



# Adaptive Trade Based Money Laundering Detection in European Banking Networks Using Explainable Graph Learning and Sanctions Data

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| ARTICLE INFORMATION                                                                                                                                                                                                                                                                                                                                      | ABSTRACT                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                             |
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| <p><b>Submitted:</b> March 02, 2025<br/><b>Accepted:</b> May 25, 2025<br/><b>Published:</b> December 30, 2025<br/><b>Volume:</b> 1<br/><b>Issue:</b> 1</p> <hr/> <p><b>KEYWORDS</b></p> <p>Trade-based money laundering; anti-money laundering; graph learning; explainable artificial intelligence; sanctions screening; European banking networks.</p> | <p>Trade-based money laundering relies on the lawful nature of trade, settlement across borders and a disintegrated banking system, in which transaction-monitoring systems do not have a good visibility about the risk at the network-level. In this work, we propose an adaptive, interpretable graph-learning model to learn the most relevant suspicious pathways in the European banking network for TBML. To analyze the data, public FinCEN Files transaction-map records were processed, first for European-internal bank flows, then as temporal weighted graphs, and then compared to the European Union consolidated sanctions list, by isolating anomalies using anomaly learning and providing block-ablation explanations. This network comprised 2126 suspicious activity reports (SAR), 878 banks, 1035 bank pairs and USD 21.05 billion of reported flows. Adaptive ranking in 2016 gave a post-hoc sanctions-linkage ROC AUC 0.701 and top-five-percent review gave 3.47-fold enrichment compared to a frozen representation of 0.665. Explanations in the form of structural embeddings were predominant. The framework enhances the difference between suspicious reporting, sanctions risk and actual laundering, while giving better auditable prioritization of risks. Designed to be an investigative triage, not a legal adjudication.</p> |

## 1. Introduction

The involvement of the money-laundering aspect of international trade is a particularly complicated issue in financial-crime prevention, due to the fact that the payment layer, the commercial layer and the ownership layer are frequently in different institutional systems. In trade-based money laundering (TBML) money laundering is affected through manipulation of trade documents, trade amounts, trade prices, trade routes, or the trade settlement process, with the outward appearance of legitimate trade transactions (Blanuša et al., 2024). However, the research conducted on the basis of discrepancies of the mirror type has revealed that the specifics of abnormal discrepancies between exports and imports contain information on the manifestation of the act of settlement, but such discrepancies at macro level do not provide data on the banking channels, via which the settlement takes place (Cheng et al., 2025). The prudential monitoring approaches also suggest that TBML risk is not only a function of transactional behavior and/or amount thresholds but also a function of the wider trade context (Deprez et al., 2025). Misreporting evidence also builds a case for tariff incentives, corruption and institutional quality to be associated with abnormal trade reporting, which further argues for abnormal trade to be a relational and contextual phenomenon (Dumitrescu et al., 2022). Bank transaction monitoring will always stay the key operational place that numerous suspicious settlement patterns are discovered. Traditional AML systems are heavily dependent on customer profiles, rules that are preconfigured, thresholds for the scenarios and cases escalation. Network analysis provides an alternative view of financial actors as networked entities where the risk of the actors is partially described by other actors they are connected to, by their brokerage roles, by reoccurring paths and by the geographical scope (Fan et al., 2026). AML research that relies on technology has also been reported to generate operational burden due to inflexibility of profiles and a lack of monitoring process (Gezici & Sefer, 2025). However, supervised transaction-ranking models have been developed when a sufficiently good collection of labels is available, in which the labels tend to be those used in previous reports, rather than a complete set of the outcomes of the transactions' laundering (Huong et al., 2024). Adopting machine-learning, then, also helps pose a central governance question: More sophisticated analyses of the data does not eliminate uncertainty over what the observed label actually means (Tejraj Jain & Ghimire, 2025). The application of

