Liquidity, Size, and Regulatory Design in Banking: Consolidation Dynamics and Performance under Basel III

A Dissertation Submitted in Partial Fulfilment of the Requirements for the Degree of Doctor of Philosophy

by

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Declaration

I hereby declare that this thesis is my own original work and has not been submitted elsewhere for any degree or qualification. All sources of information have been duly acknowledged.

Faiza Asad Date

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Abstract

This dissertation examines how liquidity and size shape banks' responses to two defining post-crisis forces: mergers and acquisitions (M&A) and regulatory flexibility under Basel III.

Study 1 shows that stronger liquidity and larger size raise the likelihood of acquisition, as expected. Yet paradoxically, the weakest liquidity group—Large–Red banks—are the most acquisitive. This suggests that scale can override regulatory constraints, enabling fragile institutions to expand most aggressively. Post-merger outcomes confirm the divide: strong acquirers consolidate their advantages, while fragile ones fail to improve. Thus, M&A is not inherently stabilizing and may instead reinforce too-big-to-fail risks.

Study 2 analyzes how entry pressure, capitalization thresholds, enforcement, and insurance risk affect bank profitability (ROA), stability ($\ln Z$) and changes in the business model. The stability measure, $\ln Z$, captures the distance a bank from default by combining profitability, leverage, and earnings volatility, where higher values indicate greater resilience. The results show that competition increases profitability, structural funding supports stability, and enforcement mainly reflects risk-targeted supervision. Smaller banks shift back to traditional intermediation under entry pressure, while larger banks absorb regulatory burdens more easily. Taken together, the findings provide new evidence on how regulatory flexibility and balance sheet conditions jointly shape bank performance, stability, and strategic adaptation in the post-Basel III era.

Together, the studies highlight liquidity and size as organizing principles that condition both strategic consolidation and regulatory adaptation. The core conclusion is that resilience in modern banking does not arise from mergers or regulation in isolation, but from their interaction under the structural realities of liquidity and scale.

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Chapter 1

General Introduction

The 2008 global financial crisis reshaped the landscape of banking and financial regulation worldwide. It exposed vulnerabilities in banks' funding structures, revealed the systemic risks of excessive leverage, and highlighted the insufficiency of pre-crisis capital and liquidity frameworks (Brzoza-Brzezina et al., 2015; Brunnermeier, 2009; Shin, 2009). In response, international reforms under Basel III introduced new capital standards and, critically, the Net Stable Funding Ratio (NSFR) as a structural liquidity requirement designed to reduce dependence on short-term wholesale funding (King, 2013; Bonner and Hilbers, 2015; Chiaramonte and Casu, 2017). Alongside these rules, regulators increasingly embraced *regulatory flexibility*—a multi-dimensional approach encompassing competitive entry pressures, differential capitalization thresholds, supervisory enforcement intensity, and insurance-based risk mechanisms—to balance resilience with efficiency in diverse banking environments (Barth et al., 2004; Delis and Staikouras, 2011; Tsoumas, 2021). Together, these reforms created a dual system of hard constraints and adaptive levers, fundamentally altering how banks manage balance sheets and strategic choices.

At the same time, market-driven consolidation through mergers and acquisitions (M&A) remained a defining feature of banking systems. M&A offered banks a pathway to scale, efficiency, and market power, but its implications for post-merger performance and funding stability remained contested (Knapp et al., 2006; Cornett et al., 2006a; Focarelli et al., 2002). While efficiency arguments suggest consolidation may pool resources and strengthen liquidity, empirical evidence shows mixed results, with many acquirers failing to achieve improvements in post-merger performance. Against the backdrop of Basel III, these questions have become more pressing: do acquirers with stronger liquidity and larger size dominate consolidation activity, and do such mergers enhance structural funding resilience in the years that follow? Answering these questions requires considering not only strategic incentives but also the regulatory landscape that now places liquidity resilience at the center of stability.

In parallel, the expanded scope of regulatory flexibility raises further questions about how banks adjust profitability, stability, and business models under multiple, overlapping pressures. Entry by new competitors may erode margins but enhance efficiency. Capitalization requirements for entrants may shape contestability, while enforcement intensity may alter risk-taking. Additionally, insurance exposure may affect stability through moral hazard. While each dimension has been studied individually, the combined effects of these regulatory levers—and their interactions with bank size and NSFR conditions—remain underexplored in the empirical literature (Buch and Prieto, 2013; Ongena et al., 2015; Aiyar et al., 2014). As with consolidation, structural characteristics such as liquidity and size are likely to moderate how banks respond to these regulatory pressures.

1.1 Regulatory Framework Overview

The 2008 global financial crisis exposed how thin liquidity buffers and fragile funding models could destabilize entire banking systems. In response, Basel III ushered in the most ambitious reforms since the Great Depression, with far-reaching rules for capital, liquidity, and systemic risk (Vousinas, 2015). These reforms combine two distinct but complementary approaches. On one hand, structural requirements such as the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR) impose binding constraints on balance sheets. On the other hand, new flexibility mechanisms—buffers, supervisory discretion, and differentiated thresholds—aim to account for institutional heterogeneity and mitigate pro-cyclicality (Baldwin and Wyplosz, 2012). Together, these reforms have reshaped how banks think about growth, consolidation, and performance, while also altering the regulatory calculus around stability and efficiency.

1.1.1 Structural Liquidity Requirements and NSFR

The NSFR, binding from 2018, requires banks to maintain stable funding equal to at least 100% of their required needs (Hlebik and Stránský, 2017). By directly targeting funding structures, it represents a decisive shift from earlier frameworks that focused narrowly on capital. Implementation pressures, however, have not been uniform. Deposit-rich banks found themselves at an advantage, while wholesale-funded institutions faced costly adjustments (Penczar et al., 2022). These differences have practical consequences: some banks can internalize compliance as part of their normal operations, while others face strategic choices, such as deleveraging or consolidating, to achieve compliance.

Size further amplifies these dynamics. Large banks benefit from economies of scale and market access (Fecht et al., 2012; Bassett and Berrospide, 2016), whereas mid-sized banks often struggle with disproportionate compliance costs. As a result, NSFR pressures have generated new incentives for M&A, with consolidation offering a potential pathway to optimize funding structures and reduce compliance burdens. Regulators themselves now explicitly evaluate proposed mergers not only for their competition implications but also for their liquidity implications. These institutional realities provide the foundation for Study 1, which examines how size and liquidity shape M&A decisions and post-merger funding stability.

1.1.2 Regulatory Flexibility and Adaptive Supervision

While the NSFR and similar rules establish hard constraints, Basel III also embeds a degree of flexibility. Countercyclical buffers, conservation rules, and supervisory discretion were designed to strike a balance between stability and adaptation (Calomiris and Mamaysky, 2019; Coffinet and Lin, 2017). Yet their effectiveness depends on institutional characteristics. Well-capitalized or liquid banks are better positioned to benefit, while weaker institutions often remain constrained (Couaillier and Reghezza, 2024). Moreover, flexibility interacts with structural requirements: banks close to binding NSFR thresholds may find little room to maneuver, while those comfortably above can exploit flexibility more fully.

The uneven distribution of benefits means that flexibility not only shapes outcomes in terms of profitability, stability, and diversification, but also amplifies differences across size and liquidity groups. This dynamic provides the empirical motivation for Study 2, which analyzes how regulatory flexibility translates into ROA, stability ($\ln Z$), and business-model choices under varying conditions of bank size and liquidity.

1.1.3 Integration and Relevance

The post-crisis regulatory environment is thus best understood as a dual system: binding structural rules on one side, adaptive mechanisms on the other. Both approaches converge on liquidity and size as key factors shaping whether banks absorb or leverage regulatory pressure. Study 1 focuses on the consolidation channel, examining whether M&A improves funding stability under NSFR constraints. Study 2 examines ongoing performance, analyzing how regulatory flexibility—entry conditions, capitalization, enforcement, and insurance exposure—affects profitability, stability, and diversification across heterogeneous banks.

Taken together, these studies demonstrate how structural constraints and supervisory discretion interact to shape banks' strategic choices and operational outcomes. By placing liquidity and size at the core of the analysis, the dissertation advances beyond fragmented assessments and offers a more integrated perspective on resilience in the post-crisis financial landscape.

1.2 Study 1: Liquidity, Size, and the Dynamics of Bank Mergers

Problem Statement. M&A has long been viewed as a strategic path to scale, efficiency, and competitive positioning. Yet, its implications for post-merger liquidity and funding stability remain contested. While efficiency arguments suggest consolidation should strengthen liquidity by pooling resources, empirical evidence shows that post-merger performance often fails to improve, raising doubts about stability benefits (Kyriazopoulos, 2015). A central research question is whether liquidity positions and bank size jointly determine both the likelihood of initiating M&A and the subsequent evolution of funding stability (NSFR) after consolidation.

Motivation. Post-crisis reforms placed liquidity resilience at the center of financial stability. However, the M&A literature has mainly focused on profitability and market power, leaving structural liquidity underexplored. Evidence shows that banks adjust their liability and asset portfolios in response to liquidity regulation (Penczar et al., 2022); however, the direct link between M&A events and funding stability outcomes remains insufficiently examined. Furthermore, the moderating role of size—whether large, liquid banks are most likely to acquire, or whether weaker banks gain more post-merger—requires systematic empirical testing.

Contribution. Study 1 advances the literature in three main ways:

1. It models acquisition likelihood with explicit size–liquidity interactions, thereby identifying which types of banks are most likely to drive consolidation.

2. It applies a difference-in-differences framework to trace post-merger changes in structural liquidity (NSFR), providing causal evidence on how mergers reshape funding stability.

3. It demonstrates the heterogeneous nature of post-merger outcomes: well-capitalized (Green) banks tend to consolidate their advantages, while weaker (Red) banks often fail to improve and, in some cases, deteriorate. This pattern underscores that regulatory requirements can exert differential impacts across bank characteristics.

Significance. This study extends the M&A literature by shifting the focus from profitability to liquidity as a key post-merger outcome, thereby linking consolidation research with prudential regulation debates. For policy, the findings emphasize that merger evaluation should account for funding stability alongside efficiency and competition. For practice, they provide guidance on when consolidation strengthens resilience and when alternative strategies may be more appropriate.

1.3 Study 2: Regulatory Flexibility and Bank Performance

Problem Statement. Banks also face evolving regulatory regimes that combine rule-based requirements with a degree of flexibility. Entry pressure, capitalization requirements for new entrants, supervisory enforcement intensity, and insurance risk jointly shape profitability, stability, and business models. Yet empirical studies often analyze these dimensions in isolation. The challenge is to understand how such forms of *regulatory flexibility* interact, and how their effects vary by bank size and liquidity positions (NSFR). Institutional theory suggests that flexible arrangements encourage innovative opportunities, while stability-oriented frameworks foster imitation, but banking-specific evidence remains scarce.

Motivation. While capital regulation and competition have been widely studied, less is known about the combined impact of regulatory levers. Evidence shows that countercyclical regulatory mechanisms can have complex effects on bank behavior and market stability (Neuner and Reitz, 2022; Coffinet and Lin, 2017). At the same time, regulatory approaches must balance multiple objectives, including financial stability, competition, and innovation. These debates motivate a multi-dimensional analysis of regulatory flexibility and its heterogeneous consequences for bank performance.

Contribution. Study 2 contributes by:

1. Integrating four dimensions of regulatory flexibility: entry pressure, capitalization thresholds, enforcement intensity, and insurance risk.
2. Testing their effects on profitability (ROA), stability ($\ln Z$), and diversification (non-interest income).
3. Identifying heterogeneity by size and NSFR, addressing concerns that uniform liquidity requirements may have differential effects across banking institutions.

Significance. For research purposes, the study operationalizes regulatory flexibility and empirically links it to multiple performance dimensions. For policy, it provides evidence on how regulatory design choices affect bank behavior and performance across different institutional characteristics. In practice, it informs banks on how to adapt their strategies to overlapping regulatory and market pressures.

1.4 Structure of the Thesis

The thesis is organized into four main chapters, supplemented by appendices.

Chapter 1 introduces the research background, problem statement, and motivation. It positions the two studies within the post-crisis banking landscape and outlines their respective contributions. The chapter highlights the central role of liquidity and size in both merger activity and regulatory flexibility, setting the stage for the empirical analyses.

Chapter 2 presents *Study 1: Liquidity, Size, and the Dynamics of Bank Mergers*. This chapter begins with a focused introduction and literature review that covers Basel III liquidity regulation, bank mergers and acquisitions, and the interaction between liquidity and strategic behavior. It then develops a theoretical framework that links liquidity to acquisition capacity and post-merger outcomes. The methodology section details the dataset, variable construction, and econometric models, including logit, rare-events logit, and difference-in-differences specifications. Results, robustness checks, and discussion follow, highlighting how pre-merger liquidity and size shape both the likelihood of M&A and post-merger funding stability.

Chapter 3 develops *Study 2: Regulatory Flexibility and Bank Performance*. The chapter begins with an introduction and a literature review on regulatory flexibility and bank performance, followed by a discussion of the theoretical framework. The methodology outlines the data, construction of dependent and explanatory variables, and the econometric strategies employed. Models include baseline panel regressions, interaction specifications, and difference-in-differences designs. The results section examines profitability, stability, and business-model diversification, with particular attention to how size and NSFR moderate the effects of entry pressure, capitalization, enforcement, and insurance risk.

Chapter 4 provides the general discussion and conclusion. It synthesizes findings from both studies, evaluates their theoretical and policy implications, reflects on limitations and avenues for future research, and discusses economic significance. This chapter highlights the connection between liquidity and size in the dynamics of M&A and regulatory flexibility, offering an integrated perspective on sustainable banking outcomes.

Appendices contain additional robustness checks, model specifications, and supporting material such as survey instruments and model code for regulatory flexibility measures. These provide transparency and replicability for the empirical analyses.

Chapter 2

Liquidity, Size, and the Dynamics of Bank Mergers: Evidence on Acquisition Likelihood and Post-Merger Funding Stability

2.1 Introduction

The global financial crisis of 2007–2009 fundamentally reshaped banking regulation, with liquidity risk emerging as a central concern for both policymakers and practitioners. In response, the Basel Committee on Banking Supervision introduced comprehensive liquidity standards under Basel III, most notably the Liquidity Coverage Ratio (LCR) for short-term resilience and the Net Stable Funding Ratio (NSFR) for structural funding stability (Basel Committee on Banking Supervision, 2014a). While these regulations were primarily designed to enhance individual bank resilience, they also carry wider implications for industry structure by altering the strategic calculus of financial institutions, particularly in the sphere of mergers and acquisitions (M&A).

Although prior research has linked liquidity to bank consolidation dynamics, the role of *structural funding stability*—as measured by the NSFR—remains less well understood. This distinction is critical, since the NSFR directly reflects the regulatory framework that now governs post-crisis banking strategies and shapes the conditions under which banks pursue consolidation.

Against this backdrop, classic theories of consolidation emphasize efficiency gains, market power, and diversification benefits (Berger et al., 1999a; DeYoung et al., 2009). Yet the imposition of binding liquidity constraints introduces new incentives and frictions that reshape acquisition strategies. Banks with robust liquidity positions are better equipped to pursue acquisitions, whereas institutions with weaker funding profiles may find their strategic options constrained. Paradoxically, fragile but large banks may still seek to expand through M&A, raising questions about the unintended consequences of regulatory design and the persistence of systemic vulnerabilities.

This study examines how Basel III liquidity requirements, specifically the NSFR, impact bank M&A behavior through several interconnected channels. Five research questions guide the analysis: (i) do stronger pre-merger liquidity positions increase acquisition propensity? (ii) how does bank size moderate this relationship? (iii) how do structural liquidity profiles evolve in the years following mergers? (iv) do these dynamics vary across regulatory jurisdictions such as the EU and the United States? and (v) what are the causal effects of mergers on post-transaction liquidity outcomes?

To address these questions, I adopt an empirical strategy that combines rare-events logistic regression to capture acquisition propensity, interaction models to test the moderating role of size, and a difference-in-differences framework—augmented by propensity score matching—to identify causal post-merger effects while mitigating concerns of selection bias. This integrated design enables both cross-sectional and dynamic insights into how liquidity regulation conditions M&A activity.

The contributions of this study are threefold. First, it provides the first systematic analysis of how Basel III structural liquidity requirements shape bank consolidation, using NSFR as a regulation-consistent measure of funding stability rather than conventional liquidity proxies. Second, it uncovers significant heterogeneity across size categories, showing that scale amplifies the capacity to translate liquidity strength into acquisition activity. Third, it demonstrates that post-merger liquidity outcomes are path-dependent: strong acquirers consolidate their advantages, whereas fragile banks do not systematically improve their positions.

These findings carry implications that extend beyond individual bank stability. Liquidity regulation shapes not only balance-sheet resilience but also the structure of the banking industry by influencing acquisition capacity and incentives. Large banks with strong liquidity emerge as the most active consolidators, while small banks remain constrained by limited funding flexibility. These dynamics underscore the need for regulators to consider the industry-level consequences of prudential requirements when evaluating mergers and designing supervisory frameworks.

The remainder of the study is structured as follows. Section 2.2 reviews the relevant literature on liquidity regulation, bank mergers and acquisitions, and strategic balance sheet adjustments. Section 2.3 develops the theoretical framework, introducing the liquidity-enabled acquisition capacity mechanism, the scale amplification channel, and the funding-integration synergy hypothesis, and formally states the testable hypotheses. Section 2.4 discusses the research significance and the study's contribution to the literature.

Section 2.5 describes the data sources, sample construction, and variable definitions, while Section 2.6 outlines the econometric models and estimation strategy, including the baseline logit specification, interaction models capturing size heterogeneity, fixed-effects estimations of post-merger liquidity dynamics, and the difference-in-differences design. Section 2.7 presents the main empirical results on acquisition likelihood and post-merger funding stability. Section 2.8 provides graphical evidence to illustrate dynamic patterns, and Section 2.9 reports robustness checks to assess the stability of the findings. Finally, Section 2.10 discusses the broader implications of the results and conclusion.

2.2 Literature Review

2.2.1 Basel III Liquidity Regulation and Bank Behavior

A substantial body of work has examined how Basel III liquidity standards influence bank decision-making. Bonner and Hilbers (2015), using Dutch supervisory data, show that banks subject to Liquidity Coverage Ratio (LCR) constraints rebalance portfolios toward liquid assets and reduce lending, demonstrating that liquidity requirements directly alter core business activity. Similarly, Banerjee and Mio (2018), drawing on UK data, find that weaker banks adjust more aggressively, both by extending funding maturities and by increasing liquid asset holdings, with smaller institutions bearing disproportionately higher costs.

Evidence on the NSFR is less extensive but growing. Duijm and Wierts (2016) find that Dutch banks primarily adjust via liability-side changes, consistent with incentives to secure longer-term funding. More broadly, Cecchetti and Kashyap (2018) argue that Basel III liquidity requirements enhance resilience at a manageable cost, though the full impact will unfold only as banks recalibrate long-term strategies. Together, this literature highlights how liquidity regulation directly shapes funding choices and indirectly constrains strategic options, such as M&A.

2.2.2 Bank Mergers and Acquisitions: Determinants and Outcomes

The determinants and outcomes of bank M&A have been widely studied, though liquidity remains a neglected dimension. Wheelock and Wilson (2000) provides foundational evidence that larger banks are more likely to act as acquirers, while smaller banks typically serve as targets. Hagendorff et al. (2007) show that cross-border European mergers, though not always efficiency-enhancing, often improve risk management by subjecting transactions to diverse supervisory regimes.

Other studies stress that acquirer strength conditions outcomes. Cornett et al. (2006a) find that well-capitalized and efficient banks achieve superior post-merger performance, while Beccalli and Frantz (2009) demonstrate that efficiency gains are conditional on transaction type and institutional context. These findings imply that liquidity, as a dimension of financial strength, is equally critical in shaping both the likelihood of an acquisition and post-merger performance.

2.2.3 Liquidity and Bank Strategic Behavior

Liquidity has increasingly been recognized as central to banks' broader strategic choices. Berger and Bouwman (2009) conceptualize liquidity creation as a function of bank activity, showing how it varies across time and institutional form. Acharya and Naqvi (2012) extend this perspective theoretically, linking liquidity constraints to lending, investment, and risk-taking. Their framework suggests that liquidity-constrained banks may pursue unconventional strategies, including acquisitions, to offset their limitations.

Empirical studies reinforce these insights. Allen and Carletti (2007) shows that effective liquidity management provides competitive advantages that translate into market share and acquisition opportunities, while Imbierowicz and Rauch (2014) demonstrates that weak liquidity increases failure probabilities and erodes strategic flexibility. Collectively, these findings underscore that liquidity conditions not only influence short-term operations but also shape long-term strategic paths such as consolidation.

2.2.4 Regulatory Effects on Industry Structure

Prudential regulation also affects industry structure. Carletti and Hartmann (2003) highlight how banking competition policy interacts with regulatory reform to influence market concentration. Berger et al. (2017) show that capital requirements affect lending and competition in heterogeneous ways, with large banks better positioned to absorb compliance costs. Wheelock and Wilson (2000) observe that consolidation waves often accompany regulatory reform, while Corbae and D'Erasmo (2021) argue that regulation generates threshold effects, pushing smaller banks toward consolidation when compliance becomes disproportionately costly. Together, this body of work suggests that Basel III liquidity rules have indirect industry-level consequences by shaping consolidation incentives.

In sum, the literature shows that Basel III liquidity requirements reshape bank behavior (Bonner and Hilbers, 2015; Banerjee and Mio, 2018; Duijm and Wierts, 2016), that size and financial strength condition both acquisition likelihood and outcomes (Wheelock and Wilson, 2000; Cornett et al., 2006a), that liquidity affects strategic decision-making beyond lending (Berger and Bouwman, 2009; Acharya et al., 2012), and that regulation influences competition and consolidation incentives (Berger et al., 2017; Corbae and D'Erasmo, 2021). Cross-border and methodological studies further highlight the importance of regulatory context and causal identification. These insights motivate my hypotheses (H1–H5) on how liquidity and size shape M&A activity, post-merger liquidity, and jurisdictional variation.

2.3 Theoretical Framework

This study develops a framework linking Basel III's NSFR to bank mergers and acquisitions. I highlight three mechanisms: the liquidity-enabled acquisition capacity channel, the scale amplification mechanism, and the funding-integration synergy hypothesis. Together, these channels explain both the likelihood of acquisition and the post-merger liquidity outcomes observed in banking markets.

2.3.1 Liquidity-Enabled Acquisition Capacity

Banks with stronger liquidity positions are better able to pursue acquisitions. The NSFR requires stable funding over a one-year horizon, with a minimum of 100% (Basel Committee on Banking Supervision, 2014a). Institutions comfortably above this threshold enjoy financing flexibility and reduced vulnerability to market shocks. Strong liquidity also strengthens regulatory approval prospects—supervisory guidance explicitly emphasizes liquidity adequacy for acquirers (Board of Governors of the Federal Reserve System, 2024)—and provides the balance-sheet space to absorb targets while remaining compliant. This predicts a positive association between pre-merger liquidity and acquisition propensity.

2.3.2 Scale Amplification Mechanism

Liquidity advantages are not uniformly translated into acquisitions; their effect is conditioned by size. Large banks benefit from diversified funding, sophisticated treasury operations, and economies of scale in compliance and integration, making M&A relatively less costly. Enhanced prudential standards for large holding companies also heighten scrutiny, rewarding strong liquidity positions (Board of Governors of the Federal Reserve System, 2022). Smaller banks, even if liquid, often lack such capacity. This predicts that size amplifies the effect of liquidity on acquisition, with large, liquid banks the most acquisitive and small, fragile banks the least.

2.3.3 Funding-Integration Synergy Hypothesis

Post-merger liquidity dynamics depend critically on pre-merger positions. Strong acquirers can optimize combined funding portfolios, reduce redundancies, and enhance access to stable funding through scale and diversification. Weak acquirers, by contrast, may struggle to restructure inherited liabilities, leaving them with persistent or worsened liquidity profiles. This predicts conditional post-merger effects: strong banks consolidate advantages, while fragile acquirers fail to improve weaknesses.

2.3.4 Hypotheses

Building on the theoretical mechanisms and prior literature reviewed above, this study formulates five testable hypotheses linking banks' liquidity positions, size, and merger activity. Each hypothesis is explicitly motivated by the underlying mechanisms and examined using multiple econometric specifications (logit, rare-events logit, and fixed-effects models) to ensure robustness.

H1: Higher liquidity increases the likelihood of initiating M&A

Hypothesis. Banks with stronger structural liquidity, proxied by a higher lagged Net Stable Funding Ratio (NSFR), are more likely to act as acquirers in mergers and acquisitions.
Motivation. Financial flexibility enables banks to pursue expansion strategies more aggressively (Myers and Majluf, 1984; Cornett et al., 2011). A stronger NSFR indicates capacity to fund acquisitions without jeopardizing liquidity thresholds, consistent with evidence that abundant liquidity fosters deal activity.

H2: Size and liquidity jointly shape acquisition activity

Hypothesis. The effect of liquidity on M&A activity depends on bank size. Large banks with strong liquidity positions ("green" NSFR category) are expected to be the most acquisition-prone, while small banks in weaker positions ("red" category) are least likely to initiate mergers.
Motivation. Larger institutions benefit from scale economies and easier market access, magnifying the strategic impact of liquidity strength on acquisition capacity (Konstantaras and Sogiakas, 2019).

H3: Mergers improve post-acquisition liquidity

Hypothesis. Acquiring banks experience improvements in structural liquidity following mergers, reflected in higher NSFR levels within one to three years post-acquisition.
Motivation. Post-merger integration may generate funding synergies and efficiency gains, consistent with evidence of mean reversion and consolidation-driven liquidity enhancement (Hagendorff et al., 2012).

H4: Post-merger liquidity gains vary by pre-merger condition

Hypothesis. Liquidity improvements after mergers differ according to pre-merger strength: the largest gains are expected among initially weak ("red") banks, moderate among "yellow" banks, and smallest among already strong ("green") banks.
Motivation. Consolidation effects depend critically on baseline funding conditions, with weaker

institutions benefiting most from liquidity reallocation and scale economies (Khoo et al., 2024; Brealey et al., 2017; Hagendorff and Nieto, 2015).

H5: M&A participation causally raises liquidity

Hypothesis. Participation in an M&A causally increases a bank's NSFR relative to non-participating banks.
Motivation. Using a difference-in-differences framework, this effect captures the structural improvement in funding stability beyond time trends and bank-specific factors, consistent with Basel III's emphasis on liquidity resilience (Chiaramonte and Casu, 2017; Hlebik and Stránský, 2017).

2.4 Research Significance

This framework advances the literature in three ways. First, it introduces a regulation-consistent measure of liquidity (NSFR) into the analysis of M&A, moving beyond conventional proxies such as liquid asset ratios. Second, it integrates liquidity with size to explain heterogeneity in acquisition behavior, showing that scale magnifies the translation of liquidity into strategic action. Third, it extends M&A research by linking pre-merger liquidity to post-merger dynamics, demonstrating that outcomes hinge on the initial strength of acquirers. While prior studies document how liquidity regulation affects lending and balance-sheet adjustments Cornett et al. (2011); Banerjee and Mio (2018), little is known about its role in strategic consolidation. Similarly, while M&A studies emphasize efficiency and capitalization Wheelock and Wilson (2000); Beccalli and Frantz (2009) liquidity has rarely been central. By bridging the literature, this study demonstrates how Basel III liquidity rules stabilize individual banks while simultaneously reshaping industry structure.

From a policy perspective, the framework underscores that regulation can produce unintended consequences. Strong banks emerge as the most acquisitive, consolidating their advantages, while fragile but large banks may still expand through acquisitions without repairing weaknesses. This dynamic raises concerns about systemic risk and the persistence of the "too big to fail" problem. For regulators, the implication is clear: structural liquidity rules should be complemented with qualitative assessments of acquirer resilience when evaluating mergers.

2.5 Methodology

I study how liquidity and size shape both the likelihood of initiating mergers and post-merger liquidity outcomes, using an annual panel of banks from the EU and the USA over 2014–2024 (bank–years). To ensure comparability across specifications, I employ a consistent set of lagged bank-level and macro controls. Two structural characteristics—**Size** (log of GDP-deflated assets) and **NSFR**—enter the baseline regressions as key explanatory variables. Pre-processing removes duplicates, trims/winsorizes outliers, and deflates assets for cross-country comparability. Estimation relies on logit and rare-events logit models for acquisition propensity, and on fixed effects with bank and year dummies for post-merger outcomes, with bank-clustered standard errors throughout. I do not include lagged dependent variables, given the short time dimension. Detailed variable definitions, formulas (including Basel-consistent NSFR construction), and full model specifications are provided in the following subsections.

