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« *The opinion expressed in this thesis are those of the PhD candidate and do not necessarily reflect the views of the University of Limoges"*

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In loving memory of my Mum Mrs. Victoria. O. Aibinu

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GENERAL INTRODUCTION

In the past decade, a prominent topic in finance and economics has been the exploration of strategies for regulators and policymakers to prevent worldwide systemic risk. Systemic risk, as defined in 2009 by the International Monetary Fund (IMF), the Financial Stability Board (FSB), and the Bank for International Settlements (BIS), is the possibility that any disruption of the financial system, whether it affects parts of the system or the entire system, has the potential to have significant negative effects on the larger real economy. In the wake of the Global Financial Crisis (GFC) of 2007–2009, several attempts have been made to highlight the root causes and channels through which systemic risks can occur. Earlier studies (Glattfelder et al. 2011, Battiston 2016, Battiston et al. 2016, Acemoglu et al. 2015, Battiston et al. 2012, Elliot et al. 2014, Galbiati et al. 2013, Delpini et al. 2013) have concentrated on direct contagion through complex network systems whose nodes are the financial system, and the links are the financial dependencies. Systemic risk can result from the failure of a single financial institution because interrelated elements, including interbank loans, counterparty risk, liquidity problems, and bank runs, cause a domino effect that eventually causes the failure of other banks. This stems from the fact that banks engage in interbank loans (short-term loans) amongst themselves to invest in projects, while the bank may also have other claims that are connected to other financial institutions (Acemoglu et al., 2015).

More recently, other papers have identified the indirect forms of contagion arising from common exposures, portfolio overlap, or correlated features of banking activities (Clerc et al., 2016; Wagner, 2009; Beale et al., 2011; Ibragimov et al., 2011; Liu, 2018; Kopytov, 2019). Asset commonality occurs when assets held by banks can expose them to similar or underlying risks. Thus, it increases the likelihood of a joint or simultaneous failure of banks or financial institutions across the globe. Also, it may be because of information spill over, such as negative news about a particular bank's activity, which may impact the entire banking industry or banks with specific similar investment profiles. Simply put, once there is negative news or a bank's collapse, it triggers a signal or raises an alarm to investors and market participants that other banks may suffer from the same risk. Allen et al. (2012) advocate that the pattern of asset commonality between different banks determines the level of information contagion and the probability of a systemic crisis.

Furthermore, asset commonality can also occur via the following channels: (i) common regulations; (ii) herding behavior; (iii) multiple lending to the same borrower; (iv) adopting the same diversification and risk management strategy; (v) overinvestment in certain asset pools, among others, such that a sudden change in macroeconomic factors can exacerbate a bank's exposure to systemic risk (Kosenko and Michelson, 2022; Cai et al., 2018; Acharya and Yorulmazer, 2008). To begin with, banks are frequently subject to the same sets of rules set by the

Basel Committee on Banking Supervision (BCBS) across the globe. Acharya (2009) highlighted the deficiency in the Basel Rules, pointing out their failure to consider the possibility of simultaneous failures caused by correlated risks when mandating that banks maintain a specific level of capital to mitigate liquidity risk. While the goal of a common regulatory framework is to enable adequate monitoring, supervision, and comparable reporting standards, critics have argued that the easy spread of the GFC witnessed in 2007-2009 can be attributable to the inappropriate, ineffective monitoring and supervision by regulators (Goodhart 2008; Schwarcz 2008; Acharya 2009; Laeven and Levine 2009). Also, due to monetary policy or regulatory constraints such as tightening capital requirements, banks with lower levels of capital may be forced to reduce their liquidity buffers or their loan to buy more liquid assets. Moreso, banks may sometimes take advantage of low interest rates to invest in a certain assets profile which may lead to commonality and ultimately expose them to new or emerging risk. For instance, during the period of loose monetary policy in response to the pandemic and the investment surge in private technology firms, SVB significantly expanded its portfolio of highly rated government bonds, reaching a total of $120 billion. Notably, $91 billions of this portfolio was comprised of fixed-rate mortgage bonds with long-term maturities (Choi et al 2023,). However, this strategic move exposed SVB to interest rate risk when the Federal Reserve responded to soaring inflation by raising interest rates. Consequently, SVB's mark-to-market model implied that they incurred substantial losses, totalling $15 billion as of March 2022. Unfortunately, these losses ultimately led to the bank's failure, mirroring the challenges faced by other financial institutions during this period across the globe (Choi et al 2023). This also relates to the overinvestment viewpoint, which is based on the idea that banks may choose to invest in certain risky assets on purpose to take advantage of attractive return profiles while underestimating the amount of liquidity necessary to mitigate the effects of a macroeconomic shock. Zingh He and Kondor (2016) reveal that there can be overinvestment in risky assets in boom periods and underinvestment in recessions.

In addition, asset commonality could also arise from the implementation of macroprudential policies. To tackle systemic risk arising from correlated failures, procyclicality, risk concentrations, linkages, and interdependencies within the financial system, central banks worldwide have increasingly adopted macro-prudential policies (Crockett, 2000; Borrio, 2003; Caruana, 2010; Meuleman and Vennet, 2020). These policies are targeted to improve supervision and monitoring beyond the micro-prudential policies and, therefore, assess the whole bank's activities. They include instruments that set limits or ceilings on loan coverage, liquidity, concentration, debt-to-income ratio, etc. However, these policies may result in asset commonality because banks engage in risk-shifting by adjusting their asset composition towards other asset classes, e.g., securities that are not affected by the restrictions. This may increase assets' commonality for other asset classes, rendering them more vulnerable to additional market risks. Loan and borrower-focused policies may be desirable for reducing credit demand and limiting supply. However, they may also prompt banks to redirect their available funds towards higher-yield assets or substitute across other asset classes. This could potentially lead to a scenario where loan-assets commonality emerges when multiple banks lend to the same borrower. Additionally, it might lead to an increase in loan syndicates, thereby elevating the interconnectedness of banks.

Another source of asset commonality stemming from common green policies, which potentially could also increase exposure to systemic risk, relates to the global drive to achieve the Paris Net Zero agreement (Claassen's et al. 2022, FSB 2022, European Systemic Risk Board (ESRB) 2021, 2022, ECB 2021, BIS 2021a, 2021b). From the perspective of central banks (CBs), a key element in this shift involves establishing financial mechanisms to provide readily available capital for supporting environmentally sustainable development, in accordance with the net-zero goals set out in the Paris Climate Agreement (BIS 2021b; ESRB, 2021; Financial Stability Oversight Council (FSOC) 2021; Carney 2021). Both governmental and non-governmental entities have made concerted efforts to ensure that banks and corporations align with the net-zero objectives outlined in the Paris Climate Agreement (BIS 2021b; ESRB 2021; FSOC 2021; Carney 2021). This process involves implementing levies on high carbon emissions and providing subsidies for green innovations, as well as advocating for adherence to Environmental, Social, and Governance (ESG) principles, among other strategies (Bruno and Lagasio, 2021; Volz et al., 2015; Batten et al., 2016; Volz, 2017; Campiglio et al., 2018; Dikau and Volz, 2019; Matallín-Saez et al., 2019). Due to these policies, total alignment with cleaner and eco-friendly objectives by banks might lead banks to reallocate investments similarly (Kruger et al., 2020). In other words, banks follow the same environmental factors and will largely have the same investment pattern, i.e., invest in the same eco-friendly market segments. These policies could inevitably result in excessive credit provisioning to eco-friendly industries, and a shock in the sector may affect all banks. Critics have highlighted that an abrupt or chaotic transition to a low-carbon economy could lead to a market bubble, ultimately resulting in a burst during the market's adjustment period (Carney, 2015). Due to the banking sector's high degree of interconnectedness, all banks could experience negative effects from a single shock if they make significant investments in the same types of assets.

Aside from common regulation of assets, commonality also occurs because of herding behavior. This stems from the fact that banks often mimic their competitors or associates to avoid regulatory sanctions, resulting in similar asset portfolios (Acharya and Yorulmazer, 2008). This occurs mainly in the loan markets as banks continue to select firms or borrowers already chosen by other banks for loans. In a syndicate loan market, the syndicate leader may select another partner based on previous industry experience in administering loans within the same sector. Thus, this process increases the level of bank interconnectedness and asset profiles. In essence, the prospect of a joint failure is also presenting an attractive option for banks, as they may benefit from government bailouts if multiple entities fail, encouraging them to invest in the same asset classes or more risky assets or ultimately leading them to take excessive risks (Gropp et al., 2014; Laeven et al., 2016; Allen et al., 2018).

Moreover, asset commonality can also occur when banks lend to multiple customers. Kosenko and Michelson (2022) also provide evidence that multiple-bank lending in the Israeli banking system is an important source of contagion across banks that contributes to the propagation of systemic risk across banks. In addition, it can also occur as result of convergence of investment approaches as banks adopt common diversification and risk management practices. Wagner (2006) contended that while bank diversification serves to shed risk, it can also lead to a similar risk profile. Banks have achieved economies of scale through portfolio diversification across various asset classes, engaging in multilateral and bilateral deals and transactions to distribute and mitigate risk (Blei and Ergashev, 2014).

Wagner (2006), Allen and Gale (2004), Carletti and Acharya (2006), and other scholars argued that diversification essentially entails risk sharing among institutions while also bringing their risk profiles closer together. This similarity in risk exposure can arise from both geographical and structural diversification. For example, when a US-based bank acquires a European entity, it becomes susceptible to European economic shocks, illustrating geographical diversification. Similarly, when a bank acquires an insurance company, it faces loan default risks and assumes liability for insured activities, introducing risks inherent to the insurance industry. Bank diversification may diminish the individual institution's risk (unsystematic risk), but it merely reallocates that risk. Given the consolidation of banking, insurance, and various operations under a single entity, shocks specific to one segment of the financial system may now affect a larger number of institutions.

The objective of this thesis is to determine whether convergence of behavior among banks in terms of investment and activities contributes to the increase of systemic risk. Firstly, we seek to explore whether the overlap in asset portfolios between banks has the potential to increase systemic risk, and whether this adverse impact on financial stability is contingent upon the specific macroprudential policies in place. Secondly, our objective is to investigate whether governmental efforts to hold firms accountable for environmental risks, coupled with the growing expectation that banks play a pivotal role in addressing climate change and promoting sustainability, inadvertently drive banks to adopt similar behaviors that may increase systemic risk. Given the heavily regulated nature of the banking industry, designed to mitigate bankruptcy and contagion risk, it becomes imperative to analyze whether the expanding regulatory landscape inadvertently contributes to an increase in systemic risk through the unexpected consequence of a commonality of bank behavior. The broader goal is to shed light on whether well-intentioned regulatory efforts might inadvertently lead to unforeseen systemic risks, challenging conventional wisdom in risk management and financial stability. This thesis consists of three chapters. Each chapter is self-contained and can be read individually. The first, and third chapters use the same empirical setting to address specific but related issues. Specifically, the first chapter discusses the impact of asset commonality on systemic risk, while the second chapter considers the impact of asset commonality under varying degrees of macroprudential policy. Chapter 3 discusses the effects of the commonality of banks' environmental behavior on systemic risk.

The first chapter is based on the impacts of asset commonality on systemic risk using a wider range of both the traded and non-traded asset portfolios. Most of the studies focus on traded assets and highlight the role of asset fire sales in aggravating contagion and fragility in the financial system (Greenwood et al., 2015; Duarte and Eisenbach, 2021; Girardi et al., 2021; Cont and Schaanning, 2019; Barucca et al., 2021). Our sample consists of 72 large U.S. bank holding companies (BHCs) over the period 2000-2020. We consider 16 asset classes categorized by FR Y-9C to compute our measure of asset commonality. Thus, we estimated the impact of asset commonality on systemic risk. Precisely, our findings show that in large U.S. BHCs, asset commonality and systemic risk have a U-shaped relationship. According to our research, higher levels of asset commonality are harmful to financial stability, whereas lower levels are linked to lower systemic risk. Over 75% of the banks in the sample have asset commonality levels beyond what is deemed detrimental to financial stability, according to our findings. Furthermore, our comprehensive investigations confirm the U-shaped relationship even after differentiating between liquid and illiquid assets and show how crucial it is to maintain a low level of asset commonality to improve financial stability, not only in normal and crisis situations but also for banks with shorter funding maturities.

Expanding on insights from the first chapter, the second chapter delves into the impact of varying levels of macroprudential policies designed to reduce systemic risk in banks. It explores whether these policies might inadvertently heighten systemic risk through the asset commonality channel. This is rooted in the idea that banks may shift their asset portfolios in response to strict regulations, potentially exposing themselves to new risks, particularly if they emulate each other's behavior due to regulatory uniformity. The empirical analysis encompasses 103 banks across 29 countries from 2000 to 2020. The research demonstrates that while the implementation of macroprudential regulations aims to lower systemic risk, asset commonality paradoxically exposes banks to systemic risk under a higher adoption of macroprudential policy. This observation holds for various macroprudential policies, such as those targeting borrowers, financial institutions, or quantity-focused measures. Moreover, the study reveals that in countries with robust macroprudential policy adoption, cross-border asset limitations have minimal impact on the relationship between asset commonality and systemic risk. This challenges previous research suggesting the effectiveness of macroprudential measures in curbing credit expansion and housing prices. Asset commonality, especially in the context of high macroprudential intervention, can heighten a bank's vulnerability to systemic risk. Likewise, this result also holds when focusing solely on the loan market commonality.

Chapter three extend our work by examining how the similarity in environmental behavior among banks influences systemic risk. Banks and corporations are increasingly encouraged to align with low-carbon emission goals, often guided by Environmental, Social, and Governance (ESG) principles. At the same time, central banks (CBs) play a vital role in facilitating accessible funding for environmentally sustainable initiatives, in line with the objectives of the Paris Climate Agreement. However, the shift toward sustainability and reduced carbon emissions poses notable risks to the financial sector. A sudden move away from fossil fuels can disrupt financial assets associated with them. The transition to a green economy may render formerly profitable sectors, like those dependent on coal or fossil fuels, obsolete, leading to the devaluation of "stranded assets." Moreover, the transition from fossil fuels to eco-friendly alternatives could potentially trigger a systemic crisis if banks collectively withdraw loans and services from fossil fuel clients, impacting their assets significantly. This chapter adds to the existing literature by exploring whether the shift towards a more sustainable economy prompts banks to embrace similar environmentally responsible practices, potentially leading to an elevation in systemic risk. Our findings reveal a non-linear relationship between the commonality of environmental behavior among banks and systemic risk. When the degree of commonality in environmental behavior falls below a specific threshold, we observe a reduction in systemic risk with increased commonality. Conversely, beyond this threshold, a higher degree of environmental commonality increases systemic risk. Notably, the results indicate that banks become more susceptible to systemic risk when their environmental behavior surpasses the threshold of the 75th percentile. This research extended its investigation into the effects of the commonality of banks' environmental policies on systemic risk within different levels of asset commonality. Our findings reveal a non-linear relationship between the commonality of environmental behavior among banks and systemic risk under varying degrees of assets commonality. When the degree of commonality in environmental behavior falls below a specific threshold under a high level of assets commonality, we observe a reduction in systemic risk with increased commonality. Conversely, beyond this threshold, a higher degree of environmental commonality increases systemic risk under a high level of assets commonality. This study highlights that if banks adopt a similar behaviour to enhance their environmental practices, it may elevate systemic risk. Essentially, the global adoption of eco-friendly practices may lead to higher asset commonality, not only within green sectors.

CHAPTER 1

Bank Asset Commonality: Good or Bad for Systemic Risk?

This paper is co-authored with L. Lepetit. An earlier version of this article was presented at the International Finance and Banking Society (IFAB) Naples, Italy Conference 7-9th of September 2022, French Economic Association (AFSE) 70th conference held in Dijon France 14-16, 2022, and European Research Group (GDRE) conference 23rd-24th June 2022

1.1. Introduction

The events of the global financial crisis (GFC) in 2007-2009 highlighted the far-reaching effects of risk spillovers among banks. These spillovers ultimately led to a systemic crisis on a global scale and a downturn in the economy worldwide. More recently, the Covid-19 health crisis has also drawn the attention of regulators to ensure that a bank's resilience to negative shocks is improved. Financial contagion could come through two different channels. One plausible channel arises from direct linkages between banks that arise when they borrow from each other. The collapse of the interbank market at the beginning of the GFC highlights that such interconnections are an important channel of contagion across banks (Allen and Gale, 2000; Allen and Babus, 2009; Gorton and Metrick, 2012; Giglio, 2016). A second channel of contagion could arise from "indirect" linkages between banks when they invest in the same assets, exposing them to the same underlying risks. This indirect connection is referred to as asset commonality, i.e., the overlap in banks' asset portfolios.

While there is a large literature exploring the contagion effects of direct linkages (see Shi et al, 2022 for a survey), the literature on how asset commonality evolves and contributes to financial contagion is recent and still scanty. There is a growing body of theoretical literature studies analyzing the systemic implications of commonalities in financial firms' asset holdings. Although diversification may be good for individual banks (Wagner, 2008), diversification may increase systemic risk. Given that the number of available asset classes is finite, portfolio diversification on the part of individual firms increases the prevalence of overlaps. Banks with similar assets may be subject to common shocks, which may trigger joint liquidation and in turn depress asset prices (Wagner, 2010; Allen et al., 2012; Caccioli et al., 2014; Goldstein et al., 2020). When many banks diversify in similar ways, they are more likely to fail jointly (Beale et al., 2011; Ibragimov et al., 2011), and the risk of contagion is stronger in the presence of fire sales (Cifuentes et al, 2005; Shleifer and Vishny, 2011). In contrast to the previous papers, Biswas, and Gómez (2018) focus on non-traded assets (loans) rather than traded assets and show that lending to the same borrowers can be a source of contagion and systemic risk. Also, regarding the liability side of banks, Allen et al., (2012) demonstrates that funding maturity structure interacts with asset commonality in determining systemic risk. Asset commonality matters for systemic risk when banks use short-term finance, but not when they use long-term finance.

The occurrence of asset commonality among banks can be attributed to either deliberate strategic business decisions or unintended circumstances (Kosenko and Michelson 2022). Unintended asset commonality can arise when there is a substitution between idiosyncratic and systemic risk, particularly in situations where there are pecuniary externalities, heavy-tailed risks, and high correlations between risks within asset classes (Wagner, 2011; Ibragimov et al., 2011). Additionally, banks may inadvertently favor assets that have the lowest "distance" from those they already own, potentially motivated by perceived informational and transactional efficiencies (Raffestin, 2014). On the other hand, asset commonality can emerge because of strategic decision-making, leading to herding behavior as banks imitate each other's investment patterns. This behavior is often employed to minimize the impact of information contagion on expected borrowing costs (Acharya and Yorulmazer, 2008), or to exploit the frictions between microprudential and macroprudential policies (Osínski et al., 2013), Consequently, due to government guarantees (Eisert and Eufinger, 2018) and/or regulatory constraints (Acharya and Yorulmazer, 2007, 2008; Farhi and Tirole, 2012; Horváth and Wagner, 2017) this herding behvaior may lead them to take excessive risks (Gropp et al., 2014; Laeven et al., 2016; Allen et al., 2018). Furthermore, asset commonality can also arise when multiple banks lend to the same counterparty.

The empirical related literature measuring the degree of asset commonality in banking systems and its impact on systemic risk is not abundant and has surfaced recently. Most of the studies focus on traded assets and highlight the role of asset fire sales in aggravating contagion and fragility in the financial system (Greenwood et al., 2015; Duarte and Eisenbach, 2021; Girardi et al., 2021; Cont and Schaanning, 2019; Barucca et al., 2021). Some other papers focus on non-traded assets by studying the degree of portfolio similarity between lenders. Fricke (2016) examines the dynamics of homogeneity for Japanese banks' loans portfolio. Cai et al. (2018) study the similarity between syndicated loan portfolios in the United States and find that the overlap of bank loan portfolios makes them more vulnerable to contagious effects. Silva (2019) confirms that diversified banks are more interconnected by syndicated loan portfolios, thereby contributing more to contagion and systemic risk. Kosenko and Michelson (2022) also provide evidence that multiple-bank lending in the Israeli banking system is an important source of contagion across banks that contributes to systemic risk. Chu et al. (2020) further finds that geographical diversification of U.S. bank holding companies affects systemic risk via its impact on asset commonality.

This paper contributes to the existing literature by employing a nonlinear specification and a granular breakdown of a bank's entire balance sheet to examine the influence of bank asset commonality on systemic risk. This approach holds several advantages. Firstly, by utilizing a non-linear specification, we aim to shed new light on the relationship between asset commonality and systemic risk. While diversification can reduce the probability of individual bank defaults by mitigating idiosyncratic shocks, a high level of similarity in the diversification process may increase the probability of joint failures, as highlighted in theoretical literature. Secondly, our granular decomposition of banks' asset allows us to estimate the impact of overlap in their asset portfolios, encompassing both traded and non-traded assets. By considering all classes of assets, we aim to obtain a comprehensive measure of asset commonality and examine the extent to which different degrees of overlap significantly contribute to systemic risk. Given that banks engage in both lending and investment activities, it is crucial to assess the joint impact of these two activities on systemic risk using such a comprehensive measure of asset commonality. Diversification could help a bank to expand its business operations across different assets class to reduce its idiosyncratic risk, while it transfers the systemic risk to other institutions who engage in risk-sharing. According to Ibragimov et al. (2011), the impact of this risk-sharing approach on systemic risk depends on the number of asset classes present and the correlation between risks within each class. A lower number of asset classes increases the probability to have stronger common exposures among banks. Therefore, considering only a subset of asset classes to measure banks' asset commonality could lead to a misrepresentation of the level of homogeneity among banks. By considering the full spectrum of asset classes, we aim to provide a more accurate assessment of the level of homogeneity among banks and its contribution to systemic risk.

We extend our analysis by disentangling the effects of traded and non-traded asset commonality on systemic risk. Additionally, we investigate the potential exposure of banks to systemic risk based on varying levels of asset commonality when asset classes are subjected to a common shock. We investigate whether the GFC of 2007-2008 and the Covid health crisis exacerbate the impact of assets' commonality on systemic risk. Finally, we examine whether and how asset commonality among banks could lead to systemic risk depending on their funding maturity structure. Allen et al. (2012) identifies the interaction between asset commonality and debt maturity as an important source of systemic risk. If banks raise fund from similar sources and are reliant on short-term debt, the banking system becomes more vulnerable to information contagion and disruption in funding markets.

We consider bank holding companies (BHCs) listed as systemically important by the Federal Financial Institutions Examinations Council criteria to determine whether there is an increase in commonalities in U.S. banks and if it increases systemic risk. Our sample consists of 72 banks over the period 2000-2020. We consider 16 asset classes categorized by FR Y-9C to compute our measure of asset commonality. Our findings provide evidence of a U-shaped relationship between asset commonality and systemic risk within large U.S. BHCs. We find that lower levels of asset commonality are associated with reduced systemic risk, while higher levels are detrimental to financial stability. We find that over 75% of the banks in the sample exhibit asset commonality levels above the threshold considered harmful to financial stability. Furthermore, our in-depth investigations validate the U-shaped relationship even when distinguishing between liquid and illiquid assets and demonstrate the importance of maintaining a low level of asset commonality to enhance financial stability, not only during both normal and crisis periods but also for banks with shorter funding maturity. By recognizing and acting on these insights, bank supervisors can better mitigate systemic risk and promote a more resilient financial system.

The remainder of the paper is organized as follows. Section 1.2 describes our sample and explains how we measure asset commonality and systemic risk. Section 1.3 analyses the trend in asset commonality among large BHCs, introduces the baseline specification, and presents the primary findings. Section 1.4 presents further investigations and various tests to ensure the robustness of our results. Section 1.5 concludes the paper.

1.2 Sample and data description

1.2.1 Presentation of the Sample

We focus on the impact of assets commonality of large US BHCs on systemic risk over the period 2000 to 2020. Our sample construction starts with BHCs listed as systemically important (GSIBs) by the Federal Financial Institutions Examinations Council in the last quarter of 2019. We source quarterly consolidated balance sheets and income statements from the FR Y-9C report from the SNL Market Intelligence database. We obtain 105 GSIBs BHCs with a minimum of 10 years of consecutive data. We then combine these data with the Eikon DataStream (Refinitiv), which provides the inputs needed to calculate the systemic-risk measures. We dropped banks for which we could not calculate the systemic risk measures due to non-standard data (no stock price variation); we ended up with a final sample of 72 banks and 5,789 quarter observations. The list of GSIBs BHCs included in the sample is provided in Table A.1 in the Appendix. All continuous variables are winsorized at the top and bottom 1% levels. The definition of the variables used in the empirical analysis and their descriptive statistics are provided in Table 1.2.

1.2.2 Variable Construction

1.2.3 Asset Commonality

Large BHCs are highly susceptible to engaging in universal banking practices after the Gramm-Leach-Bliley Act of 1999 that allowed them to expand their activities, such as dealing in securities and underwriting insurance, participating in merchant banking, and offering securitized interests in bank-eligible assets. The concern is if this broadening of activities results in similarities among banks through common asset holdings. However, the implementation of the Volcker Rule, which is part of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, may restrict the extent of diversification and overlapping portfolios as it limits BHCs participation in hedge funds, private equity funds, and proprietary trading.

To determine if banks with similar investment portfolios are exposed to the same underlying risks leading to an increase in systemic risk, we need a metric that captures the overlap in a pair's assets. To accomplish this, we use the Euclidean similarity to calculate the similarity of all types of asset classes. The Euclidean similarity is an effective method for comparing the distance between two vectors and has been used in previous studies to measure bank asset commonality (e.g., Cai et al., 2018; Fricke, 2016). The basic idea is that two banks are more similar if they hold the same assets.

We first consider the 16 asset classes categorized by FR Y-9C reports to compute a measure of bank asset commonality that encompasses all assets (see Table 1.1). We compute portfolio weights for each bank in each asset class. We note $\mathrm{w}_{i,k,t}$ the weight bank *i* invests in asset class *k*, with $\sum_{k=1}^{K} \mathrm{w}_{i,k,t} = 1$. We then compute the distance between two banks for each quarter as the Euclidean distance between them for all the asset classes considered:

$$Distance_{i,j,t} = \sqrt{\sum_{k=1}^{K} \left(\mathrm{w}_{i,k,t} - \mathrm{w}_{j,k,t}\right)^2} \tag{1}$$

where $Distance_{i,j,t}$ is the distance between bank *i* and bank *j* ($i \neq j$) in quarter *t*, and K is the number of asset classes. The distance measure is normalized to range from 0 to 1. Banks with distances close to zero have similar portfolios (similarity) as they are not far from each other, while banks with higher distances have low portfolios overlap (dissimilarity). We then compute the average distance of bank *i* to the rest of all other banks per quarter:

$$AverageDistance_{i,j,t} = \frac{\sum_{k}^{K} Distance_{i,j,t}}{N_t - 1}$$

where N_t is the number of banks as of quarter *t*. As the average distance is a dissimilarity measure (lower asset commonality for higher values), we transform it to obtain a quarterly measure of asset commonality per bank as follows:

$$AllAssetCOM_{i,t} = \frac{1}{1 + Average\ Distance_{i,t}} \tag{2}$$

$AllAssetCOM_{i,t}$ also ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).

The descriptive statistics in Table 1.2 indicate that large U.S. BHCs exhibit an average degree of asset overlap of 0.80. These statistics suggest that, on average, these BHCs have a relatively high level of asset overlap. However, there is significant variation between banks, as indicated by the standard deviations. Figure 1.1 presents the average value for the asset commonality measure over the period from 2000 to 2020. The figure consistently shows a high degree of asset overlap among large BHCs during this time frame. Nevertheless, notable decreases in asset commonality are observed during the Dotcom and Global Financial Crisis (GFC) periods.

Figure 1.1 Asset Commonality (*AllAssetCom*) for large US BHC over the period 2000 – 2020

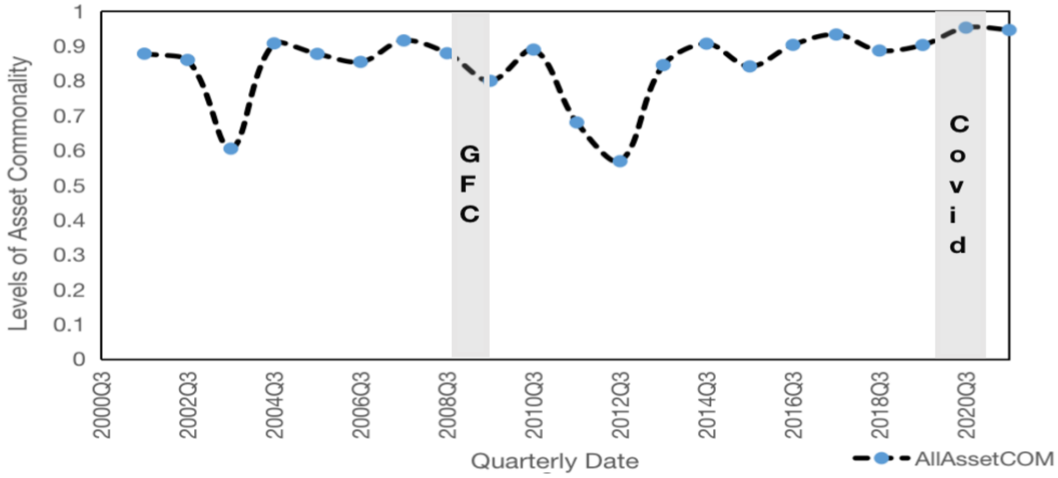


Table 1.1 List of Assets Classes and NSFR Weights

A	**ALL ASSETS CLASSES (B+C)**	**NSFR weight**
B	**LIQUID ASSETS**	
1	**Cash**	0%
2	**US Treasuries**	
	Available for Sale Total US Treasury Securities Held to Maturity US Total Treasury Securities	5% 5%
3	**Total Federal Funds Reverse & Repos**	10%
4	**Agency Securities**	15%
	Available for Sale Total US Govt Agency Sponsoring and Agent Obligations Held to Maturity Total Govt Sponsoring Agency	15% 15%
5	**Agency MBS Securities**	15%
	Available for Sale Pass Through RMBS Guaranteed by GNMA Available for Sale Pass Through RMBS Issued by FNAMA FHLMC Held to Maturity Pass Through RMBS Guaranteed by GNMA Held to Maturity Pass Through RMBS Issued by FNMA FHLMC	15% 15% 15% 15%
6	**Total Trading Assets**	35%
7	**ABS and Other Debt Securities**	35%
	Available for sale_ Total ABS Held to Maturity_ Total ABS Available for sale Foreign Debt Securities Available for sale Structured Financial Products Held to Maturity Foreign Debts Available for sale US securities Debt Held to Maturity Structured Finance Products Held to Maturity US Securities Debts	35% 35% 35% 35% 35% 35% 35% 35%
C	**ILLIQUID ASSETS**	
8	Real Estate Loans	65%
9	Total Intangible Assets	75%
10	Total other Real Estate Assets	75%
11	Investment in Unconsolidated Subsidiaries	75%
12	Other Assets	75%
13	Commercial Industrial Loans	75%
14	Agricultural Loans	75%
15	Consumer Loans	75%
16	Fixed Assets	100%

This table present the list of asset classes as provided by SNL Market Intelligence and their NSFR weight based on "Basel III: The Net Stable Funding Ratio," issued in October 2014 by the Basel Committee on Banking Supervision.

1.2.4 Risk measures

To analyze the link between asset commonality and systemic risk, we use several bank-level systemic risk measures commonly used in the literature. We calculate our risk measures after sourcing data on market value, S&P 500 index, and share price from Eikon DataStream (Refinitiv). We compute the Marginal Expected Shortfall ($MES_{i,t}$) in line with Acharya et al (2017) and Brownlees and Engle (2017). The $MES_{i,t}$ of firm *i* characterizes its expected equity loss conditional on the whole market performing poorly; it is defined as

$$MES_{i,t}(\mathrm{Q}) = \mathrm{E}[\mathrm{R_{i,t}}|\mathrm{R_{m,t}} < \mathrm{VaR^{Q}_{m,t}}] \qquad (3)$$

where $R_{i,t}$ denotes the daily stock returns of bank *i* at time *t*, $R_{m,t}$ the return of the S&P 500 index at time *t*, and $VaR^{Q}_{m,t}$ is the market Value-at-Risk at confidence level *Q*. In line with common practice in the literature, we report the negative of *MES* so that higher *MES* means larger systemic risk. We also compute the $SRISK_{i,t}$ measure, introduced by Acharya et al. (2012) and Brownlees and Engle (2016), defined as the expected capital shortfall of a bank conditional on a prolonged market decline by the latter; it represents an extension of the $MES_{i,t}$ that also allows for the liabilities and size of the financial institution. In line with Acharya et al. (2012), it can be calculated as $SRISK_t(X_i) = kD_{i,t} - (1 - k)[1 - LRMES_t(X_i)]E_{i,t}$, with $D_{i,t}$ the book value of debt, $E_{i,t}$ the market value of equity and *k* the prudential capital ratio. The Long Run Marginal Expected Shortfall $LRMES_t(X_i)$ is defined as the bank's expected drop in equity value if the market falls by more than a given threshold *C* within the next 6 months; we use the approximation $LRMES_{i,t} = (1\text{-}exp(\text{-}18{*}MES_{i,t}))$, as in Benoit et al. (2013). We further consider the $DCoVaR_{i,t}$ measure introduced by Adrian & Brunnermeier (2016), which corresponds to the VaR of the financial system conditional on a specific event for a given bank. Specifically, the $DCoVaR_{i,t}$ for a bank is the difference between the VaR of the market return conditional on the bank being in financial distress and the VaR of the market return conditional on the bank being in its median state. We use standard quantile regressions, as in Adrian and Brunnermeier (2016), to calculate the $DCoVaR_{i,t}$ measures.

1.3 Asset commonality and systemic risk

1.3.1 Econometric specification

The basic econometric specification we use to examine whether different levels of asset commonality affect bank risk is as follows:

$$Risk_{i,t} = \alpha + \beta_1\, AllAssetCom_{\mathrm{i,t}} + \beta_2 SQAllAssetCom_{\mathrm{i,t}} + \textstyle\sum_p \delta_p \mathrm{X_{i,t}} + \gamma_{\mathrm{i}} + \varepsilon_{\mathrm{i,t}} \qquad (4)$$

where the subscript *i* denotes the bank, *t* the period, and $\varepsilon_{i,t}$s the idiosyncratic error term. The dependent variable is bank systemic risk, which we measure using three alternative metrics (*$MES_{i,t}$*, *$SRISK_{i,t}$* and *$DCoVaR_{i,t}$*). The variable $AllAssetCOM_{i,t}$ measures the degree of asset commonality between banks. We include the square term of the commonality asset measure (*$SQAllAssetCom_{i,t}$*) in Equation (4) to capture any potential nonlinear relationship between asset overlap and systemic risk.

To minimize the possibility of omitted variable bias, we include a comprehensive set of bank-related control variables ($X_{i,t}$). We adopt the ratios used by regulators in the CAMELS approach to measure a bank's financial health, as in Berger et al. (2020). We incorporate *Capital Adequacy* through the Tier 1 capital ratio (*$Tier1Ratio_{i,t}$*) to reflect a bank's ability to withstand potential losses. *Asset Quality* is controlled for by the non-performing loans ratio (*$NPL_{i,t}$*). *Management Quality* is considered through the ratio of total non-interest expenses to operating income (*$Efficiency_{i,t}$*). *Earnings* are considered with the return on assets (*$ROA_{i,t}$*), as more profitable banks may have a greater capacity to reduce risk. *Liquidity* is accounted for through the liquidity ratio (*$Liquidity_{i,t}$*). Finally, we consider *Sensitivity to Market Risk* with the ratio of total securities to total assets (*$SMR_{i,t}$*).

Additionally, we control for other factors that may be related to systemic risk, such as bank size, bank distance to default, debt maturity, the competitive environment, and geographical complexity. Bank size is accounted for through the logarithm of total assets (*$lnTA_{i,t}$*). We include the distance to default (*$DD_{i,t}$*), computed through the Merton Model (1977), to assess the impact of individual bank risk on systemic risk. A higher *DD* indicates a lower default risk for a bank. We also consider how banks finance their investments, as banks relying on short-term debt may increase systemic risk. We introduce the dummy variable *$HighSTDebt_{i,t}$*, which takes the value of 1 for a specific bank in a quarter if its wholesale funding exceeds the quarterly sample mean. Competition is measured by the concentration ratio, which is defined as the top five largest banks' share of total assets (*$Concentration\_Ratio_{i,t}$*) within the US in our sample. We calculate this using the data sourced from SNL Organizational complexity is considered through two variables: the level of diversification with the ratio of net interest income to total revenue (*$Diversification_{i,t}$*), and the degree of geographical complexity (*$Geo\_Complexity_{i,t}$*). We capture the degree of geographical complexity of a bank, by the span of regions or countries where the bank has affiliates. We used the Herfindahl concentration index from Cetorelli and Goldberg (2014) to measure this complexity:

$$Geo\_Complexity_{i,t} = \frac{\mathrm{R}}{\mathrm{R}-1}\left(1 - \sum_{r=1}^{R}\left(\frac{Subsd_{i,t,r}}{Total\_subsd_{i,t,r}}\right)^2\right) \qquad (5)$$

where *$Subsd_{i,t,r}$* is the number of subsidiaries the bank *i* has at the quarter *t* in the region *r*, *$Total\_Subsd_{i,t,r}$* is the total number of subsidiaries the bank *i* has at the quarter *t* in all the regions, and *R* is the number of regions. We consider eight regions: North America, South America, Oceania, Asia, the Middle East, Africa, the European Union, and the U.S. The index ranges from 0 to 1, with lower complexity closer to 0 and higher complexity closer to 1.

The impact of the global financial crisis (GFC_t) and the Covid pandemic ($Covid_t$) is also controlled for. Based on the NBER data, GFC_t is set to 1 for the period 2007q4 - 2009q2 during the global financial crisis of 2007-2008, and $Covid_t$ is set to 1 for the period 2019q4 - 2020q4 during the Covid pandemic. Finally, the specification also includes individual fixed effects (γ_i). The Hausman test indicates that the fixed-effects model is a more suitable choice than the random-effects model. Table 1.2 lists all the variables and their descriptive statistics. We examined the correlation between our variables of interest by computing the variance inflation factors (VIF), which have a mean value of 1.75 with a maximum of 2.46 (see Table 1.3). We address potential multicollinearity issues by orthogonalizing the relevant variables (see Table 1.2.).