graph learning is especially relevant to European banking networks, as a dependency is created when the transactions are handled cross-border which is lost when the transactions are analyzed separately. The temporal link prediction problem has been addressed in large financial graphs that leverage on the topology of financial relationships and transactions history (Johannessen & Jullum, 2023) and network analysis of AML policy reveals the impact of the structure of financial relations and regulations on laundering behavior (Karim et al., 2024). In the context of illicit-finance, another example of the interaction of neighborhood structure and sequence information to influence risk discrimination is presented in temporal graph models (Kute et al., 2021). These developments, however, still leave three questions unanswered regarding the surveillance of TBML banking. Yet these developments pose three questions of TBML-oriented banking surveillance: First, the majority of graph methods are geared towards cryptocurrency, customer-level banking or just generic fraud, and not towards cross-border settlement related to trade. Secondly, counter-parties, corridors and transaction structures are changing, which results in a change in distribution for fixed models. The concept drift research has already been proven that when the process of the learner's generation changes, the frozen learner will deteriorate (Li et al., 2023). Third, when using complex network models, investigators frequently have to work out the reasons for the scores, which can be a challenge. Explainability is particularly crucial in AML due to the fact that an alert triggers an investigation that is time consuming and for some settings, regulatory reporting. The imperative for interpretability as a key challenge for operational deployment of deep learning systems in money-laundering detection is highlighted in reviews (Mir Mohtasam Hossain Sizan, 2025). Explainable-AI work is also more general in highlighting the important role of quality and the intended recipient, the model structure and the level of accountability (Ouyang et al., 2024). Recent work on heterogeneous graph data in real banking data reinforces the move towards a relational approach to learning, but also shows the need for relying on limited banking institutions for performance claims (Raja et al., 2025). The public-data research process must thus be transparent, and it should clearly distinguish between suspicious activity and exposure to sanctions and between legitimate and illegal laundering. The current research tackles this challenge by proposing an adaptive, explainable graph-learning framework for risk prioritization tasks within European banks' networks that are relevant to TBML. The empirical design employs public transaction map records of FinCEN to create temporally growing weighted graphs of banks and maps bank identifiers to the EU consolidated sanctions list in a conservative way. It is not the objective of the SUSPICION IS PROVEN TBML to classify an SAR as proven TBML. Rather, the goal is to find structures in the network that are significant to the cross-border suspicious traffic, to measure if annual graph adaptation is able to better rank the risks for the external world in comparison to a frozen representation and to generate local explanations that would be useful for investigative triage. We provide an analysis of four objectives: characterizing topology of European-internal suspicious payment flows; learning of graph representations that adaptively change with the evolution of bank relationships; evaluating the relevance of the risk-ranking using a post-hoc sanctions-linkage test without relying on the labels of the sanctions lists for model fitting; and providing explanations for high ranked suspicious payment alerts using transparent feature-block perturbation. In turn, the study questions whether the suspicious European payment networks are structurally similar to corridors and intermediaries, whether, and to what extent, temporal representation updates boost discrimination of the ranking of bank identifiers, whether unsupervised graph anomalies are more likely to enrich the representation of bank identifiers in later sanctions and whether certain dimensions of the structure are more important for local explanations. Table 1 presents the alignment among these questions, analytical constructs, and operational measures.

**Table 1 Research questions, objectives, constructs, and operational measures.**

| <b>Research question</b>                                                                                                               | <b>Objective</b>                                    | <b>Construct</b>                           | <b>Operational measure</b>                                                                                                |
|----------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------|--------------------------------------------|---------------------------------------------------------------------------------------------------------------------------|
| <b>RQ1: How is suspicious payment exposure distributed across European bank corridors and network positions?</b>                       | Characterize network topology and concentration     | Relational exposure                        | Nodes, bank pairs, network density, component size, incident flow, and corridor concentration                             |
| <b>RQ2: Does annual graph refresh improve risk ranking compared with a frozen network representation?</b>                              | Evaluate adaptive temporal graph learning           | Temporal representation                    | 16-dimensional adjacency SVD and structural features; frozen versus adaptive AUC, AP, and lift                            |
| <b>RQ3: Are high-risk anomaly rankings externally relevant to EU sanctions and explainable through identifiable relational blocks?</b> | Validate risk relevance and explain model reasoning | Sanctions linkage and local explainability | Normalized enterprise-name matching, sanctions lift at review depth, and anomaly-score change under median block ablation |

The alignment looks at detection as a process of prioritizing risks when facing uncertainty and not as a legal classification. As described in Table 1, the study is focused on detection as a prioritization in the face of uncertainty instead of a legal classification. Descriptive objective: network concentration addresses this; Temporal change: adaptive anomaly ranking addresses this; Sanctions Enrichment: provides an external check of relevance; Block-ablation: gives case level interpretability. The contribution is an audit trail of workflows that include: relational learning, temporal updating, sanctions-aware triage and explicitly limits the claims in public suspicious-activity data.

