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A credit risk-based clustering approach for banks in Malta

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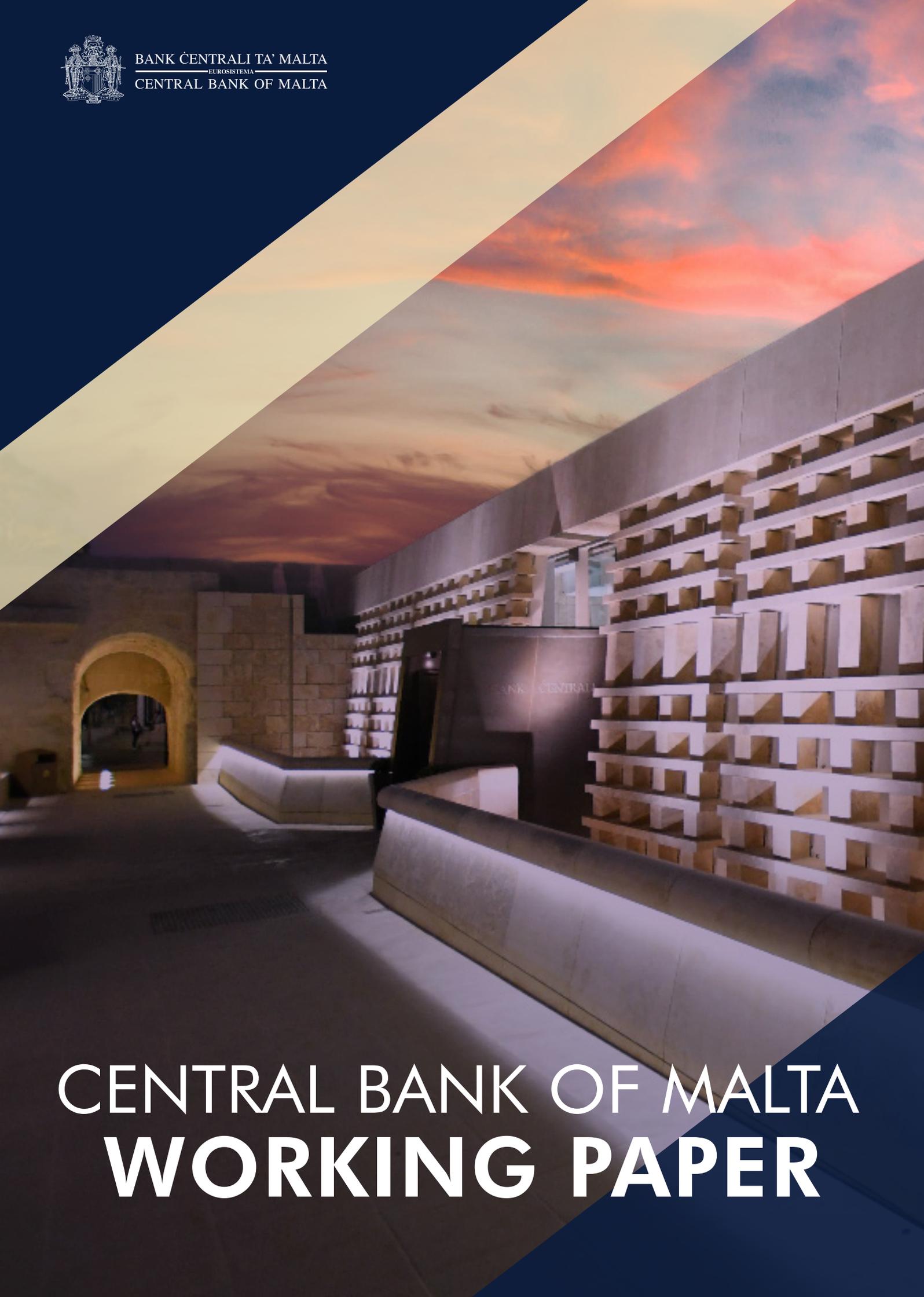
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A credit risk-based clustering approach for banks in Malta*

Michele Andreani[†]

William Gatt[‡]

WP/07/2025

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The views expressed in this paper are the authors' own and do not necessarily reflect the views of the Central Bank of Malta. Any queries should be sent through the [contact us link](#).

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Abstract

In this paper we construct a bipartite network model for the Maltese banking sector and identify communities of banks based on overlapping credit exposures. By leveraging confidential supervisory bank-level data on total exposures, we identify four distinct bank clusters and compute relevant network metrics. This approach enables the assessment of exposure concentration, network nestedness, and the centrality of individual institutions within the system. Finally, we use this information to identify banks' business models based on their credit risk profiles. In particular, we distinguish between generalist and specialist banks, based on their position within identified communities and the geographical composition of their exposures. This analysis complements the existing classification framework employed by the Central Bank of Malta from a credit risk perspective, and lays the groundwork for future research on the transmission of credit risk shocks within the banking system.

JEL Classification: C63, C88, E44, G21

Keywords: Bipartite network model, Overlapping portfolios, Banking networks, Bank communities

Contents

1	Introduction	4
2	Literature review	5
3	The Macroprudential Two-mode Network model (M2MN)	8
3.1	Bank community detection via weighted modularity	9
3.2	Network bank-level metrics	11
3.2.1	Herfindahl-Hirschman Index (HHI)	11
3.2.2	Weighted Nestedness ranking	12
3.2.3	Normalised Degree	12
3.2.4	Weighted Betweenness	13
3.3	Data	13
4	Results	15
4.1	Banks' materiality assessment	15
4.2	Community detection	17
4.3	Assessing the stability of communities across methods and time	23
4.4	Bank business models based on credit risk	24
5	Conclusion	25
	Appendix A	30

1 Introduction

Identifying similarities among banks and categorising those with shared characteristics is of significant interest to policymakers, as it sheds light on the propensity for any subset of banks to be jointly affected by an unfavourable shock to their exposures, or any particular bank’s role in spreading shocks across the rest of the financial network. A key challenge lies in establishing criteria that effectively differentiate these features, enabling the detection of well-defined and distinct clusters. For instance, the European Central Bank (ECB) maintains a comprehensive list of Significant Institutions (SIs) under its direct supervision, and Less Significant Institutions (LSIs), which are subject to indirect supervision through national authorities. The significance criteria include banks’ size and economic importance, among others.¹ The Central Bank of Malta (CBM) classifies banks operating in Malta into three categories: core banks, non-core banks, and international banks (Central Bank of Malta, 2011, 2014; Mamo, 2020). Core domestic banks have strong ties to the local economy and serve as key credit providers, while non-core domestic banks play a more limited role with smaller operations. In contrast, international banks have minimal connections to the domestic economy. This classification method highlights the institutions’ connections with the domestic economy, and their possible impact on the financial system. However, this classification is mostly based on the extent of interaction with the local economy, but does not explore interlinkages between the banks through their holdings of similar assets.

In this paper, we introduce a bank clustering framework based on overlapping exposures for the Maltese banking sector. To this end, we utilise bank-level data from supervisory financial reporting on credit risk to detect communities using a bipartite network model. A community of banks is defined as a group of financial institutions interconnected by a significant number of shared exposures. The detection of such communities is instrumental in revealing latent substructures within banking networks, thereby highlighting subsets of banks that are closely linked through overlapping portfolios. We determine a set of bank clusters that reflect 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

We draw a materiality assessment of the pattern of exposures across sectors, or counterparties, and their geography. We then identify four distinct communities of banks and study the network properties of their exposures using a set of node-level network metrics, namely concentration, nestedness, and the centrality of banks within the network. Nestedness, in particular, measures the degree to which exposures are shared among banks – that is – banks with fewer exposures tend to hold subsets of the exposures held by more diversified banks. Details on how this is calculated are provided further below. Finally, we determine the business models of each bank community by combining granular information on the characteristics of credit exposures, the identified communities and the associated bank network metrics. Our results are intended to

¹The criteria for determining whether banks are considered significant are set out in the SSM Regulation and the SSM Framework Regulation. See [European Central Bank - Supervisory framework](#) for additional details.

²We use the terms ‘cluster’ and ‘community’ interchangeably in this paper.

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.

The rest of this paper is organised as follows; Section 2 reviews the existing literature on bipartite network models and community detection. Section 3 provides an overview of the bipartite network model and the community detection methodology, alongside other network connectivity measures, together with the supervisory data for Maltese banks which is used in our analysis. Section 4 presents the main findings on bank communities, network metrics, business model classifications, and discusses the key policy implications of these results.

