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A CREDIT RISK-BASED CLUSTERING APPROACH FOR BANKS IN MALTA

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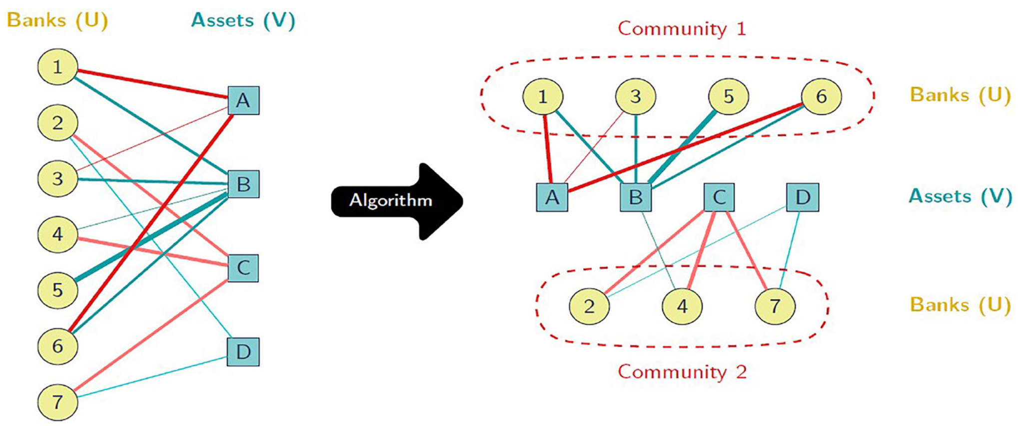
BOX 2: A CREDIT RISK-BASED CLUSTERING APPROACH FOR BANKS IN MALTA[1]

In this box we introduce a bank clustering framework based on credit risk for the Maltese banking sector. To this end, we use bank-level data from supervisory financial reporting on credit risk to build a bipartite network model and detect communities within the network. The detection of these communities reveals latent subsets of banks that are closely linked through overlapping portfolios. Our results are intended to complement the official classification of banks by domestic relevance as published in the Central Bank of Malta's Financial Stability Reports. Importantly, the proposed framework contributes to the assessment of credit risk interconnectedness across banks as a potential channel for systemic risk propagation, offering a valuable foundation for future research on the potential impact of shocks to key exposures.

We determine a set of bank clusters that reflects similarities in key exposure patterns, incorporating information on both geographical distribution and credit counterparty, using the Macroprudential Two-mode Network Model (M2MN) developed by Maas et al. (2025).[2] The model has three modules, one to construct the bipartite network and conduct network analysis, including community detection, one to apply an exposure-specific credit risk shock and study the capital impact on banks via direct losses, and a third module to study the second-round effects (default cascades) brought about by a depreciation in the value of overlapping assets via their liquidation, which result in losses to other banks not directly impacted by the original shock.

This box presents the key results based on the first module of the M2MN model. Figure 2a presents a schematic illustration of a bipartite network and what the communities detection procedure

Figure 2a
BIPARTITE GRAPH (LEFT) AND DETECTED COMMUNITIES (RIGHT)



Source: Authors' illustrations.
Notes: The illustration provides a hypothetical representation of a bipartite network composed of banks and assets. The width of the links indicates varying values of relative holdings of assets, with thicker links indicating higher shares. Red lines denote banks' exposures to assets A and C, whereas teal lines indicate exposures to assets B and D. Community 1 consists of banks 1, 3, 5, and 6, grouped based on their overlapping exposures to A and B, while Community 2 includes banks 2, 4 and 7, which share exposures to B, C and D.

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[2] Maas, D., Panzica, R., and Saldias, M. (2025), Developing a Financial Stability Network Model: The Macroprudential Two-Mode Network (M2MN) toolbox, *Working Paper Series*, Banco de Portugal, 12.

returns. An extended discussion of the methodology and more detailed discussion of the results is provided in Andreani and Gatt (2025).[3]

Data

We use confidential supervisory data from Maltese resident banks. These data comprise total exposures disaggregated by geography and counterparty, as reported by banks in accordance with the Common Reporting framework (COREP) established by the European Banking Authority (EBA). The data include 17 banks which are active in Malta and have a banking licence granted by the Malta Financial Service Authority (MFSA). Branches of international banks located in the EU and the Rest of the World (RoW) are excluded from our sample.[4] We aggregate the country-specific granular exposure data into six geographical regions and seven counterparty categories, resulting in a total of 42 distinct exposure types. Table 2a presents the geographical aggregation alongside the corresponding counterparty metadata. "M3C" refer to non-euro area countries that are deemed to be of significant relevance to the euro area banking sector.[5] We also highlight a group called "Main SSM", which includes Germany, the Netherlands, and France.[6] Additionally, we refine the standard NFCs category by distinguishing between "small and medium enterprises" (SMEs) and "large" NFCs.[7] Throughout this box bank names and their respective exposures are not shown to preserve confidentiality.