## **2. Literature Review**

### **2.1 TBML as a multi-layer trade and payment problem**

In all its variants, TBML research represents international trade as a laundering process, where value is transacted via seemingly commonplace trade and settlement. Invoice manipulation, over- and under shipment, false description, multiple invoicing, and routing via intermediaries are cited as common tactics used in invoice manipulation (Blanuša et al., 2024). Mirror-statistics approaches build on this approach, by looking at the reports of partner countries and detecting discrepancies related to illegal financial flows (Huang, 2024). The behavior-monitoring research suggests that payment characteristics should be combined with macro conditions, as the same conditions on the transactions have different meanings in different sectors, jurisdictions and customer relationships (Deprez et al., 2025). There are also a number of studies that have correlated the problems of trade misreporting with tariff avoidance, corruption and quality of the auditing (Dumitrescu et al., 2022). However, mineral-trade research cautions that trade gaps exhibit noise stemming from discrepancy (transport, timing, valuation and classification) and abnormal trade gaps do not necessarily reflect illicit transfer (Zia Ur Rashid & Tanvir Hayat, 2025). The methodology's central implication is that screening for TBML should not be based on one proxy, but rather triangulation should be done. Trade anomalies can be used to establish an overall sense of suspicion, and banking networks to trace the relationship of settlements in which value flows. Another drawback of this is granularity. The international trade methods are aggregate trade methods and banks investigate customers, counterparties, transactions and correspondent relationships. This level of granularity is a barrier for directly moving macro indicators towards case management. The most powerful design therefore associates the relationship between payment and the risk in the context with the perception of the risk rather than the concept of trade discrepancy as a stamping ground.

### **2.2 From transaction rules to relational AML learning**

Besides independently scored events, suspicious activity can be manifested by brokerage, positioning in peripheral neighborhoods, risky counterparts, or unusual network neighborhoods, as revealed in traditional relational studies (Fan et al., 2026). that explored these other aspects of transactions. Where historical labels and features of customers are available, machine-learning transaction ranking can enhance the prioritization (Huong et al., 2024). For supervised learning, gains in classification are also reported to be significant in the context of cryptocurrency, though the availability of the labels and its applicability to domain transfer are also significant issues (Usman et al., 2023). In contrast, active-learning frameworks adapt to the few labels available, by coupling unsupervised screening with the analyst feedback of a subset of the unlabeled data to aid in model refinement (Wang et al., 2025). Building on top of the transactional approach of banking research, graph-based banking research moves from transactions to systems connected to each other. The authors of (Johannessen & Jullum, 2023) found that transaction histories and neighborhoods in financial networks can be jointly used to improve the representation of their temporal, evolving financial relations by experimenting with a large European bank. Network-level AML policy analysis also demonstrates that laundering is more about structural and regulatory factors than individual factors (Karim et al., 2024). In the context of illicit cryptocurrency transactions, temporal graph convolution has shown that it brings additional value over the static topology (Kute et al., 2021). Graph contrastive learning aims to achieve better representations under the scenario of small amounts of labeled AML instances (Xu et al., 2024) and reinforcement-enhanced multi-relational models are based on multiple types of interactions and adaptive decision processes (Yuan et al., 2025). Irregular fund transfers are also connected with graph neural models that link the transaction behavior in time with the customer relations (Elmougy & Liu, 2023). All of these studies show that the direction should be towards the addition of relational context to the information used to rank suspicious activity. The question remains whether external validity can be achieved, as the data sources used by banks in the private sector are not necessarily representative of banks in Europe in settlement networks. Both adaptation and drift pose serious problems for the research of validation.