2 Literature review

Complex network models have proved to be useful tools in examining multidisciplinary entropy-based systems. These represent systems as nodes and edges, facilitating the study of local interactions and their emergent global behaviours in real-world phenomena. A non-exhaustive list of key surveys in complex network analysis includes Boccaletti et al. (2006), Jackson (2008), Goldenberg et al. (2010), and Boccaletti et al. (2014). Guillaume and Latapy (2006) describe the key properties of bipartite network graphs for modelling complex networks, offering a realistic framework for representing real-world systems.³ These models can aid in reconstructing the structure of complex networks even when only partial data is available (Straka et al., 2018).

The analysis of bipartite networks, namely networks consisting of two distinct sets of entities, has gained significant popularity in fields such as biology and ecology. More recently, these methodologies have been increasingly adopted in other domains, including finance and macroprudential policy. Caccioli et al. (2018) review the application of complex network models in modelling the financial system, with a particular focus on the propagation of financial risks. The author also highlights that the interconnectedness of financial entities plays a critical role in the transmission of financial shocks, thereby contributing to the amplification of systemic risk (Acemoglu et al., 2015; Lavin et al., 2019; Hasse, 2022; Mikropoulou and Vouldis, 2023). The transmission of external financial shocks within the financial system can occur through a loop of cascading failures, where an initial default at one node in the network triggers a chain reaction affecting other nodes. These methods have proven effective in analysing interbank markets and performing stress testing exercises, identifying the most vulnerable banks and providing insights for policy recommendations (Espinosa-Vega and Solé, 2011; Huang et al., 2013; Bargigli et al., 2015; Levy-Carciente et al., 2015; Zhang et al., 2021; Vodenska et al., 2021). Acemoglu et al. (2015) also underline the effectiveness of networking methods in identifying financially significant institutions for financial stability purposes.

Networks allow for node clustering, such as community detection, enabling the identification of subsets of agents that exhibit shared characteristics within the network. Barber (2007)

³The authors show that nearly all real-world complex networks possess an underlying bipartite structure or can be decomposed into subcomponents that exhibit such a structure.

pioneered the application of modularity, a measure that quantifies the extent of connections between nodes, for detecting communities in bipartite networks. Building on this foundation, [Alzahrani and Horadam \(2015\)](#); [Pesantez-Cabrera and Kalyanaraman \(2016\)](#) and [Gmati et al. \(2019\)](#) contributed further methodological advancements. [Beckett \(2016\)](#) introduced a refined framework that maximises weighted modularity, allowing for community detection which takes into account not only the existence of a link but also the strength of that link. Many studies have developed a comprehensive array of network connectedness measures, including metrics for nestedness ([Rodríguez-Gironés and Santamaría, 2006](#)), network normalisation degree and betweenness ([Dalsgaard et al., 2008](#)), and network concentration ([Herfindahl, 1950](#); [Rhoades, 1993](#); [Matsumoto et al., 2012](#)). [Billio et al. \(2012\)](#) apply these metrics to assess systemic risk by examining the interconnected returns of insurance companies, hedge funds, and other financial institutions. Similarly, [Baitinger \(2021\)](#) leverages topological network measures to enhance the accuracy of stock return forecasting models. [Alexandre et al. \(2024\)](#) examine the relationship between Individual Nestedness Contribution (INC) and systemic risk in the Brazilian interbank market, emphasising that nestedness is a useful measure for identifying generalist and specialist nodes in financial networks.

[Maas et al. \(2025\)](#) construct a modular two-mode network-based framework, which they name Macroprudential Two-Mode Network toolbox (M2MN), to study the network structure of, and assess the impact of credit risk shocks across the Portuguese banking system. 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 depreciation of overlapping assets via their liquidation, which result in losses to other banks not directly impacted by the original shock. The authors identify three bank communities each with their specific exposures and differing levels of specialisation. They then simulate the effects of credit risk shocks under different scenarios and find that first-round losses are largely absorbed by voluntary capital buffers held by Portuguese banks, with marginal losses brought about by second-round effects, impacting banks which tend to have more overlapping exposures than other, more specialised banks.

Another approach involves classifying banks based on their business models, providing a foundational framework for tailoring regulatory measures to the distinct characteristics of each group. This method, proposed by the European Banking Authority, enables proportionate regulation, aligning oversight with the specific risk profiles and operational structures of various business models ([Cernov and Urbano, 2018](#)). [Farnè and Vouldis \(2017\)](#) use FINREP supervisory data for 365 euro area banks for 2014 to categorise banks by business model. They apply a variation of the factorial k -means algorithm, a high-dimensional clustering technique, on these banks and obtain four unique clusters, which they label as *Wholesale funded banks*, *Securities holding banks*, *Traditional commercial banks* and *Complex commercial banks*. They show that the clusters differ in outcomes; traditional commercial banks hold more capital and take on more credit risk than complex commercial banks. Traditional banks also have better profitability metrics in general compared to complex banks, and interest income is their largest income source, a feature also shared by wholesale funded banks. Meanwhile, securities holding banks

earn the largest share of income from fees and commissions, as expected.

Marques and Alves (2020) use data for 524 European banks with total assets of at least €5 billion between the period 2005 and 2016 and apply three different clustering algorithms and then filter these results using a cluster ensemble step.⁴ They identify four business models, which they label *Retail focused*, *Retail diversified funding*, *Retail diversified assets* and *Large diversified*. The authors argue that this exercise allows for further analysis of banks, potentially distinguishing each cluster on topics such as bank performance and systemic risk. Ayadi and de Groen (2016) follow a similar approach, using a sample of 147 large banks operating within the European Economic Area over the period 2006 to 2013. They apply Ward’s algorithm (Ward Jr, 1963) on selected variables to determine the optimal number of bank clusters, and identify four distinct business models.⁵ Importantly, they show that this classification is broadly stable over time, as banks tended to keep the same business model. In a notable exception, about 12% of *Diversified retail banks* became *Focused retail banks*. However, there was more transition across business models by banks which received some form of government support or restructured after the Great Financial Crisis, with more than half of investment and wholesale banks changing business model by 2013, most moving to focused retail.

Turning to the local context, the categorisation of banks based on domestic relevance in Malta was initially introduced in Central Bank of Malta (2011), with subsequent methodological updates in Central Bank of Malta (2014) and Mamo (2020).⁶ This framework classifies Maltese banks into three categories: core, non-core, and international banks. The categorisation relies on a weighted indicator-based approach that assesses banks’ linkages with the domestic economy and their potential systemic impact on the financial system. Figure 1 illustrates the variables used and the weighting given to each. Credit to residents and resident deposits are allocated 30% of the weight each, while holdings of domestic bonds, resident contingent liabilities and market capitalisation each equally share the remaining 40% of the weight. Table 1 presents the results of this classification procedure as at 2024Q1.⁷

⁴The three methods are *Partitioning around Medoids*, *Fuzzy Clustering* and *Self-Organising Maps*.

⁵The optimal number of clusters in this context is that which maximises the ratio of between-cluster to within-cluster variance.

⁶The revised methodology includes a second step which addresses business models in borderline cases Mamo (2020, p. 21).

⁷The most recent version of this table includes a new bank (The Access Bank Malta Limited) and the declassification of an international bank (Credorax Bank Limited). The analysis carried out in this paper is based on the list of banks as it appears in Table 1, which was unchanged for several years. This makes it feasible to run some of the robustness checks we conduct further below.



Figure 1: Variables and weights used in the CBM’s bank categorisation

Source: [Mamo \(2020\)](#).

Table 1: The CBM’s categorisation of banks by domestic relevance

Banks		
Core Domestic Banks	Non-core Domestic Banks	International Banks
APS Bank plc	FCM Bank Limited	Akbank T.A.S. (Branch)
Bank of Valletta plc	FIMBank plc	Credit Europe Bank NV (Branch)
BNF Bank plc	IIG Bank (Malta) Limited	Credorax Bank Limited
HSBC Bank Malta plc	Izola Bank plc	European Depository Bank SA (Malta Branch)
Lombard Bank Malta plc	Merkanti Bank Limited	ECCM Bank plc
MeDirect Bank (Malta) plc	Sparkasse Bank Malta plc	Lidion Bank plc
		Multitude Bank plc
		Novum Bank Limited
		Turkiye Garanti Bankasi A S (Branch)

Notes: Adapted from Financial Stability Report 2023. The table is a extract from a larger table titled ‘The Domestic Financial Sector’.

