stock $return_2$, the change is 5.9% for large Islamic banks and -19% for large commercial banks. The mean difference is statistically significant at 1% in all cases. We also find that large Islamic banks were more profitable and relied more on non-traditional banking activities, while large commercial banks had lower insolvency risk. Unlike our previous results for all bank sizes, we find that large commercial banks had significantly higher market risk in the periods leading up the COVID-19 crisis. Our results also show that large Islamic banks were better capitalized in both normal periods as well as in times of crisis. The mean difference is statistically significant for all the solvency indicators in the pre-COVID-19 crisis period, and only differ in terms of capital ratio during the crisis period, suggesting that there were no significant differences between the two large bank groups during the COVID-19 crisis. In addition, we see that large Islamic banks had significantly more deposit financing and relied more on long-term funding both before and during the COVID-19 crisis. The mean difference is statistically significant at 1%. As for bank efficiency, we observe that large Islamic banks had higher overhead costs than commercial banks in the periods leading up to and during the COVID-19 crisis. The mean difference is statistically significant in all cases at 1%. We do not find statistically significant differences in the cost-to-income ratio either before or during the COVID-19 crisis.

3.4.2. Bank stock market performance and its determinants during the COVID-19 pandemic: *Equation 1*

While our previous analysis shows significant differences in stock market performance between the two types of banks during the COVID-19 crisis, they could be attributed to different institutional, macroeconomic, or bank-level factors. Following previous studies (Aebi et al., 2012; Beck et al., 2013; Beltratti and Stulz, 2012; Demirguc-Kunt et al., 2013; Fahlenbrach et al., 2012; Mirzae et al., 2022; Pelster et al., 2018) we use capital adequacy, liquidity structure, asset quality, profitability, total assets, market risk, stock market performance in the year leading up the crisis (COVID-19 crisis), insolvency risk, market value, efficiency, non-traditional banking activities and funding fragility as potential determinants of stock market performance during the pandemic. We also include GDP growth and inflation rates to control for the overall economic conditions in each market.

Table 3.2. shows the results for those markets where both Islamic and commercial banks operate. Columns (1)-(2)-(3) report the findings when the dependent variable is stock $return_1$. The coefficient of the Islamic banks is 0.078, and it is statistically significant at 1% across all models. This suggests that Islamic banks experienced higher stock returns than commercial banks during COVID-19. Columns (4)-(5)-(6) report the results when the dependent variable is stock $return_2$. The coefficient of the Islamic banks is 0.085 and it is statistically significant.

As for the determinants of bank stock returns during the COVID-19 crisis, we find that the bank liquidity pre-COVID-19 is positively related to stock market performance, and it is statistically significant at 1% across all models. This appears to suggest that liquid banks had better stock market performance than illiquid banks during the COVID-19 crisis. The coefficient on bank market risk pre-COVID-19 is negative, and it is statistically significant at 1% in all specifications. The coefficient on bank insolvency risk pre-COVID-19 is positive and statistically significant at 1%, suggesting that banks with low pre-COVID-19 insolvency risk performed better during the crisis. Our findings also suggest that banks that relied more on non-traditional banking activities in the pre-COVID-19 period performed better in the stock market during the crisis. We find that the coefficients on non-interest income and income diversity are positive and statistically significant at 10% and 1%, respectively. As for funding structure, the coefficients on bank deposits and funding fragility are positive and statistically significant at 1% and 5%, respectively. This suggests that banks that relied more on deposit financing experienced higher stock returns during the crisis. As for bank profitability and pre-COVID-19 returns, they are positively and significantly related to the stock returns during the crisis. This appears to suggest that more profitable banks as well as banks with better stock returns in the pre-COVID-19 crisis period had larger stock returns during the pandemic. Finally, the coefficient on cost-to-income ratio is negative and statistically significant at 5%, suggesting that banks with a higher level of cost efficiency performed better in the stock market during the crisis.

We also re-estimate these equations only for the markets where both types of banks operate. As shown in Table 3.3., Islamic banks yielded higher stock returns than commercial banks during the COVID-19 crisis in these markets. The results are similar to the baseline regression results in terms of liquidity, market risk, financial risk, efficiency and stock performance.

3.4.3. Bank stock market performance and its determinants in the early recovery period: *Equation 2*

The baseline analysis shows that commercial banks have stronger stock performance than Islamic banks in the early recovery period. We explore the determinants of these differences. As shown in table 3.4., the coefficient of the commercial banks is 0.073, and is statistically significant across all models. As for the determinants of bank stock returns in the early recovery period, we find that loan loss reserves are negatively related to stock returns. This seems to suggest that banks with better asset quality during the COVID-19 crisis had larger stock returns in the early recovery period. The coefficient on ROAA is negative and statistically significant at 5%. This implies that less profitable banks during the pandemic had higher stock returns in the early recovery period. Our results also provide evidence that small banks and those that were better capitalized during the COVID-19 crisis performed better in the early recovery period.

3.4.4. Robustness check

In order to provide further evidence on the impact of COVID-19 on banking performance and financial stability, we conduct the analysis using quarterly data given that the intensity of the pandemic was larger in the first and second quarters of 2020. We compare some univariate statistics for the two bank groups in terms of profitability, asset quality, liquidity and capital. We compute the average for each financial indicator over the first and second quarters of each year (2019, 2020, 2021). The last two quarters of 2019 correspond to the pre-COVID-19 period and the first and second quarters of 2020 represent the COVID-19 period. The early recovery period corresponds to the first two quarters of 2021. As shown in table 3.8., Islamic banks exhibited a significantly higher return on assets and return on equity than commercial banks during the first two quarters of 2020 and 2021. However, commercial banks were found to be more profitable than Islamic banks in the period prior to the pandemic. These findings are consistent with our previous results using yearly data.

We also re-run the univariate and OLS analysis to check for changes from the pre-pandemic to the post-pandemic period in all bank groups together. As shown in Table

3.9. in the appendix, banks had a 0.9% return-on-assets average ratio before the crisis, which declined to 0.5% in the first two quarters of 2020. As for the return on equity, the percentage was 8.6% in the first two quarters of 2019 with a decline to 6.6 % during the crisis. The mean difference is statistically significant in all cases at 1%. We observe a substantial recovery in the first quarter of 2021. The return on assets and return on equity ratios increased to 0.9% and 9.3%, respectively. We also observe a negative impact on the asset quality in the global banking industry. The results show that the NPL ratio of the global banking sector was 4.6% in the first two quarters of 2019 and 4.8% during the pandemic. A similar pattern emerged when examining the loan-loss-reserve ratio, which was 4% in the pre-COVID-19 period compared to 4.3% in the COVID-19 crisis. The results also show a significant improvement in both ratios for the first two quarters of 2021.

As for liquidity, the global banking sector showed a 27.4% liquid-assets-to-total-deposit and short-term funding ratio in the first two quarters of 2019 compared to 28.8% during the pandemic. This ratio increased to 31.6% during the early recovery period. As for bank capital, banks had a 16.4% total capital ratio and 15% Tier 1 ratio in the first two quarters of 2019. These ratios increased to 16.6% and to 15.3%, respectively, during the pandemic.

Table 3.10. in the Appendix explores the impact of COVID-19 using a large set of control variables. Following Beck et al., (2013) and Elnahass et al., (2021) we include bank size, cash-to-total assets ratio, equity-to-total assets ratio, and non-loan-earnings-assets-to-total-earnings-assets ratio. We create a dummy variable (*covid-19*) that equals one in the first and second quarters of 2020, and 0 otherwise. The columns differ in terms of the variables of interest used in the model and the inclusion of time-country fixed effects. Columns (1)-(2)-(3)-(4) in Panel A show the results of the impact of COVID-19

on bank profitability. The coefficient on *covid-19* is negative and statistically significant at 1% in all specifications. This suggests that the pandemic significantly reduced global bank profitability, providing support for the results observed in the univariate analysis. Columns (5)-(6)-(7)-(8) in Panel A show the results of the impact of COVID-19 on bank asset quality. The coefficient of the *covid-19* dummy is negative and statistically significant at 5% in most model specifications. This finding implies that the pandemic outbreak significantly increased asset risk. These findings are also consistent with the univariate analysis.

Columns (1)-(2)-(3)-(4) in Panel B show the results of the impact of COVID-19 on bank liquidity. The negative sign on the *covid-19* dummy is found in all models, although it is only statistically significant when we control for time and country fixed effects. Columns (5)-(6)-(7)-(8) in Panel B show the results of the impact of COVID-19 on bank capital. The coefficient is negative and statistically significant in all specifications.

3.5. Conclusion

This article aims to measure the impact of the COVID-19 outbreak on global banking performance and financial stability. We compare Islamic and commercial banks before and during the pandemic, as well as in the early recovery period. Our empirical analysis is conducted using univariate statistics and ordinary least squares.

Overall, the results show that the COVID-19 pandemic has negatively affected the global banking sector. We find that banks experienced a drop in stock returns during the first quarter of 2020 when compared to the pre-COVID-19 period. We also conclude that bank profitability and asset quality were adversely affected by the pandemic. We do not find a significant impact of COVID-19 on either bank capital or liquidity. Furthermore, in the case of Islamic banks, we find that they experienced higher stock market performance during the COVID-19 period compared to commercial banks. Yet commercial banks outperformed Islamic banks on the stock market during the pre-pandemic and in the early recovery period. Banks with low stock volatility and insolvency risk had more liquidity and relied more on non-traditional banking activities in the year leading up the COVID-19 crisis, and also experienced higher stock returns during the pandemic. Islamic banks were better capitalized, relied more on long-term funding, were more involved in non-traditional banking business and were more profitable during the pandemic. We also show that commercial banks were more efficient, had higher asset quality and lower insolvency risk during the health crisis.

Our study has a number of limitations. Considering our analysis was only conducted on publicly traded banks around the world, we believe further studies examining both listed and non-listed banks during the COVID-19 crisis could provide additional evidence. Furthermore, further investigation is needed on how the differences in board characteristics between Islamic and commercial banks affect their performance during the pandemic. Mollah et al. (2021) find that large Shariah boards at Islamic banks may help reducing risk-taking which in turn may provide more financial stability. Additionally, more attention should be paid to the role of macroeconomic factors in financial stability and bank performance during the pandemic.

This study has important policy implications. Previous studies observe higher performance for Islamic banks during times of financial crises, while our findings show this phenomenon also occurs during a pandemic. As a result, some features of Islamic banking should be further explored to check for a potential impact on resiliency in crises, especially relational issues.

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Table 3.1. DESCRIPTION OF THE VARIABLES

Variables	Description	Source and references
Stock returns $_1$	Log return form Dec 31, 2019 to Mar 31, 2020 by using monthly closing prices.	Orbis database (Bureau van Dijk) and our calculation.
Stock returns $_2$	Log return form the average closing prices of (Nov30,2019 and Dec 31, 2019) to (Feb 28,2020 and Mar 31, 2020).	Orbis database (Bureau van Dijk) and our calculation.
Early recovery stock	Log return form Dec 31, 2020 to Mar 31, 2021 by using monthly closing prices.	Orbis database (Bureau van Dijk) and our calculation.
Pre-COVID returns	Log return form Dec 31, 2018 to Dec 31, 2019 by using monthly closing prices.	Orbis database (Bureau van Dijk) and our calculation.
Covid-19	Dummy variable equals 1 in the first and second quarters of the 2020 and 0 otherwise	Orbis database (Bureau van Dijk) and our calculation.
Islamic banks	Dummy variable that takes the value 1 if the bank is Islamic and 0 otherwise	Orbis database (Bureau van Dijk) and our calculation.
Commercial banks	Dummy variable that takes the value 1 if the bank is commercial and 0 otherwise	Orbis database (Bureau van Dijk) and our calculation.
Total capital	Total capital (tier1+tier2) ratio.	Orbis database (Bureau van Dijk). (Pelster et al., 2018)
Tangible equity	Ratio of total tangible equity to tangible assets.	Orbis database (Bureau van Dijk) and our calculation. (Demirguc-Kunt et al., 2013)
Equity to Assets	Ratio of total equity to total assets.	Orbis database (Bureau van Dijk). (Beck et al., 2013)
Liquid assets	Ratio of total liquid assets to total assets.	Orbis database (Bureau van Dijk). (Beltratti and Stulz., 2012) and (Demirguc-Kunt et al., 2013)
Liquid assets to Dep	Ratio of total liquid assets to total deposits and short-term funding.	Orbis database (Bureau van Dijk). (Beck et al., 2013)
Non-Perf Loans	Ratio of non -performing loans to gross loans.	Orbis database (Bureau van Dijk). (Beck et al., 2013) and (Mirzae et al., 2022)

