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The origin of financial instability and systemic risk: Do Bank Business Models Matter?

Rym Ayadi
rym.ayadi@city.ac.uk
Bayes Business School (UK)
106 Bunhill Row, London EC1Y 8TZ, UK
EMEA Associasion (ES)

Paola Bongini
paola.bongini@unimib.it
University of Milano Bicocca (IT)
Piazza dell'Ateneo Nuovo, 1, 20126 Milano

Barbara Casu
b.casu@city.ac.uk
Bayes Business School (UK)
106 Bunhill Row, London EC1Y 8TZ, UK

*Doriana Cucinelli**
doriana.cucinelli@unipr.it
University of Parma (IT)
Via Kennedy, 6 Parma, 43121
EMEA Association (ES)

Abstract

Using a large sample of European listed banks, we investigate the relationship between a bank's business model and systemic risk between 2005 and 2020, a period which includes various episodes of instability. Our findings indicate that, during tranquil periods, banks with different business models exhibit similar sensitivity to systemic risk. However, during periods of instability, the type of business model becomes critical: investment banks contribute more to and are more exposed to systemic risk. Distinguishing between endogenous and exogenous crises, our results reveal that market-oriented banks contribute more to systemic risk when instability is endogenous to the financial sector. Conversely, focused retail banks consistently show lower contributions and exposures to systemic risk. Additionally, our findings highlight the importance of business model migrations in reducing systemic risk. Banks transitioning from diversified to more retail-oriented models reduce their systemic risk, whereas migrations in the opposite direction do not exhibit the same benefit. These findings underscore the importance of maintaining diverse business models in the banking sector to enhance financial stability.

Keywords: systemic risk, bank business models, conditional value at risk, marginal expected shortfall, crises

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1. Introduction

Over the past twenty years, European banks have navigated numerous challenges, including the global financial crisis (GFC), the European sovereign debt crisis, and an evolving regulatory and competitive landscape. They have also contended with instability arising from geopolitical events and the COVID-19 pandemic. Additionally, changing market conditions, such as tighter regulation and a prolonged period of low interest rates, have impacted banks' incentives to lend, their risk appetite, and, ultimately, their financial stability. In response, banks have adjusted their business models. While there is broad agreement that bank profitability has suffered during the past two decades, it is less clear which types of bank business models have proved more resilient.

Against this background, we aim to identify the relationship between banks' business models and systemic risk in regular times and during periods of financial distress. Several studies have demonstrated that business models offer insights beyond conventional indicators of bank risk and return, giving regulators and supervisors a deeper understanding of the sustainability of bank profits (Lartey et al., 2022). The recent failures of medium-sized US banks (such as Silicon Valley Bank) have further highlighted the critical role of business models and the need for a comprehensive assessment of their relationship with financial stability.

Our main premise is that specific business models impact systemic risk in different ways, which allows us to derive two overarching hypotheses. The first, the Market Oriented Business Model Hypothesis, posits that banks with higher levels of trading assets and higher levels of non-deposit funding contribute more and are more exposed to systemic risk, while banks with funding models more dependent on customer deposits are more resilient during turbulent times. The second hypothesis, the Migration Under Stress Hypothesis, posits that banks change business models during periods of distress and that migrations from diversified to focused retail business models reduce systemic risk.

The first step in our analysis involves defining and evaluating bank business models. There is extensive literature on business models (see Zott et al., 2024, for a review) focused on how firms create value through their business operations. Bank business models have also been studied, from early works on strategic groups (Amel and Rhoades, 1988) to more recent studies examining similarities in balance sheet structures, business activities, and risk profiles. One branch of this literature classifies business models based on banks' asset and liability composition, known as the *Activity-Funding Approach* (AFA). This approach considers retail-related activities (loans to customers) and market-related activities (loans from banks, government, and stock market activities) in relation to funding sources, divided into retail funding (customer deposits) and market funding (interbank activities, market borrowing, and stock market activities). A business model is then defined by a combination of activities and funding indicators, following a cluster analysis approach (Ayadi et al., 2011; Ayadi and de Groen, 2014; Roengipitya et al., 2014; Roengpitya et al., 2017; Hryckiewicz and Kozlowski, 2017; Flori et al., 2021).

Banks' choice of business model is influenced by many factors, both endogenous to the bank (such as managerial goals toward increased size and market share, improved profitability, and diversification into new business lines) and driven by exogenous circumstances, such as changes in the macro-economic, regulatory, and competitive environment in which banks operate. Although the literature often considers business models as static, it is important to recognize that banks might change their strategic focus in response to crises and regulatory changes (Gambacorta et al., 2019). Banks also change their business models to achieve their strategic objectives: reducing costs, improving efficiency and profitability, and curbing risk-taking activities (Ayadi et al., 2016). Building on the multidimensional framework developed by Ayadi et al. (2021), we identify the key business models adopted by European banks and chart their dynamic changes between 2005 and 2020. We then extend the analysis by considering the direction of migrations (from a more retail-oriented to a more diversified business model and vice versa).

Given the importance of the external operating environment, we distinguish between tranquil times and periods of instability and posit that how banks respond to shocks impacts their business model choices and migrations. Banks might move towards safer, more retail-oriented models during crises, or they could increase diversification in an attempt to boost revenues. From a financial stability perspective, banks need to be agile in steering their business models to adapt to changing macroeconomic conditions, as this is crucial for managing risks. Regulators require banks to articulate their strategies to ensure they are "*viable and sustainable*" (ECB, 2023). Therefore, we investigate how business model migrations impact systemic risk, particularly during periods of instability. We also argue that the origin of the instability influences the choice of business model. To this end, we classify periods of instability as endogenous to the financial sector, such as the global financial crisis (2007-09) and the sovereign debt crisis (2010-12), and periods of instability exogenous to the financial sector, for example, the political instability of 2016 following the Brexit referendum and Trump's election as president of the US, and the outbreak of the COVID-19 pandemic.[1]

We measure systemic risk through two key metrics: a bank's *contribution* to systemic risk, determined by the change in conditional value at risk (ΔCoVaR), and a bank's *exposur*e to systemic risk, assessed using the marginal expected shortfall (MES). More specifically, the ΔCoVaR, introduced by Adrian and Brunnermeier (2016), measures a financial institution's systemic risk contribution as the difference between its value-at-risk in distress and in normal conditions. The MES, developed by Acharya et al. (2012), is defined as the expected daily percentage decrease in a financial institution's equity value when the national stock market declines by at least 5 percent in a single day.

Our evaluation focuses on both the exposure and contribution to systemic risk to understand how a financial institution's business model impacts systemic risk and its resilience to market events. The theoretical foundation for this analysis is based on the Extreme Value Theory framework developed by Van Oordt and Zhou (2019). This framework decomposes systemic risk into two components: tail risk, which reflects the independent risk exposure of a bank, and systemic linkage, which captures the interconnectedness of a bank within the financial system. Van Oordt and Zhou (2019) demonstrate that ΔCoVaR is particularly suited to measuring systemic linkages, while MES effectively captures tail risk, representing the likelihood of substantial independent losses.

The connection between systemic risk measures like ΔCoVar and MES and different bank business models lies in how these BM manage and influence risk exposure and financial linkages. Business models differ in how they allocate capital, structure portfolios and generate income, which in turn affects how they respond to systemic shocks and how much risk they may pose to the broader financial system. Banks with market-oriented business models, such as those heavily involved in market-making, proprietary trading, and investment banking, are

[1] While there may be some disagreement about the exact start and end dates of these events, we adhere to the most widely accepted definitions. Regulators and international institutions traditionally mark 2007 as the beginning of the Global Financial Crisis (see, among others, ECB, 2010; Bengtsson, 2013; Meegan et al., 2018; Basten and Sanchez Serrano, 2019; de Haan and Kakes, 2020). Most commentators trace the onset of the Sovereign Debt Crisis to late 2009, when Greece disclosed that its budget deficit was 12.7% of its gross domestic product (GDP) (Source: Reuters 2010). By May 2010, the Greek Sovereign Debt Crisis had erupted and spread across Europe (European Parliament, 2010). The ECB's Financial Stability Review of November 2016 notes that "*the immediate stress following the UK referendum outcome lifted the indicator [of systemic distress] temporarily to levels last observed at the height of the euro area sovereign debt crisis*" (p. 26). March 2020 is recognized as the starting point of the COVID-19 pandemic, categorized as a health and economic crisis by the World Health Organization. (https://www.who.int/news/item/13-10-2020-impact-of-covid-19-on-people's-livelihoods-their-health-and-our-food-systems).

expected to exhibit high systemic linkages. These institutions are more exposed to market fluctuations and interconnected financial positions, making ΔCoVaR a more appropriate measure of their systemic risk. The interconnected nature of these activities makes them more susceptible to cascading failures triggered by market shocks.

Conversely, retail-oriented banks tend to have high tail risks due to their significant loan portfolios, which are vulnerable to economic downturns (e.g., mortgage defaults). For these banks, MES is better suited to capture the expected losses during adverse market conditions.

In addition, different periods bring forth distinct risks that impact business models in varying ways. During instability, systemic linkages dominate, disproportionately affecting market-oriented models, while tail risks tied to credit exposure might impact retail-oriented models during downturns. Recognising these dynamics is essential for tailoring risk assessment and regulatory frameworks to the unique vulnerabilities of each business model.

Our empirical approach, therefore, necessitates the use of both ΔCoVaR and MES, as these metrics provide complementary information, making them the most suitable for generating time-varying estimates of systemic risk from individual financial institutions to the overall financial system (Bellavite Pellegrini et al., 2022). Furthermore, as noted by Kleinow et al. (2017), systemic risk assessments based on a single metric should be approached with caution. Billio et al. (2012) emphasize the importance of using a combination of systemic risk measures to improve forecasting accuracy and better understand banks' performance during crises.

Previous literature highlights the strong relationship between systemic risk and periods of financial crisis (Varotto and Zhao, 2018; Meuleman and Vander Vennet, 2020; Borri and Di Giorgio, 2022). Building on this foundation, we extend the analysis by examining the origins of crises, distinguishing between those that are endogenous—arising within the financial system itself—and those driven by exogenous events, which impact the financial system from outside. This distinction allows us to explore how different types of crises manifest distinct risks and affect various business models in different ways.

Building on this framework, we develop our first overarching research hypothesis and formally test:

H1: Market-Oriented Business Model Hypothesis

H1.a: Market-oriented business models' contribution and exposure to systemic risk is higher during crisis periods.
H1.b: Market-oriented business models' exposure (contribution) to systemic risk is higher during exogenous (endogenous) crisis periods.

Next, we shift the focus of our analysis to the decision to change the business model, examining the Migration Under Stress Hypothesis. This hypothesis suggests that banks might move towards safer, more retail-oriented models during crises. Therefore, we aim to investigate how business model migrations impact systemic risk, particularly during periods of instability. Formally, we test:

H2: Migration Under Stress Hypothesis

H2a: Business models' migrations from diversified to focused retail business models during crisis periods reduce systemic risk (and vice versa for migrations from focused retail to diversified).

H2b: Business models' migrations from diversified to focused retail business models during endogenous crisis periods reduce systemic risk (and vice versa for migrations from focused retail to diversified).

In line with previous literature, we run a cluster analysis on bank balance sheet indicators and identify five business models: (i) focused retail, (ii) diversified (asset side), (iii) diversified (liability side), (iv) wholesale, and (v) investment. Examining business model changes, we find that while migrations occur throughout the sample period, the pace of change is higher during crises. Adopting a specific business model is a managerial decision based on the bank's board of directors and the shareholders' risk appetite, which, in turn, influences the bank's contribution to and exposure to systemic risk. To mitigate potential endogeneity issues that may arise when analysing the relationship between systemic risk and business models using an OLS regression, we use Heckman's two-step model. As a robustness test, we also use an instrumental variable (IV) approach. Finally, to address possible self-selection bias deriving from the endogeneity of the decision to change the business model, we use a propensity score matching (PSM) approach.

Our results highlight that during tranquil periods, banks operating under different business models exhibit similar sensitivity to systemic risk. However, during periods of instability, the type of business model matters: our results show that investment banks contribute more to and are more exposed to systemic risk. Our findings offer additional insights when distinguishing between endogenous and exogenous crises, highlighting that more market-oriented banks seem to contribute more to systemic risk when the instability stems from an endogenous source. Additionally, we find that focused retail banks consistently show a lower contribution to and exposure to systemic risk across different crisis periods. Moreover, our findings underline the importance of business model migrations in reducing systemic risk, specifically for those migrations from more diversified to more retail-oriented business models.

The contributions of our paper are manifold. First, we contribute to the literature on bank business models (Roengpitya et al., 2017; Hryckiewicz and Kozłowski, 2017; Ayadi et al., 2021) by examining the impact of business models and their changes on systemic risk. Understanding the relationship between a bank's business model and systemic risk is particularly relevant since the adopted business model may represent a risk (business model risk) that can affect a bank’s ability to generate revenues. Second, we contribute to the literature on systemic risk (for a review, see Ellis et al., 2022). Various measures have been proposed in the literature to quantify systemic risk (Acharya et al., 2012; Acharya et al., 2017; Adrian and Brunnermeier, 2016; Brownlees and Engle, 2017). While all these measures have strengths and weaknesses, recent studies tend to use multiple indicators to proxy systemic risk (De Jonghe et al., 2015; Pagano and Sedunov, 2016; Laeven et al., 2016; Cincinelli et al., 2021). We build upon this stream of literature and consider two measures of systemic risk: Adrian and Brunnermeier's (2016) ΔCoVaR and Acharya et al.'s (2012) MES. However, we do not view these two metrics as alternatives but as complementary, demonstrating that they provide different information during periods of crisis.

Third, we contribute to the literature by analyzing the drivers of systemic risk (Wagner, 2010; De Jonghe, 2010; Ibragimov et al., 2011; Brunnermeier et al., 2012; Demirguc-Kunt and Huizinga, 2013; De Jonghe et al., 2015; Adrian and Brunnermeier, 2016; Laeven et al., 2016; Bostandzic and Weiβ, 2018; Van Oordt and Zhou, 2019; Brunnermeier et al., 2020; Chu et al., 2020; Bellavite Pellegrini et al., 2022). These studies underline the importance of bank size, highlighting that larger banks affect or are affected by systemic risk more significantly. However, they focus on bank characteristics without identifying and including bank business models. The work closest to ours is the recent study by Borri and Di Giorgio (2022), which analyzes the contribution to systemic risk of a small sample of European listed banks over the last twenty years. The authors show that although all banks contribute to systemic risk, larger institutions and those with more trading assets contribute more. However, the authors do not identify specific business models nor consider a bank’s exposure to systemic risk. Finally, notwithstanding the long sample period, the authors mainly focus on the COVID-19 crisis.

While previous literature highlights a strong relationship between systemic risk and periods of crisis (Varotto and Zhao, 2018; Meuleman and Vander Vennet, 2020; Borri and Di Giorgio, 2022), little is known about whether this relationship varies depending on the origin of the crisis. We extend the existing literature by considering a 15-year period, allowing us to include periods of instability of different origins and investigate how different bank business models are subject to and contribute to systemic risk when the source of instability is either endogenous to the financial sector or exogenous and caused by economic, political, or health-related events. Our findings provide additional insights and highlight that more market-oriented and diversified banks tend to contribute more to systemic risk when the instability originates endogenously in the financial sector. Additionally, we emphasize the differences in both exposure to and contribution to systemic risk, underscoring the importance of using multiple measures to thoroughly analyze this risk.

Finally, we contribute to the policy debate on the regulation of banks by adding both a micro-prudential and macro-prudential perspective. From a micro-prudential perspective, our analysis assesses banks' strategic decisions with respect to their business models. From a macro-prudential perspective, our findings support regulatory efforts and provide evidence on systemic risk concentrations and financial stability. Regulators aim to limit systemic risk in the financial system, particularly in the banking sector, by introducing macro-prudential rules to improve bank stability and reduce the probability of future banking crises. However, our results show that a "one-size-fits-all" regulation cannot achieve this goal, as banks operating under different business models contribute to and are exposed to systemic risk differently during periods of turbulence.