Source: Financial Stability Report 2023, Central Bank of Malta.

3 The Macprudential Two-mode Network model (M2MN)

Bipartite networks constitute a class of network models widely used to model systems comprising two distinct types of entities, where actors do not interact directly with each other, but are linked together via a connection to a common object. Such relationships naturally arise between two distinct sets, such as plants and pollinators, users and products, or in this paper, banks and assets. We use the Macprudential Two-Mode Network model (M2MN) ([Maas et al., 2025](#)) to analyse systemic risk in financial systems by representing interactions between banks and assets, within a bipartite network structure ([Espinosa-Vega and Solé, 2011](#); [Levy-Carciente et al., 2015](#)).

In this study, we denote banks as the entities in the first set, U , and exposures (assets) as the entities in the second set V .⁸ A bipartite *graph* G is formally defined as:

$$G = (U, V, E), \tag{1}$$

where U and V are disjoint sets of nodes, and E represents the set of edges connecting nodes from U to V such that $e = (u, v) \in E$, where $u \in U$ and $v \in V$. Within this framework, banks U are not directly connected to one another, but are instead linked through their shared exposures to nodes V , representing overlapping portfolios. Figure 2 presents a schematic illustration of this overlapping portfolio structure. This degree of shared exposures provides crucial insights into

⁸We use the terms assets and exposures interchangeably in the paper.

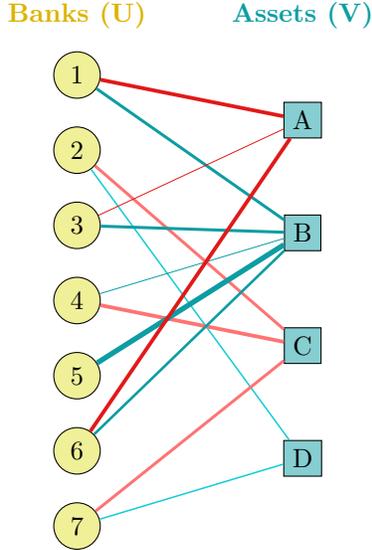


Figure 2: A bipartite graph of a network of overlapping portfolios

Notes: The illustration provides a hypothetical representation of a bipartite network composed of banks and assets. The width of the links indicate 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.

Source: Authors' illustration.

the network structure connecting financial institutions together, and offers a basis to evaluate the systemic risk effects of financial shocks to the vulnerability of banks. A devaluation of an exposure $v_i \in V$, held by multiple banks simultaneously, weakens the balance sheets of all affected institutions. As banks operate under capital constraints, losses force them to liquidate parts of their holdings, potentially triggering downward pressure on asset values and propagating systemic risk.

In this paper, we exploit the functionalities of the M2MN model to construct a bipartite network of the Maltese banking system and examine a comprehensive set of metrics that facilitate the identification of communities of banks with shared characteristics. The following subsections present a detailed analysis of the community detection procedure (Section 3.1), together with the key metrics incorporated within the M2MN model (Section 3.2).

3.1 Bank community detection via weighted modularity

Communities represent clusters of vertices that exhibit a greater number of, or stronger connections, among themselves compared to the rest of the network. These clusters form relatively homogeneous groups, distinguished by a higher internal connection density, such as shared exposures, relative to the broader network.

Let G be a bipartite graph, as in Equation (1). A *community* C of banks represents a subset of U and corresponding assets V defined as a sub-graph of G

$$C = (\hat{U}, \hat{V}, \hat{E}) \subseteq G \quad (2)$$

where $\hat{U} \subseteq U$ and $\hat{V} \subseteq V$. These consist of banks that are strongly connected, which in our application translates to banks which are vulnerable to similar credit risks. The strength of these connections is determined by the relative size of the shared exposures. As discussed above, these communities aid in the study of systemic risk in the financial system, as shocks to the value of a common asset can propagate throughout the community, affecting multiple banks simultaneously.

Figure 3 depicts the same hypothetical bipartite graph shown in Figure 2, but split into two communities, which are not readily apparent. For instance, banks 1, 3, 5 and 6 form a community since they all hold assets A or B, or both. Meanwhile, banks 2, 4 and 7 form another distinct community through their exposures to assets C and D.⁹ Within this community structure a shock to asset A can affect banks 1 and 6, which are directly exposed to it. However, if the balance sheets of these banks suffer to the extent that fire sales of asset B drive its value down, then the balance sheets of banks 3 and 5 can also be impacted. Moreover, the shock can also transmit to community 2 via bank 4’s holding of asset B. If the initial shock is large enough it could potentially also transmit to banks 2 and 7 through bank 4’s holding of asset C, via the same mechanism as for asset B.

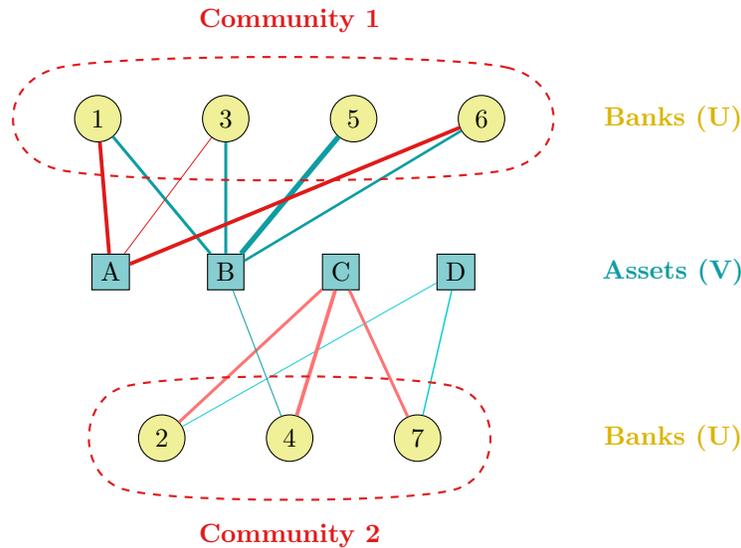


Figure 3: Communities in a bipartite graph

Notes: The illustration provides a hypothetical representation of two communities. The thickness of the edges indicates the proportion of each bank’s share of a given asset. 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.

Source: Authors’ illustration.

The algorithm we use to identify the communities relies on the network’s *modularity*. Tra-

⁹Although bank 4 also has some exposure to asset B, the low exposure (represented by the thin edge) and strong exposure to asset C imply that it belongs more to the second community. Bank 5 only has exposure to asset B, but it is a large exposure and so that bank belongs in community 1 since other banks within that community also hold significant exposures to asset B.

ditional modularity focuses solely on the number of connections between nodes, as described in [Boccaletti et al. \(2006, p.281\)](#), which is a weak measure of connectedness. In contrast, weighted modularity accounts for the strength of these connections. [Barber \(2007\)](#) proposes a measure of modularity for bipartite networks while [Beckett \(2016\)](#) extends the computation of modularity to the case of weighted bipartite networks, which we use. This weighted modularity Q_W is given by

$$Q_W = \frac{1}{M} \sum_{u=1}^U \sum_{v=1}^V \left(\widetilde{W}_{uv} - \frac{y_u z_v}{M} \right) \delta(g_u, h_v) \quad (3)$$

where M is the sum of the weighted connections across all banks, \widetilde{W} is the weighted incidence matrix which summarises the bank-exposure links, y_u is the row and z_v the column marginal sums of \widetilde{W} , and $\delta(g_u, h_v)$ is the Kronecker delta function which takes the value of 1 when nodes (u, v) are in the same community, and 0 otherwise. While there are some competing algorithms to measure modularity, [Liu and Murata \(2010\)](#) show that the *Label Propagation Algorithm bipartite plus* (LPAwb+) dominates in terms of speed and ability to handle large networks.¹⁰ We use the LPAwb+ in our application, which is a modification of the algorithm by [Beckett \(2016\)](#) to maximise the weighted modularity in the detection of communities.¹¹

3.2 Network bank-level metrics

To supplement our community detection exercise and to understand further the structure of the Maltese banking network, we employ a set of bank-level metrics which are tailored for bipartite networks. These metrics enable a detailed characterisation of the role played by individual banks within the system, providing insights into their degree of diversification, systemic importance, and their potential role in the transmission of credit risk. [Table 2](#) summarises the main properties of each metric, including their interpretation and relevance within the bipartite network context.