Loan Loss	Ratio of loan loss reserves to gross loans.	Orbis database (Bureau van Dijk). (Beck et al., 2013) and (Mirzae et al., 2022)
ROAA	Return on average assets.	Orbis database (Bureau van Dijk). (Pelster et al., 2018)
ROAE	Return on average total equity	Orbis database (Bureau van Dijk).
Overhead ratio	Ratio of operating expenses to total assets.	Orbis database (Bureau van Dijk) and our calculation. (Beck et al., 2013)
Cost to income	Cost to income ratio.	Orbis database (Bureau van Dijk). (Beck et al., 2013)
Deposits	Ratio of customer deposits to total assets.	Orbis database (Bureau van Dijk) and our calculation. (Beltratti and Stulz., 2012)and (Demirguc-Kunt et al., 2013)
Funding fragility	Ratio of customer deposits to total liabilities.	Orbis database (Bureau van Dijk) and our calculation. (Fahlenbrach et al., 2012)
Long-term Funding	Ratio of long-term borrowings and debt securities at historical cost > 1 to total debt.	Orbis database (Bureau van Dijk) and our calculation. (Pelster et al., 2018)
Short-term Funding	Ratio of short-term borrowings and debt securities at historical cost < 1 year to total debt.	Orbis database (Bureau van Dijk) and our calculation. (Fahlenbrach et al., 2012)
Market risk	Volatility of a stock against the volatility of the market over a three-year window.	Orbis database (Bureau van Dijk). (Beltratti and Stulz., 2012) and (Demirguc-Kunt et al., 2013)
Insolvency risk	Defined as the sum of return on assets and equity to asset ratios to the volatility of ROAA over a three-year window.	Orbis database (Bureau van Dijk) and our calculation. (Beltratti and Stulz., 2012) and (Pelster et al., 2018)
Bank size	The natural logarithm of total assets.	Orbis database (Bureau van Dijk) and our calculation. (Beck et al., 2013) and (Demirguc-Kunt et al., 2013)
Bank value	Ratio of market capitalization to total assets (Tobin's Q).	Orbis database (Bureau van Dijk). (Fahlenbrach et al., 2012)
Non-interest	Ratio of non-interest income to operating revenues	Orbis database (Bureau van Dijk). (Pelster et al., 2018)

Income diversity	Ratio of net fees and commissions to operating income.	Orbis database (Bureau van Dijk) and our calculation. (Aebi et al., 2012)
Fixed Assets	Ratio of total fixed assets to total assets.	Orbis database (Bureau van Dijk) and our calculation. (Beck et al., 2013)
Loans to Assets	Ratio of net loans to total assets.	Orbis database (Bureau van Dijk). (Beltratti and Stulz., 2012) and (Demirguc-Kunt et al., 2013)
Loans to Deposit	Ratio of gross loans and advances to customers to customer deposit.	Orbis database (Bureau van Dijk). (Beck et al., 2013)
Non-Earn	Ratio of non-earning assets to total earning assets	Orbis database (Bureau van Dijk) and our calculation. (Beck et al., 2013)
Cash to assets	Ratio of total cash to total asset	Orbis database (Bureau van Dijk) and our calculation. (Elnahass et al., 2021)
GDP	GDP growth (annual %)	WDI database. (Pelster et al., 2018)
Inflation	Inflation rate %	WDI database. (Pelster et al., 2018)

Table 3.2. Bank stock market performance during the COVID-19 crisis: All Markets.

This table shows OLS regression results estimating ***Equation 1***. The dependent variable is *Stock Returns 1* measured as the log return form (Dec 31, 2019 to Mar 31, 2020) and *Stock Returns 2* measured as the log return form the average closing prices of (Nov 30, 2019 and Dec 31, 2019) to (Feb 28, 2020 and Mar 31, 2020). The independent variables are Islamic banks is a dummy variable that takes the value 1 if the bank is Islamic and 0 otherwise, the ratio of total equity to total assets, ratio of total liquid assets to total assets, ratio of loan loss reserves to gross loans, the return on average assets, the natural logarithm of bank total assets, the volatility of a stock against the volatility of the market over a three-year window, pre-COVID returns measured as the log return form Dec 31, 2018 to Dec 31, 2019 by using monthly closing prices, insolvency risk measured as the sum of return on assets and equity to asset ratios to the volatility of ROAA over a three-year window, the ratio of market capitalization to total assets (Tobin's Q- Bank value), cost to income ratio, ratio of non-interest income to operating revenue, ratio of net fees and commissions to operating income, ratio of customer deposits to total assets, ratio of customer deposits to total liabilities, GDP annual growth, and inflation rate. All explanatory variables are winsorized at the 1st and 99th percentile. Robust standard errors are in parentheses. Columns 1-3 report the results when stock market performance measured by *Stock Returns1* and columns 4-6 report the results when stock market performance measured by *Stock Returns2.*

Dependent Variables	***Stock Returns 1*** **(1)**	***Stock Returns 1*** **(2)**	***Stock Returns 1*** **(3)**	***Stock Returns 2*** **(4)**	***Stock Returns 2*** **(5)**	***Stock Returns 2*** **(6)**
Independent Variables						
Islamic Banks	0.130***	0.125***	0.078**	0.105***	0.110***	0.085***
	(0.044)	(0.045)	(0.036)	(0.032)	(0.034)	(0.03)
Equity to Assets	-0.267	-0.454	-0.329	0.021	-0.09	-0.003
	(0.172)	(0.445)	(0.425)	(0.099)	(0.278)	(0.298)
Liquid assets	0.30***	0.285***	0.365***	0.267***	0.254***	0.231***
	(0.103)	(0.101)	(0.093)	(0.067)	(0.069)	(0.07)
Loan Loss	-0.139	-0.313	0.057	-0.18	-0.516*	-0.313
	(0.234)	(0.373)	(0.369)	(0.236)	(0.3)	(0.313)
ROAA	1.604	-0.448	-1.363	1.249**	-0.329	-0.607
	(1.032)	(1.399)	(1.302)	(0.587)	(0.948)	(1.078)
Bank size	-0.009	0.003	-0.004	-0.001	0.005	-0.002
	(0.006)	(0.008)	(0.008)	(0.005)	(0.006)	(0.006)
Market risk		-0.288***	-0.252***		-0.184***	-0.152***
		(0.035)	(0.036)		(0.024)	(0.025)
Pre-COVID-19 returns		-0.023	-0.002		0.077**	0.063
		(0.063)	(0.059)		(0.037)	(0.039)
Insolvency risk		0.048***	0.065***		0.019**	0.035***
		(0.012)	(0.01)		(0.009)	(0.009)
Bank value		-2.69	-10.224		-5.471	-11.439
		(14.807)	(15.142)		(11.716)	(11.953)
Cost to income		-0.064	-0.089		-0.049	-0.098**
		(0.079)	(0.083)		(0.05)	(0.046)
Non-interest		0.151*			0.063	
		(0.08)			(0.062)	
Deposits		0.232***			0.028	
		(0.079)			(0.065)	
Income diversity			0.138			0.263***
			(0.109)			(0.085)
Funding fragility			0.166**			0.038
			(0.082)			(0.064)
GDP Growth			-0.001			0.003
			(0.006)			(0.005)
Inflation			-0.011***			-0.004
			(0.004)			(0.003)
_cons	-0.258***	-0.47***	-0.419***	-0.238***	-0.195	-0.221*
	(0.082)	(0.155)	(0.146)	(0.061)	(0.121)	(0.118)
Observations	516	444	431	516	444	431
R-squared	0.06	0.385	0.402	0.069	0.294	0.314

Robust standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1

Table 3.3. Bank stock market performance during the COVID-19 crisis: Markets hosting both types of banks.

This table shows OLS regression results estimating ***Equation 1***. The dependent variable is *Stock Returns 1* measured as the log return form (Dec 31, 2019 to Mar 31, 2020) and *Stock Returns 2* measured as the log return form the average closing prices of (Nov30, 2019 and Dec 31, 2019) to (Feb 28, 2020 and Mar 31, 2020). The independent variables are Islamic banks is a dummy variable that takes the value 1 if the bank is Islamic and 0 otherwise, the ratio of total equity to total assets, ratio of total liquid assets to total assets, ratio of loan loss reserves to gross loans, the return on average assets, the natural logarithm of bank total assets, the volatility of a stock against the volatility of the market over a three-year window, pre-COVID returns measured as the log return form Dec 31, 2018 to Dec 31, 2019 by using monthly closing prices, insolvency risk measured as the sum of return on assets and equity to asset ratio to the volatility of ROAA over a three-year window, the ratio of market capitalization to total assets (Tobin's Q- Bank value), cost to income ratio, ratio of non-interest income to operating revenue, ratio of net fees and commissions to operating income, ratio of customer deposits to total assets, ratio of customer deposits to total liabilities, GDP annual growth, inflation rate. All explanatory variables are winsorized at the 1st and 99th percentile. Robust standard errors are in parentheses. Columns 1-3 report the results when stock market performance measured by *Stock Returns 1* and columns 4-6 reports the results when stock market performance measured by *Stock Returns 2*.

Dependent Variables	***Stock Returns 1*** **(1)**	***Stock Returns 1*** **(2)**	***Stock Returns 1*** **(3)**	***Stock Returns 2*** **(4)**	***Stock Returns 2*** **(5)**	***Stock Returns 2*** **(6)**
Independent Variables						
Islamic Banks	0.167***	0.093*	0.082**	0.138***	0.116***	0.086***
	(0.046)	(0.052)	(0.038)	(0.036)	(0.043)	(0.032)
Equity to Assets	-0.209	-0.5	0.21	0.214	-0.008	0.571*
	(0.289)	(0.455)	(0.377)	(0.142)	(0.319)	(0.298)
Liquid assets	0.087	0.044	0.249	0.223**	0.257**	0.302**
	(0.188)	(0.177)	(0.187)	(0.11)	(0.127)	(0.148)
Loan Loss	0.235	-0.122	0.08	-0.053	-0.302	-0.266
	(0.344)	(0.679)	0(.594)	(0.36)	(0.62)	(0.574)
ROAA	2.126	-0.079	-3.404*	1.089	-0.767	-3.761**
	(1.603)	(1.794)	(1.978)	(0.828)	(1.272)	(1.694)
Bank size	-0.013	0.001	0.005	0.004	0.017	0.017
	(0.011)	(0.016)	(0.015)	(0.009)	(0.013)	(0.012)
Market Risk		-0.307***	-0.26***		-0.189***	-0.154***
		(0.058)	(0.046)		(0.042)	(0.035)
Pre-COVID-19returns		-0.072	0.019		0.094	0.173*
		(0.092)	(0.082)		(0.068)	(0.092)
Insolvency risk		-0.005	0.035*		-0.011	0.018
		(0.027)	(0.018)		(0.021)	(0.017)
Bank value		14.506	-0.912		0.487	-9.018
		(19.31)	(20.225)		(16.095)	(16.978)
Cost to income		-0.11	-0.168*		-0.056	-0.175**
		(0.086)	(0.089)		0(.07)	(0.067)
Non-interest		0.18			0.036	
		(0.111)			(0.095)	
Deposits		-0.101			-0.142	
		(0.155)			(0.116)	
Income diversity			-0.239			-0.038
			(0.291)			(0.267)
Funding fragility			0.002			-0.029
			(0.157)			(0.134)
GDP Growth			0.001			-0.001
			(0.008)			(0.007)
Inflation			0-.002			0.002
			(0.006)			(0.005)
_cons	-0.245*	0.046	-0.235	-0.338***	-0.099	-0.272
	(0.137)	(0.274)	(0.225)	(0.095)	(0.221)	(0.204)
Observations	179	135	123	179	135	123
R-squared	0.108	0.433	0.435	0.123	0.349	0.367

Robust standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1

Table 3.4. Bank stock market performance in the early recovery period: All Markets.

This table shows OLS regression results estimating ***Equation 2***. The dependent variable *Early Recovery Stock* measured as the change in log stock return from Dec 31, 2020 to Mar 31, 2021. The independent variables are commercial banks is a dummy variable that takes the value 1 if the bank is commercial and 0 otherwise the ratio of total equity to total assets, ratio of total liquid assets to total assets, ratio of loan loss reserves to gross loans, the return on average assets, the natural logarithm of bank total assets, the volatility of a stock against the volatility of the market over a three-year window, insolvency risk measured as the sum of return on assets and equity to asset ratio to the volatility of ROAA over a three-year window, the ratio of market capitalization to total assets (Tobin's Q- Bank value), cost to income ratio, ratio of non-interest income to operating revenue, ratio of net fees and commissions to operating income, ratio of customer deposits to total assets, ratio of customer deposits to total liabilities, GDP annual growth, inflation rate. All explanatory variables are winsorized at the 1st and 99th percentile. Robust standard errors are in parentheses.