Table 1.2 Definitions, Data Sources and Summary Statistics for Variables

Variables	Definition	Source	N	Mean	Std. Dev	min	max
RISK MEASURES							
MES	Marginal Expected Shortfall (MES), introduced by Acharya et al. (2017) and Brownlees and Engle (2017), is defined as the marginal contribution of a bank to systemic risk as measured by the Expected Shortfall of the financial system.	Refinitiv Eikon (Datastream)	5775	0.02	0.02	-0.01	0.19
DCoVaR	Delta-CoVaR (DCoVar), introduced by Adrian and Brunnermeier (2016), corresponds to the Value at Risk of the financial system obtained conditionally on a specific event affecting a given bank.	Refinitiv Eikon (Datastream)	5775	0.01	0.01	0	0.06
SRISK	Systemic capital shortfall developed by Acharya et al (2017)	Refinitiv Eikon (Datastream)	5775	-2470	17801	-153	1372
ASSETS COMMONALITY MEASURES							
AllAssetCom	Banks measure of similarities for all asset classes (see Table 1.1) using the Euclidean distance measure that captures the average level of similarity between one bank to the total sample of banks for all asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).	SNL Market Intelligence	5789	0.80	0.18	0	1
SQAllAssetCom	The squared measure of banks of similarities for all asset classes (see Table 1.1) using the Euclidean distance measure that captures the average level of similarity between one bank to the total sample of banks for all asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).	SNL Market Intelligence	5789	0.67	0.23	0	1
IliquidAssetCom	Banks measure of similarities for assets classified as illiquid (see Table 1.1) using the Euclidean distance measure that captures the average level of similarity between one bank to the total sample of banks within the asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).	SNL Market Intelligence	5789	0.83	0.17	0	1
SQIliquidAssetCom	The squared measure of banks for assets classified as illiquid (see Table 1.1) using the Euclidean distance measure that captures the average level of similarity between one bank to the total sample of banks within the asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).	SNL Market Intelligence	5789	0.57	0.22	0	1

LiquidAssetCom	Banks measure of similarities for assets classified as liquid (see Table 1.1) using the Euclidean distance measure that captures the average level of similarity between one bank to the total sample of banks within the asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).	SNL Market Intelligence	5789	0.74	0.16	0	1
SQLiquidAssetCom	The squared measure of banks for assets classified as liquid (see Table 1.1) using the Euclidean distance measure that captures the average level of similarity between one bank to the total sample of banks within the asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).	SNL Market Intelligence	5789	0.72	0.22	0	1
COSINE_ AllAssetCom	Banks measure of similarities for all asset classes (see Table 1.1) using the Euclidean distance measure that captures the average level of similarity between one bank to the total sample of banks for all asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).	Fitch Connects	5789	.83	0.217	0	1
COSINE_ SQAllAssetCom	Banks measure of similarities for all asset classes (see Table 1.1) using the Euclidean distance measure that captures the average level of similarity between one bank to the total sample of banks for all asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).	Fitch Connects	5879	.73	0.260	0	1
OffBalanceCom	Banks measure of similarities for assets classified as off-balance sheet financing items (see Table A.3 in appendix A) using the Euclidean distance measure that captures the average level of similarity between one bank to the total sample of banks within the asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).	SNL Market Intelligence	5789	0.66	0.14	0	1
SQOffBalanceCom	The squared measure of banks similarities for assets classified as off-balance sheet financing items (see Table A.3 in appendix A) using the Euclidean distance measure that captures the average level of similarity between one bank to the total sample of banks within the asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).	SNL Market Intelligence	5789	0.21	0.45	0	1
BANK CONTROL VARIABLES							

NPL	Non-performing loans divided by total assets	SNL Market Intelligence	5785	0.01	0.01	0	0.12
lnTA	Natural logarithm of total assets (orthogonalized on Liquidity)	SNL Market Intelligence	5789	17.04	1.77	14.05	21.54
DD	Distance to default computed using the Merton (1977) model; uses 10-year treasury bills rates for the risk-free rate, with the volatility measure constructed as the annual volatility of daily stock returns.	Refinitiv, Eikon, Datastream	5586	3.98	1.76	-0.88	11.94
Concentration_ratio	Concentration Ratio measured by the total assets of the five largest banks divided by the total assets of the banking system	SNL Market Intelligence	5789	0.66	0.05	0.53	0.74
Tier1Ratio	Tier 1 capital adequacy ratio (Tier1 Capital divided by risk weighted Assets)	SNL Market Intelligence	5663	0.12	0.03	.0005	0.51
ROA	Net income divided by total assets	SNL Market Intelligence	5785	0.003	0.002	-0.03	0.06
Efficiency	Operating expense divided by operating income	SNL Market Intelligence	5785	0.94	3.0	-1.02	213
Liquidity	Cash Balances Due+ Securities+ Fed. Funds Sold and Repos +Trading Account Assets-Pledged Securities) divided by total assets (orthogonalized on asset commonality)	SNL Market Intelligence	5789	0.22	0.17	0.015 5	0.945
Geo_Complexity	Herfindahl Hirschman Index for geographical complexity computed using the number of subsidiaries a bank has in 8 regions (North America, South America, Oceania, Asia, the Middle East, Africa, the European Union, and the U.S). The index ranges from 0 to 1, with lower complexity closer to 0 and higher complexity closer to 1.	SNL Market Intelligence	5015	0.057	0.15	0	0.86
Diversification	Herfindahl Hirschman Index for diversification computed using the Net interest income divided by total revenue	SNL Market Intelligence	5789	0.93	0.22	0	1
HighSTDebt	Dummy variable taking the value of one if a bank's short-term debt ratio is higher than the median in the sample for a given year. Short-term debt ratio is the sum of total deposit, Federal funds purchased and security to be repurchased divided by total assets	SNL Market Intelligence	5789	0.30	0.46	0	1
SMR	Total Securities divided by total assets	SNL Market Intelligence	5789	0.21	0.11	0.002	0.62
GFC	Dummy variable taking the value of one for 1 for the period 2007q4 - 2009q2	NBER	5789	0.08	0.28	0	1
Covid	Dummy variable taking the value of one for 1 for the period 2019q4 - 2020q4	NBER	5789	0.06	0.24	0	1

This table defines the variables and reports summary statistics for the full sample.

Table 1.3 Correlation and Multicollinearity
Panel A: Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	AllAssetCom	1																			
2	SQAllAssetCom	0.99	1																		
3	LiquidAssetCom	0.45	0.45	1																	
4	SQLiquidAssetCom	0.42	0.42	0.99	1																
5	IliquidAssetCom	0.91	0.88	0.33	0.30	1															
6	SQIliquidAssetCom	0.92	0.91	0.33	0.30	0.98	1														
7	covid	-0.02	-0.04	0.08	0.09	-0.04	-0.01	1													
8	GFC	0.001	0.01	-0.07	-0.09	-0.01	-0.001	-0.08	1												
9	Tier1Ratio	-0.18	-0.21	-0.14	-0.15	-0.19	-0.20	-0.004	-0.08	1											
10	EFRatio	-0.19	-0.17	-0.11	-0.1	-0.18	-0.17	-0.017	0.004	0.08	1										
11	SMR	-0.03	-0.04	-0.03	-0.04	-0.05	-0.05	-0.04	-0.08	0.33	-0.05	1									
12	NPL	0.14	0.119	0.07	0.06	0.14	0.12	-0.07	0.07	0.18	-0.05	-0.2	1								
13	LiquidityRatio	-0.76	-0.73	-0.42	-0.41	-0.63	-0.63	0.07	-0.09	0.18	0.22	0.13	-0.136	1							
14	Div	-0.07	-0.06	-0.03	-0.06	-0.08	-0.08	-0.57	0.05	-0.02	0.03	-0.1	0.08	0.04	1						
15	lnTA	-0.48	-0.49	-0.21	-0.19	-0.37	-0.39	0.13	-0.02	-0.2	0.09	-0.2	0.04	0.55	0.10	1					
16	Geo_complexity	-0.5	-0.47	-0.22	-0.21	-0.43	-0.40	0.04	-0.05	0.08	0.09	0.02	-0.008	0.40	0.07	0.40	1				
17	Concentration_ratio	0.17	0.23	-0.07	-0.07	0.13	0.16	-0.59	0.22	-0.3	0.02	0.04	-0.109	-0.15	0.33	-0.3	-0.1	1			
18	HighSTDebt	-0.40	-0.40	-0.33	-0.33	-0.28	-0.29	0.0001	0.04	0.05	0.10	0.14	-0.045	0.49	0.09	0.39	0.34	0.05	1		
19	ROA	-0.02	-0.02	0.03	0.05	-0.07	-0.06	-0.07	-0.24	0.08	-0.01	0.12	-0.261	-0.05	0.02	-0.1	0.07	0.06	-0.1	1	
20	DD	0.003	0.01	-0.004	0.001	0.04	0.05	-0.26	-0.39	-0.10	-0.025	0.05	-0.301	0.002	0.20	0.12	0.06	0.08	0.07	0.26	1

This table shows the correlation matrix, (Panel A) and the variance inflation factors (VIF) in Panel B All variables are as defined in Table 1.2

Panel B: Variance inflation factor	
Variable	VIF
LiquidityRatio	1.61
lnTA	2.46
Covid	2.44
Concentration_ratio	2.25
DD	1.86
Tier1Ratio	1.76
Diversification	1.61
NPL	1.62
GFC	1.53
HighSTDebt	1.51
Geo_Complexity	1.50
SMR	1.37
AllAssetCOM	2.47
ROA	1.20
EFRatio	1.08
Mean VIF	1.75

1.3.2 Result

We use panel regressions with individual-fixed effects to analyze the impact of asset commonality on systemic risk. The results, presented in Table 1.4, show that there is a nonlinear relationship between the measure of asset commonality and systemic risk. Specifically, the coefficient for $AllAssetCom_{i,t}$, is negatively significant for the systemic risk measures *MES* and *SRISK*, indicating that a higher level of similarity in the asset portfolios of large BHCs reduces systemic risk. However, the quadric term, $SQAllAssetCom_{i,t}$, is positively significant for *MES* and *SRISK*, suggesting a U-sharped relationship between asset commonality and systemic risk. To validate this nonlinear relationship, we conduct a test proposed by Lind and Mehlum (2010). The p-value indicates statistical significance for rejecting a linear relationship, thus supporting the acceptance of a U-shaped relationship. The turning point, calculated as (-coefficient *AllAssetCom*/2*coefficient $SQAllAssetCom_{i,t}$) is found to be 0.55 for *ME*S and 0.77 for *SRISK*, approximately corresponding to the 25th percentile for all risk measures, respectively. These results imply that when asset commonality is above the turning point, an increase in the similarity of exposure to assets leads to higher systemic risk.

Our results suggest that when the diversification is relatively low, it reduces bank systemic risk. However, the benefits of bank diversification diminish as asset commonality exceeds a certain threshold. This non-linear relationship can be attributed to two opposing effects of diversification discussed in theoretical literature. While diversification helps mitigate the probability of individual bank defaults by addressing unique shocks, a high level of similarity in the diversification process can increase the risk of joint failures. The advantages of diversification outweigh the costs when asset commonality is low, but as commonality increases, the costs gradually dominate. These findings emphasize the significance of asset commonality and its association with systemic risk. Proper management and understanding of the threshold and asset types held by banks are crucial for maintaining financial stability. Our results show that over 75% of the banks in our sample have a level of asset commonality above the threshold at which it becomes detrimental to financial stability. It is, therefore, crucial for regulators to incorporate the level of asset commonality into the criteria used to measure systemic risk and to constrain banks from exceeding the critical threshold.

Table 1.4 Asset Commonality and Systemic Risk

Variables	*MES*	*SRISK*	*DCoVaR*
Models	(1)	(2)	(3)
AllAssetCom	**-0.0368***	**-2.0046****	-0.0084
	(0.0206)	(0.9579)	(0.0081)
SQAllAssetCom	**0.0332****	**1.3013***	0.0076
	(0.0148)	(0.6608)	(0.0056)
GFC	**0.0249*****	**0.1779*****	**0.0076*****
	(0.0012)	(0.0599)	(0.0004)
Covid	-0.0003	**-0.0818***	**0.0043*****
	(0.0007)	(0.0440)	(0.0006)
HighSTDebt	0.0003	0.0441	**0.0005***
	(0.0008)	(0.0332)	(0.0003)
Diversification	**-0.0067*****	-0.0597	**-0.0046*****
	(0.0014)	(0.0416)	(0.0012)
Concentration_ratio	**0.0215****	**-0.9805****	-0.0054
	(0.0090)	(0.3915)	(0.0037)
lnTA	**0.0040*****	0.0471	0.0003
	(0.0006)	(0.0372)	(0.0002)
Geo_Complexity	**-0.0053****	0.0653	-0.0005
	(0.0021)	(0.1727)	(0.0008)
DD	**-0.0041*****	**-0.0550*****	**-0.0016*****
	(0.0002)	(0.0101)	(0.0001)
ROA	**-0.6389****	**-26.0207****	**-0.1396****
	(0.2417)	(10.4945)	(0.0531)
Tier1Ratio	**0.0441*****	-2.8599	0.0019
	(0.0145)	(1.7475)	(0.0047)
Efficiency	0.00002	**0.0014***	-2.62
	(0.00002)	(0.0007)	(5.62)
SMR	-0.0034	0.2347	**-0.0038****
	(0.0049)	(0.3074)	(0.0016)
NPL	**0.0602***	**14.0405*****	-0.0079
	(0.0345)	(4.1374)	(0.0094)
Liquidity	-0.0006	0.0258	0.0000
	(0.0006)	(0.0222)	(0.0002)
Constant	**-0.0343****	0.9576	**0.0208*****
	(0.0165)	(0.7485)	(0.0064)
Nbr. of obs.	4847	4847	4847
Individual fixed Effects	Yes	Yes	Yes
Lind-Mehlum U-test			
P-value	(0.0394)	(0.0763)	-
Turning point	**0.55****	**0.77***	-
R^2	0.5860	0.3639	0.6710

This table reports fixed effects estimation of systemic risk measures (*MES, SRISK, and DCoVaR*) on the measure of asset commonality (*AllAssetCom*) and its squared term (*SQAllAssetCom*) and control variables. All variables are defined in Table 1.2. The Lind and Mehlum test are a test of non-linearity. The turning point is computed as (-coefficient *AllAssetCom*/2*coefficient *SQAllAssetCom*). The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

1.4. Extension to analysis and robustness checks

Next, we first examine whether the influence of asset portfolio overlap on systemic risk differs based on the liquidity characteristics of the assets involved. Subsequently, we investigate whether the effect of asset commonality on systemic risk is more pronounced during crisis periods and for banks heavily reliant on short-term funding.

1.4.1 Distinguishing liquid and illiquid asset commonality

We compute two narrow asset commonality measures that differentiate overlap in asset portfolios for liquid and illiquid asset groups. The risk of spillover effect of asset commonality is likely to be more pronounced when banks have similar exposure to liquid assets due to fire sale externalities (e.g., Shleifer and Vishny, 1992, 2011). We differentiate liquid and illiquid assets using the weights laid out under the Net Stable Funding Ratio (NSFR). We follow Duarte and Esienbach (2021) for the mapping between asset classes and NSFR weights. We classify an asset as liquid (illiquid) if it has an NSFR weight not greater (higher) than 35%. Table 1.1 presents our asset classification based on the NSFR weight, with seven assets classified as liquid and nine as illiquid. As in Section 1.2.3, we use the Euclidean distance between pairs of banks to compute a measure of asset commonality for liquid assets ($LiquidAssetCom_{i,t}$) and illiquid assets ($IliquidAssetCom_{i,t}$).

We rerun Equation (4) by substituting the general asset commonality measure *AllAssetCom* with alternatively the narrower measures $LiquidAssetCom_{i,t}$ (Table 1.5) and $IliquidAssetCom_{i,t}$ (Table 1.6). Likewise, as observed in the previously mentioned all asset commonality measure, our research demonstrates a nonlinear link between the commonality of liquid and illiquid assets and systemic risk. More precisely, the coefficient linked to $LiquidAssetCom_{i,t}$ displays a significant negative association with *MES*. This signifies that higher similarity in exposure to liquid assets corresponds to reduced levels of systemic risk. The quadratic term, $SQLiquidAssetCom_{i,t}$ is positively significant, indicating a U-shaped relationship. The p-value for the U-sharped relation is significant for *MES*. The findings shows that individual and systemic risk begin to increase when the similarity of exposure to liquid assets exceeds 0.61 for the *MES*, corresponding to the 10th percentile.

Table 1.6 also reveals a nonlinear relationship between asset commonality on illiquid asset and *SRISK*. The variable $IlliquidAssetCom_{i,t}$ and its quadratic term $SQIlliquidAssetCom_{i,t}$ are significant in columns (2) and (4). $IlliquidAssetCom_{i,t}$ exhibits a negative sign while $SQIlliquidAssetCom_{i,t}$ has a positive sign, indicating a U-shaped relationship. The p-value for the U-sharped relation is significant. These results indicate that when asset commonality on illiquid asset is below 0.64, corresponding to 25th of the *SRISK*, an increase in the similarity of exposure to illiquid assets leads to lower systemic risk. However, if the level of illiquid asset commonality exceeds these thresholds, it results in increased systemic risk.

Our findings clearly indicate that, irrespective of the specific measure employed to assess the overlap in asset portfolios, whether it considers all assets or differentiates between liquid and illiquid assets, there exists a non-linear association between asset commonality and systemic risk. Importantly, our results suggest the existence of an asset commonality threshold that should not be surpassed by the banking system to prevent an escalation of financial instability. Our results highlight that a majority of large U.S. BHCs are above this critical threshold of asset commonality.

Table 1.5 Asset Commonality on Liquid Assets and Systemic Risk

Variables	*MES*	*SRISK*	*DCoVaR*
Model	(1)	(2)	(3)
LiquidAssetCom	**-0.0214****	0.2927	-0.0055
	(0.0094)	(0.3866)	(0.0035)

SQLiquidAssetCom	**0.018****	-0.3564	**0.0050***
	(0.0074)	(0.3100)	(0.0027)
GFC	**0.0249*****	**0.1629****	**0.0077*****
	(0.0013)	(0.0630)	(0.0004)
Covid	0.0005	**-0.0714***	**0.0046*****
	(0.0007)	(0.0408)	(0.0007)
HighSTDebt	0.0003	0.0408	**0.0005***
	(0.0008)	(0.0317)	(0.0003)
Diversification	**-0.007*****	**-0.0861****	**-0.0047*****
	(0.0015)	(0.0366)	(0.0012)
Concentration_ratio	**0.0348*****	**-0.6779***	-0.0015
	(0.0083)	(0.4024)	(0.0030)
lnTA	**0.0038*****	0.0439	0.0002
	(0.0006)	(0.0368)	(0.0002)
Geo_Complexity	**-0.0040***	0.0446	-0.0000
	(0.0021)	(0.1763)	(0.0008)
DD	**-0.004*****	**-0.0554*****	**-0.0016*****
	(0.0002)	(0.0101)	(0.0001)
ROA	**-0.647*****	**-25.4294****	**-0.1428*****
	(0.2408)	(10.1976)	(0.0528)
Tier1Ratio	**0.0395*****	-3.0168	0.0006
	(0.0136)	(1.8126)	(0.0046)
Efficiency	0.00002	**0.0018*****	-2.84
	(0.00001)	(0.0007)	(4.98)
SMR	-0.0027	0.1026	**-0.0033****
	(0.0049)	(0.2731)	(0.0016)
NPL	**0.0565***	**13.6541*****	**-0.0085**
	(0.0335)	(4.0125)	(0.0091)
LiquidityRatio	-0.0041	0.2963	0.0005
	(0.0051)	(0.1863)	(0.0017)
Constant	**-0.0386****	0.0802	**0.0190*****
	(0.0158)	(0.8311)	(0.0054)
Nbr. of obs.	4847	4847	4847
Individual fixed Effects	Yes	Yes	Yes
Lind-Mehlum U-test			
P-value	(0.0129)		
Turning point	**0.61****		
R^2	0.5858	0.3629	0.6712

This table reports fixed effects estimation of systemic risk measures (*MES, SRISK, and DCoVaR*) on the liquid assets asset commonality (*LiquidAssetCom*) and its quadratic term (*SQLiquidAssetCom*), and control variables. All variables are defined in Table 1.2. The Lind and Mehlum test is a test of non-linearity. The turning point is computed as (-coefficient *LiquidAssetCom*/2*coefficient *SQLiquidAssetCom*). The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table 1.6 Asset Commonality on Illiquid Assets And Systemic Risk

Variables	*MES*	*SRISK*	*DCoVaR*
Model	(1)	(2)	(3)
IlliquidAssetCom	0.0023	**-1.4674***	0.0048
	(0.0100)	(0.7737)	(0.0041)

SQIlliquidAssetCom	0.0066	**1.1549***	-0.0015
	(0.0087)	(0.5939)	(0.0034)
GFC	**0.0248*****	**0.1820*****	**0.0076*****
	(0.0012)	(0.0600)	(0.0004)
Covid	-0.0001	**-0.0837***	**0.0044*****
	(0.0007)	(0.0449)	(0.0007)
HighSTDebt	0.0001	0.0410	0.0005
	(0.0008)	(0.0316)	(0.0003)
Diversification	**-0.0072*****	-0.0566	**-0.005*****
	(0.0014)	(0.0420)	(0.0012)
Concentration_ratio	**0.0299*****	**-1.1030****	-0.0027
	(0.0080)	(0.4787)	(0.0033)
lnTA	**0.0039*****	0.0370	0.0002
	(0.0006)	(0.0355)	(0.0002)
Geo_Complexity	**-0.0049****	0.0523	-0.0002
	(0.0022)	(0.1733)	(0.0008)
DD	**-0.0042*****	**-0.0537*****	**-0.002*****
	(0.0002)	(0.0102)	(0.0001)
ROA	**-0.6371****	**-26.3029****	**-0.1378****
	(0.2409)	(10.5147)	(0.0524)
Tier1Ratio	**0.0443*****	-2.7598	0.0015
	(0.0144)	(1.7508)	(0.0046)
Efficiency	**0.00004*****	0.0013	4.14
	(8.72)	(0.0010)	(5.25)
SMR	-0.0044	0.2630	**-0.005*****
	(0.0050)	(0.3159)	(0.0015)
NPL	0.0535	**14.1135*****	-0.0102
	(0.0335)	(4.1634)	(0.0092)
LiquidityRatio	-0.0006	0.0220	0.0002
	(0.0006)	(0.0232)	(0.0002)
Constant	**-0.0502*****	0.8406	**0.0155****
	(0.0154)	(0.7830)	(0.0059)
Nbr. of obs.	4847	4847	4847
Individual fixed Effects	Yes	Yes	Yes
Lind-Mehlum U-test			
P-value		(0.0439)	
Turning point		**0.64****	
R^2	0.5855	0.3644	0.6709

This table reports fixed effects estimation of systemic risk measures (*MES, SRISK, and DCoVaR*) on the Illiquid Asset commonality (*IlliquidAssetCom*) and its quadratic term (*SQIlliquidAssetCom*), and control variables. The Lind and Mehlum test is a test of non-linearity. The turning point is computed as (-coefficient *IlliquidAssetCom*/2*coefficient *SQIlliquidAssetCom*). All variables are defined in Table 1.2. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

1.4.2 The role of crises periods

Similar exposure to assets could be of first order importance for systemic risk during times of crisis. Our analysis period contains two major crisis periods, the GFC and the Covid crisis. The Global Financial Crisis (GFC) showed how interconnections between financial institutions led to a global systemic crisis and a worldwide economic downturn. Banks had similar exposure to assets like CDOs and mortgage-backed securities. The banking system could be adversely affected by a decline in the value of these assets due to fire sales, particularly if banks have similar direct exposure, as explained by Shleifer and Vishny (1992, 2011) and Kiyotaki and Moore (1997). However, Beltran et al. (2013) argue that large banks during the GFC held onto structured finance products as prices were below their true value and selling would have reduced their capital even further. Additionally, potential buyers struggled to obtain funds to buy these assets even at low prices (Krishnamurthy, 2010). Consequently, the expected impact of asset similarity on systemic risk during the GFC, particularly for liquid assets, is not straightforward.

The Covid pandemic has significantly impacted U.S. consumer behavior and business operations in many ways. It has also led to changes in BHCs' balance sheets. Wang (2021) report a growing trend in the similarity of the largest U.S. BHCs in terms of their credit portfolio allocation from 2010 to 2015, with a more pronounced increase during the Covid crisis. They find that this convergence among banks was mainly driven by an increase in lending to domestic commercial and industrial borrowers during the Covid crisis. As a result, we anticipate a stronger impact of the commonality of illiquid assets on systemic risk during the Covid crisis.

To determine if the results we previously found in Section 1.3.2 still holds during both crisis and normal periods, we modify Equation (4) by adding an interaction term between the measures of asset commonality and its squared term ($AllAssetCom_{i,t}$ and $SQAllAssetCom_{i,t}$,) and the two dummy variables, GFC_t and $Covid_t$, as follows:

$$Risk_{i,t} = \alpha + \beta_1 AllAssetCom_{i,t} + \beta_2 AllAssetCom_{i,t}{}^2 + \beta_3 AllAssetCom_{i,t} \times GFC_t + \beta_4 AllAssetCom_{i,t}{}^2 \times GFC_t + \beta_5 AllAssetCom_{i,t} \times Covid_t + \beta_6 AllAssetCom_{i,t}{}^2 \times Covid_t + \beta_7 GFC_t + \beta_8 Covid_t + \sum_p \delta_p X_{i,t} + \gamma_i + \varepsilon_{i,t} \quad (6)$$

where $Risk_{i,t}$ stands for one of the systemic risk measures ($MES_{i,t}$, $SRISK_{i,t}$ and $DCoVaR_{i,t}$), $AllAssetCom_{i,t}$, refers to the measure of asset commonality and $SQAllAssetCom_{i,t}$, to its squared term; GFC_t and $Covid_t$ are set to 1 during the global financial crisis of 2007-2008 (2007q4 to 2009q2) and during the Covid pandemic (2019q4 to 2020q4), respectively.

The estimation procedure for Equation (6) follows the same panel data estimation method as Equation (4), and the results are presented in Table 1.7. Our findings support the previous results, indicating a non-linear relationship between asset commonality and systemic risk, regardless of whether the economy is in a crisis or non-crisis period. The variable $AllAssetCom_{i,t}$ exhibits consistently negative and significant coefficients across all risk measures. Its quadratic term ($SQAllAssetCom_{i,t}$), however, shows a positive and significant coefficient, implying a U-shaped relationship in normal times. Additionally, interaction terms are not significant for the GFC crisis, indicating a similar non-linear relationship to the non-crisis period, except for where we find an opposite sign for both $AllAssetCom_{i,t}$ and $SQAllAssetCom_{i,t}$. The Wald tests indicate that the asset commonality has an insignificant impact on during the GFC.

For the Covid crisis, we observe a similar U-shaped relationship to the normal period, as the interaction terms are not significant for *SRISK* and *DCoVaR*. However, for *MES*, we find that the impact of $AllAssetCom_{i,t}$ and $SQAllAssetCom_{i,t}$. on systemic risk is more pronounced during the Covid crisis, with significant interaction terms indicating a reduction and increase in individual and systemic risk, respectively.

In general, our results show that maintaining a relatively low level of asset commonality is beneficial to financial stability, regardless of the period under consideration. Conversely, a relatively high level of asset commonality proves detrimental to financial stability during both normal and crisis periods.

Table 1.7 Asset Commonality, Crises Periods, And Systemic Risk

Models	(1)	(2)	(3)
Variables	*MES*	*SRISK*	*DCoVaR*
AllAssetCom (β_1)	**-0.0386***	**-2.5448****	**-0.0136***
	(0.0196)	(1.0704)	(0.0073)
SQAllAssetCom(β_2)	**0.0347****	**1.6899****	**0.0110****
	(0.0141)	(0.7508)	(0.0050)
AllAssetCom x GFC (β_3)	0.0208	**3.2441***	-0.0002
	(0.0437)	(1.6723)	(0.0129)
SQAllAssetCom x GFC (β_4)	-0.0191	**-2.6106***	-0.0007
	(0.0356)	(1.4552)	(0.0102)
AllAssetCom x Covid (β_5)	**-0.060****	-1.3365	**-0.0319**
	(0.0263)	(1.0971)	(0.0242)
SQAllAssetCom x Covid (β_6)	**0.0454****	1.1282	**0.0172**
	(0.0209)	(0.8882)	(0.0176)
GFC	**0.0212***	**-0.6531***	**0.0083****
	(0.0114)	(0.3676)	(0.0037)
Covid	**0.0181****	0.2516	**0.0180****
	(0.0073)	(0.3179)	(0.0080)
HighSTDebt	0.0003	0.0433	0.0005
	(0.0008)	(0.0336)	(0.0003)
Tier1Ratio	**0.0428*****	-2.8869	0.0020
	(0.0152)	(1.7404)	(0.0051)
Efficiency	0.00002	**0.0015****	-1.78
	(0.00002)	(0.0007)	(5.62)
SMR	-0.0032	0.2620	-0.0044***
	(0.0049)	(0.3059)	(0.0015)
NPL	**0.0604***	**14.1110*****	-0.0095
	(0.0351)	(4.1334)	(0.0097)
LiquidityRatio	-0.0006	0.0257	0.0001
	(0.0006)	(0.0220)	(0.0002)
Div	**-0.0068*****	-0.0447	**-0.0051*****
	(0.0014)	(0.0429)	(0.0014)
lnTA	**0.0041*****	0.0512	**0.0004***
	(0.0006)	(0.0394)	(0.0002)
Geo_Complexity	**-0.0053****	0.0311	-0.0008
	(0.0023)	(0.1726)	(0.0008)
Concentration_ratio	**0.0216****	**-1.0314****	-0.0054
	(0.0087)	(0.4017)	(0.0037)
ROA	**-0.6497****	**-26.6476****	**-0.1409****
	(0.2454)	(10.7149)	(0.0544)
DD	**-0.0041*****	**-0.0544*****	**-0.0017*****
	(0.0002)	(0.0101)	(0.0001)
Constant	**-0.0347****	1.0773	**0.0216*****
	(0.0165)	(0.7924)	(0.0065)
Nbr. of obs.	4847	4847	4847
Fixed Effects	Yes	Yes	Yes
Lind-Mehlum U-test (β_1 and β_2)			
P-value	(0.0262)	(0.101)	(0.0324)
Turning point	**0.56****	**0.69***	**0.62****
Lind-Mehlum U-test (β_3 and β_4)			
P-value		(0.0684)	
Turning point		**0.54***	
R^2	0.5865	0.3681	0.6741

This table reports fixed effects estimation of systemic risk measures (*MES, SRISK, and DCoVaR*) on the measure of asset commonality (*AllAssetCom*) and its quadratic term (*SQAllAssetCom*), its interaction with two dummy variables taking the value of one for the global financial crisis (GFC) and for the Covid crisis (Covid), and control variables. The Lind and Mehlum test is a test of non-linearity. The turning point is computed as (-coefficient *AllAssetCom*/2*coefficient *SQAllAssetCom*). All variables are defined in Table 1.2. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

1.4.3 The role of bank debt maturity

The impact of asset commonality on systemic risk can be affected by the debt maturity of banks, as demonstrated by Allen et al. (2012). They found that asset commonality only has an impact on systemic risk in conjunction with the use of short-term financing, but not with long-term financing. This is because when banks rely on short-term financing, they are interconnected through informational links. The arrival of negative information about the solvency of one bank can cause investors to reassess the default probability of their own bank and decide whether to renew their debt. This can result in information contagion among financial institutions, with the degree of overlap in their portfolios playing a role in the extent of the impact. When banks have similar asset structures, a shock to one bank may be seen as a signal of potential adverse shocks to all other banks in the system due to the similarities in their assets.

To investigate whether our results differ for banks with different debt maturity profiles, we conducted an analysis by augmenting Equation (4) with interaction terms between the asset commonality measure, its quadratic term, and the dummy variable $HighSTDebt_{i,t}$. The dummy variable $HighSTDebt_{i,t}$ is equal to 1 in a specific quarter if the whole sale funding is higher than the quarterly sample mean. The estimation results are presented in Table 1.8. The results reveal a U-shaped relationship between asset commonality and systemic risk (measured by *SRISK*), for banks with shorter maturity of funding. These findings indicate that even for banks heavily reliant on short-term financing, a relatively low level of similarity in asset portfolios does not lead to an increase in systemic risk. However, higher levels of asset similarity are associated with an increase in systemic risk.

In summary, our analysis demonstrates that the degree of bank similarity across asset classes plays a crucial role in determining systemic risk for banks with shorter funding maturity. Specifically, maintaining a relatively low level of asset commonality is essential for mitigating systemic risk.

Table 1.8 Asset Commonality, Debt Maturity, And Systemic Risk

Models	(1)	(2)	(3)
Variables	*MES*	*SRISK*	*DCoVaR*
AllAssetCom (β1)	-0.0277	**-2.8745****	-0.0106
	(0.0308)	(1.1340)	(0.0102)
SQAllAssetCom(β2)	0.0295	**1.9463****	0.0100
	(0.0211)	(0.8003)	(0.0069)
AllAssetCom x GFC (β3)	-0.0105	**1.5204***	0.0052
	(0.0292)	(0.8116)	(0.0085)
SQAllAssetCom x GFC (β4)	0.0021	**-1.2695****	-0.0058
	(0.0200)	(0.6239)	(0.0061)
GFC	**0.0249*****	**0.1766*****	**0.0076*****
	(0.0012)	(0.0599)	(0.0004)
Covid	-0.0003	**-0.0909****	**0.0043*****
	(0.0007)	(0.0436)	(0.0006)
HighSTDebt	0.0076	-0.3126	0.0004
	(0.0104)	(0.2307)	(0.0028)
Tier1Ratio	**-0.0069*****	-0.0648	**-0.0047*****
	(0.0014)	(0.0400)	(0.0012)
Efficiency	**0.0446*****	**-2.9320***	0.0017
	(0.0136)	(1.7580)	(0.0044)
SMR	0.00002	**0.0015****	-1.79
	(0.00002)	(0.0007)	(5.59)
NPL	-0.0027	0.2452	**-0.0036****
	(0.0047)	(0.3113)	(0.0015)
LiquidityRatio	**0.0604***	**14.1336*****	-0.0074
	(0.0339)	(4.1192)	(0.0093)
Div	-0.0007	0.0237	0.00001
	(0.0006)	(0.0223)	(0.0002)
lnTA	**0.0042*****	0.0557	**0.0004***
	(0.0006)	(0.0396)	(0.0002)
Geo_Complexity	**-0.0058*****	0.0411	-0.0007
	(0.0022)	(0.1759)	(0.0008)
Concentration_ratio	**0.0221****	**-1.0080****	-0.0054
	(0.0091)	(0.3857)	(0.0037)
ROA	**-0.6308****	**-25.7800****	**-0.1366****
	(0.2410)	(10.4389)	(0.0528)
DD	**-0.0041*****	**-0.0551*****	**-0.0016*****
	(0.0002)	(0.0101)	(0.0001)
Constant	**-0.0420****	1.0975	**0.0197*****
	(0.0182)	(0.7529)	(0.0070)
Nbr. of obs.	4847	4847	4847
Individual fixed Effects	Yes	Yes	Yes
Lind-Mehlum U-test (β1 and β2)			
P-value		(0.0303)	
Turning point		**0.75****	
Lind-Mehlum U-test (β3 and β4)			
P-value		(0.0589)	
Turning point		**0.60***	
R^2	0.5865	0.3648	0.6715

This table reports fixed effects estimation of systemic risk measures (*MES, SRISK, and DCoVaR*) on asset Commonality (*AllAssetCom* and its quadratic term (*SQAllAssetCom*), its interaction with a dummy variable taking the value of one if a bank's short-term debt ratio is higher than the median in the sample for a given year (*HighSTDebt*), and control variables. The Lind and Mehlum test is a test of non-linearity. The turning point is computed as (-coefficient *AllAssetCom*/2*coefficient *SQAllAssetCom*). All variables are defined in Table 1.2. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

1.4.4 Robustness tests

We carry out several additional robustness checks on our empirical results.

Alternative asset commonality measure

We begin by examining the cosine-similarity measure, originally designed by Salton and McGill (1987), as a proxy for asset portfolio overlap, serving as an alternative to the Euclidean measure. To compute the distance measures for each asset class ratio, we adopt the methodology outlined in the works of Barucca et al. (2021), Fricke (2016), and Getmansky et al. (2016) as follows:

$$Cosine_{i,t} = \frac{\sum_{k=1}^{k} w_{i,k} w_{j,k}}{\sqrt{\sum_{k=1}^{k} w_{i,k}^2} \, x \sqrt{\sum_{k=1}^{k} w_{j,k}^2}} \quad (7)$$

$$Cosine\_AllAssetCom_{i,t} = \frac{\sum_{i \neq j, i=1}^{i} Cosine_{i,t}}{N_t - 1} \quad (8)$$

where $Cosine_{i,t}$ represents the cosine similarity between bank *i* to all other bank *j* for each quarter *t* and asset class *k*. is the weight bank *i* invests in asset class *k*, with $\sum_{k=1}^{K} w_{i,k,t} = 1$. This enables us to compute the cosine similarity based on the angle formed between two-coordinate vectors. A smaller angle signifies greater similarity, with cosine similarity values ranging from -1 (indicating dissimilarity) to 1 (indicating similarity). It is important to note that due to the non-negative nature of the matrix *W*, the minimum value for *Cosine* is 0. Therefore, we transform this measure into an average cosine similarity by taking into consideration the number of banks per quarter. To validate the robustness of our findings, we reevaluate Equation (4) using this alternative measure of asset commonality. The results, presented in Table A.2 in the Appendix, confirm that our main conclusions remain unchanged.

Off-balance sheet commonality

We next consider a measure of asset commonality focusing on off-balance sheet items (*OBS*) (see Table A.3 in the Appendix). Previous studies have argued that *OBS* can serve as a risk-reducing mechanism, allowing parent companies to explore new business lines without exposing shareholders to such risks (Karim et al., 2013). This means that banks could hold minority interest in legally separated entities that bear the risk of those investments. Additionally, Hassan (1993) argues that certain products, such as standby letters of credit (SLC), can enhance the senior sequential claims for uninsured liability holders in the event of bank failure. Similarly, Sharp and Tuzun (1998), supports the use of SLC and highlight that loan sales have payoff characteristics like secured debt, improving the selection of loans granted by offsetting the moral hazard incentives associated with deposit insurance. However, the growth of *OBS*, particularly through risky securitization and over the counter (OTC) derivatives trading, has introduced higher levels of non-interest income for banks. Securitization has increased fee-based income while including the assets as off-balance sheet items. In other words, the expansion of off-balance sheet items has been associated with increased risk,

especially in the period leading up to the GFC, as banks were able to avoid holding capital against these assets by using asset-backed securities (Acharaya and Richardson, 2009; Altunbas et al., 2009). Hence, in our analysis, we evaluate the commonality of off-balance sheet financing (assets) using an extensive group of classes as defined by Hassan (1993). This allows us to explore the potential risks associated with similar exposures to off-balance sheet items and its impact on systemic risk.