3.2.1 Herfindahl-Hirschman Index (HHI)

The Herfindahl–Hirschman Index (HHI) concentration measure ([Herfindahl, 1950](#); [Hirschman, 1945](#)) is calculated as the sum of squared shares of exposures:

$$\text{HHI} = \sum_{i=1}^V s_i^2, \quad (4)$$

where s_i represents the share of the i -th exposure relative to the total portfolio, and V is the total number of exposures. The HHI approaches $1/V$ under conditions of perfect diversification, while a value of 1 represents complete concentration. In this context, higher HHI values indicate concentrated vulnerabilities in a limited number of exposures, whereas lower values signify greater risk diversification. To facilitate the interpretation of the results, we normalise the

¹⁰[Liu and Murata \(2010\)](#) build on an earlier version of the algorithm, see the references therein.

¹¹We use the R package `bipartite`, which includes Beckett’s implementation. This function is also publicly available on the author’s [Github](#) page in a number of languages.

HHI using the following transformation

$$\widehat{\text{HHI}} = \frac{\text{HHI} - \frac{1}{V}}{1 - \frac{1}{V}} \in [0, 1] \quad (5)$$

such that $\widehat{\text{HHI}}$ is bounded between 0 and 1, with 0 denoting perfect diversification and 1 complete concentration.

3.2.2 Weighted Nestedness ranking

Weighted Nestedness is a measure used to quantify the extent to which interactions between two sets of nodes follow a nested pattern (Rodríguez-Gironés and Santamaría, 2006; Alarcón et al., 2008). Nestedness highlights how exposures overlap across banks: banks with a limited number of exposures generally hold only a subset of the assets owned by larger banks, indicating a hierarchical structure of overlapping portfolios in the network. The Nestedness based on Overlap and Decreasing Fill (NODF) is defined as:

$$\text{NODF} = 2 \times \frac{\left(\sum_{i < j} N_{ij}^{\text{row}} + \sum_{k < l} N_{kl}^{\text{col}} \right)}{m(m-1) + n(n-1)} \in (0, 1), \quad (6)$$

where $\sum_{i < j} N_{ij}^{\text{row}}$ is the total nestedness contributions from pairs of rows m , and $\sum_{k < l} N_{kl}^{\text{col}}$ captures the total nestedness contributions from pairs of columns n . High nestedness corresponds to a rank near 0 and full specialisation equates to a rank of 1. Banks with low nestedness (approaching 1) typically exhibit widely shared exposures, indicating high diversification or minimal specialisation. The latter are commonly referred to as *generalists*. As a result, their portfolios substantially overlap with those of other banks, covering a broad range of common exposures. However, since concentration and nestedness are not necessarily correlated, these banks may still face systemic risk. This measure helps identify whether a hierarchical structure of exposure overlaps exists, where banks with fewer, more specialised, or selective exposures are connected to subsets of exposures already linked to larger, more diversified banks.

3.2.3 Normalised Degree

This centrality measure is derived from a one-mode weighted projection of a bipartite network, as described in Dalsgaard et al. (2008) and González et al. (2010). In this framework, the degree d_i of a node represents the total number of direct connections it maintains within the network. However, since different nodes may have varying maximum possible connections based on the network's structure, a raw degree count alone may not provide a fully comparable measure of connectivity. The Normalised Degree (N.D.) accounts for the maximum potential connections a node could achieve. It is defined as

$$\text{N.D.} = \frac{d_i}{d_{\max}} \in [0, 1] \quad (7)$$

Table 2: Summary of node network metrics

Metric		Range	Description
Herfindahl–Hirschman (HHI) (normalised)	Index	[0, 1]	A concentration measure, with 1 representing total concentration and 0 perfect diversification
Weighted Nestedness Rank		[0, 1]	Captures hierarchical exposure overlaps, with values approaching 1 indicating broad diversification yet potential systemic risk
Normalised Degree		[0, 1]	A measure of a node’s connectivity relative to its potential, with a value approaching 1 indicating high connectivity, and values near 0 suggest a more isolated node.
Weighted Betweenness		[0, 1]	Measures a node’s influence in propagating connections, with high values indicating high propagation of shocks

where d_{max} represents the highest possible degree a node can have within a given network. By normalising the degree in this manner, the measure facilitates a comparative analysis across nodes, allowing for an assessment of their connectivity relative to the theoretical upper bound. A value closer to 1 indicates that a node is highly connected, approaching its maximum possible connections, while values near 0 suggest a more isolated position within the network.

3.2.4 Weighted Betweenness

Expanding on the traditional concept of betweenness centrality, this measure evaluates the frequency with which a given node serves as an intermediary on the shortest paths between other nodes in a network (Borgatti and Everett, 1997; Dalsgaard et al., 2008). In the context of financial systems, it provides a quantitative assessment of a bank’s strategic significance within the interconnected structure of exposures and transactions. Given a bipartite interaction matrix \widetilde{W} , as defined in Equation (3), weighted betweenness centrality (W.B.) is calculated as:

$$\text{W.B.} = \frac{\sigma_{uv}(v)}{\sigma_{uv}} \in [0, 1], \tag{8}$$

where σ_{uv} denotes the total number of shortest paths between nodes u and v , and $\sigma_{uv}(v)$ represents the number of those paths that pass through node v . A value of W.B. close to 1 indicates that a bank plays a pivotal role in facilitating the flow of financial resources and information between other institutions. Such a position implies that the bank is highly influential within the network, functioning as a bridge that connects otherwise distant nodes. The centrality of these institutions makes them critical conduits for the transmission of systemic risk: in the event of financial shocks or liquidity disruptions, banks that occupy highly central positions within the network may amplify and propagate distress throughout the broader financial system.

3.3 Data

We use confidential supervisory data from Maltese resident banks. These data comprise total exposures disaggregated by geography and obligor, as reported by banks in accordance with

Geography	Counterparty
Domestic	Sovereign
Material Third Countries (M3C)	Financial institutions
Rest of the World	Non-financial corporations (small)
Main SSM (DE, NL, FR)	Non-financial corporations (large)
Other SSM	Retail
Other EU	Residential real estate (RRE)
	Other

Table 3: Geographical aggregation and counterparty categories.

Notes: ‘Main SSM’ refers to a subset of euro area countries which includes Germany (DE), the Netherlands (NL), and France (FR).

Source: Central Bank of Malta, EBA, ESRB, authors’ calculations.

the Common Reporting framework (COREP) established by the European Banking Authority (EBA). Each observation is linked to a specific geographical entity, denoting the residence of the counterparty or obligor, as well as the corresponding counterparty category.¹² Given the availability of supervisory data at both individual and consolidated levels, we use consolidated data for each bank that provides such reporting. Our sample includes 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 are excluded from our sample.¹³

The geographical breakdown of exposures covers up to 251 countries, allowing for a detailed and comprehensive mapping of the jurisdictions associated with all reported exposures. After some initial analysis of the distribution of exposures by geography and counterparty we aggregate the granular exposure data into six geographical regions and seven counterparty categories, resulting in a total of 42 distinct exposure types. Table 3 presents the geographical aggregation alongside the corresponding obligor metadata. This includes the definition of Material Third Countries (M3C), as provided by the European Systemic Risk Board (ESRB). M3C refer to non-euro area countries that are deemed to be of significant relevance to the euro area banking sector.¹⁴ We also highlight a group called ‘Main SSM,’ which includes Germany, the Netherlands, and France.¹⁵

The sectoral aggregation of counterparties directly follows the reporting framework outlined in the Common Reporting framework (COREP) established by the EBA. Additionally, we refine the standard Non-financial Corporations (NFCs) category by distinguishing between ‘small and

¹²This is in line with the classification in the [Capital Requirements Regulation \(CRR\): REGULATION \(EU\) No 575/2013 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL](#).

¹³These four branches—Akbank and Türkiye Garanti Bankasi (both headquartered in Turkey), Credit Europe Bank (Netherlands), and European Depositary Bank (Luxembourg) do not engage in any domestic banking activity.

¹⁴This 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.