Dependent Variable	***Early Recovery Stock*** **(1)**	***Early Recovery Stock*** **(2)**	***Early Recovery Stock*** **(3)**
Independent Variables			
Commercial Banks	0.065***	0.073**	0.082*
	(0.023)	(0.029)	(0.043)
Equity to Assets	0.276**	0.161	-0.049
	(0.127)	(0.325)	(0.372)
Liquid Assets	0.081	0.083	0.033
	(0.07)	(0.065)	(0.081)
Loan Loss	-0.73***	-.935***	-0.773***
	(0.2)	0(.245)	(0.284)
ROAA	-2.395**	-4.663***	-3.31
	(0.941)	(1.642)	(2.563)
Bank Size	-0.001	-0.009	-0.017*
	(0.006)	0(.008)	(0.01)
Market Risk		-0.014	-0.002
		(0.024)	(0.029)
Insolvency risk		-0.0001**	-0.0001
		(0.00004)	(0.00009)
Bank Value		12.412	3.328
		(15.232)	(16.172)
Cost to income		-0.08	-0.056
		(0.099)	(0.153)
Non-interest		-0.023	
		(0.065)	
Deposits		-0.038	
		(0.067)	
Income diversity			0.083
			(0.13)
Funding fragility			-0.007
			(0.085)
GDP Growth			0.004
			(0.003)
Inflation			-0.006**
			(0.003)
_cons	-0.003	0.209	0.270
	(0.07)	(0.146)	(0.212)
Observations	509	446	353
R-squared	0.074	0.115	0.081

Robust standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1

Appendix

Table 3.5.Univariate Analysis (t-test P-value)
The table shows the univariate t-test of differences between Islamic (**IBs)** and commercial (**CBs)** banks before and during the COVID-19 pandemic: All markets.

Variables	Full Sample (**CBs +IBs**)			***Pre -COVID -19 Crisis***						***During COVID -19 Crisis***		
				CBs 2019	**IBs** 2019	**Two-sided p-value**	**CBs** Avg(2018+19)	**IBs** Avg(2018+19)	**Two-sided p-value**	**CBs** 2020	**IBs** 2020	**Two-sided p-value**
	N	Mean	Std. Deviation	Mean	Mean	Difference t-test P-value	Mean	Mean	Difference t-test P-value	Mean	Mean	Difference t-test P-value
Stock returns$_1$	582	-0.278	0.277	-	-	-	-	-	-	-0.296	-0.129	0.000
Stock returns$_2$	582	-0.162	0.201	-	-	-	-	-	-	-0.175	-0.051	0.000
Early recovery stock returns	582	0.051	0.201	-	-	-	-	-	-	0.060	-0.027	0.001
Total capital	1416	0.17	0.067	0.167	0.188	0.042	0.169	0.192	0.021	0.177	0.185	0.482
Tangible equity	1670	0.118	0.109	0.117	0.147	0.039	0.115	0.151	0.014	0.114	0.149	0.019
Equity to Assets	1670	0.122	0.113	0.121	0.15	0.062	0.119	0.154	0.023	0.118	0.151	0.030
Liquid assets	1670	0.244	0.137	0.241	0.237	0.860	0.245	0.235	0.566	0.250	0.238	0.532
Liquid assets to Dep	1612	0.279	0.233	0.277	0.29	0.709	0.279	0.308	0.342	0.286	0.328	0.209
Non-Perf Loans	1488	0.055	0.074	0.053	0.083	0.010	0.053	0.089	0.001	0.050	0.088	0.000
Loan Loss	1549	0.046	0.055	0.043	0.071	0.000	0.044	0.075	0.000	0.044	0.074	0.000
ROAA	1661	0.009	0.018	0.009	0.006	0.192	0.008	0.01	0.498	0.007	0.013	0.012
Cost to income	1661	0.604	0.332	0.599	0.623	0.586	0.606	0.616	0.818	0.612	0.605	0.895
Overheads	1661	0.026	0.029	0.025	0.037	0.000	0.025	0.038	0.000	0.024	0.041	0.000
Deposits	1592	0.691	0.149	0.690	0.691	0.977	0.690	0.685	0.785	0.691	0.687	0.857
Funding fragility	1592	0.774	0.16	0.774	0.783	0.685	0.772	0.777	0.843	0.773	0.774	0.933
Long-term Funding	1017	0.532	0.319	0.524	0.658	0.132	0.510	0.723	0.005	0.529	0.72	0.024
Short-term Funding	539	0.275	0.287	0.253	0.288	0.776	0.291	0.355	0.590	0.290	0.213	0.584
Market risk	1545	0.784	0.44	0.792	0.702	0.177	0.792	0.702	0.177	0.792	0.702	0.177
Insolvency risk	1658	96.345	139.023	101.233	61.357	0.031	100.362	62.398	0.040	98.728	61.604	0.044
Bank size	1670	9.532	2.305	9.661	8.375	0.000	9.656	8.382	0.000	9.782	8.509	0.000
Bank value	1684	0.001	0.002	0.001	0.001	0.878	0.001	0.001	0.439	0.001	0.002	0.154
Non-interest	1661	0.359	0.258	0.348	0.481	0.000	0.344	0.486	0.000	0.339	0.501	0.000
Income diversity	1597	0.155	0.113	0.159	0.127	0.046	0.158	0.118	0.011	0.155	0.091	0.000
Fixed Assets	1660	0.013	0.015	0.013	0.022	0.000	0.012	0.021	0.000	0.012	0.019	0.000
Loans to Assets	1648	0.567	0.165	0.571	0.58	0.718	0.563	0.579	0.485	0.550	0.584	0.119
Loans to Deposit	1592	0.907	0.312	0.917	0.921	0.931	0.906	0.936	0.478	0.880	0.946	0.134
Pre-COVID-19 returns	572	0.044	0.338	0.049	0.007	0.359	-	-	-	-	-	-

Table 3.6. Univariate Analysis (t-test P-value)
The table shows the univariate comparison t-test of differences between Islamic (**IBs**) and Commercial (**CBs**) banks before and during the COVID-19 pandemic: Markets hosting both types of banks.

Variables	Full Sample (**CBs +IBs**)			***Pre-CPVID-19 crisis***			***During Covid-19 crisis***		
				CBs 2019	**IBs** 2019	**Two-sided p-value**	**CBs** 2020	**IBs** 2020	**Two-sided p-value**
	N	Mean	Std. Deviation	Mean	Mean	Difference t-test P-value	Mean	Mean	Difference t-test P-value
Stock returns$_1$	197	-0.264	0.29	-	-	-	-0.328	-0.129	0.000
Stock returns$_2$	197	-0.149	0.218	-	-	-	-0.196	-0.051	0.000
Early recovery stock returns	197	-0.014	0.272	-	-	-	-0.008	-0.027	0.654
Total capital	315	0.201	0.076	0.198	0.188	0.404	0.217	0.185	0.0187
Tangible equity	386	0.161	0.145	0.168	0.147	0.327	0.167	0.149	0.4191
Equity to Assets	386	0.166	0.151	0.174	0.15	0.291	0.172	0.151	0.3796
Liquid assets	386	0.264	0.144	0.261	0.237	0.253	0.293	0.238	0.0169
Liquid assets to Dep	359	0.294	0.251	0.276	0.29	0.727	0.297	0.328	0.4457
Non-Perf Loans	336	0.07	0.093	0.069	0.083	0.419	0.057	0.088	0.0342
Loan Loss	357	0.063	0.072	0.057	0.071	0.268	0.060	0.074	0.2166
ROAA	386	0.009	0.024	0.011	0.006	0.220	0.007	0.013	0.1472
Cost to income	386	0.642	0.467	0.638	0.623	0.811	0.674	0.605	0.3795
Overheads	386	0.034	0.036	0.031	0.037	0.203	0.031	0.041	0.1290
Deposits	353	0.68	0.137	0.678	0.691	0.562	0.671	0.687	0.4883
Funding fragility	353	0.783	0.144	0.787	0.783	0.832	0.782	0.774	0.7440
Long-term Funding	163	0.53	0.328	0.494	0.658	0.101	0.500	0.72	0.0174
Short-term Funding	116	0.28	0.243	0.291	0.288	0.974	0.273	0.213	0.5818
Market risk	308	0.753	0.498	0.776	0.702	0.397	0.776	0.702	0.3978
Insolvency risk	384	66.148	108.483	69.465	61.357	0.630	67.375	61.604	0.7289
Bank size	386	8.562	2.151	8.571	8.375	0.553	8.670	8.509	0.6275
Bank value	380	0.002	0.002	0.002	0.001	0.007	0.002	0.002	0.0440
Non-interest	386	0.4	0.345	0.362	0.481	0.030	0.349	0.501	0.0026
Income diversity	347	0.121	0.089	0.134	0.127	0.631	0.117	0.091	0.0511
Fixed Assets	386	0.019	0.019	0.019	0.022	0.341	0.019	0.019	0.9928
Loans to Assets	381	0.53	0.188	0.518	0.58	0.036	0.491	0.584	0.0012
Loans to Deposit	353	0.895	0.324	0.890	0.921	0.528	0.861	0.946	0.1181
Pre-COVID-19 returns	195	0.065	0.405	0.091	0.007	0.178	-	-	-

Table 3.7. Univariate Comparison (t-test P-value)
The table shows the univariate t-test of differences between ***large*** Islamic (**IBs**) and ***large*** Commercial (**CBs**) banks before and during the COVID-19 pandemic: All markets.

Variables	Full Sample (CBs +**IBs**)			***Pre-COVID -19 crisis***			***During COVID-19 crisis***		
				CBs 2019	**IBs** 2019	**Two-sided p-value**	**CBs** 2020	**IBs** 2020	**Two-sided p-value**
	N	Mean	Std. Deviation	Mean	Mean	Difference t-test P-value	Mean	Mean	Difference t-test P-value
Stock returns$_1$	297	-0.296	0.268	-	-	-	-0.312	-0.0008	0.000
Stock returns$_2$	297	-0.178	0.185	-	-	-	-0.190	0.059	0.000
Early recovery stock returns	297	0.059	0.155	-	-	-	0.061	0.003	0.103
Total capital	516	0.156	0.043	0.152	0.215	0.000	0.157	0.183	0.027
Tangible equity	557	0.081	00.031	0.081	0.099	0.020	0.079	0.089	0.136
Equity to Assets	557	0.084	0.031	0.085	0.102	0.041	0.083	0.092	0.201
Liquid assets	557	0.233	0.114	0.232	0.207	0.381	0.237	0.202	0.177
Liquid assets to Dep	555	0.248	0.177	0.246	0.235	0.794	0.254	0.229	0.549
Non-Perf Loans	528	0.033	0.033	0.033	0.023	0.261	0.033	0.036	0.709
Loan Loss	536	0.032	0.027	0.030	0.026	0.564	0.033	0.038	0.478
ROAA	557	0.007	0.009	0.008	0.015	0.002	0.006	0.019	0.000
Cost to income	557	0.532	0.19	0.536	0.532	0.927	0.533	0.465	0.116
Overheads	557	0.016	0.011	0.016	0.026	0.000	0.015	0.025	0.000
Deposits	554	0.683	0.146	0.682	0.734	0.159	0.679	0.723	0.187
Funding fragility	554	0.749	0.158	0.748	0.824	0.059	0.743	0.803	0.094
Long-term Funding	438	0.515	0.291	0.498	0.765	0.039	0.521	0.754	0.038
Short-term Funding	229	0.255	0.267	0.234	0.085	0.267	0.289	0.062	0.200
Market risk	556	0.893	0.426	0.917	0.543	0.000	0.907	0.539	0.000
Insolvency risk	557	110.617	144.66	117.884	42.258	0.037	112.397	39.666	0.027
Bank size	557	11.347	1.217	11.327	10.612	0.018	11.395	10.707	0.016
Bank value	586	0.001	0.001	0.001	0.002	0.000	0.001	0.002	0.000
Non-interest	557	0.337	0.161	0.331	0.537	0.000	0.320	0.474	0.000
Income diversity	553	0.163	0.094	0.168	0.12	0.040	0.164	0.113	0.026
Fixed Assets	557	0.01	0.011	0.009	0.027	0.000	0.009	0.021	0.000
Loans to Assets	557	0.574	0.12	0.582	0.63	0.118	0.560	0.642	0.002
Loans to Deposit	554	0.906	0.276	0.921	0.886	0.614	0.888	0.933	0.468
Pre-COVID-19 returns	292	0.039	0.321	0.036	0.102	0.419	-	-	-

Table 3.8. **Univariate Analysis (t-test P-value)**
The table shows the t-test of differences between Islamic **(IBs)** and commercial **(CBs)** banks prior to and during the COVID-19 crisis, as well as in the early recovery period: ***Quarterly basis.***