Our analysis, presented in Table A.4 in the Appendix, reevaluates Equations (4) using this new measure. The results indicate that there exists a U-shaped relationship between off-balance sheet commonality and systemic risk for *MES* and *DCoVaR*. Like the commonality observed in assets, our findings indicate the presence of an off-balance sheet commonality threshold beyond which it becomes detrimental to financial stability.

Alternative specification

To ensure the validity of our results, we add another variable to control for the occurrence of mergers and acquisitions through the dummy variable MA_t which is set to 1 from the time that a bank acquired another institution. The results of our analysis, presented in Table A.5 in the appendix, show that our main conclusions remain unchanged even with this additional control variable. There is no evidence to suggest that the occurrence of mergers and acquisitions has a significant an impact on systemic risk.

1.5. Conclusion

This paper examined the extent to which overlap in the asset portfolios of large U.S. BHCs has grown over the last two decades and its implication for systemic risk. To analyze this relationship, we employ a nonlinear specification and a comprehensive measure of asset commonality that includes both liquid and illiquid assets.

Our findings reveal a U-shaped relationship between asset commonality and systemic risk in large U.S. BHCs. These results indicate that lower levels of asset commonality decrease systemic risk, whereas higher levels prove detrimental to financial stability. Notably, over 75% of the banks in the sample have a level of asset commonality above the threshold detrimental to financial stability.

Further investigations show that there is a U-shaped relationship between the level of asset portfolio overlap and systemic risk when we differentiate between liquid and illiquid assets. Our study also provides evidence that maintaining a low level of asset commonality is crucial for enhancing financial stability, regardless of the period examined and for banks with shorter funding maturity.

Our findings hold significant implications for both banks and bank supervisors. The research highlights the potential threat to financial stability caused by high levels of asset similarity among banks, as it increases systemic risk. As a result, regulators should permit banks to diversify their activities, but with a careful attention on avoiding excessive asset similarity. To strengthen the supervisory framework, banking supervisors should integrate the average similarity distance between banks into macro stress tests. This measure will provide a better understanding of interconnectedness and systemic risks. Moreover, the Bank of International Settlements (BIS) should consider adding an asset commonality measure alongside existing criteria for identifying Global Systemically Important Financial Institutions (G-SIFIs). Furthermore, in assessing capital surcharge requirements for large banks, banking regulators should consider the degree of asset commonality with other banks within the same country. By adopting the threshold derived from the U-shaped relationship we have highlighted and considering individual asset diversification, regulators can effectively address systemic risks associated with asset commonality and foster a more resilient financial system. By implementing these measures, regulators can enhance their ability to mitigate systemic risks arising from asset commonality and promote a more resilient financial system.

Appendix A Table A.1 List of Systemically Important Bank Holdings Companies

	Company Name	Ticker		Company Name	Ticker
1	American Express Company	AXP	37	IBERIABANK Corporation	IBKC
2	Ameris Bancorp	ABCB	38	Independent Bank Corp.	INDB
3	Associated Banc-Corp	ASB	39	International Bancshares Corporation	IBOC
4	Atlantic Union Bankshares Corporation	AUB	40	JPMorgan Chase & Co.	JPM
5	Bank of America Corporation	BAC	41	KeyCorp	KEY
6	Bank of Hawaii Corporation	BOH	42	M&T Bank Corporation	MTB
7	Banner Corporation	BANR	43	Morgan Stanley	MS
8	BBVA USA Bancshares, Inc.	BBVA	44	MUFG Americas Holdings Corporation	MUFG
9	BOK Financial Corporation	BOKF	45	New York Community Bancorp, Inc.	NYCB
10	Capital One Financial Corporation	COF	46	Northern Trust Corporation	NTRS
11	Cathay General Bancorp	CATY	47	Old National Bancorp	ONB
12	Citigroup Inc.	C	48	Pacific Premier Bancorp, Inc.	PPBI
13	Columbia Banking System, Inc.	COLB	49	PNC Financial Services Group, Inc.	PNC
14	Comerica Incorporated	CMA	50	Popular, Inc.	BPOP
15	Commerce Bancshares, Inc.	CBSH	51	Prosperity Bancshares, Inc.	PB
16	Community Bank System, Inc.	CBU	52	Regions Financial Corporation	RF
17	Cullen/Frost Bankers, Inc.	CFR	53	Renasant Corporation	RNST
18	CVB Financial Corp.	CVBF	54	Simmons First National Corporation	SFNC
19	DB USA Corporation	DB	55	South State Corporation	SSB
20	East West Bancorp, Inc.	EWBC	56	State Street Corporation	STT
21	F.N.B. Corporation	FNB	57	Stifel Financial Corp.	SF
22	Fifth Third Bancorp	FITB	58	SVB Financial Group	SIVB
23	First BanCorp.	FBP	59	Synovus Financial Corp.	SNV
24	First Citizens BancShares, Inc.	FCNC.A	60	TCF Financial Corporation	TCF
25	First Financial Bancorp.	FFBC	61	The Bank of New York Mellon Corporation	BK
26	First Horizon National Corporation	FHN	62	Truist Financial Corporation	TFC
27	First Merchants Corporation	FRME	63	Trustmark Corporation	TRMK
28	First Midwest Bancorp, Inc.	FMBI	64	U.S. Bancorp	USB
29	Fulton Financial Corporation	FULT	65	UMB Financial Corporation	UMBF
30	Glacier Bancorp, Inc.	GBCI	66	Umpqua Holdings Corporation	UMPQ
31	Goldman Sachs Group, Inc.	GS	67	United Bankshares, Inc.	UBSI
32	Hancock Whitney Corporation	HWC	68	Valley National Bancorp	VLY
33	Heartland Financial USA, Inc.	HTLF	69	Webster Financial Corporation	WBS
34	Hope Bancorp, Inc.	HOPE	70	Wells Fargo & Company	WFC
35	HSBC North America Holdings Inc.	HSBC	71	WesBanco, Inc.	WSBC
36	Huntington Bancshares Incorporated	HBAN	72	Wintrust Financial Corporation	WTFC

This table present the list of our sample of systemically important bank holding companies based on the list of GSIBs provided by the Federal Financial Institutions Examinations Council.

Table A.2 Robustness Check (1): Alternative Measure Of Asset Commonality (Cosine)

Models	*MES*	*SRISK*	*DCoVaR*
	(1)	(2)	(3)
Cosine_AllasetCom	-0.0164	**-1.3005****	-0.0049
	(0.0152)	(0.6281)	(0.0077)
Cosine_SQAllasetCom	**0.0236****	**0.7785***	0.0074
	(0.0116)	(0.4393)	(0.0054)
GFC	**0.0248*****	**0.1743*****	**0.0076*****
	(0.0012)	(0.0601)	(0.0004)
Covid	-0.0007	**-0.0755***	**0.0041*****
	(0.0007)	(0.0423)	(0.0007)
HighSTDebt	0.0002	0.0449	0.0005
	(0.0008)	(0.0326)	(0.0003)
Div	**-0.007*****	**-0.0709***	**-0.005*****
	(0.0014)	(0.0376)	(0.0012)
Concentration_ratio	**0.0194****	-**0.8628***	**-0.0072***
	(0.0094)	(0.4684)	(0.0041)
lnTA	**0.0042*****	0.0440	0.0003
	(0.0006)	(0.0359)	(0.0002)
Geo_Complexity	**-0.0051****	0.0636	-0.0004
	(0.0025)	(0.1715)	(0.0009)
DD	**-0.004*****	**-0.0546*****	**-0.002*****
	(0.0002)	(0.0100)	(0.0001)
ROA	**-0.64*****	**-25.80****	**-0.143*****
	(0.2423)	(10.4095)	(0.0534)
Tier1Ratio	**0.0496*****	-2.9058	0.0043
	(0.0145)	(1.8180)	(0.0047)
Efficiency	**0.00003***	**0.0014****	-7.56
	(0.00001)	(0.0007)	(5.52)
SMR	-0.0034	0.1914	**-0.0036****
	(0.0050)	(0.2883)	(0.0015)
NPL	**0.0668***	**14.0895*****	-0.0049
	(0.0351)	(4.0832)	(0.0096)
LiquidityRatio	-0.0004	0.0248	0.0001
	(0.0005)	(0.0202)	(0.0002)
Constant	**-0.046*****	0.7305	**0.0179*****
	(0.0170)	(0.8138)	(0.0064)
Nbr. of obs.	4847	4847	4847
Fixed Effects	Yes	Yes	Yes
Lind-Mehlum U-test			
P-value		(0.22)	
Turning point		0.84	
R^2	0.5865	0.2901	0.6722

This table reports fixed effects estimation of systemic risk measures (MES, SRISK, and DCoVaR) on the broader measure of asset commonality (*AllAssetCOM*),(*SQAllAssetCom*) and control variables. All variables are defined in Table 1.2. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table A.3 Off Balance Sheet Asset Classes

Panel A

S/N	Off Balance Sheet Items	Item N° as in Hassan (1993)
A	**Unused Loan commitment**	
	Unused Commitment for Family Lines	11
	Unused Commitment Consumer Credit card lines	11
	Unused Commitment Other Unused Credit Card Lines	11
	Unused Commitments Credit Card Lines	11
	Unused Commitment Construction Loans	11
	Unused Commitment Commercial Real Estate and Others	11
	Unused Commitment Securitized Commercial Real Estate	11
	Unused Commitment Not Securitized Commercial Real Estate	11
	Unused Commitment Securitized Underwriting	11
	Unused Commitment Commercial and Industrial Loans	11
	Unused Commitment Loans to financial Institutions	11
	Unused commitment All Others	11
B	**Participations in acceptances conveyed to others**	16
C	**Participations in acceptances conveyed from others**	17
D	**SLC to US addresses**	6
E	**SLC to non-US addresses**	7
F	**SLC participated to others**	8
G	**commercial letters of credit**	9
H	**securities borrowed**	1
I	**securities lent**	2
J	**Notational value of interest rate swaps**	5
K	**Commitment to purchase when issued securities**	3
L	**commitments to sell when issued securities**	4

Panel B: Off Balance Sheet items Grouping

S/N	Off Balance Sheet Items Group Name	Grouping
1	OB	3+6+7-8-9+11
2	PART	8+16+17
3	SWAP	5
4	SLC	6+7-8
5	CLC	9

We follow Hassan (1993) in grouping our off-balance sheet items and thereafter calculated our off-balance sheet assets commonality measure.

Table A.4 Robustness Check (2): Alternative Measure of Off-Balance Sheet Result

	MES	*SRISK*	*DCoVaR*
	(1)	(2)	(4)
OffBalSim	**-0.0312****	0.5970	**-0.0192*****
	(0.0152)	(0.8629)	(0.0069)
SQOffBalSim	**0.0219****	-0.5859	**0.0166*****
	(0.0100)	(0.7203)	(0.0053)
GFC	**0.0246*****	**0.2812*****	**0.0076*****
	(0.0012)	(0.0588)	(0.0004)
Covid	-0.0003	0.0177	**0.0033*****
	(0.0006)	(0.0538)	(0.0006)
HighSTDebt	0.0003	**0.0561***	0.0004
	(0.0008)	(0.0325)	(0.0003)
Div	**-0.0072*****	**-0.1840*****	**-0.0039*****
	(0.0014)	(0.0415)	(0.0011)
Geo_Complexity	**-0.0046****	0.0731	-0.0006
	(0.0021)	(0.1588)	(0.0007)
Tier1Ratio	**0.0399*****	-2.9833	0.0027
	(0.0135)	(1.8554)	(0.0046)
Efficiency	**0.00003***	**0.0015*****	1.74
	(0.00001)	(0.0005)	(3.79)
SMR	-0.0041	0.0277	**-0.0032****
	(0.0048)	(0.2694)	(0.0015)
NPL	0.0538	**12.9925*****	-0.0076
	(0.0333)	(3.7867)	(0.0103)
Concentration_ratio	**0.0381*****	-0.3972	0.0030
	(0.0081)	(0.3138)	(0.0031)
lnTA	**0.0043*****	0.0206	**0.0007*****
	(0.0006)	(0.0249)	(0.0002)
LiquidityRatio	-0.0042	**0.3849***	0.0002
	(0.0048)	(0.1963)	(0.0016)
ROA	**-0.6397*****	**-25.4110****	**-0.1451*****
	(0.2406)	(10.7330)	(0.0538)
DD	**-0.0041*****	**-0.0771*****	**-0.0016*****
	(0.0002)	(0.0110)	(0.0001)
Constant	**-0.0438*****	0.2359	**0.0111****
	(0.0154)	(0.6232)	(0.0055)
Nbr. of obs.	4847	4847	4847
Individual Fixed Effects	Yes	Yes	Yes
Lind-Mehlum U-test			0.4203
P-value	(0.0217)		(0.00344)
Turning point	**0.71****		**0.577*****
R^2	0.5856	0.3641	0.6763

This table reports fixed effects estimation of systemic risk measures (MES, SRISK, and DCoVaR) for the Off-balance sheet Asset commonality (*OffBalSim*) and its quadratic term (*SQOffBalSim*) and control variables. The Lind and Mehlum test is a test of non-linearity. The turning point is computed as (-coefficent *OffBalSim* /2*coefficient *SQOffBalSim*). All variables are defined in Table 1.2. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% level

Table A.5 Robustness check (3): alternative specification

Variables	*MES*	*SRISK*	*DCoVaR*
Models	(1)	(2)	(4)
AllAssetCom	**-0.0367***	**-2.1300****	-0.0084
	(0.0206)	(0.9500)	(0.0080)
SQAllAssetCom	**0.0332****	**1.3752****	0.0076
	(0.0148)	(0.6575)	(0.0056)
GFC	**0.0249*****	**0.2862*****	**0.0076*****
	(0.0013)	(0.0599)	(0.0004)
Covid	-0.0003	-0.0545	**0.0043*****
	(0.0007)	(0.0394)	(0.0006)
HighSTDebt	0.0003	0.0506	**0.0005***
	(0.0008)	(0.0329)	(0.0003)
Diversification	**-0.01*****	**-0.1190*****	**-0.0046*****
	(0.0014)	(0.0325)	(0.0012)
Concentration_ratio	**0.0215****	-0.6182	-0.0054
	(0.0090)	(0.3799)	(0.0037)
lnTA	**0.0040*****	0.0416	0.0003
	(0.0006)	(0.0368)	(0.0002)
Geo_Complexity	**-0.0053****	0.0502	-0.0005
	(0.0021)	(0.1723)	(0.0008)
DD	**-0.0041*****	**-0.0753*****	**-0.0016*****
	(0.0002)	(0.0100)	(0.0001)
ROA	**-0.6387****	**-25.8047****	**-0.1396****
	(0.2418)	(11.0881)	(0.0531)
Tier1Ratio	**0.0440*****	-2.7816	0.0019
	(0.0145)	(1.7587)	(0.0047)
Efficiency	0.00002	**0.0011****	-2.60
	(0.00002)	(0.0006)	(5.69)
SMR	-0.0034	0.1182	**-0.0038****
	(0.0049)	(0.3134)	(0.0016)
NPL	**0.0602***	**13.4007*****	-0.0079
	(0.0345)	(4.0228)	(0.0094)
Liquidity	-0.0006	0.0343	0.00004
	(0.0006)	(0.0225)	(0.0002)
MA	-0.0001	-0.0100	0.00001
	(0.0005)	(0.0141)	(0.0001)
Constant	**-0.0343****	0.9155	**0.0208*****
	(0.0165)	(0.7308)	(0.0064)
Nbr. of obs.	4847	4847	4847
Individual fixed effects	Yes	Yes	Yes
Lind-Mehlum U-test			
P-value	(0.0395	(0.0768)	
Turning point	**0.55****	**0.77***	
R^2	0.5860	0.3640	0.6710

This table reports fixed effects estimation of systemic risk measures (MES, SRISK, and DCoVaR) on the asset commonality (*AllAssetCOM*) and its quadratic term (*SQAllAssetCom*) when we add the dummy variable *MA* taking the value of one from the time that a bank acquired other institutions among the set of control variables. The Lind and Mehlum test is a test of non-linearity. The turning point is computed as (-coefficent AllAssetCOM/2*coefficient *SQAllAssetCom*). All variables are defined in Table 1.2. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% level

CHAPTER 2

MACROPRUDENTIAL POLICIES AND SYSTEMIC RISK: UNVEILING THE HIDDEN RISKS OF ASSET COMMONALITY

2.1. Introduction

Considering the repercussions of the previous Global Financial Crisis (GFC), central banks worldwide have increasingly adopted macro-prudential policies to mitigate systemic financial risks. As stated by the Financial Stability Board (FSB), International Monetary Fund (IMF), and Bank for International Settlements (BIS) in 2016, the primary goal of these regulations is to prevent interruptions in the delivery of crucial financial services, which can have serious effects on the real economy. Macroprudential tools ideally operate through a variety of banks' balance sheet channels, either through assets or liabilities. However, these channels are often grouped into different categories such as borrowers, financial institutions (FIT), quantity, price measures, etc. The objective is to tackle systemic risk arising from the accumulation of financial imbalances and the pro-cyclicality of the financial system (Morgan, et al., 2018). Additionally, it involves examining the cross-sectional dimension across firms and markets, considering common exposures, risk concentrations, linkages, and interdependencies within the financial system (Crockett, 2000; Borrio, 2003; Caruana, 2010; Meuleman and Vennet, 2020). Macroprudential policies also address vulnerabilities arising from financial linkages and common exposures, which result from banks holding similar asset portfolios (referred to as asset commonality). These vulnerabilities can expose banks to macroeconomic shocks, potentially leading to multiple bank failures.

While many studies have shown the efficacy of macroprudential policies in controlling credit growth and stabilizing real estate prices (Bengui and Bianchi 2014, Aiyar et al. 2014, Reinhardt and Sowerbutts 2015, Claessen et al. 2014, Lim et al. 2011, Aiyar et al. 2014), it is crucial to acknowledge that not all policy instruments are aimed at curbing excessive credit expansion. Some are specifically designed to enhance the resilience of banks in the face of economic shocks, thereby promoting financial stability. Furthermore, there is a literature analysing the influence of macroprudential policies on banks' competitive conduct and their potential to worsen financial stability (Gonzales, 2022; Mizaei & Moore, 2021), leading to competition fragility and stability arguments. The outcomes of these studies present a diverse range of findings. Primarily, policies targeting financial institution activities have been observed to generally enhance bank competition. Specifically, macroprudential measures concentrating on a bank's loan supply and liquidity demonstrate a significant and positive impact on fostering competition among banks (Gonzales, 2022). Conversely, policies cantered around capital aspects, such as requirements for systemically important financial institutions (SIFIs), taxes, and reserve mandates, typically result in a reduction of competitive dynamics (Gonzales, 2022). However, Meuleman and Vennet (2020) provide evidence that liquidity-focused macroprudential policy instruments can effectively reduce the systemic linkage of bank risk.

This study contributes to the existing literature by examining the impact of the degree of macroprudential policy implementation on the way asset commonality influences systemic risk. The underlying argument suggests that, in response to robust macroprudential measures, banks might opt to shift their asset portfolios from high-weighted to low-weighted asset categories or even invest in entities operating outside the regulatory framework (Houdal and Ngo, 2021). Subsequently, such risk-shifting actions may inadvertently expose banks to new or emerging risks. For instance, banks could transition their substantial mortgage loan holdings into a diversified assortment of fixed-income securities, consequently increasing their susceptibility to interest rate fluctuations. Another significant concern arises when all banks are mandated to adhere to identical regulations, potentially triggering similar responses. Banks tend to mimic the behavior of their competitors in the market, leading to a phenomenon known as herding (Aiyar et al., 2014; Reinhardt and Sowerbutts, 2015; Acharya and Yorulmazer, 2008). The attractiveness of shared failure costs incentivizes banks to collectively undertake excessive risk as regulatory authorities struggle to distinguish deliberate high-risk behavior among banks. Consequently, this environment fosters heightened risk-taking and amplifies systemic risk exposure. To the best of my knowledge, this study is the first to investigate how asset commonality can exacerbate systemic risk exposure under conditions of high macroprudential policy implementation.

The empirical analysis is conducted on a sample of 103 banks across 29 countries from 2000 to 2020. This cross-country approach allows for the inclusion of diverse macroprudential policies implementations across nations. The study employs 17 measures from the IMF's Integrated Macroprudential Policy Database (iMaPP) for a comprehensive assessment of macroprudential policies. The level of asset commonality is assessed through the application of both Euclidean and Cosine methods across a set of 15 asset classes. To understand the link between asset commonality and systemic risk, the sample is segmented into subsets based on varying levels of macroprudential policy adoption across countries and periods. This analysis acknowledges that the impact of asset commonality on systemic risk varies across different macroprudential policy categories.

Beyond the asset commonality link, there is a recognized argument that liberalization and internationalization policies have played a role in increasing systemic risk contagion. While cross-border lending can bring benefits like capital inflows, economic growth, risk-sharing, and diversified banking resilience, it is important to note that shocks can also spread through foreign entities, amplifying systemic risk. Macroprudential policies might inadvertently expose vulnerabilities when banks exploit regulatory differences between countries, resulting in capital shifts and shock transmission. This could impact asset commonality, as banks may favor investments in countries or sectors with more favorable regulations. To investigate this, the study utilizes the overall outflow restriction index to assess whether stronger cross-border asset restrictions affect the way asset commonality influences systemic risk under varying degrees of macroprudential policies.

In summary, the study highlights a significant positive association between asset commonality, (spanning all assets and loans commonality), and systemic risk, particularly evident under a high implementation of macroprudential policies. This impact is notably pronounced, especially within the context of high Financial Institution Targeted (FIT) and quantity-focused macroprudential policies. Furthermore, the interaction of asset commonality with cross-border asset restrictions substantially amplifies systemic risk, particularly when coupled with an extensive quantity-focused macroprudential policy implementation. In conclusion, the study underscores the importance of vigilant and periodic oversight of quantity-based macroprudential policies to avert adverse outcomes arising from the commonality of assets within banking institutions. Additionally, a suggestion is made for the Bank of International Settlements (BIS) to improve its standards for evaluating Global Systemically Important Financial Institutions (G-SIFIs) by combining an evaluation of asset similarity with interconnectivity factors.

The remainder of the paper is organized as follows. Section 2.2 presents the related literature; Section 2.3 describes the data and define the main variables of interest; Section 2.4 presents the main results and provides some robustness tests; Section 2.5 presents further investigations. Ultimately, Section 2.6 concludes the paper.

2.2. Literature Review

After the occurrence of the GFC, it became increasingly clear that relying solely on macroprudential policies was insufficient in effectively regulating credit expansion among institutions and addressing interdependencies within the financial industry (Crockett, 2000; Borrio, 2003, Davis 1999, Cehaijc and Kosak 2021). Consequently, there has been significant scrutiny regarding the effectiveness of macroprudential policies in attaining their objectives. Macroprudential policy's main objective is to reduce the risks brought on by excessive leverage and debt build-up as well as to deal with the systemic risk that accumulates over time. Additionally, macroprudential policies concentrate on identifying vulnerabilities within individual entities that may have spillover effects and potentially result in the collapse of the entire financial system. Ideally, macroprudential tools function across both the assets and liabilities sides of the balance sheet. Macroprudential policies are therefore classified into various categories, such as borrower, financial institution, quantity, and price-related measures, among others. Each category has a varying degree of influence when it comes to controlling systemic risk. Borrower-focused policies involve implementing limits on the debt service-to-income ratio (DSTI), and loan-to-value (LTV) while still considering the customer's overall financial situation, including investments held with other banks. Changes to the Loan-to-Value (LTV) ratio restrict borrowing by linking it to a fraction of the underlying asset value. These regulations are designed to improve the loan portfolio quality of a bank (Meuleman and Vennet 2020). However, it can only strengthen the bank's resilience by limiting new lending opportunities rather than impacting existing loans. This policy meets the criteria for a quantity-based macroprudential tool since it has an immediate effect on the amount of loans that people can get based on their present debt and income profile. Rather than focusing on loan supply, these policies primarily target loan demand to mitigate the risk of excessive loan expansion. A stricter LTV ratio may prompt banks to adjust their credit supply composition, potentially shifting from mortgage markets to other sectors or expanding lending internationally where more favorable instruments are accessible (Cizel et al., 2016).

In continuation, the FIT policies encompass a wide range of tools that specifically aim to regulate the activities of banks. The objective is to restrict excessive credit growth, interbank exposure, concentration, and liquidity risk concerns (Cizel et al., 2016). These instruments comprise capital and liquidity weights, taxes, loan coverage, and loan restriction measures. By building up capital reserves or allocating them to future or emerging risks, capital and liquidity policies seek to increase a bank's resilience. These measures include sector-based capital requirements for individuals and businesses, countercyclical buffers, and buffers for systemically significant financial institutions (SIFIs). If raising capital becomes expensive, banks may decrease the supply of credit. The effect of capital may also differ based on a bank's profitability, liquidity position, and degree of internationalization (Buch and Goldberg, 2016). Liquidity restrictions imply that banks may not extend credit facilities beyond a certain threshold to limit their risk exposure. Additionally, due to their high level of leverage, banks must retain a sizeable amount of their deposits to meet their daily cash withdrawal needs. Quantity-based measures act as a volume constraint on credit by restricting the capacity or amount of investment that is accommodated in a specific asset class. These measures include limits on interbank lending, loan-to-value (LTV) ratios, debt service-to-income ratio (DSTI), Leverage Limits (LVR), Limits on Credit growth (LCG), and other loan restrictions, among others (Cizel et al., 2016).

While the existing literature has primarily concentrated on how macroprudential policies mitigate credit growth (Altunbas et al., 2018; Bengui and Bianchi, 2014; Aiyar et al., 2014; Reinhardt and Sowerbutts, 2015; Claessen et al., 2014; Lim et al., 2011; Aiyar et al., 2012), Meuleman and Vennet, (2020) examine the effects of these policies on bank risk-taking incentives and financial stability. The study focuses on European data spanning from 2007 to 2017 and finds that macroprudential policies overall effectively reduce bank systemic risk. Specifically, borrower-focused macroprudential policy and exposure limits have a more beneficial impact by reducing individual bank risk. Also, Meuleman and Vennet, (2020) argue that liquidity tools help to reduce the systemic linkage component of bank risk. This is because they push banks to maintain higher levels of liquid assets or prioritize long-term funding over short-term funding options. These measures aim to bolster the resilience of banks by ensuring they possess adequate resources to withstand potential losses during macroeconomic shocks. Consequently, banks may need to curtail lending activities to meet liquidity requirements. As a result, this process may lead to a notable concentration of investments among banks in the same pool of assets, as they are subject to the same macroprudential regulations, assuming all other factors remain unchanged. Meuleman and Vennet, (2020) further study the impact of macroprudential policies on various types of banks. Their findings reveal that credit growth tools and exposure limits have the most significant effects in reducing bank risk, especially for retail banks. This is attributable to the fact that loan and borrower-focused macroprudential policies place limits on both types and quantities of bank loans, thus reducing their exposure to default risk. Nevertheless, these measures were observed to have a more pronounced effect in increasing systemic linkage among retail banks. In response to a policy change, banks engage in risk-shifting by adjusting their asset composition towards other asset classes, e.g., securities that are not affected by the restrictions. This may increase assets' commonality for other asset classes, rendering them more vulnerable to additional market risks. Loan and borrower-focused policies may be desirable for reducing credit demand and limiting supply. However, they may also prompt banks to redirect their available funds towards higher-yield assets or substitute across other asset classes. Additionally, banks might create new products or increase investment in unsecured non-mortgage products (Meuleman and Vennet, 2020).

There is a literature showing that while diversifying the banks' asset portfolio could be beneficial, it could also lead to a new level of concentration or commonality among banks (Cai et al, 2018, Getmansky et al 2021). This is because all banks are affected by the same policies and may sometimes engage in herding behavior, mimicking the behavior of their competitors in the market in response to policy change. Thus, asset commonality occurs when banks follow each other's investments pattern to minimize the impact of information contagion on expected borrowing costs (Acharya and Yorulmazer, 2008), exploit the frictions between micro-prudential and macroprudential policies (Osínski et al., 2013), or due to government guarantees (Eisert and Eufinger, 2019) and/or regulatory constraints (Acharya and Yorulmazer, 2007, 2008; Farhi and Tirole, 2012; Horváth and Wagner, 2017) which may lead them to take excessive risks (Gropp et al., 2014; Laeven et al., 2016; Allen et al., 2018).

Banks could employ arbitrage strategies to circumvent regulatory constraints by reallocating investments to jurisdictions with more lenient regulations. This practice is closely tied to the concepts of risk-shifting and herding behavior. For instance, when policies like sectoral loan caps impact a bank's loan supply and profitability, the bank might engage in transactions in unregulated zones or financial entities. While macroprudential policies influence the operations of both domestic and foreign subsidiaries within host countries, they typically do not extend to foreign branches. Consequently, foreign branches can serve as conduits for transactions that bypass the initial regulations. Furthermore, the implementation of macroprudential policies varies across countries, allowing banks to exploit these discrepancies by shifting investments across nations, thereby prompting capital flows. Claessen et al. (2013) even suggest that the effectiveness of macroprudential policies might be influenced by the degree of international integration, implying that countries with open capital accounts and a substantial presence of foreign banks could struggle to enforce such policies effectively. Some contend that increased systemic risk is a direct result of liberalization and internationalization policies (Berger et al., 2016). This implies that while cross-border lending activities can bring benefits upon an economy, such as capital influx, improved economic performance, risk-sharing, diversification, and reduced vulnerability of banks to domestic shocks, there is a need to acknowledge that shocks can also propagate through these foreign entities to the host community. This can intensify systemic risk (Berger et al., 2016; Bruno and Shin, 2015; Philipp Schnabl, 2012). Consequently, macroprudential policies may inadvertently increase risk exposure as banks shift investments to other countries in pursuit of regulatory arbitrage.

Moreover, macroprudential policies can have unintended repercussions on competition and stability, giving rise to two contrasting viewpoints: competition-fragility and competition-stability. Francisco Gonzales (2022) emphasizes that shifts in policy tools can influence bank charter value, credit supply, entry, and constraints on bank activities, ultimately affecting the concentration of bank assets. Capital and tax-based macroprudential measures can amplify banks' costs, diminish their profitability and margins, and erode charter value. This could push banks toward excessive risk-taking behavior. Conversely, Mirzaei and Moore (2021) suggest that higher taxes and capital-focused macroprudential policies might intensify competition in credit and deposit markets, negatively impacting profits and driving bank mergers and acquisitions. In turn, this could result in a rise in asset concentration, especially if these regulations are likely to affect smaller banks. This potential rise in concentration could lead to fewer and larger banks, potentially becoming "too big to fail" and subject to implicit guarantees. This could disrupt their risk-taking incentives, heightening fragility. Similarly, stricter entry rules and limitations on bank activities might reduce competition, resulting in fewer active banks and a concentration of assets among a handful of players. This exposure amplifies systemic risk during adverse shocks (Gonzales, 2022). Also, stricter macroprudential policies that curb credit supply might prompt banks to offset the impact by raising interest rates on viable regulatory credit offerings compared to situations without such caps. However, elevated loan interest rates could lead to a surge in loan defaults or non-performing loans. It is important to note that banks could face higher monitoring costs, potentially losing the economies of scale derived from a large capital supply, thus significantly affecting their risk exposure.

In the context of reduced credit supply due to macroprudential policies, borrowers may need to seek funds from multiple banks to fulfill their requirements. This could potentially lead to a scenario where loan-assets commonality emerges when multiple banks lend to the same borrower. Additionally, it might lead to an increase in loan syndicates, thereby elevating the interconnectedness of banks. According to Kosenko and Michelson (2022), multiple-bank lending within the Israeli banking system significantly contributes to the spread of contagion among banks and systemic risk. Similarly, Cai et al. (2018) investigate syndicated loan portfolios in the United States and find that the overlap of bank loan portfolios renders them more susceptible to contagion effects. Furthermore, Silva (2019) affirms that diversified banks are more interconnected through syndicated loan portfolios, thereby amplifying their contribution to contagion and systemic risk.

Consistent with the arguments outlined above, the aim of this study is to investigate whether higher levels of asset commonality among banks lead to an increase in systemic risk, especially in countries with stronger macroprudential policy implementation compared to those with weaker implementation. Additionally, this study explores the conditions under which macroprudential policies might shape the extent to which asset commonalities exert a stronger negative or positive influence on systemic risk.

2.3. Sample Data Description

2.3.1 Presentation of the Sample

We utilize a worldwide sample of SIFIs banks to assess how asset commonality influences a bank's exposure to systemic risk across different levels of macroprudential policy implementation. To mitigate the impact of the COVID-19 pandemic, we restrict our analysis to large banks with total assets equal to or higher than USD 50 billion as of 2019. The annual consolidated balance sheets and income statements are sourced from the Fitch Connects database, covering the period from 2000 to 2020. Subsequently, financial data from 133 banks across 29 countries is sourced from the Fitch Connects database, encompassing a minimum of 10 consecutive years of data ranging from 2000 to 2020. In addition, country-level macroeconomic variables are obtained from the World Bank Global Financial Development Database. Central Bank Policy and house prices for each country are obtained from the Bank for International Settlements statistics, while Gross Domestic Product (GDP) and macroprudential data indices are sourced from the International Monetary Fund database. The market data for systemic risk were sourced from the Refinitiv Eikon DataStream which includes the bank's market value, stock price, total liabilities, and the World market index (MSCI). We have excluded banks that lack standard data, such as stock price information. This results in a final sample of 103 banks, totaling 1,994 observations spanning from 2000 to 2020. The list of banks is provided in Appendix Table B.1. Table B.2 gives the number of banks by country. The sample consist of 28, 41, and 18 banks from the US, Europe, and Asia continents, respectively. In the sample, there are about 24 banks in the GSIB category published by the Financial Stability Board on 21st November 2022. The largest bank in the sample is the Bank of China with total assets well above the US $3 trillion mark.

All continuous financial variables are winsorized after construction at the 1% and 99% percentile to eliminate the impact of a potential outlier. Table 2.1 lists comprehensive descriptive statistics. We address potential multicollinearity issues by orthogonalizing the relevant variables (see Table 2.1.). A comprehensive overview of variable correlations is outlined in Table 2.2.

Table 2.1 Definitions, Data Sources and Summary Statistics for Variables

Variables	Definition	Source	N	Mean	Std. Dev.	min	max
RISK MEASURES							
MES	Marginal Expected Shortfall (*MES*), introduced by Acharya et al. (2017) and Brownlees and Engle (2017), is defined as the marginal contribution of a bank to systemic risk as measured by the Expected Shortfall of the financial system.	Refinitiv Eikon (DataStream)	1780	.011	.019	-.161	.287
DCoVaR	Delta-CoVaR (*DCoVar*), introduced by Adrian and Brunnermeier (2016), corresponds to the Value at Risk of the financial system obtained conditionally on a specific event affecting a given bank.	Refinitiv Eikon (DataStream)	1780	.002	.003	-.003	.03
ASSETS COMMONALITY MEASURES							
AllAssetCom	Banks measure of similarities for all asset classes (see Table 2.3) using the Euclidean distance measure that captures the average level of similarity between one bank to the total sample of banks for all asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).	Fitch Connects	1994	.81	.15	0	1
Cosine_AllAssetCom	Banks measure of cosine similarities for all asset classes (see Table 2.3) using the cosine distance measure that captures the average level of similarity between one bank to the total sample of banks for all asset's portfolio. The measure	Fitch Connects	1994	0.75	0.20	0	1

	ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).						
LoansAssetCom	Banks measure of similarities for all loans asset classes (see Table 2.3) using the Euclidean distance measure that captures the average level of similarity between one bank to the total sample of banks for all asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching).	Fitch Connects	1994	.79	0.18	0	1
MACROPRUDENTIAL VARIABLES							
Cum_Comprehensive	The sum of all (17) Macroprudential Index; equals to 1 if any were implemented during the year.	IMF Database: https://www.elibrary-areaer.imf.org/Macroprudential/Pages/Home.aspx	1994	3.26	3.48	0	17
Cum_FIT	The sum of macroprudential policies that directly affects financial institution as the primary agent. Details of each instrument underneath this category are enumerated in Table B.3 in appendix B	IMF Database: https://www.elibrary-areaer.imf.org/Macroprudential/Pages/Home.aspx	1994	2.78	3.03	0	15
Cum_Borrower	The sum of Macroprudential policies that affects the borrower although implemented by the bank (LTV and DTI).	IMF Database: https://www.elibrary-areaer.imf.org/Macroprudential/Pages/Home.aspx	1994	0.48	0.67	0	2
Cum_Quantity	The sum of Macroprudential policies that serves as a restriction on the amount of investment a bank can partake in. Details of each instrument underneath this category are enumerated in Table B.3 in appendix B	IMF Database: https://www.elibrary-areaer.imf.org/Macroprudential/Pages/Home.aspx	1994	1.73	1.68	0	8
BANK CONTROL VARIABLES							

lnTA	Natural logarithm of total assets (orthogonalized on Liquidity)	Fitch Connects	1994	25.723	1.621	20.684	28.673
Equityratio	Equity ratio (Total Equity divided by risk weighted Assets),	Fitch Connects	1979	.076	.037	0	.362
ROA	Net income divided by total assets,	Fitch Connects	1942	.007	.01	-.162	.057
Efficiency	Operating expense divided by operating income,	Fitch Connects	1942	.774	1.098	.264	35.325
Liquidity	Cash Balances Due+ Securities+ Fed. Funds Sold and Repos +Trading Account Assets-Pledged Securities) divided by total assets (orthogonalized on SMR),	Fitch Connects	1979	.318	.171	.011	1.583
Diversification	Net interest income divided by total revenue	Fitch Connects	1943	.411	.215	0	.999
HighSTDebt	Dummy variable taking the value of one if a bank's Wholesale funding ratio is higher than the median in the sample. Wholesale funding ratio is wholesale funding divided by total assets	Fitch Connects	1994	.405	.491	0	1
SMR	Total Securities divided by total assets,	Fitch Connects	1977	.22	.123	.005	.876
GFC	Dummy variable taking the value of one for 1 for the period 2007- 2009	NBER	1994	.13	.336	0	1
Concentration_ratio	Concentration Ratio measured by the total assets of the five largest banks divided by the total assets of the banking system	Concentration Ratio measured by the total assets of the five largest banks divided by the total assets of the banking system	1,994	0.25	0.016	0.23	0.29
COUNTRY SPECIFIC CONTROL VARIABLES							
Asset_Restriction	Dummy variables taking the value of one for countries with higher cross-border restrictions (mean value of cross-border index higher than the sample mean). The index captures a country's stance towards capital controls on outflows. It is an average on outflow control restrictions across ten asset categories: 1) Money market instruments; 2) Equities; 3) bonds; 4) Collective investment securities; 5)	Fernandez et al. (2015). https://www.nber.org/research/data/international-finance-and-macroeconomics-catalogue-data-sources	1944	.30	.46	0	1

	Financial credits; 6) Derivatives; 7) Commercial credits; 8) Guarantees, sureties, and financial back-up facilities; 9) Real Estate transactions, and 10) Direct investment accounts.						
Stockmcap_GDP	Stock Market Capitalization, lagged by one year. Total value of all listed shares in a stock market as a percentage of GDP. Total value of all listed shares in a stock market as a percentage of GDP.	World Bank Financial Development Data-World Federation of Exchanges; Global Stock Markets Factbook and supplemental S&P data, Standard & Poor's (IMF)	1593	.986	.516	.103	2.98
△_House Price Index	Annual Change in House Price Index	Bank of International Settlement, except for Taiwan, Russia, extracted from https://fred.stlouisfed.org/	1535	.049	.254	-.963	5.063
△_Central Bank Policy	Central Bank Policy	Bank of International Settlement, except for Taiwan, Russia, extracted from St louis Fred Website	1763	-.006	.699	-14	1.308
△_GDP	Change in GDP: Annual change in Gross Domestic Products	IMF Statistics	1784	.019	.032	-0.113	.244
Institutional_environment	Institutional Environment: computed following taking the average of 6 variables namely (i) Control of Corruption (ii) Government Effectiveness (iii) Political Stability/Absence of Violence/Terrorism (iv) Regulatory Quality: (v) Rule of Law (vi) Voice and Accountability: Estimate. I normalized the variable to values between 0 and 1. The variable was developed by Kaufman et al (2009) and known as (KKZ)	World Bank Data	1994	0.42	0.35	0	1
Inflation	Inflation Rate: Level of inflation in each country.	World Bank	1842	0.23	0.41	-0.05	0.55
Credit_GDPgap	Credit to GDP gap to measure level procyclicality (not in percentages)	Bank of International Settlement	1994	0.11	0.14	-.0.98	0.81

This table defines the variables and reports summary statistics for the full sample.