¹⁵These countries are highlighted due to the significant share of geographical exposures held by Maltese banks, as identified through a country-specific materiality assessment.

medium enterprises’ (SMEs) and ‘large’ non-financial corporations.¹⁶

4 Results

In the first part of our analysis we assess the materiality of exposures across the entire Maltese banking sector. This allows for a top-down understanding of the distribution of risks across counterparties and geography. We then run the community detection algorithm on our bipartite network and interpret the results with the help of bank and exposure-level network metrics, such as connectedness and centrality. This also allows us to identify the bank business model of each community. We then comment on the stability of these results. Our reference period is 2024Q3. We do not use the most recent data due to changes in some banks which would create a discontinuity and prevent us from assessing the stability of our key findings (refer to Section 4.3).

4.1 Banks’ materiality assessment

Figure 4 presents a materiality assessment of exposures by geography and obligors for the entire banking sector. The data is visualised using a heat map, an effective tool for representing the distribution of total exposure shares.¹⁷ This visualisation provides crucial insights into key exposure classes that are likely to shape the formation of bank communities.¹⁸

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). The absolute majority of banks’ exposures – around 91% – are therefore 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.

Figure 5 below shows our anonymised bipartite graph, with banks on the left in yellow and exposures in geography-counterparty pairs on the right in teal.¹⁹ In Appendix A we also show bipartite graphs with a more granular view of the network of exposures across banks

¹⁶See 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.

¹⁷Exposure 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.

¹⁸Our framework also allows for a bank-by-bank analysis of exposure concentration, which is not shown in this paper to preserve confidentiality, but is used internally.

¹⁹That is, Domestic-Sovereign, Domestic-RRE, Main SSM-Sovereign, and so on.

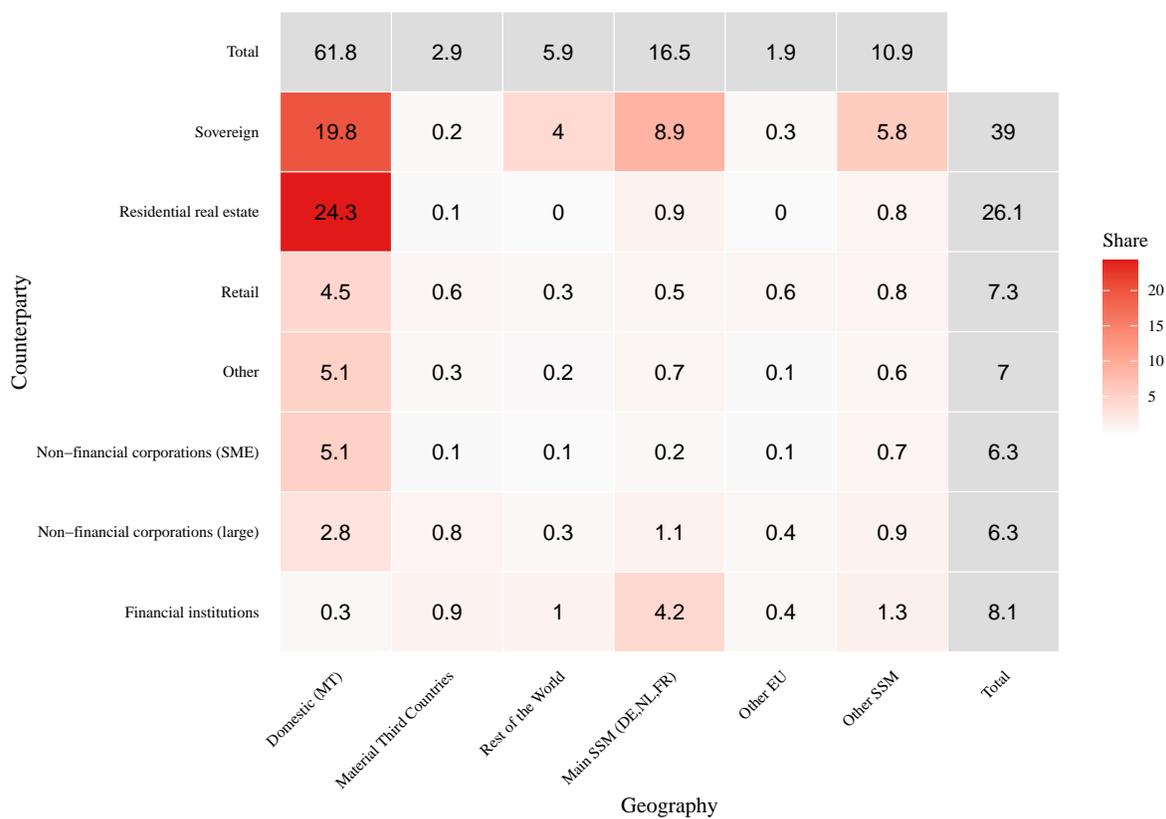


Figure 4: Materiality assessment of exposures by counterparty and geography

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.

Source: Central Bank of Malta, authors' calculations.

Table 4: Network metrics as at 2024Q3

Metrics	Value
Number of banks	17
Number of exposures	42
Mean number of exposures per bank	12.9
Mean number of banks servicing a sector	5.2
Weighted nestedness (NODF)	0.416

Source: Authors' calculations.

by geographical jurisdiction and counterparty type, respectively. The graph below shows the significant interlinkages in the network, and the width of the connections represents the relative size of each exposure. Although the materiality assessment shown above places significantly more emphasis on some exposures than others, the graph in Figure 5 shows that the network is still relatively dense, with potentially a strong role for both direct and second-round effects following a shock to any of these exposures, as discussed in Section 3.1.

In our preliminary analysis of the network we also show some network-level metrics in Table 4. On average, each bank is connected to about 12.9 exposures, while each exposure is serviced by an average of 5.2 banks. This indicates that while Maltese banks share certain common exposures, they also retain distinct markets. Such diversification potentially reduces intense direct competition among banks and mitigates the likelihood of simultaneous exposure to identical risks. A weighted nestedness index of 0.416 reveals a hierarchical structure in the overlap of exposures within the Maltese banking sector. This suggests that banks with fewer, more specialised, or selective exposures are linked to a subset of exposures which in turn, are already linked to larger and more diversified banks. As a result, shocks to a subset of exposures have the potential to spread across a number of banks.

4.2 Community detection

In the next step of studying the banking bipartite network, we apply the LPAwb+ algorithm Beckett (2016) to identify the optimal clustering of banks based on their portfolio structures. Since the concept of weighted modularity as shown in equation (3) includes a stochastic component, we run a Monte Carlo exercise over the algorithm by evaluating it 1,500 times, and select the output that maximises the weighted modularity Q_W for a given community size. We refer to this as the maximised Weighted Modularity.²⁰ Figure 6 shows the value of the Maximised Weighted Modularity at each community size. As expected, there are strong gains in the score when we depart from the case of no communities (one large community) up to 5 communities, beyond which the score levels off. Although a high Weighted Modularity score can be achieved with 5 communities, we find that allowing for this many (or more) communities introduces excessive flexibility, leading some communities to be occupied by a single bank, which runs counter to the objective of the exercise. We therefore opt for 4 communities, as this achieves the most

²⁰We also fix the random seed generator to ensure that the results we obtain are not driven by statistical noise across different community sizes.