Variables	**IBs** Q1+Q2 (2019)	**CBs** Q1+Q2 (2019)	**Two-sided p-value**	**IBs** Q1+Q2 (2020)	**CBs** Q1+Q2 (2020)	**Two-sided p-value**	**IBs** Q3+Q4 (2020)	**CBs** Q3+Q4 (2020)	**Two-sided p-value**	**IBs** Q1+Q2 (2021)	**CBs** Q1+Q2 (2021)	**Two-sided p-value**
	Mean	Mean	Difference t-test P-value	Mean	Mean	Difference t-test P-value	Mean	Mean	Difference t-test P-value	Mean	Mean	Difference t-test P-value
Total Capital	0.182	0.162	0.000	0.186	0.165	0.000	0.195	0.175	0.000	0.194	0.173	0.000
Tier 1 Capital	0.165	0.148	0.000	0.171	0.152	0.000	0.176	0.161	0.000	0.175	0.161	0.000
Liquid assets	0.002	0.001	0.001	0.002	0.002	0.618	0.00201	0.00215	0.017	0.00208	0.00223	0.011
Liquid assets to Dep	0.325	0.266	0.000	0.310	0.287	0.021	0.331	0.307	0.035	0.361	0.318	0.000
ROAA	0.008	0.009	0.063	0.0134	0.0051	0.000	0.009	.0057	0.000	0.015	0.009	0.000
ROAE	0.085	0.086	0.755	0.128	0.060	0.000	0.081	0.062	0.000	0.123	0.089	0.000
Non-Perf Loans	0.071	0.044	0.000	0.077	0.049	0.000	0.076	0.044	0.000	0.067	0.044	0.000
Loan Loss	0.064	0.038	0.000	0.063	0.041	0.000	0.071	0.042	0.000	0.077	0.040	0.000

Table 3.9. Univariate analysis (t-test P-value)
The table shows the t-test of differences of time differences in several accounting ratios of the ***global banking sector (full sample)*** prior to and during the COVID-19 crisis, as well as in the early recovery period: ***Quarterly basis.***

Variables	Q1+Q2 (2019)	Q1+Q2 (2020)		Q1+Q2 (2020)	Q1+Q2 (2021)	
	Mean	Mean	Difference t-test P-value	Mean	Mean	Difference t-test P-value
Total Capital	0.164	0.166	0.000	0.166	0.175	0.000
Tier 1 Capital	0.150	0.153	0.000	0.153	0.162	0.000
Liquid assets	0.001	0.0020	0.000	0.0020	0.0022	0.000
Liquid assets to Dep	0.274	0.288	0.000	0.288	0.316	0.000
ROAA	0.009	0.005	0.000	0.005	0.009	0.000
ROAE	0.086	0.066	0.000	0.066	0.093	0.000
Non-Perf Loans	0.046	0.048	0.000	0.048	0.045	0.000
Loan Loss	0.040	0.043	0.000	0.043	0.043	0.000

Table 3.10. Impact of COVID-19 on the global banking performance and financial stability: *Quarterly basis*.

This table shows OLS regression using quarterly data for the whole sample. The dependent variables in Panel A are the return on average assets (ROAA), the return on equity (ROEA), ratio of non-performing loans to gross loans and ratio of loan loss reserves to gross loans to measure the impact of COVID-19 on banks profitability and asset quality. The dependent variables in Panel B are the total capital (tier1+tier2) ratio, Tier 1 ratio, ratio of total liquid assets to total assets, and ratio of total liquid assets to total deposits and short-term funding to measure the impact of COVID-19 on banks' capital and liquidity. The variable of interest is *Covid-19,* a dummy variable equals 1 in the first and second quarters of the 2020 and 0 otherwise. Control variables are the natural logarithm of bank total assets, the ratio of non-earning assets to total earning assets, total equity to total assets, and the ratio of total cash to total assets. All explanatory variables are winsorized at the 1st and 99th percentile. Standard errors are clustered at the bank level.

Panel A: Impact of Covid-19 pandemic on banks profitability and assets quality

	Profitability				***AssetQuality***			
Dependent Variables	ROAA	ROAA	ROEA	ROEA	Loan loss	Loan loss	N/P loan	N/P loan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent Variables								
Covid19	-0.332***	-0.457***	-1.927***	-2.812***	0.173*	0.18	0.351**	0.539**
	(0.067)	(0.103)	(0.341)	(0.53)	(0.092)	(0.197)	(0.143)	(0.243)
Total Assets	0.078**	0.202***	0.479***	1.353***	-0.349***	-0.294*	-0.57***	-0.589***
	(0.031)	(0.042)	(0.176)	(0.232)	(0.133)	(0.164)	(0.172)	(0.199)
Non-Earn assets	-0.011	0.025	-0.134	0.072	-0.238	-0.094	-0.112	-0.172
	(0.023)	(0.015)	(0.123)	(0.078)	(0.486)	(0.394)	(0.571)	(0.458)
Equity to assets	0.039***	0.046***	-0.018	0.026	0.148***	0.124**	0.065	0.059
	(0.01)	(0.011)	(0.031)	(0.037)	(0.056)	(0.05)	(0.083)	(0.071)
Cash to assets	2.209***	0.744	10.158**	5.245	2.526	2.79	1.491	2.885

	(0.834)	(0.924)	(4.816)	(4.579)	(3.025)	(4.137)	(3.952)	(5.583)
_cons	-0.467	-2.135***	3.398	-7.407**	5.56***	3.365	9.189***	7.516***
	(0.394)	(0.572)	(2.119)	(3.217)	(1.726)	(2.053)	(2.435)	(2.583)
Observations	3936	3936	3934	3934	3181	3181	3021	3021
R-squared	0.081	0.255	0.029	0.298	0.145	0.415	0.066	0.379
Time Fixed Effect	NO	YES	NO	YES	NO	YES	NO	YES
Country Fixed Effect	NO	YES	NO	YES	NO	YES	NO	YES

Panel B: Impact of Covid-19 pandemic on banks' capital and liquidity

	Liquidity				***Capital***			
Dependent Variables	Liquid/Asset (1)	Liquid/Asset (2)	Liquid/Deposits (3)	Liquid/Deposits (4)	T.Capital (5)	T.Capital (6)	Tier 1 (7)	Tier 1 (8)
Independent Variables								
Covid19	-0.002	-0.024***	-0.123	-3.294***	-0.394***	-1.014***	-0.31**	-1.024***
	(0.002)	(0.004)	(0.352)	(0.835)	(0.108)	(0.192)	(0.128)	(0.228)
Total Assets	0.004	0.006*	1.054**	0.882	-.881***	-0.178	-0.905***	-0.363**
	(0.003)	(0.003)	(0.491)	(0.569)	(0.165)	(0.167)	(0.165)	(0.18)
Non-Earn	0.005	0.004	0.496	0.294	3.084***	3.139***	0.652	-2.395
	(0.009)	(0.009)	(1.567)	(1.453)	(0.286)	(0.316)	(2.814)	(4.098)
Equity to assets	0.001	0.001	1.217***	1.308***				
	(0.001)	(0.001)	(0.226)	(0.221)				
Cash to assets					-2.568	4.136	12.466*	14.878*
					(4.254)	(4.382)	(6.651)	(7.92)
_cons	0.158***	0.108**	5.595	6.661	25.432***	17.661***	23.524***	17.239***
	(0.032)	(0.052)	(5.951)	(8.748)	(1.786)	(2.204)	(1.84)	(2.334)

Observations	3995	3995	3826	3826	3135	3135	2540	2540
R-squared	0.006	0.418	0.16	0.473	0.165	0.486	0.143	0.397
Time Fixed Effect	NO	YES	NO	YES	NO	YES	NO	YES
Country Fixed Effect	NO	YES	NO	YES	NO	YES	NO	YES

Standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1

CHAPTER 4

A Machine Learning Approach for Identifying the Drivers of Global Banking Profitability

Abstract

This paper uses a machine learning approach to identify drivers of global banking profitability in two distinct timeframes, in both conventional and alternative banking systems. The algorithm was over 93% accurate in predicting all empirical approaches. We discover that the period of the pandemic, indicators related to bank soundness, efficiency, total amount of loans issued, liquidity/capital structures and size are the factors that most accurately predict bank profitability. While drivers of profitability pre-pandemic are similar to the results from the pandemic period, there is a difference in the total amount of loans issued. Additionally, the algorithm reveals that the profitability of Islamic and commercial banks is due to different factors. Islamic bank´s profitability is explained by soundness, revenue mix, market power, funding structure, efficiency, liquidity, capital structure and size. In their commercial bank counterparts, however, the algorithm suggests that bank soundness, efficiency, liquidity/capital structure and size are the strongest predictors of profitability. Interestingly, unlike previous literature, none of the macroeconomic factors seem to have played a role in predicting bank profitability in all the above-mentioned approaches.

Keywords: Bank profitability, machine learning, random forest

JEL Classification: C45, C53, G15, G20, G21

4.1. Introduction

Over the last few years, the banking industry has been faced with significant shifts regarding its core profitability. Since the global financial crisis of 2008 bank profitability around the world has been significantly affected, along with facing several other challenges such as a low interest rate environment, the emerging market of new competing firms in the banking industry, and most recently, the coronavirus pandemic. The overwhelming worry among policymakers in the long-term resilience of banks as non-stop adverse market shifts keep threatening the sustainability of the traditional bank business model (IMF, 2022).

It has been demonstrated that banks saw lacklustre profitability during the pandemic. As documented by White (2021), banks' return-on-assets was 0.38% in 2020Q1 as compared to 1.30% in 2019Q4. However, a recovery has been also observed in the post-pandemic period. Specifically, the return-on-equity was 7.4% in 2021Q2 as compared to 0.4% in 2020Q2 (European Banking Authority, 2021). Asian and other emerging market banks also suffered declines in their profitability during the pandemic (BIS, 2021). As noted by Ikeda et al. (2021), banks that had lower profitability and non-performing loans during years leading up the pandemic reported a significant difference in the return-on-assets metric during the pandemic as compared to those banks that had sustainable profitability —around 0.3% compared to 0.9% in Q4 2020.

Islamic banks' profitability was also negatively affected by the health crisis, despite their relatively positive performance during the pandemic, when compared to their peers. As noted by the Islamic Financial Services Board (2021), the return-on-asset metric for global Islamic banks was 1.3% in 2020Q3 as compared to 1.6% in 2019Q3. In 2021, they surpassed their pre-pandemic level. This improvement is due to the increased demand for their products (IFSB, 2022), in addition to the low provisions for credit losses.

Similarly, this trend also occurred during the global financial crisis. As discussed by Beck et al. (2013), the outperformance of Islamic banks over their peers during the Global Financial Crisis (GFC) has driven policymakers to focus on features that relate to Sharia-compliant financial products.

The concerns among policymakers about continuous shifts in bank profitability, as well significant shifts in profits during times of crises, have raised many concerns. This study applies a machine learning approach to study the determinants of banks' profitability on a large and varied sample of banks across the world and over different timeframes, including alternative banking systems (commercial and Islamic). In particular, we explore the drivers of global banking profitability before and during the pandemic. We also examine the differences in the determinants of bank profitability between commercial and Islamic banks in all the time periods considered.

We consider a large number of potential factors that may influence banking profitability to feed the machine learning algorithm, including industrial-level, bank-level and macroeconomic factors. To our knowledge, this is the first study to explain the main driving factors of global banking profitability in different periods (pre-pandemic and pandemic) as well as in alternative banking systems, applying a hybrid machine learning technique.

The algorithm reveals that the key factors driving bank profitability during the pandemic were bank soundness, efficiency, total loans issued, liquidity/capital structures and size. The algorithm also finds similar drivers for global banking profitability in the period leading up to the pandemic, except in the amount of total loans issued. Additionally, the algorithm reveals that the drivers of profitability in Islamic and commercial banks are different. Islamic banks´ profitability is explained by their soundness, revenue mix, market power, funding structure, efficiency, liquidity/capital structures and size. As for commercial bank profitability, the algorithm shows that soundness, efficiency, liquidity, capital adequacy and size are the strongest predictors. However, none of the macroeconomic variables, credit risk or stock market indicators are shown to be accurate predictors of profitability in all cases.

The paper is organized as follows: Section 2 discusses prior studies related to the topic, Section 3 describes the data and sample, Section 4 explains the methodology and variable measurements, Section 5 outlines the main findings from the empirical analysis and Section 6 draws conclusions and makes suggestions for future related studies.