2.5.1 Data Sources and Sample Design

This study utilizes a multi-source panel dataset that contains bank-level, institutional, macroeconomic, and merger-specific information. The sample encompasses commercial, cooperative, and savings banks from 2014 to 2024 for the 27 EU member countries and the USA.

Bank-level Data

For the bank-level data, I utilize BankFocus/Orbis, a product of Bureau van Dijk, covering both the EU and the USA. Some banks appeared more than once under the same Legal Entity Identifier (LEI). To maintain unique observations, I retained only those banks with a consolidation code of C1 (consolidated statements with no unconsolidated partner), C2 (consolidated statements with an unconsolidated partner), and U1 (unconsolidated statements with no consolidated partner), resulting in 62,482 observations. Furthermore, I consider only domestic banks, as they follow a consistent set of national regulations and supervisory frameworks. In contrast, foreign-owned banks may rely on support from their parent institutions to comply with the host country's regulatory requirements.

Merger Data

Merger and acquisition information is obtained from S&P Capital IQ Pro. I restrict the sample to transactions in which both the acquiring and target institutions are domiciled in the same country, ensuring consistency with national regulatory and supervisory environments. Only mergers involving entities operating within the same industry, specifically the banking sector, are considered. Furthermore, this analysis focuses exclusively on the buyer side of transactions and includes only completed deals, thereby excluding any announced or withdrawn mergers.

To integrate merger events with the bank-level panel, each acquiring institution is matched to its corresponding observation in the financial dataset. This matching process ensures that pre- and post-merger characteristics are consistently aligned. After applying all selection filters and removing unmatched cases, the final sample includes 636 completed bank mergers: 246 in the EU and 390 in the United States. Furthermore, I exclude government-owned entities, as their merger behavior may be driven by policy or strategic mandates that differ fundamentally from privately owned banks.

These restrictions ensure that the analysis captures realized, market-driven consolidation among banks, reflecting genuine strategic outcomes rather than announcements, cross-industry diversification, or state-led interventions.

Macroeconomic Data

Macroeconomic indicators, including GDP growth, inflation, and unemployment, are sourced from the World Bank's *World Development Indicators* (WDI) database, providing the country-level context for bank performance. To provide an overview of the sample coverage, Table 2.1 reports the distribution of banks, bank–year observations, and M&A deals across countries. This breakdown helps to contextualize the scope of the data and highlights the variation in representation across jurisdictions.

Table 2.1: Distribution of banks, observations, and M&A deals by country

Country	Number of Banks	Bank–Year Observations	M&A Deals
Austria	388	2744	23
Belgium	20	144	4
Bulgaria	14	111	5
Croatia	19	151	6
Cyprus	16	73	1
Czech Republic	9	64	2
Denmark	48	330	28
Estonia	7	47	1
Finland	95	643	9
France	122	875	11
Germany	1082	9201	51
Greece	10	30	1
Hungary	12	64	4
Ireland	24	120	3
Italy	300	2309	46
Latvia	9	50	1
Lithuania	4	35	1
Luxembourg	21	108	1
Malta	8	69	0
Netherlands	17	99	3
Poland	125	866	15
Portugal	87	566	1
Romania	11	83	3
Slovakia	6	65	1
Slovenia	9	61	5
Spain	35	272	20
Sweden	74	432	0
United States of America	4335	42870	390

Notes: The table reports the distribution of banks, bank–year observations, and M&A deals across countries in the sample. *Number of Banks* refers to distinct institutions observed at least once in the panel, while *Bank–Year Observations* reflect the total count of yearly balance-sheet records. M&A deals are identified through S&P Capital IQ Pro databases. The distribution highlights the natural imbalance between the U.S. and EU banking systems, with the U.S. contributing a much larger share of observations. To address this, EU-specific estimations are conducted separately to ensure that results are not driven by U.S. dominance. Some European countries have relatively few banks (e.g., Malta, Lithuania, Estonia), but are retained for completeness and are absorbed by country fixed effects in regression designs. Variation in sample sizes across countries partly reflects data coverage differences across underlying databases and the availability of balance sheet reporting for NSFR computation, which explains the loss of observations for certain countries.

2.5.2 Variable Construction

Dependent Variables

Construction of the *M&A Buyer Dummy*
The dependent variable for acquisition propensity is a bank–year indicator defined as:

$$\text{MA}_{it} = \begin{cases} 1, & \text{if bank } i \text{ is the } \textit{buyer} \text{ in a completed, domestic, banking-sector M\&A in year } t, \\ 0, & \text{otherwise.} \end{cases}$$

Implementation. (i) M&A events are sourced from *S&P Capital IQ Pro*. (ii) I retain only *completed* deals (exclude announced/withdrawn) in which both acquirer and target are domiciled in the same country and classified in the banking industry; government-owned entities are excluded. (iii) The acquirer from the deals file is matched to the bank panel (BankFocus/Orbis) using LEI/name harmonization; unmatched cases are dropped. (iv) The indicator equals one in the *calendar year of completion* for bank i; it is zero otherwise. If a bank completes multiple deals in year t, $\text{MA}_{it} = 1$ once. A robustness check (reported in the appendix) shifts the event to $t+1$ to allow for reporting lags.
Rationale and precedent. This buyer-side, completion-based construction follows standard practice in the banking M&A literature, which focuses on acquirer behavior and outcomes and timestamps events at completion rather than announcement (Hagendorff et al., 2007; Wheelock and Wilson, 2000). The domestic, same-industry restriction ensures a common regulatory and supervisory environment for both parties and avoids cross-industry dynamics that are outside the scope of bank consolidation.

2.5.3 Explanatory Variables

Bank Size. Size is a central determinant of how banks perform, absorb shocks, and adapt to changing market conditions. Larger institutions benefit from economies of scale: they can spread fixed costs, diversify product lines, and access a wider range of markets. These advantages often translate into smoother earnings and stronger competitive positions. At the same time, size introduces complexity. When markets anticipate too-big-to-fail (TBTF) support, funding costs may fall, but discipline weakens and risk-taking incentives rise. As noted in Kaufman (2014), TBTF works as an *ex-post* resolution regime: creditors are protected from losses, spillovers are limited, and funding costs decline—but at the expense of market discipline. By contrast, capital and liquidity requirements such as the NSFR act as *ex-ante* tools that aim to reduce the probability of failure in the first place. More recent cross-country evidence shows that global systemically important banks (G-SIBs) are more likely to be rescued, but bailouts tend to be smaller, arrive later, and come with stricter conditions, so any *ex-ante* advantage may be offset by harsher *ex-post* treatment (Berger and Roman, 2015). Moreover, large, internationally active banks tend to have more complex funding structures, which is why I consider size together with structural liquidity (NSFR) (Vázquez and Federico, 2015).

Measurement. I measure bank size as the natural logarithm of real total assets:

$$\text{Size}_{b,t} \equiv \ln\left(\text{TA}_{b,t} \times \frac{100}{\text{GDPDeflator}_{c,t}}\right),$$

Where the GDP deflator is normalized to 2015 = 100, deflating ensures comparability across countries and over time and prevents inflation-driven size distortions. For heterogeneity analysis, banks are further classified into *small*, *medium*, and *large* groups based on total assets thresholds commonly used in the literature: *small* banks have assets up to \$1 billion, *medium* banks have assets between \$1 and \$3 billion, and *large* banks have assets exceeding \$3 billion.

Net Stable Funding Ratio (NSFR) The NSFR is one of Basel III's cornerstone liquidity requirements, introduced to ensure banks maintain stable funding profiles that match the liquidity characteristics of their assets (Basel Committee on Banking Supervision, 2010; Vázquez and Federico, 2015). It is defined as:

$$\text{NSFR}_{b,t} = \frac{\text{ASF}_{b,t}}{\text{RSF}_{b,t}} \times 100, \tag{2.1}$$

Where *Available Stable Funding* (ASF) weights liabilities by stability (equity and long-term debt receive the highest weights; short-term wholesale liabilities the lowest), and *Required Stable Funding* (RSF) weights assets and off-balance sheet exposures according to their liquidity risk. A ratio above 100 indicates that a bank's stable funding at least covers its liquidity needs for the coming year.

Interpretation. In practice, the NSFR rewards banks that rely on long-term, stable funding while penalizing those that rely on short-term, volatile sources. To capture non-linear differences, I also classify banks into three liquidity categories: *Red* (NSFR $<$ 100), *Yellow* (100 $\leq$ NSFR $<$ 120), and *Green* (NSFR $\geq$ 120). This classification helps distinguish between weakly funded banks and those that comfortably exceed the Basel requirements.

Table 2.2: Classification thresholds for bank size and NSFR categories

Variable	**Category**	**Definition / Threshold**
Bank Size	Small	Total assets ≤ 1 billion USD
	Medium	1 billion < Total assets ≤ 3 billion USD
	Large	Total assets > 3 billion USD
NSFR	Red	NSFR < 100
	Yellow	100 ≤ NSFR < 120
	Green	NSFR ≥ 120

Note: Bank size categories are based on absolute asset thresholds in line with Berger and Bouwman (2009); NSFR thresholds follow Basel III standards. NSFR categories are defined by the author for sub-sample analysis. The 100% cut-off follows Basel III requirements; the 120% threshold distinguishes banks with particularly stable funding.

Other Controls. In line with the banking and M&A literature (Focarelli et al., 2002; Hernando et al., 2009), I include a lean set of bank-level and macroeconomic controls to isolate the effect of liquidity and size from other drivers of acquisition behavior and results. All bank-level variables are lagged by one year to mitigate concerns about simultaneity (Roodman, 2009).

L.**CARs_w** *Capital adequacy.* Reported regulatory capital ratio, winsorized. Higher values proxy greater loss-absorbing capacity (Kweh et al., 2024; Tsionas et al., 2022). [1]

L.**ln_cst_inc** *Cost efficiency.* Log of the cost-to-income ratio. Higher values indicate weaker operating efficiency and lower cost discipline (Berger and Mester, 2007).

L.**ast_grth_w** *Asset growth.* Annual growth in total assets, winsorized. Captures the dynamics of expansion and credit supply shocks (Foos et al., 2010).

L.**nii_w** *Business model mix.* Share of non-interest income in total operating revenues, winsorized. Higher shares indicate greater reliance on fee-based activities (Stiroh, 2004a).

L.**nim** *Pricing/earning power.* Net interest income over interest-earning assets. Reflects banks' ability to generate margin-based profits (Angbazo, 1997).

L.**uepm_rate** *Unemployment rate.* Country-level unemployment (%). Captures macroeconomic slack and credit demand conditions (Bernanke and Gertler, 1995).

L.**gdp_grth** *GDP growth.* Country-level real GDP growth rate. Captures the macroeconomic cycle and aggregate demand conditions (Rajan, 2010).

[1] CARs, asset growth, and non-interest income ratio, are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme tail observations. No other variables are winsorized.

Pre-processing. I drop records with more than seven missing values, remove duplicates at the bank–year level, and apply winsorization to CARs, non-interest income, and asset growth (Dixon, 1960). Histograms and skewness checks guide the log transforms; the +1 offset preserves zeros.
Panel setup. All bank-level controls are lagged by one period ($L.$) to reduce simultaneity bias, while macroeconomic controls enter contemporaneously. Estimations include bank and year fixed effects, with bank-clustered standard errors (Cameron and Miller, 2015).

2.6 Econometric Model and Estimation Strategy

This section presents the empirical framework for examining how the Net Stable Funding Ratio (NSFR), regulatory phases, and bank size influence merger and acquisition (M&A) activity, profitability, and liquidity stability in the banking sector.

- The implementation of NSFR drives the likelihood of M&A activity among banks.
- Bank size influences how NSFR pressure affects banks engaged in M&A.
- The empirical models incorporate interaction effects (Brambor et al., 2006), rare-event corrections (King and Zeng, 2001), and post-merger liquidity analyses (Cornett et al., 2006b) to address the multi-dimensional nature of regulatory impacts.

2.6.1 Control Variables

The control vector $\mathbf{X}'_{i,t-1}$ includes:

- Capital adequacy ratio (CAR)
- Log cost-to-income ratio
- Asset growth
- Non-interest income ratio
- Net interest margin
- National unemployment rate
- GDP growth

2.6.2 Baseline Logit Model: M&A Likelihood

$$\begin{aligned}\Pr(\mathrm{MA}_{it} = 1) = \mathrm{logit}^{-1}\Big(&\beta_0 + \beta_1 \cdot \ln(\mathrm{NSFR}_{i,t-1}) + \beta_2 \cdot \ln(\mathrm{Size}_{i,t-1}) \\ &+ \mathbf{X}'_{i,t-1}\boldsymbol{\gamma} + \delta_r + \delta_t + \varepsilon_{it}\Big)\end{aligned} \tag{2.2}$$

Where:

- $\Pr(\mathrm{MA}_{it} = 1)$: Probability that bank i acts as the acquirer in a merger or acquisition during year t.
- $\ln(\mathrm{NSFR}_{i,t-1})$: Log of lagged Net Stable Funding Ratio, reflecting structural liquidity.
- $\ln(\mathrm{Size}_{i,t-1})$: Log of total assets deflated by the GDP deflator, capturing inflation-adjusted size.
- $\mathbf{X}'_{i,t-1}\boldsymbol{\gamma}$: Vector of control variables (see Section 2.6.1).
- δ_r: Region fixed effects.
- δ_t: Year fixed effects.
- ε_{it}: Idiosyncratic error term.

Model Description: This model estimates the likelihood that a bank initiates an M&A based on its prior liquidity position and size, while controlling for financial and macroeconomic factors across regions and time. The approach builds on established work predicting acquisition behavior in banking (Palepu, 1986) and reflects the growing role of funding stability in regulatory frameworks and bank strategy (Basel Committee on Banking Supervision, 2014b).[2]

2.6.3 Interaction Logit Model: Bank Size × NSFR Category

$$\begin{aligned}\Pr(\mathrm{MA}_{it} = 1) = \mathrm{logit}^{-1}\Big(&\beta_0 + \sum_{j=1}^{2}\sum_{k=1}^{2} \beta_{jk} \cdot \mathrm{BankSize}_j \times \mathrm{NSFRcat}_k \\ &+ \mathbf{X}'_{i,t-1}\boldsymbol{\gamma} + \delta_r + \delta_t + \varepsilon_{it}\Big)\end{aligned} \tag{2.3}$$

Where:

- $\mathrm{BankSize}_j \in \{\mathrm{Small}, \mathrm{Large}\}$: Bank size categories (reference group may be omitted).
- $\mathrm{NSFRcat}_k \in \{\mathrm{Red}, \mathrm{Green}\}$: Liquidity categories based on Net Stable Funding Ratio.
- $\mathrm{BankSize}_j \times \mathrm{NSFRcat}_k$: Full factorial interactions between size and liquidity categories.
- $\mathbf{X}'_{i,t-1}\boldsymbol{\gamma}$: Control vector (see Section 2.4.1).

[2] See also Hannan and Wolken (1991) for efficiency-based explanations of bank M&A and Demirgüç-Kunt and Huizinga (2013) on funding structures as key determinants of bank behavior.

- δ_r: Region fixed effects.
- δ_t: Year fixed effects.
- ε_{it}: Error term.

Model Description: This model tests whether the effect of liquidity on M&A likelihood varies by bank size, reflecting the idea that large and small institutions face different constraints and opportunities in merger markets (Berger et al., 1999b). To interpret these interactions, marginal effects are calculated at representative values (Ai and Norton, 2003).[3]

2.6.4 Fixed Effects: Post-Merger Liquidity Trends

$$\ln(\text{NSFR}_{it}) = \alpha_i + \delta_t + \theta_1 D_{\text{Post1}} + \theta_2 D_{\text{Post2}} + \theta_3 D_{\text{Post3}} + \mathbf{X}'_{i,t-1}\boldsymbol{\gamma} + \varepsilon_{it} \tag{2.4}$$

Where:

- $\ln(\text{NSFR}_{it})$: Log of Net Stable Funding Ratio of bank i in year t.
- α_i: Bank-specific fixed effects.
- δ_t: Year fixed effects.
- $D_{\text{Post1}}, D_{\text{Post2}}, D_{\text{Post3}}$: Dummies for 1, 2, and 3 years post-merger, respectively.
- $\mathbf{X}'_{i,t-1}\boldsymbol{\gamma}$: Vector of lagged bank-level control variables.
- ε_{it}: Idiosyncratic error term.

Model Description: This model examines whether structural liquidity (NSFR) improves in the 1– to 3–year period following a merger, while controlling for unobserved bank-specific and time-specific heterogeneity(Cornett et al., 2006b; DeLong, 2001). The specification adopts an event–study approach, a standard method in the banking M&A literature for examining how performance evolves after mergers (Houston et al., 2001).

2.6.5 Interaction: Post-Merger Effects by NSFR Category

$$\ln(\text{NSFR}_{it}) = \alpha_i + \delta_t + \sum_{j,k} \phi_{jk}(D_{\text{Post}k} \times \text{NSFRcat}_j) + \mathbf{X}'_{i,t-1}\boldsymbol{\gamma} + \varepsilon_{it} \tag{2.5}$$

Where:

- $D_{\text{Post}k} \times \text{NSFRcat}_j$: Interaction terms between post-merger year $k \in \{1, 2, 3\}$ and liquidity category $j \in \{\text{Red}, \text{Yellow}, \text{Green}\}$.

[3] For a broader discussion of interaction models and heterogeneous effects, see Brambor et al. (2006). On the role of liquidity in shaping M&A outcomes, see Cornett et al. (2011)

Model Description: This model examines whether liquidity recovery post-merger varies by pre-merger liquidity conditions, utilizing interaction terms between the NSFR category and post-merger years (Brambor et al., 2006). This approach recognizes that merger effects depend on banks' initial liquidity positions, in line with evidence that post-merger outcomes are shaped by pre-existing conditions (DeLong, 2001; Berger et al., 2000).

2.6.6 Difference-in-Differences (DiD)

$$\ln(\text{NSFR}_{it}) = \alpha_i + \delta_t + \beta_1 D_{\text{Treat}} + \beta_2 D_{\text{Post}} + \beta_3 (D_{\text{Treat}} \times D_{\text{Post}}) + \mathbf{X}'_{i,t-1}\boldsymbol{\gamma} + \varepsilon_{it} \tag{2.6}$$

Where:

- D_{Treat}: Dummy variable equal to 1 if bank i participated in an M&A.
- D_{Post}: Dummy variable equal to 1 for all years following the M&A.
- $D_{\text{Treat}} \times D_{\text{Post}}$: Interaction term capturing the treatment effect.

Model Description: This DiD specification provides a causal estimate of the effect of mergers on bank liquidity by comparing treated and non-treated banks before and after the merger, controlling for observed and unobserved heterogeneity (Angrist and Pischke, 2009).

2.7 Results

Table 2.3: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ln_NSFR	62,482	4.616	0.279	3.759	5.853
sizel	58,284	13.089	1.594	8.581	21.786
ROA	53,328	0.695	0.505	-1.005	3.207
CARs_w	37,878	18.130	6.147	10.937	46.410
ln_cst_inc	62,482	4.273	0.198	3.590	4.731
ast_grth_w	53,328	6.953	10.536	-10.876	55.761
nonintinc_w	62,482	25.017	13.686	1.604	63.745
nim	62,482	2.965	0.975	0.853	5.765
uepm_rate	62,482	7.585	1.510	2.015	26.708
gdp_grth	58,284	2.121	3.057	-10.940	24.616

Interpretation. Table 1 shows that liquidity (ln_NSFR) is relatively stable across banks, while size varies widely, encompassing both small and large institutions. Profitability averages below 1%, with some banks loss-making and others highly profitable. Capital ratios are comfortably above the regulatory minimums, although uneven across banks. Asset growth, revenue mix, and margins also exhibit substantial variation, and the macro environment encompasses both crises and expansions. This diversity provides a suitable setting to test the likelihood of M&A (H1), post-merger liquidity outcomes (H2–H4), and the causal effect (H5). [4]

Table 2.4: Correlation Matrix of Key Variables

	ln_NSFR	sizel	ROA	CARs_w	ln_cst_inc	ast_grth_w	nonintinc_w	nim	uepm_rate	gdp_grth
ln_NSFR	1.000									
sizel	-0.172	1.000								
ROA	0.140	-0.056	1.000							
CARs_w	0.327	-0.166	-0.136	1.000						
ln_cst_inc	0.038	-0.198	-0.494	0.010	1.000					
ast_grth_w	-0.023	0.052	0.147	-0.161	-0.082	1.000				
nonintinc_w	-0.071	0.346	-0.368	0.121	0.186	-0.052	1.000			
nim	0.117	-0.298	0.617	-0.241	-0.177	0.045	-0.613	1.000		
uepm_rate	-0.072	0.074	-0.123	-0.098	0.040	-0.004	0.091	-0.221	1.000	
gdp_grth	0.047	-0.019	-0.033	0.045	0.001	-0.199	0.076	-0.015	-0.068	1.000

Interpretation. Table 2 highlights expected relationships. Stronger liquidity correlates positively with profitability and capital, supporting H1's focus on liquidity as a driver of acquisition capacity. Larger banks exhibit weaker liquidity buffers, underscoring the relevance of size–liquidity interactions. Profitability is strongly linked to efficiency and margins, while non-interest income is negatively related to ROA, suggesting revenue diversification does not always enhance performance. Unfavorable macro conditions (high unemployment) reduce margins

[4] CARs, asset growth, and the non-interest income ratio are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme tail observations. No other variables are winsorized.

and profitability, while stronger growth modestly supports liquidity and capital, providing the backdrop for H2–H4.

In sum, the descriptive evidence aligns with the study's hypotheses: liquidity and size shape acquisition likelihood (H1), and macroeconomic and balance-sheet conditions frame the post-merger liquidity effects (H2–H4).

Table 2.5: Regression Results by Likelihood of M&A and Region split (Panel A)

Outcome Var	*M&A Buyer Dummy*				
	(1)	(2)	(3)	(4)	(5)
Sample	Full Sample	EU Region	Full Sample	EU Region	US Region
Estimation	Logit	Logit	Relogit	Relogit	Relogit
Key Variables					
L_ln_NSFR	0.009	0.882**	-0.127	0.847**	-1.513***
	(0.304)	(0.411)	(0.290)	(0.398)	(0.539)
Control Variables					
L_sizel	0.498***	0.698***	0.487***	0.663***	0.348***
	(0.027)	(0.043)	(0.026)	(0.042)	(0.043)
L_CARs_w	-0.014	-0.062*	-0.003	-0.063*	0.022
	(0.017)	(0.033)	(0.015)	(0.034)	(0.020)
L_ln_cst_inc	0.296	-0.091	0.326	0.114	0.227
	(0.398)	(0.639)	(0.395)	(0.626)	(0.530)
L_ast_grth_w	0.023***	0.044***	0.024***	0.038***	0.013*
	(0.005)	(0.008)	(0.004)	(0.007)	(0.006)
L.nii_w	0.008	0.030***	0.013**	0.033***	0.003
	(0.005)	(0.009)	(0.005)	(0.008)	(0.008)
L_nim	0.393***	0.576***	0.309***	0.512***	-0.045
	(0.099)	(0.135)	(0.081)	(0.137)	(0.144)
L_uepm_rate	-0.221***	-0.169***	-0.223***	-0.168**	1.005**
	(0.056)	(0.065)	(0.052)	(0.067)	(0.402)
L_gdp_grth	0.045**	0.046**	0.046**	0.060***	-0.140**
	(0.019)	(0.021)	(0.019)	(0.018)	(0.070)
Additional Controls					
region_num	-0.388*				
	(0.217)				
nsfr_phase2			-0.589***	-1.080***	0.210
			(0.167)	(0.304)	(0.245)
nsfr_phase3			-0.931***	-1.386***	-1.960***
			(0.171)	(0.334)	(0.489)
covid_period			0.067	0.315	-0.587**
			(0.158)	(0.237)	(0.256)
Year Effects	Yes	Yes	Yes	Yes	Yes
Region Effects	Yes	No	Yes	No	No
Constant	-11.778***	-18.288***	-11.731***	-18.520***	-9.961**
	(2.363)	(3.733)	(2.195)	(3.699)	(4.500)
Observations	29,206	10,666	29,206	11,008	18,198

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table Description. This table reports the determinants of banks' likelihood of acting as M&A acquirers 2.2. Columns (1)–(2) present baseline logit estimates, while Columns (3)–(5) report rare-events logit (relogit) specifications. Models control for lagged bank characteristics, macroeconomic conditions, year effects, and, where indicated, region effects and regulatory dummies. Robust standard errors are shown in parentheses.

Interpretation of Regression Results. Across all columns, bank size consistently and strongly increases the probability of initiating M&A, confirming **H1**. Liquidity effects are context-dependent: insignificant in the full sample (Cols. 1, 3), positive and significant in the EU (Cols. 2, 4), but negative in the U.S. (Col. 5). This suggests that stable funding facilitates acquisitions in Europe, while U.S. acquirers rely less on it. Profitability (nim) and asset growth support deal activity, whereas higher unemployment rates lower it. Regulatory transition phases (Cols. 3–5) exhibit a marked decline in M&A likelihood, particularly in the EU, with COVID-19 primarily affecting U.S. deals. Taken together, the results indicate that, while size is the most robust driver of acquisitions, the role of liquidity varies across regions and regulatory environments. The positive effect of size remains robust when accounting for potential non-linear scale effects by including a quadratic size term, which does not alter the qualitative conclusion Laeven and Levine (2016). (see Section 2.9)

Table 2.6: Average Marginal Effects (AMEs): M&A Buyer Dummy

	Pr(M&A Buyer = 1)	
	Full Sample	EU Sample
L_ln_NSFR	0.0001	0.0091**
	(0.0028)	(0.0043)
L_sizel	0.0046***	0.0072***
	(0.0003)	(0.0006)
L_ast_grth_w	0.0002***	0.0005***
	(0.0000)	(0.0001)
L_nii_w	0.0001	0.0003***
	(0.0001)	(0.0001)
L_nim	0.0037***	0.0060***
	(0.0009)	(0.0014)
L_uepm_rate	-0.0021***	-0.0018**
	(0.0005)	(0.0007)
L_gdp_grth	0.0004**	0.0005**
	(0.0002)	(0.0002)
Year Effects	Yes	Yes
Region Effects	Yes	No
Observations	29,206	10,666

Entries report average marginal effects (dy/dx) from logit models with robust standard errors (in parentheses).
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table Description. The table reports AMEs from logit models of the M&A buyer dummy for the full sample and the EU subsample. All models include bank-level controls, macroeconomic variables, year effects, and region effects where applicable. Robust standard errors are reported in parentheses. Marginal effects measure the change in predicted acquisition probability associated with a one-unit increase in each covariate.

Economic Significance: Average Marginal Effects Table 2.6 reports average marginal effects (AMEs) from the logit estimations, which allow direct interpretation in probability terms.

In the full sample, bank size (log total assets) has a statistically and economically meaningful effect. A one-unit increase in log assets increases the probability of being an M&A buyer by 0.46 percentage points. In the EU subsample, the magnitude is larger: a one-unit increase in size raises acquisition probability by 0.72 percentage points. These results indicate that scale plays an important role in acquisition decisions, particularly within the European banking environment.

Liquidity, measured by lagged log NSFR, is economically negligible and statistically insignificant in the full sample. However, in the EU subsample, a one-unit increase in NSFR increases the probability of acquisition by 0.91 percentage points, suggesting that stronger structural liquidity positions facilitate expansion through acquisitions under the European regulatory framework.

Among the control variables, asset growth exhibits a positive but modest economic effect. A one-unit increase in asset growth raises acquisition probability by 0.02 percentage points in the full sample and 0.05 percentage points in the EU subsample. Greater reliance on non-interest income increases acquisition likelihood by 0.03 percentage points in the EU sample, while its effect remains economically small and statistically insignificant in the full sample.

Profitability, proxied by the net interest margin, has a sizeable impact. A one-unit increase in the net interest margin increases acquisition probability by 0.37 percentage points in the full sample and by 0.60 percentage points in the EU subsample, consistent with more profitable banks being more likely to initiate acquisitions.