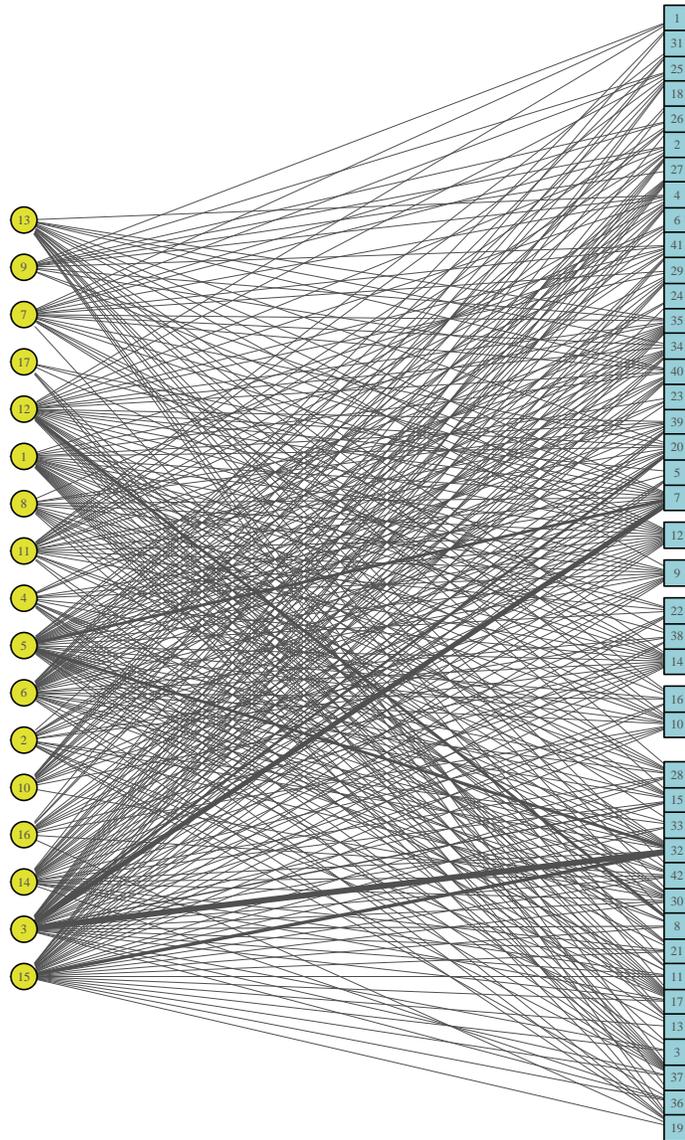


Figure 5: Bipartite graph of Maltese banks (left) and their exposures (right)

Notes: Banks are represented on the left-hand side (in circles), while exposures are shown on the right-hand side (in squares). To ensure confidentiality, the names of both banks and exposures have been anonymised and are denoted numerically as 1, 2, ..., and so on. The ordering is arbitrary and does not reflect any specific ranking or classification.

Source: Central Bank of Malta, authors' calculations.

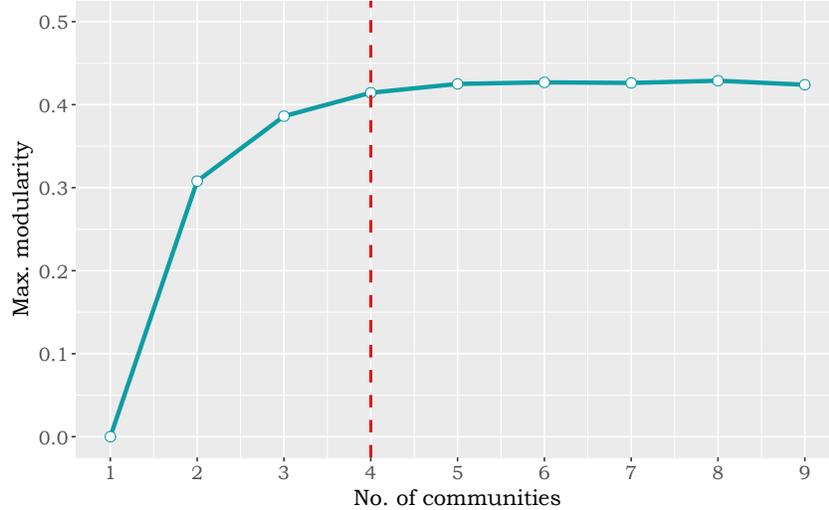


Figure 6: Maximum modularity across the number of communities

Notes: The figure shows the maximised Weighted Modularity obtained using the LPAwb+ algorithm (Beckett, 2016) for each community dimension. The dashed vertical line marks the chosen number of communities.

Source: Authors' calculations.

interpretable and meaningful grouping. Conversely, limiting the analysis to 3 communities is too restrictive, as it results in assimilating banks that share only minimally common exposures.

The two largest communities comprise six banks each, while the other two communities are composed of three and two banks, respectively. Figure 7 displays the bipartite network with both banks and exposures ordered by their respective community labels. We do not show the bank names and exposures to preserve confidentiality. 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, which in turn, can contribute to a higher value of weighted modularity, as outlined in Section 3.1. 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. For instance, a shock to the exposure with a nestedness rank of 0.0 (see Figure 7, seventh row from the top) would affect almost all banks directly, and could trigger further cascading effects if the shock erodes more than the regulatory minimum capital requirement of a bank. Barring any direct supervisory intervention, this would lead to the bank failing and liquidating its other exposures. This could potentially reduce the market value of some of these exposures via fire sales, which could in turn affect the capital levels of the other banks (Huang et al., 2013). The node-level metrics shown in Table 5 shed more light on this, by ranking banks on the basis of four indicators as discussed in Section 3.2. These are the Herfindahl-Hirschman Index (HHI), a concentration measure, Nestedness Rank, a score of exposure specialisation, Normalised

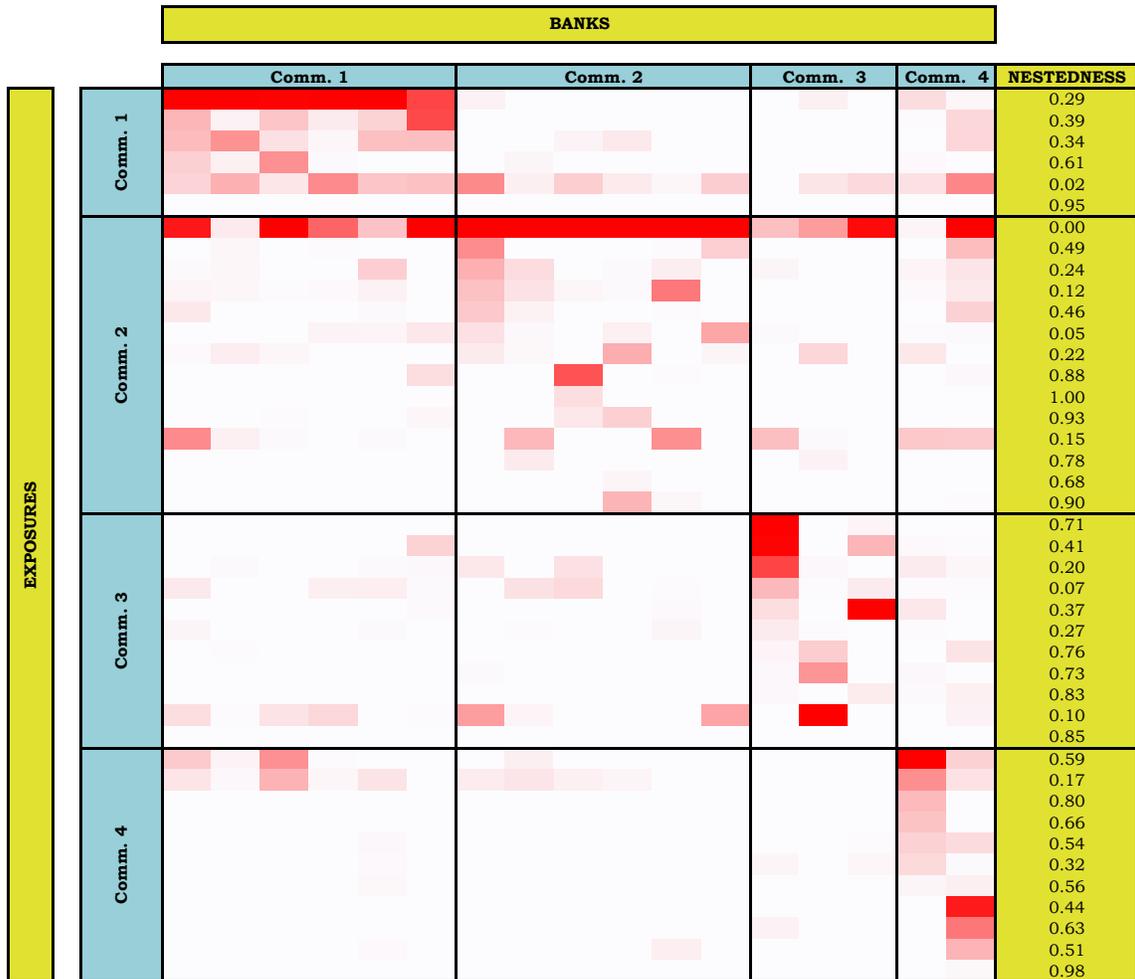


Figure 7: Bank and exposure communities

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.