Table 2.2 Correlation and Multicollinearity

Panel A: Correlation matrix

S/N		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	AllassetCom	1																			
2	LoanAssetCom	0.929	1																		
3	Asset_restriction	0.162	0.169	1																	
4	StockMap_GDP	-0.024	-0.012	-0.216	1																
5	Equityratio	0.084	0.138	0.108	0.074	1															
6	Concentratio_Ratio	-0.173	-0.139	-0.027	-0.032	-0.054	1														
7	Institutional_environment	-0.043	-0.036	-0.385	0.419	-0.163	0.009	1													
8	Efficiency	-0.026	-0.022	0.008	-0.085	-0.105	0.058	0.016	1												
9	Liquidity Ratio	-0.228	-0.275	0.009	0.036	-0.121	-0.166	-0.084	0.015	1											
10	Inflation	-0.112	-0.055	0.293	-0.270	0.206	0.153	-0.254	0.007	0.054	1										
11	HighSTDebt	-0.007	0.023	-0.136	-0.156	-0.313	-0.019	0.163	0.071	-0.016	-0.102	1									
12	Credit_GDPgap	-0.087	-0.082	0.073	-0.061	-0.141	0.185	-0.023	-0.025	-0.076	0.090	0.039	1								
13	SMR	-0.363	-0.391	-0.038	0.041	-0.138	0.045	-0.024	-0.012	0.803	0.121	-0.091	-0.009	1							
14	ROA	-0.048	-0.036	0.113	0.075	0.364	0.055	-0.080	-0.260	0.016	0.093	-0.142	0.046	0.049	1						
15	Diversification	0.092	0.092	0.132	-0.221	0.208	-0.066	-0.200	0.116	-0.194	0.065	-0.228	-0.083	-0.240	-0.123	1					
16	lnTA	0.268	0.217	-0.148	0.004	-0.462	-0.122	0.153	0.046	0.114	-0.190	0.404	-0.021	0.019	-0.129	-0.313	1				
17	△_House Price Index	-0.002	-0.004	0.079	0.052	0.015	-0.103	-0.031	-0.019	0.019	0.024	0.006	-0.024	-0.001	0.056	-0.001	-0.035	1			
18	△_Central Bank Policy	-0.027	-0.024	0.017	-0.215	-0.070	0.041	-0.014	0.065	0.028	-0.065	0.065	0.098	0.017	-0.142	-0.025	0.037	-0.163	1		
19	△_GDP	0.001	0.020	0.287	0.022	0.150	0.095	-0.057	-0.111	0.005	0.180	-0.188	-0.101	0.066	0.348	0.042	-0.117	0.075	-0.28	1	
20	GFC	-0.075	-0.052	-0.196	-0.113	0.018	0.202	0.016	0.176	-0.022	0.084	0.034	0.085	-0.005	-0.249	0.113	0.003	-0.158	0.19	-0.29	1

This table shows the correlation matrix, (Panel A) and the variance inflation factors (VIF) in Panel B All variables are as defined in Table 2.1.

Panel B: Variance inflation factor	
Variable	VIF
stockmcap_GDP	2.51
Institutional environment	2.43
Diversification	2.39
Equity ratio	2.34
ROA	2.09
Asset_restriction	1.77
GFC	1.74
△_GDP	1.71
Inflation	1.58
AllAssetCom	1.52
SMR	1.50
lnTA	1.47
HighSTDebt	1.43
Efficiency	1.36
Liquidity Ratio	1.32
Concentration Ratio	1.29
△_Central Bank Policy	1.22
Credit_GDPgap	1.17
△_House Price Index	1.03
Mean VIF	1.55

2.3.2 Asset Commonality

It is required to use a metric that measures the degree of asset overlap between pairs of banks to determine whether banks with comparable investment portfolios have comparable underlying risks that could increase systemic risk. In this case, Euclidean similarity is used as a metric to express the degree of similarity between various asset classes. The Euclidean similarity method effectively measures the distance between two vectors and has been utilized in prior research to gauge bank asset commonality (Cai et al., 2018; Fricke, 2016). The basic idea is that when two banks invest in the same assets, their similarities increase. This study identifies 15 asset classes (see Table 2.3) to come up with a comprehensive measure of bank asset commonality that takes into consideration all asset categories.

TABLE 2.3 List of Asset Classes

S/N	ASSET CLASSES
1	Cash
2	Available for Sale Securities
3	Government Securities
4	Trading Securities
5	Derivative Assets
6	Mortgage Loans
7	Other Intangibles
8	Goodwill
9	Other Assets
10	Corporate and Commercial Loans
11	Loans & Advances to Banks
12	Other Loans
13	Customer Loans
14	Total Consumer Loans
15	Fixed Assets

This table presents the list of asset classes used to compute the measure of asset commonality.

Additionally, the commonality of assets is assessed by considering a diverse range of asset classes that encompass various combinations of liquid and illiquid assets, as shown by the NSFR weights. Thus, the study computes the distance between two banks for each year as the Euclidean distance between them for all the asset classes considered:

$$\text{Distance}_{i,j,t} = \sqrt{\sum_{k=1}^{K} \left(w_{i,k,t} - w_{j,k,t}\right)^2} \qquad (1)$$

where $Distance_{i,j,t}$ is the distance between bank i and bank j ($i \neq j$) in year t, and k is the number of asset classes. Thus, I compute portfolio weights for each bank in each asset class. Hence, $w_{i,k,t}$ is the weight bank i invests in asset class k, with $\sum_{k=1}^{K} w_{i,k,t} = 1$. Banks with distances close to zero have similar portfolios (similarity) as they are not far from each other, while banks with higher distances have low portfolios overlap (dissimilarity). Next, the average distance between each bank *(i)* and all other banks is computed on a yearly basis.: $Average\ Distance_{i,t} = \frac{\sum_k^K Distance_{i,j,t}}{N_t - 1}$ where N_t is the number of banks as of year *t*. The measure of asset commonality per bank is obtained by transforming it into a yearly metric using the approach below

$$AllAssetCom_{i,t} = \frac{1}{1 + Average\ Distance_{i,t}} \quad (2)$$

The mean value of $AllAssetCom_{i,t}$ is 0.81, as detailed in Table 2.1. This indicates a relatively high level of asset overlap among the large banks included in the sample.

2.3.3 Risk Measures

To investigate the relationship between asset commonality and systemic risk, various widely used bank-level measures of systemic risk are computed. The Marginal Expected Shortfall ($MES_{i,t}$) is computed following the methodology outlined by Acharya et al. (2017) and Brownless and Engle (2017). The $MES_{i,t}$ of firm *i* characterizes its expected equity loss conditional on the whole market performing poorly; it is defined as

$$MES_{i,t}(\mathrm{Q}) = \mathrm{E}[\mathrm{R_{i,t}} | \mathrm{R_{m,t}} < \mathrm{VaR^{Q}_{m,t}}] \quad (3)$$

where $R_{i,t}$ denotes the daily stock returns of bank *i* at time *t*, $R_{m,t}$ the return of World market index (MSCI) at time *t*, and $VaR^{Q}_{m,t}$ is the market Value-at-Risk at confidence level *Q*. Consistent with common practice in the literature, the negative of $MES_{i,t}$ is reported, where higher values indicate larger systemic risk. This study also incorporates the $DCoVaR_{i,t}$ measure, initially introduced by Adrian & Brunnermeier (2016). This measure represents the Value at Risk (VaR) of the financial system under a specific event condition for a given bank. More specifically, the $DCoVaR_{i,t}$ for a bank represents the difference between the VaR of market returns conditioned on the bank being in a state of financial distress and the VaR of market returns conditioned on the bank being in its median state. Hence, the study employs standard quantile regressions, as outlined in Adrian and Brunnermeier (2016), to compute the $DCoVaR_{i,t}$ measures. The mean values for MES and $DCoVaR_{i,t}$ are 0.011 and 0.002, respectively, as outlined in Table 2.1.

2.3.4 Macroprudential Policies

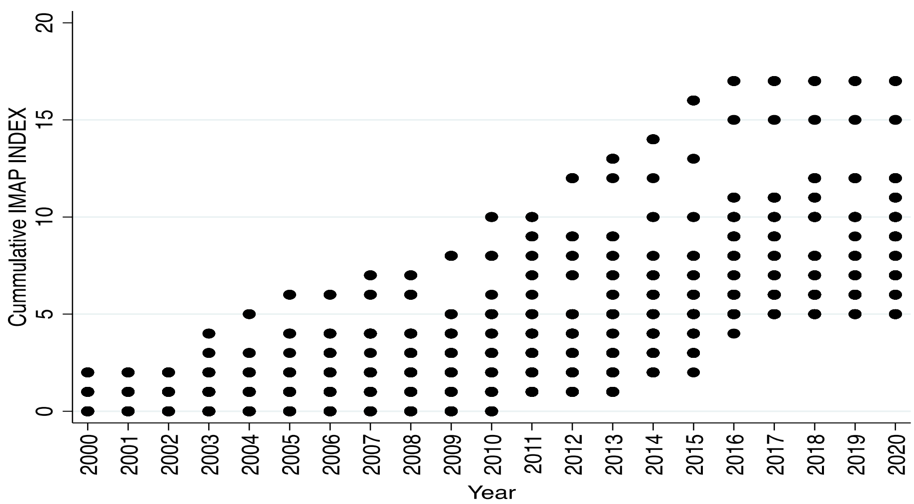
The Integrated Macroprudential Policy Database (iMaPP), which was created by Alam et al. (2019) and made accessible through the IMF database, is where the macroprudential policy instruments come from. The database integrates information from five major existing databases and expands the data with more information from the IMF's Macroprudential Policy Survey, in conjunction with additional information from the BIS and FSB. The iMaPP indices encompass 17 macroprudential policies across 135 countries, with annual data ranging from 2000 to 2020. A detailed description of each policy and classification are displayed in Table B.3 in appendix B. Each instrument is captured from the year of policy implementation until its discontinuation if applicable within the analysis period. The study assigns a value of 1 to each policy implemented starting from its effective implementation year. The index *Cum_Comprehensive* represents the cumulative value of the various policies implemented, ranging from 0 to 17. The examined instruments include taxes, capital requirements, loan restrictions, leverage ratios, loan coverage ratios, liquidity requirements, and countercyclical buffers, detailed in Table B.3 in appendix B. Higher values on the index indicate a stronger implementation of macroprudential policies.

The study uses the macroprudential index *Cum_Comprehensive* to categorize countries based on the extent of macroprudential policy implementation. This is accomplished by calculating the index's median for each year in the sample. If a country's index value is higher than the median for a given year, it is considered to have a high macroprudential policy deployment. On the other hand, it is classified as having low macroprudential policy deployment if it is below the median. Subsequently, the study utilizes the mode to determine the classification of a country into either high or low macroprudential policy deployment. This classification system enables us to assess and compare the varying levels of macroprudential policy implementation across countries under analysis.

The primary index *Cum_Comprehensive* is divided into three sub-group indices based on the type of policies for further analysis of the effects of these policies: *Cum_Borrower*, *Cum_FIT*, and *Cum_Quantity*. These sub-indices stand for macroprudential policies that are, in sequence, quantity-, borrower-, and financial institution-focused. The borrower policies (*Cum_Borrower*) involves Loan-to-Value (*LTV*) and Debt-Service-to-Income (*DSTI*) measures, although they are deployed by only a few countries, such as Ireland, Portugal, Norway, Canada, Singapore, Malaysia, China, and Hungary, amongst others. The quantity (*Cum_Quantity* focused*)* restrictions have a dual impact on both loan supply and demand. It involves *LTV, DSTI*, loan restrictions, leverage ratios, loan coverage ratios instruments etc. While the Financial Institution-Targeted (*Cum_FIT)* covers all instruments directly or implemented by the institutions themselves e.g., LTV, DSTI, Loan coverage etc. Table B.2 in the appendix provides general statistics for each cumulative macroprudential policy index. Table B.3 details full make-up of each sub-group of macroprudential policies.

Since the aftermath of the GFC, there has been considerable growth in the use of macroprudential policies across several regions including in emerging economies as shown in Figure 2.1.

Figure 2.0.1 Macroprudential Policy Implementation Per Year, Average for All Countries



Source: IMF Database: https://www.elibrary-areaer.imf.org/Macroprudential/Pages/Home.aspx.

Note: Accessed on 10/05/2022 shows the gradual rate of deployment of Macroprudential Policies (17 instruments) across time (2000-2020) for 29 countries in the sample. See Table B.2 in the appendix for country list.

2.4 Asset commonality on systemic risk: does the level of macroprudential policy matters?

2.4.1 Baseline Specification

This study examines if the extent of macroprudential policy influences how the assets commonality contributes to systemic risk using the following econometric specification.

$$Risk_{i,t} = \alpha + \beta_1 \ AllAssetCom_{\mathrm{i,t}} + \sum_p \lambda_p \mathrm{Country}_{\mathrm{j,t}} + \sum_p \delta_p \mathrm{X}_{\mathrm{i,t}} + \gamma_{\mathrm{i}} + \varepsilon_{\mathrm{i,t}} \qquad [4]$$

This paper employs a fixed-effects model for its primary analysis. This research addresses the potential strong correlation between macroprudential policies and assets commonality, as previously discussed above, by running equation (4) to sub-samples that represent high and low levels of macroprudential policy implementation.

The dependent variable $Risk_{i,t}$ refers to the systemic risk measures defined in section 2.3.3. The independent variable of interest $AllAssetCom_{i,t}$ refers to the asset's commonality variables discussed in section 2.3.2. Additionally, a series of country-level variables are included ($Country_{j,t}$), representing country-specific macroeconomic factors. This is particularly important as the sample comprises of 29 countries with varying levels of income and exposure to systemic risk. Following Gonzalez (2022), the variable $Institutional\_Environment_{j,t}$, developed by Kaufman et al. (2009), is incorporated to measure the level of institutional environment of each country. The ability of each country to monitor and implement overall regulatory guidance may vary around the institutional environment beyond banking industry alone and as such reduce their exposure to risk. The variable is computed by taking the average of 6 variables namely (i) Control of Corruption (ii) Government Effectiveness (iii) Political Stability/Absence of Violence/Terrorism (iv) Regulatory Quality: (v) Rule of Law (vi) Voice and Accountability. Thus, countries with stronger $Institutional\_Environment_{j,t}$ may experience lower bank default rates. The analysis includes variations in income levels and economic activity, which can fluctuate with the financial cycle or trend. These captured through two variables, the credit-to-GDP gaps ($credit\_GDPgap_{j,t}$) and changes in GDP ($\Delta\_GDP_{j,t}$). Financial crises can be predicted by the credit gap, which evaluate the discrepancy between the credit-to-GDP ratio and a one-sided Hodrick-Prescott (HP)-filtered trend. The term "filter" describes a data-smoothing method. When conducting analysis, the HP filter is frequently used to eliminate transient changes related to the economic cycle. Long-term tendencies are shown when these short-term oscillations are eliminated. This can be beneficial for forecasting the economy or other aspects of the business cycle. This is particularly relevant as developing economies often adopt more macroprudential policy due to their higher exposure to capital inflows, commodity price shocks, external risks, and other factors that fluctuate with business and financial cycles (Claessens et al., 2013). Hence, it is crucial to account for country-level differences that can have impact on systemic risk exposure.

Moreover, the study acknowledges the significance of year-on-year changes in country-level residential property prices *(△_House Price Index$_{j,t}$)* to capture developments in real estate markets. This is crucial as housing booms and bursts have been associated with systemic distress (Herring and Watcher, 1999; Reinhart and Rogoff, 2008). The increase in house prices amplifies the perceived risk of real estate financing for banks, leading to excessive lending to risky real estate borrowers (Dell'Ariccia and Marquez, 2006). Additionally, the change in each country's Central Bank Policy (△*_Central Bank Policy$_{j,t}$*) is included to account for the influence of monetary policy. This is because significant changes (increase) in interest rates may result in higher level of non-performing loans due to the increased cost of debt servicing (Jiménez et al., 2014) and borrowing.

Conversely, lower changes (reduction) encourage increased bank investment or lending, thus exposing banks to excessive risk-taking. The study also considers the effects of inflation *(Inflation$_{j,t}$)* since it can impact banks' profitability and can increase the value of loans or jeopardize a bank's susceptibility to default if costs continue to rise.

Furthermore, the study controls for the impact of financial globalization, liberalization, and cross-border openness on systemic risk. The transmission of capital and shocks across borders has raised concerns about whether financial liberalization policies strengthen or endanger the financial industry. In addition, macroprudential policies may exacerbate these tendencies as banks exploit regulatory differences between host and foreign countries. Banks capitalize on these disparities by rearranging their investment portfolios, setting off capital movements and shocks through various channels (refer to Table B.4 in the Appendix for further details). Macroprudential policies can reshape banks' motivations to transfer credit risk across borders, potentially influencing the originate-to-distribute business model and international funding reliance. Additional channels encompass shifts in banks' cross-border portfolio allocation, affecting their foreign credit holdings, including cross-border direct lending, securities exposures, and operations via subsidiaries or branches in other countries.

Therefore, this paper utilizes the IMFs annual report on exchange arrangements and exchange restrictions (AREAER), to examine whether asset restrictions on both inflows and outflows can mitigate systemic risk in the context of high and low macroprudential policy. An index that incorporates information derived from AREAER reports are computed to assess the existence of rules, and regulations governing international transactions and monitor the exchange rate and trade regimes of all International Monetary Fund members across different asset categories. These includes (i) Money Market instruments (ii) Bonds or other debt securities (iii) Equity shares (iv) collective investment securities e.g., mutual funds investment or trust (v) Financial Credit (vi) Derivatives (vii) Commercial credits (viii) Guarantees, Securities (ix) Real Estate transactions (x) Direct investment accounts for transactions. Following Karolyi et al. (2016) and Fernandez et al. (2015), the index measures the overall outflow restriction to investigate if countries with higher cross-border asset restrictions are less likely to be vulnerable to systemic risk contagion. Subsequently, a dummy variable $Asset\_restriction_{j,t}$ is introduced to denote the overall measure of outflow restriction. If the level of limitation is greater than the sample mean, this dummy variable is given the value 1, otherwise, it is given the value 0. Since the avenues for exposure have been reduced, higher levels of cross-border asset limitations will imply that a country should be resilient (reduce) to systemic risk. Lastly, the research considers the level of financial development by considering stock market capitalization to GDP ($stockmarkcap\_GDP_{j,t}$). Banks with significant financial resources are likely to be found in countries with strong stock market access. This advantage sets these banks apart from their competitors by enabling them to efficiently fund their operations and perhaps display increased resilience in the face of economic turbulence.

To mitigate the risk of omitted variable bias, a large set of bank-related control variables ($X_{i,t}$) is incorporated. Following Berger et al. (2020), bank characteristics that influence a bank's contributions to systemic risk are also included in the analysis. These includes Capital Adequacy ($Equityratio_{i,t}$), *Management Quality* ($EfficiencyRatio_{i,t}$), *Earnings Quality* ($ROA_{i,t}$), $Liquidityratio_{i,t}$, and Sensitivity to market risk ($SMR_{i,t}$ -Total Securities/Total Assets). This research considers the $Liquidityratio_{i,t}$ since banks are highly leveraged yet require daily cash flow to meet their obligation to prevent bank runs and liquidity crises. The Liquidity was orthogonalized on the sensitivity to market risk due to high correlation. Hence, this research expects a negative relationship and as such higher liquidity ratio should reduce a bank's susceptibility to systemic risk. In addition, this research also captures Management Quality using the bank's $Efficiencyratio_{i,t}$. This paper also considers the size effects by taking into consideration the logarithm of the total asset. This implies that higher costs relative to revenue may depict poor managerial decision-making. The Equity Ratio ($Equityratio_{i,t}$) is included to measure the level of funding; a negative relationship is expected as banks with higher equity are less susceptible to systemic risk. Nonetheless, banks may decide to engage in excessive risk since they believe they have sufficient capital to cover up against any shocks.

Additionally, the study considers the effect of short-term funding, which is acquired on a roll-on basis and supplements retail deposits, in line with the findings of Lopez-Espinosa et al.

(2012). Due to information connections, banks with a higher percentage of short-term funding are more vulnerable to these systemic contagion effects when there is bad news about a failing bank. To accurately track this annual impact on systemic risk, the dummy variable $HighSTDebt_{i,t}$ is computed, taking the value of 1 for a given year if wholesale funding exceeds the annual sample mean. As a result, this makes it possible for the variable to change every year, accurately recording its impact on systemic risk. Also, this study controls for the concentration level in the banking system ($concentration\_ratio_{j,t}$). This is measured as the ratio of the total assets of the five largest banks to the total assets of the entire banking system, on a per-country basis. Bank size is accounted for through the logarithm of total assets ($lnTA_{i,t}$). The level of diversification within a banks is calculated as the ratio of net interest income to total revenue ($Diversification_{i,t}$).

The study also accounts for the impact of the GFC_t. Based on the World Bank Global Financial Development Database, GFC_t is set to 1 for the period 2007-2009 during the global financial crisis of 2007-2008. Finally, the specification also includes individual fixed effects (γ_i). The Hausman test indicates that the fixed-effects model is a more suitable choice than the random-effects model. The correlation between the variables of interest is examined by computing the variance inflation factors (VIF), which have a mean value of 1.55 with a maximum of 2.51 (see Table 2.2).

2.4.2 Results

The results, presented in Table 2.4, show that when a low comprehensive macroprudential regulation is adopted, asset commonality has no impact on systemic risk. On the contrary, the results provide evidence that under high levels of comprehensive macroprudential implementation, asset commonality has a positive impact on systemic risk ($MES_{i,t}$). This trend is particularly notable in countries such as Austria, Norway, Switzerland, Canada, Greece, Ireland, Spain, Australia, Brazil, Colombia, Korea, Russia, China, and Hungary within our sample. These countries, characterized by a more extensive adoption of comprehensive macroprudential measures, demonstrated higher systemic risk levels when there is an increase in the overlap within banks' portfolios. Banks may adopt similar responses when confronted with uniform regulations or restrictions imposed on their investment portfolios. This is explained by the possibility that banks reallocate risk to alternative asset classes, which could unintentionally increase asset commonality. Consequently, such actions expose banks to new or additional risks. Adjustments in asset investment preferences can influence their risk exposure.

Table 2.4 Asset Commonality and Systemic Risk Under High and Low Comprehensive Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High Comprehensive macroprudential policy		Low Comprehensive macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
AllAssetCom	**0.0381***	0.0009	-0.0044	0.0005
	(0.0195)	(0.0024)	(0.0056)	(0.0010)
stockmarkcap_GDP	**-0.0089****	**-0.0012****	-0.0037	**-0.0008***
	(0.0035)	(0.0006)	(0.0032)	(0.0004)
Equityratio	0.0758	0.0047	-0.0536	**-0.0117***
	(0.0968)	(0.0053)	(0.0415)	(0.0066)
Efficiency	0.0026	0.0001	0.0003	**0.00005****
	(0.0030)	(0.0002)	(0.0002)	(0.00002)
Liquidity	0.0047	0.0004	-0.0012	-0.00003
	(0.0030)	(0.0004)	(0.0010)	(0.0001)
SMR	-0.0004	0.00004	-0.0003	-0.0001
	(0.0013)	(0.0001)	(0.0010)	(0.0001)
ROA	-0.1302	-0.0107	**-0.1549*****	**-0.0309*****
	(0.1122)	(0.0086)	(0.0526)	(0.0106)
△_House Price Index	-0.0004	6.69	-0.0043	-0.0006
	(0.0005)	(0.0001)	(0.0075)	(0.0007)
△_Central Bank Policy	-0.0005	1.35	**0.0010***	**0.0003***
	(0.0015)	(0.0001)	(0.0006)	(0.0001)
GFC	0.0050	-0.0001	0.0001	0.00004
	(0.0034)	(0.0005)	(0.0023)	(0.0002)
△_GDP	-0.0106	**-0.0042****	-0.0561	-0.0059
	(0.0234)	(0.0021)	(0.0434)	(0.0053)
Diversification	**-0.0160***	-0.0015	0.0050	0.0003
	(0.0090)	(0.0013)	(0.0057)	(0.0009)
Concentration_ratio	**0.1161***	0.0210	0.0280	**0.0096***
	(0.0638)	(0.0166)	(0.0396)	(0.0056)
Institutional_environment	-0.0035	-0.0006	0.0019	-0.0003
	(0.0032)	(0.0004)	(0.0033)	(0.0002)
lnTA	-0.0027	0.0003	-0.0006	**-0.0003***
	(0.0034)	(0.0004)	(0.0015)	(0.0002)
HighSTDebt	**-0.0053*****	**-0.0005****	-0.0008	0.0001
	(0.0019)	(0.0002)	(0.0010)	(0.0003)
Inflation	0.0239	0.0121	**0.0920***	0.0152
	(0.0479)	(0.0072)	(0.0520)	(0.0091)
credit_GDPgap	**0.0317***	0.0009	**-0.0119***	**-0.0015****
	(0.0179)	(0.0014)	(0.0060)	(0.0007)
Constant	0.0235	-0.0107	0.0262	**0.0082***
	(0.0812)	(0.0128)	(0.0430)	(0.0046)
Nbr. of obs.	434	434	631	631
R^2	0.1501	0.0837	0.1539	0.2308
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	18	18	11	11

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR*) on the asset commonality for All assets classes (*AllAssetCom*) and control variables under a high and low *Comprehensive Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

The analysis further investigates whether the type of macroprudential policy implemented plays a role in shaping the relationship between asset commonality and systemic risk. Firstly, results in Table 2.5 show that asset commonality has a positive effect on systemic risk

($MES_{i,t}$ and $DCoVaR_{i,t}$) in countries with stronger adoption of financial institution-targeted macroprudential policy (*Cum_FIT*). Increased loan caps or coverage limits might drive banks to seek higher yields by shifting risk to asset categories not subject to regulations. This, however, exposes them to greater risk and elevated monitoring costs. Conversely, reduced loan levels could erode economies of scale for banks, resulting in higher costs and reduced profits. Consequently, banks may raise interest rates, transferring the burden to borrowers, potentially affecting asset quality, increasing the likelihood of non-performing loans. On the flip side, banks with limited capital might curtail loans but still assume additional risk to maintain their initial profit levels. Moreover, given regulatory caps that might constrain individual customer demands, multiple financial institutions may need to collaborate to meet these demands. This heightened collaboration (syndicated loans) among banks not only fosters asset commonality but also amplifies systemic risk when a macro shock occurs.

Secondly, the study examines the impact of asset commonality on systemic risk within the context of high and low-borrower-focused macroprudential policies (*Cum_Borrower*). Results in Table 2.6 indicate that under a high borrower-focused macroprudential policy, assets commonality increases exposure to systemic risk ($MES_{i,t}$), with statistical significance at the 10% level. On the contrary, higher degrees of asset commonality do not contribute to increase systemic risk in countries with lower adoption of borrower-focused macroprudential policies.

Lastly, the study investigates the effect of asset commonality in the presence of high and low macroprudential policies (*Cum_Quantity*), with the findings presented in Table 2.7. These results also show higher levels of assets commonality increase systemic risk ($MES_{i,t}$ and $DCoVaR_{i,t}$), but again exclusively in countries with stronger adoption of quantity-focused macroprudential policies. Quantity restrictions have a dual impact on both loan supply and demand. These limitations can naturally reduce overall bank lending while simultaneously leading to a heightened concentration of assets within and across specific asset classes. The imposition of loan restrictions on certain customer segments might inadvertently stimulate demand from others. For instance, the application of Debt-Service-to-Income (DSTI) and Loan-to-Value (LTV) measures could affect demand for mortgage loans while potentially increasing demand for consumer loans, such as credit cards. This interplay suggests that the implementation of a quantity-focused macroprudential policy may hold unintended consequences, potentially counterproductive to managing systemic risk.

To summarize, the results show that while the implementation of macroprudential policies aims to mitigate systemic risk, a stronger adoption of such policies implies that higher levels of asset commonality are associated with an increase in financial instability. These findings remain consistent regardless of the specific macroprudential policies under consideration.

Table 2.5 Asset Commonality and Systemic Risk Under High and Low Financial Institution Targeted (FIT) Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High FIT macroprudential policy		Low FIT macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
AllAssetCom	**0.0523****	**0.0045****	-0.0015	-0.0009
	(0.0259)	(0.0018)	(0.0037)	(0.0012)
stockmarkcap_GDP	-0.0042	**-0.0007****	-0.0056	**-0.0011****
	(0.0027)	(0.0004)	(0.0034)	(0.0006)
Equityratio	0.0890	0.0044	-0.0530	**-0.0118***
	(0.1151)	(0.0048)	(0.0417)	(0.0069)
Efficiency	0.0029	0.0002	**0.0004****	**0.00004****
	(0.0030)	(0.0002)	(0.0002)	(0.00002)
Liquidity	0.0028	0.0004	-0.0006	-0.00004
	(0.0028)	(0.0004)	(0.0009)	(0.0001)
SMR	-0.0010	0.0001	-0.00004	**-0.0002***
	(0.0017)	(0.0001)	(0.0009)	(0.0001)
ROA	-0.1667	-0.0077	**-0.1686*****	**-0.0305*****
	(0.1514)	(0.0082)	(0.0518)	(0.0104)
△_House Price Index	-0.0001	0.0009	-0.0144	-0.0009
	(0.0006)	(0.0001)	(0.0119)	(0.0012)
△_Central Bank Policy	-0.0009	-0.0001	0.0008	**0.0003***
	(0.0013)	(0.0001)	(0.0006)	(0.0001)
GFC	**0.0051***	0.0001	-0.0021	-0.0002
	(0.0026)	(0.0003)	(0.0025)	(0.0003)
△_GDP	-0.0083	**-0.0045****	-0.0701	-0.0082
	(0.0237)	(0.0022)	(0.0435)	(0.0056)
Diversification	**-0.0110***	-0.0017	0.0023	0.0006
	(0.0064)	(0.0012)	(0.0054)	(0.0010)
Concentration_ratio	**0.1528***	0.0145	-0.0101	**0.0127***
	(0.0830)	(0.0136)	(0.0372)	(0.0069)
Institutional_environment	-0.0021	-0.0001	0.0008	**-0.0006***
	(0.0032)	(0.0002)	(0.0030)	(0.0003)
lnTA	-0.0037	-0.0001	-0.0011	-0.0002
	(0.0038)	(0.0003)	(0.0017)	(0.0002)
HighSTDebt	**-0.0038*****	**-0.0005****	-0.0002	0.0001
	(0.0013)	(0.0002)	(0.0010)	(0.0003)
Inflation	-0.0029	**0.0129***	**0.0919***	**0.0204****
	(0.0344)	(0.0074)	(0.0506)	(0.0090)
credit_GDPgap	0.0277	0.0008	**-0.0099***	**-0.0016****
	(0.0184)	(0.0013)	(0.0057)	(0.0008)
Constant	0.0267	-0.0015	0.0519	0.0066
	(0.0873)	(0.0104)	(0.0500)	(0.0059)
Nbr. of obs.	466	466	599	599
R^2	0.1241	0.0798	0.1759	0.2312
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	18	18	11	11

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR*) on the asset commonality for All assets classes (*AllAssetCom*) and control variables under a high and low *Financial Institution targeted Macroprudential Policy*. All variables are defined in Appendix Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table 2.6 Asset Commonality and Systemic Risk Under High and Low Borrower Focused Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High Borrower Focused macroprudential policy		Low Borrower Focused macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
AllAssetCom	**0.0347***	-0.0016	0.0016	0.0007
	(0.0180)	(0.0019)	(0.0068)	(0.0008)
stockmarkcap_GDP	-0.0069	-0.0005	-0.0046	**-0.0009****
	(0.0041)	(0.0007)	(0.0030)	(0.0004)
Equityratio	**-0.0819*****	-0.0010	-0.0304	-0.0076
	(0.0211)	(0.0098)	(0.0567)	(0.0056)
Efficiency	**0.0154*****	**0.0009*****	0.00002	0.**00004***
	(0.0018)	(0.0002)	(0.0002)	(0.00002)
Liquidity	0.0013	-0.0006	-0.0003	0.0002
	(0.0022)	(0.0006)	(0.0011)	(0.0001)
SMR	-0.0010	-0.0003	-0.0012	-0.0001
	(0.0009)	(0.0002)	(0.0011)	(0.0001)
ROA	**0.5750****	-0.0014	**-0.1254****	**-0.0228****
	(0.2446)	(0.0416)	(0.0551)	(0.0106)
△_House Price Index	-0.0007	0.0001	-0.0006	**-0.0003***
	(0.0009)	(0.0002)	(0.0013)	(0.0001)
△_Central Bank Policy	**-0.0017****	-0.0001	**0.0020****	**0.0003****
	(0.0008)	(0.0002)	(0.0009)	(0.0001)
GFC	0.0107	-0.0008	0.00005	0.0001
	(0.0159)	(0.0013)	(0.0018)	(0.0002)
△_GDP	-0.0311	**-0.0072***	-0.0020	-0.0008
	(0.0275)	(0.0040)	(0.0237)	(0.0029)
Diversification	0.0005	0.0024	-0.0039	-0.0009
	(0.0064)	(0.0017)	(0.0045)	(0.0007)
Concentration_ratio	0.0377	0.0363	**0.1282***	**0.0138****
	(0.0370)	(0.0291)	(0.0663)	(0.0059)
Institutional_environment	0.0023	-0.00001	0.0021	-0.0002
	(0.0016)	(0.0004)	(0.0033)	(0.0002)
lnTA	-0.0039	0.0008	0.0002	-0.0002
	(0.0027)	(0.0008)	(0.0012)	(0.0002)
HighSTDebt	-0.0017	-0.0002	**-0.0029****	-0.0001
	(0.0022)	(0.0003)	(0.0012)	(0.0003)
Inflation	-0.0166	0.0143	0.0295	0.0080
	(0.0313)	(0.0153)	(0.0419)	(0.0049)
credit_GDPgap	**0.0305*****	-0.0015	-0.0110	-0.0007
	(0.0084)	(0.0027)	(0.0078)	(0.0007)
Constant	0.0661	-0.0277	-0.0187	0.0040
	(0.0630)	(0.0257)	(0.0348)	(0.0042)
Nbr. of obs.	245	245	820	820
R^2	0.5151	0.1294	0.0733	0.1657
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	10	10	19	19

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR*) on the asset commonality for All assets classes (*AllAssetCom*) and control variables under a high and low *Borrower focused Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table 2.7 Asset Commonality and Systemic Risk Under High and Low Quantity Focused Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High Quantity Focused macroprudential policy		Low Quantity Focused macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
AllAssetCom	**0.0950***** (0.0246)	**0.0080**** (0.0030)	-0.0016 (0.0039)	-0.0006 (0.0012)
stockmarkcap_GDP	**-0.0060*** (0.0034)	-0.0004 (0.0004)	-0.0049 (0.0030)	**-0.0012**** (0.0005)
Equityratio	0.0924 (0.1051)	0.0062 (0.0051)	-0.0653 (0.0411)	**-0.0115*** (0.0064)
Efficiency	**0.0105***** (0.0038)	**0.0007**** (0.0003)	0.0001 (0.0002)	0.00003 (0.00003)
Liquidity	**0.0044*** (0.0025)	-0.0001 (0.0005)	-0.0010 (0.0009)	0.0001 (0.0001)
SMR	-0.0008 (0.0013)	0.0000 (0.0002)	-0.0007 (0.0009)	**-0.0002**** (0.0001)
ROA	0.1401 (0.1533)	0.0073 (0.0066)	**-0.1625***** (0.0528)	**-0.0322***** (0.0101)
△_House Price Index	-0.0006 (0.0007)	0.0001 (0.0002)	-0.0013 (0.0010)	**-0.0004***** (0.0001)
△_Central Bank Policy	0.0004 (0.0020)	-0.00004 (0.0002)	**0.0011**** (0.0005)	**0.0002*** (0.0001)
GFC	**0.0111**** (0.0049)	0.0004 (0.0005)	-0.0001 (0.0019)	-0.0001 (0.0003)
△_GDP	-0.0001 (0.0280)	-0.0034 (0.0028)	-0.0285 (0.0300)	-0.0049 (0.0032)
Diversification	-0.0188 (0.0129)	-0.0002 (0.0012)	-8.16 (0.0049)	-0.0003 (0.0008)
Concentration_ratio	0.0773 (0.0479)	0.0297 (0.0216)	0.0435 (0.0330)	0.0082 (0.0058)
Institutional_environment	0.0021 (0.0019)	0.0002 (0.0003)	0.0014 (0.0031)	**-0.0005*** (0.0003)
lnTA	**-0.0113***** (0.0039)	-0.0004 (0.0007)	0.0001 (0.0012)	-0.0001 (0.0002)
HighSTDebt	**-0.0049**** (0.0024)	**-0.0006**** (0.0003)	-0.0009 (0.0008)	0.0002 (0.0002)
Inflation	0.1159 (0.0759)	**0.0136*** (0.0067)	**0.0887**** (0.0386)	**0.0169**** (0.0067)
credit_GDPgap	**0.0516***** (0.0138)	0.0008 (0.0021)	**-0.0086*** (0.0046)	-0.0004 (0.0006)
Constant	**0.1765**** (0.0774)	-0.0018 (0.0201)	0.0080 (0.0341)	0.0040 (0.0049)
Nbr. of obs.	325	325	740	740
R^2	0.2660	0.1311	0.1338	0.2042
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	12	12	17	17

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR*) on the asset commonality for All assets classes (*AllAssetCom*) and control variables under a high and low Quantity focused Macroprudential Policy. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

2.5 Further Analysis

2.5.1 Loan Asset Commonality

As bank loans constitute a substantial portion of their total assets, this study further evaluates the specific influence of loan asset commonalities ($LoanAssetCom_{i,t}$) on systemic risk across different levels of macroprudential policy implementation. Notably, 36% of loans are for consumer loans, with mortgages coming in just behind at about 15%. This is a significant concern owing to the historical concentration in subprime mortgages, real estate, and commercial loans in the lead-up to the GFC, which had profoundly adverse effects on global financial stability. It is crucial to emphasize that a considerable number of banks experienced substantial losses primarily attributed to real estate and mortgage loans. Demayank and Van Hemert (2007) provide evidence that delinquencies and foreclosures among subprime borrowers are, in part, influenced by high loan-to-value ratios. Similarly, Mian and Sufi (2010) link an increase in delinquency rates to an increase in loan originations, those loans considered to be easily securitized, default more frequently (Keys et al. 2010). Such loans could become risky and volatile, particularly when banks operate in a competitive environment with low-interest rates that may not adequately cover monitoring costs. Additionally, loan diversification might be less attractive for banks' lending to risky borrowers or holding a considerable amount of commercial or real estate loans (Cole and White, 2012; DeYoung and Roland, 2001). The evolution of banking practices, where banks no longer solely originate to hold but also originate to distribute, has led to increased interconnectedness between banks as risks are traded and transferred. To allay these worries, macroprudential rules, such as the enactment of LTV and DSTI cap requirements, were established.