Macroeconomic conditions also influence acquisition activity. Higher unemployment reduces the probability of acquisition by 0.21 percentage points in the full sample (0.18 in the EU subsample), whereas GDP growth increases acquisition likelihood by approximately 0.04–0.05 percentage points, confirming the procyclical nature of M&A activity.

Overall, the marginal effects indicate that bank size and profitability are the primary economically meaningful drivers of acquisition behavior, while structural liquidity plays a more pronounced role within the European banking sector.

Table 2.7: Regression Results by Size and Liquidity Interaction Effect on M&A (Panel B)

Outcome Var	*M&A Buyer Dummy*	
	(1)	(2)
Sample	Full Sample	Full Sample
Base Category	Medium_Green	Medium_Yellow
Key Variables		
Small	-0.904***	-0.861***
	(0.291)	(0.302)
Large	1.074***	1.336***
	(0.268)	(0.250)
Red	-1.150**	-0.970*
	(0.554)	(0.556)
Yellow	-0.180	
	(0.317)	
Green		0.180
		(0.317)
Small × Red	0.734	0.691
	(0.625)	(0.630)
Small × Yellow	0.043	
	(0.411)	
Small × Green		-0.043
		(0.411)
Large × Red	1.277**	1.014*
	(0.592)	(0.584)
Large × Yellow	0.263	
	(0.369)	
Large × Green		-0.263
		(0.369)
Control Variables		
L_CARs_w	-0.017	-0.017
	(0.016)	(0.016)
L_ln_cst_inc	-0.093	-0.093
	(0.363)	(0.363)
L_ast_grth_w	0.017***	0.017***
	(0.005)	(0.005)
L.nii$_w$	0.015***	0.015***
	(0.005)	(0.005)
L_nim	0.292***	0.292***
	(0.100)	(0.100)
L_uepm_rate	-0.271***	-0.271***
	(0.056)	(0.056)
L_gdp_grth	0.056***	0.056***
	(0.019)	(0.019)
Region FE	Yes	Yes
Year FE	Yes	Yes
Constant	-2.585	-2.765
	(1.758)	(1.737)
Observations	29,206	29,206

Robust standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table Description. This table presents regression results on the interaction between bank size and liquidity categories in determining the likelihood of acting as a mergers and acquisitions (M&A) acquirer (Eq 2.3). Column (1) uses medium–green banks as the reference group, while Column (2) uses medium–yellow banks. The specifications include lagged bank-level controls (capital, cost efficiency, asset growth, revenue mix, and margins), macroeconomic conditions (GDP growth and unemployment), and both regional and year fixed effects. Robust standard errors are reported in parentheses.

Interpretation of Regression Results (Panel B). Panel B examines how the interaction between size and liquidity influences the likelihood of banks initiating mergers and acquisitions (M&A). The results reveal a clear and consistent size effect: large banks are significantly more likely to acquire, while small banks are less likely to do so, relative to their medium-sized peers. Liquidity also matters, as institutions in the red category show lower acquisition propensity compared to those with stronger liquidity positions.

The interaction terms provide further nuance. Large banks with weak liquidity (Large $\times$ Red) are still more likely to acquire, suggesting that their scale allows them to overcome liquidity constraints—whether through easier access to funding markets or strategic motives that outweigh balance-sheet weaknesses. Small banks in weak liquidity positions, by contrast, display no such offset, underscoring their limited capacity to participate in mergers and acquisitions (M&A).

Control variables behave as expected: faster asset growth, greater reliance on non-interest income, more substantial margins, and higher GDP growth all increase the likelihood of acquisitions, while higher unemployment reduces it. Overall, the evidence supports **H2**: acquisition propensity differs systematically across size–liquidity groups, with scale consistently emerging as the dominant driver of M&A activity.

As a robustness check, Table A.2 reports results from a manual interaction model that assigns banks into mutually exclusive size–liquidity categories (e.g., Red–Large, Green–Small) and explores regional variation. The findings strongly reinforce the baseline: large banks remain acquisitive across all liquidity groups, while small banks are largely inactive regardless of liquidity position. These patterns hold in the full sample, the EU, and the U.S., confirming that scale dominates liquidity in driving acquisition likelihood, with regulatory phases and macroeconomic shocks further shaping the intensity of activity across regions. In particular, *T*able A.6 shows that even banks with weak liquidity (Red) are significantly more likely to acquire when they are large, whereas small Red banks remain largely absent from M&A activity—underscoring that scale can offset liquidity constraints, but not the other way around.

Table 2.8: Post Merger Analysis Across Liquidity Dynamics and Region

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome Var				*NSFR*		
Model Specification		(Baseline)		(Interaction with Liquidity Interaction)		
Sample	Full Sample	EU	US	Full Sample	EU	US
Post Indicators						
post1	0.002	0.008	-0.006	-0.002	0.016	-0.010
	(0.006)	(0.013)	(0.005)	(0.007)	(0.030)	(0.006)
post2	0.009	-0.009	0.012**	0.016**	0.022	0.010
	(0.006)	(0.013)	(0.006)	(0.007)	(0.031)	(0.007)
post3	0.002	-0.011	0.007	0.010	0.015	0.011
	(0.006)	(0.015)	(0.006)	(0.008)	(0.040)	(0.007)
Interactions: NSFR Category × Post						
post1_red				-0.034*	-0.041	-0.026**
				(0.018)	(0.037)	(0.013)
post2_red				-0.059***	-0.081**	-0.032**
				(0.015)	(0.036)	(0.015)
post3_red				-0.054***	-0.070	-0.029**
				(0.016)	(0.045)	(0.013)
post1_yellow				0.010	-0.015	0.007
				(0.014)	(0.033)	(0.013)
post2_yellow				0.001	-0.018	0.003
				(0.013)	(0.034)	(0.014)
post3_yellow				-0.002	-0.020	-0.001
				(0.013)	(0.041)	(0.015)
post1_green				0.087***	0.060	0.098***
				(0.020)	(0.042)	(0.016)
post2_green				0.059**	0.022	0.093***
				(0.023)	(0.043)	(0.022)
post3_green				0.050**	0.025	0.011
				(0.020)	(0.047)	(0.023)
Control Variables						
L_CARs_w	0.011***	0.008***	0.014***	0.011***	0.008***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L_ln_cst_inc	-0.049***	-0.016	-0.008	-0.049***	-0.016	-0.008
	(0.011)	(0.020)	(0.012)	(0.011)	(0.020)	(0.012)
L_ast_grth_w	0.000**	-0.000***	0.000**	0.000**	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.nii_w	0.000	0.001***	-0.000	0.000	0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L_nim	-0.018***	0.005	-0.035***	-0.019***	0.005	-0.035***
	(0.003)	(0.006)	(0.004)	(0.003)	(0.006)	(0.004)
L_uepm_rate	0.019***	0.041***	-0.034***	0.019***	0.041***	-0.032***
	(0.002)	(0.005)	(0.012)	(0.002)	(0.005)	(0.012)
L_gdp_grth	0.000	-0.002***	0.005***	0.000	-0.002***	0.006***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Year FE	Yes	No	No	Yes	No	No
Constant	4.595***	4.114***	4.894***	4.598***	4.121***	4.876***
	(0.058)	(0.121)	(0.084)	(0.058)	(0.121)	(0.084)
Observations	29,206	11,008	18,198	29,206	11,008	18,198
R-squared	0.150	0.081	0.306	0.152	0.083	0.308
Number of Banks	4,661	2,001	2,660	4,661	2,001	2,660

Robust standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table Description. This table reports post-merger regression results on banks' structural liquidity (NSFR). Columns (1)–(3) present the baseline fixed-effects specification (Eq 2.4) for the full sample, the EU, and the U.S., respectively. Columns (4)–(6) extend the model by interacting post-merger years with pre-merger liquidity categories, allowing for heterogeneous post-merger dynamics (Eq 2.5). Post 1, Post 2, and Post 3 indicate one, two, and three years after the merger. Control variables include capitalization, cost efficiency, asset growth, revenue structure, margins, and macroeconomic conditions. Year fixed effects are included in the full-sample specifications. Robust standard errors are reported in parentheses.

Interpretation of Regression Results. Columns (1)–(3) show that, on average, mergers do not systematically improve banks' structural liquidity. Post-merger indicators are small and mostly insignificant in the full sample and EU, with only U.S. banks showing a modest positive effect in the second post-merger year. This suggests that mergers yield only modest improvements in liquidity when initial bank conditions are overlooked.

Columns (4)–(6) highlight essential heterogeneity. Banks entering mergers in weak liquidity positions (red category) experience significant post-merger declines in NSFR across all horizons, with the most pronounced decline occurring in year two. By contrast, green-category banks exhibit intense and persistent improvements: the NSFR rises sharply in the first post-merger year and remains elevated in years two and three, particularly in the U.S. Yellow-category banks, on the other hand, show no meaningful change, consistent with their intermediate pre-merger position.

The controls behave as expected: higher capital ratios and stronger macroeconomic conditions are associated with better liquidity, while inefficiency and adverse cycles weaken it. Taken together, these results support **H3 and H4**. Liquidity trajectories after mergers differ systematically by pre-merger conditions: strong banks consolidate their advantage post-merger, while weak banks struggle to recover, underscoring that M&A is not a uniform remedy for liquidity fragility and its effects vary by region.

Table 2.9: DiD Analysis of Liquidity Changes by Region, Size, and NSFR Category

	(1) Full Sample	(2) EU	(3) US	(4) EU Red_Large	(5) EU Yellow_Large	(6) EU Green_Large	(7) US Red_Large	(8) US Yellow_Large	(9) US Green_Large
Key Effects									
Treated	-0.015	-0.014	-0.022	0.038	-0.062*	0.013	-0.002	0.071*	-0.075
	(0.014)	(0.035)	(0.016)	(0.030)	(0.034)	(0.062)	(0.023)	(0.037)	(0.049)
Post	-0.005	0.168***	0.005	0.083***	0.031**	-0.008	0.001	-0.027**	0.040
	(0.004)	(0.018)	(0.004)	(0.023)	(0.016)	(0.067)	(0.008)	(0.011)	(0.044)
Treated × Post	0.011	0.016	0.022	**-0.063***	**0.060**	**-0.031**	**0.006**	**-0.071***	**0.110****
	(0.015)	(0.034)	(0.017)	(0.032)	(0.039)	(0.071)	(0.022)	(0.038)	(0.052)
R-squared	0.150	0.080	0.306	0.100	0.169	0.174	0.117	0.310	0.444
Observations	29,206	11,008	18,198	1,324	959	647	789	826	394
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table Description. This table reports the estimates from the Difference-in-Differences (DiD) analysis examining the impact of mergers on banks' structural liquidity (NSFR) (Eq 2.6). The DiD approach identifies causal effects by comparing the change in outcomes over time between a treatment group (merged banks) and a control group (non-merged banks). By taking differences across both groups and time, this method controls for time-invariant unobserved heterogeneity, isolating the effect attributable to mergers under the assumption of parallel trends.

Columns (1)–(3) present the baseline specification for the full sample, the EU, and the U.S., respectively. Columns (4)–(9) extend the model by interacting the treatment indicator with post-merger years for specific size–liquidity categories, focusing on large banks within the red, yellow, and green NSFR groups in the EU and U.S. samples. All models include bank and year fixed effects as well as the complete set of control variables. Robust standard errors are reported in parentheses.

Interpretation of Regression Results. The baseline DiD results in Columns (1)–(3) show no significant overall effect of M&A participation on structural liquidity. The estimated coefficients on the *Treated* × *Post* interaction are small and statistically insignificant, suggesting that, on average, mergers do not materially alter NSFR levels in either the combined or region-specific samples.

In contrast, the extended models in Columns (4)–(9) reveal substantial heterogeneity across liquidity conditions and regions. Among EU banks, large institutions in the red NSFR category experience a significant post-merger decline in liquidity (−0.063), implying that mergers may have exacerbated their already fragile funding positions. Large banks with stronger pre-merger liquidity (yellow and green groups) show modest improvements, though these effects are not statistically significant. In the U.S. sample, large banks in the green category display a significant post-merger increase in liquidity (+0.110), while those in the yellow category experience declines (−0.071) and those in the red category show no notable improvement.

Overall, these findings indicate that the liquidity effects of mergers are not uniform. Instead, they depend on banks' initial balance sheet strength and the regional context. Weakly funded large banks may fail to convert mergers into stronger liquidity positions, whereas financially sound institutions tend to consolidate their advantages. These results are consistent with Hypothesis 5, suggesting that the causal effect of mergers on structural liquidity is heterogeneous—beneficial for strong banks, neutral or adverse for fragile ones, and varying across regions.

Identification Strategy and Trend Adjustment. The baseline DiD specification relies on the standard parallel trends assumption, which requires that, in the absence of mergers, treated and non-treated banks would have followed similar liquidity trajectories. While the baseline results in Columns (1)–(3) indicate no statistically significant average treatment effect, this interpretation is potentially restrictive if underlying liquidity trends differ systematically across regions or across pre-merger liquidity conditions.

Preliminary inspection of pre-merger dynamics and region-specific estimations suggests that EU and U.S. banks experienced structurally different liquidity adjustments during the post-crisis regulatory period. Moreover, banks in weaker (red) NSFR categories display distinct pre-treatment adjustment patterns relative to stronger (yellow and green) institutions. These differences raise concerns that the strict parallel trends assumption may not hold uniformly across subsamples, particularly when liquidity status and regional regulatory environments interact with merger incentives.

To address this potential violation, the extended specifications in Columns (4)–(9) relax the homogeneous treatment effect assumption by allowing the merger effect to vary by pre-merger liquidity category and region. By interacting the treatment indicator with size–liquidity groups and estimating region-specific models, the framework accommodates heterogeneous adjustment paths and mitigates bias arising from differential underlying trends.

Importantly, the trend-adjusted specification does not overturn the baseline conclusion that mergers do not produce uniform liquidity gains. Rather, it reveals that the insignificant average effect conceals economically meaningful heterogeneity: liquidity declines among fragile EU banks coexist with improvements among well-capitalized U.S. institutions. The adjustment therefore strengthens the internal validity of the DiD design by demonstrating that the main conclusions are robust to relaxing the strict parallel trends assumption and accounting for differential pre-merger dynamics.

2.8 Graphical Evidence

To illustrate the interaction between bank size and liquidity, I present two complementary visualizations. The first figure provides an intuitive snapshot of the fitted probabilities across groups, while the second shows how predicted probabilities vary jointly with size and liquidity. Together, they complement the regression evidence for **H2** by visually confirming both the group ordering and the interaction pattern. To illustrate post-merger liquidity dynamics, I present a visualization of NSFR trajectories across regions and pre-merger liquidity groups. The figure complements the regression results for **H3–H5** by highlighting how post-merger outcomes differ between strong, medium, and weak banks, and how these effects vary across the EU and the U.S.

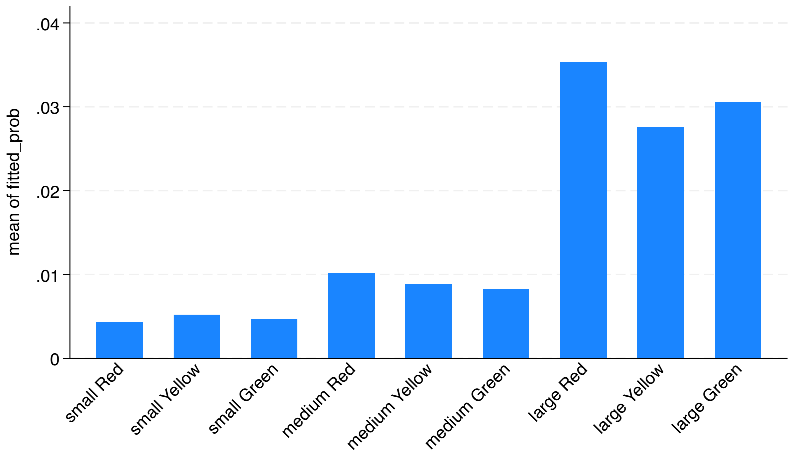

Figure 2.1: Mean of Fitted Probability by Size and Risk Group

Interpretation: The fitted probabilities follow the expected ranking. Within each liquidity group, acquisition likelihood rises with size, and within each size category, Green ≥ Yellow ≥ Red. Large green banks have the highest propensity to acquire, while small red banks have the lowest. Importantly, Large–Red banks still show higher acquisition likelihood than all small banks, indicating that scale partly offsets weak liquidity.

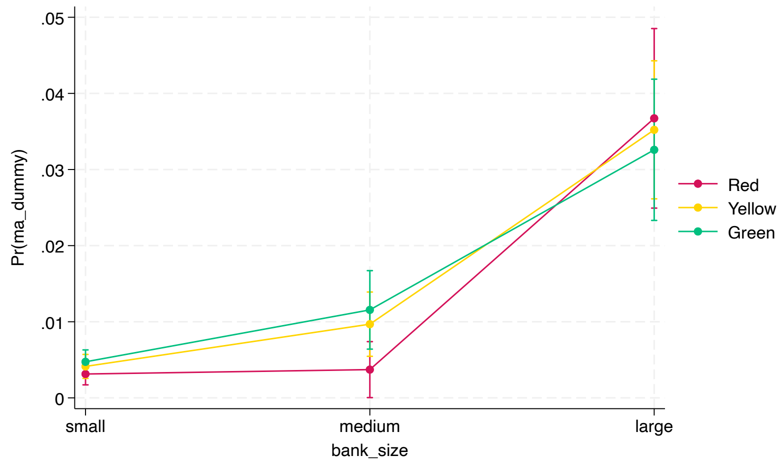

Figure 2.2: Predicted M&A Probability by Size and Liquidity, Marginsplot

Interpretation: Predicted probabilities show clear non-parallel slopes across liquidity groups. The size gradient is steepest for Green banks, moderate for Yellow, and flat for Red. This confirms the interaction pattern: liquidity amplifies or dampens the effect of size on acquisition likelihood, with strong liquidity reinforcing size effects and weak liquidity limiting them. The estimated margins corresponding to Figure 2.2 are reported in Table A.3.

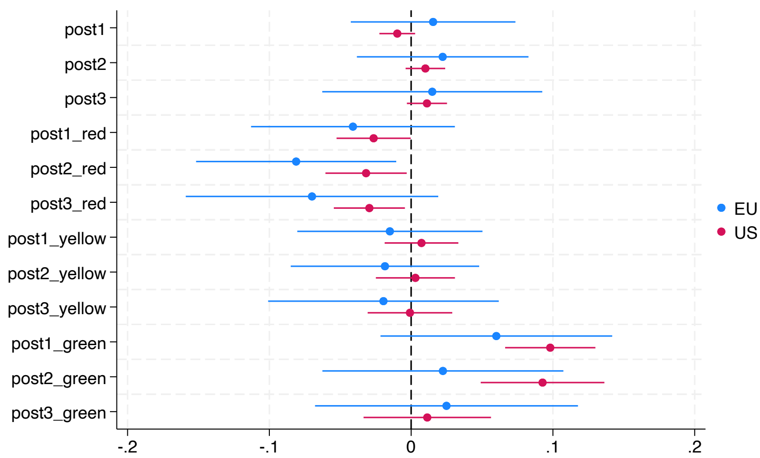

Figure 2.3: Post-Merger Liquidity Effects by Region

*Interpretation:*Estimated post-merger liquidity effects by region and pre-merger condition. Dots represent average treatment effects, while horizontal lines denote 95% confidence intervals. The results show that post-merger liquidity trajectories diverge across regions and pre-merger bank conditions. In the United States, Green banks experience pronounced gains in the first two years, while Red banks decline and Yellow banks remain broadly stable. In the European Union, Green banks achieve only modest improvements, whereas Red banks exhibit increasingly adverse outcomes, especially around the second year. Overall, the findings suggest that mergers tend to reinforce the resilience of already healthy institutions but offer limited remediation for weaker ones, with the clearest benefits concentrated among U.S. Green banks and the sharpest losses among EU Red banks.

2.9 Robustness Checks

To verify the stability of the main findings, two additional robustness exercises are conducted. First, the acquisition likelihood is re-estimated using a manual interaction specification that assigns banks to mutually exclusive size–liquidity groups (e.g., Red – Large, Green – Small). TableA.2 Second, a propensity score matching (PSM) framework is applied to ensure that treated and untreated banks are comparable on pre-merger characteristics. The propensity score matching (PSM) is implemented separately for EU and US banks. Treated units are defined as Red–Large, Yellow–Large, or Green–Large banks, with all other banks serving as potential controls. Propensity scores are estimated using a logit model based on pre-merger bank characteristics, macroeconomic conditions, and regulatory phases. Matching is performed with 1:1 nearest neighbour, a caliper of 0.05, and common support enforced. The reported effects are average treatment effects on the treated (ATT), complemented by weighted regressions and balance diagnostics to ensure comparability between treated and control groups. Both EU Red–Large and EU Green–Large banks show a treatment effect of 0.031, but the more minor standard error for Red–Large (0.006 vs. 0.011) implies a more precise and statistically stronger effect. This supports the conclusion that mergers consistently improve liquidity for fragile but large banks, while improvements for already firm (Green–Large) banks, though positive, are estimated with less precision (Heckman et al., 1998; Stuart, 2010). The formal model specifications are reported in A.1. TableA.5 presents the full set of estimation results from the propensity score matching exercise, showing treatment effects for all Red–Large, Yellow–Large, and Green–Large banks in both EU and US samples.

The robustness results align closely with the baseline findings. The manual interaction model confirms that large banks remain significantly more acquisitive across all liquidity categories, while small banks are largely inactive. The PSM results reinforce the difference-in-differences estimates by showing that liquidity gains are concentrated in European banks—especially those entering mergers in weak (red) or strong (green) liquidity positions—while effects in the U.S. are more muted. Taken together, these exercises reinforce the internal validity of the identification strategy and suggest that the main conclusions are robust to alternative specifications and sample splits.

Non-linear size effects. To verify whether the relationship between size and M&A activity is non-monotonic, I re-estimate the baseline logit specification including a quadratic term in size. The linear coefficient remains positive and statistically significant, while the squared term is negative and weakly significant, indicating diminishing marginal effects at very high size levels. The implied turning point lies outside the observed size distribution, implying that size remains monotonic within the sample. The inclusion of the quadratic term does not materially affect the magnitude or significance of the other regressors. The formal model specifications and estimations are reported in A.2 TableA.4.

2.10 Discussion

The empirical findings provide a coherent narrative of how liquidity and size jointly shape bank M&A decisions and their aftermath under Basel III's NSFR regime. This section interprets the results hypothesis by hypothesis and connects them with established evidence in the literature.

Liquidity, Size, and Acquisition Propensity (H1 and H2)

The analysis reveals that both structural liquidity, as measured by the NSFR, and bank size are significant drivers of acquisition activity. Consistent with **H1**, stronger liquidity positions raise the likelihood of initiating M&A, particularly in the EU. This finding aligns with broader corporate finance evidence that financial flexibility underpins acquisition activity (Myers and Majluf, 1984) and with the banking literature, which shows that favorable liquidity conditions foster more aggressive deal strategies (Baxamusa and Jalal, 2015).

The results also demonstrate that size is the dominant factor: large banks are systematically more acquisitive, while small banks are almost absent from M&A markets. Interaction models confirm **H2**: Liquidity effects are amplified by size, with Small–Red banks least active. Importantly, Large–Red banks emerge as the most acquisitive overall, even surpassing Large–Green, consistent with theories that scale eases funding constraints by expanding access to markets. These findings refine earlier work on liquidity transfer and synergies (Konstantaras and Sogiakas, 2019), highlighting not only how liquidity and size interact to shape strategic behavior but also how scale can enable even fragile institutions to dominate consolidation.

The Dark Side of Basel Regulation: Fragile Banks as Acquirers

An essential and unintended implication of the results is that Basel III's liquidity regulation may encourage fragile banks to pursue acquisitions as a form of regulatory arbitrage. The evidence shows that Large–Red banks remain significantly acquisitive, despite their weak funding profiles. In principle, the NSFR was designed to discourage such institutions from expanding risk exposures; in practice, scale enables them to offset liquidity shortfalls through market access or by acquiring targets with stronger funding bases. Yet the post-merger evidence indicates that these banks do not systematically repair their liquidity and, in some cases, further deteriorate.

This dynamic highlights a potential "dark side" of Basel regulation: rather than mitigating systemic fragility, it may inadvertently foster consolidation led by weak acquirers, concentrating risks in fewer, larger, but still underfunded institutions. Such a trajectory raises concerns about the re-emergence of the *too-big-to-fail* problem. Suppose fragile banks become larger through acquisition without addressing their underlying vulnerabilities. In that case, regulators may face increased pressure to support these institutions in times of stress, amplifying moral hazard and undermining the prudential intent of Basel III. This concern is consistent with longstanding arguments in the literature that bank consolidation can exacerbate systemic risk and reinforce TBTF incentives (Berger and Roman, 2015; Kaufman, 2014).

Post-Merger Liquidity Dynamics (H3 and H4)

Turning to post-merger outcomes, the fixed-effects results provide only limited evidence of average liquidity improvement, consistent with **H3**. This echoes Hagendorff et al. (2012), who document mean reversion in the liquidity and capitalization of EU banks after consolidation. The evidence suggests that while synergies may exist, they are not automatic and depend on integration capacity.

Interaction models sharpen the picture by confirming **H4**: post-merger outcomes depend strongly on pre-merger liquidity. Green banks consolidate their advantages, Red banks continue to deteriorate, and Yellow banks remain flat. This heterogeneity reconciles mixed evidence in prior work: some studies find liquidity creation after consolidation (Khoo et al., 2024), while others observe negligible changes in prudential metrics (Brealey et al., 2017; Hagendorff and Nieto, 2015). My results clarify that these divergent findings reflect differences in pre-merger conditions rather than contradictions in the underlying mechanisms.

Causal Effects and Robustness (H5)

The difference-in-differences framework establishes a causal link between mergers and liquidity outcomes, supporting **H5**. The results show positive causal effects for banks already in strong liquidity positions, neutral or adverse outcomes for fragile banks, and notable regional differences: U.S. Green banks improve significantly post-merger, while EU Red banks deteriorate further. These findings complement earlier work on regulatory constraints (Chiaramonte and Casu, 2017; Hlebik and Stránský, 2017), underscoring that the Basel III framework interacts with market structure to shape heterogeneous outcomes.

Robustness checks using propensity score matching confirm the heterogeneity: EU Red — Large and Green — Large banks experience significant liquidity gains, while U.S. effects are more minor and less precise. This consistency across specifications strengthens the causal interpretation and addresses concerns of selection bias that have hampered earlier M&A studies.

Implications and Limitations

Taken together, the findings contribute to the literature by showing that liquidity under Basel III is both a constraint and an enabler of consolidation. Liquidity advantages and scale increase acquisition propensity, but post-merger liquidity outcomes depend critically on pre-merger conditions. Academically, this study advances the M&A literature by providing NSFR-specific, causally identified evidence, extending earlier work that was often correlational or based on broader liquidity proxies. For policy, the results caution that mergers are not a universal remedy for liquidity fragility: strong banks become stronger, while fragile banks risk further deterioration. Supervisors should therefore incorporate both size and pre-merger liquidity into merger evaluations.

Limitations remain. The analysis focuses on the NSFR and does not test other Basel III liquidity metrics, such as the LCR. Deal-level heterogeneity (domestic versus cross-border, method of payment) may further influence outcomes, but is beyond the scope of the present study. Future work should also deepen the cross-country comparison to capture institutional differences in regulatory implementation and resolution regimes.

Chapter 3

Regulatory Flexibility and Bank Performance: Entry, Capitalization, Enforcement, Insurance Risk, and the Moderating Role of Liquidity and Size

3.1 Introduction

The structure and regulation of banking markets significantly influence how financial institutions compete, manage risks, and adjust their business models. Competition, supervisory oversight, and evolving sources of bank revenues are central to understanding not only institutional outcomes but also broader questions of financial stability and efficiency. This area remains significant in both academic debates on industrial organization and banking, as well as in policy discussions on the resilience of financial systems and the sustainability of banking practices. As banks continue to operate under heightened competitive pressure, stricter prudential requirements, and ongoing structural change, it becomes essential to clarify the mechanisms through which these forces affect profitability, stability, and business strategy.