The remainder of the paper is structured as follows: Section 2 describes the data, and Section 3 the empirical methods. Section 4 shows our empirical results, and Section 5 reports robustness checks and additional analyses. Section 6 outlines the discussion and conclusion.

2. Sample

To construct our sample, we consider all publicly traded banks in the European Economic Area (EEA) and Switzerland. For computational reasons, we include only countries for which we have data available for at least two listed banks; therefore, our sample comprises 23 EEA countries plus Switzerland. Since systemic risk measures are based on equity returns, we focus on publicly traded banks. We collect data on daily banks' stock-adjusted returns and market capitalization, as well as relevant macroeconomic measures (Euribor interest rate, government bond returns, corporate bond returns, house price index, and European market indices) from Thomson Reuters Eikon and the Bloomberg database. For our analysis, we exclude non-trading days for each country. Our market data spans from 01/01/2005 to 31/12/2020, encompassing the global financial crisis (2007-2009), the sovereign debt crisis (2010-2012), some disruptive political events (2016), and the pandemic crisis of 2020. We collect balance sheet and income statement data from SNL Financial (S&P Global Market Intelligence), focusing on banks with data on total assets during the period investigated (2005 to 2020). Our final dataset covers 217 listed banks from 24 European countries.

Table 1. Sample distribution

Country	N. of banks	N. of Obs	Market value (Euro mil) (average)	Total assets (Euro mil) (average)
AT	10	107	2,848.08	44,916.14
BE	2	32	13,472.05	334,878.8
BG	5	62	151.82	1,747.42
CH	22	326	6,131.03	104,153.61
CY	3	40	625.8	15,342.51
DE	16	213	4,257.33	185,696.95
DK	27	374	1,150.38	23,548.24
EE	2	22	229.43	674.8
ES	11	122	20,769.27	325,101.83
FI	4	56	4,064.81	48,385.27
FR	4	54	28,494.59	926,988.88
GB	15	194	29,305.86	534,606.26
GR	7	94	3,490.01	51,919.46
IE	3	48	5,346.83	109,065.78
IT	24	320	6,111.63	116,247.49
LT	2	19	119.91	1,670.23
LV	2	21	931.13	11,760.64
LU	2	21	744.93	381.96
MT	3	44	330.35	3,260.43
NL	6	78	13,152.82	254,186.31
NO	36	471	896.32	12,061.08
PT	2	32	3,307.29	61,238.73
SE	9	104	9,774.74	175,257.61
Total	**217**	**2,854**	**6,769.84***	**14,6995.85***

Notes: AT = Austria; BE = Belgium; BG=Bulgaria; CH = Switzerland; CY = Cyprus; DE = Germany; EE = Estonia; ES = Spain; FIN = Finland; FR = France; GB = Great Britain; GR = Greece; IE = Ireland; IT = Italy; LT = Lithuania; LV = Latvia; LU = Luxemburg; MT = Malta; NL = the Netherlands; NO= Norway; PT = Portugal; SE = Sweden. *The amount is the average market value and total asset observed during the period analysed of the total sample.

3. Empirical design

3.1 Bank Business Models

3.1.1 Bank business models identification

A business model can be seen as a template of how firms (and banks) conduct their business activities and deliver value to their shareholders and stakeholders (Zott and Amit, 2009). Bank business model diversity is assessed via the different behaviors of banks (irrespective of their ownership structure) in the system where they operate, using the Activity-Funding Approach (AFA). This approach fits with the conceptual toolbox needed to address the complexity of a bank's operations.

The level of aggregation of balance sheet items utilized in our analysis reflects the standard production process of a bank, which includes activities such as deposit-taking, loan-granting, and if permitted by regulations and implemented by the bank, active participation in the financial market.

Consistently with previous literature (Ayadi et al., 2021), we base our analysis on five balance-sheet indicators that summarize the asset and liability sides of bank balance sheets:

- Loans to banks (as % of assets). This indicator is a measure of the wholesale and interbank activities carried out by banks, and it is a proxy of the possible risks arising from interconnectedness in the banking sector.
- Debt liabilities (as % of assets). This indicator is measured as non-equity liabilities other than deposits and derivatives over total assets. It is a proxy of the bank's exposure to the funding market.
- Customer loans (as % of assets). This indicator expresses the level of traditional activities carried out by banks. A greater value of this indicator would indicate the prevalence of traditional activities.
- Trading assets (as % of assets). The indicator is defined as non-cash assets other than loans; a greater value would indicate the prevalence of investment activities prone to market and liquidity risks.
- Derivatives (as % of assets). The indicator is the ratio between total bank derivatives over total assets. A high indicator suggests a more market-oriented bank.

In additional tests, we evaluated various alternative configurations by adding or removing variables. However, these adjustments significantly deteriorated the statistical validity of the clusters, underscoring the effectiveness of the selected indicators in accurately identifying them. The five chosen indicators allow us to distinguish both similarities and differences among banks, resulting in clusters that group institutions with a high degree of similarity in their financial instruments.

We base our analysis exclusively on asset and liability data, deliberately excluding income statement information. This approach reflects the understanding that a bank's business strategy is best captured through its asset composition and funding sources. Assets and liabilities represent the fundamental inputs and outputs of banking activities, which drive revenue generation and, ultimately economic income. The superiority of the asset-liability approach over the revenue-expense approach is well-supported in the literature (Benston et al., 2007).
Our methodological focus on balance sheet variables aligns with the theoretical foundations of micro-founded banking models, such as those by Diamond-Dybvig and Monti-Klein. These models conceptualise a bank's objective as a wealth maximisation problem, where wealth is derived from economic outcomes linked to balance sheet quantities. Changes in assets and liabilities reflect the bank's risk-return expectations for budget allocations, which ultimately shape its economic performance.
By concentrating on asset-liability variables, we effectively identify benchmark compositions or business models and subsequently examine their corresponding economic impacts. This approach is consistent with prior research (e.g., Demirgüç-Kunt and Huizinga, 2010) and provides a theoretically grounded framework for analysing business strategies and their financial outcomes.

To identify our business models, we use Hierarchical Cluster Analysis, allowing our cluster analysis to define the optimal number of clusters based on our data. More specifically, we apply Ward's (1963) method to the entire sample period without distinguishing by year. We chose the initial five clusters based on the following metrics: (i) Pseudo F-statistic; (ii) Pseudo T-statistic; (iii) the Dendrogram; (iv) the semi-partial R-squared; and (v) the Cubic Clustering Criterion (CCC). We report the quantitative information on the cluster analysis in the Online Appendix.
Running the cluster analysis, in line with Ayadi et al. (2021), we identify five distinct business models. Focused Retail institutions adhere to the traditional intermediation model, using customer deposits as their primary funding source and focusing mainly on customer loans. Diversified Retail (Type 1) institutions are similar to focused retail on the liability side, with customer deposits as the main funding source, but they diversify on the asset side with a mix of customer loans and a higher proportion of trading assets. Diversified Retail (Type 2) institutions are similar to focused retail on the asset side with a strong emphasis on customer loans, but they differ on the liability side, using both customer deposits and other forms of funding. Wholesale institutions concentrate more on interbank markets and are oriented toward

wholesale activities. Finally, Investment institutions are geared towards trading activities and include both universal banks with significant investment banking divisions and pure investment banks.

As shown in Table 2, banks in each cluster exhibit significant differences in asset and liability structures, reflecting variations in their core activities. As expected, investment banks are the largest, followed by diversified retail type 1 banks, which have asset structures similar to those of investment banks, and diversified retail type 2 banks, which have asset structures more akin to those of focused retail banks. Wholesale banks are the smallest due to their emphasis on asset management over traditional banking activities.

No country in our sample has banks concentrated in a single business model. Table A.1 in Appendix A indicates that all the countries studied have at least three business models represented, except for Latvia, which has two. Figure A.1 in Appendix A graphically presents the balance sheet information of these business models.

Table 2 Bank business models' characteristics

BM	**Total asset (Euro mil)**	**Debt liabilities**	**Customer loans**	**Trading assets**	**Bank loans**	**Derivatives**
Focused retail	23,390.11	13.57%	73.34%	15.38%	5.28%	0.56%
Diversified Type 1	211,942.41	14.17%	44.37%	40.53%	7.17%	3.84%
Diversified Type 2	155,308.83	38.60%	70.38%	22.05%	4.42%	2.74%
Wholesale	2690.54	8.71%	16.87%	27.83%	38.91%	0.37%
Investment	604,276.76	52.53%	16.24%	72.67%	5.03%	9.84%
Sample average	**136179.915**	**23.20%**	**60.96%**	**26.46%**	**6.59%**	**2.45%**

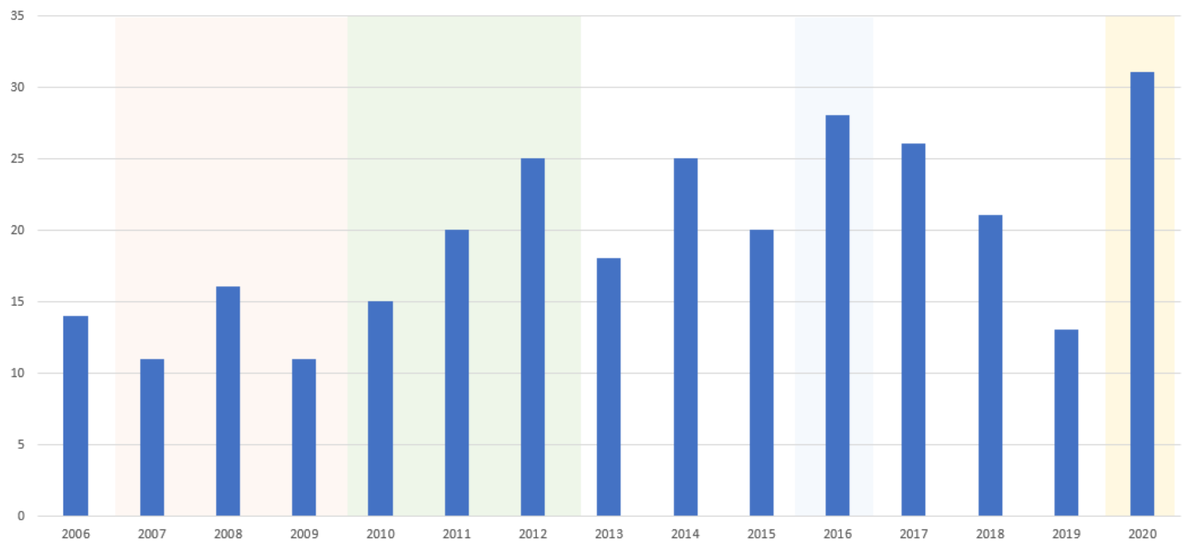
Note: Table reports the indicators used in the cluster analysis to identify BBM: Debt liabilities, Customer loans, Trading assets, Bank loans and Derivatives are reported percentage (over total assets). Total assets are in millions of euros.

The number of business models we identify aligns with previous literature that uses cluster analysis. For instance, Roengpitya et al. (2017) identified four bank business models in a sample of 178 European banks. Similarly, Farnè and Vouldis (2017), analyzing a sample of 365 banks in 19 Euro-area countries, detected four business models and noted several outlier banks that did not fit into any identified groups, mainly small investment firms and specialized lenders. Taking a different approach, Cernov and Urbano (2018) proposed a mixed methodology for business model classification, combining qualitative and quantitative components. Despite the differing methodologies, all studies consistently identify four to five distinct clusters that distinguish between retail-oriented and market-oriented business models. Some banks adhere closely to the traditional intermediation role, relying on retail funding and customer loans, while others engage in less stable funding and trading activities, such as wholesale and investment banking.

3.1.2 Bank business model migrations

Our cluster analysis also allows us to identify banks that changed their business model during the observation period. We identify 2,854 bank-year observations and 294 migrations, representing 10.30% of the total. This suggests that while bank business models are generally stable, some banks do change their models over time. In line with our expectations, we observe an increase in migrations during periods of instability. Figure 1 illustrates the correlation between periods of financial distress and changes in business models; the highest number of migrations occurred during the peak of crises in 2008, 2012, 2016, and 2020.

Figure 1 Bank business model migrations (2005 – 2020).



Note: The figure shows the number of bank business model migrations during the period investigated. The orange area in the graph denotes the global financial crisis; the green area denotes the sovereign debt crisis; the blue area indicates the period of political events, and the yellow area represents the COVID-19 pandemic. The first two crises are considered endogenous crises, while the last two crises are considered exogenous.

Table 3 reports the migration matrix, where the percentage of banks that remain in the same business model from *t* to *t+1* is listed on the diagonal. The data emphasize that, in general, bank business models are persistent: all models report a percentage higher than 88% (Panel A), except for wholesale banks. However, during periods of financial distress (Panels C and D), the percentage of banks that remain in the same business models is lower than during periods of stability (Panel B). Comparing Panel B (no crisis period) with Panels C and D (endogenous and exogenous crises, respectively), there is a noticeable increase in bank migrations. Banks tend to move more towards retail-oriented business models, while migrations to more market-oriented models, such as investment and wholesale, are limited.

Overall, the data show that bank migrations are concentrated in focused retail banks and diversified business models.

Table 3 Bank business model migrations across BBMs and crises

Time t+1 → Time t ↓	Focused retail	Diversified type 1	Diversified type 2	Wholesale	Investment
Panel A Total sample					
Focused retail	89.97%	5.21%	4.72%	0.10%	0.10%
Diversified type 1	6.34%	90.67%	1.94%	1.90%	1.06%
Diversified type 2	8.35%	2.74%	88.65%	0.12%	0.25%
Wholesale	4.35%	14.13%	1.09%	78.26%	2.17%
Investment	0.00%	9.03%	0.69%	0.69%	90.28%
Panel B No crisis					
Focused retail	90.87%	4.76%	4.17%	0.20%	0.20%
Diversified type 1	6.58%	91.54%	1.25%	1.54%	0.63%
Diversified type 2	8.70%	2.32%	88.41%	0.00%	0.58%
Wholesale	6.52%	10.87%	0.00%	82.61%	0.00%
Investment	0.00%	12.33%	1.37%	0.00%	86.30%
Panel C Endogenous crisis					
Focused retail	89.94%	5.17%	4.89%	0.00%	0.00%
Diversified type 1	7.35%	90.44%	1.47%	2.16%	0.74%
Diversified type 2	6.89%	3.03%	90.08%	0.27%	0.00%
Wholesale	3.03%	15.15%	0.00%	81.82%	0.00%
Investment	0.00%	8.00%	0.00%	0.00%	92.00%
Panel D Exogenous crisis					
Focused retail	87.27%	6.67%	6.06%	0.00%	0.00%
Diversified type 1	4.42%	88.50%	4.42%	2.59%	2.65%
Diversified type 2	12.77%	3.19%	84.04%	0.00%	0.00%
Wholesale	0.00%	23.08%	7.69%	53.85%	15.38%
Investment	0.00%	0.00%	0.00%	4.55%	100.00%

Note: The table reports the percentage of changes across business models during the period investigated. Panel A refers to the total period, Panel B to the period of no crisis (2005-2006; 2013-2015; 2017-2019); Panel C refers to endogenous crises (2007-2009; 2010-2012); Panel D shows the exogenous crisis (2016; 2020). The percentages on the diagonal relate to the banks that did not change their business model during the period observed.

3.2 Systemic risk measures

This section describes the systemic risk measures used in our empirical analysis. Following the 2007-2009 financial crisis, numerous researchers have explored the phenomenon of systemic risk; however, no consensus has been reached on a single definition or measure. Kleinow and Nell (2015) categorize the measurement of systemic risk into contribution measures (ΔCoVar) and sensitivity measures (MES). Despite this categorization, there remains debate on whether these measures are complementary or convergent (Lee et al., 2019). Considering both measures provides a comprehensive understanding of systemic risk, encompassing both exposure and contribution. Given that regulations are often based on estimates of systemic risk, it is essential to evaluate systemic risk from both perspectives to thoroughly assess the systemic volatility of financial institutions.