Table 2a
GEOGRAPHICAL AGGREGATION AND COUNTERPARTIES

Geography	Counterparty
Domestic	Sovereign
M3C	Financial institutions
RoW	NFCs (small)
Main SSM (DE, NL, FR)	NFCs (large)
Other SSM	Retail
Other EU	RRE
	Other

Sources: Central Bank of Malta; EBA; ESRB; authors' calculations.

Figure 2b presents a materiality assessment of exposures by geography and counterparty for the entire banking sector. The data is visualised using a heat map, an effective tool for representing the distribution of total exposure shares.[8] This visualisation provides crucial insights into key exposure classes that are likely to shape the formation of bank communities. The first key observation is that exposures are not equally distributed. Maltese banks predominantly hold domestic exposures, representing just over 61% of their total portfolios. About 27% of the rest of their exposures pertain to entities domiciled in SSM countries, and 16% of which are concentrated within the Main SSM countries (Germany, Netherlands and France). Most banks' exposures – around 91% – are therefore

[3] Andreani, M., and Gatt, W. (2025), A credit risk-based clustering approach for banks in Malta, Central Bank of Malta *Working Paper* WP/07/2025.

[4] These four branches – Akbank and Turkiye Garanti Bankasi (both headquartered in Turkey), Credit Europe Bank (Netherlands), and European Depositary Bank (Luxembourg) do not engage in any domestic banking activity.

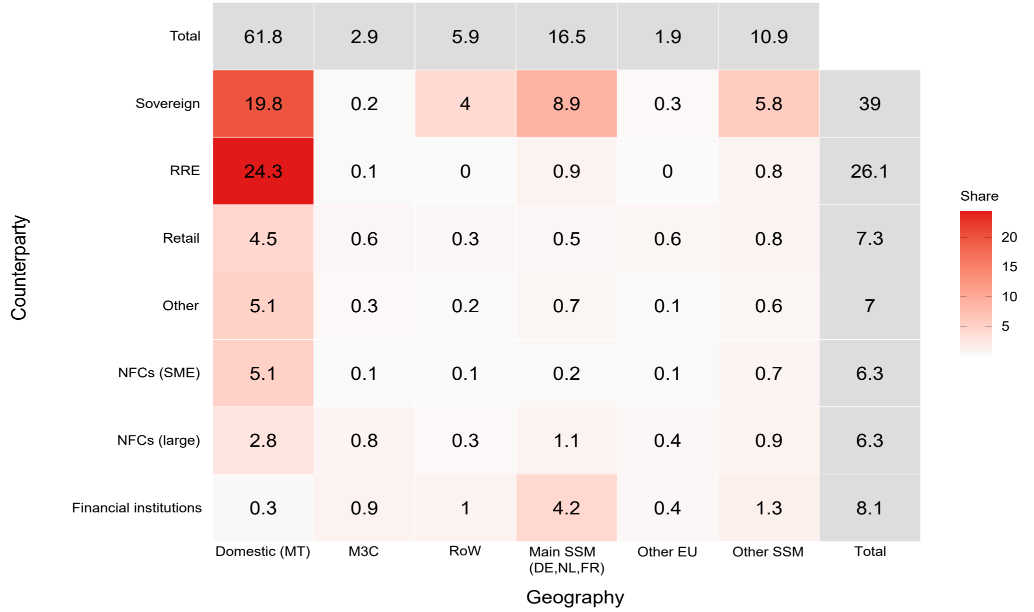
[5] This list includes Brazil, China, Hong Kong, Mexico, Russia, Singapore, Switzerland, Turkey, the United Kingdom, and the United States of America. The initial list was adopted under Decision ESRB/2015/3, which provides for annual revisions of the list starting from 2017. Last update: 23 June 2022.

[6] These countries are highlighted due to the significant share of geographical exposures held by Maltese banks, as identified through a country-specific materiality assessment.