To specifically investigate the impact of higher levels of overlap in bank loan portfolios on systemic risk across different levels of stringency in macroprudential policy adoption, a measure of loan asset commonality ($LoanAssetCom_{i,t}$) is computed using the methodology outlined in section 2.3.2. Various loan asset classes are considered, as detailed in Table 2.3, such as customer loans, consumer loans, and mortgages. $LoanAssetCom_{i,t}$ is normalized within a range of 0 to 1, with 0 indicating no asset commonality (no overlapping portfolios), and 1 representing complete asset commonality (exact portfolio matching). The mean value of $LoanAssetCom_{i,t}$ is approximately 0.79 (see Table 2.1). The analysis employs a fixed-effects model using the same baseline equation (4) outlined in section 2.4.1.

The findings, displayed in Table 2.8-2.11 (for comprehensive, financial institution-targeted, borrower-focused, and quantity-focused macroprudential policy, respectively), show that loan asset commonality significantly contributes to increased systemic risk in the context of strong macroprudential policy implementation, regardless of the policy type. On the contrary, there is no significant evidence that loan asset commonality has an impact on systemic risk under a low macroprudential policy implementation. Overall, these results are closely aligned with those found previously when the overall asset commonality measure is used.

Table 2.8 Loan Commonality and Systemic Risk Under High and Low Comprehensive Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High Comprehensive macroprudential policy		Low Comprehensive macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
LoanAssetCom	**0.0299****	0.0013	0.0018	0.0006
	(0.0136)	(0.0022)	(0.0038)	(0.0007)
stockmarkcap_GDP	**-0.0087****	**-0.0012****	-0.0042	**-0.0008***
	(0.0034)	(0.0006)	(0.0033)	(0.0004)
Equityratio	0.0902	0.0053	-0.0565	**-0.0118***
	(0.0987)	(0.0055)	(0.0416)	(0.0067)
Efficiency	0.0023	0.0001	0.0003	**0.00005****
	(0.0030)	(0.0002)	(0.0002)	(0.00002)
Liquidity	0.0045	0.0004	-0.0012	-0.00002
	(0.0031)	(0.0004)	(0.0010)	(0.0001)
SMR	-0.0004	0.0001	-0.0003	-0.0001
	(0.0013)	(0.0001)	(0.0010)	(0.0001)
ROA	-0.1496	-0.0110	**-0.1507*****	**-0.0307*****
	(0.1115)	(0.0086)	(0.0524)	(0.0106)
△_House Price Index	-0.0005	0.0000	-0.0043	-0.0006
	(0.0005)	(0.0001)	(0.0075)	(0.0007)
△_Central Bank Policy	-0.0005	-2.75	**0.0010***	**0.0003***
	(0.0015)	(0.0001)	(0.0006)	(0.0001)
GFC	0.0051	-0.00004	0.0001	0.00003
	(0.0036)	(0.0005)	(0.0023)	(0.0002)
△_GDP	-0.0099	**-0.0043****	-0.0562	-0.0058
	(0.0227)	(0.0021)	(0.0435)	(0.0053)
Diversification	**-0.0154***	-0.0015	0.0045	0.0003
	(0.0088)	(0.0013)	(0.0056)	(0.0009)
Concentration_ratio	0.1028	0.0202	0.0250	**0.0097***
	(0.0646)	(0.0166)	(0.0396)	(0.0056)
Institutional_environment	-0.0038	-0.0006	0.0020	-0.0003
	(0.0032)	(0.0004)	(0.0033)	(0.0002)
lnTA	-0.0022	0.0003	-0.0010	**-0.0003***
	(0.0032)	(0.0004)	(0.0016)	(0.0002)
HighSTDebt	**-0.0050*****	**-0.0005****	-0.0005	0.0001
	(0.0018)	(0.0002)	(0.0010)	(0.0003)
Inflation	0.0280	**0.0126***	**0.0934***	**0.0154***
	(0.0490)	(0.0071)	(0.0521)	(0.0091)
credit_GDPgap	**0.0306***	0.0009	**-0.0115***	**-0.0014****
	(0.0176)	(0.0014)	(0.0059)	(0.0006)
Constant	0.0199	-0.0095	0.0337	**0.0082***
	(0.0778)	(0.0129)	(0.0442)	(0.0045)
Nbr. of obs.	375	375	695	695
R^2	0.3593	0.1701	0.0893	0.1755
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	18	18	11	11

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR*) on the asset commonality for Loan Asset classes (*LoanAssetCom*) and control variables under a high and low *Comprehensive Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table 2.9 Loan Commonality and Systemic Risk Under High and Low Financial Institution Targeted Macroprudential policy (FIT)

Model	(1)	(2)	(3)	(4)
Levels	High FIT macroprudential policy		Low FIT macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
LoanAssetCom	0.0328	**0.0052*** **	-0.0001	-0.0008
	(0.0202)	(0.0015)	(0.0030)	(0.0008)
stockmarkcap_GDP	0.0053	0.0034	0.0039	**0.0010** **
	(0.0048)	(0.0022)	(0.0027)	(0.0005)
Equityratio	-0.0953	-0.0041	0.0006	-0.0052
	(0.0824)	(0.0071)	(0.0355)	(0.0031)
Efficiency	**0.0070*** **	**0.0005*** **	0.0002	0.00001
	(0.0016)	(0.0002)	(0.0001)	(0.00002)
Liquidity	0.0014	-0.0002	-0.0010	-0.0001
	(0.0017)	(0.0003)	(0.0009)	(0.0001)
SMR	-0.0007	0.0002	0.0001	**-0.0002** **
	(0.0011)	(0.0001)	(0.0009)	(0.0001)
ROA	0.1235	0.0042	**-0.1352***	**-0.0152*** **
	(0.0947)	(0.0124)	(0.0692)	(0.0057)
△_House Price Index	-0.0006	0.0001	-0.0024	**-0.0005*** **
	(0.0008)	(0.0002)	(0.0016)	(0.0002)
△_Central Bank Policy	**-0.0015** **	-0.0001	**0.0018***	**0.0003** **
	(0.0006)	(0.0002)	(0.0009)	(0.0001)
GFC	**0.0078** **	0.0002	0.0014	**0.0006***
	(0.0038)	(0.0004)	(0.0025)	(0.0003)
△_GDP	-0.0227	**-0.0127** **	**-0.0849** **	**-0.0099** **
	(0.0204)	(0.0059)	(0.0353)	(0.0042)
Diversification	0.0113	0.0007	0.0006	0.0004
	(0.0075)	(0.0008)	(0.0061)	(0.0007)
Concentration_ratio	0.0406	0.0082	0.0341	**0.0109***
	(0.0509)	(0.0092)	(0.0286)	(0.0058)
Institutional_environment	-0.0032	-0.0009	0.0036	0.0002
	(0.0050)	(0.0006)	(0.0026)	(0.0002)
lnTA	-0.0041	**-0.0008** **	-0.0020	**-0.0004** **
	(0.0028)	(0.0003)	(0.0016)	(0.0002)
HighSTDebt	**-0.0033** **	-0.0003	0.0002	0.0002
	(0.0015)	(0.0003)	(0.0012)	(0.0002)
Inflation	-0.0347	0.0029	**0.1485** **	**0.0185*** **
	(0.0223)	(0.0039)	(0.0575)	(0.0063)
credit_GDPgap	**0.0351***	0.0005	**-0.0192** **	**-0.0019** **
	(0.0177)	(0.0018)	(0.0076)	(0.0008)
Constant	0.0752	0.0133	0.0433	**0.0086***
	(0.0667)	(0.0083)	(0.0408)	(0.0050)
Nbr. of obs.	379	379	691	691
R^2	0.3397	0.1461	0.1222	0.1723
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	18	18	11	11

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR*) on the asset commonality for Loan assets classes (*LoanAssetCom*) and control variables under a high and low *Financial Institution targeted Macroprudential Policy*. All variables are defined in Appendix Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table 2.10 Loan Asset Commonality and Systemic Risk Under High and Low Borrower Focused Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High Borrower Focused macroprudential policy		Low Borrower Focused macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
LoanAssetCom	0.0328	**0.0052*****	-0.0001	-0.0008
	(0.0202)	(0.0015)	(0.0030)	(0.0008)
stockmarkcap_GDP	0.0053	0.0034	0.0039	**0.0010****
	(0.0048)	(0.0022)	(0.0027)	(0.0005)
Equityratio	-0.0953	-0.0041	0.0006	-0.0052
	(0.0824)	(0.0071)	(0.0355)	(0.0031)
Efficiency	**0.0070*****	**0.0005*****	0.0002	0.00001
	(0.0016)	(0.0002)	(0.0001)	(0.00002)
Liquidity	0.0014	-0.0002	-0.0010	-0.0001
	(0.0017)	(0.0003)	(0.0009)	(0.0001)
SMR	-0.0007	0.0002	0.0001	**-0.0002****
	(0.0011)	(0.0001)	(0.0009)	(0.0001)
ROA	0.1235	0.0042	**-0.1352***	**-0.0152*****
	(0.0947)	(0.0124)	(0.0692)	(0.0057)
△_House Price Index	-0.0006	0.0001	-0.0024	**-0.0005*****
	(0.0008)	(0.0002)	(0.0016)	(0.0002)
△_Central Bank Policy	**-0.0015****	-0.0001	**0.0018***	**0.0003****
	(0.0006)	(0.0002)	(0.0009)	(0.0001)
GFC	**0.0078****	0.0002	0.0014	**0.0006***
	(0.0038)	(0.0004)	(0.0025)	(0.0003)
△_GDP	-0.0227	**-0.0127****	**-0.0849****	**-0.0099****
	(0.0204)	(0.0059)	(0.0353)	(0.0042)
Diversification	0.0113	0.0007	0.0006	0.0004
	(0.0075)	(0.0008)	(0.0061)	(0.0007)
Concentration_ratio	0.0406	0.0082	0.0341	**0.0109***
	(0.0509)	(0.0092)	(0.0286)	(0.0058)
Institutional_environment	-0.0032	-0.0009	0.0036	0.0002
	(0.0050)	(0.0006)	(0.0026)	(0.0002)
lnTA	-0.0041	**-0.0008****	-0.0020	**-0.0004****
	(0.0028)	(0.0003)	(0.0016)	(0.0002)
HighSTDebt	**-0.0033****	-0.0003	0.0002	0.0002
	(0.0015)	(0.0003)	(0.0012)	(0.0002)
Inflation	-0.0347	0.0029	**0.1485****	**0.0185*****
	(0.0223)	(0.0039)	(0.0575)	(0.0063)
credit_GDPgap	**0.0351***	0.0005	**-0.0192****	**-0.0019****
	(0.0177)	(0.0018)	(0.0076)	(0.0008)
Constant	0.0752	0.0133	0.0433	**0.0086***
	(0.0667)	(0.0083)	(0.0408)	(0.0050)
Nbr. of obs.	379	379	691	691
R^2	0.5151	0.1294	0.0733	0.1657
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	10	10	19	19

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR*) on the asset commonality for Loan assets classes (*LoanAssetCom*) and control variables under a high and low *Borrower focused Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table 2.11 Loan Commonality and Systemic Risk Under High and Low Quantity Focused Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High Quantity Focused macroprudential policy		Low Quantity Focused macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
LoanAssetCom	**0.0549****	**0.0061*****	0.0018	-0.0002
	(0.0233)	(0.0020)	(0.0028)	(0.0009)
stockmarkcap_GDP	**-0.0060***	-0.0004	**-0.0051***	**-0.0012****
	(0.0035)	(0.0004)	(0.0030)	(0.0005)
Equityratio	0.1115	**0.0092***	-0.0673	**-0.0117***
	(0.1091)	(0.0053)	(0.0412)	(0.0064)
Efficiency	**0.0108*****	**0.0007****	0.0001	0.00003
	(0.0037)	(0.0003)	(0.0002)	(0.00003)
Liquidity	0.0042	-0.0001	-0.0010	0.0001
	(0.0026)	(0.0005)	(0.0009)	(0.0001)
SMR	-0.0008	0.0001	-0.0007	**-0.0002****
	(0.0013)	(0.0002)	(0.0009)	(0.0001)
ROA	0.1093	0.0038	**-0.1591*****	**-0.0318*****
	(0.1510)	(0.0063)	(0.0528)	(0.0101)
△_House Price Index	-0.0005	0.0001	-0.0013	**-0.0004*****
	(0.0008)	(0.0002)	(0.0010)	(0.0001)
△_Central Bank Policy	0.0003	-0.0000	**0.0011****	**0.0002***
	(0.0019)	(0.0002)	(0.0005)	(0.0001)
GFC	**0.0115***	0.0004	-0.0000	-0.0001
	(0.0057)	(0.0005)	(0.0019)	(0.0003)
△_GDP	0.0051	-0.0031	-0.0287	-0.0049
	(0.0248)	(0.0027)	(0.0301)	(0.0032)
Diversification	-0.0196	-0.0002	-0.0003	-0.0004
	(0.0125)	(0.0011)	(0.0049)	(0.0008)
Concentration_ratio	0.0728	0.0273	0.0426	0.0080
	(0.0534)	(0.0219)	(0.0333)	(0.0057)
Institutional_environment	0.0012	0.0001	0.0015	**-0.0005***
	(0.0020)	(0.0003)	(0.0031)	(0.0003)
lnTA	**-0.0073***	-0.0003	-0.0002	-0.0001
	(0.0041)	(0.0006)	(0.0012)	(0.0002)
HighSTDebt	**-0.0047***	**-0.0005****	-0.0009	0.0002
	(0.0023)	(0.0003)	(0.0008)	(0.0002)
Inflation	0.1049	**0.0137****	**0.0895****	**0.0168****
	(0.0753)	(0.0066)	(0.0383)	(0.0067)
credit_GDPgap	**0.0466*****	0.0006	**-0.0085***	-0.0004
	(0.0142)	(0.0020)	(0.0045)	(0.0006)
Constant	0.1113	-0.0035	0.0124	0.0046
	(0.0893)	(0.0191)	(0.0353)	(0.0047)
Nbr. of obs.	325	325	740	740
R^2	0.2588	0.1341	0.1339	0.2036
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	12	12	17	17

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR*) on the asset commonality for Loan assets classes (*LoanAssetCom*) and control variables under a high and low Quantity focused Macroprudential Policy. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

2.5.2 The Role of Cross-border Assets Restriction

Financial liberalization has an impact on the stability of the financial sector. While cross-border lending activities can enhance risk-sharing, diversification, and industry resilience (Allen et al., 2012; Schoenmaker and Wagner, 2011), they have also been associated with increased risk and the transmission of foreign shocks, amplifying systemic risk contagion (Berger et al., 2016; Bruno and Shin, 2015; Schnabl, 2012). Moreover, international integration's impact on macroprudential policies' effectiveness has been acknowledged (Claessen et al., 2013), and macroprudential measures themselves could potentially increase exposure through regulatory arbitrage as banks shift investments across nations due to policy disparities. Addressing these dynamics, the study augments Equation (4) by introducing an interaction term between the dummy variable $Asset\_restriction_{j,t}$ measuring the level of cross-border asset restriction and the assets commonality variable. The aim is to assess overall effects of the interplay between cross-border asset restriction and asset commonality on systemic risk across different levels of macroprudential policy adoption. It is expected that higher cross-border asset restrictions limit the impact of asset commonality on systemic risk by limiting the cross-border transmission of shocks.

Tables 2.11 to 2.15 present the results for the different macroprudential policy types, namely comprehensive, financial institution-targeted, borrower-focused, and quantity-focused. Across all estimations, the interaction term between asset commonality and cross-border asset restrictions is not significant. These findings suggest that the increasing influence of asset commonality on systemic risk in the presence of stronger macroprudential policies adoption remains consistent regardless of the extent of cross-border asset restrictions. Similarly, the neutral impact of asset commonality on systemic risk for banks operating under lower levels of macroprudential policy adoption is unaffected by the level of cross-border asset restrictions.

Table 2.12 Asset Commonality, Cross Border Asset Restriction and Systemic Risk Under High and Low Comprehensive Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High Comprehensive macroprudential policy		Low Comprehensive macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
AllAssetCom (β_1)	**0.0351***	0.0008	-0.0049	0.0005
	(0.0189)	(0.0023)	(0.0057)	(0.0010)
AllAssetCom x *Asset_Restriction* (β_2)	0.0446	0.0007	0.0118	-0.00005
	(0.0409)	(0.0024)	(0.0132)	(0.0027)
Asset_Restriction	-0.0237	0.00004	-0.0084	0.0005
	(0.0264)	(0.0018)	(0.0114)	(0.0023)
stockmarkcap_GDP	**-0.0077****	**-0.0012****	-0.0036	**-0.0008***
	(0.0030)	(0.0006)	(0.0032)	(0.0004)
Equityratio	0.0611	0.0044	-0.0535	**-0.0117***
	(0.0841)	(0.0053)	(0.0416)	(0.0066)
Efficiency	0.0031	0.0002	0.0003	**0.00005****
	(0.0030)	(0.0002)	(0.0002)	(0.00002)
Liquidity	0.0051	0.0004	-0.0013	-0.00003
	(0.0032)	(0.0004)	(0.0010)	(0.0001)
SMR	0.0000	0.00005	-0.0003	-0.0001
	(0.0012)	(0.0001)	(0.0010)	(0.0001)
ROA	-0.0896	-0.0101	**-0.1550*****	**-0.0309*****
	(0.0943)	(0.0084)	(0.0527)	(0.0106)
△_House Price Index	-0.0005	5.34	-0.0043	-0.0006
	(0.0005)	(0.0001)	(0.0076)	(0.0007)
△_Central Bank Policy	-0.0009	-4.23	**0.0010***	**0.0003***
	(0.0013)	(0.0002)	(0.0006)	(0.0001)
GFC	0.0056	-0.00004	0.0001	0.00004
	(0.0038)	(0.0005)	(0.0023)	(0.0002)
△_GDP	-0.0084	**-0.0042***	-0.0561	-0.0059
	(0.0236)	(0.0021)	(0.0435)	(0.0053)
Diversification	**-0.0151***	-0.0015	0.0051	0.0003
	(0.0085)	(0.0013)	(0.0057)	(0.0009)
Concentration_ratio	**0.1194***	0.0210	0.0284	**0.0096***
	(0.0650)	(0.0166)	(0.0397)	(0.0056)
Institutional_environment	-0.0031	-0.0006	0.0019	-0.0003
	(0.0030)	(0.0004)	(0.0033)	(0.0002)
lnTA	-0.0030	0.0003	-0.0006	**-0.0003***
	(0.0037)	(0.0004)	(0.0015)	(0.0002)
HighSTDebt	**-0.0057*****	**-0.0005****	-0.0008	0.0001
	(0.0021)	(0.0002)	(0.0010)	(0.0003)
Inflation	0.0245	0.0121	**0.0917***	0.0152
	(0.0464)	(0.0072)	(0.0521)	(0.0091)
credit_GDPgap	**0.0315***	0.0009	**-0.0120***	**-0.0015****
	(0.0177)	(0.0014)	(0.0060)	(0.0007)
Constant	0.0311	-0.0106	0.0256	**0.0082***
	(0.0864)	(0.0128)	(0.0430)	(0.0046)
Nbr. of obs.	434	434	631	631
R^2	0.1556	0.0838	0.1540	0.2308
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	18	18	11	11

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR*) on the asset commonality for All assets classes (*AllAssetCom*) its interaction with a dummy variable taking the value of one for countries with higher cross-border asset restrictions (*Asset_restriction*), and control variables under a high and low *Comprehensive Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and ***denoting the significance at 10%, 5% and 1% levels.

Table 2.13 Asset Commonality, Cross Border Asset Restriction and Systemic Risk Under High and Low Financial Institution Targeted Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High FIT macroprudential policy		Low FIT macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
AllAssetCom (β_1)	0.0451	**0.0045****	-0.0018	-0.0009
	(0.0302)	(0.0019)	(0.0038)	(0.0012)
AllAssetCom x *Asset_Restriction* (β_2)	0.0442	0.0004	0.0089	0.0018
	(0.0431)	(0.0026)	(0.0097)	(0.0035)
Asset_Restriction	-0.0236	0.0003	-0.0061	-0.0011
	(0.0281)	(0.0019)	(0.0086)	(0.0030)
stockmarkcap_GDP	**-0.0064****	**-0.0009****	-0.0056	**-0.0011****
	(0.0028)	(0.0004)	(0.0034)	(0.0006)
Equityratio	0.0563	0.0042	-0.0530	**-0.0118***
	(0.0811)	(0.0049)	(0.0417)	(0.0069)
Efficiency	0.0031	0.0002	**0.0004****	**0.00004***
	(0.0030)	(0.0002)	(0.0002)	(0.00002)
Liquidity	0.0042	0.0004	-0.0006	-0.00005
	(0.0031)	(0.0004)	(0.0009)	(0.0001)
SMR	-0.0004	0.0001	-0.0000	**-0.0002***
	(0.0013)	(0.0001)	(0.0009)	(0.0001)
ROA	-0.0700	-0.0073	**-0.1687*****	**-0.0305*****
	(0.0915)	(0.0082)	(0.0519)	(0.0104)
△_House Price Index	-0.0004	0.0000	-0.0145	-0.0009
	(0.0005)	(0.0001)	(0.0119)	(0.0012)
△_Central Bank Policy	-0.0010	-0.0001	0.0008	**0.0003***
	(0.0012)	(0.0001)	(0.0006)	(0.0001)
GFC	**0.0068****	0.0001	-0.0021	-0.0002
	(0.0032)	(0.0003)	(0.0025)	(0.0003)
△_GDP	-0.0073	**-0.0045****	-0.0701	-0.0082
	(0.0230)	(0.0022)	(0.0436)	(0.0056)
Diversification	-0.0140	-0.0017	0.0023	0.0006
	(0.0084)	(0.0012)	(0.0055)	(0.0010)
Concentration_ratio	**0.1258***	0.0145	-0.0100	**0.0127***
	(0.0682)	(0.0136)	(0.0373)	(0.0069)
Institutional_environment	-0.0026	-0.0001	0.0008	**-0.0006***
	(0.0033)	(0.0002)	(0.0030)	(0.0003)
lnTA	-0.0044	-0.0001	-0.0011	-0.0002
	(0.0042)	(0.0003)	(0.0017)	(0.0002)
HighSTDebt	**-0.0054****	**-0.0005****	-0.0002	0.0001
	(0.0021)	(0.0002)	(0.0010)	(0.0003)
Inflation	0.0314	**0.0129***	**0.0918***	**0.0204****
	(0.0473)	(0.0074)	(0.0507)	(0.0090)
credit_GDPgap	0.0305	0.0007	**-0.0099***	**-0.0016****
	(0.0187)	(0.0013)	(0.0057)	(0.0008)
Constant	0.0553	-0.0015	0.0516	0.0065
	(0.0901)	(0.0104)	(0.0500)	(0.0060)
Nbr. of obs.	466	466	599	599
R^2	0.1505	0.0836	0.1760	0.2315
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	18	18	11	11

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR*) on the asset commonality for All assets classes (*AllAssetCom*) its interaction with a dummy variable taking the value of one for countries with higher cross-border asset restrictions (*Asset_restriction*), control variables under a high and low *Financial Institution Targeted Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table 2.14 Assets Commonality, Cross Border Asset Restriction and Systemic Risk Under High and Low Borrower Focused Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High Borrower Focused macroprudential policy		Low Borrower Focused macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
AllAssetCom (β1)	**0.0357***	-0.0022	-0.0041	0.0008
	(0.0183)	(0.0024)	(0.0088)	(0.0009)
AllAssetCom x *Asset_Restriction* (β2)	0.0209	-0.0138	0.0443	-0.0007
	(0.0308)	(0.0131)	(0.0488)	(0.0027)
Asset_Restriction	0.00001	0.00001	-0.0260	0.0011
	(0.00002)	(0.00002)	(0.0327)	(0.0020)
stockmarkcap_GDP	-0.0068	-0.0006	-0.0043	**-0.0009****
	(0.0041)	(0.0007)	(0.0029)	(0.0004)
Equityratio	**-0.0841*****	0.0005	-0.0394	-0.0078
	(0.0197)	(0.0102)	(0.0470)	(0.0055)
Efficiency	**0.0155*****	**0.0009*****	0.0001	0.00004
	(0.0018)	(0.0002)	(0.0001)	(0.00002)
Liquidity	0.0014	-0.0006	-0.0002	0.0002
	(0.0022)	(0.0006)	(0.0010)	(0.0001)
SMR	-0.0012	-0.0002	-0.0008	-0.0001
	(0.0009)	(0.0001)	(0.0010)	(0.0001)
ROA	**0.6027****	-0.0197	**-0.0991***	**-0.0222****
	(0.2586)	(0.0564)	(0.0503)	(0.0107)
△_House Price Index	-0.0007	0.0001	-0.0007	**-0.0003****
	(0.0009)	(0.0002)	(0.0013)	(0.0001)
△_Central Bank Policy	**-0.0018****	-0.00003	**0.0020****	**0.0003****
	(0.0008)	(0.0002)	(0.0010)	(0.0001)
GFC	0.0105	-0.0006	0.0005	0.0001
	(0.0158)	(0.0013)	(0.0016)	(0.0002)
△_GDP	-0.0305	-0.0077	-0.0038	-0.0009
	(0.0281)	(0.0045)	(0.0227)	(0.0028)
Diversification	0.0012	0.0019	-0.0051	-0.0010
	(0.0065)	(0.0016)	(0.0050)	(0.0008)
Concentration_ratio	0.0339	0.0388	**0.1163****	**0.0131****
	(0.0393)	(0.0315)	(0.0561)	(0.0057)
Institutional_environment	0.0024	-0.0001	0.0018	-0.0003
	(0.0017)	(0.0003)	(0.0033)	(0.0002)
lnTA	-0.0048	0.0014	0.0007	-0.0002
	(0.0033)	(0.0013)	(0.0012)	(0.0002)
HighSTDebt	-0.0016	-0.0002	**-0.0047****	-0.0001
	(0.0022)	(0.0003)	(0.0022)	(0.0003)
Inflation	-0.0194	0.0161	0.0632	**0.0092***
	(0.0288)	(0.0167)	(0.0529)	(0.0055)
credit_GDPgap	**0.0316*****	-0.0022	-0.0106	-0.0006
	(0.0088)	(0.0033)	(0.0074)	(0.0006)
Constant	0.0817	-0.0380	-0.0244	0.0043
	(0.0716)	(0.0356)	(0.0366)	(0.0043)
Nbr. of obs.	245	245	820	820
R^2	0.5156	0.1384	0.0953	0.1682
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	10	10	19	19

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR*) on the asset commonality for All assets classes (*AllAssetCom*) its interaction with a dummy variable taking the value of one for countries with higher cross-border asset restrictions (*Asset_restriction*), control variables under a high and low *Borrower Focused Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and ***denoting the significance at 10%, 5% and 1% levels.

Table 2.15 Assets Commonality, Cross Border Asset Restriction and Systemic Risk Under High and Low Quantity Focused Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High Quantity Focused macroprudential policy		Low Quantity Focused macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
AllAssetCom (β_1)	**0.0357***	-0.0022	-0.0041	0.0008
	(0.0183)	(0.0024)	(0.0088)	(0.0009)
AllAssetCom x *Asset_Restriction* (β_2)	0.0209	-0.0138	0.0443	-0.0007
	(0.0308)	(0.0131)	(0.0488)	(0.0027)
Asset_Restriction	0.00001	0.00001	-0.0260	0.0011
	(0.00002)	(0.00002)	(0.0327)	(0.0020)
stockmarkcap_GDP	-0.0068	-0.0006	-0.0043	**-0.0009****
	(0.0041)	(0.0007)	(0.0029)	(0.0004)
Equityratio	**-0.0841*****	0.0005	-0.0394	-0.0078
	(0.0197)	(0.0102)	(0.0470)	(0.0055)
Efficiency	**0.0155*****	**0.0009*****	0.0001	0.00004
	(0.0018)	(0.0002)	(0.0001)	(0.00002)
Liquidity	0.0014	-0.0006	-0.0002	0.0002
	(0.0022)	(0.0006)	(0.0010)	(0.0001)
SMR	-0.0012	-0.0002	-0.0008	-0.0001
	(0.0009)	(0.0001)	(0.0010)	(0.0001)
ROA	**0.6027****	-0.0197	**-0.0991***	**-0.0222****
	(0.2586)	(0.0564)	(0.0503)	(0.0107)
△_House Price Index	-0.0007	0.0001	-0.0007	**-0.0003****
	(0.0009)	(0.0002)	(0.0013)	(0.0001)
△_Central Bank Policy	**-0.0018****	-0.00003	**0.0020****	**0.0003****
	(0.0008)	(0.0002)	(0.0010)	(0.0001)
GFC	0.0105	-0.0006	0.0005	0.0001
	(0.0158)	(0.0013)	(0.0016)	(0.0002)
△_GDP	-0.0305	-0.0077	-0.0038	-0.0009
	(0.0281)	(0.0045)	(0.0227)	(0.0028)
Diversification	0.0012	0.0019	-0.0051	-0.0010
	(0.0065)	(0.0016)	(0.0050)	(0.0008)
Concentration_ratio	0.0339	0.0388	**0.1163****	**0.0131****
	(0.0393)	(0.0315)	(0.0561)	(0.0057)
Institutional_environment	0.0024	-0.0001	0.0018	-0.0003
	(0.0017)	(0.0003)	(0.0033)	(0.0002)
lnTA	-0.0048	0.0014	0.0007	-0.0002
	(0.0033)	(0.0013)	(0.0012)	(0.0002)
HighSTDebt	-0.0016	-0.0002	**-0.0047****	-0.0001
	(0.0022)	(0.0003)	(0.0022)	(0.0003)
Inflation	-0.0194	0.0161	0.0632	**0.0092***
	(0.0288)	(0.0167)	(0.0529)	(0.0055)
credit_GDPgap	**0.0316*****	-0.0022	-0.0106	-0.0006
	(0.0088)	(0.0033)	(0.0074)	(0.0006)
Constant	0.0817	-0.0380	-0.0244	0.0043
	(0.0716)	(0.0356)	(0.0366)	(0.0043)
Nbr. of obs.	245	245	820	820
R^2	0.5156	0.1384	0.0953	0.1682
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	12	12	17	17

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR*) on the asset commonality for All assets classes (*AllAssetCom*) its interaction with a dummy variable taking the value of one for countries with higher cross-border asset restrictions (*Asset_restriction*), and control variables under a high and low *Quantity Focused Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and ***denoting the significance at 10%, 5% and 1% levels.

2.5.3 Robustness test

Several additional robustness checks are carried out. First, an alternative measure of asset commonality is used to test the robustness of our results. The cosine similarity measure developed by Salton and McGill (1987) is used to evaluate the degree of asset commonality between banks. Following Barucca et al. (2021), Daniel Fricke (2016), and Getmansky et al. (2016), the distance measures for each weight of asset class ratio is computed as follows:

$$Cosim_{i,t} = \frac{\sum_{k=1}^{k} w_{i,k} w_{j,k}}{\sqrt{\sum_{k=1}^{k} w_{i,k}^2}\ x \sqrt{\sum_{k=1}^{k} w_{j,k}^2}} \qquad (5)$$

$$Cosine\_AllAssetCom_{i,t} = \frac{\sum_{i \neq j, i=1}^{i} Cosim_{i,t}}{N_t - 1} \qquad (6)$$

where $Cosim_{i,t}$ represents the cosine similarity between bank *i* to all other bank *j* for each year and asset class *k* in each year *t*; $w_{i,k,t}$ is the weight bank *i* invests in asset class *k*, with $\sum_{k=1}^{K} w_{i,k,t} = 1.$ Thus, the greater angle formed between the two-coordinate vector comparison relates to the cosine similarity. In other words, the smaller degree captures similarity such that similarity ranges from -1(dissimilar) to 1 (similar). However, the *W* matrix is non-negative, thus the minimum value for Cosim is 0. The variable $Cosine\_\ AllAssetCom_{i,t}$ is the average cosine similarity measure by taking into consideration the number of banks N_t per year. Equation (4) is re-estimate using this alternative measure of asset commonality. Results, reported in Tables B.5 to B.8 in the appendix for comprehensive, financial institution- targeted, borrower-focused, and quantity-focused macroprudential policy, respectively, show that our conclusions remain unchanged. The findings indicate that higher levels of asset commonality are associated with an increase in systemic risk, but only among banks in countries with stronger adoption of macroprudential policy, regardless of the specific policy type.

Next, the study recognizes the potential for arguments that the findings' impact may be influenced by bias stemming from countries with many banks, such as the United States with 28 banks, in contrast to countries with just one or two banks, as seen in the cases of Austria and Belgium. To address this concern, the observations are weighted to give the same weight for each country. Tables B.9-B.12 in the Appendix (for comprehensive, financial institution- targeted, borrower-focused, and quantity-focused macroprudential policy, respectively) show that our results are unchanged. Higher levels of asset commonality exert a significant and increasing effects on systemic risk in the context of stronger macroprudential policy adoption, irrespective of the policy type.

2.6. Conclusion

The study analyzed the impact of asset commonality on systemic risk across a panel of large banks in 29 countries, considering different levels and types of macroprudential policies adoption.

The results indicate that in a context where comprehensive macroprudential policies are not widely adopted, asset commonality does not exert any significant influence on systemic risk. Conversely, when comprehensive macroprudential policies are strongly implemented, higher levels of asset commonality contribute to increase systemic risk. This evidence indicates that while the implementation of macroprudential policies aims to reduce systemic risk, a stronger adoption of such policies is paradoxically associated with an increase in financial instability when associated with higher levels of asset commonality. Moreover, the results demonstrate the robustness of these findings across different types of macroprudential policies, namely financial institution-targeted, borrower-focused, and quantity-focused. Additionally, varying degrees of cross-border asset restrictions do not shape the way higher levels of asset commonality contribute to systemic risk in countries with stronger macroprudential policy adoption.

Further investigations show that higher levels of loan asset commonality contribute to significantly increase systemic risk in the presence of stronger macroprudential policy implementation, irrespective of the policy type. In contrast, higher levels of loan asset commonality do not lead to higher systemic risk under conditions of low macroprudential policy implementation.