The first measure is the ΔCoVar proposed by Adrian and Brunnermeier (2016). Following the authors' methodology, we define the ΔCoVar as the marginal contribution of a bank to the financial sector's overall systematic risk. The ΔCoVar can be defined as the difference between the financial system VaR conditional on bank distress ($CoVar_q^{system,|i}$) and the financial system's VaR conditional on bank *i* functioning on its median state ($CoVar_q^{system,|i,median}$).

$$\Delta CoVar_q^i = CoVar_q^{system,|i} - CoVar_q^{system,|i,median} \tag{1}$$

To estimate the $CoVar_q^{system,|i}$ and$CoVar_q^{system,|i,median}$, we run a 5% quantile regression using weekly data. [2] We collect data from the Refinitiv Eikon Database.

We use the value-weighted daily market returns from Eurostoxx50 as the financial market index of European countries. We measure market volatility as the 22-day rolling standard deviation of the daily equity market return. Liquidity is defined as the difference between the three-month Euribor and the three-month government bond rate. Moreover, we calculate the change of three different variables: a) the default risk measured as the change in the credit spread between 10 years of BAA eurozone corporate bonds and ten-year government bonds of each country of our sample; b) the interest rate risk is the change in the one-year government

[2] For more details on the $\Delta CoVar_q^i$ measurement, see Brunnermeier, M. K., Dong, G. N., & Palia, D. (2020). Banks' noninterest income and systemic risk. *The Review of Corporate Finance Studies*, *9*(2), 229-255.

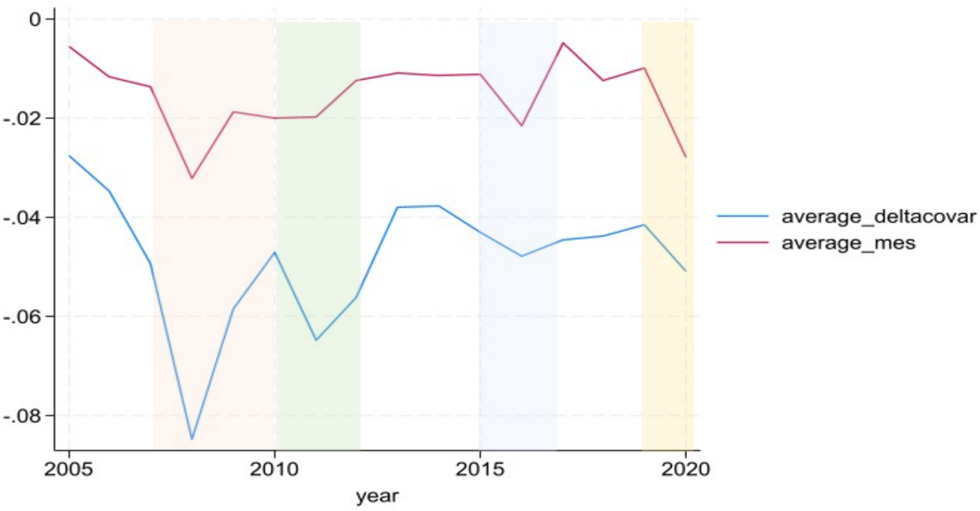
bond rate of each country considered in our analysis; c) term structure measured as the change in the slope of the yield curve of government bonds issued by each government of countries analyzed (the yield spread between the ten-year government bond rate and the one-year government bond rate). Lastly, we include each country's house price index (HPI) to proxy the real estate return.

Next, we estimate the marginal expected shortfall (MES) as our second measure of systemic risk. Following Acharya et al. (2017), we define the MES of a bank as its expected equity loss when the market itself is in its left tail. Using the daily market return of the banks in our sample, we estimate the banks' MES at a 5% risk level. We consider the 5% worst days for the Eurostoxx50 returns in any given year of our analysis to define the systemic crisis event. Then, we consider the average equity returns of each bank on these worst days:

$$MES_{5\%}^{i} = \frac{\Sigma R_t^i}{\#days_{t,system\ in\ the\ tail\ 5\%}} \qquad (2)$$

Figure 3 reports the evolution of systemic risk during the period observed, confirming the findings highlighted by Weiβ et al. (2014), which point out that during periods of financial distres,s systemic risk in the banking system rises. In particular, we observe that during the subprime crisis (2007-2009), the sovereign debt crisis (2010-2012), the political events of 2016, and the pandemic crisis of 2020, the systemic risk, both in terms of MES and ΔCoVar increases. The evolution of the two measures of systemic risk per country and year is reported in Appendix A (Tables A.1 and A.2).

Figure 3 Average ΔCoVar and average MES



Note: Figure 1 reports the evolution of ΔCoVar and MES from 2005 to 2020. The orange area in the graph denotes the global financial crisis; the green area denotes the sovereign debt crisis; the blue area indicates the political events period, and the yellow area represents the COVID-19 pandemic.

3.3 Empirical Model

3.3.1 Systemic risk and bank business models

Our objective is to investigate whether systemic risk is associated with specific business models or if the choice of a business model has no effect on a bank's contribution to or exposure to systemic risk. Additionally, we aim to disentangle this relationship during specific periods of financial distress to ascertain whether the origins of the instability impact each business model differently.

Our estimation model takes the following form.

$$SYSTEMIC\_RISK_{i,t} = \alpha_0 + \ \beta_1 \ SISTEMIC\_RISK_{i,t-1} + \ \rho \ BM_{i,t-1} + \gamma \ S_t + +\eta \ I_t + \delta \ Z_{i,t-1} + \ FEc + \varepsilon_{i,t} \qquad (3)$$

Where α_0 is a constant, SYSTEMIC_RISK is the dependent variable that can assume the value referring to the $-\Delta CoVar^i_{5\%}$ or $-MES^i_{5\%}$ of bank *i* at time *t*; following (López-Espinosa et al., 2012; Bostandzic and Weiβ, 2018; Meuleman and Vander Vennet, 2020; Borri and Di Giorgio, 2022), the lagged dependent variable at time t-1 is also included as an independent variable; $BM_{i,t-1}$ denotes the business model adopted by bank *i* at time t-1*;* S_t is a dummy variable that takes value 1 during the four periods of instability that characterized our sample period (endogenous crises, i.e. global financial crisis, 2007-2009; sovereign debt crisis, 2010-2012; and exogenous crises, i.e. political instability, 2016; pandemic turmoil, 2020) and zero otherwise; the term (I_t) captures the interaction effect of bank business models during instability periods. The term I_t is included only in the second step of our analysis. Following previous literature (López-Espinosa et al., 2012; Laeven et al., 2016; Varotto and Zhao, 2018), the vector $Z_{i,t-1}$ controls for banks' characteristics such as bank size[3], leverage, market-to-book value, risk appetite, cost efficiency, and market share in the payment system. We also control if the bank is systemically important globally and domestically. Variable descriptions are reported in Table A.3 in Appendix A. Following Ayadi et al. (2021), we do not include any

[3] Note that instead using directly the natural logarithm of total asset as measure of bank size, we first orthogonalize it, following Idier et al. (2014), De Jonghe (2010) and Varotto and Zhao (2018). The idea is to orthogonalize the size with respect to all other variables to derive the pure effects of size.

balance sheet or income statement variables used to define the business models. Finally, to control for differences that vary over time, we include time fixed-effects (TIME_FE), and $\varepsilon_{i,t}$ is the error term.

3.3.2 Endogeneity concerns

Adopting a specific business model is a managerial decision. In normal times, this decision primarily depends on the strategy defined by the bank's board of directors and the shareholders' risk appetite, which also influences the bank's contribution to and exposure to systemic risk. Consequently, endogeneity issues may arise when analyzing the relationship between systemic risk and business models using an OLS regression. A common method to address this endogeneity is Heckman's two-step model. In this approach, the first step estimates the decision equation using a logit or probit model to obtain the inverse Mills ratio (IMR), where the dependent variable in the decision equation is binary. The second step includes the generated IMR as an additional explanatory variable in the performance equation (see Heckman, 1979; Hamilton and Nickerson, 2003). By incorporating the IMR into the performance equation, the estimated coefficient of the endogenous variable becomes unbiased. Lee (1983) first proposed an extended version of the Heckman two-step model, where selectivity is modeled using a multinomial logit case with a simple approach that requires estimating only one parameter in the correlation term. However, due to the restrictive assumption of this approach, as suggested by Bourguignon et al. (2007), we prefer the method proposed by Dubin and McFadden (1984), which involves estimating one IMR for each category assumed by the endogenous variable.

First, the multinomial logit model estimates for the bank business model's adoption are used to compute the IMR. The multinomial logit equation is reported below:

$$\Pr\left(BM_{i,t} = s\right) = \alpha_0 + \beta\, M\&A_{i,t-1} + +\delta\, STATE_{AID_{i,t-1}} + \eta\, DISTANCE_{BM_{COUNTRY_t}} + \sigma\, Z_{i,t-1} + \varepsilon_{i,t} \tag{4}$$

$BM_{i,t}$ is the probability of adopting a specific business model. As highlighted in Ayadi et al. (2021), the adoption of a specific business model is, among other factors, the outcome of strategic choices, both endogenously driven (e.g., M&A operations) and exogenously driven (e.g., fostered by state interventions during crisis periods). Additionally, a banking system could be more concentrated or diversified in terms of business models due to historical reasons or characteristics of the demand side (e.g., a productive structure mainly composed of SMEs highly dependent on bank credit). Although the first and second-step regressions can contain common variables, the identification via the exclusion restriction scheme requires the first step to contain at least one variable that is not included in the main equation (second-step regression) and that displays significant time variability (Matyas and Sevestre, 2008; Semykina and Wooldridge, 2013). Therefore, we include the following variables in the multinomial logit regression:

i) two dummy variables that refer to the involvement in an M&A operation. The first is equal to one if the bank is involved in an M&A operation as the acquiror and zero otherwise; the second dummy variable takes the value of 1 if the bank is involved in an M&A operation as a target, zero otherwise. We collect data on M&A operations from Zephyr;

ii) a vector ($STATE\_AID_{t-1}$) which collects information on whether the bank was the recipient of an *ad hoc state aid* or of a *scheme state aid* implemented at the country level to support the entire banking sector. During our sample period, several governments supported their banking system through state aid with ad hoc and scheme interventions; state aid may represent an exogenous force pushing banks to adopt a specific business model. We use information from the European Commission database to construct this variable.

iii) a measure of the relative relevance of each business model within a country's banking system ($DISTANCE_{BM_{COUNTRY}}$). To construct these five variables (one for each business model), we first consider the overall distribution of banks (listed and non-listed at the consolidated level) across the five business models each year and calculate yearly averages per business model. For instance, in 2019, the European banking market was composed, on average, of 55.43% focused retail banks, 30.46% diversified banks, 6.71% wholesale banks, and 7.41% investment banks. Next, we calculate the same yearly averages at the country level and determine the distance from the percentages measured at the European level for each business model and each year.

iv) a vector of bank characteristics $Z_{i,t-1}$.

From equation (4), we obtain the IMRs following the specification of Dubin and McFadden (1984):

$$\lambda_{ist} \quad = \sum_{\substack{j=0 \\ j\neq s}}^{5} \left(\frac{P^{\wedge}{}_{ijt} * lnP^{\wedge}{}_{ijt+1}}{1-P^{\wedge}{}_{ijt}} - lnP^{\wedge}{}_{ist}\right) \tag{5}$$

Where $P^{\wedge}{}_{ist}$= P^(BM_{it}= s).

Therefore, we include in equation (6) λ_{ist} that is the vector collecting the IMR used as controls for the endogeneity of the dummies of BMs.

$$SYSTEMIC\_RISK_{i,t} = \alpha + \ SISTEMIC\_RISK_{i,t-1} + \beta BM_{i,t-1} + \gamma S_t + + \eta I_t + \ \delta Z_{i,t-1} + FEc + \lambda_{ist} + \varepsilon_{i,t} \tag{6}$$

In the second step of our analysis, we substitute the dummy variable "Instability" with two dummy variables that refer to the specific origins of instability. One dummy variable represents endogenous crises, including the global financial crisis and the sovereign debt crisis, while the other dummy variable represents exogenous crises, including the political events of 2016 and the health crisis related to the COVID-19 pandemic. Moreover, we add a set of interactions between business models and each instability dummy.[4] To simplify the reading and the interpretation of results, the two diversified retail business models are merged into one. We therefore consider four business models: focused retail, diversified, wholesale and investment. The interaction variables allow us to observe whether the different business models exhibit varying levels of exposure to or contribution to systemic risk depending on the origin of the crisis, i.e., endogenous or exogenous.

3.3.2 Bank business model migrations and systemic risk

To mitigate possible endogeneity concerns regarding a bank's decision to change its business model, we employ a propensity-matching approach (Caliendo and Kopleing, 2008). We distinguish between the treated group (banks that change their business model in a specific year) and the control group (banks that do not change their business model in the same year). The treatment in our study is the migration from one business model to another.

To measure the propensity scores, we run the following probit regression:

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[4] For each BM, we construct a dummy variable that equals one if the bank adopts a specific BM, zero otherwise. The dummy variables are then used to create the interaction variable with the dummy variable of each crisis.

$$P(w_{it} = 1) = P(\alpha_0 + \sum_{k=1}^{K} \alpha_k X_{kit-1} + \varepsilon_{it} > 0) \quad (7)$$

where α_0 is a constant, K denotes the number of explanatory variables $X_{k,it-1}$ in the selection equation, and ε_{it} is an identically and independently distributed error term. On the left-hand side, the dependent variable w_{it} is set to 1 in the year t in which bank *i* migrates from one business model to another.

In vector X, the confounding variables used to determine the propensity scores are the same variables used in equation (4), which refers to the probability of adopting a business model. We calculate the propensity scores and match migrating and non-migrating banks. Finally, we estimate the effect of migration on bank systemic risk. We employ the nearest-neighbor matching algorithm with replacement and measure the average treatment effect on treated (ATET), which is calculated by comparing the outcomes of treated banks to the outcomes of untreated banks that are similar to the treated ones in terms of propensity scores. The ATET provides a measure of the effectiveness of the treatment specifically for those who have undergone the treatment.[5]

To detect the treatment effect on the bank systemic risk, we consider the systemic risk measures at time t and also three different time windows: i) the year of treatment (from t-1 to t); ii) the year after migration (from t to t+1); and iii) the longer-term, with a two-year window around the time of migration (from t-1 to t+1).

4. Empirical results

4.1 Descriptive statistics

Tables 4-7 present the descriptive statistics of the variables used in the empirical analysis. Table 4 shows the descriptive statistics for the total sample. Table 5 displays the number of observations and the averages of the variables, distinguishing between business models, along with the results of the ANOVA test (Bartlett's test) in the last column. Table 6 illustrates the descriptive statistics across different periods of crises, distinguishing between no crisis, endogenous crisis, and exogenous crisis. The last two columns report the significance of the Wilcoxon-Mann-Whitney test and the ANOVA test, respectively, with the Wilcoxon-Mann-Whitney test comparing the two periods of crises. Finally, Table 7 displays the number of observations and the averages of the variables for banks that change their business model at

[5] Details on our PMS approach are reported in Online Appendix – propensity score matching.

least once and banks that never do, with the results of the Wilcoxon-Mann-Whitney test in the last column.[6]

Regarding systemic risk and business models (Table 5), investment banks show the highest average MES, followed by diversified banks. In terms of ΔCoVar, diversified banks (type 2) contribute the most to systemic risk, followed by diversified (type 1) and investment banks. The difference between focused retail and wholesale banks and the other business models is smaller in the case of ΔCoVar than in MES. Investment banks have the highest leverage, while wholesale banks, as expected, have the lowest leverage ratio, consistent with their liability composition. Focused retail banks, specializing in lending activity, exhibit the highest RWA density ratio, while investment banks have the lowest. In terms of cost efficiency, wholesale banks, followed by investment banks, have the highest cost-to-income ratio, indicating lower cost efficiency. The last column of the table reports the significance of the ANOVA test p-values, revealing that the assumption of homogeneous variances can be rejected in all cases.