4.2. Related literature

As mentioned previously, there is an increased interest among academics and policymakers to better understand the drivers behind bank profitability because it is intrinsically related to the stability and the financing conditions of the global financial system. Xu et al. (2019) discuss the relationship between profitability and stability, identifying two main relationships: i) although banks have the option to use their capital to withstand negative shocks to the market, the importance of profit outweighs the impulse to cover these losses, and (ii) low profits could also drive banks to take unnecessary risks to generate larger returns, which in turn may increase systemic risk. Many banks around the world showed signs of recovery in terms of profitability after the GFC, but they still face an inefficient cost structure due to a shift to more non-traditional banking activities. However, theoretically, the most widely held approaches for explaining bank profitability are those related to efficiency structure and market power. Market power theory emphasizes that the profitability of the banking industry depends heavily on the market structure (Berger,1995). Banks with higher market share can enjoy larger loans, higher deposit volumes and a deeper involvement in non-traditional banking activities, thereby improving profitability. More recently, this theory has gained some ground due to new aggressive players entering the banking market. The efficiency structure theory states that more efficient banks record lower average costs, and therefore achieve higher returns (Peltzman, 1977). In other words, efficient banks gain a higher degree of market shares that may result in abnormal profits.

From an empirical standpoint, extensive literature already exists examining the drivers of profitability in the banking sector. Not surprisingly, these studies provide different views as to which factors play a significant role in profitability, such as market conditions, different banking systems and institutional contexts of the time period they intend to examine. Earlier evidence identifies several drivers of bank profitability and previous literature demonstrates that there are two types of relationships between capital and profitability (Detragiache et al., 2018; Lee and Hsieh, 2013; Tran et al., 2016). On the one hand, better capitalized banks face lower insolvency risk and funding costs, thereby achieving higher profits. Others argue that higher levels of capital lead banks to takes higher risks, which in turn, may decrease their returns. Some studies examine the impact of liquidity on bank profitability, as the level of liquid assets is related to the costs of financing and default (Bordeleau and Graham, 2010; Tran et al., 2016). Some studies also explore the impact of credit risk on bank profitability (Detragiache et al., 2018; Salike and Ao, 2017). In the above-mentioned cases, studies confirm a positive correlation between bank structure and its efficiency (Petria et al., 2015; Xu et al., 2019). Furthermore, it has been shown that market power and non-interest income also drive profitability (Mirzaei et al., 2013; Petria et al., 2015). Additionally, bank size has also been identified as a key determinant, as noted by Shehzad et al. (2013).

As for times of crisis, a number of studies explore the drivers of bank profitability. Among them, Dietrich and Wanzenried, (2011) analyse the drivers of commercial bank profitability during the global financial crisis using a broad set of bank and market indicators. They find that efficiency, revenue diversification, funding costs and the growth of total loans were the key factors explaining profitability during the GFC. In particular, they conclude that efficient banks and those with higher loan volumes and lower funding costs were more profitable. They also find that those banks that relied heavily on non-interest income sources saw larger profits than those who relied more on interest income sources. Additionally, Bongini et al. (2019) examine the drivers of profitability shocks and recovery in 109 European banks, considering both the years of the GFC and the sovereign debt crises. They show that the bank profitability shock is explained by pre-crisis lending activity and a riskier loan portfolio. They also show that the profitability crisis most heavily impacted those banks that were most affected by the sovereign debt crisis. Additionally, the signs of recovery in bank profitability have also been linked to an improvement in lending, along with more adequate loan loss provisions.

There is not only a variety of explanations for bank profitability in most of the previous studies but also differences in the determinants of profitability across alternative banking systems. As documented by Yanikkaya et al. (2018), the factors that explain Islamic bank profitability differ significantly from those driving commercial bank profitability. In the case of commercial banks, operational costs, market power, interest rate volatility, self-service channels (electronic payments and mobile banking transactions), credit risk and financial structure indicators are the most influential factors. As for Islamic banks the main determinants are size, risk weighted assets, and non-Murabahah (Islamic contract law) financing conditions. Additionally, they find that none of the macroeconomic nor capital structure indicators seem to explain differences in profitability between Islamic and commercial banks. However, they suggest that there is a possibility for Islamic banks to improve their profitability by providing self-service banking channels to their clients. Azad et al. (2019) examine the lending activities (measured by a loan-to-deposit ratio) and non-lending activities (measured by a non-interest income ratio), as potential factors in predicting the profitability of commercial and Islamic banks. They conclude that Islamic banks, unlike commercial banks, rely heavily on non-interest income rather than gains from loans, in order to increase their profitability.

Despite all the information we have regarding bank profitability as it relates to the GFC, literature on such a topic during the pandemic is quite sparse. Most of the extant studies have focused on one specific market or business model. In the case of the U.S. banking system, Li et al. (2021) have explored the relationship between revenue diversification, profitability, and risk in U.S. commercial banks. They find that revenue diversification is positively related to bank profitability, while it negatively affects bank risk. They argue that these results are in line with the substantial benefits gained from revenue diversification during the period when the pandemic was growing rapidly and greatly affecting the financial markets. Elnahass et al. (2021) examine the performance and stability of the international banking industry during the pandemic. They find that the pandemic significantly reduced both financial stability and performance of global banking. They also observe that the pandemic had an heterogenous impact on Islamic banks compared to commercial banks. Additionally, their analysis shows that larger and older banks exhibited less profitability during the pandemic, while leverage and auditing service indicators have a significantly positive impact on bank profitability.

Other studies investigate the impact of the pandemic on banks' market performance. Mirzaei et al. (2022) examine the impact of the pandemic on the performance of both commercial and Islamic banks. They find that the pre-pandemic efficiency level is a key factor in explaining ex-post returns for Islamic and commercial banks. They also find that bank size, market risk, non-interest income and credit risk play a significant role in predicting bank profits during the pandemic, while bank capital/liquidity structures and stability play a more limited role. Demirguc-Kunt et al. (2021) emphasize the negative effects of the pandemic on banking industry performance. They find that the health crisis reduced bank stock returns, particularly in larger, public and better capitalized banks. They also find pre-pandemic liquidity as a main factor in explaining a bank´s stock market performance. Additionally, they show that market performance has a positive influence and exhibits unusual profits to government policy mandates, especially when it comes to borrower assistance and liquidity support; however monetary policy plays a limited role in enhancing a bank´s overall market performance. Demir and Danisman (2021) find that pre-pandemic liquidity, capital adequacy, credit risk, non-interest income sources and size are the key factors predicting bank market performance during the pandemic. They also show government policy positively affects bank market performance, particularly through income support and debt-relief programs.

Some studies have examined the determinates of bank performance during the pandemic focussing on one developing or emerging market (e.g., Barua and Barua, 2021; Fajri et al., 2022; Katusiime, 2021). Other studies look at the effects of IT investments on bank profitability during the pandemic (e.g., Chen et al., 2021; Dadoukis et al., 2021). As documented by Dadoukis et al. (2021), the pre-pandemic IT adoption was the main factor in explaining U.S. bank profitability during the Covid-19. In particular, banks with higher IT adoption rates experienced higher profits during the pandemic, either in market or accounting performance.

Methodologically, previous studies are mainly based on parametric regression models. We contribute to the existing literature by applying a different approach by using machine learning to discover the patterns driving the profitability of the global banking industry. We also use this advanced technique to discover the profit drivers in alternative banking systems.

4.3. Data

Our dataset consists of a large number of publicly listed banks in 59 different markets, which we obtained from the Bureau van Dijk database. In our empirical analysis, we look at different banking systems, both commercial and Islamic. We select only fully-fledged Islamic banks, excluding any commercial banks with an Islamic window. We limit our attention only to publicly traded banks in order to extract the bank stock prices (Demirguc-Kunt et al., 2021; Mirzae et al., 2022; Sharif et al., 2020). The final sample is comprised of 583 banks. Out of those, 520 are commercial, while the remaining 63 are Islamic.

We feed the machine learning algorithm with a large set of factors that previous studies have identified as having a potential influence on bank profitability, in both normal and more stressful periods, across various banking systems. The factors we select are as follows: market power, bank soundness, revenue mix, funding and liquidity structures, capital adequacy, risk-taking, credit risk, efficiency, bank size, bank opportunity costs and stock market performance. We collect the financial data from the reported accounting statements of the banks during 2018–2020. Stock market performance is measured collected for individual banks on both a yearly and quarterly basis. We extract the data from December 31, 2018, to March 31, 2020, in order to cover both pre-pandemic and pandemic periods. We also feed the machine learning algorithm with macroeconomic factors that could explain bank profitability, as determined by the World Development Indicators (WDI) database.

4.4. Methodology

4.4.1. Machine learning technique

To explore the factors that drive bank profitability in both the pre-pandemic and pandemic periods, as well as in alternative banking systems, we apply a hybrid machine learning approach. Delen and Zolbanin (2018) argue that advanced analytics methods, including machine learning tools, can supplement traditional methods and can account for complex and non-linear issues. Several studies have documented the advantages of machine learning techniques over traditional statistical methods in financial analyses (e.g., Alessi and Detken, 2018; Casabianca et al., 2022; Suss and Treitel, 2019). As demonstrated by Gu et al. (2020), economic gains from a machine learning approach are impressive. They find a clear statistical rejection of traditional measurement tools in favour of machine learning methods in terms of identifying factors driving stock market returns.

More specifically, we apply a machine learning approach based on a random forest. This approach is an ensemble machine learning algorithm that consists of multiple decision trees in which each tree in the forest is unique, but shares the same distribution (Breiman, 2001). In the context of bank profitability, machine learning can highlight the importance of several financial factors that have been emphasized in the literature regarding bank profitability. The majority of earlier studies used well-known traditional statistical techniques to explain the main drivers influencing bank profitability (Detragiache et al., 2018; Lee and Hsieh, 2013; Tran et al., 2016). Our choice to implement this methodology rather than more traditional methods is based on its unique ability to analyze a wide range of highly correlated potential factors, allowing for the study of nonlinear relationships between features and target variables. This permits the use of uncommon factors not previously seen in existing literature and provides the ability to account for overlap, as is the case when a large number of features are employed. As such, the random forest algorithm is built upon the following steps: (1) a random forest regressor grows many trees using bootstrap samples. Bootstrap samples are created by sampling with replacements from the original dataset, (2) at each split of the tree, the special feature of a random forest regressor selects only p out of P total predictors, (3) each tree is grown to the point where it cannot split the data any further, and (4) once all the trees can no longer split any further, the random forest predictions from these trees are averaged across all decision trees (Breiman, 2001).

4.4.2. Empirical strategies and variables measurements

Our analysis is based on a five-stage approach using the random forest technique. For simplicity, as each one has differing empirical approaches, and to some extent, different features and dummies, we provide a detailed model equation for each. In the first stage, we explore the factors that drive global banking profitability (commercial and Islamic banks) for two timeframes: the pre-pandemic and pandemic periods. At this stage, we do not include all the variables as there are some that are irrelevant to this case and have an insignificant contribution. This regression analysis is structured as the following equation:

$$P_{i,t} = X_{\text{(Whole Periods)}\ i,t} + Y_{\text{(Whole Periods)}\ i,\,t} \quad (1)$$

Where *(P)* is the return-on-assets metric for bank *i* in year $_{t}$, *(X)* represents several financial indicators ($X^1,\ldots,X^b$) at the end of each year (2018-2020), and *(Y)* is a vector of macroeconomic indicators ($Y^1,\ldots,Y^p$).

In the second stage, we examine the determinants of global banking profitability (commercial and Islamic banks) just for the pre-pandemic period. At this stage, we employ stock market performance indicators to explore whether bank stock market performance influences its profitability. This regression structure is defined as the following equation:

$$P_{i,\,t} = X_{\text{(pre-pandemic period)}\ i,\,t} + Y_{\text{(pre-pandemic period)}\ i,\,t} \quad (2)$$

Where (P) is the return-on-assets metric for bank i in year t, (X) is a vector of financial indicators ($X^1,\ldots,X^p$) at the end of each year (2018 and 2019), and (Y) is a vector of macroeconomic indicators ($Y^1,\ldots,Y^d$).

In the third stage, we explore the drivers of bank profitability for both commercial and Islamic banks during the pandemic period. The regression structure in this case is defined as the following equation:

$$P_{i,t} = X_{\text{(pandemic period) } i,t} + Y_{\text{(pandemic period) } i,\, t} \quad (3)$$

Where (P) is the return-on-assets metric for bank i in year t, (X) represents several types of bank financial indicators $(Y^1,\ldots,Y^p)$ at the end of 2020, and (Y) is a vector of macroeconomic indicators $(Y1,\ldots,Yp)$.