Despite extensive prior research, three significant gaps remain. First, the literature has not resolved whether stronger entry pressure enhances profitability by fostering efficiency or undermines it through margin compression (Demsetz, 1973; Baumol et al., 1982; Berger, 1995a). Second, the stability implications of supervisory enforcement remain theoretically ambiguous: enforcement can discipline risk-taking but may also reflect supervisors' focus on fragile institutions (Dewatripont and Tirole, 1994; Mailath and Mester, 1994; Repullo, 2000). Third, although the rise of fee-based activities is well-documented, much less is known about how entry conditions and capital requirements jointly influence the balance between traditional intermediation and non-interest income streams (DeYoung and Roland, 2001; Stiroh, 2004b; Yıldırım and Kasman, 2014). Addressing these gaps is vital for understanding how banks respond heterogeneously to regulatory and market environments.

The aim of this study is to establish the *baseline associations* between key flexibility levers and core banking outcomes. I focus on three relationships: the link between competitive entry pressure and bank profitability; the association between supervisory enforcement and financial stability; and the impact of entry conditions and capitalization thresholds on business model composition. These objectives translate into three hypotheses: (1) entry pressure (*EntrySize*) affects ROA through efficiency and contestability channels; (2) supervisory enforcement (*SupEnforce*) has an ambiguous relationship with stability, proxied by the log Z-score, as it may both constrain risk-taking and target risky institutions; and (3) entry and capitalization conditions shape the share of non-interest income, with effects likely mediated by bank scale and capabilities.

The theoretical basis draws on three traditions. Efficiency and contestability theories frame the competition–profitability nexus; deterrence and risk-targeting theories clarify enforcement–stability links; and diversification and competitive response theories illuminate shifts in business models. These perspectives provide the conceptual scaffolding for my empirical design. Methodologically, I employ fixed-effects panel regressions on bank-level data, beginning with clean baseline specifications before introducing moderators. This progression allows us to isolate average associations before testing whether effects vary systematically by size and structural funding conditions.

The scope of the study covers banks across multiple jurisdictions, exploiting variation in size, funding profiles, and regulatory contexts. Data limitations remain, especially regarding detailed enforcement measures and the challenges of quantifying competition, yet my approach mitigates these through robust panel methods, lagged controls, and careful variable construction. The objective is not to establish definitive causality on every margin but to provide credible evidence on the central associations that inform further inquiry.

The remainder of this chapter is organized as follows. Section 3.2 reviews the relevant literature and develops the theoretical foundations of regulatory flexibility, outlining its expected effects on bank profitability, stability, and business-model composition, as well as the role of liquidity and size in shaping heterogeneous responses. Section 3.3 discusses the contribution of the study and its relevance to ongoing regulatory debates.

Section 3.4 describes the data sources, sample construction, and variable definitions. Section 3.5 presents the empirical strategy, including the baseline and interaction specifications, the difference-in-differences design contrasting large and small EU banks, placebo tests, and the mapping between theoretical predictions and econometric implementation.

Section 3.6 reports the empirical findings across performance dimensions—profitability (ROA), stability (log Z-score), and business-model composition (non-interest income)—followed by the difference-in-differences estimates and visual evidence. Section 3.7 interprets the results through the regulatory flexibility lens, evaluates robustness and identification, discusses policy implications, integrates the findings with the broader time-series evidence, and concludes with a synthesis.

3.2 Literature Review and Theoretical Foundations

This study sits at the intersection of three established strands of banking research: (i) how competitive *entry pressure* influences profitability, (ii) how *supervisory enforcement* relates to risk-adjusted stability, and (iii) how regulatory and competitive conditions reshape revenue composition between intermediation and *non–interest income* (NII). Building on these baselines, I develop the case for why the effects of such *flexibility levers* should vary systematically with *bank size* and *funding conditions* (NSFR), before linking these arguments directly to my empirical models (Eqs. 3.1–3.8) and hypotheses.

3.2.1 Competition and profitability (H1a: Baseline association)

Two classic perspectives yield competing predictions for how entry pressure affects ROA. The *efficiency* view holds that competition disciplines costs, reduces X-inefficiency, and rewards superior screening and monitoring, thereby raising profitability for efficient incumbents (Demsetz, 1973; Berger, 1995a; Coccorese and Pellecchia, 2022; De Cesari et al., 2024). By contrast, the *contestability* view emphasizes margin compression: credible potential entry narrows intermediation rents even without large structural change (Baumol et al., 1982; Schmaltz et al., 2018; Wang and Zhong, 2022). In banking, both forces plausibly operate, leaving the net effect of *EntrySize* on ROA an empirical matter—precisely what my baseline fixed-effects model (Eq. 3.1) seeks to capture.

3.2.2 Supervision and stability (H1b: Baseline association)

The expected relationship between enforcement and stability is theoretically indeterminate. A *deterrence* logic suggests that credible supervision reduces risk-taking and enhances solvency (Dewatripont and Tirole, 1994; Mailath and Mester, 1994; Repullo, 2000). A *risk-targeting* perspective, however, predicts a negative association because supervisors direct enforcement toward already fragile institutions (Jobst and Rieder, 2023). Empirical studies confirm this nuance: enforcement may curb specific risk margins but still coincide with higher measured insolvency risk, reflecting selection and timing effects (Neuner and Reitz, 2022; Ma and Vadasz, 2024). Hence, the *SupEnforce*–$\ln Z$ link (Eq. 3.2) is treated as ultimately an empirical question rather than one with a fixed theoretical sign.

3.2.3 Business–model composition (H1c: Baseline association)

Banks' revenue models adjust in response to competition and regulation. Diversification into NII reduces reliance on net interest margins but often increases volatility and operational complexity (Stiroh, 2004b; Wu et al., 2024). The direction of adjustment under entry pressure (*EntrySize*) and in the presence of capitalized entrants (*CapEntry*) depends on institutional scale and capability: larger platforms can expand fee businesses, while smaller banks may double down on relationship lending and core intermediation (DeYoung and Roland, 2001; Tran and Nguyen, 2023). My baseline for NII 3.3, therefore, estimates the average effect of these entry conditions without yet conditioning on size or liquidity.

3.2.4 Why heterogeneous effects? Moderators grounded in theory (H2–H4)

Bank size as a moderator. Size alters both *technology* and *incentives*. Large banks benefit from economies of scale in compliance, technology, and risk management (Wheelock and Wilson, 2012), as well as diversification across activities (Demsetz and Strahan, 1997). They may therefore absorb competitive or supervisory shocks differently than smaller institutions. At the same time, expectations of implicit support for systemically important banks can affect funding costs and risk incentives (Brewer III and Jagtiani, 2013; Zhu et al., 2023). These arguments justify allowing slopes to vary by size (Eq. 3.4), and in richer models, by size within NSFR tiers (Eq. 3.5).

Funding conditions (NSFR) as a moderator. Structural funding interacts with business strategy and risk tolerance. The NSFR directly links growth capacity and balance-sheet composition to funding stability (King, 2013). Empirical evidence demonstrates heterogeneous adjustment to liquidity rules (Banerjee and Mio, 2018; Bonner and Hilbers, 2015; Penczar et al., 2022; Chen et al., 2024). Theoretical contributions emphasize trade-offs between credit supply, liquidity risk, and funding resilience (Imbierowicz and Rauch, 2014; Berger and Bouwman, 2009; Wang, 2023). These insights motivate my dual approach: testing discrete NSFR tiers (Red/Yellow/-Green) to capture nonlinearities (Eq. 3.5), and estimating continuous NSFR slopes to examine whether marginal effects of flexibility levers vary with $L.\ln(\text{NSFR})$ (Eqs. 3.6–3.7).

Size $\times$ funding interaction. The interaction of size and liquidity conditions often proves decisive. Large, well-funded institutions may respond very differently to entry and enforcement than small, liquidity-constrained banks (Demirgüç-Kunt and Martínez Pería, 2010). Cross-country evidence confirms that structural characteristics such as size, capital, and funding profiles shape systemic risk and business-model complexity (Demirgüç-Kunt and Huizinga, 2013; Laeven and Levine, 2016). My three-way interactions (Size $\times$ NSFR tier $\times$ Lever) in Eq. 3.5 explicitly operationalize this logic.

3.2.5 Econometric mapping to hypotheses

Hypotheses

The theoretical arguments map directly into my empirical design: The baseline models examine how regulatory flexibility shapes banks' profitability, stability, and business model choices. The testable hypotheses are:

- **H1 (3.1).** Greater regulatory flexibility is associated with systematic differences in bank profitability (ROA).
- **H2 (3.2).** Regulatory flexibility affects bank stability, with implications for the distance to default (log Z-score).
- **H3 (3.3).** Regulatory flexibility influences banks' business models, shifting the balance between traditional intermediation and non–interest income activities.

The extended models allow testing of heterogeneity and timing effects:

- **H4 (3.4).** Size moderation: effects differ for large versus small banks.
- **H5 (3.5).** Funding moderation: effects vary across NSFR tiers, and further by size.
- **H6 (3.6).** Continuous NSFR moderation: lever effects vary with $\ln(\text{NSFR})$.
- **H7 (3.7).** These moderation effects may further differ by bank size or tier.
- **H8 (3.8).** A structural timing effect: the 2018 EU implementation shift for large relative to small banks, estimated via DiD.

Together, these hypotheses provide a systematic rationale for beginning with baseline models and then layering size and funding moderators, allowing us to trace not only average associations but also the structural heterogeneity at the core of regulatory flexibility.

3.3 Research Significance

The central contribution of Study 2 lies in examining *regulatory flexibility*—captured through entry pressure, supervisory enforcement, and capitalized entrants—as a determinant of bank performance. While prior research often treated regulation as a uniform constraint, this study shows that flexibility operates through heterogeneous channels, shaping profitability, stability, and business models differently across banks. By linking these mechanisms to size and liquidity conditions, the analysis demonstrates why identical rules can yield divergent outcomes, thereby refining both theoretical debates and policy discussions on efficient and resilient regulatory design.

3.4 Methodology

I study how regulatory *flexibility* relates to bank outcomes—profitability (ROA), stability (Z-score), and business model shift(non-interest income)—using an annual panel of banks in the EU and the USA over 2014–2024 (bank–years). To maintain comparability of specifications across outcomes, I employ a lean backbone of lagged bank-level and macro controls. Two structural characteristics—**Size** (log of GDP-deflated assets) and **NSFR**—enter baseline regressions as controls and later serve as moderators. Pre-processing removes duplicates, trims/winsorizes outliers, and deflates assets for cross-country comparability. Estimation relies on fixed effects with bank and year dummies, as well as bank-clustered standard errors. I do not include lagged dependent variables, given the short time dimension. Detailed variable definitions, formulas (including Basel-consistent NSFR construction), and complete model specifications are provided in the following sections.

3.4.1 Data Sources and Sample Design

This study utilizes a multi-source panel dataset that contains bank-level, institutional, and macroeconomic information. The sample encompasses commercial, cooperative, and savings banks from 2014 to 2024 for the 27 member countries from the EU and the USA.

Bank-level Data

For the bank-level data, I utilize BankFocus/Orbis, a product of Bureau van Dijk, for both regions (the EU and the USA). Some banks appeared more than once under the same Legal Entity Identifier (LEI). To maintain unique observations, I retained only those banks with a consolidation code of C1 (consolidated statements with no unconsolidated partner), C2 (consolidated statements with an unconsolidated partner), and U1 (unconsolidated statements with no consolidated partner), resulting in 62,482 observations. Furthermore, I consider only domestic banks, as they follow a consistent set of national regulations and supervisory frameworks. In contrast, foreign-owned banks may rely on support from their parent institutions to comply with the host country's regulatory requirements.

Flexibility Data

Data for the flexibility variables are obtained from the *Bank Regulation and Supervision Survey* (BRSS), published by the World Bank in 2011, 2016, and 2021. The BRSS provides institution-level information on regulatory frameworks, supervisory practices, and the financial environment in which banks operate. To construct a balanced panel, I apply a forward-fill procedure to interpolate annual data between survey years. The flexibility dataset covers the same set of banks and years as the bank-level dataset, ensuring complete consistency in sample composition.

Macroeconomic Data

Macroeconomic indicators, including GDP growth, inflation and unemployment, are sourced from the World Bank's *World Development Indicators* (WDI) and help capture country-level economic conditions, providing a macroeconomic context for bank performance. However, the inflation variable was excluded from the analysis because it exhibited a high variance inflation factor (VIF) of 10.1, indicating concerns about multicollinearity.

3.4.2 Variable Construction

Dependent variables: construction and units

Profitability (ROA). I measure profitability as the return on average assets (Demirgüç-Kunt et al., 2004):

$$\mathrm{ROA}_{it} = 100 \times \frac{\text{Net Income}_{it}}{\frac{1}{2}\big(\text{Total Assets}_{it} + \text{Total Assets}_{i,t-1}\big)}.$$

Units: percentage points. *Label in tables:* `ROA_A`. No additional transformation is applied.

Stability (ln Z). I use the standard bank Z score based on the rolling volatility of ROA (Laeven and Levine, 2016):

$$Z_{it} = \frac{\mathrm{ROA}_{it} + \frac{\text{Equity}_{it}}{\text{Total Assets}_{it}}}{\sigma\big(\mathrm{ROA}_{i,t-h:t-1}\big)}, \qquad \ln Z_{it} = \ln(Z_{it}),$$

where $\sigma(\mathrm{ROA}_{i,t-h:t-1})$ is the standard deviation of ROA computed over a backward rolling window of three years (I use the same window throughout the study for consistency). *Units:* natural log. *Label in tables:* `ln_Z_score`.

Business model (NII share). I proxy the business mix by the share of non-interest income in operating income (Stiroh, 2004a):

$$\mathrm{NII}_{it} = 100 \times \frac{\text{Non-interest Income}_{it}}{\text{Net Interest Income}_{it} + \text{Non-interest Income}_{it}}.$$

Units: percent. *Label in tables:* `nii_w`. Following data preparation, this series is winsorized at the 1st/99th percentiles to limit the influence of outliers; no log is applied. *Implementation notes.* Balance-sheet items are calendar-year aggregates; averages use adjacent-year assets to reduce mechanical scale effects. All dependent variables are contemporaneous Y_{it}; covariates enter as lagged where indicated in the specifications.

Explanatory variables

Flexibility Variables This study utilizes the World Bank's Bank Regulation and Supervision Survey (BRSS) institutional indicators as proxies for *regulatory flexibility*, which reflects the degree to which banking rules and supervisory practices can be tailored to individual bank characteristics, risk profiles, or market conditions. Prior research demonstrates that such institutional features play a central role in determining how banks adapt their strategies in response to shocks.

González (2009) demonstrates that contrasts in entry barriers, activity restrictions, deposit insurance generosity, and supervisory powers not only directly shape market structure, but also moderate how bank efficiency translates into market share and concentration. In environments with stronger private monitoring and higher-quality institutions, improvements in bank efficiency more readily translate into competitive advantage. By contrast, strict entry restrictions and overly generous deposit insurance can dampen adaptability and strategic repositioning. Similarly, Nayak (2021) finds that regulations on activities, supervision, capital requirements, and external monitoring have a significant impact on both profitability and risk management outcomes across 129 countries. Notably, operational constraints and higher supervisory intensity can enhance performance in some dimensions, while excessive capital rigidity or monitoring pressure can reduce margins.

Taken together, these findings underscore that institutional design has a significant impact on banks' ability to adjust their operations, manage risk, and adapt their business models. Flexibility, in this context, is not a procedural detail—it is a structural feature of the regulatory environment that shapes strategic capacity.

To operationalize these theoretical dimensions, I draw on specific BRSS items that capture the extent to which capital requirements, supervisory powers, and other rules can be adapted to bank-specific conditions. Among these, Question Q1.4.1 is particularly informative: it asks whether minimum capital requirements deviate from the standard rule and, if so, invites an open-ended explanation. This produces both a simple binary response (`cap_entry`) and a qualitative text field. The latter is especially valuable because it reveals *how* flexibility is applied in practice. The open-text explanations from Q1.4.1 were processed using a Python-based text analysis pipeline (Figure 3.1) and a Python script (Script C.1, following best practice in regulatory text analysis (Clapham et al., 2022). The procedure involved:

1. Converting all text to lowercase, removing punctuation, and normalizing spaces to ensure consistency in pattern recognition;

2. Removing both common English stopwords and domain-specific filler terms (e.g., "capital", "minimum", currency units) to focus on substantive content;

3. Searching for targeted keywords to classify responses into four dimensions: *business type*, *institution type*, *risk*, and *size threshold*.

Each dimension was coded as a binary indicator equal to one if the relevant keywords appeared, zero otherwise. While all four indicators were initially created, only two were retained for the main analysis, both for their stronger theoretical relevance and for showing meaningful cross-country variation:

- **Varies by risk**: equals one if national rules allow capital requirements to adjust according to institution-specific risk factors or potential adverse impacts.
- **Varies by size threshold**: equals one if the minimum capital requirement explicitly depends on the size or capital base of the institution.

These two measures capture distinct forms of regulatory flexibility: the first adjusts to differences in risk exposure, the second to disagreements in institutional scale. Other BRSS-based flexibility variables were excluded for clarity: *business-type* and *institution-type* tailoring were dropped due to multicollinearity and limited added relevance. In contrast, the supervisory-power variable (`sup_cap`, Q3.7) was excluded because it exhibited no cross-country variation in the sample. Detailed coding rules are provided in Table C.1.

Table 3.1: Flexibility variables derived from BRSS and measurement

Variable name	**BRSS code & question**	**Measurement**	**Description**
`cap_entry`	(Q1.4.1) entry capital varies by business type	Binary (Yes/No)	Whether minimum entry capital differs by license/business type (formal flexibility).
`entry_risk`	(Q1.4.1.1) open-text: tailoring by risk	Text-coded (0/1)	1 if the explanation states entry capital varies by *risk profile*; 0 otherwise.
`entry_size`	(Q1.4.1.1) open-text: tailoring by size	Text-coded (0/1)	1 if the explanation states entry capital varies by *size threshold*; 0 otherwise.
`cap_calc`	(Q3.11) credit risk capital calculation variants	Categorical (multiple choice)	Availability of alternative approaches (e.g., standardized vs. IRB).
`sup_exempt`	(Q7.1.2) exemptions from exposure limits	Binary (Yes/No)	Certain exposures (e.g., those guaranteed by the government) are exempt from these limits.
`ins_risk`	(Q8.16) risk-based deposit insurance premiums	Binary (Yes/No)	Premiums vary with bank risk, incentivizing prudent risk-taking.
`sup_enforce`	(Q11.4) early intervention framework	Binary (No/Yes)	Presence of trigger-based supervisory actions when thresholds are breached.

Note: All variables are derived from the BRSS. `cap_entry` captures whether minimum capital requirements vary by business type; `entry_risk` and `entry_size` are coded from the open-text portion of Q1.4.1. Variables for business-type and institution-type tailoring were excluded due to multicollinearity and limited relevance. The supervision-power variable (`sup_cap`, Q3.7) was dropped because it showed no cross-country variation.

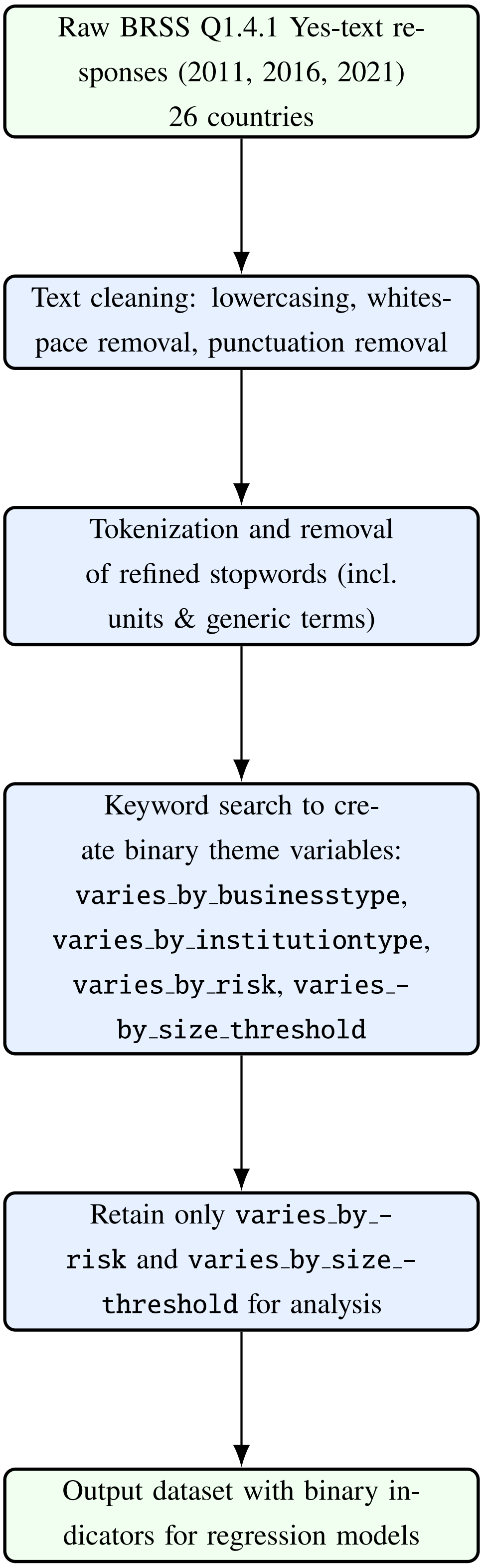

Figure 3.1: Pipeline for deriving flexibility variables from BRSS Q1.4.1 textual responses. Only `varies_by_risk` and `varies_by_size_threshold` were retained for further empirical analysis.

Structure of the BRSS Sample and Missingness The flexibility variables are derived from the World Bank's Bank Regulatory and Supervisory Survey (BRSS), which is conducted in discrete waves (2011, 2016, and 2021) rather than annually. These survey waves are merged at the country level and mapped onto the bank-year panel (2013–2024). Specifically, the 2011 wave is assigned to 2013–2016, the 2017 publication wave to 2017–2021, and the 2021 wave to 2022–2024. Within each survey wave, regulatory measures are held constant across years for a given country.

The bank-level panel itself is nearly balanced over time. Accordingly, missingness in the flexibility variables arises from survey reporting rather than bank attrition. Gaps are concentrated in specific country–wave combinations and primarily affect the open-text component of Question Q1.4.1 (minimum entry capital variation).

In the 2016 wave, several countries provide detailed textual explanations of how capital requirements vary (e.g., Austria, Germany, and France), while others report no open-text response despite indicating variation in entry capital rules. Notably, Czech Republic and Sweden provide no textual explanation in the 2016 survey wave. In these cases, the formal binary response is observed, but the qualitative explanation used to construct the `entry_risk` and `entry_size` indicators is missing.

Missingness does not affect entire survey waves, nor does it eliminate countries from the dataset. Rather, it reflects item-level non-response in particular flexibility dimensions. Other BRSS variables (including capital calculation variants, supervisory exemptions, deposit insurance risk-pricing, and early intervention frameworks) exhibit substantially higher completeness across countries and waves. As a result, the bank-year structure of the panel remains unchanged, and regulatory indicators are observed for the majority of country–wave combinations.

Non-Response and Potential Selection Bias Item-level non-response in cross-country regulatory surveys may introduce selection bias if the likelihood of providing detailed responses is systematically related to institutional characteristics. For example, jurisdictions with more developed supervisory frameworks or stronger regulatory transparency may provide more comprehensive textual explanations of capital tailoring, while countries undergoing regulatory transition or facing administrative constraints may provide less detailed responses.

If such institutional characteristics are also correlated with bank performance, stability, or business-model adaptation, estimated effects of regulatory flexibility could partially reflect differences in reporting behavior rather than purely regulatory structure. In this setting, however, non-response operates at the country–survey level rather than at the bank level, and banks are not excluded from the panel due to missing regulatory responses. Consequently, any , potential selection bias would arise from cross-country differences in reporting intensity rather than from selective bank participation. These characteristics are intrinsic to survey-based institutional data.

Structural characteristics (baseline controls; later moderators) Following the construction of the flexibility indicators, the empirical model also incorporates a set of control variables to account for other bank- and country-level characteristics that may influence performance, stability, and strategic adjustments. These controls ensure that differences in size, funding structure, macroeconomic environment, or institutional quality do not confound the estimated effects of regulatory flexibility.

In addition to these controls, the analysis focuses on two main independent variables of interest: **Bank Size** and the **Net Stable Funding Ratio (NSFR)**. Both variables are relevant in their own right and also serve as moderators in the interaction models presented in later chapters.

Bank size. Size matters for how banks perform, absorb shocks, and adapt to changing circumstances. Bigger banks can spread fixed costs, offer broader product lines, and access more markets—advantages that can smooth earnings and strengthen position. However, a larger size brings greater sophistication, and when markets expect too-big-to-fail (TBTF) support, those expectations can tilt funding terms and risk-taking incentives. In Kaufman (2014), TBTF is an *ex-post* resolution regime that protects some creditors, limiting spillovers—lowering funding costs but weakening market discipline—. In contrast, higher capital and liquidity standards (e.g., NSFR) are *ex-ante* tools that reduce failure probabilities. Recent cross-country evidence adds nuance: G–SIBs are more likely to be rescued, yet support arrives later, is smaller relative to assets, comes with more challenging conditions, and ends sooner—so any ex-ante TBTF edge may be offset by stricter ex-post treatment (Berger and Roman, 2015). Large, internationally active banks also differ in funding structure and complexity, which is why I read size alongside structural liquidity (NSFR) (Vázquez and Federico, 2015).

Measurement. I measure bank size as the log of *real* total assets:

$$\mathrm{Size}_{b,t} \equiv \ln\left(\mathrm{TA}_{b,t} \times \frac{100}{\mathrm{GDPDeflator}_{c,t}}\right),$$

Where the country-specific GDP deflator is normalized to 2015=100.

Why real. Deflating makes size comparable across countries and over time and avoids inflation-driven drift.

Net Stable Funding Ratio (NSFR). The NSFR is a Basel III liquidity regulation aimed at ensuring banks maintain a stable funding base that aligns with the liquidity profile of their assets (Basel Committee on Banking Supervision, 2010; Vázquez and Federico, 2015). It is defined as:

$$\mathrm{NSFR}_{b,t} = \frac{\mathrm{ASF}_{b,t}}{\mathrm{RSF}_{b,t}} * 100, \tag{3.1}$$

where *Available Stable Funding* (ASF) is the weighted aggregate of funding sources (equity and long-term debt receive the highest weights; see Table A.1), while short-term wholesale liabilities receive the lowest—and *Required Stable Funding* (RSF) is the weighted sum of assets and off-balance-sheet exposures, with higher weights for less liquid positions. For details on NSFR computation, see Table A.1, adapted from Vázquez and Federico (2015).

In plain terms, the NSFR rewards banks for relying on stable, long-term funding and penalizes reliance on short-term, volatile sources. A value above one hundred means the bank's stable funding at least covers its liquidity needs for the coming year.

Alongside the continuous measure, I classify banks into three NSFR categories for robustness checks and visualisation: *Red* (NSFR $<$ 100), *Yellow* (100 $\leq$ NSFR $<$ 120), and *Green* (NSFR $\geq$ 120). This helps capture non-linear differences in funding stability and examine whether the effects of regulatory flexibility differ across varying levels of structural liquidity.

Table 3.2: Classification thresholds for bank size and NSFR categories

Variable	**Category**	**Definition / Threshold**
	Small	Total assets ≤ \$1 billion
Bank Size	Medium	\$1 billion < Total assets < \$3 billion
	Large	Total assets ≥ \$3 billion
	Red	NSFR < 100
NSFR	Yellow	100 ≤ NSFR < 120
	Green	NSFR ≥ 120

Note: Bank size thresholds follow the classification in Berger and Bouwman (2009). NSFR categories are defined by the author for sub-sample analysis. The 100% cut-off aligns with Basel III requirements; the 120% threshold identifies banks with extreme funding stability.

Other Controls I keep the controls lean and reproducible. To limit reverse causality, all bank-level controls enter with a one-period lag ($L.$). Skewed ratios are log-transformed with a +1 offset; outliers are winsorized at the 1st/99th percentiles (Dixon, 1960). Assets are deflated by country GDP deflators (2015=100). Unless otherwise noted, ratios are expressed as percentages. *Role across specifications.* In baseline regressions, $\ln(\text{NSFR} + 1)$ and $\text{Size}_{\text{real}}$ enter as (lagged) controls; in extended models, they also serve as moderators via interactions with the flexibility indicators (e.g., $\ln(\text{NSFR} + 1) \times \mathbf{F}_{b,t}$, $\text{Size}_{\text{real}} \times \mathbf{F}_{b,t}$).