We also extend the descriptive analysis by distinguishing between crises of different origins. (Table 6) reports the descriptive statistics categorized by crisis periods: no crisis, endogenous crises, and exogenous crises. The findings suggest that the period with the highest contribution to systemic risk was during endogenous crises, which originated from within the banking system itself. The greatest overall exposure to systemic risk occurred during exogenous crises, with an average MES value of -2.4%. As expected, the period with the lowest MES and ΔCoVar was the no-crisis period. Interestingly, the exposure and contribution of bank business models to systemic risk vary depending on the origin of the instability.

Examining the contribution to systemic risk during the global financial and sovereign debt crises (endogenous crises), we find that the business models with the highest ΔCoVar were diversified retail (type 1), followed by diversified (type 2) and investment models. Conversely, during exogenous crises, diversified retail (type 2) banks exhibited the highest contribution, with an average ΔCoVar of -5%. Interestingly, during periods of no instability, the average contribution to systemic risk is similar across different business models. However, this pattern does not hold when considering banks' exposure to systemic risk, as MES shows considerable variation even during stable periods. The business models least exposed to systemic risk during financial distress are focused retail and wholesale models, while investment models have the highest MES during both endogenous and exogenous crises, followed by diversified retail models (both type 1 and type 2).

[6] The correlation matrix is reported in Online Appendix, Table OA.2.

To assess whether the variance across the three periods (no crisis, endogenous crises, and exogenous crises) is equal, we conducted an ANOVA test, which rejected the assumption of homogeneous variances in all cases. Additionally, the Wilcoxon-Mann-Whitney test was used to compare the means of the two instability periods. The results indicate that, with the exception of the MES for wholesale and investment banks, the MES and ΔCoVar recorded by banks with different business models during the two crisis periods are statistically different.

Migrating banks exhibit a higher exposure to and contribution to systemic risk. On average, they are smaller and have lower leverage and market-to-book values but demonstrate a higher risk appetite and greater cost inefficiency (Table 7).

Table 4. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
MES	2,854	-0.014	0.019	-0.104	0.079
ΔCoVar	2,854	-0.048	0.012	-0.085	-0.028
SIZE	2,637	9.174	2.49	2.966	14.738
LEVERAGE	2,635	13.916	7.839	1.731	51.907
MBV	2,350	3.176	5.974	-16.524	83.187
RWA_TA	2,530	0.564	0.196	0.218	0.946
WPS	2,631	0.128	0.231	0	1
COST_INCOME	2,617	0.634	0.215	0.227	1.785
FOCUSED	2,854	0.386	0.487	0	1
DIV TYPE 1	2,854	0.226	0.419	0	1
DIV TYPE 2	2,854	0.297	0.457	0	1
WHOLESALE	2,854	0.035	0.183	0	1
INVESTMENT	2,854	0.055	0.228	0	1

Note: This table reports the descriptive statistics of the variables used in the empirical analysis for the total sample. MES and ΔCoVar are two measures of systemic risk in terms of exposure and contribution, respectively. SIZE is the natural logarithm of total bank assets. LEVERAGE is the ratio of total assets to total equity. MBV is the ratio of the bank's market value to its equity book value. RWA_TA is the ratio of risk-weighted assets to total assets. COST_INCOME measures bank cost efficiency and is given by the ratio of operating costs to operating income. FOCUSED is a dummy variable that equals 1 if the bank adopts the focused retail business model, and zero otherwise. DIV TYPE 1 is a dummy variable that equals 1 if the bank adopts the diversified retail type 1 business model, and zero otherwise. DIV TYPE 2 is a dummy variable that equals 1 if the bank adopts the diversified retail type 2 business model, and zero otherwise. WHOLESALE is a dummy variable that equals 1 if the bank adopts the wholesale business model, and zero otherwise. INVESTMENT is a dummy variable that equals 1 if the bank adopts the investment business model, and zero otherwise.

Table 5. Descriptive statistics and Anova test of variance across Business Models

	FOCUSED RETAIL		DIV TYPE 1		DIV TYPE 2		WHOLESALE		INVESTMENT		ANOVA
Variable	**Obs**	**Mean**	**Obs**	**Mean**	**Obs**	**Mean**	**Obs**	**Mean**	**Obs**	**Mean**	**Sign**
MES	1,103	-0.008	646	-0.017	849	-0.017	99	-0.005	157	-0.023	***
ΔCoVar	1,103	-0.040	646	-0.042	849	-0.044	99	-0.037	157	-0.041	***
SIZE	1,018	8.344	579	9.344	803	10.151	92	6.494	145	10.609	***
LEVERAGE	1,018	11.473	579	13.117	803	15.297	92	9.679	143	23.294	***
MBV	875	3.169	524	2.366	739	3.115	86	1.977	126	7.767	***
RWA_TA	980	0.627	553	0.532	776	0.542	84	0.554	137	0.364	***
WPS	1,018	0.072	577	0.179	803	0.152	92	0.133	141	0.191	***
COST_INCOME	1,015	0.617	579	0.704	799	0.561	92	0.899	132	0.723	***

*Note: The table reports the descriptive statistics of variables used in the empirical analysis. Data refers to the subsamples regarding the business models. MES and ΔCoVar are two measures of systemic risk in terms of exposure and contribution, respectively. SIZE is the natural logarithm of total bank assets. LEVERAGE is the ratio of total assets to total equity. MBV is the ratio of the bank's market value to its equity book value. RWA_TA is the ratio of risk-weighted assets to total assets. COST_INCOME measures bank cost efficiency and is given by the ratio of operating costs to operating income. The last column reports the significance of the ANOVA test of variance. *, **, and *** indicate statistical significance at $p<0.01$, $p<0.05$, and $p<0.1$, respectively.*

Table 6. Descriptive statistics, Wilcoxon-Mann-Whitney test, and ANOVA test across Crises

	TOTAL		**NO CRISIS**		**ENDOGENOUS CRISIS**		**EXOGENOUS CRISIS**		**Wilcoxon–Mann–Whitney test**	**Wilcoxon–Mann–Whitney test**	**ANOVA**
Variable	**Obs.**	**Mean**	**Obs.**	**Mean**	**Sign**	**Mean**	**Obs.**	**Mean**	**P-value**	**Sign**	**Sign**
MES	2,854	-0.014	1,415	-0.009	1,017	-0.017	422	-0.024	0.000	***	***
ΔCOVAR	2,854	-0.048	1,415	-0.035	1,017	-0.051	422	-0.042	0.000	***	***
ΔCOVAR_FOCUSED	1,011	-0.041	502	-0.034	353	-0.052	156	-0.041	0.000	***	***
ΔCOVAR_TYPE1	576	-0.043	322	-0.037	142	-0.056	112	-0.044	0.000	***	***
ΔCOVAR_TYPE2	799	-0.047	350	-0.038	360	-0.054	89	-0.050	0.001	***	***
ΔCOVAR_WHOLESALE	90	-0.038	47	-0.031	33	-0.051	10	-0.033	0.003	***	***
ΔCOVAR_INVESTMENT	136	-0.044	71	-0.036	45	-0.054	20	-0.044	0.002	***	***
MES_FOCUSED	882	-0.010	425	-0.007	311	-0.009	146	-0.022	0.000	***	***
MES_TYPE1	532	-0.019	292	-0.012	133	-0.028	107	-0.028	0.776		***
MES_TYPE2	753	-0.020	334	-0.012	332	-0.025	87	-0.032	0.010	*	***
MES_WHOLESALE	77	-0.007	40	-0.005	28	-0.007	9	-0.012	0.357		***
MES_INVESTMENT	122	-0.027	63	-0.017	40	-0.038	19	-0.038	0.357		***

*Note: This table reports the descriptive statistics of the variables used in the empirical analysis. Data refers to the total sample and the subsamples regarding the four periods of instability. MES and ΔCoVar are our two measures of systemic risk in terms of exposure and contribution, respectively. ΔCoVar_FOCUSED, ΔCoVar_TYPE1, ΔCoVar_TYPE2, ΔCoVar_WHOLESALE, and ΔCoVar_INVESTMENT are interaction variables between ΔCoVar and the bank business models. Similarly, MES_FOCUSED, MES_TYPE1, MES_TYPE2, MES_WHOLESALE, and MES_INVESTMENT are interaction variables between MES and the different bank business models. The Wilcoxon-Mann-Whitney test assesses the hypothesis that two independent samples (i.e., unmatched data) are from populations with the same distribution. The test is conducted on the two groups of endogenous and exogenous periods of instability. The last column reports the significance of the ANOVA test in evaluating the hypothesis of differences in means among more than two groups, i.e., no-instability, endogenous crises, and exogenous crises. *, **, *** indicate statistical significance at p<0.01, p<0.05, and p<0.1, respectively.*

Table 7. Bank systemic risk and migrations

Variable	Non-migrating banks Obs	Mean	Migrating banks Obs	Mean	Wilcoxon–Mann–Whitney test P-value	Wilcoxon–Mann–Whitney test Sig.
MES	766	-0.013	2,088	-0.014	0.108	
ΔCoVar	766	-0.039	2,088	-0.042	0.005	***
SIZE	705	9.661	1,932	8.996	0.000	***
LEVERAGE	705	15.740	1,930	12.789	0.000	***
MBV	635	4.444	1,715	2.706	0.000	***
RWA_TA	678	0.522	1,852	0.579	0.000	***
WPS	705	0.136	1,926	0.126	0.000	***
COST_INCOME	705	0.583	1,912	0.653	0.000	***

*Note: This table reports the averages and the number of observations of the variables used in the empirical analysis. Data refers to banks that change their business model at least once (migrating banks) and banks that never change their business model (non-migrating banks). MES and ΔCoVar are two measures of systemic risk in terms of exposure and contribution, respectively. SIZE is the natural logarithm of total bank assets. LEVERAGE is the ratio of total assets to total equity. MBV is the ratio of the bank's market value to its equity book value. RWA_TA is the ratio of risk-weighted assets to total assets. COST_INCOME measures bank cost efficiency and is given by the ratio of operating costs to operating income. FOCUSED is a dummy variable that equals 1 if the bank adopts the focused retail business model, and zero otherwise. DIV TYPE 1 is a dummy variable that equals 1 if the bank adopts the diversified retail type 1 business model, and zero otherwise. DIV TYPE 2 is a dummy variable that equals 1 if the bank adopts the diversified retail type 2 business model, and zero otherwise. WHOLESALE is a dummy variable that equals 1 if the bank adopts the wholesale business model, and zero otherwise. INVESTMENT is a dummy variable that equals 1 if the bank adopts the investment business model, and zero otherwise. The Wilcoxon-Mann-Whitney test assesses the hypothesis that two independent samples (i.e., unmatched data) are from populations with the same distribution. The test is conducted on the two groups of migrating and non-migrating banks. The last two columns report the p-value and the statistical significance. *, **, and *** indicate statistical significance at p<0.01, p<0.05, and p<0.1, respectively.*

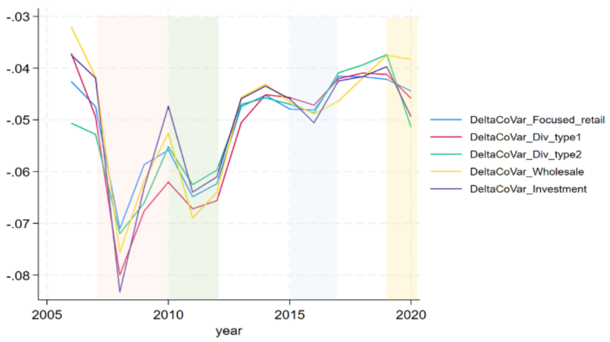
Figure 4 illustrates the average ΔCoVar (Panel a) and MES (Panel b) by business model over the period under investigation (refer to Table A.2 ie Appendix A for details).

Figure 4 (Panel a) shows that, during periods of no instability, the contributions to systemic risk (ΔCoVar) of different business models were largely aligned. While all business models tracked each other closely, some variations appeared during crises without consistent patterns. Notably, the investment business model contributed the most to systemic risk during the subprime crisis, especially in 2008 and 2016, likely due to concerns over Brexit's impact on London’s financial center. In contrast, during the sovereign debt crisis in 2011, the diversified retail (type 1) and wholesale business models were the highest contributors. During the COVID-19 crisis, contributions to systemic risk were limited and similar across business models, with wholesale banks not contributing.

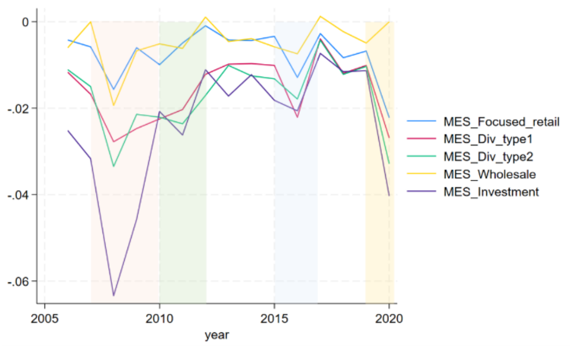
Figure 4 (Panel b) reveals that banks’ exposure to systemic risk (MES) varied according to the business model throughout the period. Investment banks consistently exhibited the highest exposure, while wholesale banks had the lowest. During the COVID-19 pandemic, exposure to systemic risk increased across all business models except wholesale. Interestingly, the political events of 2016 (e.g., the Brexit referendum and Trump's election) led to increased exposure to systemic risk for all business models, although their contribution to systemic risk remained relatively stable.

Figure 4 Systemic Risk and Bank Business Models

Panel a) ΔCoVar



Panel b) MES



Note: Panel a) reports the evolution of ΔCoVar, while Panel b) shows the evolution of MES. The orange area in the graph denotes the global financial crisis; the green area denotes the sovereign debt crisis; the blue area indicates the political events period, and the yellow area represents the COVID-19 pandemic.

4.2 Regression results: Bank business models and systemic risk

In this section, we report the empirical results of our analysis aimed at identifying whether systemic risk is associated with specific business models and if the contribution to or exposure to systemic risk of each business model changes during different periods of instability

(Hypothesis 1). Since $\Delta CoVar_q^i$ and MES typically take negative values, a more negative value indicates a more significant contribution to and exposure to systemic risk, respectively. To ease the interpretation of our findings, we multiply $\Delta CoVar_q^i$ and MES by -1 in the regression models, allowing an increase in the variable to be interpreted as an increase in systemic risk.

We use a Heckman two-step extended approach, with the first step being a multinomial logistic regression. The results of the first step, from which we obtain the IMRs, are reported in Table A.4, Appendix A. Tables 8 and 9 show the results of the second step, in which we include the IMRs to control for endogeneity problems.

Table 8 presents the baseline results.[7] Focused retail and diversified (type 2) banks exhibit lower exposure to systemic risk compared to investment banks. In contrast, the other business models do not show statistically significant differences from investment banks in terms of exposure (Models 1 and 2). Regarding systemic risk contribution (Models 3 and 4), no business models have statistically significant coefficients, indicating that without distinguishing between periods of instability and stability, there are no significant differences among business models. These findings suggest that, in the absence of this distinction, the contribution to systemic risk is similar across different business models.

Systemic risk is higher during periods of instability, both in terms of exposure and contribution, as indicated by the positive and statistically significant coefficient of the INSTABILITY dummy variable. Notably, when differentiating between endogenous and exogenous crises, the magnitude of the coefficients changes significantly. MES shows higher coefficients during exogenous crises, while ΔCoVar displays higher coefficients during endogenous crises, confirming their respective roles in systemic risk exposure and contribution.

Our findings align with previous studies on bank characteristics. We find that the contribution to systemic risk depends on the previous year's level of systemic risk contribution (López-Espinosa et al., 2012; Bostandzic and Weiβ, 2018; Meuleman and Vander Vennet, 2020; Borri and Di Giorgio, 2022). Additionally, we find that systemically important and larger banks with higher risk appetites are more exposed to systemic risk (Varotto and Zhao, 2018; Brunnermeier et al., 2020). In terms of ΔCoVar, banks with higher market-to-book values, indicating greater growth opportunities and higher risk appetites, contribute more to systemic risk.