In conclusion, while existing research suggests that macroprudential policies effectively curb credit growth and house prices, this study unveils a potential concern. Asset commonality can increase a bank's vulnerability to systemic risk, particularly in the presence of intense macroprudential intervention. Therefore, careful, and consistent monitoring of bank asset portfolios becomes imperative, especially in the context of strong macroprudential policies implementation, as it might inadvertently exacerbate systemic risk. The Bank for International Settlements (BIS) should consider asset commonality in addition to the established interconnectivity criteria for recognizing G-SIFIs to improve financial stability. Additionally, while establishing capital surcharge requirements for larger banks, regulatory authorities should take a bank's asset diversity and asset similarity to domestic peers into consideration

APPENDIX B

Table B.1 List of Systemically Important Bank Holding Companies

S/N	Bank Name	S/N	Bank Name	S/N	Bank Name
1	Morgan Stanley & Co. LLC	37	Jyske Bank A/S	73	Taishin Financial Holding Co., Ltd.
2	Citibank, N.A.	38	Allied Irish Banks, plc	74	Resona Holdings, Inc.
3	Wells Fargo Bank, N.A.	39	Oversea-Chinese Banking Corporation Limited	75	Hong Leong Financial Group Berhad
4	The Bank of Nova Scotia	40	Erste Group Bank AG	76	Hua Nan Financial Holdings Co., Ltd.
5	Ally Financial Inc.	41	Swedbank AB	77	Banca Mediolanum S.p.A.
6	The Goldman Sachs Group,	42	Alpha Services and Holdings.	78	Nordea Bank Abp
7	Capital One Financial Corporation	43	National Bank of Greece.	79	Sumitomo Mitsui Financial Group, Inc.
8	Royal Bank of Canada	44	Banco Comercial Portugues,	80	Umpqua Holdings Corporation
9	Canadian Imperial Bank of Commerce	45	BPER Banca S.p.A.	81	Volkswagen Bank GmbH
10	Societe Generale	46	Turkiye Is Bankasi A.S.	82	SinoPac Financial Holdings Company Limited
11	Zions Bancorporation,	47	Credit Suisse Group AG	83	Mega Financial Holding Co., Ltd.
12	First Republic Bank	48	Public Bank Berhad	84	Hokuhoku Financial Group, Inc.
13	UBS AG	49	Sberbank of Russia	85	Grupo Aval Acciones y Valores
14	JPMorgan Chase Bank,.	50	Bancolombia S.A.	86	Harbin Bank Co., Ltd.
15	BNP Paribas S.A.	51	OTP Bank Plc.	87	Raiffeisen Bank International AG
16	Banca Monte dei Paschi di Siena S.p.A.	52	UniCredit S.p.A.	88	First Financial Holding Co., Ltd.
17	Agricultural Bank of China Limited	53	The Shanghai Commercial & Savings Bank, Ltd.	89	Signature Bank
18	Banco Bradesco	54	Intesa Sanpaolo S.p.A.	90	E. Sun Financial Holding Company, Ltd
19	Bank of Montreal	55	Banco Santander, S.A.	91	Korea Investment Holdings Co., Ltd.
20	Banque Cantonale Vaudoise	56	Banco Bilbao Vizcaya Argentaria,	92	Pinnacle Financial Partners, Inc.
21	Barclays plc	57	Piraeus Financial Holdings	93	Standard Chartered PLC
22	The Charles Schwab Corporation	58	Turkiye Vakiflar Bankasi T.A.O.	94	People's United Financial, Inc.
23	Eurobank Ergasias Services and Holdings S.A.	59	VTB Bank (Public Joint-Stock Company)	95	Macquarie Group Limited
24	HSBC Holdings plc	60	Synovus Financial Corp.	96	Shengjing Bank Co., Ltd.
25	Landesbank Baden-Wuerttemberg	61	BOK Financial Corporation	97	ServisFirst Bancshares, Inc.
26	National Australia Bank Limited	62	Regions Financial Corporation	98	Western Alliance Bancorporation
27	RHB Bank Berhad	63	M&T Bank Corporation	99	PacWest Bancorp
28	Skandinaviska Enskilda Banken AB	64	New York Community Bancorp, Inc.	100	Mebuki Financial Group, Inc.
29	State Street Corporation	65	Bank of China Limited	101	Julius Baer Group Ltd
30	Bank of America Corporation	66	Turkiye Halk Bankasi A.S.	102	Taiwan Cooperative Financial Holding Company
31	Toronto-Dominion Bank (The)	67	Taiwan Business Bank, Ltd.	103	Synchrony Financial
32	Lloyds Banking Group plc	68	KBC Group NV		
33	NatWest Group plc	69	The PNC Financial Services Group, Inc.		
34	National Bank of Canada	70	Citizens Financial Group, Inc.		
35	Credit Agricole	71	ING Groep N.V.		
36	Commerzbank AG	72	Itau Unibanco Holding		

Table B.2 Distribution of banks by country in 2012 and macroprudential policy statistics (sample period 2000-2020)

		Cum_Comprehensive		Cum_Borrower		Cum_FIT		Cum_Quantity	
Country	Nbr. of Banks	Min	Max	Min	Max	Min	Max	Min	Max
United States	28	0	7	0	1	0	6	0	3
United Kingdom	5	0	10	0	1	0	9	0	4
Austria	1	1	8	0	0	1	8	1	3
Belgium	1	1	9	0	1	1	8	1	3
Denmark	1	0	10	0	1	0	9	0	4
France	3	1	10	0	1	1	9	1	4
Germany	3	1	7	0	0	1	7	1	2
Italy	5	1	7	0	0	1	7	1	2
Norway	1	1	11	0	2	1	9	0	5
Sweden	2	0	9	0	1	0	8	0	3
Switzerland	4	0	8	0	0	0	8	0	3
Canada	6	0	12	0	2	0	10	0	5
Japan	4	0	6	0	0	0	6	0	2
Finland	1	1	9	0	1	1	8	1	3
Greece	4	2	9	0	1	2	8	2	4
Ireland	1	1	10	0	2	1	8	1	4
Portugal	1	1	11	0	2	1	9	1	5
Spain	2	2	9	0	1	2	8	1	4
Turkey	3	0	12	0	1	0	11	0	6
Australia	2	1	9	0	0	1	9	1	4
Brazil	2	2	11	0	1	2	10	1	4
Colombia	2	2	8	2	2	0	6	2	4
Taiwan	9	0	5	0	1	0	4	0	2
Korea	1	10	15	2	2	8	13	5	7
Malaysia	3	0	10	0	2	0	8	0	5
Singapore	1	0	10	0	2	0	8	0	5
Russia	2	1	10	0	0	1	10	1	4
China	4	0	17	0	2	0	15	0	8
Hungary	1	0	12	0	2	0	10	0	6

This table reports the number of listed banks in the sample for the year 2012 by country list and that were sourced from Fitch connects database. The macroprudential policy relates 17 instruments for which are listed in Table B.3. The study assigns a value of 1 to each policy implemented, starting from its effective implementation year. As a result, we compute the comprehensive (*cum_Comprehensive)*, Financial Institution (*cum_FIT)*, Borrower focused (*cum_Borrower)*, and Quantity focused (*cum_Quantity)* cumulative macroprudential policies, ranging from 0 to 17. The components of each instrument are also tabulated in Table B.3 The maximum (max) and minimum (min) values for each policy are listed per country, along with the number of banks in the sample.

Table B.3 Distribution of Banks by Country In 2012 and Macroprudential Policy Statistics (Sample Period 2000-2020)

INSTRUMENTS	DESCRIPTION	Borrower	Quantity	Financial Institution
1 Countercyclical Buffers (CCB)	A requirement for banks to maintain a countercyclical capital buffer. Implementations at 0% are not considered as a tightening in dummy-type indicators.	—	—	X
2 Conservation	Requirements for banks to maintain a capital conservation buffer, including the one established under Basel III.	—	—	X
3 Capital Requirements*	Capital requirements for banks, which include risk weights, systemic risk buffers, and minimum capital requirements. Countercyclical capital buffers and capital conservation buffers are captured in their sheets respectively and thus not included here. Subcategories of capital measures are also provided, (Gen), and FX-loan targeted (FX) measures.	—	—	X
4 Leverage Limits (LVR)	A limit on leverage of banks, calculated by dividing a measure of capital by the bank's non-risk weighted exposures (e.g., Basel III leverage ratio).	—	X	X
5 Loan Loss Provisions (LLP)	Loan loss provision requirements for macroprudential purposes, which include dynamic provisioning and sectoral provisions (e.g., housing loans).	—	—	X
6 Limits on Credit Growth (LCG)*	Limits on growth or the volume of aggregate credit, the household-sector credit, or the corporate-sector credit by banks, and penalties for high credit growth. Subcategories of limits to credit growth are also provided, classifying them into household sector targeted (HH), corporate sector targeted (Corp), and broad-based (Gen) measures.	—	X	X
7 Loan Restrictions (LoanR)*	Loan restrictions, that are more tailored than those captured in "LCG". They include loan limits and prohibitions, which may be conditioned on loan characteristics (e.g., the maturity, the size, the LTV ratio, and the type of interest rate of loans), bank characteristics (e.g., mortgage banks), and other factors. Subcategories of loan restrictions are also provided, classifying them into household sector targeted (HH), and corporate sector targeted (Corp) measures. Restrictions on foreign currency lending are captured in "LFC".	—	—	X
8 Limits on Foreign Currency (LFC)	Limits on foreign currency (FC) lending, and rules or recommendations on FC loans.	—	—	X
9 Limits on the Loan-to-Value Ratio (LTV)	Limits to the loan-to-value ratios, including those mostly targeted at housing loans, but also includes those targeted at automobile loans, and commercial real estate loans.	X	X	—
10 Limits on the Debt-Service-to to Income Ratio (DSTI)	Limits to the debt-service-to-income ratio and the loan-to-income ratio, which restrict the size of debt services or debt relative to income. They include those targeted at housing loans, consumer loans, and commercial real estate loans.	X	X	—

11 Tax Measures	Taxes and levies applied to specified transactions, assets, or liabilities, which include stamp duties, and capital gain taxes.	__	__	X
12 Liquidity Requirements	Measures taken to mitigate systemic liquidity and funding risks, including minimum requirements for liquidity coverage ratios, liquid asset ratios, net stable funding ratios, core funding ratios and external debt restrictions that do not distinguish currencies.	__	__	X
13 Limits on the Loan-to-Deposit Ratio (LTD)	Limits to the loan-to-deposit (LTD) ratio and penalties for high LTD ratios.	__	__	X
14 Limits on Foreign Exchange Positions (LFX)	Limits on net or gross open foreign exchange (FX) positions, limits on FX exposures and FX funding, and currency mismatch regulations.	__	__	X
15 Reserve Requirements (RR)*	Reserve requirements (domestic or foreign currency) for macroprudential purposes. Please note that this category may currently include those for monetary policy as distinguishing those for macroprudential or monetary policy purposes is often not clear-cut. A subcategory of reserve requirements is provided for those differentiated by currency (FCD), as they are typically used for macroprudential purposes.	__	__	X
16 SIFI	Measures taken to mitigate risks from global and domestic systemically important financial institutions (SIFIs), which includes capital and liquidity surcharges.	__	__	X
17 Other Macroprudential measures	measures not captured in the above categories—e.g., stress testing, restrictions on	__	X	X

This table shows the list of macroprudential instruments. It also shows the constituents of each policy grouping i.e., Borrower, FIT and Quantity focused macroprudential policy.

Table B.4 Cross-Border Transmission Channels

Channel	Transmission	Description
1. Cross-border risk adjustments	A. Adjustments of cross-border credit exposures	Macroprudential policy affects banks' cross-border portfolio allocation in that banks change their holdings of foreign credit exposures, be they in the form of cross-border direct lending or securities exposures or through subsidiaries or branches active in the other country
	B. Adjustments of cross-border securitisation activity	Macroprudential policy may alter banks' incentives to transfer credit risk to another country, for instance by encouraging/discouraging the originate-to-distribute business model, which may also rely on international funding sources.
	C. Access to cross border capital markets	Access to capital markets and the related ability/willingness to raise funds may be an important facilitating/mitigating factor for deleveraging, which affects the second-round effects of shocks.
2. Network formation and potential for contagion	D. Adjustments of cross-border liquidity/funding lines	Macroprudential policy may affect banks' instrument mix on the liability side, in terms of reliance on cross-border funding, e.g., subordinated loans and liquidity (interbank and repo markets). This, in turn, affects the network structure of the system, which is an important factor determining contagion.
	E. Adjustment of asset prices	Macroprudential policies may change the demand for certain financial assets and thus their prices. Asset prices, in turn, may affect banks' portfolio choices: overvaluation can invite pro-cyclical risk-taking, while extreme downward price adjustments can lead to portfolio rebalancing and spur fire sales.
	F. Common exposures	Macroprudential policies, in particular the introduction of large exposure limits, can make banks' portfolio composition more granular, thereby reducing common exposures to certain sectors within the system, for instance to sovereign risk. This in turn increases the system's resilience to sectoral shocks and decreases the potential for cross-border contagion as a result.
3. Regulatory arbitrage	G. Capital regulatory arbitrage	Increasing capital requirements may alter incentives for circumventing the regulatory restrictions by actively shifting capital within the group, by shedding capital-intensive activity off the balance sheet to special purpose vehicles, or by opening (or converting subsidiaries into) branches in jurisdictions where capital requirements are higher.
	H. Liquidity regulatory arbitrage	Liquidity restrictions could lead to liquid assets being moved abroad, mostly in the form of intragroup transfers, without, however, changing the liquidity position of the entire banking group.

	I. Shadow banking activity	Stricter regulation of banks could also lead to “waterbed effects” by paving the way for credit growth in a non-regulated (shadow) banking sector. As the shadow banking system operates more strongly internationally, liquidity conditions can easily be transmitted across borders. On the other hand, macroprudential instruments targeting financial markets and non-bank financial institutions can help prevent such leakages and ensure consistency in regulation across sectors.
4. Altering monetary transmission	J. Relative cost of lending	Macroprudential policy can affect the relative cost of lending in a cross-border context. This may reinforce or weaken the monetary policy transmission depending on whether monetary and macroprudential policy work in tandem or in opposite directions. Macroprudential policy may provide a more targeted instrument to account for different cross-country positions in the financial cycle.
	K. Changing term structure	Amending bank liquidity and funding requirements or restricting investment funds’ liquidity mismatch may affect the term structure of the yield curve. In a cross-border context, this may lead to a different level of propagation of monetary policy across countries owing to the relative importance of demand for and supply of longer-term assets, as well as through differing expectations about their timing
5. Trade effects	L. Foreign trade	By influencing credit, macroprudential policy may affect economic activity, which in turn could lead to changes in foreign trade activity by altering exports and imports.
	M. Relative prices of tradeable and non-tradeable goods	Housing cannot be traded across borders. However, macroprudential policy can change the relative prices of certain tradable and non-tradeable goods and in this way affect foreign trade patterns

This table refers to the different cross-border channels here in macroprudential policy can affects a foreign (home) country. Source: ECB: Financial Stability Review 2015

Table B.5 Robustness Check (1): Cosine Similarity Measure (Comprehensive Macroprudential Policy)

Model	(1)	(2)	(3)	(4)
Levels	High Comprehensive macroprudential policy		Low Comprehensive macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
Cosine_AllAssetCom	**0.0298***	0.0011	-0.0026	0.0006
	(0.0172)	(0.0018)	(0.0041)	(0.0007)
stockmarkcap_GDP	**-0.0089****	**-0.0012****	-0.0038	**-0.0008***
	(0.0035)	(0.0006)	(0.0033)	(0.0004)
Equityratio	0.0758	0.0047	-0.0540	**-0.0117***
	(0.0966)	(0.0052)	(0.0416)	(0.0067)
Efficiency	0.0026	0.0002	0.0003	**0.0000****
	(0.0030)	(0.0002)	(0.0002)	(0.0000)
Liquidity	0.0049	0.0004	-0.0013	-0.00002
	(0.0031)	(0.0004)	(0.0010)	(0.0001)
SMR	-0.0003	0.0001	-0.0003	-0.0001
	(0.0013)	(0.0001)	(0.0010)	(0.0001)
ROA	-0.1278	-0.0102	**-0.1544*****	**-0.0307*****
	(0.1134)	(0.0085)	(0.0528)	(0.0105)
△_House Price Index	-0.0005	0.0000	-0.0043	-0.0006
	(0.0005)	(0.0001)	(0.0075)	(0.0007)
△_Central Bank Policy	-0.0005	1.03	**0.0009***	**0.0003***
	(0.0015)	(0.0001)	(0.0006)	(0.0001)
GFC	0.0053	-0.00004	0.0001	0.00003
	(0.0034)	(0.0005)	(0.0023)	(0.0002)
△_GDP	-0.0116	**-0.0043****	-0.0564	-0.0058
	(0.0240)	(0.0021)	(0.0435)	(0.0053)
Diversification	**-0.0162***	-0.0016	0.0050	0.0003
	(0.0091)	(0.0013)	(0.0058)	(0.0009)
Concentration_ratio	**0.1191***	0.0210	0.0270	**0.0096***
	(0.0645)	(0.0165)	(0.0394)	(0.0056)
Institutional_environment	-0.0034	-0.0006	0.0019	-0.0003
	(0.0031)	(0.0004)	(0.0033)	(0.0002)
lnTA	-0.0031	0.0002	-0.0007	**-0.0003***
	(0.0040)	(0.0004)	(0.0015)	(0.0002)
HighSTDebt	**-0.0051*****	**-0.0005****	-0.0008	0.0001
	(0.0018)	(0.0002)	(0.0010)	(0.0003)
Inflation	0.0261	**0.0124***	**0.0912***	**0.0155***
	(0.0483)	(0.0073)	(0.0514)	(0.0091)
credit_GDPgap	**0.0315***	0.0009	**-0.0121***	**-0.0014****
	(0.0182)	(0.0014)	(0.0061)	(0.0007)
Constant	0.0419	-0.0091	0.0265	**0.0087***
	(0.0976)	(0.0130)	(0.0425)	(0.0049)
Nbr. of obs.	434	434	631	631
R^2	0.1499	0.0847	0.1537	0.2311
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	18	18	11	11

This table reports fixed effects estimation of systemic risk measures (*MES, and DCoVaR)* on the asset commonality for All assets classes (cosine_*AllAssetCom*) and control variables under a high and low *Comprehensive Focused Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and ***denoting the significance at 10%, 5% and 1% levels.

Table B.6 Robustness Check (1): Cosine Similarity Measure (Financial Institution Targeted Macroprudential Policy)

Model	(1)	(2)	(3)	(4)
Levels	High FIT macroprudential policy		Low FIT macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
Cosine_AllAssetCom	0.0312	**0.0029****	-0.0012	-0.0004
	(0.0205)	(0.0012)	(0.0036)	(0.0010)
stockmarkcap_GDP	**-0.0075****	**-0.0009****	-0.0056	**-0.0012****
	(0.0033)	(0.0004)	(0.0034)	(0.0005)
Equityratio	0.0674	0.0041	-0.0530	**-0.0119***
	(0.0934)	(0.0048)	(0.0417)	(0.0069)
Efficiency	0.0026	0.0002	**0.0004****	**0.00004****
	(0.0031)	(0.0002)	(0.0002)	(0.00002)
Liquidity	0.0040	0.0004	-0.0006	-0.0001
	(0.0030)	(0.0004)	(0.0009)	(0.0001)
SMR	-0.0008	0.0001	-0.00004	**-0.0002***
	(0.0015)	(0.0001)	(0.0009)	(0.0001)
ROA	-0.1098	-0.0075	**-0.1686*****	**-0.0303*****
	(0.1117)	(0.0082)	(0.0520)	(0.0104)
△_House Price Index	-0.0003	0.0009	-0.0144	-0.0009
	(0.0005)	(0.0001)	(0.0119)	(0.0011)
△_Central Bank Policy	-0.0006	-0.0001	0.0008	**0.0003***
	(0.0014)	(0.0001)	(0.0006)	(0.0001)
GFC	**0.0059****	0.0001	-0.0021	-0.0002
	(0.0028)	(0.0003)	(0.0025)	(0.0003)
△_GDP	-0.0113	**-0.0047****	-0.0702	-0.0083
	(0.0232)	(0.0022)	(0.0437)	(0.0056)
Diversification	-0.0144	-0.0017	0.0023	0.0005
	(0.0088)	(0.0012)	(0.0056)	(0.0010)
Concentration_ratio	**0.1326***	0.0153	-0.0102	**0.0125***
	(0.0657)	(0.0137)	(0.0371)	(0.0069)
Institutional_environment	-0.0031	-0.0001	0.0008	**-0.0006***
	(0.0035)	(0.0002)	(0.0030)	(0.0003)
lnTA	-0.0041	-0.0001	-0.0011	-0.0002
	(0.0042)	(0.0003)	(0.0017)	(0.0002)
HighSTDebt	**-0.0050*****	**-0.0005****	-0.0002	0.0002
	(0.0018)	(0.0002)	(0.0010)	(0.0003)
Inflation	0.0283	0.0127	**0.0914***	**0.0202****
	(0.0501)	(0.0076)	(0.0501)	(0.0089)
credit_GDPgap	0.0304	0.0007	**-0.0100***	**-0.0016****
	(0.0189)	(0.0013)	(0.0059)	(0.0007)
Constant	0.0619	-0.0003	0.0515	0.0069
	(0.0988)	(0.0103)	(0.0487)	(0.0062)
Nbr. of obs.	399	399	671	671
R^2	0.1428	0.0830	0.1759	0.2307
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	18	18	11	11

This table reports fixed effects estimation of systemic risk measures (*MES*, *DCoVa*R,) on the asset commonality for All assets classes (Cosine_*AllAssetCom*) and control variables under a high and low *Financial Institution Targeted Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table B.7 Robustness Check (1): Cosine Similarity Measure (Borrower Focused Macroprudential Policy)

Model	(1)	(2)	(3)	(4)
Levels	High Borrower Focused macroprudential policy		Low Borrower Focused macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
Cosine_AllAssetCom	**0.0374***	-0.0013	0.0026	0.0008
	(0.0180)	(0.0025)	(0.0049)	(0.0006)
stockmarkcap_GDP	**-0.0073***	-0.0005	-0.0046	**-0.0009****
	(0.0042)	(0.0006)	(0.0030)	(0.0004)
Equityratio	**-0.0833*****	-0.0010	-0.0309	-0.0077
	(0.0229)	(0.0098)	(0.0566)	(0.0056)
Efficiency	**0.0152*****	**0.0009*****	0.00003	**0.00004***
	(0.0016)	(0.0002)	(0.0002)	(0.00002)
Liquidity	0.0017	-0.0006	-0.0002	0.0002
	(0.0023)	(0.0006)	(0.0011)	(0.0001)
SMR	-0.0008	-0.0003	-0.0012	-0.0001
	(0.0010)	(0.0002)	(0.0011)	(0.0001)
ROA	**0.5850****	-0.0005	**-0.1242****	**-0.0226****
	(0.2568)	(0.0423)	(0.0548)	(0.0105)
△_House Price Index	-0.0007	0.0001	-0.0006	**-0.0003***
	(0.0009)	(0.0002)	(0.0013)	(0.0001)
△_Central Bank Policy	**-0.0017****	-0.0001	**0.0020****	**0.0003****
	(0.0008)	(0.0002)	(0.0009)	(0.0001)
GFC	0.0108	-0.0008	0.0001	0.0001
	(0.0149)	(0.0013)	(0.0018)	(0.0002)
△_GDP	-0.0349	**-0.0071***	-0.0020	-0.0008
	(0.0298)	(0.0041)	(0.0236)	(0.0029)
Diversification	-0.0016	0.0024	-0.0040	-0.0009
	(0.0073)	(0.0018)	(0.0045)	(0.0008)
Concentration_ratio	0.0202	0.0368	**0.1281***	**0.0139****
	(0.0386)	(0.0298)	(0.0664)	(0.0059)
Institutional_environment	0.0021	-0.00002	0.0021	-0.0002
	(0.0017)	(0.0003)	(0.0033)	(0.0002)
lnTA	-0.0064	0.0009	0.00003	-0.0002
	(0.0038)	(0.0009)	(0.0012)	(0.0002)
HighSTDebt	-0.0013	-0.0002	**-0.0029****	-0.0001
	(0.0018)	(0.0003)	(0.0012)	(0.0003)
Inflation	-0.0001	0.0138	0.0307	**0.0083***
	(0.0271)	(0.0150)	(0.0412)	(0.0050)
credit_GDPgap	**0.0340*****	-0.0015	-0.0109	-0.0007
	(0.0100)	(0.0028)	(0.0078)	(0.0007)
Constant	0.1349	-0.0292	-0.0153	0.0048
	(0.0922)	(0.0293)	(0.0352)	(0.0044)
Nbr. of obs.	245	245	820	820
R^2	0.5217	0.1291	0.0734	0.1664
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	10	10	19	19

This table reports fixed effects estimation of systemic risk measures (*MES*, *DCoVaR*,) on the asset commonality for All assets classes (Cosine_*AllAssetCom*) and control variables under a high and low *Borrower focused Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table B.8 Robustness Check (1): Cosine Similarity Measure (Quantity Focused Macroprudential Policy)

Model	(1)	(2)	(3)	(4)
Levels	High Quantity focused macroprudential policy		Low Quantity Focused macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
Cosine_AllAssetCom	**0.0706***	**0.0051**	-0.0007	-0.0001
	(0.0181)	(0.0019)	(0.0034)	(0.0009)
stockmarkcap_GDP	**-0.0062**	-0.0004	-0.0043	**-0.0011**
	(0.0029)	(0.0004)	(0.0030)	(0.0005)
Equityratio	0.1372	0.0073	-0.0652	**-0.0117***
	(0.1468)	(0.0061)	(0.0413)	(0.0065)
Efficiency	**0.0099**	**0.0007**	0.0001	0.00003
	(0.0045)	(0.0003)	(0.0002)	(0.00003)
Liquidity	**0.0033***	-0.00004	-0.0010	0.0001
	(0.0017)	(0.0005)	(0.0009)	(0.0001)
SMR	-0.0015	0.0000	-0.0007	**-0.0002**
	(0.0016)	(0.0002)	(0.0010)	(0.0001)
ROA	0.0255	0.0045	**-0.1621***	**-0.0318***
	(0.2308)	(0.0084)	(0.0532)	(0.0101)
△_House Price Index	-0.0004	0.0001	-0.0013	**-0.0003***
	(0.0008)	(0.0002)	(0.0010)	(0.0001)
△_Central Bank Policy	-0.0000	-0.0000	**0.0011**	**0.0002***
	(0.0016)	(0.0002)	(0.0005)	(0.0001)
GFC	**0.0084**	0.0003	0.0002	-0.0001
	(0.0034)	(0.0005)	(0.0019)	(0.0003)
△_GDP	-0.0077	-0.0037	-0.0258	-0.0043
	(0.0282)	(0.0026)	(0.0304)	(0.0033)
Diversification	-0.0106	-0.0001	0.0002	-0.0003
	(0.0085)	(0.0011)	(0.0049)	(0.0008)
Concentration_ratio	**0.1482***	0.0323	0.0442	0.0082
	(0.0728)	(0.0211)	(0.0332)	(0.0057)
Institutional_environment	0.0027	0.0002	0.0017	-0.0005
	(0.0019)	(0.0003)	(0.0031)	(0.0003)
lnTA	**-0.0110***	-0.0004	-0.0000	-0.0001
	(0.0038)	(0.0007)	(0.0012)	(0.0002)
HighSTDebt	**-0.0030**	**-0.0005**	-0.0007	0.0002
	(0.0014)	(0.0003)	(0.0008)	(0.0002)
Inflation	0.0357	**0.0114***	**0.0877**	**0.0167**
	(0.0392)	(0.0064)	(0.0384)	(0.0067)
credit_GDPgap	**0.0447***	0.0006	**-0.0089***	-0.0005
	(0.0133)	(0.0020)	(0.0048)	(0.0006)
Constant	**0.1850**	-0.0011	0.0082	0.0046
	(0.0809)	(0.0204)	(0.0344)	(0.0051)
Nbr. of obs.	245	245	820	820
R^2	0.5217	0.1291	0.0734	0.1664
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	12	12	17	17

This table reports fixed effects estimation of systemic risk measures (*MES*, *DCoVaR*,) on the asset commonality for All assets classes (Cosine_*AllAssetCom*) and control variables under a high and low *Quantity focused Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table B.9 Robustness Check (2): Frequency Weights Estimation (Fweight)- Comprehensive Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High Comprehensive macroprudential policy		Low Comprehensive macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
AllAssetCom	**0.0464****	0.0020	-0.0094	0.0008
	(0.0207)	(0.0024)	(0.0079)	(0.0008)
stockmarkcap_GDP	**-0.0048***	**-0.0010****	**-0.0103***	**-0.0008*****
	(0.0027)	(0.0005)	(0.0059)	(0.0003)
Equityratio	0.0730	0.0041	-0.0143	**-0.0096***
	(0.1008)	(0.0056)	(0.0492)	(0.0050)
Efficiency	0.0037	0.0002	0.0002	**0.0001*****
	(0.0034)	(0.0002)	(0.0002)	(9.21)
Liquidity	0.0034	0.0002	**-0.0038***	0.00005
	(0.0026)	(0.0005)	(0.0020)	(0.0001)
SMR	-0.0010	0.00002	0.0004	-0.0002
	(0.0014)	(0.0001)	(0.0018)	(0.0001)
ROA	-0.1331	-0.0102	**-0.1241****	**-0.0275****
	(0.1388)	(0.0105)	(0.0613)	(0.0111)
△_House Price Index	-0.0003	0.0001	0.0040	0.00002
	(0.0005)	(0.0002)	(0.0041)	(0.0003)
△_Central Bank Policy	-0.0009	-0.00005	**0.0012****	**0.0002***
	(0.0010)	(0.0002)	(0.0005)	(0.0001)
GFC	0.0031	-0.0001	-0.0001	0.0001
	(0.0031)	(0.0005)	(0.0022)	(0.0001)
△_GDP	-0.0084	**-0.0052****	-0.0118	0.0022
	(0.0205)	(0.0025)	(0.0258)	(0.0026)
Diversification	**-0.0108***	-0.0016	0.0048	-0.0000
	(0.0059)	(0.0014)	(0.0059)	(0.0005)
Concentration_ratio	**0.1358***	0.0268	0.0345	**0.0055***
	(0.0788)	(0.0220)	(0.0440)	(0.0029)
Institutional_environment	-0.0025	-0.0004	0.0028	0.0001
	(0.0038)	(0.0005)	(0.0028)	(0.0002)
lnTA	-0.0025	0.0004	0.0024	-0.0001
	(0.0031)	(0.0005)	(0.0021)	(0.0002)
HighSTDebt	**-0.0044*****	**-0.0005***	-0.0011	-0.0004
	(0.0013)	(0.0003)	(0.0019)	(0.0004)
Inflation	-0.0022	0.0132	0.0452	-0.0006
	(0.0309)	(0.0083)	(0.0477)	(0.0047)
credit_GDPgap	**0.0295***	0.0002	-0.0073	0.0004
	(0.0159)	(0.0019)	(0.0060)	(0.0003)
Constant	0.0068	-0.0138	-0.0514	0.0042
	(0.0765)	(0.0162)	(0.0469)	(0.0039)
Nbr. of obs.	7639	7639	1977	1977
R^2	0.1319	0.0787	0.1681	0.1976
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	18	18	11	11

This table reports frequency weight estimation of systemic risk measures (*MES*, *DCoVaR*,) on the asset commonality for All assets classes (*AllAssetCom*) and control variables under a high *Comprehensive Focused Macroprudential Policy*. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table B.10 Robustness Check (2): Frequency Weights Estimation (Fweight) Financial Institution Targeted Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High FIT macroprudential policy		Low FIT macroprudential policy	
Variables	MES	*DCoVaR*	MES	*DCoVaR*
AllAssetCom	**0.0595****	**0.0047****	-0.0036	-0.0020
	(0.0247)	(0.0020)	(0.0043)	(0.0013)
stockmarkcap_GDP	-0.0042	**-0.0008***	**-0.0161****	-0.0025
	(0.0027)	(0.0004)	(0.0072)	(0.0015)
Equityratio	0.0720	0.0043	-0.0113	-0.0083
	(0.0985)	(0.0052)	(0.0550)	(0.0062)
Efficiency	0.0037	0.0002	**0.0003****	**0.00004****
	(0.0034)	(0.0002)	(0.0001)	(0.00002)
Liquidity	0.0030	0.0003	-0.0014	0.0001
	(0.0025)	(0.0005)	(0.0014)	(0.0001)
SMR	-0.0011	0.0001	0.0004	-0.0003
	(0.0014)	(0.0001)	(0.0018)	(0.0002)
ROA	-0.1198	-0.0085	**-0.1830*****	**-0.0308*****
	(0.1381)	(0.0104)	(0.0553)	(0.0090)
△_House Price Index	-0.0003	0.0001	-0.0006	0.0004
	(0.0005)	(0.0002)	(0.0039)	(0.0007)
△_Central Bank Policy	-0.0009	-0.0001	**0.0013****	**0.0003****
	(0.0010)	(0.0002)	(0.0006)	(0.0002)
GFC	0.0042	0.0000	-0.0042	-0.0007
	(0.0027)	(0.0003)	(0.0026)	(0.0008)
△_GDP	-0.0077	**-0.0054****	-0.0350	-0.0037
	(0.0204)	(0.0026)	(0.0285)	(0.0048)
Diversification	**-0.0106***	-0.0017	-0.0018	-0.0002
	(0.0060)	(0.0014)	(0.0056)	(0.0006)
Concentration_ratio	0.1306	0.0220	0.0275	**0.0201***
	(0.0782)	(0.0206)	(0.0441)	(0.0118)
Institutional_environment	-0.0018	-0.0000	0.0012	-0.0008
	(0.0039)	(0.0004)	(0.0022)	(0.0006)
lnTA	-0.0040	0.0001	0.0027	0.0003
	(0.0035)	(0.0005)	(0.0024)	(0.0004)
HighSTDebt	**-0.0041*****	**-0.0005***	-0.0002	-0.0002
	(0.0012)	(0.0003)	(0.0019)	(0.0004)
Inflation	0.0052	**0.0143***	0.0464	0.0138
	(0.0306)	(0.0083)	(0.0481)	(0.0125)
credit_GDPgap	**0.0297***	0.0003	-0.0034	-0.0001
	(0.0165)	(0.0019)	(0.0061)	(0.0006)
Constant	0.0324	-0.0076	-0.0521	-0.0056
	(0.0784)	(0.0153)	(0.0584)	(0.0117)
Nbr. of obs.	7880	7880	1736	1736
R^2	0.1318	0.0794	0.2200	0.2126
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	18	18	11	11

This table reports frequency weight estimation of systemic risk measures (*MES, DCoVaR*,) on the asset commonality for All assets classes (*AllAssetCom*) and control variables under a high and low Financial Institution Targeted Macroprudential Policy. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table B.11 Robustness Check (2): Frequency Weights Estimation (Fweight) Borrower Focused Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High Borrower Focused macroprudential policy		Low Borrower Focused macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
AllAssetCom	**0.0432***	-0.0001	0.0112	0.0013
	(0.0237)	(0.0027)	(0.0151)	(0.0013)
stockmarkcap_GDP	-0.0049	-0.0003	**-0.0145*****	**-0.0018*****
	(0.0039)	(0.0004)	(0.0054)	(0.0007)
Equityratio	**-0.0701*****	0.0001	0.0338	0.0026
	(0.0238)	(0.0100)	(0.1118)	(0.0060)
Efficiency	**0.0161*****	**0.0010*****	-0.0001	**0.0001****
	(0.0013)	(0.0002)	(0.0003)	(0.00007)
Liquidity	0.0017	-0.0008	-0.0005	**0.0006***
	(0.0020)	(0.0008)	(0.0019)	(0.0003)
SMR	-0.0010	-0.0004	-0.0016	0.0000
	(0.0009)	(0.0002)	(0.0020)	(0.0001)
ROA	**0.5242****	-0.0022	-0.1097	**-0.0120****
	(0.1853)	(0.0425)	(0.1064)	(0.0057)
△_House Price Index	-0.0006	0.0002	0.0005	-0.0001
	(0.0007)	(0.0002)	(0.0012)	(0.0002)
△_Central Bank Policy	**-0.0017****	-0.0002	0.0010	0.0001
	(0.0008)	(0.0001)	(0.0016)	(0.0001)
GFC	0.0055	-0.0008	-0.0009	-0.0001
	(0.0120)	(0.0012)	(0.0019)	(0.0002)
△_GDP	-0.0271	**-0.0089***	-0.0009	-0.0025
	(0.0230)	(0.0046)	(0.0218)	(0.0029)
Diversification	-0.0014	0.0019	**-0.0175*****	**-0.0023****
	(0.0061)	(0.0019)	(0.0065)	(0.0010)
Concentratio_ratio	0.0343	0.0461	**0.2493****	**0.0177***
	(0.0378)	(0.0379)	(0.1098)	(0.0094)
Institutional_environment	0.0040	0.0002	0.0030	-0.0001
	(0.0026)	(0.0005)	(0.0038)	(0.0003)
lnTA	-0.0044	0.0008	0.0029	0.0001
	(0.0032)	(0.0009)	(0.0019)	(0.0002)
HighSTDebt	-0.0015	-0.0003	**-0.0050****	-0.0004
	(0.0020)	(0.0003)	(0.0019)	(0.0003)
Inflation	0.0021	0.0183	-0.0045	0.0037
	(0.0289)	(0.0170)	(0.0459)	(0.0046)
credit_GDPgap	**0.0328*****	-0.0019	-0.0037	0.0009
	(0.0094)	(0.0032)	(0.0062)	(0.0008)
Constant	0.0711	-0.0295	**-0.1159****	-0.0036
	0.0432*	-0.0001	0.0112	0.0013
Nbr. of obs.	245	245	820	820
R^2	0.5217	0.1291	0.0734	0.1664
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	10	10	19	19

This table reports frequency weight estimation of systemic risk measures (*MES, DCoVaR*,) on the asset commonality for All assets classes (*AllAssetCom*) and control variables under a high and low Borrower focused Macroprudential Policy. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table B.11 Robustness Check (2): Frequency Weights Estimation (Fweight) Quantity Focused Macroprudential Policy

Model	(1)	(2)	(3)	(4)
Levels	High Quantity Focused macroprudential policy		Low Quantity Focused macroprudential policy	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
AllAssetCom	**0.0977*****	0.0071	0.0008	-0.0021
	(0.0250)	(0.0042)	(0.0059)	(0.0015)
stockmarkcap_GDP	-0.0044	-0.0004	**-0.0098***	**-0.0015****
	(0.0030)	(0.0004)	(0.0050)	(0.0007)
Equityratio	0.0997	0.0048	-0.0774	-0.0067
	(0.1212)	(0.0051)	(0.0567)	(0.0049)
Efficiency	**0.0102****	**0.0008****	0.0001	**0.0001****
	(0.0044)	(0.0003)	(0.0002)	(0.00003)
Liquidity	0.0026	-0.0004	**-0.0030***	0.0004
	(0.0017)	(0.0006)	(0.0018)	(0.0003)
SMR	-0.0016	-0.0000	-0.0005	-0.0001
	(0.0014)	(0.0003)	(0.0015)	(0.0001)
ROA	0.0592	0.0079	**-0.1109***	-0.0174
	(0.2075)	(0.0087)	(0.0628)	(0.0152)
△_House Price Index	-0.0005	0.0001	**-0.0009***	**-0.0004****
	(0.0006)	(0.0002)	(0.0005)	(0.0002)
△_Central Bank Policy	-0.0005	-0.0001	0.0002	**0.0002***
	(0.0012)	(0.0002)	(0.0010)	(0.0001)
GFC	**0.0068****	0.0001	-0.0003	-0.0004
	(0.0032)	(0.0005)	(0.0017)	(0.0004)
△_GDP	-0.0050	-0.0048	0.0107	-0.0007
	(0.0240)	(0.0033)	(0.0153)	(0.0020)
Diversification	-0.0082	-0.0000	**-0.0128****	**-0.0019***
	(0.0074)	(0.0013)	(0.0058)	(0.0011)
Concentratio_ratio	**0.1322***	0.0423	0.0805	0.0051
	(0.0697)	(0.0295)	(0.0634)	(0.0084)
Institutional_environment	0.0033	0.0003	0.0027	-0.0005
	(0.0026)	(0.0004)	(0.0025)	(0.0004)
lnTA	**-0.0093****	-0.0002	0.0034**	0.0004
	(0.0035)	(0.0010)	**(0.0016)**	(0.0003)
HighSTDebt	**-0.0034****	**-0.0007****	-0.0016	0.0002
	(0.0014)	(0.0003)	(0.0018)	(0.0002)
Inflation	0.0329	**0.0133***	**0.0835****	**0.0150***
	(0.0315)	(0.0072)	(0.0387)	(0.0088)
credit_GDPgap	**0.0433*****	0.00003	**-0.0066***	0.0003
	(0.0119)	(0.0028)	(0.0036)	(0.0006)
Constant	0.1185	-0.0101	-0.0831*	-0.0070
	(0.0717)	(0.0277)	(0.0430)	(0.0071)
Nbr. of obs.	5926	5926	3690	3690
R^2	0.2140	0.1288	0.1352	0.1859
Individual fixed Effects	Yes	Yes	Yes	Yes
Nbr. of countries.	12	12	17	17

This table reports weighted frequency weights estimation of systemic risk measures (*MES, DCoVaR*,) on the asset commonality for All assets classes (*AllAssetCom*) and control variables under a high and low Quantity focused Macroprudential Policy. All variables are defined in Table 2.1. The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

CHAPTER 3

Does similarity in environmental behavior amongst banks contribute to an increase in systemic risk?