The empirical specification employs a set of well-established control variables capturing key aspects of bank structure, performance, and macroeconomic conditions. These variables proxy for funding stability, capitalization, asset quality, diversification, liquidity, size, profitability, efficiency, and economic context, all of which are expected to influence banks' resilience and profitability.

$L.\ln(\textbf{NSFR})$ Funding stability is proxied by the Net Stable Funding Ratio (NSFR), transformed as $\ln(\text{NSFR}+1)$. As discussed by Vázquez and Federico (2015), a higher NSFR indicates a more durable funding structure, mitigating liquidity risk and strengthening resilience. Accordingly, a **positive relationship** with bank performance and stability is expected.

L.**CARs_w** The regulatory capital ratio, winsorized to limit outlier influence, reflects banks' loss-absorbing capacity. In line with Berger (1995b), well-capitalized banks are better able to absorb shocks and sustain lending during stress periods. Hence, the expected sign is **positive**. CARs and the non-interest income ratio are winsorized at the 1st and 99th percentiles. [1]

L. ln(**Asset quality**) Defined as $\ln\left(1 + \frac{\text{Net impairment charges}}{\text{Net interest income}} \times 100\right)$, this measure captures loan portfolio soundness. Following Berger and DeYoung (1997), higher values denote weaker credit quality, reflecting greater impairment charges relative to income. A **negative effect** on performance and resilience is therefore anticipated.

L.**Non-interest income_w** Calculated as $\frac{\text{Non-interest income}}{\text{Operating revenues}} \times 100$, this variable proxies for the bank's business mix and is winsorized to mitigate extremes. The expected sign is theoretically **ambiguous**: diversification into fee-based activities may stabilize revenues and reduce dependence on interest margins, but may also expose banks to higher income volatility in stress conditions (Berger and DeYoung, 1997).

L. ln(**Liquid assets**) Measured as $\ln(1 + \frac{\text{Liquid assets}}{\text{Total assets}})$, this ratio indicates the extent of easily realizable assets available to meet obligations. As Kashyap and Stein (2002) argue, higher liquidity buffers reduce fire-sale risks and enhance short-term resilience, suggesting a **positive expected effect**.

L.**Size**$_{\textbf{real}}$ Defined as $\ln\left(\text{Total assets} \times \frac{100}{\text{GDP Deflator}_{c,t}}\right)$, this variable controls for scale effects. Larger banks may benefit from diversification and economies of scale, yet excessive size can generate complexity and moral hazard. The expected relationship is thus **nonlinear or ambiguous** (Berger and DeYoung, 1997).

L.**Net interest margin** The net interest margin (NIM) captures the bank's earning power and efficiency in pricing risk. In accordance with Angbazo (1997), higher NIMs typically reflect stronger intermediation margins and risk management capability, implying a **positive association** with stability and performance.

L.**Cost-to-income** This ratio, $\frac{\text{Operating expenses}}{\text{Operating income}} \times 100$, measures cost efficiency. A higher value denotes weaker operational control and lower profitability. Berger and Mester (2007) find a negative relationship between cost inefficiency and performance, hence the expected sign is **negative**.

Unemployment rate The national unemployment rate (in %) captures cyclical labor market conditions. Rising unemployment signals weaker demand and higher default probabilities, suggesting a **negative relationship** with bank performance.

[1] CARs and the non-interest income ratio are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme tail observations. No other variables are winsorized.

GDP growth The annual real GDP growth rate (in %) proxies for macroeconomic dynamism. Higher growth fosters loan demand and reduces default risk, thereby supporting profitability and resilience. The expected sign is **positive**.

Together, these variables represent the main structural, financial, and macroeconomic determinants of bank performance and stability within the empirical framework.
Pre-processing. I drop near-empty records (more than seven missing fields), remove duplicates at the bank×year level, and apply winsorization to CARs and non-interest income ratios. Histograms and skewness checks guide the log transforms; the +1 offset preserves zeros.
Panel setup. Regressions are run with bank and time effects Wooldridge (2010); all bank-level controls above enter as L.lags to reduce simultaneity. Macro controls (unemployment, GDP growth) enter contemporaneously.

Variable Selection and exclusion

Table 3.3: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
entry_risk	62,482	0.686	0.464	0.000	1.000
entry_size	62,482	0.109	0.311	0.000	1.000
cap_entry	61,986	0.959	0.198	0.000	1.000
sup_enforce	62,413	0.027	0.162	0.000	1.000
ins_risk	62,482	0.964	0.186	0.000	1.000
sup_exempt	62,050	0.982	0.132	0.000	1.000
ROA_A	62,482	0.690	0.520	-1.117	3.231
ln_Z_score	62,482	4.558	1.158	2.265	8.375
L.nii_w	53,328	25.167	13.499	1.604	63.745
L.ln_NSFR	53,328	4.603	0.321	2.334	5.852
L.CARs_w	32,360	18.004	6.037	10.937	46.410
L.ln asstqual	47,770	1.612	1.082	-9.676	4.152
L.ln_liqasst	53,328	3.361	0.465	1.988	4.290
L.sizel	53,328	13.071	1.587	8.581	21.786
L.nim	53,328	2.971	0.960	0.854	5.762
L.cst_inc	53,328	72.104	13.341	35.317	112.412
uepm_rate	62,482	7.585	1.510	2.015	26.708
gdp_grth	58,284	2.121	3.057	-10.940	24.616

Notes: L.x denotes the first lag of variable x. All figures rounded to three decimals.

Descriptive statistics. Table 3.3 shows substantial cross-sectional and time variation across policy dummies, performance indicators, and core controls. Policy variables display highly uneven distributions, with some (such as entry size and supervisory enforcement) rarely binding, while others (including capital entry and insurance risk) are almost always active. Bank performance also varies widely, as reflected in the dispersion of ROA, Z-scores, and non-interest income shares. Core controls—such as NSFR, capital ratios, size, cost-to-income, liquidity, and net interest margins—exhibit meaningful heterogeneity across banks. Finally, macroeconomic conditions fluctuate appreciably, underscoring the inclusion of bank and year fixed effects to absorb persistent heterogeneity and common shocks, as well as the need for heterogeneity analysis by size and liquidity categories through interaction terms and marginal effects. [2]

Table 3.4: Correlation Matrix

Panel A: Core variables

	entry_risk	entry_size	cap_entry	sup_enforce	ins_risk	sup_exempt	ROA_A	ln_Z_score
entry_risk	1.000							
entry_size	-0.389	1.000						
cap_entry	0.283	0.068	1.000					
sup_enforce	-0.169	0.174	-0.283	1.000				
ins_risk	0.254	-0.070	0.192	-0.183	1.000			
sup_exempt	0.130	-0.065	0.333	-0.038	0.477	1.000		
ROA_A	0.563	-0.196	0.033	-0.037	0.012	-0.017	1.000	
ln_Z_score	-0.356	0.115	0.098	-0.044	0.102	0.060	-0.405	1.000

Panel B: Additional variables vs. Panel A columns

	entry_risk	entry_size	cap_entry	sup_enforce	ins_risk	sup_exempt	ROA_A	ln_Z_score
L.nii$_w$	-0.672	0.208	-0.215	0.098	-0.104	-0.109	-0.347	0.189
L.ln_NSFR	0.174	-0.155	0.055	-0.092	-0.021	0.023	0.060	-0.021
L.CARs_w	-0.230	0.054	-0.247	0.018	-0.017	-0.036	-0.145	0.109
L.ln_asstqual	-0.474	0.164	-0.107	0.065	-0.113	-0.064	-0.239	0.063
L.ln_liqasst	-0.206	0.101	-0.066	0.035	-0.154	-0.058	-0.153	0.119
L.sizel	-0.259	0.098	-0.128	0.152	0.065	-0.041	-0.086	0.086
L.nim	0.769	-0.217	0.175	-0.080	-0.006	-0.053	0.615	-0.369
L.cst_inc	-0.100	0.023	0.028	-0.032	-0.018	0.001	-0.506	0.111
uepm_rate	-0.005	0.358	0.350	-0.056	0.345	0.158	-0.178	0.292
gdp_grth	-0.143	0.051	-0.012	0.025	-0.014	-0.022	-0.053	-0.025

Panel C: Additional variables among themselves

	L.nii_w	L.ln_NSFR	L.CARs_w	L.ln_asstqual	L.ln_liqasst	L.sizel	L.nim	L.cst_inc	uepm_rate	gdp_grth
L.nii_w	1.000									
L.ln_NSFR	-0.069	1.000								
L.CARs_w	0.123	0.281	1.000							
L.ln_asstqual	0.407	-0.140	-0.030	1.000						
L.ln_liqasst	0.183	0.604	0.355	-0.017	1.000					
L.sizel	0.374	-0.212	-0.169	0.254	-0.083	1.000				
L.nim	-0.617	0.072	-0.268	-0.339	-0.267	-0.324	1.000			
L.cst_inc	0.169	0.062	0.070	-0.112	0.105	-0.211	-0.147	1.000		
uepm_rate	-0.021	-0.079	-0.105	-0.044	0.039	0.075	-0.082	0.019	1.000	
gdp_grth	0.173	0.028	0.065	0.248	0.059	0.035	-0.149	0.014	-0.072	1.000

[2] CARs and the non-interest income ratio are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme tail observations. No other variables are winsorized.

Correlation patterns (descriptive, not causal). The matrix in Table 3.4 highlights three blocks. First, a business-model block around the net interest margin: *L.nim* correlates strongly with *entry_risk* (ρ=0.769) and ROA (0.615), and moves inversely with lagged non-interest income (−0.617), consistent with a fee-vs–spread composition trade-off (Nguyen, 2012). Second, liquidity measures overlap: *L. ln_NSFR* and *L. ln_liqasst* are closely related (0.604), indicating that they capture similar structural liquidity. Third, profitability and stability are moderately inversely related (ROA vs. ln(Z-score), −0.405). Most other pairwise correlations are modest, suggesting that conventional controls (capital, asset quality, size, costs, macro) contribute distinct variation. Two practical cautions follow from these patterns: (i) avoid stacking highly collinear liquidity measures in the same baseline; and (ii) be mindful that NIM and non-interest income are mechanically intertwined, so specifications should not over-control one when the other is the outcome.

Variable selection and exclusions. To avoid redundancy and improve precision, I exclude *L.ln_liqasst* from baselines that include *L.ln_NSFR* given their substantial overlap ($\rho \approx 0.604$). I also omit the near-constant dummy *sup_exempt* (mean $\approx$ 0.982), which provides little identifying variation. Because *L.nii_w* is a lagged dependent variable, I do not include it in fixed-effects models of non-interest income to avoid dynamic panel bias. Finally, owing to its strong association with both policy variables and the outcome mix (*entry_risk* with *L.nim* $\rho \approx 0.769$; *L.nim* with *L.nii_w* $\rho \approx -0.617$), I exclude *L.nim* from the main non-interest-income specifications.

3.5 Econometric Framework

3.5.1 Baseline and Interaction Specifications

To examine how regulatory flexibility and funding stability influence bank performance, I estimate fixed–effects panel regressions for three dependent variables: profitability (ROA), stability (log Z–score), and business model composition (non–interest income, NII). Each specification includes year fixed effects and standard errors clustered at the bank level to account for serial correlation and unobserved heterogeneity (Cameron and Miller, 2015).

The explanatory focus lies on a set of "flexibility" indicators— EntryRisk_{it}, EntrySize_{it}, CapEntry_{it}, SupEnforce_{it}, and InsRisk_{it}— which collectively capture the intensity of entry conditions, capitalization thresholds for entrants, supervisory enforcement, and insurance–related risk exposure. These variables operationalize different channels of the Basel regulatory and supervisory framework that jointly determine how banks adapt their behavior under varying competitive and prudential environments.

To control for structural and macroeconomic conditions, I include a vector of lagged covariates $\mathbf{X}_{i,t-1}$, defined as:

$$\mathbf{X}_{i,t-1} = \big\{\text{CAR}_{i,t-1},\ \text{AssetQuality}_{i,t-1},\ \text{Size}_{i,t-1},\ \text{CostIncome}_{i,t-1},\\ \text{M\&A dummy}_{i,t-1},\ \text{UnempRate}_{it},\ \text{GDPGrowth}_{it}\big\}.$$

This set captures capitalization, credit risk, efficiency, and macroeconomic context. In all baseline specifications, I further include $\ln(\text{NSFR}_{i,t-1})$ to represent structural funding strength. For ROA and stability regressions, the lagged net interest margin (NIM) enters as an additional control, while for NII models, it is omitted to avoid mechanical endogeneity with the dependent variable (Roodman, 2009).

The first model examines profitability as a function of regulatory flexibility, funding stability, and lagged fundamentals:

$$\text{ROA}_{it} = \alpha + \sum_k \theta_k \,\text{Flex}_k^{it} + \beta \ln(\text{NSFR}_{i,t-1}) + \mathbf{X}'_{i,t-1}\gamma + \delta_t + \varepsilon_{it}. \tag{3.1}$$

This formulation captures how variation in regulatory flexibility translates into profitability differences, conditional on liquidity strength and bank characteristics.

A parallel specification is used for financial stability, where the log of the Z–score serves as the dependent variable:

$$\ln(\text{ZScore}_{it}) = \alpha + \sum_k \theta_k \,\text{Flex}_k^{it} + \beta \ln(\text{NSFR}_{i,t-1}) + \mathbf{X}'_{i,t-1}\gamma + \delta_t + \varepsilon_{it}. \tag{3.2}$$

The log transformation facilitates interpretation of coefficients as semi–elasticities, with $100 \times (\exp(\theta) - 1)$ representing the percentage change in the distance-to-default resulting from a one-unit increase in a flexibility variable (Halvorsen and Palmquist, 1980). This allows direct economic interpretation of how supervisory or entry-based changes affect resilience.

Finally, I estimate a corresponding model for the share of non–interest income, which captures shifts in banks' business models:

$$\text{NII}_{it} = \alpha + \sum_k \theta_k \,\text{Flex}_k^{it} + \beta \ln(\text{NSFR}_{i,t-1}) + \mathbf{X}'_{i,t-1}\gamma + \delta_t + \varepsilon_{it}. \tag{3.3}$$

Here, a positive coefficient indicates that flexibility is associated with greater diversification into fee-based income, whereas a negative one suggests a reversion toward core intermediation.

Together, these baseline models provide a unified empirical framework to evaluate how regulatory flexibility interacts with structural funding to shape bank profitability, stability, and business model outcomes across institutions and over time.

Interaction Models (EU Focus)

Building on the baseline regressions, I examine how the impact of regulatory flexibility varies systematically across banks. Heterogeneity is explored through interaction models and post-estimation marginal effects (Brambor et al., 2006). To ensure robustness, I begin with a comprehensive specification that includes all interactions of flexibility with both bank size and funding stability. Nested models are then re-estimated, each time removing one interaction term to assess coefficient stability (Hendry, 1995). Interactions are retained only when signs and magnitudes remain stable across these nests, avoiding spurious or collinear effects. Two empirical regularities guide the final model selection: (i) `sup_exempt` is nearly constant (98% exempt) and thus omitted; and (ii) `entry_risk` is dropped whenever it becomes collinear.

Size × Flexibility (Base Interaction).

$$Y_{it} = \alpha + \boldsymbol{\theta}^{\top}\mathbf{Flex}_{it} + \lambda\,\mathrm{Large}_i + \phi\left(\mathrm{Flex}^{\star}_{it} \times \mathrm{Large}_i\right) + \beta\,\ln(\mathrm{NSFR}_{i,t-1}) + \mathbf{X}^{\top}_{i,t-1}\boldsymbol{\gamma} + \delta_t + \varepsilon_{it}. \quad (3.4)$$

In this baseline interaction model, Large_i identifies large banks, and $\mathrm{Flex}^{\star}_{it}$ represents the focal flexibility indicator—$\mathrm{EntrySize}_{it}$ for ROA, $\mathrm{SupEnforce}_{it}$ for Z-score, and either $\mathrm{EntrySize}_{it}$ or $\mathrm{CapEntry}_{it}$ for NII. The interaction term $\left(\mathrm{Flex}^{\star}_{it} \times \mathrm{Large}_i\right)$ tests whether regulatory flexibility operates differently across bank sizes. The coefficient ϕ thus captures the incremental effect for large relative to small banks. A positive ϕ implies stronger flexibility benefits among large banks, while a negative value suggests that smaller banks leverage flexibility more effectively. Other parameters follow the same definitions as in the baseline specification.

Size × NSFR Category × Flexibility (Preferred).

$$\begin{aligned} Y_{it} = \alpha &+ \boldsymbol{\theta}^{\top}\mathbf{Flex}_{it} + \lambda\,\mathrm{Large}_i + \boldsymbol{\eta}^{\top}\mathbf{D}^{\mathrm{NSFR}}_{it} + \beta\,\ln(\mathrm{NSFR}_{i,t-1}) \\ &+ \beta_1\left(\mathrm{Flex}^{\star}_{it} \times \mathrm{Large}_i\right) + \boldsymbol{\beta}_2^{\top}\left(\mathrm{Flex}^{\star}_{it} \times \mathbf{D}^{\mathrm{NSFR}}_{it}\right) + \boldsymbol{\beta}_3^{\top}\left(\mathrm{Flex}^{\star}_{it} \times \mathrm{Large}_i \times \mathbf{D}^{\mathrm{NSFR}}_{it}\right) \\ &+ \mathbf{X}^{\top}_{i,t-1}\boldsymbol{\gamma} + \delta_t + \varepsilon_{it}. \end{aligned} \quad (3.5)$$

Equation (3.5) enriches the baseline heterogeneity framework by introducing joint moderation through size and funding tiers. $\mathbf{D}^{\mathrm{NSFR}}_{it}$ denotes the vector of NSFR-category dummies—Red, Yellow, and Green—classified by fixed liquidity thresholds, with the Green tier omitted as the reference group. Coefficient vectors $\boldsymbol{\eta}$, $\boldsymbol{\beta}_2$, and $\boldsymbol{\beta}_3$ capture level and interaction effects across these tiers. The triple interaction $\left(\mathrm{Flex}^{\star}_{it} \times \mathrm{Large}_i \times \mathbf{D}^{\mathrm{NSFR}}_{it}\right)$ isolates whether the influence of regulatory flexibility differs not only by size but also by banks' funding stability. This preferred formulation therefore provides a multidimensional view of flexibility, identifying contexts—such as weak funding positions or large institutional scale—where its impact on performance is amplified or diminished.

Continuous heterogeneity. While the categorical NSFR specification captures discrete funding regimes, the next two models extend the analysis by treating funding stability as a continuous measure. This approach offers a finer view of how regulatory flexibility operates across the full liquidity distribution, avoiding arbitrary threshold effects.

NSFR × Flexibility (Baseline Continuous Interaction).

$$Y_{it} = \alpha + \boldsymbol{\theta}^\top \mathbf{Flex}_{it} + \boldsymbol{\phi}^\top\big(\mathbf{Flex}^\star_{it} \times \ln(\text{NSFR}_{i,t-1})\big) + \beta \ln(\text{NSFR}_{i,t-1}) + \mathbf{X}^\top_{i,t-1}\boldsymbol{\gamma} + \delta_t + \varepsilon_{it}. \quad (3.6)$$

This specification replaces discrete NSFR categories with a continuous measure of funding stability, allowing the marginal effect of each flexibility variable to vary smoothly with ln(NSFR). The interaction coefficient $\boldsymbol{\phi}$ thus captures how flexibility's influence changes across different liquidity environments. For instance, flexibility might enhance profitability more strongly when funding structures are stable, but less so when liquidity is strained.

NSFR–Slope with Size and NSFR–Category Heterogeneity (Preferred Continuous Model).

$$\begin{aligned} Y_{it} = {} & \alpha + \boldsymbol{\theta}^\top \mathbf{Flex}_{it} + \lambda\,\text{Large}_i + \boldsymbol{\eta}^\top \mathbf{D}^{\text{NSFR}}_{it} \\ & + \psi\left(\text{Flex}^\star_{it} \times \ln(\text{NSFR}_{i,t-1})\right) + \delta_1\left(\text{Large}_i \times \ln(\text{NSFR}_{i,t-1})\right) + \boldsymbol{\delta}_2^\top\left(\mathbf{D}^{\text{NSFR}}_{it} \times \ln(\text{NSFR}_{i,t-1})\right) \\ & + \beta \ln(\text{NSFR}_{i,t-1}) + \mathbf{X}^\top_{i,t-1}\boldsymbol{\gamma} + \delta_t + \varepsilon_{it}. \end{aligned} \quad (3.7)$$

Equation (3.7) extends the interaction framework by integrating both continuous and discrete moderation. The parameter ψ identifies how the slope of the focal flexibility variable varies with funding stability, while δ_1 and $\boldsymbol{\delta}_2$ capture, respectively, the additional heterogeneity associated with bank size and NSFR tiers. Together, these terms provide a flexible, continuous mapping of how regulatory flexibility interacts with structural funding resilience across heterogeneous banking environments.

Regressions are estimated using two-way fixed effects with bank and year dummies (Wooldridge, 2010). Lagged bank-level controls mitigate simultaneity and reverse-causality concerns, while contemporaneous macroeconomic variables such as unemployment and GDP growth capture cyclical variation.

3.5.2 Difference-in-Differences Design (EU—Large vs. Small Banks)

The analysis further explores the 2018 regulatory tightening within the EU using a two-way fixed-effects Difference-in-Differences (DiD) framework (Angrist and Pischke, 2009). The design exploits a clear pre- and post-policy division, with large banks treated and small banks serving as the control group.

Baseline Specification.

$$Y_{it} = \alpha_i + \delta_t + \beta\,(\text{LargeBank}_i \times \text{Post}_t) + \mathbf{F}'_{it}\theta + \mathbf{X}'_{i,t-1}\gamma + \varepsilon_{it}. \tag{3.8}$$

The coefficient β measures the differential change in outcomes post-2018 for large (treated) versus small (control) EU banks, conditional on controls and fixed effects. Identification hinges on the parallel pre-trend assumption.

3.5.3 Placebo Test (Pre-Period Only)

To validate the parallel trends assumption, I conduct a placebo test restricted to the pre-2018 sample, defining a pseudo-post period (2016–2017) (Bertrand et al., 2004):

$$Y_{it} = \alpha_i + \delta_t + \alpha\,(\text{LargeBank}_i \times \text{PlaceboPost}_t) + \mathbf{F}'_{it}\theta + \mathbf{X}'_{i,t-1}\gamma + \eta_{it}, \qquad t \le 2017. \tag{3.9}$$

An insignificant $\hat{\alpha}$ supports the absence of differential pre-trends, reinforcing DiD validity. All variables and transformations (e.g., $\ln(\cdot + 1)$, winsorization, and dummy construction) follow the definitions detailed in the data appendix. These models together provide a consistent and transparent empirical structure linking flexibility, funding stability, and bank performance under evolving regulatory environments.

Reporting. I report $\hat{\beta}$ for each outcome alongside clustered standard errors, R^2, and the count of banks. For transparency, I also show the placebo estimates $\hat{\alpha}$ restricted to $t \le 2017$ with the 2016 pseudo-post.

3.5.4 How Size and Funding Stability Moderate Flexibility–Performance Links

Economic motivation. Theory suggests that the impact of a flexibility lever $F^{\star}_{it}$ may depend on two environments: (i) *bank size* (scale, diversification, TBTF expectations), and (ii) *funding stability* (NSFR), which shapes risk tolerance and business-model choices. I therefore allow the slope on $F^{\star}_{it}$ to vary by size and by NSFR.

Baseline (no moderation). The baseline ROA, $\ln Z$, and NII models (Eqs. (3.1)–(3.3)) include *all* flexibility variables as direct regressors, $L.\ln \text{NSFR}$, lagged bank controls, and year fixed effects; standard errors are clustered at the bank level—these estimate average partial associations without heterogeneity.

Introducing moderation. I add interactions on top of the same baseline controls and fixed effects:

1. **Size moderation** (Eq. (3.4)): $\text{Large}_i \times F_{it}^{\star}$ lets the slope on $F_{it}^{\star}$ differ for large vs. small banks.

2. **Discrete funding moderation** (Eq. (3.5)): $\text{Large}_i \times \mathbf{D}_{it}^{\text{NSFR}} \times F_{it}^{\star}$ lets the slope vary across NSFR tiers (Red, Yellow; Green omitted) and by size.

3. **Continuous funding moderation** (Eqs. (3.6)–(3.7)): $F_{it}^{\star} \times L.\ln \text{NSFR}_{i,t-1}$ makes the marginal effect of $F_{it}^{\star}$ move with funding stability, optionally allowing size/NSFR-tier heterogeneity in that slope.

Which interactions are retained (diagnostic screening). For each outcome, I estimate (i) models with a single focal interaction and (ii) a joint model containing the relevant set. I *retain* an interaction only if (a) its sign is stable and (b) its magnitude remains economically reasonable across (c), and it is not removed by collinearity. Two data features guide exclusions: `sup_exempt` is nearly constant and is dropped from preferred models; `entry_risk` is omitted wherever Stata drops it due to collinearity. The focal interactions that pass this screening are:

- ROA: `entry_size` as the flexibility driver of interest;
- $\ln Z$: `sup_enforce` to capture risk-based supervisory pressure;
- NII: `entry_size` and `cap_entry` to capture business-mix responses to entry.

How results are summarized. Because high-order interactions are not directly comparable across groups, I report **average marginal effects (AMEs)** by Size×NSFR cell. AMEs translate the interactions into interpretable within-cell slopes. All estimates are conditional on the same lagged controls and year fixed effects; standard errors are clustered by bank. (Stata may omit AMEs for a regressor if it is collinear in a given specification.)

Relation to the DiD. The EU DiD in Eq. (3.8) identifies a *timing* effect around 2018 via $\text{LargeBank}_i \times \text{Post}_t$ and is conceptually distinct from the moderation analyses above. Placebo estimates (pre-2018 with a 2016 pseudo-post) assess parallel trends.

3.6 Results

3.6.1 Profitability (ROA)

I begin with the analysis of profitability. Table 3.5 presents the fixed-effects OLS estimates from Eq. (3.1). The coefficients show that regulatory flexibility at the entry level is significantly related to bank profitability. Specifically, both *entry_risk* and *entry_size* are positively associated with ROA in the full sample, suggesting that jurisdictions allowing greater discretion or scale in entry tend to exhibit stronger profitability outcomes. In contrast, *cap_entry* loads negatively, indicating that stricter capitalization requirements at entry correlate with lower near-term profitability. These results are consistent with the idea that greater initial capital buffers may constrain the capacity for return generation in the short run.

Focusing on the EU subsample, the coefficient on *entry_size* remains economically and statistically significant, confirming that larger entry thresholds are associated with higher profitability among European banks. Meanwhile, *ins_risk* turns negative in the EU, consistent with the interpretation that stricter insurance risk-based pricing mechanisms compress margins and profitability. The control variables behave in the expected way: higher net interest margins (L.nim) and lower cost-to-income ratios (L.cst_inc) are both linked to higher profitability, whereas weaker asset quality (L.ln_asstqual) has an adverse effect.

Interestingly, the sign of the lagged NSFR coefficient differs by region: it is negative in the EU and positive in the US. This divergence implies distinct balance-sheet adjustment dynamics, with U.S. banks translating higher structural funding into stronger profitability, while European institutions might still be adapting to regulatory funding constraints. These results are estimated under two-way (bank and year) fixed effects with robust standard errors clustered at the bank level and should be interpreted as conditional associations rather than causal effects.

Table 3.5: Determinants of Profitability (ROA) — Baseline Regression Results

Description. Eq. (3.1) is estimated via two-way (bank and year) fixed-effects OLS for ROA, including the flexibility proxies *entry_risk*, *entry_size*, *cap_entry*, *sup_enforce*, and *ins_risk*, plus the standard lagged controls (variables prefixed by "L."). Bank and year fixed effects are included in all columns. Standard errors are clustered at the bank level. Column headings indicate the estimation sample.