[7] As a robustness check, we also ran the regression models excluding the dependent variable at time t-1 and our main results are confirmed. Moreover, we also define the IMR using in the first step of the two step Heckman model only the bank characteristics included in the second step and their square values, as Caselli et al. (2021) and Cucinelli et al. (2018). Results are not reported in the text but are available upon request.

Table 8 Performance equation: the second step of the extended Heckman model – business models, crises periods, and systemic risk

	Model 1			
	(1)	(2)	(3)	(4)
VARIABLES	MES	MES	ΔCoVar	ΔCoVar
FOCUSED $_{t-1}$	-0.467***	-0.481***	0.023	0.016
	(0.158)	(0.186)	(0.084)	(0.115)
DIV_TYPE1 $_{t-1}$	-0.228	-0.184	-0.013	-0.002
	(0.158)	(0.187)	(0.083)	(0.115)
DIV_TYPE2 $_{t-1}$	-0.519***	-0.547***	-0.045	-0.064
	(0.159)	(0.187)	(0.084)	(0.118)
WHOLESALE $_{t-1}$	0.002	-0.040	-0.083	-0.032
	(0.206)	(0.229)	(0.118)	(0.148)
INSTABILITY	0.444**	-	0.815***	-
	(0.175)		(0.102)	
ENDOGENOUS	-	0.665***	-	1.380***
		(0.082)		(0.063)
EXOGENOUS	-	1.802***	-	0.631***
		(0.112)		(0.045)
Dependent$_{t-1}$	0.398***	0.289***	0.534***	0.348***
	(0.032)	(0.031)	(0.025)	(0.023)
GSIB$_{t-1}$	0.198*	0.263**	0.060	0.094
	(0.103)	(0.112)	(0.048)	(0.059)
SIZE$_{t-1}$	0.588***	0.735***	0.046	0.073**
	(0.062)	(0.068)	(0.029)	(0.035)
LEVERAGE $_{t-1}$	-0.000	-0.000	0.001***	0.000**
	(0.001)	(0.001)	(0.000)	(0.000)
MBV $_{t-1}$	0.003	0.010	0.007**	0.010***
	(0.005)	(0.007)	(0.003)	(0.004)
RWA_TA $_{t-1}$	0.978***	1.238***	0.330***	0.601***
	(0.226)	(0.239)	(0.109)	(0.123)
WPS $_{t-1}$	-0.112	-0.058	0.022	-0.016
	(0.167)	(0.196)	(0.077)	(0.102)
COST_INCOME $_{t-1}$	0.055	0.033	0.036	0.020
	(0.086)	(0.080)	(0.037)	(0.039)
IMR1	0.041***	0.042***	0.006	0.020**
	(0.011)	(0.013)	(0.006)	(0.008)
IMR2	-0.023*	-0.011	-0.019***	-0.022***
	(0.012)	(0.013)	(0.006)	(0.007)
IMR3	-0.023***	-0.022***	-0.004	-0.008
	(0.007)	(0.008)	(0.004)	(0.006)
IMR4	0.000	-0.000	-0.002*	-0.005***
	(0.002)	(0.002)	(0.001)	(0.001)
Constant	0.343	0.248	1.724***	2.568***
	(0.215)	(0.238)	(0.168)	(0.199)
TIME FE	YES	YES	YES	YES
Observations	1,985	1,985	1,977	1,977
R-squared	0.595	0.507	0.712	0.569

Note: This table reports Heckman's second-step regression results. The dependent variable is the proxy for systemic risk (MES or ΔCoVar). Model 0 is the baseline model with the business model (BM) at time t-1 and the crisis dummies. CRISIS is a dummy variable equal to 1 during 2007-2009, 2010-2012, 2016, and 2020, and 0 otherwise. ENDOGENOUS is a dummy variable equal to 1 during 2007-2009 and 2010-2012, and 0 otherwise. EXOGENOUS is a dummy variable equal to 1 in 2016 and 2020, and 0 otherwise. The bank characteristics at t-1 are included and they are: the dependent variable at time t-1; GSIB is a dummy variable if the bank is a domestic or global systemically important bank; SIZE is the orthogonalized natural logarithm of total assets with respect to all other bank-specific characteristics included in the regression model; LEVERAGE is the total asset over total equity ratio; MBV is the ratio between the bank's market value and its equity book value; RWA_TA is the ratio of risk-weighted assets to total assets; WPS is the level of deposits of bank i divided by the level of deposits *of the bank's home country; COST_INCOME measures bank cost efficiency, given by the ratio of operating costs to operating income. The IMRs are obtained from the first step of the Heckman regression. The business models refer to focused retail banks (FOCUSED), diversified retail type 1 (DIV_TYPE1), diversified retail type 2 (DIV_TYPE2), and wholesale banks (WHOLESALE). The investment business model is the reference category. All regression models include time fixed effects. Robust standard errors are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.*

Having observed that all our sample banks exhibit higher exposure to and contribution to systemic risk during periods of financial instability, we now proceed to test our first overarching hypothesis that market-oriented business models (i.e., investment and diversified) are more systemically risky. In addition, we also test the exposure and contribution of each business model to endogenous and exogenous crises.

For simplicity, we combine diversified type 1 and type 2 into a single category, representing banks with diversified activities in both assets and liabilities. To test our hypothesis, we define market-oriented business models as those that are either diversified or investment-focused. These models are characterized by higher levels of trading assets and non-deposit funding.

In Table 9, Model 3, we explore the relationship between financial instability periods and business models by interacting bank business models with the two types of distress periods. Our findings highlight the variability in how each business model influences systemic risk, showing that different bank business models respond differently depending on the origin of the crisis.

During generalized periods of instability (columns 5 and 7), investment and diversified BMs show the highest MES and ΔCoVar, confirming our H1a. [8]

Considering the nature of the crisis, our results need to be commented on by the type of systemic risk measure analyzed. Regarding the exposure to systemic risk, investment banks increase their exposure to systemic risk the most in both types of crises. Investment banks' MES increases from 0.027% to 1.523% during endogenous crises, and from 0.027% to 2.826% during exogenous crises, indicating a higher systemic risk exposure during exogenous crises. Diversified banks show no statistically significant difference in exposure to systemic risk compared to investment banks during either endogenous or exogenous crises (H1b). Conversely, focused retail and wholesale banks exhibit lower exposure to systemic risk. Focused retail banks' MES increases from 0.188% during periods of no instability to 0.432% during endogenous crises and 1.742% during exogenous crises. Meanwhile, wholesale banks' MES increases from 0.625% during periods of no instability to 0.634% during endogenous

[8] The Wholesale Business Model encompasses a few small banks with diverse activities and customer bases, resembling investment banks in some respects, while being highly specialized in others. Due to these unique characteristics, we excluded them from both market-oriented and retail business models.

crises and 1.427% during exogenous crises (Model 2, Column 6). These results indicate that during tranquil periods, focused retail and wholesale banks exhibit higher exposure to systemic risk than investment banks, but during crises, investment banks become more systemically risky.

Conversely, when analyzing the contribution to systemic risk, we observe different results (Model 2, Column 8). Investment banks' ΔCoVar increases by 1.748% during endogenous crises and by 0.984% during exogenous crises, rising from 0.016% to 1.764% and to 1.000%, respectively. Diversified banks show a statistically significant lower contribution than investment banks only during exogenous crises, with a ΔCoVar of 0.664%, and exhibit no statistically significant difference from investment banks during endogenous crises (again confirming H1b). Focused retail banks remain the least contributors to systemic risk in both crises, with a ΔCoVar of 1.540% during endogenous crises and 0.837% during exogenous crises.

Table 9 Performance equation: The second step of the extended Heckman model- business models, origin of the crisis and systemic risk

	Model 2				Model 3			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	MES	MES	ΔCoVar	ΔCoVar	MES	MES	ΔCoVar	ΔCoVar
FOCUSED $_{t-1}$	-0.448***	-0.468**	0.028	0.025	0.081	0.161	0.263***	0.271***
	(0.159)	(0.186)	(0.083)	(0.114)	(0.229)	(0.252)	(0.080)	(0.089)
DIVERSIFIED $_{t-1}$	-0.315**	-0.317*	-0.018	-0.011	-0.037	0.044	0.156**	0.163*
	(0.148)	(0.177)	(0.079)	(0.111)	(0.222)	(0.243)	(0.074)	(0.083)
WHOLESALE $_{t-1}$	-0.148	-0.192	-0.111	-0.085	0.410	0.625**	0.037	0.150
	(0.201)	(0.225)	(0.116)	(0.152)	(0.280)	(0.301)	(0.115)	(0.127)
INSTABILITY	0.416**		0.804***		1.111***		1.162***	
	(0.173)		(0.102)		(0.400)		(0.163)	
ENDOGENOUS		0.647***		1.372***		1.496***		1.748***
		(0.082)		(0.063)		(0.378)		(0.262)
EXOGENOUS		1.803***		0.632***		2.799***		0.984***
		(0.112)		(0.045)		(0.694)		(0.166)
INSTABILITY#FOCUSEDt-1					-1.038***		-0.450***	
					(0.370)		(0.144)	
INSTABILITY#DIVERSIFIEDt-1					-0.515		-0.320**	
					(0.366)		(0.142)	
INSTABILITY#WHOLESALEt-1					-1.117***		-0.262	
					(0.429)		(0.218)	
ENDOGENOUS#FOCUSEDt-1						-1.252***		-0.495*
						(0.391)		(0.270)
ENDOGENOUS#DIVERSIFIEDt-1						-0.592		-0.323
						(0.393)		(0.269)
ENDOGENOUS#WHOLESALEt-1						-1.514***		-0.393
						(0.441)		(0.386)
EXOGENOUS#FOCUSED t-1						-1.245*		-0.434**
						(0.720)		(0.181)

EXOGENOUS#DIVERSIFIEDt-1						-0.852		-0.311*
						(0.710)		(0.175)
EXOGENOUS#WHOLESALEt-1						-2.024**		-0.566**
						(0.793)		(0.245)
MILLS1	0.037***	0.037***	0.005	0.019**	0.030**	0.027**	0.003	0.016**
	(0.012)	(0.014)	(0.006)	(0.008)	(0.011)	(0.013)	(0.006)	(0.008)
MILLS2	-0.023**	-0.014	-0.018***	-0.021***	-0.021**	-0.013	-0.017***	-0.020***
	(0.010)	(0.011)	(0.005)	(0.006)	(0.010)	(0.012)	(0.005)	(0.006)
MILLS3	0.001	-0.000	-0.002	-0.004***	0.001	-0.000	-0.002	-0.004***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Constant	0.037***	0.037***	0.005	0.019**	0.030**	0.027**	0.003	0.016**
	(0.012)	(0.014)	(0.006)	(0.008)	(0.011)	(0.013)	(0.006)	(0.008)
TIME FE	YES	YES	YES	YES	YES	YES	YES	YES
BANK CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,985	1,985	1,977	1,977	1,985	1,985	1,977	1,977
R-squared	0.592	0.503	0.712	0.569	0.597	0.511	0.713	0.571

*Note: This table reports Heckman's second-step regression results. The dependent variable is the proxy for systemic risk (MES or ΔCoVar). Model 2 is the basic model with the business model (BM) at time t-1, crisis dummies, i.e., CRISIS is a dummy variable equal to 1 during 2007-2009, 2010-2012, 2016, and 2020, and 0 otherwise; ENDOGENOUS is a dummy variable equal to 1 during 2007-2009 and 2010-2012, and 0 otherwise; EXOGENOUS is a dummy variable equal to 1 in 2016 and 2020, and 0 otherwise; all the bank characteristics at t-1 reported in the vector BANK CONTROLS; and the IMR obtained from the first step of the Heckman regression. In Model 3, the interaction between BM at time t-1 and the crises is introduced. The business models refer to focused retail banks (FOCUSED), wholesale banks (WHOLESALE), and diversified banks, which group diversified retail type 1 and type 2 (DIVERSIFIED). The investment business model is the reference category. All regression models include time fixed effects. Robust standard errors are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.*

These results suggest that, depending on the specific period observed, banks adopting different business models can have varying levels of exposure to and contribution to systemic risk. However, it is also evident that the investment business model is consistently riskier from a systemic perspective during all periods of financial turmoil. Our results align with Köhler (2015) and Borri and Di Giorgio (2022), who provide evidence that more investment-oriented banks contribute more to and are more exposed to systemic risk. However, our findings offer additional insights when distinguishing between endogenous and exogenous crises, highlighting that more market-oriented and diversified banks seem to contribute more to systemic risk when the instability stems from an endogenous source. We also shed light on the differences in terms of exposure to and contribution to systemic risk, underscoring the importance of using multiple measures of systemic risk to adequately analyze this risk.

5.3 Propensity score matching results: bank migrations and systemic risk

The next step in our analysis examines bank business model migrations (i.e., banks changing business models) and their association with systemic risk (Hypothesis 2). As highlighted in Section 3.1.2, the percentage of changes in BBM during the period observed is about 10%. Although migrations occurred throughout the entire period, there was a higher level of migrations during the peak of the crises (see Figure 1). Therefore, we aim to investigate the effect of these migrations on bank systemic risk during periods of instability using propensity score matching.

Looking at the number of migrations among business models in Table 3, it is evident that the highest number of migrations occurs between diversified retail and focused retail, and vice versa. Therefore, we consider these two movements: (i) from focused retail to diversified (FOCUSED_DIVERSIFIED) and (ii) from diversified to focused retail (DIVERSIFIED_FOCUSED). For each type of migration, we analyze the effect of migration on bank systemic risk compared to the bank's original business model.

The goal of this analysis is to determine whether banks exhibit lower systemic risk after changing their business compared to banks that do not change.

Our results are reported in Table 10. The coefficients represent the Average Treatment Effect on the Treated (ATET) and indicate that, compared to their original business model, banks that migrate tend to decrease systemic risk. This decrease is particularly evident for diversified banks that transition to focused retail, with significant results for both ΔCoVar and MES, thus confirming H2a. Furthermore, when analyzing the migration from diversified to more focused retail, the reduction in systemic risk persists over the medium term. (t; t+2).

For banks moving from focused retail to diversified, we observe a statistically significant negative effect on ΔCoVar in only two time-windows, and this significance is weak. In terms of MES, there appears to be no statistically significant effect.

To summarize our findings, the PSM results reveal a statistically significant effect of migrations on systemic risk, which is more pronounced for banks that reduce their diversification and focus on retail and less risky activities. In general, this kind of migration can be seen as a strategic change in the business model aimed at managing risk and decreasing the complexity of activities. We do not find evidence that migrations from retail to diversified business models impact systemic risk, either positively or negatively. These migrations can be seen as driven by profitability concerns or by strategic decisions to broaden the range of activities rather than reducing risk.