In the fourth stage, we examine only the drivers of commercial bank profitability for two periods: pre-pandemic and pandemic. The regression structure in this case is defined as the following equation:

$$P_{i,t} = \textit{commercial banks}_{\,i,\,t} + X_{\text{(Whole Periods) } i,t} + Y_{\text{(Whole Periods) } i,\, t} \quad (4)$$

Where (P) is the return-on-assets metric for bank i in year $_t$, *Commercial banks* is a dummy variable that takes on the value of 1 if bank i is commercial, and 0 otherwise, (X) represents several types of bank financial indicators $(X^1,\ldots,X^p)$ at the end of each year (2018-2020) and (Y) is a vector of macroeconomic indicators $(Y^1,\ldots,Y^p)$.

In the last stage, we follow steps similar to stage four, but only for Islamic banks. This regression analysis is structured as the following equation:

$$P_{i,t} = \textit{Islamic banks}_{\,i,\,t} + X_{\text{(Whole Periods) } i,t} + Y_{\text{(Whole Periods) } i,\, t} \quad (5)$$

Where (P) is the return-on-assets metric for bank i in year $_t$, *Islamic banks* is a dummy variable that takes on the value of 1 if bank i is Islamic, and 0 otherwise, (X) represents several types of bank financial indicators $(X^1,\ldots,X^p)$ at the end of each year (2018-2020), and (Y) is a vector of macroeconomic indicators $(Y^1,\ldots,Y^p)$.

In our empirical analysis, we employ accounting-based, market-based and risk-based indicators. We measure bank profitability by the return-on-assets metric. Following Beck et al. (2013), we do not use the net interest margin (NIM) as an alternative metric of bank profitability since *Sharia* law prohibits the use of interest. As for bank-specific financial variables, we calculate the soundness of banks by adding the return on average assets to the equity-to-assets ratios, then divide by the volatility of return on average assets over a three-year window. As for the market risk, we calculate the volatility of a stock against the volatility of the market over a three-year window. We calculate the stock market performance indicators by using the change-in-log stock returns from Dec 31, 2018, to Dec 31, 2019, to account for the pre-pandemic period. As for the pandemic period, we employ two measures. Initially, we compute SMP1 measured as the log returns from Dec 31, 2019, to Mar 31, 2020. Additionally, for the purposes of robustness testing, we compute SMP2 measured as the log returns from the average closing prices from November 30, 2019, and December 31, 2019, to February 28, 2020, and March 31, 2020. As for the revenue mix, we use the ratio of non-interest income to operating revenue. We also divided the net fees and commission-to-operating income. Regarding bank funding structure, we use four different indicators. Specifically, we measure funding fragility by dividing customer deposits over total liabilities. We also divide customer deposits over total assets, and both long-term funding and short-term funding are divided over total debt. The indicators used for measuring credit risk are loan loss reserves to gross loans and non-performing loans to gross loans. We implement total-equity-to-total-assets, total capital (Tier1+Tier2) and tangible equity ratios to account for capital adequacy. As for the liquidity structure, we employ the ratio of total liquid assets to total deposits, short-term funding and total liquid assets to total assets ratio, and total loans to total assets ratio. As for efficiency, we use cost-to-income ratio, and we also divide total bank operating expenses by total assets. Finally, we compute the natural logarithm of total bank assets in order to account for bank size, we measure market power as the ratio of market capitalization to total assets and calculate bank opportunity costs by dividing total fixed assets over total assets.

4.5. Results

By using a machine learning algorithm, we are able to identify the features with the greatest predictive power in driving bank profitability. To do so, two important measures are implemented: the mean decrease in accuracy (MDA) and the mean decrease in Gini (MDG). The mean decrease in accuracy is a score estimated during the construction of the decision trees and it reflects the mean decrease in the model accuracy, if we leave out a predictor from the model. Therefore, the predictor with the greatest mean decrease is the most relevant for explaining bank profitability. As for mean decrease in Gini, a score provides information about each predictor´s contribution to the homogeneity of the nodes and leaves in the resulting random forest model. To measure the performance of the random forest algorithm for each approach, we use the out-of-bag (OOB) prediction accuracy score. The percentage of correct predictions is high in all empirical approaches: 95% (global banking profitability in pre-pandemic and pandemic periods), 94% (global banking profitability during pre-pandemic period), 93% (global banking profitability during the pandemic period), 93% (Islamic bank profitability in pre-pandemic and pandemic periods) and 94% (commercial bank profitability in pre-pandemic and pandemic periods).

In the interest of simplicity, the figures with the MDA and MDG can be found in the Appendix. As shown in Figures 4.1. through 4.5., the predictors are listed on the y-axis from most important (top) to least important (bottom), while their relative statistical importance is outlined on the x-axis. Figure 4.1. offers the results for the overall sample in all periods. The machine learning algorithm shows that the first five predictors (out of 27) that have the greatest predictive power in driving profitability in both pre-pandemic and pandemic periods are bank efficiency, bank soundness, liquidity structure, capital adequacy and bank size. We observe that the cost-to-income and overhead cost ratios have the largest predictive power. The MDA suggests these two factors alone improve predictions by 25.51% and 23.57%, respectively. It is also interesting to note that efficiency indicators have almost twice as much predictive power in assessing bank profitability than the second-best predictor. This appears to suggest that the level of bank profitability is significantly driven by a bank´s ability to control and screen its operational costs. In addition, as we measured bank efficiency by cost-to-income and overhead cost ratios, more conservative investment portfolios also play a significant role in driving bank profitability. This finding is consistent with previous evidence and falls in line with the theoretical approach to the relationship between bank efficiency and profitability (e.g., Kosmidou, 2008; Peltzman, 1977; Petria et al., 2015; Xu et al., 2019). Furthermore, we observe that bank soundness as an indicator for insolvency risk places third among all features and improves the model predictions by 14.89%. Our calculation for the insolvency risk considers the summation of bank capitalization and ROAA, along with the volatility of ROAA, which tends to be one of the main influencing factors in bank profitability. As discussed by Beck et al. (2013), the level of insolvency risk plays a significant role in return volatility. As for capital adequacy indicators, two out of three take fourth and sixth places among all predictors (tangible equity and equity-to-assets ratios). They improve model predictions by 13.10 % and 14.26 %, respectively. However, total capital ratio also takes eighth place (out of 27) and improves the model predictions by 7.98%. These results appear to suggest that risk-taking by banks to comply with regulatory mandates has an important impact on bank profitability, which supports the findings in previous studies (e.g., Detragiache et al., 2018; Lee and Hsieh, 2013). As for bank liquidity, liquid assets-to-total-assets as well as total loans-to-total-assets ratios have higher predictive power in driving profitability both during the pre-pandemic and pandemic periods, while there seems to be no significant predictive power in terms of the liquid assets-to-total deposits and short-term funding ratio. In line with Bordeleau and Graham (2010), these findings suggest that the amount of liquid assets and loans issued (generally because they have a low return) play an important role in imposing opportunity cost, which in turn may influence the overall profitability of a bank. Additionally, the algorithm also reveals that the size of the bank is a contributing factor in predicting its profitability. Surprisingly, however, it is important to note that the algorithm indicates that none of the macroeconomic indicators have a substantial predictive power over other factors. Non-traditional bank activities play a secondary role in predicting profitability, as they are among the top ten determining factors, while funding structure and credit risk indicators are not found to be significant drivers of profitability, either in MDA or MDG metrics.

Unlike typical baseline analyses, we have the advantage to be able to train the machine learning algorithm using data from the pre-pandemic period. Inputting data from 2018 and 2019, we exclude the dataset that encompasses pandemic implications. We also feed the machine learning algorithm with a new indicator that captures the stock market performance of each bank in the sample group. As shown in Figure 4.2., both MDA and MDG metrics almost agreed on what were the greatest predictors of bank profitability pre-pandemic. The algorithm suggests that bank efficiency, soundness, size, liquidity, and capital structure indicators are the key features, and whose order remains almost unchanged compared to the baseline analysis. Similarly, macroeconomic, funding structure and credit risk indicators are found to have a limited role in driving bank profitability in the years leading up the pandemic. Additionally, the algorithm reveals that the pre-pandemic stock market indicators are not among the main predictors.

We further train the machine learning algorithm using information from just a single year (2020) in order to identify the adverse impact of the pandemic. We feed the algorithm with two additional indicators for bank stock market performance. As expected, because the sample is decidedly skewed toward one year only, the relative statistical importance of such features is to some extent relatively lower than in previous analyses. As depicted in Figure 4.3., the algorithm shows that the main factors influencing bank profitability during the pandemic are the identical set of factors that explain profitability in the pre-pandemic period. We find bank efficiency, soundness, size, liquidity, and capital structure are the most relevant predictors. Again, macroeconomic indicators play a limited role in driving bank profitability.

As previously mentioned, we aim to obtain as much information as possible on the potential drivers of bank profitability in both pre-pandemic and pandemic periods. We train the machine learning using data for each bank type. As we cannot combine Islamic or commercial banks before and during the pandemic due to data limitations, we include a broader timeframe in our analysis. As shown in Figure 4.4., the algorithm reveals that the top factors influencing Islamic banks' profitability are efficiency, the revenue mix, market power, funding and liquidity structure, soundness, and size. The cost-to-income ratio takes first place based on MDA and MDG metrics and improves model predictions by 16%. As discussed by Beck et al. (2013), the lower agency problems faced by Islamic banks due to prohibitions on risk shifting and over-dependence on risk-sharing, do indeed lead to gains while they simultaneously decrease monitoring and screening costs. Non-interest income takes second place among all predictors. Not surprisingly, Islamic banks depend heavily on such non-traditional banking activities in order to cover the income loss from lack of interest due to Sharia law. This supports earlier findings of (Azad et al., 2019) who find that Islamic banks, when compared to commercial banks, have a greater reliance on non-interest income to raise their profitability as opposed to a dependence on loans, when measured by a loan-to-deposit ratio. Another important determinant in driving Islamic banks' profitability is market power. We also find long term funding is a key factor in driving Islamic bank profitability. However, the algorithm suggests that capital, liquidity, and size also contribute significantly to predict Islamic banks' profitability.

Figure 4.5. offers the results for the commercial banks. The machine learning algorithm suggests that, unlike Islamic banking, revenue mix, funding structure and market power all play a limited role in explaining commercial bank profitability, while indicators related to bank efficiency, liquidity and capital structure, stability and size are the most important predictors in the periods leading up to and during pandemic. In conclusion, this difference in the determinants of profitability between commercial and Islamic banks during pre-pandemic and pandemic periods implies that the core profitability of these distinct business models relies on a set of unique dynamics, which is consistent with the conclusions of Yanikkaya et al. (2018).

4.6. Conclusion

This study aims to explore the most important potential factors influencing global banking profitability. We apply a hybrid machine learning-based random forest over different timeframes, as well as over alternative banking systems. Specifically, we identify the most important factors in driving global banking profitability in all periods examined (2018-2020), as well as in the periods before and during the pandemic. We also apply an algorithm to compare the most important factors in explaining the profitability of Islamic and commercial banks.

The algorithm provided predictions in all empirical approaches with accuracy over 93%. As far as the pandemic period is concerned, the algorithm identifies soundness, efficiency, total loans, liquidity and capital structures, and size to be the most important factors in driving bank profitability. We find similar drivers of bank profitability in the pre-pandemic period, except in the total amount of loans issued. Additionally, the algorithm reveals that the profitability of both and banks is determined by a distinct set of dynamics. The profitability of Islamic banks is driven by their soundness, revenue mix, market power, funding structure, efficiency, liquidity, capital structure and size. In the case of commercial banks, the algorithm demonstrates that soundness, efficiency, liquidity, capital adequacy and size have the highest predictive power in terms of profitability. Notably, none of the macroeconomic, credit risk or stock market indicators are identified as strong predictors of profitability in any of the empirical approaches.

Our study has important policy implications. It provides an examination of the different determining factors between the two banking systems where some of the usual suspects (macroeconomic performance or credit risk) do not turn out to be relevant predictors. Additionally, we show that different bank models (commercial vs. Islamic) are affected ty different profitability-building factors.

Yet, our empirical analysis is admittedly limited as it only covers the periods before and during the pandemic. We strongly believe further studies examining the drivers behind bank profitability should be broadened in scope to include a more extensive post-pandemic period, as there is evidence confirming signs of recovery in bank profits for the second quarter of 2021. Furthermore, including other factors related to governance structures and macroeconomic variables could provide additional and useful evidence to understand more holistically the mechanisms behind a bank´s ability to improve profits.