Source: Central Bank of Malta, authors' calculations.

Degree, 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 shocks, and Weighted Betweenness, another measure of centrality based on the shortest path between banks.²¹ 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 patterns across concentration and centrality measures are largely consistent and show similar rankings of banks by centrality, and as shown in Figure 8 they are correlated to different degrees.

Table 5: 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

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.

Source: Authors' calculations.

The pattern observed in Table 5 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. This is because certain credit risk shocks may have a limited impact if the affected exposures are not central to the system. Such a structure provides a degree of shock absorption, with banks within Communities 2 and 3 holding diversified or less critical exposures which are less affected, helping to contain the spread of risk within specific parts of the network. This resilience is particularly valuable in preventing smaller shocks from spreading widely across the banking system. However, despite their relatively lower concentration, Community 1 and 4 banks with high Nestedness Rank can play a central role in propagating shocks for certain exposures, especially when they also exhibit high centrality (high Normalised Degree).

²¹Although the `bipartite` package in R includes several other node-level indicators, most were developed for the study of ecology, such that the portability to other applications can be challenging. Nevertheless, many of these metrics correlate with the four indicators we use, such that we can obtain a reasonably detailed understanding of the structure of our bipartite network.

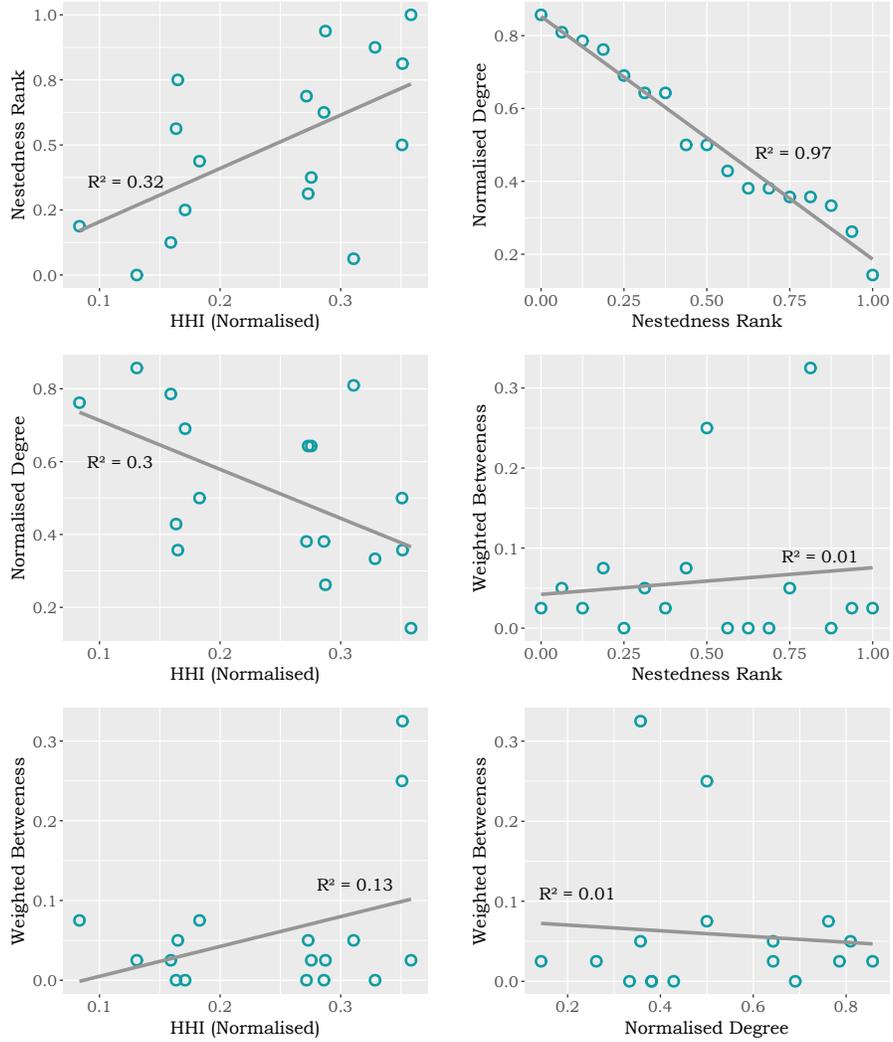


Figure 8: Network metrics scatter plots

Notes: The six scatter plots show the pairwise relationships across all of the combinations possible for the four network metrics we use in Table 5. The line of best fit and corresponding R^2 are shown to illustrate the strength of this association.

Source: Authors' calculations.

4.3 Assessing the stability of communities across methods and time

To reinforce our empirical findings, we conduct two robustness checks. First, we identify bank clusters applying the DIRTLP**Awb+** algorithm – an alternative version of LP**Awb+**. This operates under a similar setup and automatically determines the optimal number of communities by maximising weighted modularity. We find that compared to LP**Awb+**, the DIRTLP**Awb+** algorithm detects a greater number of communities, occasionally identifying clusters formed by a single bank. This is in line with our observation in the previous section that the weighted modularity of the bipartite network is maximised at a higher number of communities than 4, yet this would lead to at least one community being composed of a single bank. Nonetheless, repeated runs of this algorithm consistently identify the same Community 1, irrespective of the number of communities. The consistency of our results suggests that even under alternative specifications, we still detect communities structured around dominant exposures, particularly domestic ones. We therefore opt to retain the results from the LP**Awb+** algorithm as our baseline. This choice is motivated by its ability to identify a more parsimonious and interpretable number of communities, avoiding the over-fragmentation seen with DIRTLP**Awb+**.

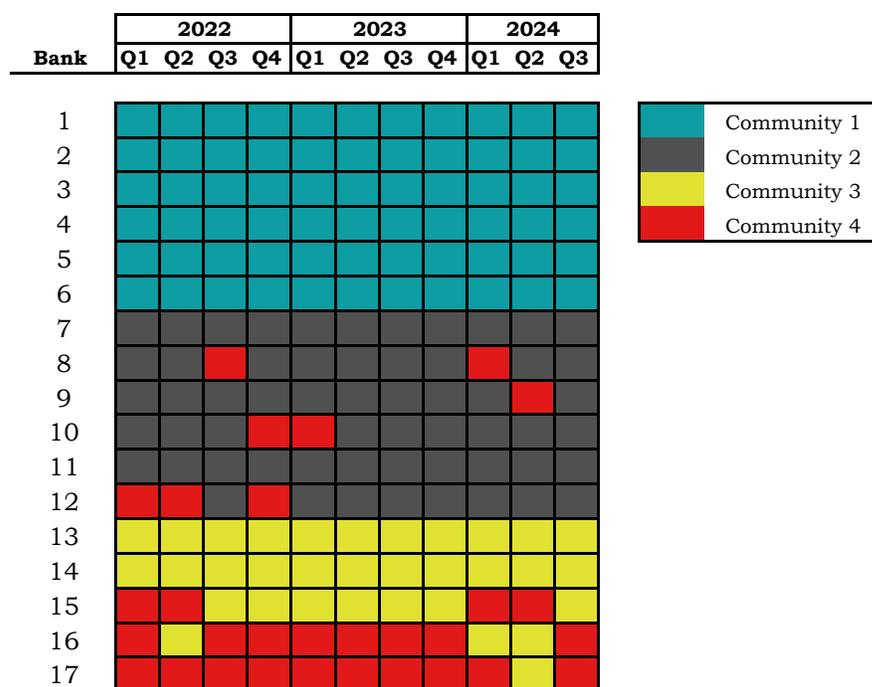


Figure 9: Robustness of community structure across time

Notes: The figure shows the category assigned to each bank using the methodology described above for each quarter from the period 2022Q1 to 2024Q3. To ensure confidentiality, bank names are anonymised and are denoted numerically as 1, 2, ..., and so on.

Source: Central Bank of Malta, authors' calculations.

In addition, we apply the LP**Awb+** algorithm to quarterly data spanning from 2022Q1 to

2024Q2, to verify the temporal robustness of our results. This exercise is intended to assess the stability of the detected communities over time and to identify potential persistence in the portfolio characteristics. As shown in Figure 9, the algorithm consistently identifies the same community 1 throughout the period. On the other hand, banks in smaller clusters tend to shift between communities – particularly from Communities 3 to 4, and from 2 to 4. These temporary transitions are due to one-off operations by relatively smaller banks which can alter their exposure composition, and therefore their contribution to the weighted modularity of the community to which they previously belonged. Some of these shifts might have been associated with adjustments following the COVID-19 pandemic, as the economy returned to normal operation. Nevertheless, the benchmark allocation of banks across communities as shown above is representative of banks’ credit risk across the recent past.