Table 10 The effect of migrations on systemic risk

Panel A: Migrations from focused retail to diversified

	ΔCoVar				MES		
Time windows	**Coeff**	**P-value**	**Obs..**	**Time windows**	**Coeff**	**P-value**	**Obs.**
At t	-0.212	0.274	383	At t	0.217	0.411	386
	(0.194)				(0.263)		
At t+1	-0.311*	0.091	304	At t+1	-0.147	0.597	302
	(0.184)				(0.279)		
(t; t+1)	-0.041	0.896	304	(t; t+1)	0.167	0.541	301
	(0.311)				(0.273)		
(t-1; t)	-0.241	0.154	383	(t-1; t)	0.298	0.410	384
	(0.169)				(0.361)		
(t-1; t+1)	-0.506**	0.037	304	(t-1; t+1)	0.220	0.375	299
	(0.243)				(0.248)		
(t; t+2)	0.292	0.175	304	(t; t+2)	-0.144	0.602	296
	(0.215)				(0.276)		

Panel B Migrations for diversified to focused retail

	ΔCoVar				MES		
Time windows	**Coeff**	**P-value**	**Obs.**	**Time windows**	**Coeff**	**P-value**	**Obs.**
At t	0.202	0.207	562	At t	0.319	0.432	569
	(0.160)				(0.263)		
At t+1	-0.176	0.329	464	At t+1	-0.390	0.008	470
	(0.181)				(0.148)		
(t; t+1)	-0.290*	0.061	464	(t; t+1)	0.319	0.460	569
	(0.154)				(0.431)		
(t-1; t)	-0.529***	0.003	562	(t-1; t)	-0.704*	0.082	470
	(0.175)				(0.404)		
(t-1; t+1)	-0.003	0.952	464	(t-1; t+1)	0.147	0.331	469
	(0.059)				(0.152)		
(t; t+2)	-0.378**	0.040	458	(t; t+2)	-0.301	0.350	464
	(0.184)				(0.322)		

*Note: Table reports the results of the PSM estimations for the period of crises. Panel A refers to the migrations from focused retail to diversified. Panel B reports the estimations of the migrations from diversified to focused retail. The time-windows used for the estimations are displayed as follows: At t refers to the level of systemic risk at time t; At t+1 refers to the systemic risk at time t+1; (t; t+1) refers to the change in systemic risk from the year of migration to the year after the migration; (t-1; t) refers to the change in systemic risk from the year previous the migration to the year of migration; (t-1; t+1) refers to the change in systemic risk from the year previous the migration to the year after the migration; (t; t+2) refers to the change in systemic risk from the year of migration to two year after the migration. Standard errors are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1*

6. Robustness checks and additional analyses

The choice of business model might be driven by the bank's risk appetite, which also influences the bank's contribution and exposure to systemic risk. To address this specific endogeneity problem, we use Heckman's two step model in our baseline analysis. As a robustness test, and to address other potential endogeneity issues, we also use an instrumental variable (IV) approach. Finally, to address possible self-selection bias deriving from the endogeneity of the decision to change business model, we use a propensity score matching (PSM) approach.

6.1 Instrumental Variable (IV) analysis

We instrument each business model using as instruments: the measure of relative relevance of each business model within a country banking system ($DISTANCE_{BM_{COUNTRY}}$); a dummy is equal one if the bank is involved in an M&A operation as an acquirer or target and zero otherwise; a vector ($STATE\_AID_{t-1}$) which collects information on whether the bank was the recipient of an *ad hoc state aid* or of a *scheme state aid* implemented at the country level to support the entire banking sector. We perform the test of overidentifying restrictions, and we report the p-value of the Sargan test. In all cases the p-values are not statistically significant, allowing the rejection of the null hypothesis, i.e. the instruments are not appropriate.[9] The results are reported in Table 11 and confirm our main findings, highlighting that focused retail and diversified retail type 2 banks show a lower exposure to systemic risk, while no statistically significant differences are observed regarding their contribution to systemic risk. Additionally, these findings confirm the higher exposure to and contribution to systemic risk during periods of financial distress.[10]

[9] To check the robustness of our findings, we also perform additional regressions using as instrumental variables the measure of relative relevance of each business model within a country banking system, which change at yearly and country level, as Wang et al (2024), and Laeven and Lavine (2007). Also in this case, the results corroborate our main analysis.

[10] The IV regression has also been run considering the interaction term, as in Table 8, and the findings confirm the main analysis. The table is not included in the text, but the results are available upon request.

Table 11 Instrumental variable regression: Bank business model and systemic risk

	Model 4			
	(5)	(6)	(7)	(8)
VARIABLES	MES	ΔCoVar	MES	ΔCoVar
FOCUSED_IV $_{t-1}$	-0.624***	0.005	-0.681***	-0.010
	(0.176)	(0.095)	(0.203)	(0.130)
DIV_TYPE1_IV $_{t-1}$	-0.277	0.039	-0.270	0.095
	(0.172)	(0.094)	(0.201)	(0.130)
DIV_TYPE2_IV $_{t-1}$	-0.420**	-0.064	-0.449**	-0.046
	(0.169)	(0.092)	(0.198)	(0.130)
WHOLESALE_IV $_{t-1}$	-0.262	-0.047	-0.268	-0.003
	(0.237)	(0.138)	(0.270)	(0.180)
INSTABILITY	0.432***	0.590***	-	-
	(0.090)	(0.083)		
ENDOGENOUS	-	-	0.645***	1.282***
			(0.072)	(0.058)
EXOGENOUS	-	-	1.812***	0.624***
			(0.108)	(0.045)
Dependent $_{t-1}$	0.419***	0.523***	0.309***	0.365***
	(0.032)	(0.024)	(0.030)	(0.022)
GSIB $_{t-1}$	0.245**	0.102**	0.316***	0.131**
	(0.096)	(0.051)	(0.103)	(0.060)
SIZE $_{t-1}$	0.649***	0.035	0.777***	0.043
	(0.057)	(0.026)	(0.062)	(0.032)
LEVERAGE $_{t-1}$	-0.000	-0.000**	-0.000	-0.000*
	(0.001)	(0.000)	(0.001)	(0.000)
MBV $_{t-1}$	0.006	0.002	0.012**	0.004
	(0.005)	(0.003)	(0.006)	(0.003)
RWA_TA $_{t-1}$	0.868***	0.355***	1.110***	0.473***
	(0.216)	(0.107)	(0.228)	(0.121)
WPS $_{t-1}$	-0.062	0.040	-0.040	0.000
	(0.141)	(0.067)	(0.167)	(0.091)
COST_INCOME $_{t-1}$	0.066	0.050	0.039	0.033
	(0.091)	(0.037)	(0.086)	(0.040)
Constant	0.243	1.649***	0.293	2.321***
	(0.199)	(0.163)	(0.220)	(0.183)
TIME FE	YES	YES	YES	YES
Sargan test (p-value)	0.100	0.6232	0.101	0.1428
Observations	2,076	2,067	2,076	2,067
R-squared	0.587	0.696	0.499	0.547

Note: This table reports Heckman second-step regression results. The dependent variable is the systemic risk (MES or ΔCoVar). MES and ΔCoVar are two measures of systemic risk in terms of exposure and contribution, respectively. FOCUSED_IV is the instrumented dummy variable equal to 1 if the bank is retail-oriented, and 0 otherwise. DIV_TYPE1_IV is the instrumented dummy variable equal to 1 if the bank adopts the diversified retail type 1 business model, and 0 otherwise. DIV_TYPE2_IV is the instrumented dummy variable equal to 1 if the bank adopts the diversified retail type 2 business model, and 0 otherwise. WHOLESALE_IV is the instrumented dummy variable equal to 1 if the bank adopts the wholesale business model, and 0 otherwise. The reference category is the investment business model. CRISIS is a dummy variable equal to 1 during 2007-2009, 2010-2012, 2016, and 2020, and 0 otherwise. ENDOGENOUS is a dummy variable equal to 1 during 2007-2009 and 2010-2012, and 0 otherwise. EXOGENOUS is a dummy variable equal to 1 in 2016 and 2020, and 0 otherwise. GSIB is a dummy variable that take a value of 1 if the bank is a domestic or global systemically important bank. SIZE is the orthogonalized natural logarithm of total assets with respect to all other bank-specific characteristics included in the regression model. LEVERAGE is the total asset over total equity ratio. MVB is the ratio between the bank's market value and its equity book value. RWA_TA is the ratio between risk-weighted assets and total assets. WPS is the level of deposits of bank i divided by the level of deposits of the bank's home country. COST_INCOME is the measure of bank cost efficiency given by the ratio between operating costs and operating income.
*Robust standard errors are reported in parentheses. The dependent variable is the dependent variable at time t-1. *** p<0.01, ** p<0.05, * p<0.1.*

6.2 Propensity Score Matching (PSM) Analysis

One remaining possible endogeneity issue in this context is self-selection with regards to the decision to change BM. To ensure that the comparison between migrating and non-migrating banks does not suffer from the endogeneity issues, we employ a propensity score matching approach (PSM).

We ran the propensity score matching using different numbers of nearest-neighbor algorithms: one, two, and three replacements. The main findings remain confirmed. The results are not included in the text but are available upon request.

To examine migrations towards more diversified and market-oriented business models and vice versa, we grouped the focused retail and wholesale business models together, as well as the investment and diversified business models. We then analyzed the effect of migrations between these groups. The aim is to observe the impact of migrations from less systemically risky business models (focused retail and wholesale) to more systemically risky ones (investment and diversified) and vice versa. The results, presented in Table 12, confirm our main findings. They suggest that migrations from a market-oriented or diversified business model to a more specialized and retail-oriented one lead to a decrease in systemic risk. Conversely, there is no impact on systemic risk for migrations from retail/specialized business models to market/diversified business models, which is consistent with our main results.

Table 12 PSM: The effect of migrations on bank systemic risk

Panel A From retail/specialised to diversified/market-oriented business models

	ΔCoVar				**MES**		
Time windows	**Coeff**	**P-value**	**Obs**	**Time windows**	**Coeff**	**P-value**	**Obs**
At t	0.317*	0.054	450	At t	0.125	0.657	457
	(0.164)				(0.283)		
At t+1	0.011	0.943	367	At t+1	0.092	0.531	369
	(0.156)				(0.148)		
(t; t+1)	-0.966	0.627	367	(t; t+1)	0.095	0.647	367
	(0.627)				(0.207)		
(t-1; t)	-0.338**	0.034	450	(t-1; t)	0.273	0.316	454
	(0.160)				(0.273)		
(t-1; t+1)	-0.310	0.295	367	(t-1; t+1)	0.152	0.444	365
	(0.296)				(0.199)		
(t; t+2)	0.238	0.149	362	(t; t+2)	-0.160	0.381	360
	(0.165)				(0.183)		

Panel B From diversified/market-oriented to retail/specialised business models

	ΔCoVar				MES		
Time windows	**Coeff**	**P-value**	**Obs**	**Time windows**	**Coeff**	**P-value**	**Obs**
At t	0.194	0.397	666	At t	0.274	0.377	673
	(0.229)				(0.310)		
At t+1	-0.105	0.485	561	At t+1	-0.418	0.159	567
	(0.150)				(0.297)		
(t; t+1)	-0.373**	0.022	561	(t; t+1)	-0.467	0.111	567
	(0.162)				(0.293)		
(t-1; t)	-0.823***	0.000	666	(t-1; t)	-0.770***	0.000	672
	(0.158)				(0.199)		
(t-1; t+1)	0.117	0.417	561	(t-1; t+1)	-0.078	0.819	566
	(0.145)				(.340)		
(t; t+2)	-0.436*	0.075	549	(t; t+2)	-0.303	0.160	555
	(0.245)				(0.215)		

*Note: The table reports the results of the PSM estimations during period of crisis. Panel A refers to the migrations from retail/specialised to diversified/market-oriented business models. Panel B reports the estimations of the migrations from diversified/market-oriented to retail/specialised business models. The time windows used for the estimations are displayed as follows: At t refers to the level of systemic risk at time t; At t+1 refers to the systemic risk at time t+1; (t; t+1) refers to the change in systemic risk from the year of migration to the year after the migration; (t-1; t) refers to change in systemic risk from the year previous the migration to the year of migration; (t-1; t+1) refers to the change in systemic risk from the year previous the migration to the year after the migration; (t; t+2) refers to the change in systemic risk from the year of migration to two years after the migration. Standard errors are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1*

Finally, we run the PSM analysis on the subperiod of endogenous crises (the subprime crisis of 2007-2009 and the sovereign crisis of 2010-2012). Our findings, reported in Table 13, corroborate the results shown in Table 10. Specifically, banks that change their BM from a more diversified to a more retail-oriented model reduce their systemic risk in terms of both exposure and contribution compared to diversified banks that do not change. These results are confirmed in the medium run (from t to t+2) but only in terms of contribution to systemic risk.

Table 13: The effect of migration on bank systemic risk during periods of endogenous crises

Panel A From focused retail to diversified

	ΔCoVar				MES		
Time windows	**Coeff**	**P-value**	**Obs**	**Time windows**	**Coeff**	**P-value**	**Obs**
At t	0.127	0.288	255	At t	0.269	0.531	253
	(0.120)				(0.430)		
At t+1	-0.142	0.548	251	At t+1	-0.080	0.729	249
	(0.236)				(0.231)		
(t; t+1)	0.031	0.906	251	(t; t+1)	0.111	0.803	248
	(0.265)				(0.447)		
(t-1; t)	-0.391	0.197	255	(t-1; t)	0.031	0.941	251
	(0.303)				(0.425)		
(t-1; t+1)	-0.581	0.105	251	(t-1; t+1)	0.312	0.346	246
	(0.358)				(0.331)		
(t; t+2)	0.266	0.349	247	(t; t+2)	-0.542	0.241	243
	(0.285)				(0.463)		

Panel B From diversified to focused retail

	ΔCoVar				MES		
Time windows	**Coeff**	**P-value**	**Obs**	**Time windows**	**Coeff**	**P-value**	**Obs**
At t	-0.321	0.050	378	At t	0.043	0.926	383
	(0.163)				(0.464)		
At t+1	-0.143	0.466	375	At t+1	-0.594*	0.077	380
	(0.196)				(0.330)		
(t; t+1)	-0.477***	0.001	375	(t; t+1)	-0.402	0.295	380
	(0.149)				(0.384)		
(t-1; t)	-0.448***	0.092	378	(t-1; t)	-0.746*	0.062	382
	(0.266)				(0.400)		
(t-1; t+1)	-0.060	0.770	375	(t-1; t+1)	0.048	0.905	379
	(0.206)				(0.404)		
(t; t+2)	-0.557***	0.000	370	(t; t+2)	-0.168	0.633	375
	(0.128)				0.352		

*Note: The table reports the results of the PSM estimations during periods of endogenous crises. Panel A refers to migrations from focused retail BMs to diversified BMs. Panel B reports estimations of migrations from diversified BMs to focused retail BMs. The time windows used for the estimations are displayed as follows: At t refers to the level of systemic risk at time t; At t+1 refers to the systemic risk at time t+1; (t; t+1) refers to the change in systemic risk from the year of migration to the year after the migration; (t-1; t) refers to the change in systemic risk from the year previous the migration to the year of migration; (t-1; t+1) refers to the change in systemic risk from the year previous the migration to the year after the migration; (t; t+2) refers to the change in systemic risk from the year of migration to two year after the migration. Standard errors are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1*

6. Conclusion

In the last fifteen years, the issue of systemic risk in the banking system has been in the spotlight, with supervisory authorities striving to identify the best tools to mitigate it and academics focusing on reaching a consensus on its definition, measurement, and triggering causes. Our study contributes to the literature and policy debates by investigating the relationship between bank business models and systemic risk during both calm and volatile periods.

Bank business models have become an important supervisory issue since the European Central Bank included their analysis in the Supervisory Review and Evaluation Process (SREP) procedure. After identifying a bank's business model, the supervisory methodology requires assessing the viability (short-term) and the sustainability (long-term) of the business model. Considering all potential risks, the goal is to understand whether a bank's business model can generate acceptable returns throughout an entire economic cycle. Our study provides robust evidence to the debate on which characteristics make a bank more resilient to systemic risk.

To better understand the impact of different sources of instability, we consider the global financial crisis and the sovereign debt crisis as examples of endogenous crises, while the COVID-19 crisis and the period of financial turmoil caused by various political events in 2016 serve as exogenous sources of instability.

Our findings suggest that during quiet periods, there are few differences among business models in terms of contribution and exposure to systemic risk. Conversely, different outcomes arise during unstable times depending on the business model adopted and the origin of the instability. Although all business models are impacted by and influence systemic risk, two stand out: the diversified and investment business models. These models share characteristics in terms of balance-sheet composition, such as high levels of debt liabilities among funding sources and trading assets on the asset side, as well as large size. Debt liabilities can threaten a bank's ability to weather instability, whether endogenous to the financial system or caused by exogenous events. Funding models more dependent on customer deposits are more resilient during turbulent times. Interestingly, wholesale banks are an exception: their systemic risk contribution does not change between calm and volatile periods. These results align with the extant literature, which highlighted that systemic risk is mostly related to banks' funding structures.

Generally, our findings suggest that during tranquil periods, banks contribute to systemic risk independently of their business models. However, during periods of financial distress, investment and diversified banks are higher contributors than other business models, revealing that ΔCoVar provides more information during such times. Similar results are observed in terms of risk exposure.