[7] See EBA, ANNEX II, REPORTING ON OWN FUNDS AND OWN FUNDS REQUIREMENTS, p. 106, and EU, Regulation No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and amending Regulation (EU) No 648/2012, Article 112, for further information on COREP templates.

[8] Exposure amounts are converted into shares of total assets for each bank. This allows the model and the algorithm we use to focus on composition similarity, regardless of bank size, which could otherwise influence the results.

Figure 2b
MATERIALITY ASSESSMENT OF EXPOSURES



Sources: Central Bank of Malta; authors' calculations.
Notes: The figures are percentages of total exposures, for the period 2024Q3. All entries sum to 100 and are based on the total exposures of the 17 banks in the sample. Figures may not add up due to rounding.

geographically concentrated within Europe. The second observation is that a significant share of most banks' portfolio is composed of holdings of sovereign bonds, constituting about 39% of total exposures, with allocations spanning most geographical regions except M3C and other EU countries. Meanwhile, exposures to RRE represent around 26%, and as expected, the absolute majority are domestic. Among holdings relating to Main SSM countries, loans to financial institutions from these jurisdictions represent the second largest share.

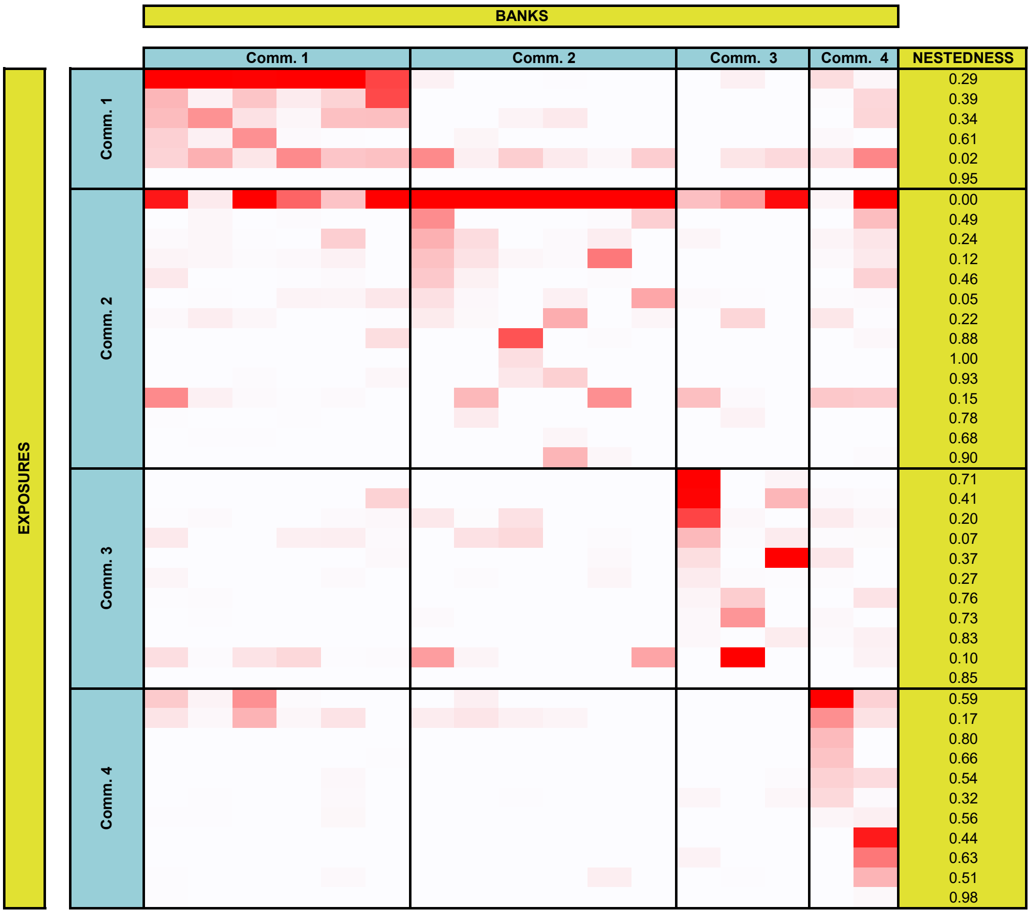
Results

Figure 2c displays the bipartite network with both banks and exposures ordered by their respective community labels. Exposures in darker red (a larger share of a given exposure) are more likely to play a significant role in determining the clustering of banks. This means that a higher share of exposures indicates a stronger link between banks and specific exposure classes. The ordering of the communities and exposures is set such that it illustrates a nested structure within each community, yielding most of the high exposures shares along the main left diagonal of this matrix.