4.4 Bank business models based on credit risk

Another important output from the bank bipartite network is the identification of bank business models for each community. This is based on the level and concentration of the exposures that are common to each community. Consequently, we emphasise that this exercise is based entirely on credit risk, and the business models may not be comparable with existing business model classifications devised using a more comprehensive assessment.²² Community 1 is composed of banks which have a significant part of their credit portfolio allocated to domestic residential real estate and sovereign bonds, but these banks also lend to several other domestic sectors, including retail, small and medium enterprises (SMEs) and large non-financial corporations, 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.²³ The low degree of nestedness observed among banks in Community 1 underlines their classification as generalists. These banks maintain a broad and diversified portfolio of exposures. This diversification, combined with relatively high connectivity, implies that these institutions are structurally better positioned to absorb or dampen idiosyncratic shocks. Their exposure profile reduces the likelihood of large capital impacts relative to more specialised banks, thereby enhancing overall systemic resilience.

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 material third countries and the rest of the world.²⁴ They also hold both domestic and foreign sovereign bonds and also lend to domestic large NFCs and to financial institutions. Given this large reach over selected sectors, banks within this community are labelled as *Global Specialists*. Similarly, banks in Community

²²For a recent bank business model classification for Malta, refer to a study by the European Banking Authority, in which [Cernov and Urbano \(2018\)](#) leverage both quantitative measures, including clustering techniques, together with a qualitative assessment that leverages expert judgement of supervisory authorities. This classification is based on the entire balance sheet and regulatory structure of the banks.

²³See [Alexandre et al. \(2024\)](#) for a discussion of nestedness and specialisation.

²⁴Where there is some heterogeneity across banks within each community, the discussion here focuses on broad patterns within each 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. These patterns of exposures among Communities 2 and 3 indicate more limited connectedness and higher exposure concentration. Their specialist business model potentially makes them more susceptible to sector-specific or regional shocks. Importantly, the Weighted Betweenness metric in Table 5 reveals that some banks occupy strategically important positions in terms of connecting different exposures across the system. Despite their peripheral location in the community structure, some banks within these communities, exhibit relatively high Nestedness Rank and Weighted Betweenness, and low Normalised Degree values, signalling a combination of influence and concentration. This suggests that these banks can act as ‘conduits’ for credit risk propagation.

Finally, the two banks in Community 4 display relatively diverse allocations across both domestic and foreign domiciles, with a significant share in holdings of sovereign bonds but also lending to financial institutions, residential real estate, retail and the ‘other’ sectors both locally and abroad. For this reason, banks in this community operate a *Global Generalist* business model.

Table 6: 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

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.

Source: Central Bank of Malta, authors’ calculations.

5 Conclusion

This paper contributes to the categorisation of banks operating in Malta and builds on the limited but diverse literature on the financial sector network by constructing the first bipartite network model of banks and their exposures. It then 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. We identify four communities of banks and provide additional insights into the characteristics of these

communities. Node and network metrics reveal the degree to which banks are diversified or concentrated, their exposure to key risks, and their centrality in shaping the systemic impact of specific asset devaluations within the banking sector. We use the resulting clusters of banks and exposures to identify bank business models, and find that two communities tend to diversify their lending either domestically or globally, and are therefore referred to as Local Generalists and Global Generalists, respectively. The other two clusters of banks focus their business activities on a more concentrated subset of sectors within different geographies, and are therefore labelled as Global Specialist and European Specialist banks, respectively.

This paper 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.

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Appendix A

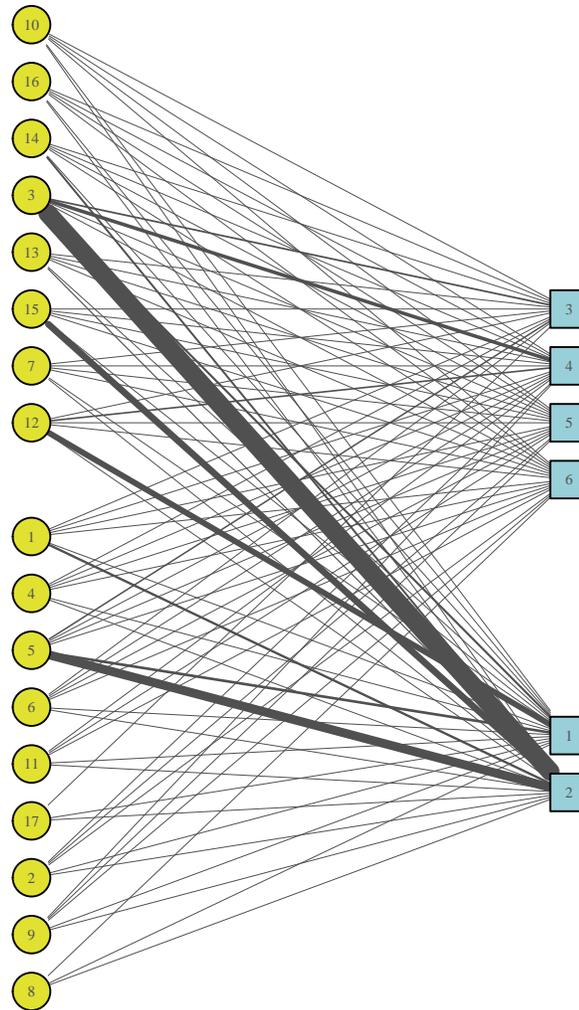


Figure A.1: Bipartite graph, aggregation by geography

Notes: Banks are represented on the left-hand side (in circles), while exposure geographies are shown on the right-hand side (in squares). To ensure confidentiality, the names of both banks and exposures have been anonymised and are denoted numerically as 1, 2, . . . , and so on. The ordering is arbitrary and does not reflect any specific ranking or classification.

Source: Authors' calculations.

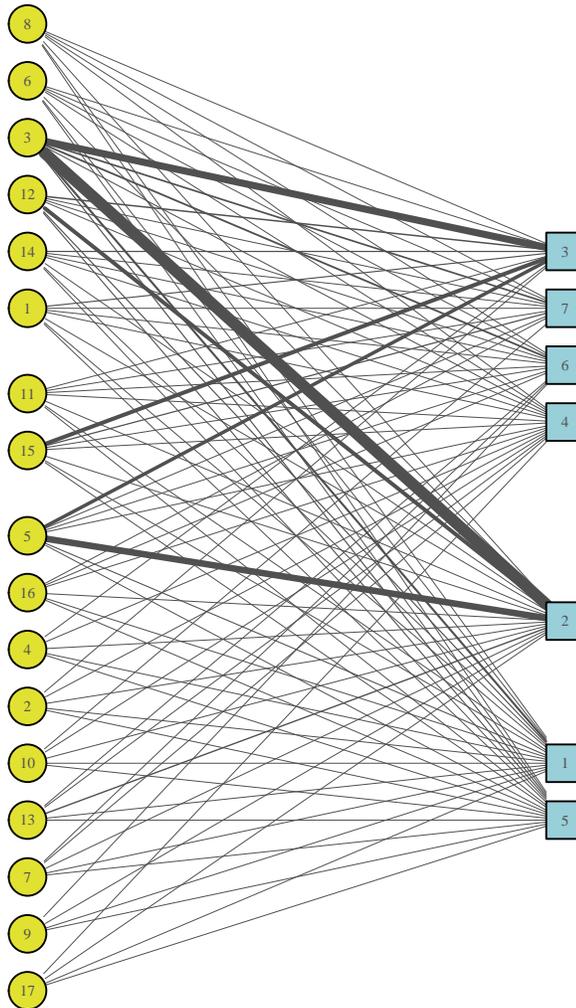


Figure A.2: Bipartite graph, aggregation by counterparty, as at 2024Q3

Notes: Banks are represented on the left-hand side (in circles), while exposure counterparties are shown on the right-hand side (in squares). To ensure confidentiality, the names of both banks and exposures have been anonymised and are denoted numerically as 1, 2, ..., and so on. The ordering is arbitrary and does not reflect any specific ranking or classification.

Source: Authors' calculations.