Moreover, our results underscore the significance of bank business model migration in reducing systemic risk, especially when the shift is from a more diversified (riskier) model to a more retail-oriented (less risky) one. Conversely, when banks transition from a retail-oriented model to a more diversified one, this change does not appear to impact systemic risk. It is likely that these banks are motivated by the pursuit of new revenue streams rather than a desire to decrease their risk.

These findings underline the importance of having a heterogeneous banking system in which different types of business models coexist. A more diversified banking system may be better able to face periods of financial distress, mediating the impact of crises. When defining new rules, regulators should consider both a bank's business model (i.e., what the banks do) and provide different measures for different crisis events.

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Appendix A

***Table A**.1 - Distribution of Bank Business Models across Countries*

COUNTRY	FOCUSED RETAIL	DIV TYPE 1	DIV TYPE 2	WHOLESALE	INVESTMENT	TOTAL
AT	78.50%	11.21%	4.67%	5.61%	0.00%	100.00%
BE	0.00%	56.25%	34.38%	0.00%	9.38%	100.00%
BG	51.61%	32.26%	16.13%	0.00%	0.00%	100.00%
CH	67.48%	8.59%	10.74%	1.53%	11.66%	100.00%
CY	40.00%	52.50%	7.50%	0.00%	0.00%	100.00%
DE	30.99%	23.94%	22.54%	14.55%	7.98%	100.00%
DK	45.72%	42.25%	12.03%	0.00%	0.00%	100.00%
EE	59.09%	27.27%	0.00%	13.64%	0.00%	100.00%
ES	21.31%	31.97%	37.70%	4.92%	4.10%	100.00%
FI	16.07%	7.14%	64.29%	0.00%	12.50%	100.00%
FR	0.00%	27.78%	1.85%	11.11%	59.26%	100.00%
GB	27.32%	43.81%	19.07%	0.52%	9.28%	100.00%
GR	62.77%	34.04%	3.19%	0.00%	0.00%	100.00%
IE	27.08%	18.75%	54.17%	0.00%	0.00%	100.00%
IT	27.19%	19.06%	47.50%	4.69%	1.56%	100.00%
LI	26.32%	31.58%	0.00%	42.11%	0.00%	100.00%
LT	42.86%	57.14%	0.00%	0.00%	0.00%	100.00%
LU	0.00%	42.86%	47.62%	0.00%	9.52%	100.00%
MT	22.73%	52.27%	0.00%	25.00%	0.00%	100.00%
NL	23.08%	25.64%	38.46%	7.69%	5.13%	100.00%
NO	38.22%	1.70%	58.81%	0.21%	1.06%	100.00%
PT	34.38%	21.88%	43.75%	0.00%	0.00%	100.00%
SE	20.19%	1.92%	57.69%	0.00%	20.19%	100.00%
TOTAL	**38.65%**	**22.63%**	**29.75%**	**3.47%**	**5.50%**	**100.00%**

Note: The table reports the distribution in percentage of BBMs across countries. AT = Austria; BE = Belgium; BG=Bulgaria; CH = Switzerland; CY = Cyprus; DE = Germany; EE = Estonia; ES = Spain; FIN = Finland; FR = France; GB = Great Britain; GR = Greece; IE = Ireland; IT = Italy; LT = Lithuania; LV = Latvia; LU = Luxemburg; MT = Malta; NL = the Netherlands; NO= Norway; PT = Portugal; SE = Sweden.

Table A.2. Evolution per year of MES and ΔCoVar

	MES						ΔCoVar					
YEAR	FOCUSED	DIV TYPE1	DIV TYPE 2	WHOLESALE	INVESTMENT	Total	FOCUSED	DIV TYPE1	DIV TYPE 2	WHOLESALE	INVESTMENT	Total
2005	-.0017	-.0065	-.0069	.0075	-.0134	-.0055	-0.026	-0.025	-0.025	-0.026	-0.027	-0.025
2006	-.0058	-.0179	-.0127	-.0060	-.0251	-.0115	-0.032	-0.031	-0.030	-0.035	-0.034	-0.031
2007	-.0068	-.0176	-.0163	-.0187	-.0325	-.0136	-0.046	-0.048	-0.045	-0.049	-0.047	-0.046
2008	-.0190	-.0454	-.0382	-.0193	-.0600	-.0320	-0.082	-0.081	-0.075	-0.082	-0.085	-0.079
2009	-.0066	-.0278	-.0234	-.0132	-.0457	-.0186	-0.055	-0.060	-0.053	-0.056	-0.061	-0.055
2010	-.0124	-.0241	-.0239	-.0096	-.0282	-.0199	-0.035	-0.043	-0.040	-0.034	-0.036	-0.038
2011	-.0080	-.0285	-.0267	-.0082	-.0360	-.0195	-0.047	-0.057	-0.057	-0.056	-0.047	-0.053
2012	-.0025	-.0181	-.0192	.0005	-.0245	-.0123	-0.039	-0.045	-0.049	-0.051	-0.042	-0.044
2013	-.0062	-.0143	-.0116	-.0064	-.0220	-.0107	-0.027	-0.031	-0.036	-0.032	-0.029	-0.031
2014	-.0061	-.0141	-.0148	-.0040	-.0196	-.0114	-0.028	-0.031	-0.033	-0.033	-0.029	-0.031
2015	-.0059	-.0134	-.0140	-.0067	-.0201	-.0110	-0.035	-0.039	-0.038	-0.035	-0.039	-0.037
2016	-.0176	-.0243	-.0236	-.0096	-.0273	-.0215	-0.040	-0.041	-0.045	-0.029	-0.045	-0.041
2017	-.0039	-.0054	-.0048	.0018	-.0080	-.0046	-0.039	-0.042	-0.040	-0.025	-0.044	-0.040
2018	-.0105	-.0139	-.0141	-.0039	-.0164	-.0124	-0.039	-0.041	-0.044	-0.020	-0.037	-0.040
2019	-.0079	-.0111	-.0109	-.0059	-.0128	-.0097	-0.035	-0.039	-0.041	-0.031	-0.041	-0.038
2020	-.0232	-.0331	-.0309	-.0038	-.0336	-.0278	-0.042	-0.043	-0.046	-0.019	-0.032	-0.042
Total	-.0097	-.0190	-.0187	-.0062	-.0258	-.0154	-0.040	-0.042	-0.044	-0.037	-0.041	-0.042

Note: The table displays the *evolution of the MES and ΔCoVar during the period investigated and for each bank business model.*

Table A.3 Variable Description

Variable	Measurement	Meaning	Source	Sign expected
MES	Marginal expected shortfall of a bank, following Acharya et al. (2017).	Exposure to systemic risk	Authors’ estimations	-
ΔCoVar	Change in conditional value at risk, following Adrian and Brunnermeier (2009, 2016)	Contribution to systemic risk	Authors’ estimations	-
GSIB	A dummy variable equals 1 if bank is domestic or global systemically important, zero otherwise	Systemically important	Financial stability board and European Banking Authority	positive
SIZE	The orthogonalized natural logarithm of total asset with respect to all other bank specific characteristics included in the regression model (De Jonghe, 2010)	Bank size	S&PCapital	positive
LEVERAGE	Total asset over total asset	Bank leverage	S&PCapital	positive
MVB	Market to book value	The market perception of the bank	Datastream Thomson Reuters	positive
RWA_TA	Risk weighted asset over total asset	Bank risk appetite	S&PCapital	positive
WPS	The level of deposits of bank *i* divided by the level of deposits of the bank's home country	The weight of bank *i* in the payment system	S&PCapital	positive
COST_INCOME	Operating cost over operating income	Cost efficiency	S&PCapital	positive
FOCUSED	Dummy variable takes 1 if bank adopts the focused retail business model, zero otherwise	Focused retail	Authors’ estimations	positive/negative
DIV TYPE 1	Dummy variable takes 1 if bank adopts the diversified retail type 1 business model, zero otherwise	Diversified retail type 1	Authors’ estimations	positive/negative
DIV TYPE 2	Dummy variable takes 1 if bank adopts the diversified retail type 2 business model, zero otherwise	Diversified retail type 2	Authors’ estimations	positive/negative
WHOLESALE	Dummy variable takes 1 if bank adopts the wholesale business model, zero otherwise	Wholesale	Authors’ estimations	positive/negative
INVESTMENT	Dummy variable takes 1 if bank adopts the investment business model, zero otherwise	Investment	Authors’ estimations	positive/negative
INSTABILITY	Dummy variable equals 1 over the periods 2007-2009; 2010-2012; 2016; 2020, zero otherwise	Crisis	Authors’ estimations	positive

ENDOGENOUS	Dummy variable equals 1 over the period 2007-2009 and 2010-2012, zero otherwise	Endogenous crises	Authors' estimations	positive
EXOGENOUS	Dummy variable equals 1 over the years 2016 and 2020, zero otherwise	Exogenous crises	Authors' estimations	positive
M&A	Two dummy variables that refer to the involvement in an M&A operation. The first is equal to one if the bank is involved in an M&A operation as the acquiror and zero otherwise; the second dummy variable takes the value of 1 if the bank is involved in an M&A operation as a target, zero otherwise. We collect data on M&A operations from Zephyr.	M&A	Authors elaborations on Zephyr data	-
STATE AID	Two dummy variable equals 1 if bank operates in a country in which a state aid programme is provide, zero otherwise. One dummy variable refers to the ad hoc state aid, and one to the scheme state aid.	State aid	European Commission database	-

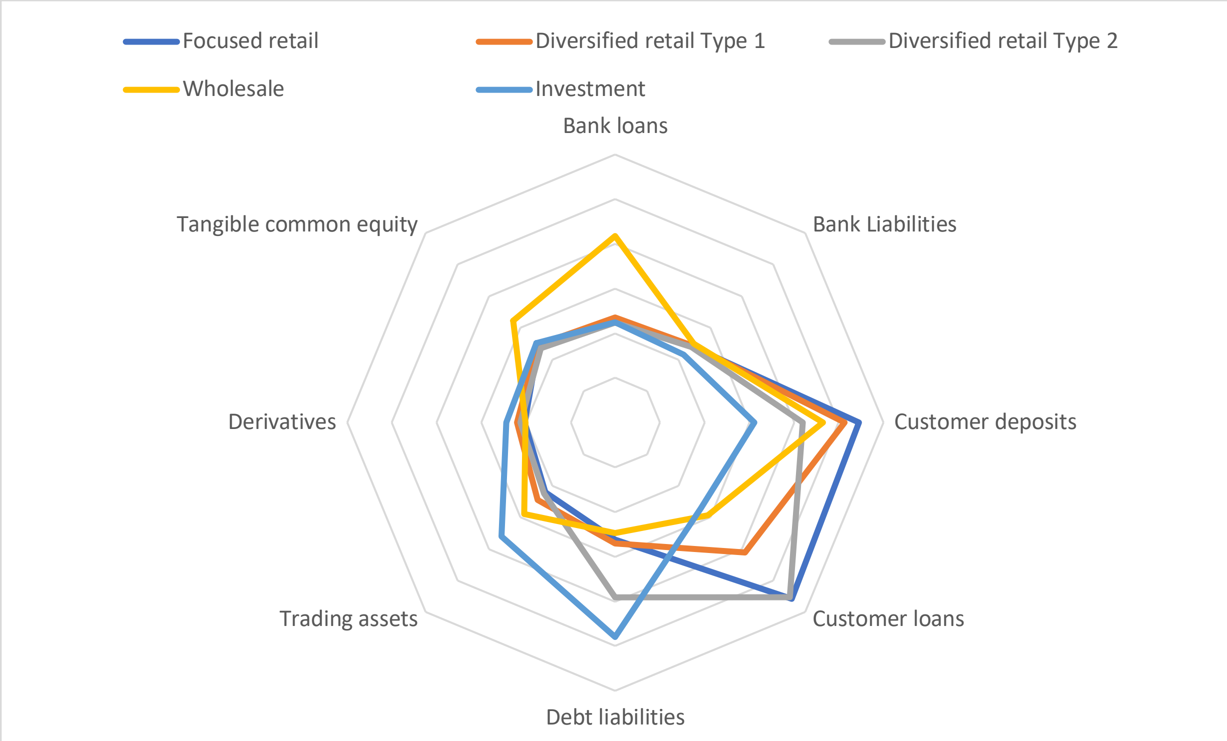
Note: The table reports the definition of the variables used in the analysis and list the sources from which the data are collected.

Table A.4 Multinomial logit regression – first step of Heckman two step multinomial logit approach

	FOCUSED			TYPE 1			TYPE 2			WHOLESALE			INVESTMENT		
	dy/dx	std. err.	P>z	dy/dx	std. err.	P>z	dy/dx	std. err.	P>z	dy/dx	std. err.	P>z	dy/dx	std. err.	P>z
SIZE	-0.046	0.005	0.000	0.000	0.004	0.969	0.058	0.005	0.000	-0.020	0.003	0.000	0.009	0.002	0.000
LEVERAGE	0.000	0.000	0.627	0.000	0.000	0.194	0.000	0.000	0.078	0.000	0.000	0.641	0.001	0.000	0.006
MVB	-0.001	0.003	0.733	0.001	0.003	0.601	0.002	0.002	0.365	-0.005	0.002	0.027	0.002	0.001	0.000
RWA_TA	-0.024	0.032	0.451	-0.005	0.028	0.869	0.008	0.035	0.816	-0.002	0.006	0.655	0.023	0.010	0.023
WPS	-0.139	0.056	0.012	0.178	0.040	0.000	-0.026	0.046	0.582	-0.018	0.026	0.491	0.005	0.018	0.790
COST_INCOME	-0.056	0.024	0.020	0.083	0.027	0.002	-0.029	0.018	0.104	0.013	0.008	0.086	-0.011	0.005	0.024
AQUIROR	-0.060	0.026	0.020	0.035	0.021	0.102	-0.010	0.020	0.615	0.007	0.011	0.514	0.027	0.009	0.002
TARGET	0.357	54.626	0.995	0.081	46.200	0.999	0.075	52.786	0.999	0.016	2.193	0.994	-0.530	155.805	0.997
SCHEME	0.023	0.030	0.444	0.089	0.024	0.000	-0.077	0.026	0.003	0.009	0.009	0.359	-0.043	0.015	0.003
ADHOC	0.364	21.764	0.987	0.270	16.012	0.987	0.286	15.228	0.985	-0.358	27.134	0.989	-0.563	44.438	0.990
COUNTRY_DISTANCE_TYPE1	-0.451	0.048	0.000	0.629	0.039	0.000	-0.198	0.046	0.000	0.039	0.021	0.066	-0.019	0.026	0.461
COUNTRY_DISTANCE_TYPE2	-0.688	0.053	0.000	0.038	0.052	0.467	0.671	0.035	0.000	0.037	0.027	0.168	-0.058	0.030	0.052
COUNTRY_DISTANCE_INVESTMENT	-0.433	0.218	0.047	0.121	0.171	0.480	0.028	0.174	0.871	0.025	0.078	0.749	0.259	0.057	0.000
COUNTRY_DISTANCE_WHOLESALE	0.088	0.112	0.433	0.404	0.093	0.000	-0.822	0.115	0.000	0.217	0.039	0.000	0.113	0.043	0.009
TIME FE	YES			YES			YES			YES			YES		
PSEUD-R_SQUARED	0.300														
Observations	2,233														

Note: The table reports the results of the multinomial logit used as the first step of the Heckman two-step regression, which allows us to measure the inverse Mills ratios. The dependent variable is a categorical variable from 1 to 5, where 1 is the focused retail BM, 2 is the diversified retail type 1 BM, 3 is the diversified retail type 2 BM, 4 is the wholesale BM, and 5 is the investment BM. SIZE is the orthogonalized natural logarithm of total assets with respect to all other bank-specific characteristics included in the regression model; LEVERAGE is the ratio of total assets to total equity; MVB is the ratio of the bank's market value to its equity book value; RWA_TA is the ratio of risk-weighted assets to total assets; WPS is the level of deposits of bank i divided by the level of deposits of the bank's home country; COST_INCOME is the measure of bank cost efficiency given by the ratio of operating costs to operating income. AQUIROR is a dummy variable equal to 1 if the bank is involved in an M&A operation as the acquirer, 0 otherwise; TARGET is a dummy variable equal to 1 if the bank is involved in an M&A operation as the target bank, 0 otherwise; SCHEME is a dummy variable equal to 1 if there is a state aid scheme supporting the banking system in the country where the bank operates, 0 otherwise; ADHOC is a dummy variable equal to 1 if the bank received ad hoc state aid in a specific year, 0 otherwise. COUNTRY_DISTANCE_TYPE1, COUNTRY_DISTANCE_TYPE2, COUNTRY_DISTANCE_INVESTMENT, and COUNTRY_DISTANCE_WHOLESALE are variables constructed by considering the overall distribution of banks (listed and non-listed at the consolidated level) across the five business models each year and calculating yearly averages per business model. Then, the same yearly averages are calculated at the country level to determine the distance from the percentage measured at the European level for each business model and each year. In all regression models, time fixed effects are included (TIME FE).