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Appendix

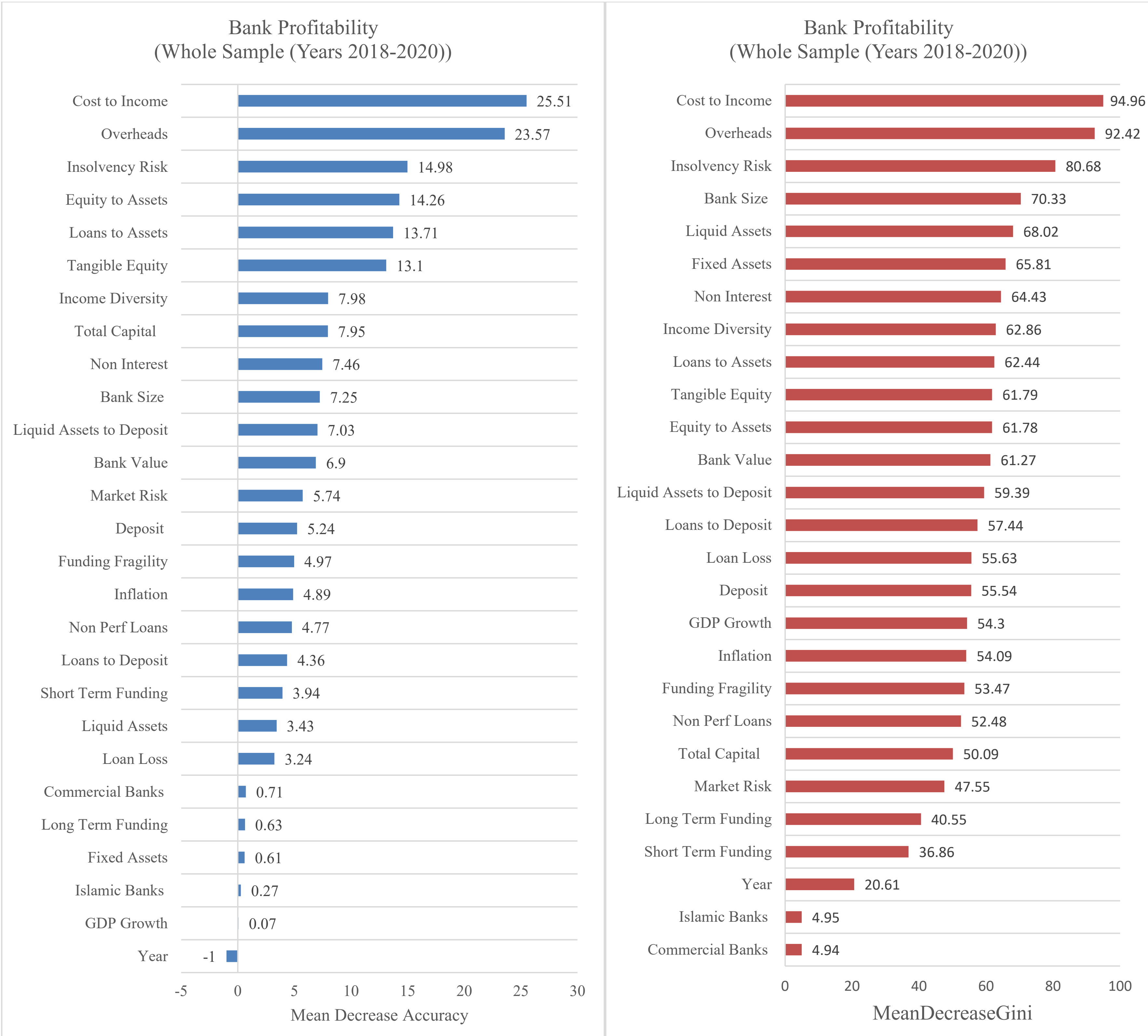

Fig 4.1. Variable importance for the random forest model on global banking industry-All years. The OOB score is 95%.

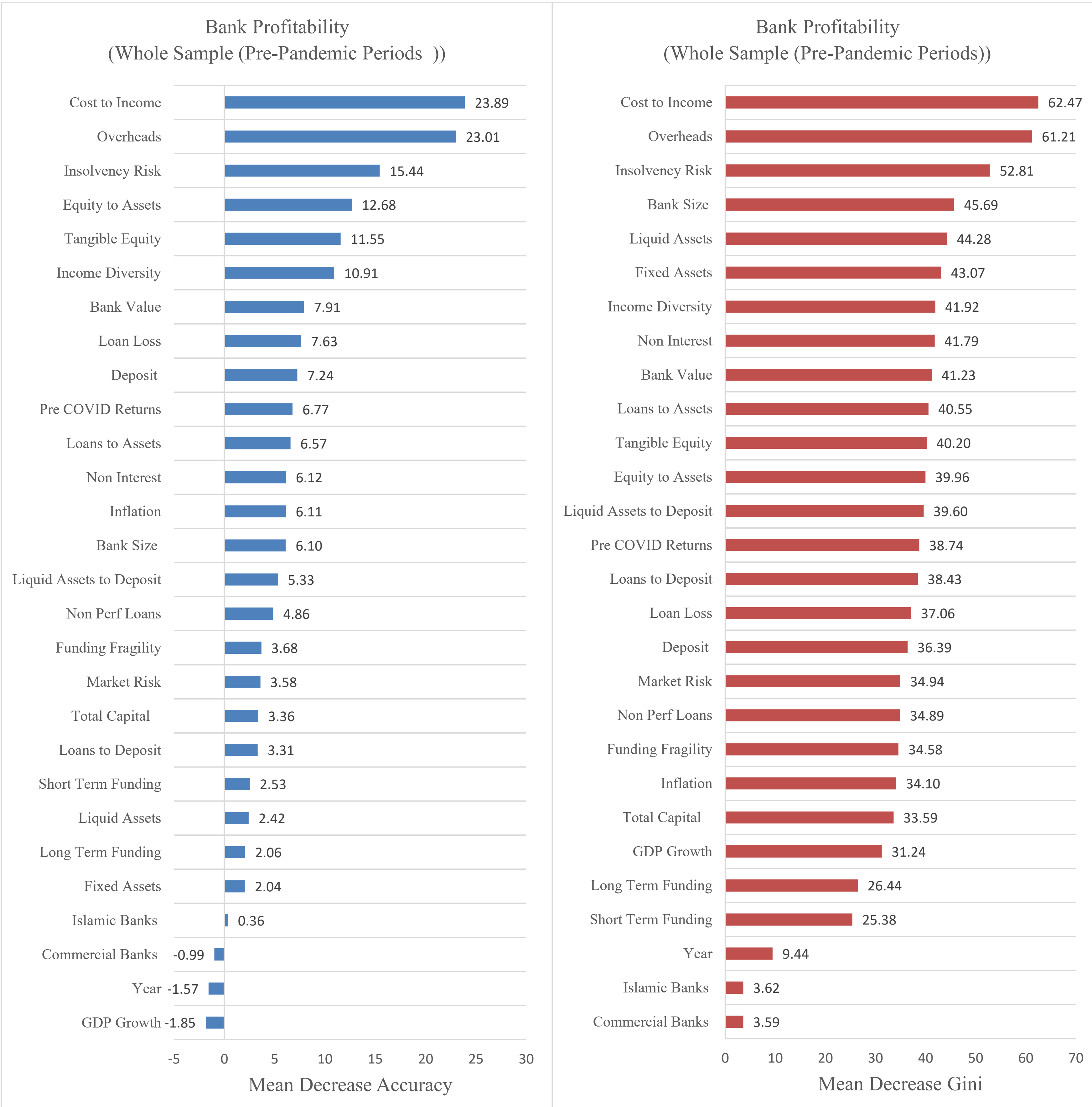

Fig 4.2. Variable importance for the random forest model on global banking industry: Pre-Pandemic periods. The OOB is 94%.

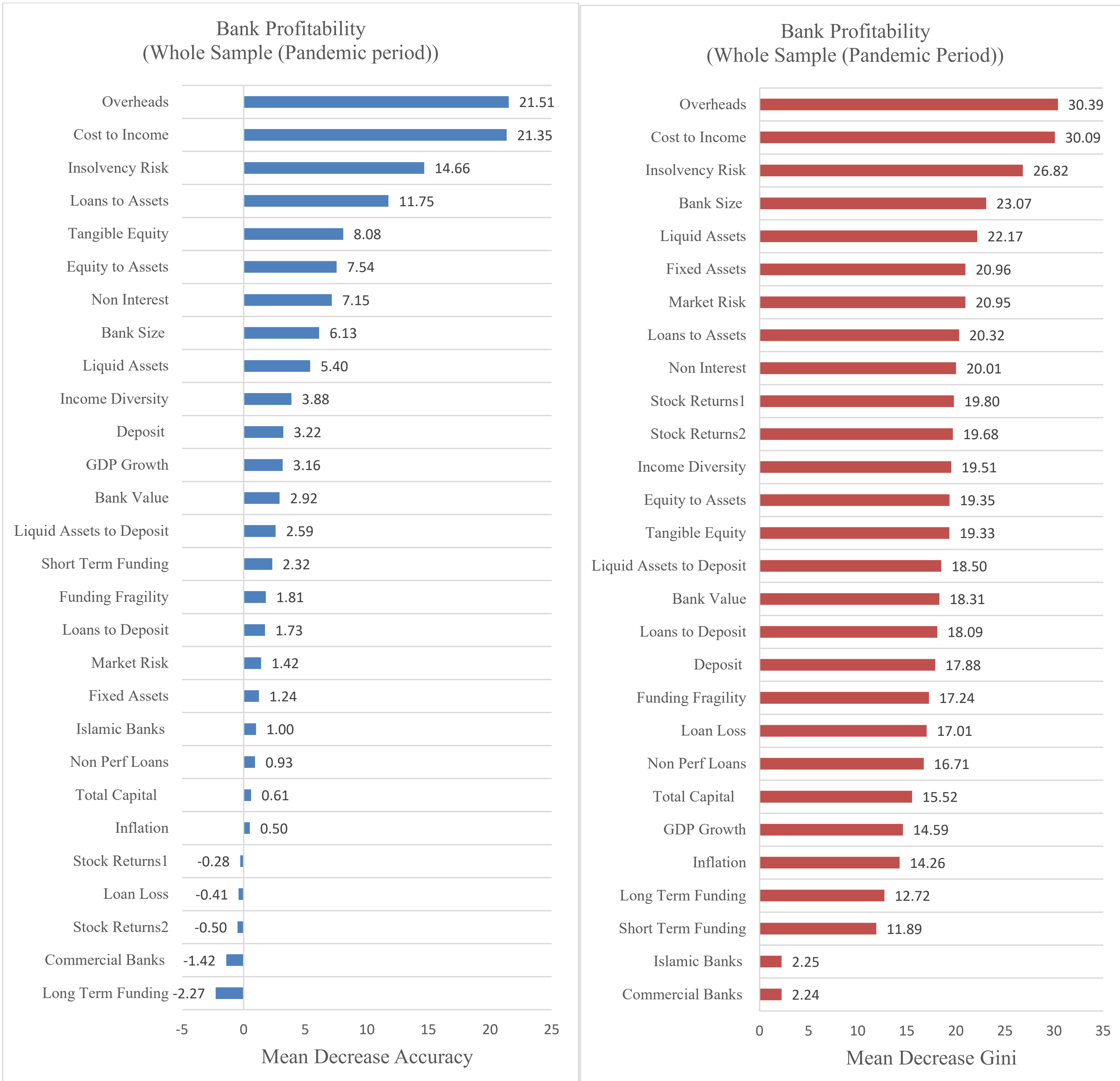

Fig 4.3. Variable importance for the random forest model on global banking industry: Pandemic period. The OOB is 93%.