3.1. Introduction

Recently, there have been considerable debates about the impacts of climate changes on financial stability (Breitenstein et al., 2021; Giglio et al., 2021; Venturini, 2022). Central Banks (CBs) around the world have also been keen to understand how the both effects of physical climate change and transition from a fossil-fuel economy to a low-carbon economy will impact financial stability given the global drive to achieve the Paris Net Zero agreement (Claassen's et al. 2022, Financial Stability Board (FSB) 2022, European Systemic Risk Board (ESRB) 2021, 2022, European Central Bank (ECB) 2021, Bank of International Settlement (BIS) 2021a, 2021b). Both banks and other corporate organizations are directed or encouraged to demonstrate their support for low-carbon emissions. Hence, corporations do this by adhering to Environmental, Social, and Governance (ESG) principles, as emphasized by several researchers (Bruno and Lagasio, 2021; Volz et al., 2015; Batten et al., 2016; Volz, 2017; Campiglio et al., 2018; Dikau and Volz, 2019; Matallín-Saez et al., 2019). At the heart of this transition, CBs are crafting financial instruments aimed at ensuring readily available funding for supporting environmentally sustainable expansion (BIS 2021b; ESRB 2021; Financial Stability Oversight Council (FSOC) 2021; Carney 2021). In addition, other governmental agencies demonstrate their support by implementing a range of policies, including levies on high carbon emissions and subsidies for green innovations, among others. Previously, several researchers have examined the implications of sustainable practices on firms performance with a major focus on non-financial corporations (Wu and Shen, 2013; Shen et al., 2016), profitability (Garcia-Sanchez and Garcia-Merca, 2017), cost of equity capital (El Ghoul et al., 2011), shareholders wealth (Krüger, 2015), and credit ratings (Jiraporn et al., 2014), and a few on the impact on risk (Santis, Albuquerque, and Lizarelli, 2016; Godfrey et al. 2020; Ameur et al., 2019; Jo and Na, 2012).

The transition to sustainability and the reduction of carbon emissions may expose the financial sector to substantial risks through the several channels. Firstly, Carney (2015) argues that a sudden shift away from fossil fuels could harm financial assets tied to them. Secondly, the transition to a green economy can render previously profitable sectors, like those relying on coal or fossil fuels, obsolete, resulting in the emergence of "stranded assets" that unexpectedly lose value (Ansari and Holz, 2020; Warwick et al., 2021). The switch from fossil fuels to environmentally friendly alternatives could also results in a systemic crisis, according to Bolton et al. (2020). Furthermore, academics like Jaffe (2020) and Palao & Pardo (2017) contend that increased focus on climate financial risk could lead to a broad reevaluation of losses brought on by climate change, which may be made worse by herd behavior. The assets of banks and financial institutions would be strongly reduced if they all stopped providing loans and other financial services to consumers of fossil fuels (Dillusio et al., 2021). The energy and fossil fuel sectors make up a sizable amount of banks' balance sheets, according to the arguments made by Dietz et al. (2016), Battiston et al. (2017), and Mercure et al. (2018). Thirdly, writing down these assets could result in network failures both within the banking industry and outside of it. Additionally, there is a chance of mispricing financial risks associated with climate change and the green transition, which could result in bad investments and loan write-offs, and endanger the stability of the financial system (Jonas et al., 2022). Fourthly, many of these fossil fuel assets still serve as collateral on the balance sheets of most banks, thus further increasing their credit risk exposure. Therefore, in the event of stranded assets and huge write-offs, these assets may suddenly become worthless, such that they are unable to recover the cost of the credit exposure or trigger a series of counterparty risks (Curcio et al., 2023). Thus, a general blanket restriction on carbon emissions for firms, coupled with financial friction, may cause huge disruptions to their balance sheets. As the value of fossil fuel-related assets decreases, fire sales could occur, further devaluing these assets (Krishnamurthy, 2010; Shleifer & Vishny, 2011; Roncoroni et al., 2021).

This paper contributes to this literature by investigating whether the transition toward a more sustainable economy might lead banks to adopt similar environmentally responsible practices, potentially resulting in an increase in systemic risk. To the best of my knowledge, this paper represents the first attempt to investigate the impact of the commonality of banks' environmental behavior on systemic risk. Kruger et al. (2020) suggest that alignment with cleaner and eco-friendly objectives might lead banks to reallocate investments similarly. If all banks heavily invest in the same pool of assets, a single shock can impact all banks and increase systemic risk, given the high degree of interconnectedness in the banking sector. We address this issue by examining how the commonality of a bank's environmental practices influences systemic risk. Specifically, we examine the presence of a non-linear relationship between the degree of commonality in banks' environmental behavior and systemic risk. The adoption of environmentally friendly practices can lead banks to invest in new sectors, enhancing the diversification of their activities and consequently reducing their probability of default. However, a high level of similarity in environmental behavior and diversification processes may increase the probability of joint failures. There is the possibility that climate change may resemble previous trends in fossil fuels when exploration began and exhibit a non-linear model with fat-tailed distributions. This simply because it may result in an excess credit supply to eco-friendly initiatives or firms (Bolton et al., 20021). Additionally, this study examines whether the relationship between commonality in environmental behavior and systemic risk is affected by the degree of banks' portfolios overlap. The combination of higher levels of commonality in both banks' assets and environmental behavior is anticipated to amplify systemic risk. Apart from the incentives to adopt environmentally friendly activities, banks often exhibit herding behavior by imitating competitors or peers to avoid regulatory penalties, resulting in similar asset portfolios (Acharya and Yorulmazer, 2008). Furthermore, the possibility of a collective failure becomes possible to banks, as the anticipation of government bailouts in the event of multiple collapses may drive them towards similar asset classes or riskier assets, potentially increasing excessive risk-taking (Gropp et al., 2014; Laeven et al., 2016; Allen et al., 2018). Higher degree of commonality in eco-friendly investments might increase systemic risk, particularly if banks also share a high level of asset overlap with other banks.

The empirical analysis is conducted using a sample comprising 91 systemically important financial institutions (SIFIs) spanning 27 countries, covering the period from 2002 to 2021. To measure the similarity of a bank's environmental practices, we consider a wide range of environmental factors, such as CO2 emissions and climate policy operations risk, extracted from the "E" score within the broader ESG scores (Environmental, Social, and Governance factors). We compute the similarity of environmental factors among the world's largest banks using the cosine approach, as commonly used in the existing literature (Salton and McGill, 1987; Barucca et al., 2021; Daniel Fricke, 2016; Getmansky et al., 2016). Our results indicate a non-linear relationship, substantiated by the significant p-value from the Lind and Mehlum test (2010). Our findings reveals that the commonality of banks' environmental behaviors bears statistical significance and holds a negative association with systemic risk, while the quadratic term exhibits a positive association with systemic risk. Specifically, the findings reveal that higher levels of commonality of banks' environmental behavior above the 75^{th} percentile threshold expose them to systemic risk.

The remainder of the paper is organized as follows. Section 3.1 describes the sample and explains how bank's environmental commonality and systemic risk are measured. Section 3.2 presents the results, while Section 3.3 presents further investigations and various tests to ensure the robustness of the results. Section 3.4 concludes the paper.

3.2. Sample and data description

3.2.1. Our sample

We conducted a global analysis to investigate whether the commonality of environmental practices among Systemically Important Financial Institutions (SIFIs) impacts systemic risk. The study focuses on major banks with total assets equal to or exceeding USD 50 billion as of 2019, identifying 133 such banks using annual consolidated balance sheets and income statements from Fitch Connects. To evaluate the commonality of environmental impacts Environmental scores from the ASSET 4 database (Refinitiv) spanning 2002–2021 were sourced, as detailed in Table 3.1. Additionally, we integrated macroeconomic indicators from the World Bank Global Financial Development Database and central bank policy rates from the Bank for International Settlements statistics.

Market data for systemic risk computation were extracted from Refinitiv Eikon DataStream, encompassing factors like bank market value, stock price, total liabilities, and the World Market Index (MSCI). Banks lacking essential data, including stock price information, were excluded, resulting in a final sample of 91 banks and 1,323 observations spanning from 2002 to 2021. These banks are listed in Table C.1 in the Appendix C, while the 27 countries are displayed in Table C.2. in Appendix C.

The sample comprises 33 banks from North America, 34 from Europe, 19 from Asia, 4 from South America, and 1 from Australia. Notably, the Bank of China emerges as the largest participant, with assets exceeding $3 trillion. To address potential outliers, all continuous financial variables are winsorized at the 1% and 99% percentiles.

Table 3.1 ESG Factors

	Environmental Factors
1	ESG Resource Use Score
2	ESG Emissions Score
3	ESG Innovation Score
4	Climate Change Commercial Risks Operations
5	Environmental Partnerships
6	Environmental Restoration Initiatives
7	Environmental Waste Reduction
8	Policy Emissions
9	Staff Transport Impact Reduction
10	Targets Emissions
11	Scope 3 To Revenues
12	CO2 Equivalent Emissions to Revenues
13	Total Waste to Revenues
14	Environmental Asset Under Management
15	Environmental Products
16	Renewable Clean Energy Products
17	Equator Principles or Environmental Project Financing
18	Environmental Materials Sourcing
19	Environment Supply Chain Management
20	Environmental Supply Chain Monitoring
21	Environment Management Team
22	Green Buildings
23	Policy Energy Efficiency
24	Policy Environmental Supply Chain
25	Policy Water Efficiency
26	Targets Energy Efficiency
27	Targets Water Efficiency
28	Total Energy Use to Revenues

Table 3.2 Definitions, Data Sources and Summary Statistics for Variables

Variables	Definition	Source	N	Mean	Std. Dev.	min	max
RISK MEASURES							
MES	Marginal Expected Shortfall (*MES*), introduced by Acharya et al. (2017) and Brownlees and Engle (2017), is defined as the marginal contribution of a bank to systemic risk as measured by the Expected Shortfall of the financial system.	Refinitiv Eikon (DataStream)	1,125	0.010	0.0168	-0.0324	0.287
DCoVaR	Delta-CoVaR (*DCoVar*), introduced by Adrian and Brunnermeier (2016), corresponds to the Value at Risk of the financial system obtained conditionally on a specific event affecting a given bank.	Refinitiv Eikon (DataStream)	1,125	0.002	0.00320	-0.003	0.0295
ENVIRONMENT RELATED VARIABLES							
ENVIRONCom	Banks measure of similarities for all Environment Pillar ONLY (see Table 3.1) using the Cosine Similarity measure that captures the average level of similarity between one bank to the total sample of banks for all Environment Score. The measure ranges between 0 and 1, with 0 reflecting no Environment commonality and the maximum value of 1 reflecting perfect similarity in bank environmental behavior	Fitch Connects	1,323	0.815	0.193	0	1
SQENVIRONCom	Squared term bank measure of similarities for all Environment Pillar ONLY (see Table 3.1) using the Cosine Similarity measure that captures the average level of similarity between one bank to the total sample of banks for all Environment Score. The measure ranges between 0 and 1, with 0 reflecting no Environment commonality and the maximum	Fitch Connects	1,323	0.701	0.236	0	1

	value of 1 reflecting perfect similarity in bank environmental behavior.						
EPI	Environmental Policy Index:	https://epi.yale.edu/downloads	1323	52	7.78	25.52	71.56
EPS	Environmental Stringency Index	oecd.org	1165	3.71	0.91	0	4.89
ASSETS COMMONALITY MEASURE							
Cosine_AllAssetCom	Banks measure of cosine similarities for all asset classes (see Table 3.5) using the cosine distance measure that captures the average level of similarity between one bank to the total sample of banks for all asset's portfolio. The measure ranges between 0 and 1, with 0 reflecting no asset commonality (i.e., no portfolio overlap) and the maximum value of 1 reflecting total asset commonality (complete portfolio matching). This variable was therefore converted to a dummy variable equal 1 if greater than the mean and 0 if otherwise.	Fitch Connects	1,323	0.68	0.46	0	1
BANK CONTROL VARIABLES							
lnTA	Natural logarithm of total assets	Fitch Connects	1,264	26.16	1.470	23.57	28.74
Equityratio	Equity ratio (Total Equity divided by risk weighted Assets),	Fitch Connects	1,257	0.0781	0.0343	0.00128	0.328
ROA	Net income divided by total assets,	Fitch Connects	1,242	0.0076	0.00764	-0.114	0.0569
Efficiency	Operating expense divided by operating income,	Fitch Connects	1,242	0.708	0.314	0.366	9.287
Liquidity	Cash Balances Due+ Securities+ Fed. Funds Sold and Repos +Trading Account Assets-Pledged Securities) divided by total assets (orthogonalized on SMR),	Fitch Connects	1,257	0.331	0.173	0.0157	1.583
Diversification	Net interest income divided by total revenue	Fitch Connects	1,242	0.406	0.208	0.00851	0.998
HighSTDebt	Dummy variable taking the value of one if a bank's Wholesale funding ratio is higher than the median in the sample. Wholesale funding ratio is wholesale funding divided by total	Fitch Connects	1,323	0.472	0.499	0	1

	assets						
SMR	Sensitivity to market Risk; defined as Total Securities divided by total assets,	Fitch Connects	1,255	0.215	0.117	0.0187	0.774
GFC	Dummy variable taking the value of one for 1 for the period 2007- 2009	NBER	1,323	0.117	0.322	0	1
Concentration_ratio	Concentration Ratio measured by the total assets of the five largest banks divided by the total assets of the banking system	Fitch Connects	1,264	0.457	0.221	0.246	1
COUNTRY CONTROL VARIABLES (COUNTRY SPECIFIC)							
StockMap_GDP	Stock Market Capitalization, lagged by one year. Total value of all listed shares in a stock market as a percentage of GDP. Total value of all listed shares in a stock market as a percentage of GDP.	World Bank Financial Development Data-World Federation of Exchanges; Global Stock Markets Factbook and supplemental S&P data, Standard & Poor's (IMF)	990	1.097	0.524	0.103	3.980
△_Central Bank Policy	Central Bank Policy Rate	Bank of International Settlement, except for Taiwan, Russia, extracted from St louis Fred Website	1,070	-0.15	3.1	-16	86
△_GDP	Change in GDP: Annual change in Gross Domestic Products	IMF Statistics	1,111	-0.06	0.267	-1	0.145
Institutional_environment	Institutional Environment: computed following taking the average of 6 variables namely (i) Control of Corruption (ii) Government Effectiveness (iii) Political Stability/Absence of Violence/Terrorism (iv) Regulatory Quality: (v) Rule of Law (vi) Voice and Accountability: Estimate. I normalized the variable to values between 0 and 1. The variable was developed by Kaufman et al (2009) and known as (KKZ)	World Bank Data	1,264	0.690	0.250	0	1
Inflation	Inflation Rate: Level of inflation in each country.	World Bank	1,323	0.022	0.0235	-0.0174	0.196
Credit_GDPgap	Credit to GDP gap to measure level procyclicality.	Bank of International Settlement	1,245	0.007	0.132	-0.538	0.413

This table defines the variables and reports summary statistics for the full sample

Table 3.3 Correlation and Multicollinearity Panel A

S/N		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	*ENVIRONCom*	1																	
2	*SQENVIRONCom*	0.89	1																
3	GFC	-0.13	-0.09	1															
4	covid	0.50	0.41	-0.19	1														
5	stockmcap_GDP	0.12	0.13	-0.08	0.18	1													
6	Equityratio	-0.01	0.02	-0.07	0.01	0.10	1												
7	credit_GDPgap	0.03	-0.01	0.21	-0.01	0.01	-0.20	1											
8	EfficiencyRatio	-0.07	-0.07	0.13	0.00	-0.11	-0.07	-0.06	1										
9	Liquidityratio	0.02	0.02	-0.09	0.09	0.02	-0.17	0.00	0.01	1									
10	SMR	-0.01	0.02	0.03	0.00	0.05	-0.18	-0.02	-0.03	0.78	1								
11	ROA	0.05	0.08	-0.09	-0.03	0.04	0.33	0.02	-0.51	0.02	0.02	1							
12	Concentration_ratio	0.04	0.06	-0.07	0.06	0.12	0.12	-0.07	0.01	0.10	0.18	-0.03	1						
13	Institutional_environment	0.59	0.54	-0.08	0.41	0.17	-0.05	-0.02	-0.04	0.03	0.01	0.01	0.04	1					
14	△_Central Bank Policy	-0.16	-0.21	0.07	-0.02	-0.11	-0.08	0.06	0.10	0.04	-0.03	-0.12	-0.02	-0.20	1				
15	Inflation	0.14	0.13	0.03	0.02	-0.33	0.17	0.13	-0.05	0.00	-0.05	0.25	-0.11	0.01	-0.08	1			
16	HighSTDebt	-0.06	-0.07	0.01	0.02	-0.18	-0.29	0.01	0.10	0.06	-0.04	-0.14	-0.13	-0.04	0.11	-0.004	1		
17	Diversification	0.08	0.08	0.00	0.04	-0.21	0.32	-0.14	0.08	-0.39	-0.43	-0.01	0.01	-0.02	-0.06	0.161	-0.17	1	
18	lnTA	-0.04	-0.07	0.02	0.06	-0.02	-0.46	0.01	-0.01	0.18	0.09	-0.10	-0.24	0.04	0.07	-0.090	0.37	-0.35	1

This table shows the correlation matrix (Panel A) and the variance inflation factors, VIF (Panel B). All variables are as defined in Table 3.2

Panel B: Variance inflation factors		
Variable	VIF	1/VIF
ROA	1.94	0.515290
EFRatio	1.91	0.523201
Equityrat	1.83	0.546741
Diversification	1.75	0.569909
lnTA	1.71	0.584727
△_Central Bank Policy	1.66	0.602912
GFC	1.60	0.623713
stckmcap_GDP	1.57	0.636791
Covid	1.42	0.706401
credit_GDPgap	1.41	0.711004
Inflation	1.36	0.736374
HighSTDebt	1.33	0.751519
Liquidity Ratio	1.31	0.764734
ENVIRONCom	1.28	0.782394
SMR	1.25	0.798662
Concentration_ratio	1.14	0.880689
Institutional_environment	1.07	0.936066
Mean VIF	1.50	

3.2 Variable Construction

3.2.1 Measurement of Environmental Behavior Commonality Amongst Banks

We analyze the commonality of the bank's environmental behavior using 29 environmental scores including in the computation of the ESG score, as listed in Table 3.1. This factor covers a wide variety of issues surrounding climate change, such as CO2 emission, climate policy operations, and risk, environmental waste reduction, etc. To determine if banks with similar environmental behavior are exposed to the same underlying risks leading to an increase in systemic risk, we need a metric that captures the similarity in environmental scores. To accomplish this, we use the cosine similarity measure which calculates the similarity of a bank's environmental behavior between bank pairs. This method has been used in earlier studies to assess the commonality of bank assets (Cai et al., 2018; Fricke, 2016). It accurately estimates the separation between two vectors. In line with the methodologies of Barucca et al. (2021), Daniel Fricke (2016), and Getmansky et al. (2016), we calculate the distance metrics for each weight of Environmental scores as follows;

$$Cosim_{i,t,} = \frac{\Sigma_{k=1}^{k} w_{i,k} w_{j,k}}{\sqrt{\Sigma_{k=1}^{k} w_{i,k}^2} \, x \sqrt{\Sigma_{k=1}^{k} w_{j,k}^2}} \qquad (1)$$

$$ENVIRONCom_{i,t} = \frac{\sum_{i \neq j, i=1}^{i} Cosim_{i,t}}{N_t - 1} \quad (2)$$

where $Cosim_{i,t}$ represents the cosine similarity between bank *i* to all other bank *j* for each environmental scores and year. $w_{i,k,t}$ refers to the weight bank i share of environmental scores *k*, with $\sum_{k=1}^{K} w_{i,k,t} = 1$. Thus, the greater angle formed between the two-coordinate vector comparison relates to the cosine similarity. In other words, the smaller degree captures similarity, such that similarity ranges from -1 (dissimilar) to 1 (similar). However, the matrix W is non-negative, so the minimum value for *Cosim* is 0. The variable $ENVIRONCom_{i,t}$ is the average cosine similarity measure by taking into consideration the number of banks *N* per year.

Lastly, we take into consideration the quadratic term of our variable to account for the non-linear relationship that may exist. Hence, it is defined as $SQENVIRONCom_{i,t}$. The summary descriptive statistics in Table 3.2 indicate that large banks across the globe exhibit an average degree of environment commonality of 0.76 and, as such, pinpoint that these banks have a relatively high similarity in their environmental behaviour or sustainable practices. However, there is significant variation between banks, as indicated by the standard deviations.

3.2.2. Risk measures

To explore the impact of commonality in banks' environmental behavior on systemic risk, this study employs bank-level systemic risk measures commonly used in the literature. The marginal expected shortfall (MESi,t) is calculated using the methodology described by Brownless and Engle (2017) and Acharya et al. (2017). $MES_{i,t}$ evaluates the anticipated loss of an equity for a specific company (Bank *i*) under adverse market conditions. Formally, it is expressed as

$$MES_{i,t}(\mathrm{Q}) = \mathrm{E}[\mathrm{R}_{i,t} | \mathrm{R}_{m,t} < \mathrm{VaR}_{m,t}^{Q}] \quad (3)$$

where $R_{i,t}$ signifies the daily stock returns of bank *i* at time *t*, $R_{m,t}$ denotes the return of the World market index (MSCI) at time t, and $VaR_{m,t}^{Q}$ represents the market Value-at-Risk at confidence level *Q*. Following established conventions, we present the negative of MES, with higher values indicating increased systemic risk. Additionally, we incorporate the $DCoVaR_{i,t}$ metric, initially introduced by Adrian & Brunnermeier (2016). This measure gauges the Value at Risk (VaR) of the financial system under specific event conditions for an individual bank. Specifically, $DCoVaR_{i,t}$ for a bank signifies the disparity between the VaR of market returns given the bank's financial distress state and the VaR of market returns given the bank's median state. To calculate the $DCoVaR_{i,t}$ measures, we employ standard quantile regressions, as outlined in Adrian and Brunnermeier (2016). The dependent variables used for systemic risk ($MES_{i,t}$ and $DCoVaR_{i,t}$) possess mean values of 0.01 and 0.002 respectively, as detailed in Table 3.2.

3.2.3. Bank's environmental behavior commonality and systemic risk

3.2.4. Econometric Specification

To evaluate the impact of commonality on banks environmental behavior on systemic risk, I use the following specification.

$$Risk_{i,t} = \alpha + \beta_1\ ENVIRONCom_{i,t} + \beta_2\ ENVIRONCom^2{}_{i,t} + \sum_p \lambda_p \mathrm{Country}_{j,t} + \sum_p \delta_p \mathrm{X}_{i,t} + \gamma_i + \varepsilon_{i,t} \qquad [4]$$

where $Risk_{i,t}$ refers to the systemic risk variable ($MES_{i,t}$ or $DCoVaR_{i,t}$), and $ENVIRONCom_{i,t}$ measures the degree of commonality in bank's environmental behavior. A series of country-level variables are included ($\mathrm{Country}_{j,t}$), representing country-specific macroeconomic factors. This is particularly important as the sample comprises of 27 countries with varying characteristics. Following Gonzalez (2022), the variable $Institutional\_Environment_{j,t}$, developed by Kaufman et al. (2009), is incorporated to measure the level of institutional environment of each country. The ability of each country to monitor and implement bank's regulatory guidance may vary around the overall institutional environment beyond banking industry alone and as such reduce their exposure to risk. The variable is computed by taking the average of 6 variables namely i) Control of Corruption ii) Government Effectiveness iii) Political Stability/Absence of Violence/Terrorism iv) Regulatory Quality: v) Rule of Law, and 6) Voice and Accountability estimates. Thus, countries with better $Institutional\_Environment_{j,t}$ may experience lower bank default rates and are less prone to systemic risk. Also, we consider variations in income levels and economic activity that may fluctuate with the financial cycle or trend by incorporating the credit-to-GDP gaps ($credit\_GDPgap_{j,t}$) into the analysis. We source the $credit\_GDPgap_{j,t}$ from the Bank of International Settlement. The credit gap, which measures the difference between the credit-to-GDP ratio and a one-sided Hodrick-Prescott (HP) -filtered trend, serves as a valuable predictor of financial crises. The filter refers to a data-smoothing technique. The HP filter is commonly applied during analysis to remove short-term fluctuations associated with the business cycle. The removal of these short-term fluctuations reveals long-term trends. This can help with economic or other forecasting associated with the business cycle. Additionally, the change in each country's *Central Bank policy rates* ($\Delta\_Central\ Bank\ Policy_{j,t}$) is included to account for the influence of monetary policy. This is because significant changes (increase) in interest rates may result in higher levels of non-performing loans due to the increased cost of debt servicing (Jiménez et al., 2014) and borrowing. Conversely, lower changes (reduction) encourage increased bank investment or lending, thus exposing banks to excessive risk-taking. Lastly, we consider the level of financial development by including the ratio stock market capitalisation to GDP (*stockmcap_GDP*$_{j,t}$). Countries with extensive access to the stock market may host banks with greater capital resources, enabling them to effectively finance their operations and potentially better withstand economic shocks compared to their counterparts.

To address the potential bias from omitted variables, a comprehensive set of bank-related control variables ($X_{i,t}$) is included. Following Berger et al. (2020), We include Capital Adequacy Equity Ratio (*Equityratio*$_{i,t}$), Management Quality (*EfficiencyRatio*$_{i,t}$), Earnings Quality (*ROA*$_{i,t}$), *Liquidityratio*$_{i,t}$, Sensitivity to market risk (*SMR*$_{i,t}$ Total Securities/Total Assets). We employ the Equity Ratio as a funding measure, anticipating a negative correlation. This suggests that banks with higher equity tend to be less susceptible to systemic risk. Such banks might engage in elevated risk-taking, assuming their capital can absorb potential shocks. Similarly, we consider the *Liquidity Ratio*, given banks' leverage and need for daily cash flow to avert liquidity crises. This research expects a negative link, implying higher liquidity should reduce systemic risk susceptibility. Note that the liquidity ratio was orthogonalized to sensitivity to market risk due to their strong correlation. Also, we incorporate *Management Quality* is considered through the ratio of interest expense to operating income (*Efficiency ratio*$_{i,t,}$) and elevated costs relative to revenue may reflect suboptimal managerial decisions. To address size effects, we factor in the logarithm of total assets. Additionally, in line with Lopez-Espinosa et al.'s (2012) findings, we address the impact of short-term funding, which is obtained on a roll-on basis and complements retail deposits. Banks reliant on such short-term funding that are intertwined with other banks, heightening vulnerability during market fluctuations due to information linkages. To capture this, we introduce a dummy variable (*HighSTDebt*$_{i,t}$) set to "1" each year if wholesale funding exceeds the annual sample mean, thus effectively tracking its annual influence on systemic risk. Bank size is accounted for through the logarithm of total assets (*lnTA*$_{i,t}$). The level of diversification within a banks is calculated as the ratio of net interest income to total revenue (*Diversification*$_{i,t}$).

Furthermore, we measure bank concentration (*concentration_ratio*$_{j,t}$) as the ratio of the total assets of the five largest banks to the total assets of the entire banking system, on a per-country basis, offering insights into industry concentration. Lastly, the study accounts for the impact of the Global Financial Crisis (GFC_t) and the $Covid_t$ pandemic ($Covid_t$). Based on the World Bank Global Financial Development Database, GFC_t is set to 1 for the period 2007-2009 during the global financial crisis of 2007-2008, and $Covid_t$ is set to 1 for the period 2019-2020 during the Covid pandemic. The Hausman test indicates that the fixed-effects model is a more suitable choice than the random-effects model. We address potential multicollinearity issues by orthogonalizing the relevant variables (see Table 3.2). The correlation between the variables of interest is examined by computing the variance inflation factors (VIF), which have a mean value of 1.50 with a maximum of 1.94 (see Table 3.3).

3.3. Results

We use non-linear panel regressions with individual-fixed effects to analyze the impact of bank environmental behavior commonality on systemic risk. The results, as displayed in Table 3.4, show a nonlinear relationship between the commonality of the bank's environmental behavior and systemic risk. Precisely, the coefficient of $ENVIRONCom_{i,t}$ demonstrates a negative and statistically significant association with $DCoVaR_{i,t}$, indicating that it curbs banks' exposure to systemic risk. However, the inclusion of the quadratic term $SQENVIRONCom_{i,t}$ is positively significant for systemic risk measure ($DCoVaR_{i,t}$), suggesting a U-shaped relationship between commonality of bank's environmental behavior and systemic risk. This non-linear connection is supported by the test proposed by Lind and Mehlum (2010), where the p-value indicates the statistical significance for rejecting a linear relationship, thus endorsing the U-shaped association. The calculated turning point ($ENVIRONCom_{i,t}$ /2*coefficient $SQENVIRONCom_{i,t}$) is situated at 0.13 and roughly corresponds to the 75th percentile. This inflection point signifies that once $ENVIRONCom_{i,t}$ commonality peaks, the benefits of diversifying into new market (i.e., eco-friendly segments) may begin to diminish. As a result, higher levels in the similarity of banks' environmental behavior poses a significant threat to their resilience and contributes significantly to systemic risk. Carney (2015) stresses that a hurried or haphazard transition to a low-carbon economy might lead to a market bubble that might eventually bust during the market's adjustment period. Given the great degree of interconnection in the banking industry, all banks could be negatively impacted by a single shock if they heavily invest in the same pool of assets.

Table 3.4 Commonality of Bank's Environmental Behavior and Systemic Risk

Models	(1)	(2)
Variables	*MES*	*DCoVaR*
ENVIRONCom	-0.0051	**-0.0070***
	(0.0157)	(0.0039)
SQENVIRONCom	0.0478	**0.0260****
	(0.0561)	(0.0114)

GFC	0.0025	0.0004
	(0.0017)	(0.0003)
covid	0.0001	0.00004
	(0.0007)	(0.0001)
stockmcap_GDP	**-0.0049***	**-0.0008****
	(0.0026)	(0.0004)
Equityratio	**-0.0959****	**-0.0181****
	(0.0409)	(0.0071)
credit_GDPgap	-0.0016	0.0006
	(0.0046)	(0.0008)
EfficiencyRatio	-0.0003	0.0004
	(0.0038)	(0.0006)
Liquidityratio	-0.0008	-0.00003
	(0.0009)	(0.0001)
SMR	-0.0004	**-0.0002****
	(0.0008)	(0.0001)
ROA	-0.0916	-0.0175
	(0.0581)	(0.0141)
Concentration_ratio	-0.0010	0.0006
	(0.0030)	(0.0006)
Institutional_environment	**-0.0007****	**-0.0002****
	(0.0003)	(0.0001)
△_Central Bank Policy	0.0003	0.0002
	(0.0008)	(0.0002)
Inflation	0.0255	0.0070
	(0.0322)	(0.0063)
HighSTDebt	-0.0017	-0.0001
	(0.0012)	(0.0002)
Diversification	-0.0022	0.0006
	(0.0052)	(0.0012)
lnTA	-0.0003	-0.0001
	(0.0014)	(0.0002)
Constant	0.0333	0.0072
	(0.0374)	(0.0063)
Nbr. of obs.	715	715
Individual Fixed Effects	Yes	Yes
Nbr. of Countries	27	27
Lind-Mehlum U-test		
P-value	_	(0.0375)
Turning point	_	**0.13****
R^2	0.1268	0.1468

This table reports fixed effects estimation of systemic risk measures (*MES and DCoVaR,)* on the measure of Bank's environmental behavior (*ENVIRONCom*) and its squared term (*SQENVIRONCom*) and control variables. All variables are defined in Table 3.2. The Lind and Mehlum test is a test of non-linearity. The turning point is computed as (-coefficient *ENVIRONCom*/2*coefficient *SQENVIRONCom*). The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

3.4 Further Analysis

Next, we investigate whether the impact of commonality in bank environmental behavior on systemic risk varies across different levels of asset commonality, institutional environment stringency.

3.4.1 The Role of Assets Commonality

In here, this paper investigates whether banks with both higher levels of asset commonality and higher commonality in their environmental behavior exhibit a greater degree of systemic risk. This stems from the fact that Kruger et al. (2020) suggests that alignment with cleaner and eco-friendly objectives might lead banks to reallocate investments similarly. In essence, when banks align with similar environmental factors and, to a significant extent, follow the same investment patterns by investing in the same eco-friendly market segments. It is essential to explore whether a specific threshold of commonality in both dimensions is necessary to influence systemic risk. Therefore, we achieve this by calculating the commonality of assets across various asset classes among banks, as detailed in Table 3.5. Applying the same approach as in Section 3.2.1, We compute the cosine similarity measure for these asset classes using equations (1) and (2) (where k represents the different asset classes). Banks with asset commonality measures close to zero are categorised as having no similarity, whereas those with values equal to or close to 1 are considered to exhibit a high degree of similarity. Notably, we classify banks into two subsamples based on their degree of asset overlap with other banks. Those with asset commonality higher than the sample mean are categorized as having "high levels of asset commonality," while those below the sample mean are identified to have "low levels of asset commonality." The mean value for our asset commonality measure stands at 0.68, with a standard deviation of 0.47.

To examine whether the relationship between commonality in environmental behavior and systemic risk is influenced by the degree of overlap in banks' portfolios, we subsequently re-run Equation (4) separately for the sub-samples representing higher and lower levels of asset commonality. The findings, presented in Table 3.6, show a non-linear relationship between the commonality of banks' environmental behaviors and systemic risk but only for banks having higher degrees of asset commonality. The variable $ENVIRONCom_{i,t}$ demonstrates statistical significance and bears a negative association with systemic risk under high asset commonality. The quadratic term $SQENVIRONCom_{i,t}$ displays a significant and positive association with systemic risk. The calculated turning point is identified at 0.17 for our systemic risk metric ($DCoVaR_{i,t}$), roughly corresponding to the 75th percentile. Therefore, in the context of high asset commonality, bank's commonality in environmental behaviour exerts a positive impact on systemic risk. This observation highlights the importance for regulators to acknowledge the complexities that influence the banking industry when adopting policies. In essence, banks with greater asset commonality are more susceptible to potential write-offs, especially if a macroeconomic shock occurs. These banks will experience more significant losses from stranded assets and may be compelled to sell assets at fire sale prices, consequently exposing them to systemic failures, given the heightened interconnectedness of banks through their asset positions. Likewise, if a macro shock occurs to the low-carbon industries, banks will be further exposed to systemic crisis due to the level of commonality within the segment.

Table 3.5 List of Assets Classes

S/N	ASSET CLASSES
1	Cash
2	Available for Sale Securities
3	Government Securities
4	Trading Securities
5	Derivative Assets
6	Mortgage Loans
7	Other Intangibles
8	Goodwill
9	Other Assets
10	Corporate and Commercial Loans
11	Loans & Advances to Banks
12	Other Loans
13	Customer Loans
14	Total Consumer Loans
15	Fixed Assets

This table presents the list of asset classes used to compute the measure of asset commonality.