Figure A.1. Comparison of Business Models



Note: Bank loans over total assets, Customer loans over total assets, Debt liabilities over total assets Trading assets over total assets and Derivative exposure over total assets are the indicators used in the cluster analysis to identify BBM. The other indicators included in the Figure are not inserted in the cluster analysis but are displayed in the Figure to better describe the asset and liability structure of bank business models.

Note: The BBM Monitor project, funded by HEC Montreal, has tested this model and several other models over several years. Annually, they apply the model to an updated sample and compare the year-over-year variations as the sample size increases. The variation is minimal, and the identified BBMs remain stable despite the annual expansion of the sample. Prior to identifying these five variables, extensive attempts and experiments were conducted, leading to the definition of these indicators based on both the literature and our analyses. The results of these analyses are published both as policy papers and in an annual report (https://bbmresearch.org/publications/studies/).

Online Appendix

Cluster Analysis

To identify our business models, we use Hierarchical Cluster Analysis This statistical technique allows us to group a set of observations into distinct homogeneous clusters that group banks with a certain degree of similarity. Among the different clustering methods, we adopt the hierarchical approach using Ward's (1963) methodology, which measures the distance between clusters. This approach starts with the largest number of clusters possible and merges clusters step by step to minimize the within-cluster sum of squared errors, arriving at the optimal number of clusters. This method allows us to avoid defining a predefined number of clusters beforehand, instead letting the data determine the optimal number of clusters based on the sample characteristics.

We chose the initial five clusters based on the following metrics: (i) Pseudo F-statistic; (ii) Pseudo T-statistic; (iii) the Dendrogram; (iv) the semi-partial R-squared; and (v) the Cubic Clustering Criterion (CCC). In the revised version of the paper, we report the quantitative information on the cluster analysis in the Appendix.

Pseudo F-statistic and the Pseudo T-statistic

A method for determining the number of clusters in a data set is to examine the pseudo-F statistic. Relatively large values indicate a potential stopping point. By reviewing the pseudo-F statistic column in Table A1, one can see that this method suggests a possible stopping point at 5 clusters. Typically, with pseudo-F statistics, we look for an increase to a maximum as the number of clusters increases by 1, and then observe when the pseudo-F starts to decrease. At that point, we select the number of clusters at the (local) maximum.

Looking at T-square statistic values, a general rule for interpreting pseudo-statistics, is to move down the column until finding the first value markedly larger than the previous one, then move back up the column by one cluster. Moving down the Pseudo T-square column in Table A1, one can identify potential clustering levels at 8 clusters, 5 clusters, and 2 clusters.

Table AO.1 Pseudo F-statistic and the Pseudo T-statistic

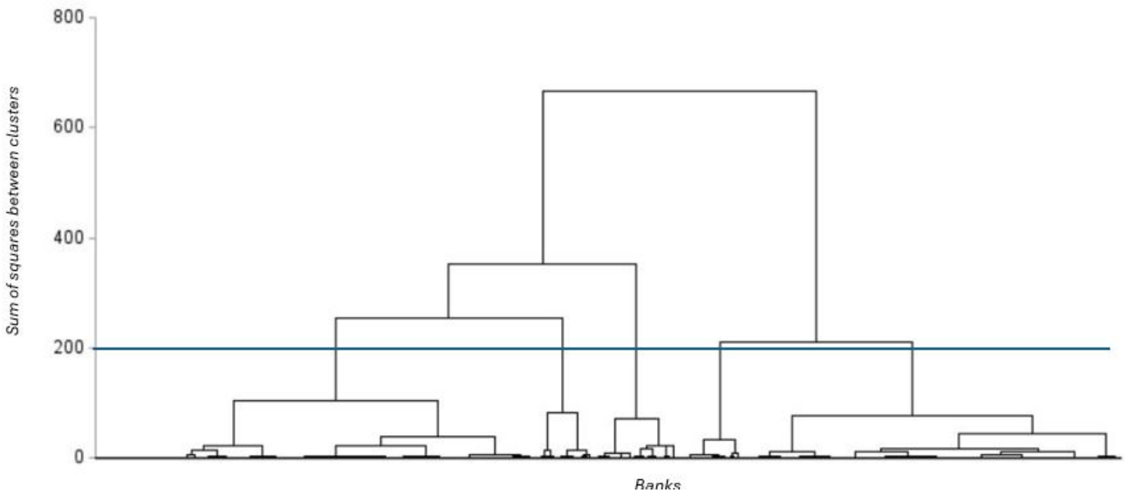
Number of clusters	Pseudo F-statistic	Pseudo T-statistic
10	7610	3281
9	7757	3249

8	7649	990
7	7653	**4137**
6	7875	1456
5	8196	4538
4	7677	**6706**
3	7578	5312
2	7925	4371
1	.	**7925**

Dendogram

We also consider the dendrogram, and by considering a sum of squares between clusters of 200, we can observe that 5 clusters are identified.

Figure AO.1: Dendogram

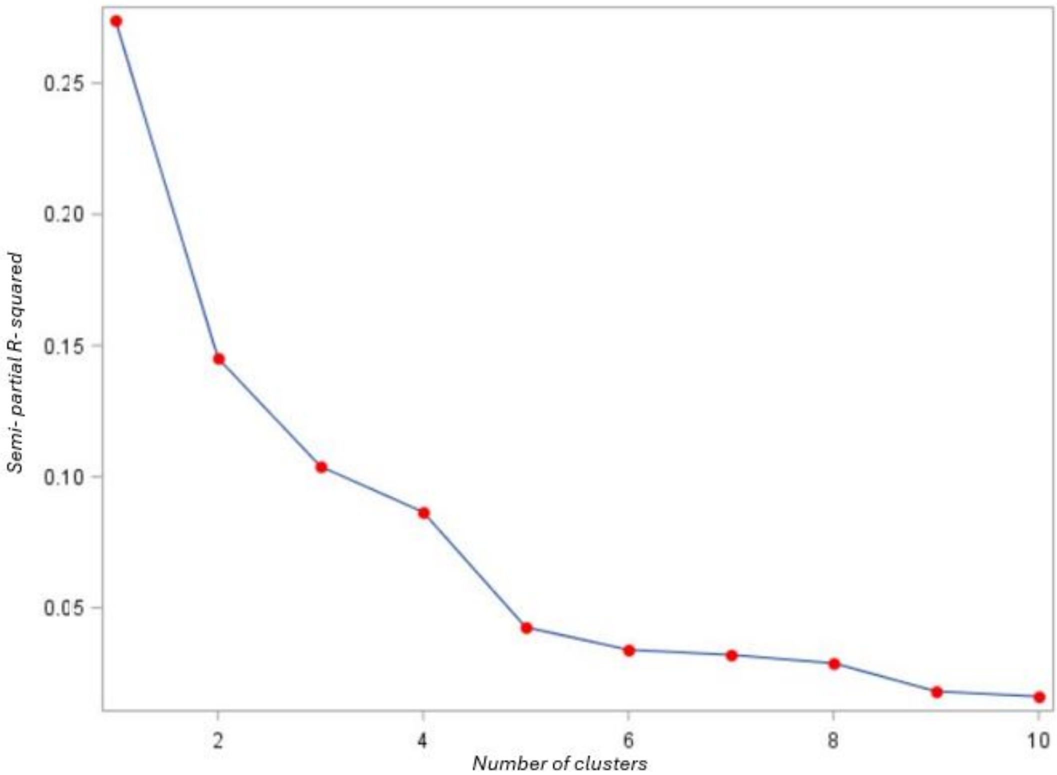


Semi-partial R-squared and Cubic Clustering Criterion (CCC)

Considering the semi-partial R-squared and the Cubic Clustering Criterion (CCC), we observe that:

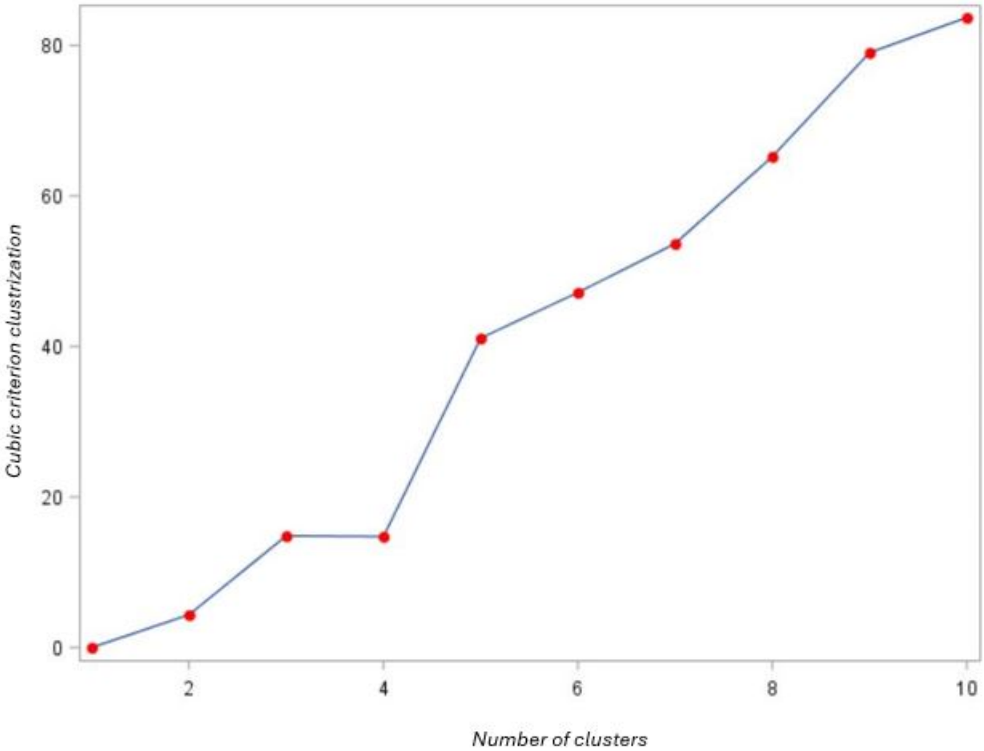
- In the case of the semi-partial R-squared, adding more than five clusters does not significantly increase the R-squared value.
- With the CCC, we detect a peak at 5 clusters. After 5 clusters, the CCC continues to increase, but more linearly.

Figure AO.2: Semi-partial R-squared



In conclusion, although the results of hierarchical clustering can lead to different definitions of clusters, considering multiple metrics helps define the number of clusters more accurately. Five clusters are suggested by more than one metric; therefore, we use this number of groups in our analysis.

Figure AO.3: Cubic Clustering Criterion (CCC)



Correlation

Table AO.2 Correlation matrix

	SIZE	ASSET_EQUITY	MVB	RWA_DENSITY	WPS	COST_INCOME
SIZE	1					
ASSET_EQUITY	0.103*	1				
MVB	-0.160*	0.138*	1			
RWA_DENSITY	-0.419*	-0.098*	0.047*	1		
WPS	0.463*	0.058*	-0.103*	-0.195*	1	
COST_INCOME	-0.048*	-0.001	-0.042*	-0.010	-0.014	1

Note: The Table reports the correlation matrix. SIZE is the orthogonalized natural logarithm of total asset with respect to all other bank specific characteristics included in the regression model; LEVERAGE is the total asset over total equity ratio; MVB is the ratio between the bank market value and the equity book value; RWA_TA is the ratio between risk weighted asset and total asset; WPS is the level of deposits of bank i divided by the level of deposits of the bank's home country; COST_INCOME is the measure of bank cost efficiency given by the ratio between operating cost and operating income. The asterisks refer to the significance of the correlation.

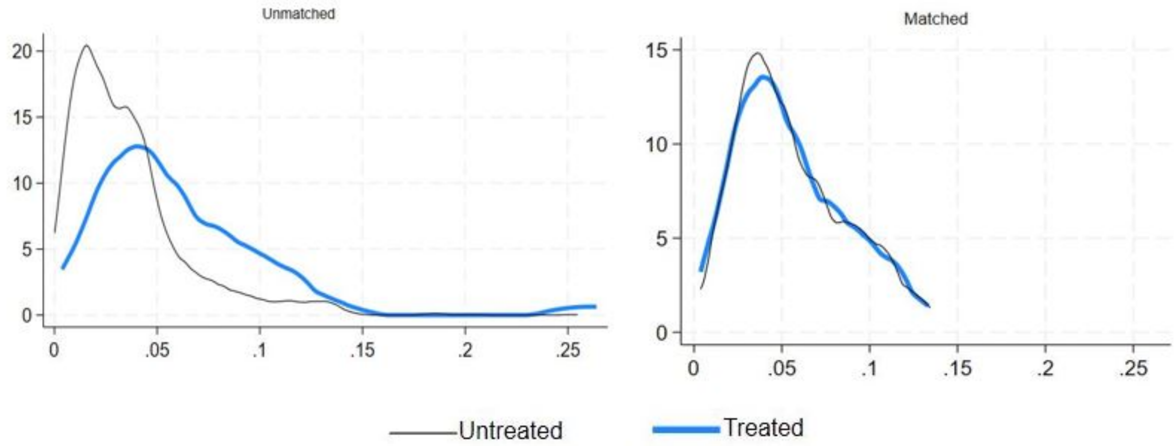
Propensity score matching

Table AO.3 Differences in means before and after matching

Variables	Unmatched-Matched	Mean		t-test	
		Treated	Control	t	p>|t|
SIZE	U	8.3204	9.3896	-3.770	0.000
	M	8.3323	8.3749	-0.130	0.901
LEVERAGE	U	9.7449	13.467	-1.060	0.288
	M	9.6994	12.822	-1.540	0.127
MVB	U	3.5662	3.1277	0.680	0.495
	M	3.6387	3.6388	0.000	1.000
RWA_DENSITY	U	0.6647	0.5613	4.670	0.000
	M	0.6612	0.6544	0.230	0.817
WPS	U	0.1156	0.1319	-0.630	0.529
	M	0.0954	0.1141	-0.520	0.601
COST_INCOME	U	0.61346	0.6278	-0.220	0.828
	M	0.61494	0.6276	-0.250	0.806
COUNTRY DISTANCE TYPE1	U	-0.0304	-0.0478	0.770	0.444
	M	-0.02633	-0.0109	-0.450	0.650
COUNTRY DISTANCE TYPE 2	U	0.01206	0.0637	-2.060	0.039
	M	0.01802	0.0144	0.110	0.912
COUNTRY DISTANCE INVESTMENT	U	-0.01948	0.0016	-3.580	0.000
	M	-0.01871	-0.0185	-0.030	0.974
COUNTRY DISTANCE WHOLESALE	U	-0.03421	0.0034	-3.080	0.002
	M	-0.03358	-0.0396	0.550	0.585
M&A	U	0.1358	0.2291	-1.970	0.049
	M	0.13924	0.1392	0.000	1.000
STATE AID	U	0.7284	0.6650	1.190	0.234
	M	0.72152	0.6899	0.430	0.665

Note: The table reports the differences in means of variables used in the PSM procedure before and after the matching procedure. This Table refers to the PSM with 4 nearest neighbours marching procedure.

Figure AO.4 Propensity score BEFORE and AFTER marching



Note: The figure reports the propensity score before and after the matching procedure. This figure refers to the PSM with 4 nearest neighbours marching procedure.