This layered structure establishes pathways for potential shock transmission within each community, which can expose the network to vulnerabilities associated with systemic exposures. One exposure has a nestedness rank of 0.0, meaning that it is the most commonly-held asset among all banks (see Figure 2c, seventh row from the top). In a hypothetical scenario in which this asset experiences a shock that impacts its value, this shock would affect almost all banks directly and could trigger further cascading effects if the impact erodes more than the regulatory minimum capital requirement of any given bank. Absent any direct supervisory intervention, the bank under pressure would likely be forced to fire sale assets, which would depress market prices further, creating additional losses for other banks which hold the same asset. This feedback loop could in turn erode the capital levels of the other banks.[9] If losses and liquidity stress cannot be contained, the bank defaults with potential cascading effects on other banks.

[9] Huang, X., Vodenska, I., Havlin, S., and Stanley, H. E. (2013), Cascading failures in bi-partite graphs: model for systemic risk propagation, *Scientific Reports*, 3(1), p.1219.

Figure 2c
BANK AND EXPOSURE COMMUNITIES



Sources: Central Bank of Malta; authors' calculations.
Notes: Each column of the heat map representing the portfolio composition in shares for each bank, which sum to 100 across the 42 exposures listed in the rows. Darker shades indicate higher shares for each bank relative to other exposures on its books. Bank names, exposure types and geographies are not shown to preserve confidentiality.

The node-level metrics shown in Table 2b shed more light on this, by ranking banks based on four indicators. These are the Herfindahl-Hirschman Index (HHI, Herfindahl, 1950; Hirschman, 1945),[10,11] a concentration measure, Nestedness Rank (Rodriguez-Girones and Santamaria, 2006; Alarcon et al., 2008),[12,13] a score of exposure specialisation, Normalised Degree (Dalsgaard et al., 2008; Gonzalez et al., 2010),[14,15] a centrality measure which indicates the relative number of connections with common exposures and its specialisation, and therefore the role that the bank plays in channelling

[10] Herfindahl, O. C. (1950), Concentration in the U.S. Steel Industry. Ph.D. Dissertation, Columbia University. Unpublished.
[11] Hirschman, A. O. (1945), *National Power and the Structure of Foreign Trade*. University of California Press, Berkeley, CA.
[12] Rodriguez-Girones, M. A. and Santamaria, L. (2006), A new algorithm to calculate the nestedness temperature of presence–absence matrices, *Journal of Biogeography*, 33(5), pp. 924-935.
[13] Alarcon, R., Waser, N. M., and Ollerton, J. (2008), Year-to-year variation in the topology of a plant–pollinator interaction network, *Oikos*, 117(12):1796-1807.
[14] Dalsgaard, B., Martin Gonz´alez, A. M., Olesen, J. M., Timmermann, A., Andersen, L. H., and Ollerton, J. (2008), Pollination networks and functional specialization: a test using Lesser Antillean plant–hummingbird assemblages, *Oikos*, 117(5), pp. 789-793.
[15] Gonzalez, A. M. M., Dalsgaard, B., and Olesen, J. M. (2010), Centrality measures and the importance of generalist species in pollination networks, *Ecological Complexity*, 7(1), pp. 36-43.

Table 2b
COMMUNITIES AND BANK-LEVEL METRICS

	Comm. 1						Comm. 2						Comm. 3			Comm. 4	
HHI (normalised)	0.13	0.31	0.16	0.27	0.28	0.18	0.16	0.35	0.27	0.35	0.33	0.36	0.16	0.29	0.29	0.17	0.08
Nestedness Rank	0.00	0.06	0.13	0.31	0.38	0.44	0.75	0.50	0.69	0.81	0.88	1.00	0.56	0.63	0.94	0.25	0.19
Normalised Degree	0.86	0.81	0.79	0.64	0.64	0.50	0.36	0.50	0.38	0.36	0.33	0.14	0.43	0.38	0.26	0.69	0.76
Weighted Betweenness	0.03	0.05	0.03	0.05	0.03	0.08	0.05	0.25	0.00	0.33	0.00	0.03	0.00	0.00	0.03	0.00	0.08

Source: Authors' calculations.
Note: The heat map for each metric shows darker shades for higher values of the node metrics, except for Normalised Degree, which is shaded darkest for the lowest values.

shocks, and Weighted Betweenness (Borgatti and Everett, 1997; Dalsgaard et al., 2008),[16,17] another measure of centrality based on the shortest path between banks. The dark red indicates a higher score for all except for the Normalised Degree, which as we show below is inversely correlated with the other indicators, since having more exposures implies lower concentration (HHI) and nestedness (Nestedness Rank). Therefore, we invert the shading pattern for Normalised Degree to make the table more legible.