Table 3.6 Commonality of Bank's Environmental Behavior and Systemic Risk Under High and Low Assets Commonality

Models	(1)	(2)	(3)	(4)
Levels	High Assets Commonality		Low Assets Commonality	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
ENVIRONCom	-0.0197	**-0.0101****	0.0794	0.0023
	(0.0165)	(0.0041)	(0.0668)	(0.0065)

SQENVIRONCom	0.0757	**0.0301*****	-0.2402	-0.0017
	(0.0547)	(0.0091)	(0.2413)	(0.0299)
GFC	0.0024	0.0006	0.0088	0.0001
	(0.0018)	(0.0004)	(0.0067)	(0.0004)
covid	0.0003	-0.0001	0.0021	-0.00005
	(0.0008)	(0.0001)	(0.0017)	(0.0002)
stockmcap_GDP	-0.0031	-0.0003	-0.0114	-0.0002
	(0.0030)	(0.0003)	(0.0075)	(0.0009)
Equityratio	**-0.1010****	**-0.0194****	-0.0608	-0.0064
	(0.0472)	(0.0079)	(0.0747)	(0.0072)
credit_GDPgap	-0.0087	-0.0008	0.0165	**0.0035***
	(0.0053)	(0.0008)	(0.0114)	(0.0019)
EfficiencyRatio	-0.0001	0.0003	-0.0205	-0.0020
	(0.0042)	(0.0007)	(0.0178)	(0.0033)
Liquidityratio	-0.0012	-0.0001	0.0018	0.0003
	(0.0010)	(0.0001)	(0.0015)	(0.0002)
SMR	-0.0003	**-0.0003****	0.0001	0.0001
	(0.0009)	(0.0001)	(0.0010)	(0.0002)
ROA	-0.1001	-0.0197	-0.2532	-0.0307
	(0.0654)	(0.0149)	(0.2559)	(0.0531)
Concentration_ratio	-0.0001	0.0008	-0.0034	-0.0001
	(0.0033)	(0.0007)	(0.0070)	(0.0011)
Institutional_environment	-0.0006	-0.0002	**-0.0009*****	**-0.0002*****
	(0.0005)	(0.0001)	(0.0002)	(0.0000)
△_Central Bank Policy	0.0012	**0.0004****	**-0.0021****	**-0.0003*****
	(0.0008)	(0.0002)	(0.0008)	(0.0001)
Inflation	0.0862	**0.0230***	0.0482	0.0042
	(0.0569)	(0.0127)	(0.0405)	(0.0042)
HighSTDebt	0.0005	0.0002	**-0.0047***	-0.0005
	(0.0010)	(0.0002)	(0.0026)	(0.0004)
Diversification	-0.0026	0.0007	-0.0080	0.0003
	(0.0068)	(0.0015)	(0.0058)	(0.0010)
lnTA	0.0004	-0.0001	-0.0059	0.0008
	(0.0016)	(0.0003)	(0.0061)	(0.0007)
Constant	0.0103	0.0063	0.1906	-0.0146
	(0.0405)	(0.0075)	(0.1690)	(0.0176)
Nbr. of obs.	542	542	173	173
Individual Fixed Effects	Yes	Yes	Yes	Yes
Nbr. of Countries	27	27	27	27
Lind-Mehlum U-test				
P-value	_	(0.0385)	_	_
Turning point	_	**0.15****	_	_
R^2	0.1449	0.1610	0.1526	0.1644

This table reports fixed effects estimation of systemic risk measures (*MES and DCoVaR,)* on the measure of Bank's environmental behavior (*ENVIRONCom*) and its squared term (*SQENVIRONCom*) and control variables under varying degrees of asset commonality. All variables are defined in Table 3.2. The Lind and Mehlum test is a test of non-linearity. The turning point is computed as (-coefficient *ENVIRONCom* /2*coefficient *SQENVIRONCom*). The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

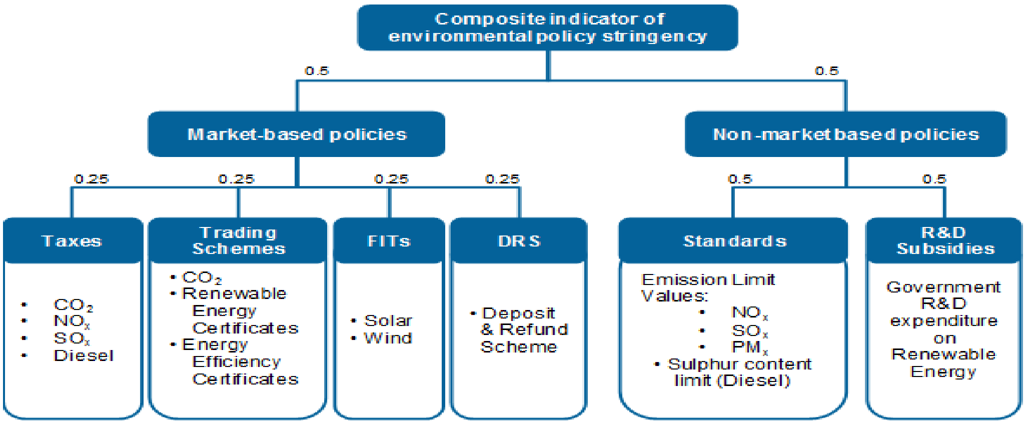
3.4.1 The role of Environmental Policy Stringency

Next, we examine whether the influence of similarity in banks' environmental practices on systemic risk is contingent upon the varying degrees of high and low environmental policy stringency. Environmental policy stringency is defined as a policy that imposes costs on pollution or environmentally harmful behaviors. We obtain the Environmental Policy Stringency (EPS) data from the Organization for Economic Co-operation and Development (OECD) database, covering 23 countries from 2002 to 2021. The EPS compiles information on the strictness of various environmental policy instruments using a simple scoring and weighting system, as depicted in Figure 3.1. It quantifies the degree to which a policy imposes costs on pollution or environmentally harmful behavior, whether through straightforward mechanisms like taxes (where higher tax rates indicate greater stringency) or through stricter emission limits. Similarly, subsidies, such as feed-in tariffs or research and development incentives, are interpreted as contributing to environmental stringency when their values are higher, as they raise the opportunity costs of pollution and are typically funded by taxpayers or consumers, providing incentives for cleaner practices. Higher taxes on carbon emissions, for instance, are expected to dissuade firms from channeling more investments into carbon-intensive business segments. It is crucial to highlight the importance of using the Environmental Policy Stringency Index (EPS) as a criterion because it focuses on a cost-oriented strategy that applies not only to businesses and organizations but also to banks. Therefore, it can be inferred that countries seeking a swift transition to lower carbon emissions are more inclined to enforce higher taxes, while those with a different approach may use lower taxes to signal a different pace of compliance. We therefore employ this index as a criterion to differentiate between high and low-stringency policy implementations. To do this, we calculate the annual median of the index and subsequently compare each country's index value to the corresponding annual median. If a country's index value exceeds the annual median value, it is classified as having a high level of environmental stringency. Conversely, if it falls below the median, it is categorized as having a low level of environmental policy stringency implementation. Afterward, the study utilizes the mode to determine the classification of a country as either high or low in terms of environmental policy stringency deployment. Following this classification system, we can assess and compare the varying degrees of environmental stringency implementation across countries in our analysis. The Table C.2 in the appendix C provides descriptive statistics for each country's EPS. In this sample, 13 and 10 countries are classified as having higher and lower stringency in their environmental policy index, respectively.

We re-run Equation (4) on these two subsamples to evaluate the impacts of the commonality of the bank's environmental behavior on systemic risk under high and low environmental policy stringency implementation. Results are displayed in Table 3.7. Firstly, the findings show a non-linear relationship between the commonality of banks environmental behavior and systemic risk under lower environmental policy stringency. Our variable $ENVIRONCom_{i,t}$ exhibits a negative and significant coefficient associated with both measures of systemic risk ($MES_{i,t}$ $DCoVaR_{i,t}$.) and is highly statistically significant under conditions of low environmental policy stringency. This pattern is observed in countries such as Australia, Brazil, Canada, China, Portugal, Russia, Spain, Turkiye, and the United States. Banks in countries with lower stringency policies, such as reduced taxes for carbon emissions and higher emission limits, might benefit from diversifying into new markets, as evidenced by the negative coefficient.

However, the quadratic term $SQENVIRONCom_{i,t}$ is positively significant for both $MES_{i,t}$ and $DCoVaR_{i,t}$, suggesting a U-shaped relationship between commonality of bank's environmental behavior and systemic risk under conditions of low environmental policy stringency. The calculated turning point ($ENVIRONCom_{i,t}$/2*coefficient $SQENVIRONCom_{i,t}$) is situated at 0.10 and 0.15 and roughly corresponds to the 75th percentile for both measures of systemic risk ($MES_{i,t}$ $DCoVaR_{i,t}$), respectively. This inflection point signifies that once $ENVIRONCom_{i,t}$ commonality peaks, the benefits of diversifying into new market (i.e., eco-friendly segments) may begin to diminish. Under a lower environmental stringency policy, banks are still susceptible to systemic crisis as benefits of diversification into new markets peak if the commonality of bank's environmental behavior goes above the threshold (0.10, 0.15). Contrary to our expectation, the research does not find the evidence that supports the argument that the commonality of bank's environmental behavior increases systemic risk in a context of strong environmental policies. Higher environmental stringency may also imply higher subsidies to eco-friendly markets segments and as such reduce bank's commitment in loans disbursement. Consequently, this may limit their exposure to systemic risk if a macroeconomic shock occurs.

Figure 3.1 Components of Environmental Policy Stringency



Source Botta and Kozluk 2014: EPS indicator

Table 3.7 Commonality of Bank's Environmental Behavior and Systemic Risk Under High and Low Environmental Policy Stringency (EPS)

Models	(1)	(2)	(3)	(4)
Levels	High Environmental Stringency Policy Index		Low Environmental Stringency Policy Index	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
ENVIRONCom	0.1030	0.0204	**-0.0339***	**-0.0118***
	(0.0599)	(0.0140)	(0.0118)	(0.0034)
SQENVIRONCom	-0.2949	-0.0308	**0.1664***	**0.0390***
	(0.1799)	(0.0306)	(0.0502)	(0.0088)
GFC	**0.0060***	0.0009	0.0022	0.0003
	(0.0033)	(0.0009)	(0.0019)	(0.0003)
covid	0.0002	0.00002	0.0003	-0.0001
	(0.0022)	(0.0003)	(0.0009)	(0.0002)
stockmcap_GDP	-0.0061	-0.0003	**-0.0034***	-0.0005
	(0.0093)	(0.0004)	(0.0019)	(0.0005)
Equityratio	0.1051	**-0.0157***	**-0.1082***	**-0.0179***
	(0.0943)	(0.0083)	(0.0396)	(0.0081)
credit_GDPgap	-0.0144	-0.0017	-0.0026	0.0004
	(0.0117)	(0.0023)	(0.0039)	(0.0007)
EfficiencyRatio	**-0.0117***	-0.0006	0.0067	0.0017
	(0.0049)	(0.0006)	(0.0052)	(0.0012)
Liquidityratio	-0.0029	-0.0004	0.0004	0.00002
	(0.0024)	(0.0003)	(0.0008)	(0.0001)
SMR	0.0009	-0.0003	**-0.0013***	**-0.0002***
	(0.0016)	(0.0003)	(0.0006)	(0.0001)
ROA	-0.0471	0.0296	0.0118	0.0006
	(0.1409)	(0.0301)	(0.0538)	(0.0156)
Concentration_ratio	-0.0000	0.0003	0.0006	0.0009
	(0.0070)	(0.0007)	(0.0034)	(0.0008)
Institutional_environment	-0.0004	-0.00002	**-0.0009***	**-0.0002***
	(0.0004)	(0.0001)	(0.0004)	(0.0001)
△_Central Bank Policy	0.0005	**0.0004***	0.0007	**0.0004***
	(0.0018)	(0.0001)	(0.0008)	(0.0002)
Inflation	0.0505	0.0245	0.0459	0.0115
	(0.1140)	(0.0221)	(0.0366)	(0.0079)
HighSTDebt	-0.0033	**-0.0014***	-0.0011	0.0001
	(0.0056)	(0.0007)	(0.0010)	(0.0001)
Diversification	0.0078	0.0009	-0.0016	0.0009
	(0.0156)	(0.0017)	(0.0063)	(0.0019)
lnTA	0.0065	-0.0003	-0.0011	-0.00002
	(0.0038)	(0.0009)	(0.0014)	(0.0003)
Constant	-0.1627	0.0083	0.0469	0.0032
	(0.1007)	(0.0241)	(0.0397)	(0.0091)
Nbr. of obs.	164	164	451	451
Individual Fixed Effects	Yes	Yes	Yes	Yes
Nbr. of Countries	13	13	10	10
Lind-Mehlum U-test				
P-value	_	_	(0.00312)	(0.000632)
Turning point	_	_	**0.101***	**0.15***
R^2	0.2081	0.2363	0.2409	0.2409

This table reports fixed effects estimation of systemic risk measures (*MES and DCoVaR,)* on the measure of Bank's environmental behavior (*ENVIRONCom*) and its squared term (*SQENVIRONCom*) and control variables under varying degrees of environmental policy stringency. All variables are defined in Table 3.2. The Lind and Mehlum test is a test of non-linearity. The turning point is computed as (-coefficient *ENVIRONCOM*/2*coefficient *SQENVIRONCom*). The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% level.

3.4.2 Robustness test

After examining the impact of the commonality of banks' environmental behavior on systemic risk, this study acknowledges other factors that could influence the validity of our findings. Researchers like Delis et al. (2021) and Capasso et al. (2020) have argued that the announcement of the Paris Climate Agreement for Net Zero in December 2015 significantly heightened discussions and the demand for sustainable practices and adoption. Considering this, it is important to account for the subsequent levels of climate policy adoption and how it may have affected bank loans and credit from that point onward. Additionally, while the risk of stranded fossil fuel reserves was initially seen as a long-term concern, the unexpected 2015 Paris Climate Agreement accelerated policy action, bringing the transition to a low-carbon economy much closer in time (Caldecott, Tilbury, and Carey 2014). Consequently, the risk of stranded fossil fuel reserves becomes increasingly relevant during our sample period, impacting loan pricing and financial sector considerations, even in the medium and short term. To address this concern, we include the dummy variable (*Paris_Netzero*) that equals 1 from December 2015 to 2021 and 0 otherwise. This dummy variable helps account for the possibility that the commonality of banks' environmental behavior may have been triggered since that date. However, the results do not show any statistical significance for our dummy variable *Paris_Netzero* as shown in Table C.3 in the appendix C.

Secondly, we consider changes in GDP ($\Delta\_GDP_{j,t}$) in the analysis. To do this, we rerun the estimates following Equation (4), and the results are consistent with those presented in Table 3.4 above. The results are tabulated in Table C.4 in appendix C and confirm the non-linear approach based on the statistically significant p-value for our $DCoVaR_{i,t}$. Additionally, both $ENVIRONCom_{i,t}$ and the quadratic term $SQENVIRONCom_{i,t}$ is statistically significant and negatively (positively) associated with systemic risk, respectively. Also, changes in ($\Delta\_GDP_{j,t}$) does not bear any statistical significance and our result still tallies with our initial result in Table 3.4 for our baseline analysis.

Furthermore, this study explores an alternative measure of environmental policy adoption distinct from the cost-centred approach. Specifically, we utilize the Yale Environmental Performance Index (EPI), developed by Wolf et al. (2022), to assess the impact of banks' environmental behavior commonality on systemic risk. The EPI adopts a unique approach, incorporating 40 indicators grouped into 11 categories to provide a comprehensive evaluation of global sustainability as shown in Table C.5 in the appendix. It ranks countries based on their performance in areas such as climate change, environmental health, and ecosystem vitality, reflecting their progress toward established environmental policy goals. While the EPI covers all countries relevant to our analysis, this study places a greater emphasis on the Environmental Policy Stringency Index (EPS) due to its focus on a cost-oriented approach, which holds significance for firms and banks in their decision-making processes. In contrast, the EPI functions as a scorecard, identifying leaders and laggards in environmental performance and providing practical recommendations for nations striving to achieve sustainable economic practices.

For our analysis, we obtain the EPI data from Yale's dedicated environmental policy platform, spanning from 2002 to 2021, and covering 27 countries. The EPI is used as a criterion to distinguish between countries with relatively high and low environmental policy performance. Like the EPS approach, we calculate the annual median of the EPI index for the entire sample. Then, we compare each country's EPI index value to the corresponding annual median. If a country's index value exceeds the annual median, it is categorized as having a high level of environmental policy performance. Conversely, if it falls below the annual median, it is classified as having a low level of environmental policy performance. We use the mode to determine whether a country should be categorized as having a high or low level of environmental policy deployment. For additional descriptive statistics on each country's EPI, please refer to Table C.2 in appendix C. In this sample, 15 countries are classified as having a higher environmental policy performance index, while 12 countries are categorized as having lower stringency. We re-evaluate our estimates using equation (4) on these two sub-samples, and the results of this analysis are presented in Table C.6 in the appendix C. These results reveal a non-linear relationship between the commonality of banks' environmental behaviors and systemic risk ($DCoVaR_{i,t}$) under a high degree of environmental policy performance. Our results reveal that $ENVIRONCom_{i,t}$ exhibits statistical significance and demonstrates a negative association with systemic risk ($DCoVaR_{i,t}$) under a low environmental performance policy. However, the quadratic term $SQENVIRONCom_{i,t}$ displays a positive and significant association with systemic risk ($DCoVaR_{i,t}$), particularly under conditions of low environmental performance policy. The calculated turning point ($ENVIRONCom_{i,t}$ /2*coefficient $SQENVIRONCom_{i,t}$) is identified at 0.17 for our systemic risk metric ($DCoVaR_{i,t}$), roughly corresponding to the 75th percentile. This suggests that the commonality of banks' environmental behaviors contributes to systemic risk in countries with a lower adoption of climate change initiatives. Examples of such countries include Brazil, China, Colombia, Hungary, South Korea, Malaysia etc. Once again, we do not find the evidence that under high environmental policy adoption, banks commonality of environmental practices increases systemic risk.

3.5 Conclusion

This study examined the influence of the commonality of banks' environmental behaviors on systemic risk, encompassing a sample of 91 banks across 27 countries. Our baseline results indicate a non-linear relationship. Our findings reveal a non-linear relationship between the commonality of environmental behavior among banks and systemic risk. When the degree of commonality in environmental behavior falls below a specific threshold, there is a decrease in systemic risk, as the study observed with increased commonality. In contrast, surpassing this threshold results in a higher degree of environmental commonality, which elevates systemic risk. More precisely, the findings indicate that banks with greater environmental commonality beyond the 75th percentile threshold are more exposed to systemic risk.

This research further explored the impacts of commonality of bank's environmental policy on systemic risk under varying degrees of asset commonality. In addition, our result also shows that when the degree of commonality in environmental behavior falls below (above) a specific threshold under a high level of assets commonality, there is a reduction (increase) in systemic risk with increased commonality.

Similarly, the results shows that when banks degree of commonality in environmental behavior is below (above) a specific threshold, it portrays a reduction (increase) in systemic risk falls under a lower environmental policy stringency index. Although, this is in contrast with our expectation, as higher adoptions should increase exposure to systemic risk. Meanwhile, the Environmental Policy Stringency Index, which takes a cost-centered approach, suggests that firms receive incentives like subsidies for eco-friendly sectors or face higher tariffs for investing in fossil fuels. Higher subsidies could limit the bank's involvement in the supply of funds and reduce its exposure to systemic risk.

In conclusion, banking supervisors should consider that banks' involvement in the energy transition can have a negative consequence on systemic risk. This study highlights that if banks adopt a similar behaviour to enhance their environmental scores, it may elevate systemic risk. Therefore, a careful approach should be done in the transition to low-carbon economy. This research advocates for more deployment of a cost-centered approach giving a mix of both subsidies to increase low-carbon emission reforms and tax measures to reduce fossil fuels investment. Also, we recommend that the Bank for International Settlements (BIS) should consider commonality in banks' environmental behavior in addition to the established interconnectivity criteria for recognizing G-SIFIs to improve financial stability. Additionally, while establishing capital surcharge requirements for larger banks, regulatory authorities should take a bank's asset diversity and asset similarity to domestic peers into consideration.

APPENDIX C

Table C.1 List of Systemically Important Banks

S/N	Bank Name	S/N	Bank Name	S/N	Bank Name
1	Morgan Stanley & Co. LLC	34	Erste Group Bank AG	67	Hong Leong Financial Group Berhad
2	Citibank, N.A.	35	Swedbank AB	68	Commerz Bank
3	Wells Fargo Bank, N.A.	36	Alpha Services and Holdings.	69	Hua Nan Financial Holdings Co., Ltd.
4	National Bank of Canada	37	Credit Agricole	70	Banca Mediolanum S.p.A.
5	The Bank of Nova Scotia	38	Banco Comercial Portugues,	71	Nordea Bank Abp
6	Ally Financial Inc.	39	BPER Banca S.p.A.	72	Sumitomo Mitsui Financial Group, Inc.
7	The Goldman Sachs Group,	40	Turkiye Is Bankasi A.S.	73	Umpqua Holdings Corporation
8	Capital One Financial Corporation	41	Credit Suisse Group AG	74	Volkswagen Bank GmbH
9	Royal Bank of Canada	42	Public Bank Berhad	75	SinoPac Financial Holdings Company Limited
10	Canadian Imperial Bank of Commerce	43	Sberbank of Russia	76	Mega Financial Holding Co., Ltd.
11	Societe Generale	44	Bancolombia S.A.	77	Hokuhoku Financial Group, Inc.
12	Zions Bancorporation,	45	OTP Bank Plc.	78	Grupo Aval Acciones y Valores
13	First Republic Bank	46	UniCredit S.p.A.	79	Raiffeisen Bank International AG
14	UBS AG	47	Intesa Sanpaolo S.p.A.	80	First Financial Holding Co., Ltd.
15	JPMorgan Chase Bank.	48	Banco Santander, S.A.	81	Signature Bank
16	BNP Paribas S.A.	49	Banco Bilbao Vizcaya Argentaria,	82	E. Sun Financial Holding Company, Ltd
17	Agricultural Bank of China Limited	50	Turkiye Vakiflar Bankasi T.A.O.	83	Korea Investment Holdings Co., Ltd.
18	Banco Bradesco	51	VTB Bank (Public Joint-Stock Company)	84	Pinnacle Financial Partners, Inc.
19	Bank of Montreal	52	Synovus Financial Corp.	85	People's United Financial, Inc.
20	Banque Cantonale Vaudoise	53	BOK Financial Corporation	86	ServisFirst Bancshares, Inc.
21	Barclays plc	54	Regions Financial Corporation	87	Western Alliance Bancorporation
22	The Charles Schwab Corporation	55	M&T Bank Corporation	88	PacWest Bancorp
23	Eurobank Ergasias Servi and Holdings	56	New York Community Bancorp, Inc.	89	Mebuki Financial Group, Inc.
24	HSBC Holdings plc	57	Bank of China Limited	90	Julius Baer Group Ltd
25	National Australia Bank Limited	58	Turkiye Halk Bankasi A.S.	91	Taiwan Cooperative Financial Holding Company
26	RHB Bank Berhad	59	Taiwan Business Bank, Ltd.		
27	Skandinaviska Enskilda Banken AB	60	KBC Group NV		
28	State Street Corporation	61	The PNC Financial Services Group, Inc.		
29	Bank of America Corporation	62	Citizens Financial Group, Inc.		
30	Toronto-Dominion Bank (The)	63	ING Groep N.V.		
31	Lloyds Banking Group plc	64	Taishin Financial Holding Co., Ltd.		
32	NatWest Group plc	65	Resona Holdings, Inc.		
33	Jyske Bank	66	Synchrony Financial		

Table C.2 Distribution of Banks by Country In 2017 and Environmental Policy Index (Sample Period 2002-2021)

			EPI		EPS	
S/N	Country Name	Nbr of Banks Per Country	Min	Max	Min	Max
1	Australia	1	49.57	63.14	1.14	3.53
2	Austria	2	54.97	61.08	3.25	3.31
3	Belgium	1	45.93	58.93	1.56	3.44
4	Brazil	2	43.54	47.02	0.17	0.89
5	Canada	6	48.49	56.64	0.72	3.61
6	China	2	25.52	34.18	0.81	3.14
7	Colombia	2	43.95	47.44	_	_
8	Denmark	1	63.45	68.05	3.81	4.22
9	France	3	54.16	63.75	3.00	4.89
10	Germany	1	63.48	65.92	3.78	3.47
11	Greece	2	54.75	56.82	3.83	3.06
12	Hungary	1	45.06	51.66	3.69	3.67
13	Italy	4	48.75	58.01	1.92	4.06
14	Japan	4	55.13	57.52	3.75	4.06
15	Korea	1	47.49	50.96	0.83	3.61
16	Malaysia	3	30.26	36.66	_	_
17	Netherlands	2	59.64	61.16	3.11	3.50
18	Portugal	1	48.88	51.38	3.39	3.78
19	Russia	2	41.84	43.25	0.67	1.17
20	Singapore	1	43.29	48.73	_	_
21	Spain	2	50.66	59.02	0.47	3.83
22	Sweden	2	58.13	71.56	3.06	3.83
23	Switzerland	4	53.77	58.84	3.25	4.50
24	Taiwan	8	43.22	47.67	_	_
25	Turkey	3	31.72	35.87	1.64	3.89
26	United Kingdom	3	54.95	66.92	1.33	3.86
27	United States	27	46.26	53.97	1.22	3.03

The table shows the number of banks sourced from Fitch database in 2017 and the basic statistics (Min, Max) of Environmental Performance Index (EPI), Environmental Stringency Policy index (EPS) by country. The following countries' EPS (Malaysia, Taiwan, Colombia, and Singapore) are not available on the OECD database; hence their scores are blank.

Table C.3 Robustness Test (1): Commonality of Bank's Environmental Behavior and Systemic Risk (Paris Netzero Agreement)

Models	(1)	(2)
Variables	*MES*	*DCoVaR*
ENVIRONCom	-0.0057	**-0.0070***
	-0.0155	-0.0038
SQENVIRONCom	0.0454	**0.0259****
	-0.0581	-0.0117
Paris_Netzero	-0.0007	-0.00002
	-0.0009	-0.0002
GFC	0.0025	0.0004
	-0.0017	-0.0003
covid	0.0005	0.0001
	-0.0006	-0.0001
stockmcap_GDP	**-0.0046***	**-0.0008***
	-0.0026	-0.0004
Equityratio	**-0.0958****	**-0.0181****
	-0.0413	-0.0071
credit_GDPgap	-0.0018	0.0006
	-0.0046	-0.0008
EfficiencyRatio	-0.0002	0.0004
	-0.0038	-0.0006
Liquidityratio	-0.0007	-0.0003
	-0.0009	-0.0001
SMR	-0.0004	**-0.0002****
	-0.0007	-0.0001
ROA	-0.0914	-0.0175
	-0.0581	-0.0141
Concentration_ratio	-0.0008	0.0006
	-0.003	-0.0006
Institutional_environment	**-0.0007****	**-0.0002*****
	-0.0003	-0.0001
△_Central Bank Policy	0.0002	0.0002
	-0.0008	-0.0002
Inflation	0.0265	0.007
	-0.0318	-0.0062
HighSTDebt	-0.0017	-0.0001
	-0.0012	-0.0002
Diversification	-0.002	0.0006
	-0.0053	-0.0013
lnTA	-0.0002	-0.0001
	-0.0016	-0.0002
Constant	0.0254	0.007
	-0.0406	-0.0063
Nbr. of obs.	715	715
Individual Fixed Effects	Yes	Yes
Nbr. of Countries	27	27
Lind-Mehlum U-test		
P-value	_	(0.1347)
Turning point	_	**0.0347****
R^2	0.1277	0.1468

This table reports fixed effects estimation of systemic risk measures (*MES and DCoVaR,)* on the measure of Bank's environmental behavior (*ENVIRONCom*) and its squared term (*SQENVIRONCom*) and control variables. All variables are defined in Table.3.2. I include the dummy variable equal to 1 and zero otherwise for periods after Paris Net Zero Agreement as a robustness test. The Lind and Mehlum test is a test of non-linearity. The turning point is computed as (-coefficient *ENVIRONCom*/2*coefficient *SQENVIRONCom*). The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table C.4 Robustness Test (2): Commonality of Bank's Environmental Behavior and Systemic Risk (△_Gdp)

Models	(1)	(2)
Variables	*MES*	*DCoVaR*
ENVIRONCom	-0.0057	**-0.0070***
	-0.0155	-0.0038
SQENVIRONCom	0.0454	**0.0259****
	-0.0581	-0.0117
△_GDP	-0.0007	-0.00002
	-0.0009	-0.0002
GFC	0.0025	0.0004
	-0.0017	-0.0003
covid	0.0005	0.0001
	-0.0006	-0.0001
stockmcap_GDP	**-0.0046***	**-0.0008***
	-0.0026	-0.0004
Equityratio	**-0.0958****	**-0.0181****
	-0.0413	-0.0071
credit_GDPgap	-0.0018	0.0006
	-0.0046	-0.0008
EfficiencyRatio	-0.0002	0.0004
	-0.0038	-0.0006
Liquidityratio	-0.0007	-0.0003
	-0.0009	-0.0001
SMR	-0.0004	**-0.0002****
	-0.0007	-0.0001
ROA	-0.0914	-0.0175
	-0.0581	-0.0141
Concentration_ratio	-0.0008	0.0006
	-0.003	-0.0006
Institutional_environment	**-0.0007****	**-0.0002*****
	-0.0003	-0.0001
△_Central Bank Policy	0.0002	0.0002
	-0.0008	-0.0002
Inflation	0.0265	0.007
	-0.0318	-0.0062
HighSTDebt	-0.0017	-0.0001
	-0.0012	-0.0002
Diversification	-0.002	0.0006
	-0.0053	-0.0013
lnTA	-0.0002	-0.0001
	-0.0016	-0.0002
Constant	0.0254	0.007
	-0.0406	-0.0063
Nbr. of obs.	715	715
Individual Fixed Effects	Yes	Yes
Nbr. of Countries	27	27
Lind-Mehlum U-test		
P-value	_	(0.134)
Turning point	_	**0.0385 ****
R^2	0.1277	0.1468

This table reports fixed effects estimation of systemic risk measures (*MES and DCoVaR,)* on the measure of Bank's environmental behavior (*ENVIRONCom*) and its squared term (*SQENVIRONCom*) and control variables. All variables are defined in Table 3.2. I include the change in GDP as additional robustness test. The Lind and Mehlum test is a test of non-linearity. The turning point is computed as (-coefficient *ENVIRONCom*/2*coefficient *SQENVIRONCom*). The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels.

Table C.5 Environmental Policy Indicators Details

S/N	Policy Objective	Issue Category	TLA	Wt(%)	Indicator	TLA	Wt(%)
1	Climate Change PCC (38%)	Climate Change Mitigation	CCH	100	Projected GHG Emissions in 2050	GHN	36.3
2					CO2 Growth Rate	CDA	36.3
3					CH4 Growth Rate	CHA	8.7
4					CO2 from Land Cover	LCB	3.9
5					GHG intensity Trend	GIB	3.9
6					F-Gas Growth Rate	FGA	3.7
7					lack Carbon Growth Rate	BCA	3.6
8					GHG Emissions per Capita	GHP	3.6
9					N2O Growth Rate	NDA	1.8
10	Environmental Health HLT (20%)	Air Quality	AIR	55	PM25 Exposure	PMD	47
11					Household Solid Fuels	HAD	38
12					Ozone Exposure	OZD	5
13					Nox Exposure	NOE	2
14					So2 Exposure	SOE	2
15					CO Exposure	COE	2
16					VOC Exposure	VOE	2
17		Sanitation and Drinking Water	H2O	25	Unsafe Drinking Water	UWD	60
18					Unsafe Sanitation	USD	40
19		Heavy Metals	HMT	10	Lead Exposure	PBD	100
20		Waste Management	WM	10	Controlled Solid Waste	MSW	50
21			G		Recycling Rates	REC	25
22					Ocean Plastic Pollution	OCP	25
23	Ecosystem Vitality ECO (42%)	Biodiversity and Habitat	BDH	43	Terrestrial Biome Protection (national)	TBN	23.2
24					Terrestrial Biome Protection (global)	TBG	23.2
25					Marine protected Areas	MPA	23.2
26					Protected Areas Rep. Index	PAR	14
27					Species Habitat Index	SHI	8.3
28					Species Protection Index	SPI	8.3
29					Biodiversity Habitat Index	BHV	3
30		Ecosystem Services	ECS	19	Tree Cover Loss	TCL	75
31					Grassland Loss	GRL	13.5

32					Wetland Loss	WTL	13.5
33		Fisheries	FSH	12	Fish Stock Status	FSS	36
34					Marine Trophic Index	RMS	36
35					Fish Caught by Trawling	FTD	28
36		Acid Rain	ACD	10	2 Growth Rate	SDA	50
37					Nox Growth Rate	NXA	50
38		Agriculture	AGR	10	Sustainable Nitrogen Mgmt. Index	SNM	50
39					Sustainable Pesticide Use	SPU	50
40		Water Resources	WRS	7	Wastewater Treatment	WWT	100

The table enumerates the 40 basic indicators in the 3 major dimension.

Table C.6 Robustness Test (3) Commonality of Bank's Environmental Behavior and Systemic Risk Under High and Low Environmental Performance Policy (EPI)

Models	(1)	(2)	(3)	(4)
Levels	High Environmental Policy Index		Low Environmental Policy Index	
Variables	*MES*	*DCoVaR*	*MES*	*DCoVaR*
ENVIRONCom	0.0606	0.0037	-0.0215	**-0.0118***
	(0.0474)	(0.0081)	(0.0156)	(0.0033)
SQENVIRONCom	-0.2564	-0.0016	**0.1130***	**0.0432***
	(0.1895)	(0.0152)	(0.0618)	(0.0118)
GFC	**0.0043***	0.0002	0.0011	0.0003
	(0.0018)	(0.0003)	(0.0022)	(0.0004)
covid	0.0010	-0.0000	0.0017	0.0002
	(0.0016)	(0.0001)	(0.0011)	(0.0002)
stockmcap_GDP	-0.0042	-0.0002	**-0.0078***	**-0.0014***
	(0.0053)	(0.0002)	(0.0029)	(0.0005)
Equityratio	0.2333**	0.0028	**-0.0873***	**-0.0177***
	(0.0895)	(0.0132)	(0.0378)	(0.0071)
credit_GDPgap	-0.0042	-0.0007	0.0109	**0.0028***
	(0.0036)	(0.0005)	(0.0074)	(0.0014)
EfficiencyRatio	**-0.0098***	-0.0003	0.0041	0.0012
	(0.0046)	(0.0003)	(0.0052)	(0.0011)
Liquidityratio	-0.0032	-0.0003	0.0007	0.0001
	(0.0021)	(0.0002)	(0.0009)	(0.0001)
SMR	**0.0022***	-0.0001	-0.0007	-0.0002
	(0.0012)	(0.0001)	(0.0006)	(0.0001)
ROA	-0.0274	**0.0503***	-0.0401	-0.0047
	(0.1816)	(0.0249)	(0.0614)	(0.0151)
Concentration_ratio	-0.0005	0.0001	0.0021	0.0012
	(0.0043)	(0.0004)	(0.0035)	(0.0009)
Institutional_environment	-0.1046	-0.0118	0.1493	0.0257
	(0.0909)	(0.0093)	(0.1042)	(0.0226)
△_Central Bank Policy	**0.0016***	**0.0003***	-0.0001	0.0001
	(0.0009)	(0.0001)	(0.0009)	(0.0002)
Inflation	**0.1501***	0.0152	0.0130	0.0007
	(0.0796)	(0.0120)	(0.0219)	(0.0040)
HighSTDebt	0.0006	-0.0001	**-0.0031***	**-0.0004***
	(0.0015)	(0.0002)	(0.0012)	(0.0002)
Diversification	0.0061	0.0008	0.0012	0.0012
	(0.0129)	(0.0006)	(0.0056)	(0.0015)
lnTA	0.0035	0.0001	-0.0008	0.0002
	(0.0026)	(0.0001)	(0.0015)	(0.0003)
Constant	-0.0646	0.0015	0.0014	-0.0080
	(0.0755)	(0.0045)	(0.0468)	(0.0095)
Nbr. of obs.	542	542	173	173
Individual Fixed Effects	Yes	Yes	Yes	Yes
Nbr. of Countries	15	15	12	12
Lind-Mehlum U-test				
P-value	_	_	_	(0.000419)
Turning point	_	_	_	**0.136***
R^2	0.1751	0.2106	0.1482	0.0824

This table reports fixed effects estimation of systemic risk measures (*MES and DCoVaR,)* on the measure of Bank's environmental behavior (*ENVIRONCom*) and its squared term (*SQENVIRONCom*) and control variables under varying degrees of environmental performance index. (EPI) as a robustness test. All variables are defined in Table 3.2. The Lind and Mehlum test is a test of non-linearity. The turning point is computed as (-coefficient *ENVIRONCom* /2*coefficient *SQENVIRONCom*). The standard errors are in parentheses with *, **, and *** denoting the significance at 10%, 5% and 1% levels

GENERAL CONCLUSION

Given the far-reaching consequences of the previous GFC and its lasting impact on the economy, it became evident that banks worldwide suffered substantial losses due to their heavy investments in the subprime mortgage market. As a result, central banks worldwide have increasingly embraced macro-prudential policies and heightened supervision to mitigate these systemic risks. While existing literature on asset commonality as an indirect contagion source is growing, this thesis adds to the discourse by providing empirical evidence that underscores both the benefits and the existence of an optimal level of diversification that enhances the overall stability of the financial landscape. This thesis aims to investigate whether the alignment of behavior among banks, particularly in terms of investment and activities, contributes to the escalation of systemic risk. It pursues two primary objectives. First, it evaluates whether there is a possibility that the overlap in asset holdings among banks could increase systemic risk, with the effects on financial stability depending on the specific macroprudential policies in place. Second, the thesis delves into whether government initiatives aimed at holding firms accountable for environmental risks, coupled with the growing expectation that banks contribute to climate change mitigation and sustainability, inadvertently lead banks to adopt similar behaviors that may increase systemic risk. Considering the extensive regulations governing the banking industry, which are designed to mitigate the risks of bankruptcy and contagion, it is crucial to examine whether the growing regulatory landscape unintentionally contributes to heightened systemic risk as banks adopt similar behaviors, resulting in unforeseen consequences. The overarching goal is to shed light on whether well-intentioned regulatory efforts might inadvertently lead to unforeseen systemic risks, challenging traditional risk management and financial stability practices.

In the first chapter, we investigate the impact of assets commonality on systemic risk. We consider 16 asset classes categorized by FR Y-9C to compute our measure of asset commonality. However, according to our research, large U.S. BHCs exhibit a clear U-shaped association between asset commonality and systemic risk. According to our findings, asset similarity levels among the sampled banks are over 75%, which is harmful to financial stability. Our comprehensive research underscores the significance of maintaining low asset commonality to enhance financial stability. This holds true in both normal and crisis scenarios and applies to banks with shorter funding maturities as well. Furthermore, our findings confirm the U-shaped relationship between asset commonality and financial stability, even when distinguishing between liquid and illiquid assets.

In the second chapter, the research examined the impacts of asset commonality on systemic risk under various degrees of macroprudential policy. While existing research suggests that macroprudential policies effectively curb credit growth and house prices, this study unveils a potential concern. The evidence suggests that asset commonality can increase a bank's vulnerability to systemic risk, particularly in the presence of high macroprudential policy implementation. Furthermore, these findings hold true across various macroprudential policy types, including those targeting financial institutions, borrowers, and quantity-focused macroprudential policy. In addition, the extent of cross-border asset restrictions does not alter the impact of asset commonality on systemic risk under a high macroprudential policy implementation.

The third chapter of this study explores the potential impact of global climate change initiatives on banks' assets, particularly in relation to systemic risk. A sudden move away from fossil fuels could harm financial assets tied to them and heighten attention to climate financial risk. Additionally, it investigates whether the transition to a more sustainable economy may lead banks to adopt similar environmentally responsible practices, potentially resulting in increased systemic risk. Our findings reveal a non-linear relationship between the commonality of environmental behavior among banks and systemic risk. When environmental commonality falls below a certain threshold, there is a reduction in systemic risk with increased commonality. Conversely, beyond this threshold (75^{th} percentile), a higher degree of environmental commonality increases systemic risk. Moreover, our results show that when environmental commonality falls below (above) a specific threshold under a high level of asset commonality, there is a reduction (increase) in systemic risk with increased commonality. Similarly, we find that when banks' environmental commonality falls below (above) a specific threshold, it leads to a reduction (increase) in systemic risk under a lower environmental policy stringency index.

Based on the findings above, this research offers several policy recommendations to mitigate the growing risk of banks being exposed to systemic risk arising from asset commonality. Firstly, this research advocates that banking supervisors should integrate the average similarity distance between banks into macro stress tests to strengthen the supervisory framework. This measure will provide a better understanding of interconnectedness and systemic risks. Also, the regulators should consider the threshold derived from the U-shaped relationship we have highlighted, and considering individual asset diversification, regulators can effectively address systemic risks associated with asset commonality and foster a more resilient financial system. This threshold can be monitored such that banks do not exceed it domestically or impose adequate and relevant sanctions when it does.

Secondly, it recommends that a careful and consistent monitoring of bank asset portfolios becomes imperative, especially in the context of high macroprudential policy implementation, as it might inadvertently exacerbate systemic risk. Thirdly, it recommends that the Bank for International Settlements (BIS) consider asset commonality and the established interconnectivity criteria for recognizing G-SIFIs to improve financial stability. Additionally, while establishing capital surcharge requirements for larger banks, regulatory authorities should take a bank's asset diversity and asset similarity to domestic peers into consideration. Lastly, also recommends that bank supervisors must consider and monitor commonality in environmental behavior in their assessment as the global push to adopt climate changes by banks may also expose banks to systemic risk. More so, this research advocates that a careful approach should be taken in the transition to a low-carbon economy. This research recommends a hybrid approach that combines subsidies to promote low-carbon emission initiatives with taxation measures to discourage investment in fossil fuels.

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