Outcome Var		*ROA*	
	(1) All	(2) EU	(3) US
Key variables			
entry_risk	0.283***	—	—
	(0.014)		
entry_size	0.183***	0.268***	—
	(0.013)	(0.025)	
cap_entry	-0.133***	-0.125***	—
	(0.021)	(0.028)	
sup_enforce	-0.013	0.028	—
	(0.023)	(0.024)	
ins_risk	-0.043***	-0.162***	—
	(0.024)	(0.030)	
Controls (lagged)			
L.ln_NSFR	0.019	-0.042***	0.223***
	(0.015)	(0.018)	(0.024)
L.CARs_w	0.001	0.009***	-0.007***
	(0.001)	(0.001)	(0.001)
L.ln_asstqual	-0.042***	-0.044***	-0.049***
	(0.003)	(0.004)	(0.005)
L.sizel	0.008***	0.024***	-0.007***
	(0.002)	(0.003)	(0.004)
L.nim	0.191***	0.162***	0.225***
	(0.007)	(0.012)	(0.009)
L.cst_inc	-0.020***	-0.011***	-0.024***
	(0.000)	(0.001)	(0.000)
L.ma_dummy	-0.008	0.044	-0.019
	(0.023)	(0.040)	(0.025)
uepm_rate	-0.048***	-0.042***	—
	(0.005)	(0.009)	
gdp_grth	0.004***	0.005***	—
	(0.001)	(0.001)	
Constant	1.671***	1.141***	0.948***
	(0.088)	(0.110)	(0.159)
Observations	26,228	10,042	16,186
R^2	0.615	0.516	0.475
Bank FE; Year FE	Yes	Yes	Yes

Robust s.e. in parentheses; clustered by bank. Em dash = not included/dropped.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

To explore heterogeneity, Table 3.6 reports the average marginal effects (AMEs) of *EntrySize* across bank size and NSFR categories in the EU sample. The results show that *EntrySize* increases profitability for both small and large banks, though the magnitude is higher for large institutions, reflecting scale advantages in regulatory flexibility. When the NSFR dimension is considered, the effects remain positive in all tiers but are strongest under Red and Yellow classifications—where liquidity constraints are tighter—and slightly smaller in Green. This pattern suggests that the profitability benefits of flexibility are most pronounced when balance-sheet pressures are binding.

Overall, these results indicate that entry-related flexibility tends to enhance profitability, particularly for large banks and in contexts of limited liquidity. The findings are consistent with the hypothesis that regulatory environments allowing more discretion at entry promote better performance outcomes, conditional on institutional and funding characteristics.

Table 3.6: Average Marginal Effects of *EntrySize* by Bank Size and NSFR Group (EU)

	Red	**Yellow**	**Green**
Small bank (0)	0.175^{***}	0.245^{***}	0.228^{***}
	(0.029)	(0.024)	(0.024)
Large bank (1)	0.347^{***}	0.344^{***}	0.248^{***}
	(0.069)	(0.037)	(0.033)
Year FE; lagged controls		Yes	
N (banks)		10,042 (2,037)	

Notes: AMEs from the preferred *LargeBank*×*NSFR*×*EntrySize* specification. Robust s.e. clustered by bank. *** $p < 0.01$.

3.6.2 Stability ($\ln Z$)

Turning to bank stability, Table 3.7 reports the fixed-effects OLS estimates from Eq. (3.2). Regulatory flexibility linked to entry—*entry_risk* and *entry_size*—is negatively associated with the log Z-score in the full sample (and for *entry_size* within the EU). This pattern is consistent with looser or larger-scale entry appearing in contexts where measured stability is weaker, rather than implying a causal deterioration. *Sup_enforce* is also negative on average, which aligns with supervisory *targeting* of already riskier banks; by contrast, *ins_risk* is positively associated with stability, suggesting better risk internalization where deposit insurance is more risk-sensitive. The slope on NSFR differs by region—positive for All/EU, negative for the US—indicating structural differences in how funding stability maps into measured distance-to-default. Controls move as expected: weaker asset quality and higher costs reduce Z; capitalization and macro conditions behave in the standard way. These are conditional associations under two-way fixed effects with bank-clustered s.e., not causal effects.

To examine heterogeneity, I report average marginal effects (AMEs) from the EU interaction models. First, the size-only AMEs (Table 3.8) show that stronger *Sup_enforce* is associated with lower Z for *small* banks on average, while the mean effect is statistically indistinguishable from zero for *large* banks. Second, refining by funding tiers (Table 3.9), small-bank AMEs are negative across all NSFR categories (largest in Yellow), whereas for large banks the adverse association is concentrated in Red and becomes statistically null in Yellow/Green. Together, these results support a targeting interpretation: enforcement intensity co-occurs with fragility at smaller or weakly funded institutions, while well-funded large banks are largely insulated.

Table 3.7: Determinants of Bank Stability ($\ln Z$) — Baseline Regression Results

Description. Eq. (3.2) is estimated via two-way (bank and year) fixed-effects OLS for $\ln Z$, including the flexibility proxies *entry_risk*, *entry_size*, *cap_entry*, *sup_enforce*, and *ins_risk*, plus the standard lagged controls (variables prefixed by "L."). Bank and year fixed effects are included in all columns. Standard errors are clustered at the bank level. Column headings indicate the estimation sample.

Outcome Var	$\ln Z$		
	(1) All	(2) EU	(3) US
Key vars			
entry_risk	-1.126^{***}	—	—
	(0.041)		
entry_size	-1.065^{***}	-0.951^{***}	—
	(0.040)	(0.087)	
cap_entry	0.818^{***}	0.516^{***}	—
	(0.067)	(0.100)	
sup_enforce	-0.345^{***}	-0.281^{***}	—
	(0.072)	(0.081)	
ins_risk	0.536^{***}	0.298^{***}	—
	(0.065)	(0.108)	
Controls (L.)			
L.ln_NSFR	0.087^{***}	0.309^{***}	-0.304^{***}
	(0.045)	(0.064)	(0.056)
L.CARs_w	0.009^{***}	-0.005	0.026^{***}
	(0.002)	(0.003)	(0.002)
L.ln_asstqual	-0.077^{***}	-0.061^{***}	-0.084^{***}
	(0.008)	(0.015)	(0.010)
L.sizel	0.003	-0.002	-0.002
	(0.008)	(0.013)	(0.007)
L.nim	-0.152^{***}	-0.181^{***}	-0.133^{***}
	(0.016)	(0.039)	(0.016)
L.cst_inc	0.000	0.010^{***}	-0.007^{***}
	(0.001)	(0.002)	(0.001)
L.ma_dummy	-0.085	-0.122	-0.043
	(0.063)	(0.112)	(0.063)
uepm_rate	0.198^{***}	0.277^{***}	—
	(0.018)	(0.037)	
gdp_grth	-0.061^{***}	-0.051^{***}	—
	(0.003)	(0.004)	
Constant	3.108^{***}	1.210^{***}	6.736^{***}
	(0.265)	(0.444)	(0.319)
Observations	26,228	10,042	16,186
R^2	0.344	0.369	0.131
Bank FE; Year FE	Yes	Yes	Yes

Robust s.e. in parentheses (clustered by bank). — = not included/dropped.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.8: Stability ($\ln Z$): AME of Supervisory Enforcement by Bank Size (EU)

	$\mathrm{d}Y/\mathrm{d}(\text{SupEnforce})$	s.e.
Small bank (0)	-0.646***	(0.114)
Large bank (1)	-0.035	(0.095)
Year FE; lagged controls	Yes	
N (banks)	10,042 (2,037)	

AMEs from LargeBank×SupEnforce model. SEs clustered at the bank level. *** $p < 0.01$.
Margins are derived from Table B.3 col.02, Eq. (3.4).

Table 3.9: Stability ($\ln Z$): AME of Supervisory Enforcement by Bank Size and NSFR (EU)

	Red	Yellow	Green
Small bank (0)	-0.502*** (0.166)	-0.870*** (0.207)	-0.563*** (0.113)
Large bank (1)	-0.577*** (0.169)	0.056 (0.115)	0.104 (0.141)
Year FE; lagged controls		Yes	
N (banks)		10,042 (2,037)	

AMEs from LargeBank×NSFR×SupEnforce model. SEs clustered at the bank level. *** $p < 0.01$.
Omitted AMEs. No marginal effects for $\ln Z$ heterogeneity by *entry_risk* are reported because `entry_risk` and `entry_risk`×$L.\ln(\text{NSFR})$ were dropped for perfect collinearity in the EU sample. Margins are derived from Table B.4 col.02, Eq. (3.5).

3.6.3 Business Model (NII)

Finally, I turn to the composition of bank income. Table 3.10 reports results from Eq. (3.3), estimated via two-way fixed effects. In the full sample, both *entry_risk* and *entry_size* exhibit strong negative associations with non–interest income (NII), while *ins_risk* loads positively. This pattern suggests that where entry regulation is more flexible—whether through risk or size thresholds—banks depend less on fee-based activities, whereas risk-sensitive deposit insurance appears to encourage a greater reliance on non–interest income. Within the EU, the signs for *entry_size* and *ins_risk* remain consistent, while *sup_enforce* is statistically imprecise.

Control variables behave in line with expectations: stronger funding structures (L.ln_NSFR) and larger bank size (L.sizel) are associated with greater NII shares, reflecting both scale economies and greater product diversification among larger, better-funded institutions. Conversely, higher capitalization (CARs_w) is negatively related to NII in the full and U.S. samples, suggesting that well-capitalized banks may rely more heavily on traditional intermediation. As throughout, these associations are conditional on bank and year fixed effects with bank-clustered standard errors, and should not be interpreted causally.

To explore heterogeneity, the EU interaction results are summarized in Tables 3.11–3.13. The first set of AMEs indicates that small banks reduce their NII share in response to greater *EntrySize* and more stringent *CapEntry*, whereas large-bank coefficients are statistically muted. Extending the analysis to funding heterogeneity, small-bank reductions in NII are most pronounced in the Yellow and Green NSFR tiers for *EntrySize*, and in the Red and Green tiers for *CapEntry*. By contrast, large banks show little systematic sensitivity across liquidity categories. Finally, the triple interaction with supervisory enforcement (Table 3.13) shows no statistically significant impact of enforcement intensity on NII across any size–NSFR combinations, suggesting that the business model response to regulatory oversight is largely neutral once balance-sheet resilience is accounted for.

Table 3.10: Determinants of Bank Business Model (NII) — Baseline Regression Results

Description. Eq. (3.3) is estimated via two-way (bank and year) fixed-effects OLS for NII, including the flexibility proxies *entry_risk*, *entry_size*, *cap_entry*, *sup_enforce*, and *ins_risk*, plus the standard lagged controls (variables prefixed by "L."). Bank and year fixed effects are included in all columns. Standard errors are clustered at the bank level. Column headings indicate the estimation sample.

Outcome Var	*NII*		
	(1) All	(2) EU	(3) US
Key vars			
entry_risk	-16.994^{***}	—	—
	(0.364)		
entry_size	-1.868^{***}	-1.033	—
	(0.482)	(0.797)	
cap_entry	-1.659^{***}	-1.765^{***}	—
	(0.785)	(0.836)	
sup_enforce	-1.907	-0.371	—
	(1.192)	(1.177)	
ins_risk	2.671^{***}	2.316^{***}	—
	(0.659)	(0.751)	
Controls (L.)			
L.ln_NSFR	4.402^{***}	2.791^{***}	8.151^{***}
	(0.576)	(0.680)	(1.024)
L.CARs_w	-0.065^{***}	0.044	-0.199^{***}
	(0.025)	(0.036)	(0.034)
L.ln_asstqual	0.861^{***}	1.354^{***}	0.608^{***}
	(0.110)	(0.136)	(0.182)
L.sizel	2.208^{***}	1.605^{***}	2.814^{***}
	(0.098)	(0.134)	(0.137)
L.nim	—	—	—
L.cst_inc	0.251^{***}	0.234^{***}	0.279^{***}
	(0.013)	(0.020)	(0.017)
L.ma_dummy	0.027	1.535	-0.072
	(0.612)	(0.960)	(0.774)
uepm_rate	0.235^{***}	0.524^{***}	—
	(0.092)	(0.129)	
gdp_grth	0.397^{***}	0.348^{***}	—
	(0.032)	(0.034)	
Constant	-35.889^{***}	-24.139^{***}	-74.317^{***}
	(3.263)	(3.958)	(5.436)
Observations	26,228	10,042	16,186
R^2	0.555	0.244	0.205
Bank FE; Year FE	Yes	Yes	Yes

Robust s.e. in parentheses (clustered by bank). — = not included/dropped.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.11: Business Model (NII): AMEs of EntrySize and CapEntry by Bank Size (EU)

	Small bank (0)	Large bank (1)
$\mathrm{d}Y/\mathrm{d}(\text{EntrySize})$	-1.683** (0.807)	0.090 (1.013)
$\mathrm{d}Y/\mathrm{d}(\text{CapEntry})$	-3.618*** (0.942)	1.273 (1.539)
Year FE; lagged controls	Yes	
N (banks)	10,042 (2,037)	

AMEs from LargeBank×{EntrySize, CapEntry} model; SEs clustered by bank. *** $p < 0.01$, ** $p < 0.05$.
Margins derived from Table B.5 col.01 Eq. (3.4).

Table 3.12: Business Model (NII): AMEs of EntrySize and CapEntry by Bank Size and NSFR (EU)

	Red	Yellow	Green
Panel A: $\mathrm{d}Y/\mathrm{d}(\mathit{EntrySize})$			
Small bank (0)	-0.608 (1.025)	-2.669*** (0.831)	-2.562** (0.908)
Large bank (1)	-2.626† (1.552)	1.166 (1.336)	-1.995† (1.073)
Panel B: $\mathrm{d}Y/\mathrm{d}(\mathit{CapEntry})$			
Small bank (0)	-6.838*** (1.333)	-1.890 (1.341)	-2.755** (1.118)
Large bank (1)	1.843 (1.808)	2.613 (1.783)	-0.132 (1.623)
Year FE; lagged controls		Yes	
N (banks)		10,042 (2,037)	

AMEs from LargeBank×NSFR×{EntrySize, CapEntry} model; SEs clustered at bank level. *** $p < 0.01$, ** $p < 0.05$, † $p < 0.10$.
Margins derived from Table B.5 col.02 Eq. (3.5).

Table 3.13: Business Model (NII): AME of Supervisory Enforcement by Bank Size and NSFR (EU)

	Red	Yellow	Green
Small bank (0)	-2.419 (1.472)	0.107 (1.241)	-1.244 (1.203)
Large bank (1)	-2.345 (1.449)	0.574 (1.342)	-1.194 (1.197)
Year FE; lagged controls		Yes	
N (banks)		10,042 (2,037)	

AMEs from the NII model with NSFR slope varying by size and category and including $c.\text{SupEnforce} \times L.\ln(\text{NSFR})$; robust s.e. clustered by bank.
Across Size×NSFR cells, enforcement shows no statistically significant average effect on NII. Margins derived from Table B.6 col.02 Eq. (3.7).

3.6.4 Difference-in-Differences (EU: Large vs. Small)

The EU DiD estimates from Eq. (3.8) provide a timing-based contrast around 2018. ROA declines for large banks relative to small banks post-2018 by a modest but precisely estimated amount; $\ln Z$ shows no average treatment effect; and NII is economically small and statistically indistinguishable from zero once group-specific trends address pre-trend concerns.

Table 3.14: Difference-in-Differences (EU, Large vs. Small): Main Estimates

	ROA (1)	$\ln Z$ (2)	**NII (trend-adjusted)** (3)
Post×Large (tp)	-0.063^{***}	-0.080	0.035
	(0.011)	(0.050)	(0.402)
Observations	10,042	10,042	10,042
R^2	0.309	0.079	0.300
Bank FE; Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Clustered s.e.	Bank	Bank	Bank

Notes: Two-way FE DiD at the bank×year level; tp is Large×Post (post-2018). All columns include lagged controls; s.e. clustered by bank. Column (3) adds group-specific linear trends for NII (preferred). *** $p < 0.01$.
Pre-trend check. Placebo estimates for $t \leq 2017$ with a 2016 pseudo-post are null for ROA and $\ln Z$, but not for NII; hence the trend-adjusted specification in Column (3).

3.6.5 Visual Evidence

Time-series plots complement the regression evidence by showing how average outcomes evolved across groups before, during, and after the 2018 regulatory adjustment and the 2020 macro shock. They serve two purposes: (i) to verify whether the group differences underlying the fixed-effects and DiD estimates are visible in levels and trends, and (ii) to illustrate the heterogeneity patterns (by size and NSFR tier) emphasized by the AME results.

For ROA (Fig. 3.2), the 2020 dip and rebound are common across groups, consistent with a broad macro shock. After 2018, large banks modestly underperform small banks, aligning with the negative DiD estimate (Table 3.14) and the slightly attenuated large-bank AMEs in the Green NSFR tier (Table 3.6). By liquidity tier, the Red group sits above Yellow/Green, consistent with tighter liquidity supporting higher profitability where *EntrySize* enhances ROA.

For stability (Fig. 3.3), a sharp 2020 decline and partial recovery dominate. No durable post-2018 divergence appears, confirming the null DiD for $\ln Z$. Higher-liquidity tiers (Yellow/Green) maintain higher stability, in line with the positive NSFR slope in the EU sample and AMEs showing that enforcement intensity lowers Z only for small banks (Table 3.9).

For NII (Fig. 3.4), a pronounced 2020 spike and normalization reflect a common aggregate shock. No sustained post-2018 gap emerges between large and small banks, consistent with the trend-adjusted DiD being economically and statistically null. The AMEs reveal that stronger entry pressure shifts small banks away from fee income—especially in Yellow/Green tiers—while large-bank effects are imprecise (Table 3.12).

Link back to models. Overall, the figures align with the sign and direction of the baseline coefficients (Eqs. (3.1)–(3.3)), the structured heterogeneity by size and liquidity (Eqs. (3.4)–(3.7)), and the 2018 DiD timing contrast (Eq. (3.8)). The visuals should be read as descriptive complements to the econometric identification, illustrating the dynamic patterns behind the fixed-effects and AME estimates rather than serving as independent causal evidence.

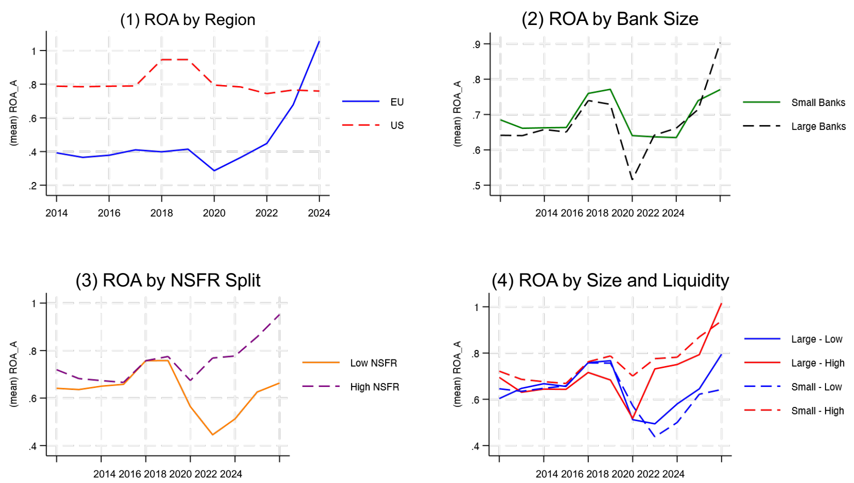

Figure 3.2: Bank Profitability Trends Across Sub-Samples

- The 2020 dip and rebound are common across groups. After 2018, large banks underperform small banks modestly and persistently—consistent with a negative DiD estimate for tp (Table 3.14). By liquidity tier, Red sits above Yellow/Green, matching the negative Yellow/Green level dummies and the AMEs showing entry raises ROA across tiers. At the same time, the large-bank increment attenuates in Green (Tables 3.6).

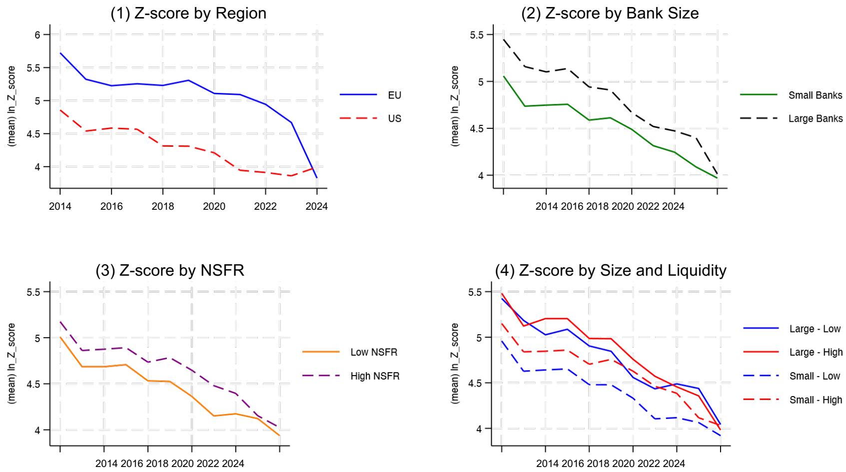

Figure 3.3: Bank Stability Trends Across Sub-Samples

- A sharp 2020 drop and partial recovery dominate; there is no durable large–small divergence post-2018, consistent with a null DiD for $\ln Z$ (Table 3.14). Higher-liquidity groups (Yellow/Green) look more stable, aligning with slope heterogeneity in the Z regressions and AMEs where enforcement reduces Z for small banks but is statistically zero for large banks in Yellow/Green (Table 3.9).

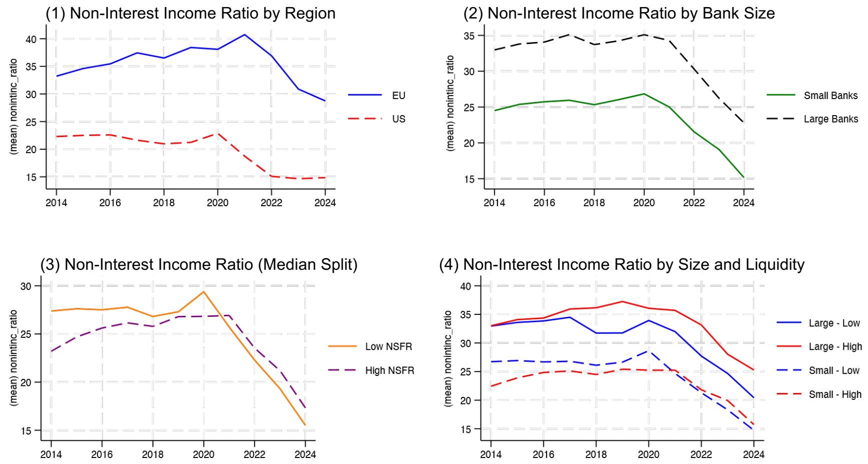

Figure 3.4: Business-Model (NII) Trends Across Sub-Samples

- A pronounced 2020 spike and normalization are evident. There is no sustained post-2018 treatment-style gap between large and small banks—consistent with the trend-adjusted DiD being economically small and statistically null (Table 3.14). Heterogeneity is muted in levels, which squares with AMEs: entry pressure tilts *small* banks away from NII (especially in Yellow/Green), while effects for *large* banks are imprecise (Table 3.12).

3.7 Discussion

This section synthesizes the evidence from fixed–effects panel regressions, the EU Difference-in-Differences (DiD), and post-estimation average marginal effects (AMEs). The explanatory variables *EntrySize*, *CapEntry*, *SupEnforce*, and *InsRisk* are treated as **BRSS flexibility indicators**—rulebook- and supervision-based levers capturing the local intensity of entry conditions and supervisory stance. Intuitively, more permissive entry (*EntrySize*, *CapEntry*) alters competitive pressure, while *SupEnforce* and *InsRisk* capture supervisory interventions and risk-based targeting. I interpret coefficients and AMEs as conditional associations under bank and year fixed effects, with causal claims supported only by the DiD design.

3.7.1 Profitability (ROA): Competition and the 2018 Timing

(i) Competition is profitability-enhancing. Across Size×NSFR strata, *EntrySize* is positively and significantly associated with ROA. AMEs are largest in the mid-tier NSFR group (Yellow), slightly smaller in Green, and weakest in Red (Table 3.6). This pattern supports the *efficiency channel* (Coccorese and Pellecchia, 2022; De Cesari et al., 2024), where competition increases profitability by rewarding efficient institutions and forcing operational improvements. The attenuated effect in Red, where funding is tight, suggests that efficiency gains are harder to realize when liquidity constraints bite. The moderation across liquidity tiers resonates with evidence that competition interacts with balance-sheet conditions and scale in shaping outcomes (Tran and Nguyen, 2023).

(ii) Large–small divergence after 2018. The EU DiD identifies a significant ROA decline for large banks after 2018 ($tp = -0.063$, $p < 0.01$; Table 3.14), while placebo tests confirm parallel pre-trends. This persistent shortfall for large institutions is consistent with contestability theory, whereby heightened entry compresses margins more than efficiency gains can offset. Similar effects are observed in contexts where revenue-based competition reduces profitability through margin pressure (Schmaltz et al., 2018; Wang and Zhong, 2022). Figure 3.2 illustrates the durable but modest divergence.

(iii) NSFR slope heterogeneity is modest. The NSFR slope is slightly negative in Yellow (negative Yellow×$L.\ln \text{NSFR}$), while the *EntrySize*×NSFR slope interaction is imprecise (Table B.2). This indicates that funding stability plays a secondary role in moderating competition's profitability effects. Overall, the findings support the efficiency hypothesis with competition raising ROA, tempered by a clear 2018 timing effect for large banks.

3.7.2 Stability ($\ln Z$): Funding Stability and Enforcement

(i) Funding stability enhances resilience. Higher lagged NSFR is consistently associated with higher $\ln Z$, with stronger slopes in the mid-tier (Yellow) group. This underscores the stabilizing role of structural funding, in line with prudential theories that emphasize liquidity and maturity transformation risks (Wang, 2023). The time-series (Figure 3.3) highlights a sharp 2020 shock and partial recovery, but no persistent large–small divergence, consistent with null DiD estimates (Table 3.14).

(ii) Enforcement effects reflect targeting, not destabilization. AMEs show that *SupEnforce* is associated with lower $\ln Z$ for small banks across NSFR tiers, but is statistically null for large banks in Yellow/Green (Table 3.9). This pattern supports the *risk-targeting hypothesis* (Jobst and Rieder, 2023): enforcement is concentrated where fragility is already present, rather than causing instability. The lack of adverse effects for well-funded large banks is consistent with recent evidence that observed negative enforcement–stability correlations reflect supervisory selection, not destabilization. These findings thus favor a targeting interpretation over deterrence in my setting.

3.7.3 Business Model (NII): Entry and Capitalized Entrants

(i) Small banks retreat from NII under stronger entry. For smaller institutions, both *EntrySize* and especially *CapEntry* reduce the NII share, while large-bank effects are muted or imprecise (Table 3.11). By NSFR tier, the strongest declines are in Yellow and Green (Table 3.12). This suggests that intensified competition pushes smaller banks back toward core intermediation, consistent with *competitive response theory* (Tran and Nguyen, 2023; Wu et al., 2024), which argues that fee-based diversification is less viable for banks with limited scale or capabilities.

(ii) No systematic enforcement effect on NII. When the NSFR slope is allowed to vary and $c.\text{SupEnforce}\times L.\ln\text{NSFR}$ terms are included, AMEs for enforcement remain imprecise and indistinguishable from zero across Size×NSFR strata (Table 3.13). This null finding aligns with mixed evidence that supervisory enforcement has little direct impact on business model composition, as fee income dynamics are primarily shaped by market competition rather than supervisory actions.

(iii) Trend-adjusted DiD confirms no durable NII effect. The preferred trend-adjusted DiD estimates are small and statistically null (Table 3.14), consistent with Figure 3.4, which shows only a transitory 2020 spike. This result echoes earlier findings that diversification effects are often fragile or offset by higher volatility in non-interest income (Wu et al., 2024).

3.7.4 Link to Hypotheses (BSSR-framed)

- **Competition and profitability (supported).** Entry flexibility (*EntrySize*) is associated with higher ROA across Size×NSFR strata, especially in Yellow; DiD evidence confirms a post-2018 ROA dip for large banks, consistent with contestability pressures (Schmaltz et al., 2018; Wang and Zhong, 2022).