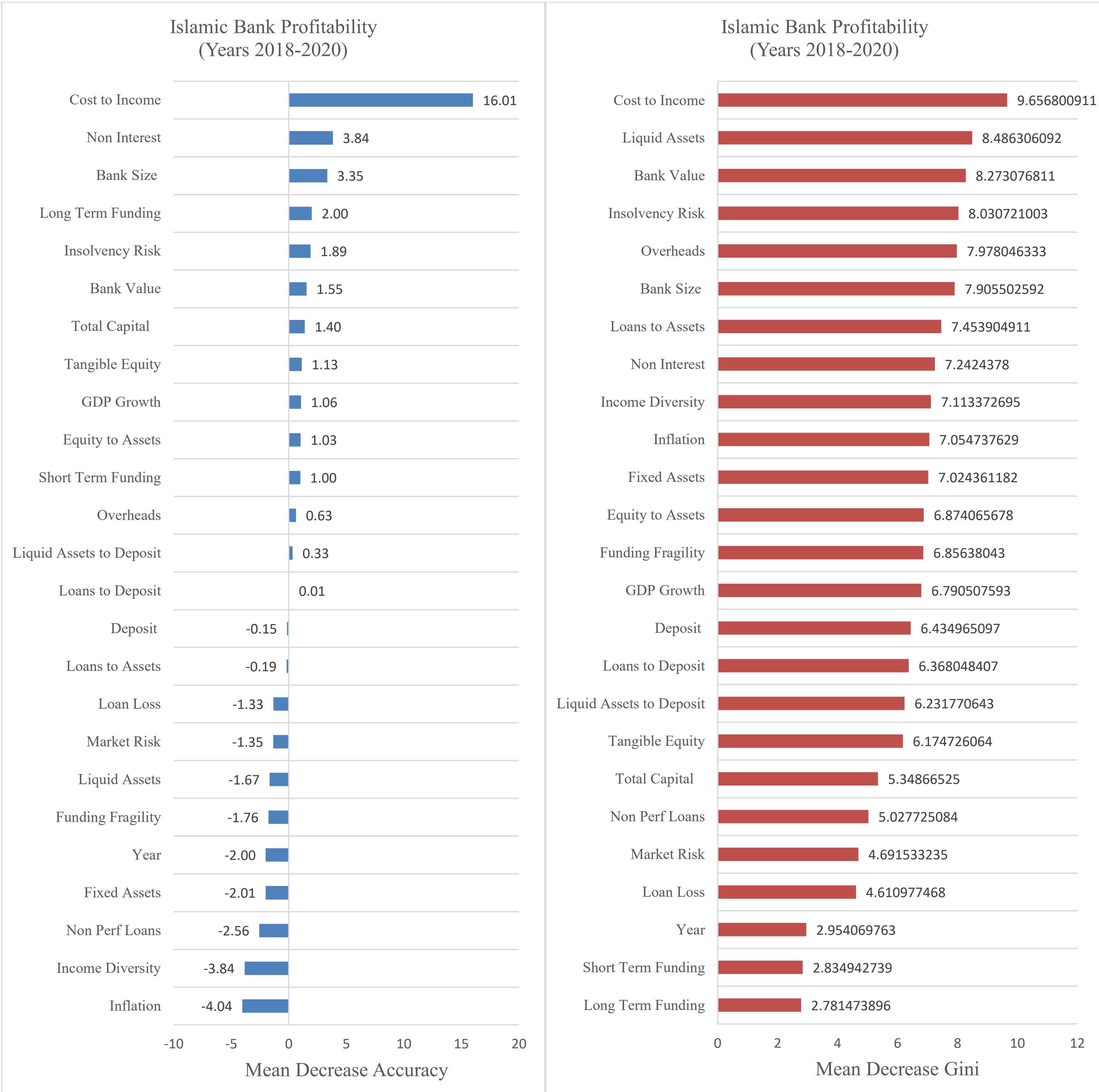

Fig 4.4. Variable importance for the random forest model on Islamic banking industry: All Years. The OOB is 93%.

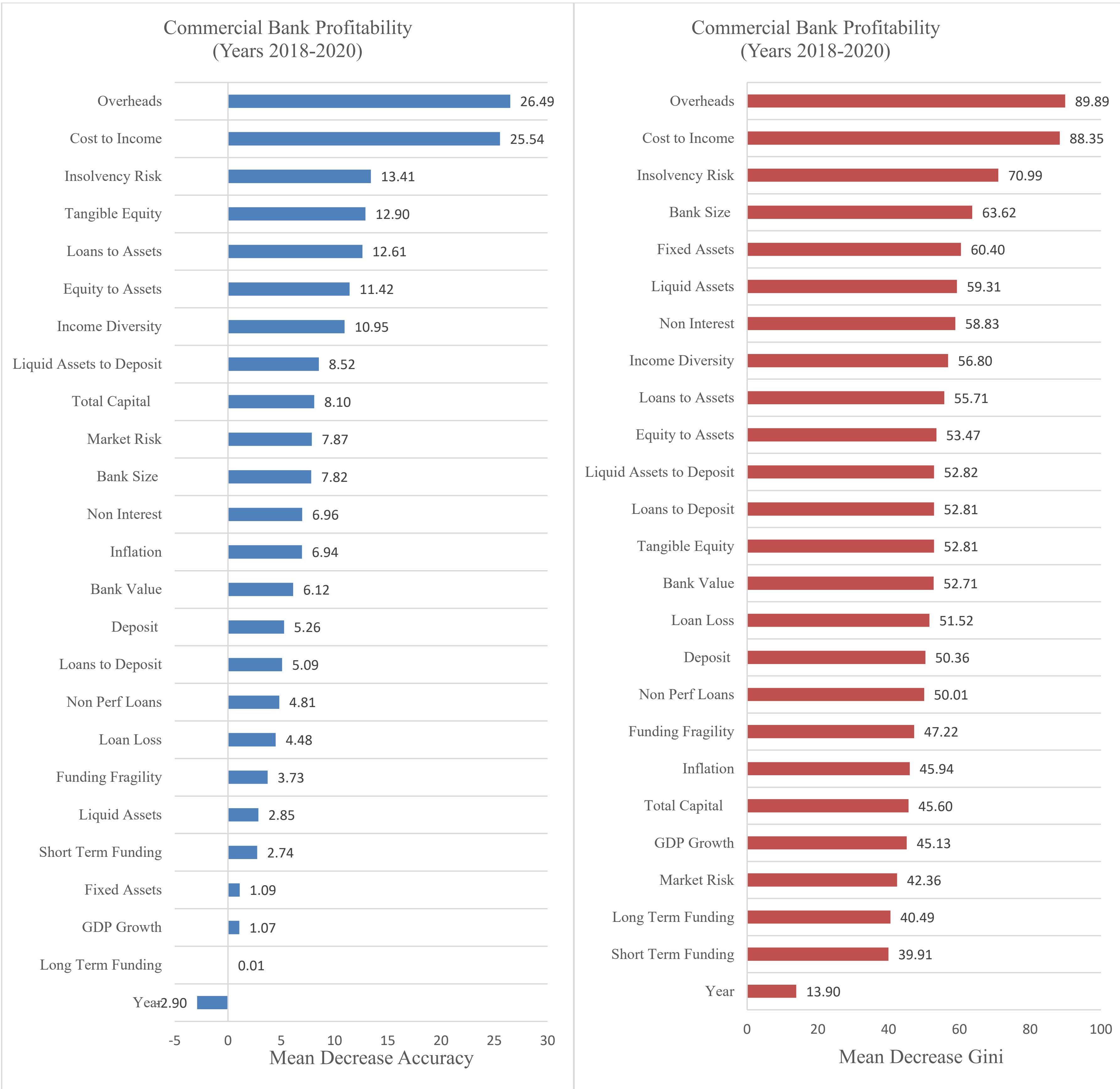

Fig 4.5. Variable importance for the random forest model on commercial banking industry: All Years. The OOB is 94%.

CHAPTER 5

Conclusions and Future Research Directions

5.1. Conclusion

This doctoral dissertation investigates various topics within the areas of corporate finance and the financial capital market. The first study (Chapter 2) examines the underlying forces behind the issuance of contingent convertible instruments (CoCos) and their impact on the quality of the issuer's assets. The second investigation (Chapter 3) explores the impact of the coronavirus pandemic on the performance of the global banking industry and its financial stability, comparing performance between commercial and Islamic banks. The third paper (Chapter 4) describes a hybrid machine learning-based random forest process designed to explore the most important potential factors influencing global banking profitability over different timeframes, as well as in alternative banking systems.

More specifically, the second chapter examines two issues associated with contingent convertible instruments (CoCos). Firstly, the study explores whether banks with riskier assets coupled with lower (regulatory and nonregulatory) liquidity and solvency are more inclined to issue CoCos. Secondly, it examines the impact of CoCos on the quality of the issuer's assets. Previous works failed to explore whether liquidity regulation is regarded as a main motivator in CoCo issuance, as well neglecting to examine the impact of these instruments on the quality of assets. For our investigation, we used a logit model, univariate analysis, and applied fixed effects regression on a sample of 413 banks across 16 European markets (92 banks have issued CoCos from 2011 to 2018). In the analysis we used 158 CoCos issuances. Out of a total of 158 issuances, we found 112 issuances with temporary and permanent write-down loss absorption mechanisms and 46 issuances with a conversion-to-equity loss absorption mechanism. Additionally, there were 99 CoCos issuances with a low trigger level (equal to 5.125%) and 59 issuances with a higher trigger level (above 5.125%). The results show that only regulatory liquidity drivers are factors in the issuance of CoCos in European banks. As of nonregulatory liquidity, the results fail to indicate any evidence suggesting that banks with lower nonregulatory liquidity ratios are more likely to issue CoCos. The study also finds that profitable and large banks, and those with lower capital and risk, are more inclined to issue CoCos. Furthermore, more capitalized banks holding lower regulatory liquidity are also more likely to issue CoCos. Additionally, the findings show that the issuance of CoCos have no significant impact on the quality of the issuer's assets. As for the type of type of loss absorption mechanism applied, neither write-down CoCos nor conversion-to-equity CoCos play a role in changing a bank´s risk after their issuance.

The third chapter aims to measure the impact of the COVID-19 crisis (a non-financially related "shock") on the performance and financial stability of the global banking industry. This section also explores whether there are differences in the performance and financial stability of commercial and Islamic banks both before and during the pandemic, as well as in the early recovery period. Empirically, the paper contributes to the literature on financial and non-financial crises, as well as to the body of work studying the alternative banking system in terms of its performance on the international stock market, especially in terms of the determinants of profitability in the early post-pandemic period. Additionally, it explores the differences between commercial and Islamic banks and their non-traditional banking activities, funding structure, profitability, credit risk, market, and insolvency risks before and during the pandemic, as well as in the early post-pandemic period. Ordinary least squares regression (OLS) and univariate statistics analysis (t-test P-value) were employed on a sample of 583 banks across 59 markets (520 commercial banks, 63 Islamic) using both yearly and quarterly data. The results show that while stock market performance of both bank groups was negatively affected during the pandemic, the stock market returns for Islamic banks were higher than their commercial counterparts. In contrast, commercial banks experienced higher returns than Islamic in both the pre-pandemic and early post-pandemic periods. Furthermore, the results indicate that banks with lower insolvency and market risks, relied heavily on non-traditional banking activities. In addition, those banks with higher liquidity and stock market returns during the period leading up pandemic showed better stock market performance during the pandemic period. The findings show that commercial banks outperform Islamic banks in terms of efficiency structure, higher asset quality and lower insolvency risk. As for Islamic banks, they performed better in terms of capital structure, profitability and securing long-term funding, and were more apt to employ and non-traditional banking activities.

The fourth chapter describes an applied hybrid machine learning-based random forest created to explain the main driving factors behind global banking profitability in different time periods, as well as in alternative banking systems. In particular, two measures were implemented: the mean decrease in accuracy (MDA) and the mean decrease in Gini (MDG). Methodologically, previous studies have used traditional statistical methods to examine the determinates of bank profitability. This is the first study to use a machine learning technique to uncover the main driving factors of global banking profitability in the pre-pandemic and pandemic periods, as well as in alternative banking systems (commercial and Islamic). The algorithm predicts over 93% of the drivers of bank profitability in all empirical approaches. Also, the algorithm reveals that bank profitability during the pandemic period can be explained by the number of total loans issued, insolvency risk, liquidity and capital structure, and efficiency. It also reveals that these drivers in the years leading up the pandemic, with the exception of the total amount of loans issued. Furthermore, the findings show that the profitability drivers for Islamic and commercial banks are distinct. Islamic bank profitability is explained by insolvency risk, non-traditional banking activities, liquidity and funding structures, capital structure, size, market power and efficiency. As for commercial banks, the algorithm shows that insolvency risk, efficiency, liquidity, capital adequacy, and size are the most important factors behind commercial bank profitability. However, none of the macroeconomic factors, credit risk or stock market indicators are shown to be accurate predictors of profitability in all empirical approaches applied.

5.2. Future Research Directions

The global financial system has experienced dramatic changes over the last few years that may have a significant impact on the overall financial stability. As such, many research avenues that should be opened. Regarding potential thesis topics, contingent convertible interments (CoCos) are relatively new to the field and possess very unique features that elicit further studies to examine their impact on the overall financial system in times of stress, explore the drivers behind their issuance both in times of financial stress and normalcy. Since these instruments could be qualified as T1 and T2 capital instruments, more attention should be paid to the impact of both ATI and Tier 2 CoCos on liquidity regulation, particularly on the Net Stable Funding ratio (NSF). Furthermore, more in-depth analyses regarding the impact of CoCos issuance at times of trigger breaches may provide further insight into the topic.

It has been observed that the business model type of a financial institution could play an important role in providing flexibility during times of stress. The features related to Sharia-compliant financial products in Islamic banking industry are a good example. In this regard, further investigation is needed on how the differences in the governance mechanism between different bank business models plays a role, especially as they relate to commercial and Islamic bank performance and financial stability during the recent non-financial global health crisis. Additionally, more light should be shone on the role macroeconomic factors, such as monetary policy, have in the performance and financial stability of alternative banking systems, both listed and non-listed, during the recent COVID crisis.