The pattern observed in Table 2b implies that Communities 2 and 3 are composed of banks which have concentrated portfolios and are therefore highly nested. Consequently, they have a lower Normalised Degree, meaning that these banks share relatively fewer connections to exposures. Although the Weighted Betweenness score is high only for two out of seventeen banks, these are both in Community 2, in line with the other measure of centrality. On the other hand, several banks within Communities 1 and 4 are highly diversified (a low HHI), have less nested portfolios and are therefore connected to relatively more exposures (high Normalised Degree). This nested structure of the Maltese banking system, with more concentration and specialisation within two communities, enhances resilience.

Another use of the bank bipartite network is the identification of bank business models for each community (see Table 2c). This can be based on the level and concentration of the exposures that are common to each community. Consequently, we emphasise that this exercise is based entirely

Table 2c
BANK BUSINESS MODELS

Comm.	Business model	Key sectors
1	Local Generalist	Domestic: **RRE, Sovereign**, Retail, Other, Large & SME NFC
		Main & Other SSM, RoW: Sovereign
2	Global Specialist	Domestic: **Sovereign**, Large NFC, Financial
		SSM, Other EU, M3C, RoW: **Large & SME NFC**, Financial, Sovereign
3	European Specialist	Domestic: Sovereign, Large NFC
		SSM, Other EU: **Retail**, Large NFC
4	Global Generalist	Domestic: **Sovereign**, Other
		Main SSM, M3C, RoW: **Sovereign**, Financial, RRE, Retail, Other

Sources: Central Bank of Malta; authors' calculations.
Notes: The table shows the business model assigned to each bank community, and the corresponding predominant sectors in each community based on whether they are domestic or domiciled abroad. Sectors marked in bold are the most sizeable across banks in each community.

[16] Borgatti, S. P. and Everett, M. G. (1997), Network analysis of 2-mode data, *Social Networks*, 19(3), pp. 243–269.
[17] See footnote 14.

on credit risk, and the business models may not be comparable with existing business model classifications devised using a more comprehensive assessment. Community 1 is composed of banks which have a significant part of their credit portfolio allocated to domestic RRE and sovereign bonds, but these banks also lend to several other domestic sectors, including retail, SMEs and large NFCs, with some holdings of sovereign bonds from SSM and other countries. Given this diversification across primarily domestic exposures, we label this community as following a *Local Generalist* business model. These banks maintain a broad and diversified portfolio of exposures.

Meanwhile, banks in Communities 2 and 3 tend to specialise in more selected sectors. Community 2 banks primarily issue credit to non-financial SMEs and large corporations and financial institutions, not only within EU countries but also across other M3C and the RoW. Given this large reach over selected sectors, banks within this community are labelled as *Global Specialists*. Similarly, banks in Community 3 tend to focus on lending to the retail sector and large NFCs in SSM and other EU countries, together with lending to domestic large NFCs and holding domestic sovereign bonds. We therefore label this business model as *European Specialist*, owing to its focus on Europe. Finally, the two banks in Community 4 display relatively diverse allocations across both domestic and foreign domiciles, with a significant share of holdings of sovereign bonds but also lending to financial institutions, RRE, retail and the ‘other’ sectors both locally and abroad. For this reason, banks in this community operate a *Global Generalist* business model.

A foundation for shock and contagion analysis

This box contributes to the categorisation of banks operating in Malta by constructing the first bipartite network model of banks and their exposures. The model leverages this network by applying a community detection methodology to emphasise the significance of overlapping exposures between banks, capturing the indirect linkages which would otherwise not be easily observed. It also lays the groundwork for future research by emphasising the role of overlapping portfolios in shaping the systemic impact of specific asset devaluations within the banking sector. This approach is ideal for studying contagion dynamics triggered by bank losses and failures, offering an understanding of how interconnected risk profiles contribute to the propagation of shocks across the banking network and, eventually, financial instability. Further extensions to the model would allow for the analysis of default not only of banks, but also of non-bank financial institutions, which until recently were typically less studied but can also pose a financial stability risk which warrants a macroprudential response.