- **Funding stability and resilience (supported).** Higher NSFR is positively related to $\ln Z$, especially in Yellow, reinforcing prudential insights about structural funding (Wang, 2023).

- **Enforcement and stability (conditionally supported via targeting).** Negative *SupEnforce*–$\ln Z$ associations for small banks, coupled with null effects for well-funded large banks, support the risk-targeting perspective (Jobst and Rieder, 2023).

- **Business model adaptation (supported for small banks).** Stronger entry, particularly from well-capitalized entrants (*CapEntry*), reduces NII shares for small banks, consistent with diversification and competitive-response theories (Tran and Nguyen, 2023; Wu et al., 2024).

3.7.5 Robustness, Identification, and Scope

The DiD for ROA offers the clearest quasi-causal evidence, with a clean placebo and robust post-2018 effect. For $\ln Z$ and NII, DiD estimates are null once pre-trends are controlled, and figures show no persistent post-2018 divergence. The remaining evidence is *associational*, estimated via two-way fixed effects with bank-clustered errors and BRSS flexibility indicators on the right-hand side. Endogeneity of these indicators and selection into enforcement remain concerns, which is why my interpretation of *SupEnforce* emphasizes targeting rather than causal impact. Collinearity explains the dropping of `entry_risk` in slope models, while `sup_exempt` is excluded due to near-constancy. All specifications use lagged controls, and NIM is excluded from NII models to avoid mechanical correlation.

3.7.6 Policy implications through the Flexibility Lens

Entry-based flexibility (*EntrySize*, *CapEntry*). Competitive entry is profitability-enhancing: AMEs show that *EntrySize* raises ROA across Size×NSFR cells, with the strongest slopes in the mid–funding tier (Yellow) and attenuation in Green for large banks. On business model choice, entry—especially by well–capitalized entrants (*CapEntry*)—tilts *small* banks away from fee income (lower NII shares), while effects for large banks are muted or imprecise. These patterns are consistent with competition sharpening margins in core intermediation and compressing fee franchises for smaller, less diversified institutions.

Supervisory flexibility (*SupEnforce*). Enforcement intensity is associated with lower stability ($\ln Z$) for small banks across NSFR tiers, but is statistically neutral for well–funded large banks (Yellow/Green). The most coherent reading is *targeting*: supervisors concentrate enforcement where underlying risk is higher, rather than enforcement causing instability. In business-mix regressions, enforcement does not display a robust average pass-through to NII once controls and fixed effects are included.

Risk signal (*InsRisk*). As a supervisory risk proxy, *InsRisk* aligns with lower profitability (negative ROA coefficients) and context-dependent associations in stability models, reinforcing its role as a contemporaneous risk signal rather than a policy lever.

Funding stability (NSFR) as the conditioning environment. Stronger structural funding aligns with higher measured stability on average, with the clearest slope differences in the Yellow tier. ROA trade–offs with NSFR are modest, and there is little evidence that entry pressure materially shifts the NSFR–ROA slope.

3.7.7 Integration with the Time–Series Evidence

All three figures line up with the flexibility–based regressions: a common 2020 shock and partial normalization; a modest, persistent post–2018 ROA shortfall for large banks (consistent with the EU DiD); no durable post–2018 divergence for $\ln Z$ or NII; and relatively flat level gaps in NII despite transparent AME gradients for small banks under entry pressure. These visuals corroborate that (i) entry-driven flexibility links to profitability, (ii) NSFR conditions the magnitude of these links, and (iii) enforcement patterns behave like targeted supervision rather than a systematic driver of business-mix or stability for well–funded large institutions.

3.7.8 Synthesis

Taken together, the evidence portrays a flexibility–centric mechanism within the EU: (1) post–2018 timing coincides with a relative ROA decline for large banks; (2) entry-based flexibility (*EntrySize*, *CapEntry*) is pro-profitability and pushes small banks toward traditional intermediation (lower NII); (3) stability rises with structural funding (NSFR), most clearly in mid–range conditions; and (4) *SupEnforce* aligns with risk-targeted supervision—adverse for small, riskier banks, but statistically neutral for well–funded large banks. These findings are robust to bank and year fixed effects with clustered inference; the strongest identification comes from the ROA DiD, while the interaction and AME results provide interpretable flexibility gradients by size and funding environment.

Chapter 4

General Discussion and Conclusion

This dissertation examined how banks navigate two interrelated forces in the post-crisis era: (1) market-driven consolidation through mergers and acquisitions (M&A), and (2) a multi-dimensional regime of regulatory flexibility that continuously shapes profitability, stability, and business models. Across both studies, liquidity—captured by the Net Stable Funding Ratio (NSFR)—and size emerged as the structural determinants of how banks respond to both event-driven and continuous pressures. By organizing the discussion around the stated hypotheses, the analysis demonstrates that the dissertation has achieved its objectives.

4.1 Study 1: M&A, Liquidity, and Post-Merger Outcomes (H1–H5)

Study 1 confirmed **H1** and **H2**: liquidity and size jointly drive acquisition activity. Banks with stronger liquidity positions were more likely to initiate M&A, but size dominated: large banks, including those with weak liquidity, remained acquisitive. This pattern aligns with corporate finance theories that financial flexibility underpins acquisitions (Myers and Majluf, 1984) and with IO perspectives that scale amplifies strategic advantage (Baxamusa and Jalal, 2015).

Evidence for **H3** was modest: post-merger liquidity did not uniformly improve, echoing prior findings of mean reversion (Hagendorff et al., 2012). Interaction models supported **H4**: post-merger liquidity trajectories diverged by pre-merger conditions—Green banks consolidated their advantages, Red banks deteriorated, and Yellow banks remained flat.

The difference-in-differences framework confirmed **H5**: mergers causally improved liquidity for already strong banks but offered little or no repair for fragile institutions. This "dark side" of Basel regulation suggests that liquidity rules may unintentionally incentivize weak banks to expand through acquisition, exacerbating too-big-to-fail dynamics (Berger and Roman, 2015).

4.2 Regulatory Flexibility and Performance (H1–H5)

Study 2 demonstrated that regulatory flexibility operates through heterogeneous channels. Supporting **H1**, entry pressure (*EntrySize*, *CapEntry*) raised ROA, especially for mid-range NSFR (Yellow) banks, consistent with Industrial Organizations' theories that competition enhances efficiency Coccorese and Pellecchia (2022); De Cesari et al. (2024).

For stability, **H2** was confirmed: higher NSFR strengthened $\ln Z$, most visibly in Yellow banks, reflecting financial intermediation arguments that stable funding reduces insolvency risk Wang (2023). **H3** was conditionally supported: enforcement was associated with lower stability only for small banks, consistent with targeted supervision rather than destabilization Jobst and Rieder (2023).

On business models, **H4** was supported: smaller banks shifted away from non-interest income when entry intensified Tran and Nguyen (2023). At the same time, large-bank effects were muted, consistent with regulatory economics theories that scale shapes diversification Wu et al. (2024). Finally, **H5** was confirmed: a clear post-2018 ROA shortfall for large banks indicated transitional costs of Basel III liquidity implementation Schmaltz et al. (2018); Wang and Zhong (2022).

4.3 Integrative Synthesis

Together, the studies highlight liquidity and size as *organizing principles* of banking behavior. In Study 1, liquidity and size determined both the likelihood of acquisitions and the trajectory of post-merger liquidity. In Study 2, liquidity and size moderated the impact of regulatory flexibility on profitability, stability, and business model choices.

Theoretically, the results integrate insights from industrial organization with perspectives on financial intermediation, funding stability, and regulatory economics, as well as supervisory design. Empirically, they reveal that neither M&A nor regulation is sufficient in isolation: consolidation improves liquidity only for already strong banks, and regulatory flexibility generates heterogeneous effects depending on structural profiles. Resilience emerges not from a single lever, but from the interaction of market structure, regulation, liquidity, and size.

4.4 Final Concluding Statement

Conclusion

This dissertation has fulfilled its objectives. **Study 1** examined who acquires and how post-merger liquidity evolves, while **Study 2** explored how regulatory flexibility shapes profitability, stability, and the business model mix across heterogeneous banks. Taken together, the findings support a central conclusion: **resilience in modern banking is not achieved through mergers or regulation in isolation, but through their interaction under the structural constraints of liquidity and size**.

From a theoretical perspective, the dissertation contributes to three major areas of research. First, it advances *industrial organization* by demonstrating that consolidation incentives are not solely determined by efficiency and market power, but also hinge on liquidity positions and scale. This dual role of scale captures both its benefits and vulnerabilities: while larger size may enable efficiency gains, weakly liquid large banks can become disproportionately fragile, raising systemic concerns. Second, it enriches *financial intermediation theory* by highlighting funding stability—captured by the NSFR—as a hinge variable that conditions both post-merger trajectories and the effectiveness of regulatory instruments. Third, it extends *regulatory economics* by conceptualizing regulatory flexibility not as a single lever, but as an interconnected system of entry, capitalization, enforcement, and insurance risk, generating heterogeneous outcomes across banks with different structural characteristics. In this way, the dissertation offers a more integrated theoretical account of how consolidation and regulation jointly shape resilience.

On the empirical side, the dissertation makes several original contributions. By combining rare-events logit, fixed effects, and difference-in-differences approaches, it provides causal evidence on post-merger liquidity dynamics and explains why earlier studies reached divergent conclusions. It is among the first to directly link M&A events to Basel III liquidity metrics, showing that liquidity gains are not automatic but contingent on pre-merger conditions. In parallel, it develops a multidimensional framework for operationalizing regulatory flexibility through BRSS indicators, enabling a granular assessment of how entry, capitalization, enforcement, and insurance risk interact with liquidity and size to influence profitability, stability, and diversification. Taken together, these advances offer a richer understanding of both event-driven and continuous dimensions of bank behavior under Basel III.

At the same time, the analysis underscores the **dark side of scale**: large banks with weak liquidity (Red–large) emerge as structurally fragile. For these institutions, mergers do not reliably deliver stability, and regulatory flexibility often proves insufficient to offset inherent vulnerabilities. Rather than strengthening resilience, their size magnifies systemic exposure, echoing long-standing concerns about “too-big-to-fail” institutions. This cautions that policies promoting consolidation must carefully weigh efficiency gains against the risks of concentrating fragility in liquidity-poor giants.

By bridging the dynamics of M&A with the mechanisms of regulatory flexibility, this dissertation provides theoretical clarity, empirical depth, and practical relevance. Its unifying message is that *liquidity and size are not peripheral controls but organizing principles of resilience in modern banking*, shaping both strategic consolidation and regulatory effectiveness. This insight carries significant implications for research, policy, and practice. Future work should continue to examine resilience through the dual lens of liquidity and scale, while regulators and practitioners must recognize that neither mergers nor regulatory rules can secure stability without considering how these structural factors interact in practice.

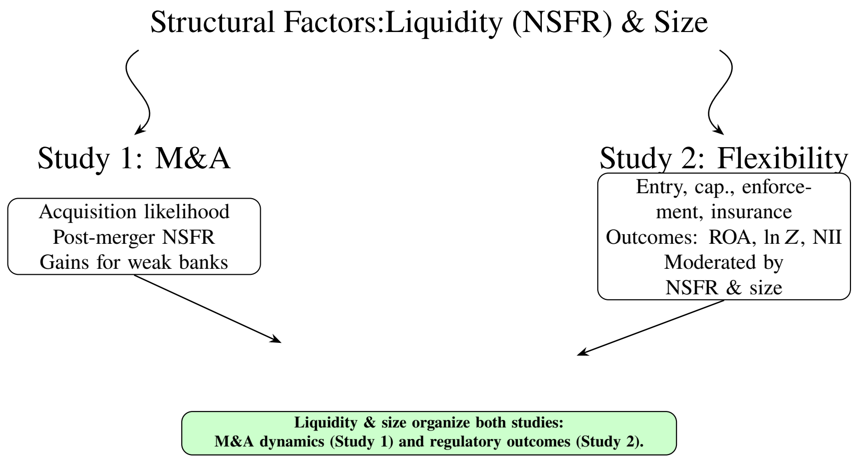

Figure 4.1: NSFR and size link both studies.

4.5 Policy Implications: Evidence-Based Recommendations for Banking Regulation

The findings from this dissertation carry clear implications for how banking regulation should be designed and implemented in the post-crisis environment. Across both studies, liquidity and size emerge not simply as control variables but as the structural conditions that shape how banks respond to strategic opportunities and regulatory constraints. In Study 1, banks with weaker liquidity positions were often more acquisitive, suggesting that mergers are sometimes pursued as a means of regulatory compliance rather than as efficiency-enhancing strategies. Yet the results also show that post-merger liquidity improvements are uneven: well-capitalized acquirers consolidate their advantages, while fragile acquirers often fail to repair their funding positions. In Study 2, regulatory flexibility, in the form of entry pressure, capitalization of entrants, enforcement intensity, and insurance risk, was shown to influence profitability, stability, and diversification in systematically heterogeneous ways. Competition enhanced ROA in mid-range liquidity banks, stability rose with higher NSFR, and enforcement aligned with supervisory targeting of riskier small banks. Large, well-funded banks tended to absorb regulatory pressure more easily, while smaller institutions or those with weak liquidity experienced sharper trade-offs.

Taken together, these findings suggest that regulatory frameworks should be carefully calibrated to reflect structural heterogeneity rather than assuming a one-size-fits-all effect Ding et al. (2021). Liquidity regulation, such as the NSFR, while necessary for resilience, risks producing unintended consolidation incentives if thresholds are applied too rigidly Wang (2023); Ma and Vadasz (2024). Supervisors should therefore complement binding requirements with proportional oversight, ensuring that small banks are not unduly burdened and that fragile large banks cannot exploit scale to expand without addressing vulnerabilities. Similarly, merger oversight should not only evaluate efficiency and market concentration but also explicitly assess whether transactions strengthen the funding resilience of the combined entity Boczar (1976). Deals driven primarily by regulatory arbitrage should be subject to conditional approvals and post-merger monitoring to ensure that projected liquidity gains are realized Mayordomo and Rachedi (2023).

The evidence on regulatory flexibility also speaks directly to the design of policy. Flexibility can be a powerful tool, but its benefits are not distributed evenly across all institutions. Large, well-funded institutions are best placed to take advantage of lighter-touch supervision or competitive entry. At the same time, smaller banks may face pressure that constrains profitability or narrows business model options. This highlights the need for flexible mechanisms that are conditional and targeted: resilience-enhancing institutions could be rewarded with reduced burdens. At the same time, fragile banks remain subject to closer scrutiny until they demonstrate improvement. In this way, flexibility supports adaptation without diluting prudential safeguards.

Perhaps the most critical policy lesson is that liquidity rules, merger oversight, and regulatory flexibility cannot be considered in isolation from one another. They interact through the standard channels of size and funding structure, producing heterogeneous effects that can either reinforce resilience or concentrate fragility Brennan and Lo (2014). Regulators who acknowledge this interplay can better prevent unintended consequences such as procyclical consolidation, regulatory arbitrage, or the reinforcement of too-big-to-fail incentives **?**. In practical terms, this means moving beyond uniform thresholds toward a more nuanced framework—one that rewards banks that build structural resilience, constrains those that remain fragile, and balances the twin objectives of financial stability and sustainable competition Benson et al. (2024). By grounding regulatory design in empirical evidence, supervisors can strengthen the resilience of banking systems without concealing their adaptive capacity, ensuring that the lessons of the crisis are translated into durable institutional practice.

4.6 Economic Significance

Beyond their academic and policy contributions, the findings of this dissertation carry clear economic significance. Banking is not only about the stability of institutions but also about the allocation of credit, the cost of funding, and the resilience of the broader economy. By demonstrating how liquidity and size influence both merger activity and the effectiveness of regulatory flexibility, the studies directly address the health of financial intermediation and, ultimately, economic growth.

From the perspective of consolidation, the results demonstrate that mergers driven by weak liquidity positions may create larger but not necessarily stronger banks. This has significant economic implications: if fragile banks expand without repairing their funding base, risks become concentrated and the potential cost of failure rises Chen et al. (2024). Such dynamics can exacerbate the 'too-big-to-fail' problem, shifting the burden of instability onto taxpayers and the real economy Zhu et al. (2023). Conversely, where mergers genuinely strengthen funding structures, they can support a more stable credit supply and reduce the likelihood of credit crunches during periods of stress. On the regulatory side, the evidence shows that flexibility mechanisms do not affect all banks equally. Well-funded and larger institutions are best placed to benefit, while smaller or liquidity-constrained banks face sharper trade-offs Ma and Vadasz (2024). This uneven playing field matters economically because it influences the distribution of credit and the diversity of business models in the banking sector. If regulation inadvertently pushes smaller banks away from diversification or forces unnecessary consolidation, communities and SMEs that rely on relationship lending may face higher costs or reduced access to finance Cowling et al. (2024); Adams et al. (2023).

Taken together, the studies underscore that liquidity and size are not abstract balance sheet variables but economic levers with direct consequences for competition, credit provision, and systemic stability. The economic significance of this work lies in making those channels visible: showing when banking strategies contribute to resilience and when they instead embed fragility that spills over into the broader economy. In this sense, the dissertation highlights why careful regulatory calibration is not only a prudential concern but also a matter of broader economic performance and social welfare.

4.7 Limitations and Future Research

Although this dissertation makes substantive contributions to understanding how liquidity, size, and regulatory design shape modern banking, it is essential to acknowledge its limitations and outline potential paths for further inquiry, the use of the Net Stable Funding Ratio (NSFR) provided a standardized and internationally comparable benchmark for structural liquidity, which was essential for testing hypotheses consistently across banks and over time. Yet, as a regulatory construct, the NSFR cannot capture every dimension of funding resilience, such as intraday liquidity flows, cross-currency mismatches, or off-balance-sheet exposures (Drehmann and Nikolaou, 2013; Cecchetti and Kashyap, 2018). Similarly, merger outcomes were primarily observed through reported post-merger balance sheet indicators, while softer dimensions, such as integration quality or managerial adaptation, remained outside the scope of this study. Future work could combine supervisory data, higher-frequency liquidity measures, or qualitative evidence from case studies to enrich the picture of how consolidation affects resilience.

Methodologically, the dissertation employed logit models, interaction designs, and difference-in-differences frameworks to enhance causal interpretation. These approaches mitigate many concerns but cannot eliminate endogeneity in settings where strategic choices, regulatory pressures, and market forces evolve simultaneously (Angrist and Pischke, 2009; Imbens and Rubin, 2015). Propensity-score matching and robustness checks provided reassurance, yet the challenge of isolating exogenous shocks remains. Future studies could leverage staggered regulatory rollouts, natural experiments, or supervisory interventions to refine causal identification further and distinguish between strategic intent and regulatory effects.

The scope of the analysis also reflects practical constraints. The focus on the EU and US was justified given the availability of reliable NSFR data and the centrality of these banking systems to global finance. Still, supervisory capacity, regulatory implementation, and market structures differ across jurisdictions (Barth et al., 2013; Djankov et al., 2007). Smaller and emerging-market banks may respond differently to liquidity requirements or regulatory flexibility, particularly when financial inclusion pressures or informal supervisory practices play a more significant role. Extending the framework to such contexts would test the generality of the findings and reveal whether liquidity and size act as universal organizing principles or are contingent on institutional environments.

Finally, the findings invite future research into new areas that are only beginning to shape the regulatory–strategic interface. The rise of fintech and digital banks redefines "entry pressure" and may alter how liquidity requirements interact with novel business models (Buchak et al., 2018; Fuster et al., 2019). Climate-related risks add another layer of regulatory challenge, with potential implications for funding stability and the calibration of supervisory flexibility (Bolton and Kacperczyk, 2021; Campiglio et al., 2018). Moreover, while this dissertation focused on bank-level behavior, system-wide consequences remain a critical open question: do liquidity-driven mergers or flexibility-based policies ultimately reduce systemic fragility, or do they shift risks in ways that create new vulnerabilities (Acharya et al., 2012; Adrian and Boyarchenko, 2012)?

In sum, the boundaries identified here do not weaken the central conclusions. Instead, they mark where the results are most reliable and where complementary research can further enhance the contribution. By situating its findings within these contours, the dissertation provides both a substantive account of how liquidity, size, and regulation jointly shape resilience and a platform on which future work can build to address emerging challenges in banking and financial stability.

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Table 1: Variable Definitions, Expected Signs, and Study Linkage

Variable	Definition	Expected Sign	Study
I. Outcome Variables			
`M&A Activity`	Binary indicator: bank acts as acquirer in a given year	Dependent	Study 1
`ROA`	Return on Assets — profitability	Dependent	Study 2
`ln Z-score`	Log of Z-score — risk-adjusted stability	Dependent	Study 2
`NII Share`	Non-interest income to total income — business model diversification	Dependent	Study 2
II. Explanatory Variables			
`NSFR`	Net Stable Funding Ratio (structural liquidity requirement, levels or log, lagged)	+	Both
`Size`	Bank size (real total assets, inflation-adjusted)	±	Both
`Entry Risk`	Entry capital tailored to risk profile	+	Study 2
`Entry Size`	Entry capital tailored to bank size	+	Study 2
`CapEntry`	Entry capital requirement exists (binary)	+	Study 2
`SupEnforce`	Supervisor discretion for early intervention	±	Study 2
`InsRisk`	Deposit insurance pricing is risk-based	+	Study 2
`SupExempt`	Low-risk loans exempt from lending limits	+	Study 2
III. Control Variables			
`CAR`	Capital Adequacy Ratio (weighted/standardized, lagged)	+	Both
`Leverage`	Leverage ratio (total debt/equity)	±	Study 1
`Equity/Assets`	Equity-to-assets ratio	+	Study 1
`Efficiency Ratio`	Cost-to-income ratio — operational efficiency	−	Both
`Asset Growth`	Annual asset growth	+	Study 1
`NIM`	Net interest margin — core profitability measure	+	Study 2
`Asset Quality`	Log of asset quality (e.g., NPL ratio, lagged)	−	Study 2
IV. Macroeconomic Controls			
`GDP Growth`	GDP growth (annual)	+	Both
`Unemployment Rate`	Labor market condition	−	Study 2

Note: Expected signs are based on prior literature and theoretical assumptions. ± indicates ambiguous or context-dependent effects. The final column indicates whether the variable is used in Study 1, Study 2, or both. scriptsize *Note:* Some variables serve dual roles. For example, NSFR is modeled as an outcome in Study 1 (post-merger liquidity) but as an explanatory variable in Study 2 (moderator of regulatory flexibility). Similarly, ROA, Z-score, and NII are outcomes in Study 2 but may also appear as lagged controls in robustness checks. Expected signs are informed by prior literature and theoretical reasoning.

Appendix A

Additional Tables and Figures

Table A.1: Stylized balance sheet and weights to compute the NSFR (adapted from Vázquez & Federico, 2015).

Assets (RSF)	WI (%)	Liabilities & Equity (ASF)	WI (%)
1. Total Earning Assets		**1. Deposits & Short-term Funding**	
1.A Loans	100	**1.A Customer Deposits**	
1.A.1 Total Customer Loans		*1.A.1 Current (stable retail)*	85
Mortgages		*1.A.2 Savings (stable retail)*	70
Other mortgage loans		*1.A.3 Term (stable retail)*	70
Other consumer/retail loans		**1.B Deposits from banks**	0
Corporate & commercial loans		**1.C Other deposits & short-term borrowings**	0
Other loans			
1.B Other Earning Assets	35	**2. Other interest-bearing liabilities**	
1.B.1 Loans & advances to banks		**2.A Derivatives**	0
1.B.2 Derivatives		**2.B Trading liabilities**	0
1.B.3 Other securities		**2.C Long-term funding (>1y)**	100
Trading securities		2.C.1 Total long-term funding	100
Investment securities		Senior debt	
1.B.4 Remaining earning assets		Subordinated borrowing	
2. Fixed Assets	100	**Other funding**	
3. Non-earning Assets		2.C.2 Preferred shares & hybrid capital	100
3.A Cash & due from banks	0	**3. Other (non-interest-bearing)**	100
3.B Goodwill	100	**4. Loan loss reserves**	100
3.C Other intangibles	100	**5. Other reserves**	100
3.D Other assets	100	**6. Equity**	100

Notes: WI(%) denotes the NSFR weight applied to each category. RSF weights reflect asset illiquidity; ASF weights reflect funding stability over a one-year horizon. This stylized mapping follows Basel-consistent approximations used when maturity detail is unavailable. See (Vázquez and Federico, 2015; Basel Committee on Banking Supervision, 2010) Federico (2015) and BCBS (2010).

A.1 Robustness Model Specifications

A.1.1 Rare-Events Logit Model with Manual Interactions

$$\begin{aligned}\Pr(\text{MA}_{it} = 1) = \text{logit}^{-1}\Big(&\beta_0 + \beta_1 \cdot \text{RedLarge}_{it} + \beta_2 \cdot \text{RedSmall}_{it} + \beta_3 \cdot \text{YellowLarge}_{it} \\ &+ \beta_4 \cdot \text{YellowSmall}_{it} + \beta_5 \cdot \text{GreenLarge}_{it} + \beta_6 \cdot \text{GreenSmall}_{it} \\ &+ \mathbf{X}'_{i,t-1}\boldsymbol{\gamma} + \delta_r + \delta_t + \varepsilon_{it}\Big)\end{aligned} \tag{A.1}$$

A.1.2 Logit Model with Quadratic Size Term

$$\begin{aligned}\Pr(\text{MA}_{it} = 1) = \text{logit}^{-1}\Big(&\beta_0 + \beta_1 \cdot \text{Size}_{i,t-1} + \beta_2 \cdot \text{Size}^2_{i,t-1} \\ &+ \mathbf{X}'_{i,t-1}\boldsymbol{\gamma} + \delta_r + \delta_t + \varepsilon_{it}\Big)\end{aligned} \tag{A.2}$$

This specification allows for potential non-monotonic scale effects by introducing a quadratic term in bank size. All other controls and fixed effects remain identical to the baseline model. This model explicitly assigns banks to size–liquidity groups, allowing for direct estimation of group-specific acquisition effects. The omitted category is medium–yellow banks A.4.

A.1.3 Propensity Score Matching (PSM) Framework

$$\Pr(D_i = 1) = \text{logit}^{-1}(\mathbf{Z}'_i\boldsymbol{\theta}) \tag{A.3}$$

$$\text{MA}_{it} = \alpha + \tau D_i + \mathbf{X}'_{i,t-1}\boldsymbol{\gamma} + \varepsilon_{it} \tag{A.4}$$

Equation (A.3) estimates the probability of receiving treatment (participating in a merger) conditional on pre-merger bank and macro characteristics $\mathbf{Z}_i$. Equation (A.4) then estimates the average treatment effect on the treated (ATT) by comparing matched treated and untreated banks. This framework balances observable covariates across groups, mitigating selection bias in the DiD estimates.

Table A.2: Logit Regression: Interaction of Size, NSFR, and Profitability

Outcome Var	*M&A Buyer Dummy*		
Model Specifications	(1) Baseline	(2) Interaction Model	(3) Interaction Model
Sample	Full Sample	Full Sample	Full Sample
Size and NSFR Group			
Small		-0.886***	-0.819***
		(0.290)	(0.301)
Large		1.036***	1.304***
		(0.267)	(0.250)
Red		-1.069*	-0.874
		(0.552)	(0.553)
Yellow		-0.194	
		(0.317)	
Green			0.194
			(0.317)
Small×Red		0.653	0.586
		(0.623)	(0.626)
Small×Yellow		0.067	
		(0.411)	
Small×Green			-0.067
			(0.411)
Large×Red		1.268**	1.000*
		(0.592)	(0.583)
Large×Yellow		0.268	
		(0.368)	
Large×Green			-0.268
			(0.368)
Key Variables			
L_ln_NSFR	0.142		
	(0.297)		
L_sizel	0.491***		
	(0.027)		
L_ROA_A	0.611***	0.301	0.301
	(0.209)	(0.203)	(0.203)
L_CARs_w	-0.025	-0.023	-0.023
	(0.017)	(0.015)	(0.015)
L_ln_cst_inc	1.023**	0.212	0.212
	(0.505)	(0.454)	(0.454)
L_ast_grth_w	0.022***	0.016***	0.016***
	(0.005)	(0.005)	(0.005)
L.nii_w	-0.001	0.009*	0.009*
	(0.006)	(0.005)	(0.005)
L_uepm_rate	-0.255***	-0.307***	-0.307***
	(0.057)	(0.055)	(0.055)
L_gdp_grth	0.044**	0.054***	0.054***
	(0.020)	(0.020)	(0.020)
Fixed Effects			
Region FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	-14.311***	-2.611	-2.805
	(2.989)	(2.231)	(2.202)
Observations	29,206	29,206	29,206

Robust standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix Table A.2 reports regression results from the manual interaction model of size and liquidity categories on the likelihood of banks acting as M&A acquirers. Column (1) presents the full-sample logit results, while Columns (2) and (3) report rare-events logit (relogit) estimates for the EU and U.S. subsamples, respectively. The key explanatory variables are mutually exclusive dummies capturing size–liquidity combinations (e.g., red_large, green_small). Medium-sized banks in the yellow or green category serve as the omitted reference groups depending on the specification. All models include standard bank-level controls (capital adequacy, cost efficiency, asset growth, non-interest income, and net interest margins) and macroeconomic controls (GDP growth, unemployment), as well as region and year effects or policy-phase dummies where relevant. Robust standard errors are reported in parentheses.

Return on assets (ROA) is excluded from these regressions to avoid multicollinearity with net interest margins and efficiency measures, as profitability may also be influenced by M&A decisions, raising concerns of endogeneity. Instead, profitability is captured indirectly through margins and revenue mix, ensuring a cleaner identification of the role of liquidity and size in driving acquisition activity.

Table A.3: Predicted M&A Probabilities by Bank Size and NSFR Category (Margins Estimates)

Bank Size × NSFR Category	Margin	Std. Err.	z-stat	[95% Conf. Interval]
Small–Red	0.0031	0.0007	4.30***	[0.0017, 0.0046]
Small–Yellow	0.0041	0.0008	5.15***	[0.0026, 0.0057]
Small–Green	0.0047	0.0008	5.94***	[0.0032, 0.0063]
Medium–Red	0.0037	0.0019	1.98**	[0.0000, 0.0074]
Medium–Yellow	0.0097	0.0022	4.49***	[0.0055, 0.0139]
Medium–Green	0.0116	0.0026	4.39***	[0.0064, 0.0167]
Large–Red	0.0367	0.0060	6.10***	[0.0249, 0.0485]
Large–Yellow	0.0352	0.0046	7.61***	[0.0261, 0.0443]
Large–Green	0.0326	0.0047	6.88***	[0.0233, 0.0419]

Table A.4: Logit Regression: Quadratic Size Specification

Outcome Var	*M&A Buyer Dummy*
Model Specification	(1) Quadratic Size
Sample	Full Sample
Key Variables	
L_ln_NSFR	0.067
	(0.305)
L_sizel	1.115***
	(0.318)
L_sizel^2	-0.019*
	(0.010)
L_CARs_w	-0.011
	(0.017)
L_ln_cst_inc	0.438
	(0.398)
L_ast_grth_w	0.021***
	(0.005)
L_nii_w	0.007
	(0.005)
L_nim	0.403***
	(0.098)
L_uepm_rate	-0.224***
	(0.055)
L_gdp_grth	0.048***
	(0.019)
EU	0.356*
	(0.216)
Fixed Effects	
Region FE	Yes
Year FE	Yes
Constant	-17.926***
	(3.844)
Observations	29,206
Pseudo R^2	0.150

Robust standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix Table A.4 reports the baseline logit model augmented with a quadratic term in bank size. The specification includes the same bank-level and macroeconomic controls as the main model, along with region and year fixed effects. The linear size coefficient remains positive and statistically significant, while the squared term is negative, indicating diminishing marginal effects at very high size levels. The inclusion of the quadratic term does not alter the qualitative conclusions of the baseline results.

Table A.5: PSM Treatment Effects by NSFR Group and Region (Panel B)

	(1) EU: Red Large	(2) EU: Yellow Large	(3) EU: Green Large	(4) US: Red Large	(5) US: Yellow Large	(6) US: Green Large
Key Variables						
treat_red_large	0.031***			0.009		
	(0.006)			(0.007)		
treat_yellow_large		0.018***			0.017**	
		(0.006)			(0.007)	
treat_green_large			0.031***			0.013
			(0.011)			(0.008)
Constant	0.008***	0.010***	0.023***	0.013***	0.012***	0.008*
	(0.003)	(0.004)	(0.007)	(0.004)	(0.004)	(0.004)
Observations	2,438	1,846	1,199	1,483	1,551	763
R-squared	0.010	0.004	0.006	0.001	0.004	0.003

Robust standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.6: Interactions Effect (Red_Large × Region)

Outcome Var	*M&A Buyer Dummy*
	(1)
Sample	Full Sample
Key Variables	
Red_Large	0.545*
	(0.279)
Region(EU)	-0.016
	(0.221)
Red_Large × Region(EU)	1.059***
	(0.325)
Control Variables	
L_CARs_w	-0.049***
	(0.015)
L_ln_cst_inc	-1.512***
	(0.355)
L_ast_grth_w	0.020***
	(0.005)
L_nii_w	0.033***
	(0.005)
L_nim	0.204**
	(0.102)
L_uepm_rate	-0.307***
	(0.058)
L_gdp_grth	0.029
	(0.019)
Year FE	Yes
Constant	3.697**
	(1.752)
Observations	29,206

Robust standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix Table A.6 provides a focused check on whether the acquisition behavior of large, low-liquidity banks (Red–Large) differs by region. The results show that while Red–Large banks are generally more likely to initiate M&A, this effect is especially pronounced in the EU, where the interaction term is positive and highly significant. This reinforces the earlier findings that scale can offset liquidity constraints and suggests that regulatory and market structures in Europe may amplify this tendency.

Appendix B

Additional Tables and Figures

Table B.1: ROA (EU): Size×EntrySize — Base and NSFR Heterogeneity

	(1) Base: Size×entry_size	(2) Size×NSFR×entry_size
Key terms		
entry_size	0.234***	0.175***
	(0.023)	(0.029)
Large×entry_size	0.093***	0.172***
	(0.024)	(0.066)
Yellow×entry_size		0.070***
		(0.022)
Green×entry_size		0.053***
		(0.020)
Large×Yellow×entry_size		-0.072
		(0.074)
Large×Green×entry_size		-0.152***
		(0.070)
Bank FE; Year FE	Yes	Yes
Controls (incl. $L.\ln(\text{NSFR})$)	Yes	Yes
Clustered s.e.	Bank	Bank
Observations	10,042	10,042
R^2	0.519	0.523

Notes: OLS with bank and year fixed effects; robust s.e. clustered at the bank level. NSFR categories: Red (omitted), Yellow, Green. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Interpretation: Entry pressure is positively associated with ROA for small banks; the large-bank increment is positive in the base model and attenuates with stronger liquidity. With NSFR heterogeneity, small-bank slopes rise in Yellow/Green; for large banks, the net increment is ≈ 0.10 in Yellow $(0.172 - 0.072)$ and ≈ 0.02 in Green $(0.172 - 0.152)$, indicating the profitability gain from entry is broad but weakest in the strongest liquidity bucket.

Table B.2: ROA (EU): NSFR–slope with *entry_size* — Base and Heterogeneity

	(1) NSFR×entry_size (base)	(2) NSFR–slope w/ size & NSFR het.
Key terms		
entry_size	0.313*	0.369*
	(0.166)	(0.202)
$L.\ln(\text{NSFR})$	-0.082***	0.006
	(0.022)	(0.047)
entry_size×$L.\ln\text{NSFR}$	-0.012	-0.048
	(0.036)	(0.045)
Large×$L.\ln\text{NSFR}$		-0.038
		(0.046)
Yellow×$L.\ln\text{NSFR}$		-0.102**
		(0.049)
Green×$L.\ln\text{NSFR}$		-0.063
		(0.065)
Bank FE	Yes	Yes
Year FE	Yes	No
Controls (std. set incl. $L.\ln(\text{NSFR})$)	Yes	Yes
Clustered s.e.	Bank	Bank
Observations	10,042	10,042
R^2	0.520	0.473

Notes: OLS; robust s.e. clustered at the bank level. Column (1) includes year FE; Column (2) follows the run without year FE and adds slope heterogeneity by size and NSFR categories (Red omitted). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Interpretation: *entry_size* is borderline positive for ROA; the average NSFR slope is modestly negative in the base model, and the *entry_size*×$L.\ln\text{NSFR}$ term is small and imprecise in both columns—little evidence that NSFR sensitivity varies with entry pressure. With heterogeneity, the NSFR slope is more negative in Yellow and does not differ by size.

Table B.3: Z (EU): Size×SupEnforce — Base and NSFR Heterogeneity

	(1) Base: Size×sup_enforce	(2) Size×NSFR×sup_enforce
Key terms		
sup_enforce	-0.646^{***}	-0.502^{***}
	(0.114)	(0.166)
large×sup_enforce	0.611^{***}	-0.075
	(0.139)	(0.215)
Yellow×sup_enforce		-0.368
		(0.251)
Green×sup_enforce		-0.061
		(0.189)
large×Yellow×sup_enforce		1.001^{***}
		(0.298)
large×Green×sup_enforce		0.742^{***}
		(0.263)
Bank FE; Year FE	Yes	Yes
Controls (incl. $L.$ lnNSFR)	Yes	Yes
Clustered s.e.	Bank	Bank
Observations	10,042	10,042
R^2	0.371	0.374

Notes: OLS for EU banks with bank and year fixed effects; robust s.e. clustered at bank level in parentheses. The red NSFR bucket is the omitted category for NSFR interactions. All standard controls (capital, asset quality, size, NIM, cost-income ratio, and macroeconomic factors) are included but not shown. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Interpretation: In the base model, enforcement is associated with lower $\ln Z$ for small banks (adverse level effect), while the positive large×enforcement term indicates a much weaker (offset) association for large banks. Allowing for NSFR heterogeneity, the small-bank association remains negative; however, for large banks, the interaction is positive and significant in the Yellow/Green categories, implying that more substantial liquidity buffers attenuate the negative link between enforcement and measured stability for large institutions.

Table B.4: Z (EU): NSFR Slope with *entry_risk* — Base vs. Heterogeneity

	(1) Base slope	(2) Preferred (size & NSFR het.)
Key slope terms		
$L.$ lnNSFR	0.394***	-0.068
	(0.075)	(0.131)
large × $L.$ lnNSFR		-0.078
		(0.140)
Yellow × $L.$ lnNSFR		0.634***
		(0.145)
Green × $L.$ lnNSFR		0.283
		(0.190)
Note on interaction	*entry_risk*× $L.$ lnNSFR omitted by Stata (collinearity).	
Bank FE; Year FE	Yes	Yes
Controls	Yes	Yes
Clustered s.e.	Bank	Bank
Observations	10,042	10,042
R^2	0.371	0.373

Notes: OLS for EU banks with bank and year fixed effects. Reported coefficients are the NSFR slope ($L.$ lnNSFR) and its heterogeneity by size (Large) and NSFR categories (Red omitted). All standard micro/macro controls are included but suppressed; Robust s.e. clustered by bank appear in parentheses. *** $p < 0.01$.

Interpretation: In the base model, a higher lagged NSFR is associated with higher $\ln Z$ on average (positive slope). Allowing for heterogeneity, the slope is significantly *steeper* in the Yellow NSFR group, insignificant for Green, and does not differ by bank size. The planned *entry_risk* × $L.$ ln NSFR term was dropped for collinearity, so slope heterogeneity should be read as driven by NSFR categories rather than the binary *entry_risk* switch.

Table B.5: NII (EU): Size×NSFR×{entry_size, cap_entry} — Interaction Coefficients

	(1) Baseline size int.	(2) Size × NSFR int.
Key interactions		
large_bank×entry_size	1.773***	-2.017
	(0.827)	(1.668)
Yellow×entry_size		-2.061***
		(0.805)
Green×entry_size		-1.954***
		(0.702)
large×Yellow×entry		5.853***
		(2.092)
large×Green×entry		2.584
		(1.840)
large_bank×cap_entry	4.891***	8.681***
	(1.769)	(1.870)
Yellow×cap_entry		4.947***
		(1.685)
Green×cap_entry		4.083***
		(1.375)
large×Yellow×cap		-4.178***
		(1.164)
large×Green×cap		-6.058***
		(1.044)
Group dummies (col. 2)		
large_bank	-5.575***	-5.403***
	(1.821)	(1.760)
NSFR: Yellow		-6.186***
		(1.622)
NSFR: Green		-4.534***
		(1.317)
Bank FE; Year FE	Yes	Yes
Controls	Yes	Yes
Clustered s.e.	Bank	Bank
Observations	10,042	10,042
R^2	0.251	0.269

Notes: OLS on EU sample with bank and year fixed effects. Table reports only interaction and group coefficients used for margins; all main controls (lagged micro and macro covariates) are included but suppressed for brevity. Robust s.e. clustered by bank in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Interpretation: Entry pressure (negative Yellow/Green interactions) reduces NII for the small-bank baseline; large banks show differentially higher sensitivity to `cap_entry` at baseline, but those gains are offset in stronger NSFR categories (negative triple terms). Overall, entry—especially by well-capitalized entrants—tends to tilt small banks away from NII, with effects varying by liquidity.

Table B.6: NII (EU): NSFR Slope with *sup_enf* — Base vs. Heterogeneity

	(1) Base slope	(2) Preferred (size & NSFR het.)
Key slope terms		
$L.$ lnNSFR	1.575**	2.911**
	(0.774)	(1.412)
sup_enf × $L.$ lnNSFR	-5.530***	-5.296***
	(2.689)	(2.747)
large × $L.$ lnNSFR		-0.088
		(1.487)
Yellow × $L.$ lnNSFR		-1.856
		(1.647)
Green × $L.$ lnNSFR		0.286
		(1.814)
Selected levels		
sup_enf	24.745**	23.633*
	(12.382)	(12.670)
Bank FE; Year FE	Yes	Yes
Controls	Yes	Yes
Clustered s.e.	Bank	Bank
Observations	10,042	10,042
R^2	0.254	0.255

Notes: OLS for EU banks with bank and year fixed effects. Columns report only the slope and interaction coefficients used for margins; all standard micro/macro controls are included but suppressed. Robust s.e. clustered by bank in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Interpretation: A higher lagged NSFR raises NII on average, but the NSFR slope is *less favorable* when supervisory enforcement is more vigorous (negative sup_enf × $L.\ln$ NSFR). Allowing for size/NSFR heterogeneity does not overturn this pattern: differential slopes by large bank and NSFR categories are small and imprecise. In contrast, the enforcement–slope interaction remains economically meaningful and statistically significant.

Table B.7: Placebo (Pre-2018) Checks: Fake Post×Large

	ROA (placebo)	$\ln Z$ **(placebo)**	**NII (baseline placebo)**
	(1)	(2)	(3)
FakePost×Large ($fake\_tp$)	0.004	−0.030	1.232***
	(0.018)	(0.067)	(0.375)
Observations	2,880	2,880	2,880
R^2	0.065	0.054	0.193
Bank FE; Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Clustered s.e.	Bank	Bank	Bank

Notes: Placebo regressions restrict to pre-2018 years and set a fake post period (≥2016). Robust s.e. clustered at the bank level in parentheses. *** $p < 0.01$.

Explanation Placebo effects are null for ROA and $\ln Z$, supporting parallel trends. The baseline NII placebo is positive and significant, indicating pre-trend violations in the unadjusted DiD; hence, I rely on the trend-adjusted NII estimate in Table 3.14 (col. 3) for inference and relegate the baseline NII DiD to the appendix.

Appendix C

Survey Instruments / Model Code

C.0.1 Regulatory Flexibility Measures (BRSS)

I construct country-level measures of supervisory *flexibility* using the 2016 World Bank BRSS items listed in Table C.1. Each measure is time-invariant over my sample and merged into bank-year observations by country. Unless noted, responses are coded as binary indicators with higher values reflecting *greater* regulatory flexibility.

Table C.1: BRSS Items and Coding Rules (Flexibility Variables)

Variables	BRSS question (Index)	Construction / Values
`cap_entry`	*Minimum capital entry requirement varies by business type* (Q1_4_1_2016)	Binary: 1 if "Yes"; `0` if "No". This variable captures the formal flexibility in entry capital rules. When "Yes", the open-ended explanation (Q1_4_1_-YesText_2016) is processed to derive two sub-dimensions (`entry_risk`, `entry_-size`).
`entry_risk`	*Q1.4.1 (open-ended) — tailoring by risk* (Q1_4_1_YesText_2016)	Text-coded (0/1): equals 1 if the explanation contains_risk-related terms (e.g., "risk", "losses", "negative impacts"); `0` otherwise. Derived from lowercased, normalized open-text responses using keyword matching.
`entry_size`	*Q1.4.1 (open-ended) — tailoring by size threshold* (Q1_4_1_YesText_2016)	Text-coded (0/1): equals 1 if the explanation references numeric thresholds indicating size-tiering (e.g., "million", "billion", or numbers with thousand separators); `0` otherwise. Processed identically to `entry_risk`.
`cap_calc`	*Variants offered to banks in calculating capital requirements for credit risk* (Q3_11_2016; options a–d)	Multiple choice scored: SSA=1 (Q3_-11a), SA=2 (Q3_11b, excluding "Simplified"), F-IRB=3 (Q3_11c), A-IRB=4 (Q3_11d). For each country, assign the *maximum* score available; set to 0 if all options are blank. Higher values = greater methodological flexibility. Only the main row (Q3_11_2016) is retained; sub-item rows (a–d) are dropped.
`sup_exempt`	*Exempted items in applying lending limits* (Q7_1_2_2016)	Binary: 1 if "Yes" (presence of exemptions ⇒ greater flexibility); `0` if "No".
`ins_risk`	*Deposit insurance fees/premiums vary based on risk* (Q8_16_2016)	Binary: 1 if "Yes" (premia vary by risk, providing operational flexibility); `0` if "No".
`sup_enforce`	*Early intervention framework with automatic action* (Q11_4_2016)	Binary: 1 if "No" (more flexibility, no automatic triggers); `0` if "Yes"; missing if "Not applicable".

Direction and interpretation. All variables are coded so that higher values represent *more regulatory or supervisory flexibility/discretion*. This harmonization simplifies the interpretation of regression coefficients and interactions.

Merging and timing. All BRSS measures originate from the 2011, 2016, and 2021 publications of the survey and are merged at the country level for each bank year. Values are held constant between survey waves (forward-filled) to provide annual coverage.

Note on exclusions. The supervision power variable from Q3.7 (`sup_cap`) was excluded due to no cross-country variation in the sample.

Listing C.1: Python script for BRSS text processing

```
import pandas as pd
import re
from collections import Counter
import os


# --- Step 0: Load  New Data into a DataFrame ---
# The country list is adapted to match the length of the new text data.
# The new text data provided has been included.
new_data = {
    'country_name': [
        'Austria', 'Belgium', 'Bulgaria', 'Croatia', 'Cyprus', 'Denmark',
        'Estonia', 'Finland', 'France', 'Germany', 'Greece', 'Hungary',
        'Ireland', 'Italy', 'Latvia', 'Lithuania', 'Luxembourg', 'Malta',
        'Netherlands', 'Poland', 'Portugal', 'Romania', 'SlovakRepublic',
        'Slovenia', 'Spain', 'UnitedStates'
    ],
    'Q1_4_1_YesText_2016': [
        'There are the following exceptions to the rule that the minimum capital has
    to be 5 million EUR: Credit institutions which are authorized to conduct
    investment fund business must have 2,5 million EUR in inital capital. If the value
     of the fund assets belonging to the investment fund management company ecxeeds
    250 million EUR, the company must have additional own funds at its disposal. In
    order to engage in E-Money Business in accordance to the E-Money Business Act, an
    initial capital of 350.000 EUR is required. Credit institutions authorised to
    conduct severance and retirement fund business must have 1.5 million EUR in
    initial capital (see Art. 3 para. 3, 6 and 7 of the Austrian Banking Act). For
    payment institutions see Art. 15 Payment Services Act.',
        '', # Belgium
        '', # Bulgaria
        'the initial capital of a bank shall not be less than hrk 40 million.the
    initial capital of a savings bank shall not be less than hrk 8 million. savings
    banks may neither operate nor establish branches and representative offices
```

```
outside the republic of croatia. the initial capital of a housing savings bank
shall not be less than hrk 20 million. they are established under the provisions
of the act on housing savings and state incentive to housing savings, unless
otherwise prescribed in other laws - for that purpose only.',
        '', # Cyprus
        '', # Denmark
        '', # Estonia
        '', # Finland
        'the minimum capital requirement depends on the envisaged activities.the
credit institutions wishing to carry out all the above mentionned activities
included in the banking license have to pay a minimum capital entry amounting
5,000,000 euros. this amount decrease as soon as the credit institution does not
collect deposits. in such a case, the minimum capital entry is about 2,200,000
euros.',
        'the initial capital which must be available is as follows:(a) in the case of
investment advisers, investment brokers, contract brokers, asset managers and
portfolio managers, operators of multilateral trading systems or enterprises
engaging in placement business who, in providing financial services, are not
authorised to obtain ownership or possession of funds or securities of customers
and who do not trade in financial instruments for their own account: an amount
equivalent to at least 50,000 euro,(b) in the case of other financial services
institutions which do not trade in financial instruments for their own account: an
 amount equivalent to at least 125,000 euro,(c) in the case of financial services
institutions which trade in financial instruments for their own account as well as
 in the case of securities trading banks: an amount equivalent to at least 730,000
 euro,(d) in the case of deposit-taking credit institutions and central
counterparties within the meaning of section 1 (31): an amount equivalent to at
least 5 million euro,(e) in the case of institutions which solely conduct e-money
business: an amount equivalent to at least 1 million euro, and(f) in the case of
investment advisers, investment brokers and contract brokers who, in providing
financial services, are not authorised to obtain ownership or possession of funds
or securities of customers and who do not trade in financial instruments for their
 own account, the amount of 25,000 euro if they are also entered in a register as
an insurance intermediary pursuant to directive 2002/92/ec of the european
parliament and of the council of 9 december 2002 on insurance mediation (oj eu l
9/3) and fulfil the requirements of article 4 (3) of directive 2002/92/ec, and(g)
in the case of enterprises which conduct proprietary business also on foreign
derivatives markets and on spot markets only for the purpose of hedging these
positions, which engage in principal broking services or investment broking only
for other members of these markets or which determine prices for other members of
these markets through proprietary trading as a market maker within the meaning of
section 23 (4) of the securities trading act, the amount of 25,000 euro if
clearing members of these markets or trading systems are liable for the fulfilment
 of the contracts which the aforementioned enterprises conclude on the said
markets or in the said trading systems.',
        '', # Greece
        'depends oh the type of institution (for a commercial bank is 2 billion HUF,
```

```
        for a mortgage loan company is 3 billion HUF), but not depends on the type and the number of the provided financial services',
        '', # Ireland
        ' 2 millions is the threshold applicable to geographically localized banks with mutualistic scope (banche di credito cooperativo - bcc).',
        '', # Latvia
        'specialized bank, authorized to issue and manage electonic money only - 1 mln eur or 3,4528 mln. ltl',
        '', # Luxembourg
        'the reply to question 1.4 (c) above should state that according to eu legislation no capital requirements may be imposed on branches established in host member states of credit institutions authorised in the eea. in the case of branches from other countries outside the eea, the mfsa may impose capital requirements but to date has chsoen not to. moreover in the case of new entities (other than branches) the mfsa always advises institutions to set a buffer over and above the minimum capital indicated in q1.4, so as to enable the institution to be in a position to withstand losses or other negative impacts which might affect it especially in the first years of its life.',
        '', # Netherlands
        'minimum initial capital for cooperative banks is 1 million eur.',
        '', # Portugal
        'the minimum level of capital entry requirement varies as indicated in point 1.4 depending on the aria of the banking businesses to be undertaken',
        "a minimum monetary deposit towards a bank's registered capital of eur 16,597 and a minimum monetary deposit towards the registered capital of a bank performing mortgage transactions of eur 33,194",
        'saving banks have min. entry capital requirement 1.000.000 eur',
        '', # Spain
        '(1) because charter proposals present varying degrees of complexity, the occ does not mandate a minimum dollar level of capital for national bank charter applications. the occ evaluates the sufficiency of the proposed capital level in light of proposed risks, not based on minimum requirement.',
    ]
}
df = pd.DataFrame(new_data)

# --- Step 1: Clean and Prepare the Text Column ---
print("--- Cleaning and Preparing Text Data ---")
df['Q1_4_1_YesText_2016'] = df['Q1_4_1_YesText_2016'].replace('', pd.NA)
df['clean_text'] = df['Q1_4_1_YesText_2016'].str.strip().str.lower()
df['clean_text'] = df['clean_text'].apply(lambda x: re.sub(r'\s+', ' ', str(x)) if pd.notna(x) else x)

# --- Step 2: Basic Text Exploration - Word Frequencies ---
print("\n--- Performing Basic Text Exploration ---")
all_words = []
for text in df['clean_text'].dropna():
```

```python
    words = re.findall(r'\b\w+\b', text)
    all_words.extend(words)

# Refined stopword list for the new data
stopwords = set([
    'the', 'be', 'to', 'of', 'and', 'a', 'in', 'that', 'have', 'is', 'it', 'for', 'or', 'as', 'are', 'by', 'an', 'on',
    'at', 'with', 'from', 'but', 'not', 'can', 'may', 'see', 'must', 'eur', 'usd', 'huf', 'lei', 'ron', 'hrk', 'ltl',
    'act', 'art', 'para', 'see', 'point', 'case', 'amount', 'minimum', 'capital', 'initial', 'level', 'entry', 'own', 'funds'
])

filtered_words = [word for word in all_words if word not in stopwords]
word_counts = Counter(filtered_words)

print("Top 20 Most Frequent Words (after removing stopwords):")
for word, count in word_counts.most_common(20):
    print(f"{word}: {count}")

# --- Step 3: Creating Dummy Variables Based on Keywords (Simple "Coding") ---
print("\n--- Creating Individual Theme-Based Dummy Variables ---")

# Keywords are updated for the new text data
df['varies_by_businesstype'] = df['clean_text'].apply(
    lambda x: 1 if pd.notna(x) and re.search(r'business|fund|e-money|investment|mortgage|payment|trading|advisers|brokers|managers|mediation|hedging', x) else 0
)
df['varies_by_institutiontype'] = df['clean_text'].apply(
    lambda x: 1 if pd.notna(x) and re.search(r'bank|savings|credit institution|cooperative|specialised|thrift|branches|counterparties|bcc', x) else 0
)
df['varies_by_risk'] = df['clean_text'].apply(
    lambda x: 1 if pd.notna(x) and re.search(r'risk|risks|losses|negative impacts', x) else 0
)
df['varies_by_size_threshold'] = df['clean_text'].apply(
    lambda x: 1 if pd.notna(x) and re.search(r'million|billion|thousand|\d{1,3}[,.]\d{3}', x) else 0
)

print("Summary Statistics for Individual Dummy Variables:")
print(df[['varies_by_businesstype', 'varies_by_institutiontype', 'varies_by_risk', 'varies_by_size_threshold']].sum())

# --- Step 4: Combine into a single binary variable (Any Relevant Details) ---
print("\n--- Creating a Combined Binary Variable (Any Relevant Details) ---")
```

```python
df['Q1_4_1_has_relevant_flex_details'] = (
    (df['varies_by_businesstype'] == 1) |
    (df['varies_by_institutiontype'] == 1) |
    (df['varies_by_risk'] == 1) |
    (df['varies_by_size_threshold'] == 1)
).astype(int)

print("Summary for New Combined Binary Variable:")
print(df['Q1_4_1_has_relevant_flex_details'].value_counts())


# --- Step 5: Save results to a NEW CSV file ---
print("\n--- Saving Results to a New CSV File ---")
# Use a new filename to avoid conflicts with previous results
output_csv_file = 'new_regulatory_flexibility_results.csv'

df['has_explanation'] = df['Q1_4_1_YesText_2016'].notna().astype(int)

print(f"Attempting to save CSV file in the current directory: {os.getcwd()}")
try:
    df.to_csv(output_csv_file, index=False)
    print(f"Results successfully saved to '{os.path.abspath(output_csv_file)}'.")
except Exception as e:
    print(f"An unexpected error occurred while saving the CSV file: {e}")
```

[1]

[1] Python script for BRSS text processing (Czech Republic and Sweden missing from responses).