### **2.3 Adaptation, drift, and temporal validation**

Financial networks evolve with clients joining and corridors growing, rules becoming tighter, institutions leaving, and crimes adapting to rules. The concept of concept drift is thus more of an AML problem and not just a nuisance. The learning-under-drift research considers the categories detection, understanding and adaptation with a focus on the loss of the relevance of a learner calibrated to a different distribution after the occurrence of a structural change (Li et al., 2023). This is particularly relevant for data from a graph as both attributes and topology change over time. A static embedding will keep the relational geometry

unchanged for given insertion, while an adaptive representation will re-calculate the neighborhoods and positions of the structures according to their insertion. Many studies of AML in use and published previously do not make the distinction between the frozen and the updated data. Although temporal graph models process sequences, there is still a need for deployment governance to have an auditable refresh rule, a comparison baseline and out-of-time evaluation. Adaptation is an added challenge for public suspicious-activity data, since the data it contains does not represent a continuous flow of normal banking transactions. Thus, it's more defensible to be talking about temporal evaluation in terms of relative risk ranking and representation drift rather than laundering incidence. Therefore, the term temporal evaluation is more defensible when it's presented in terms of relative risk ranking and representation drift rather than laundering incidence. This distinction is used for an annual graph design for the benefit of this cumulative scoring, which considers the same nodes with frozen and refreshed representations.

#### **2.4 Explainability, sanctions linkage, and accountable triage**

The problem of balancing accuracy on nonlinear prediction with investigator understanding has been a recurring theme in the field of explainability research in AML (Mir Mohtasam Hossain Sizan, 2025). Responsible-AI frameworks have considered interpretability as being audience-dependent and that explanations have to relate to model outputs to reasons that can be acted on, not just salient technically (Ouyang et al., 2024). In graph setting, explanation is more difficult as a score incorporates higher-order topology, walks, and neighbors and node attributes. Taxonomic analysis of graph explanations shows four types of perspectives: feature, edge, subgraph and counterfactual. A local perturbation approach is useful, namely the target node is explained by measuring the difference in the score of the node after removing and replacing information. The layer of sanctions data is an additional layer of governance. While not the same as money launderers, sanctions can be used to create an external list of entities to test a financial-network ranking to see if it focuses entities of compliance interest. The study of sanctions in the context of directed trade networks has revealed that sanctions have an impact on the incentives in the network and the routing within it, and the impact of trade-network effects has compounded the need to distinguish between designation status and transactional suspicion. The critical analytical protection is the separation in time and meaning. The most up-to-date list of sanctions should not be used as a past history of laundering suspicious transactions. It's defensible use is where it is used for post-hoc relevance assessment and for prioritizing investigations in the present time. In previous AML graph research, the divide between the model-fitting and external testing and the operational overlay is not fully developed, and is the main area covered in the present work. The literature paints a particular picture of a gap in the design of TBML, dynamic banking networks, external compliance lists and explanation to investigators. Current solutions typically focus on optimizing a single layer, either on the trade discrepancy, the classification of transactions, the graph representation, the temporal learning or the explainability. Those layers need to be analytically separable, but they need to be part of a unified ranking process to be used in an operation that has a well-defined design, especially if definitive laundering labels are not present and information on public transactions is not complete.

### **3. Conceptual and Technical Framework**

The study explores an integrated adaptive graph-risk approach to monitoring, where the monitoring of TBML is considered as a series of decisions over an evolving relational system. The theoretical underpinning of this is that the feeling of being suspicious cannot be pinned in a given payment sum only, but also on the role of the financial institution in the flow of transactions. The temporal component is provided by concept-drift theory (Li et al., 2023). When the joint distribution of relationships and attributes changes, then a frozen representation is misaligned with the current graph. The relational part is provided by graph-learning and data-fusion theory, in both of these the neighborhoods and weighted connections are given (Fan et al., 2026). Explainable-AI principles provide accountability since local explanations are required to be provided with a graph, which will be traceable to the behavior of the model, as mentioned in (Ouyang et al., 2024) and (Bonato et al., 2024; Yuan et al., 2025). The five constructs are included in the framework. The first one is transaction exposure which is depicted as the amount, frequency, flow direction and cross-border connection between the SAR-mapped bank-to-bank flows. The second is graph structure, which is captured by the degree, weighted strength, PageRank, betweenness and a learned low dimensional adjacency embedding. The third one is adaptive representation; which is annual updating of the graph embedding and anomaly model with the information gathered during the corresponding graph year. The fourth, investigative risk, is the unsupervised anomaly score and percentile rank in the bank identifiers set, which are currently active. The fifth is sanctions relevance: a match to enterprise aliases resolved separately from the EU consolidated list. The framework is provided in figure 1 as it is helpful to distinguish between model learning, explanation and sanctions use.

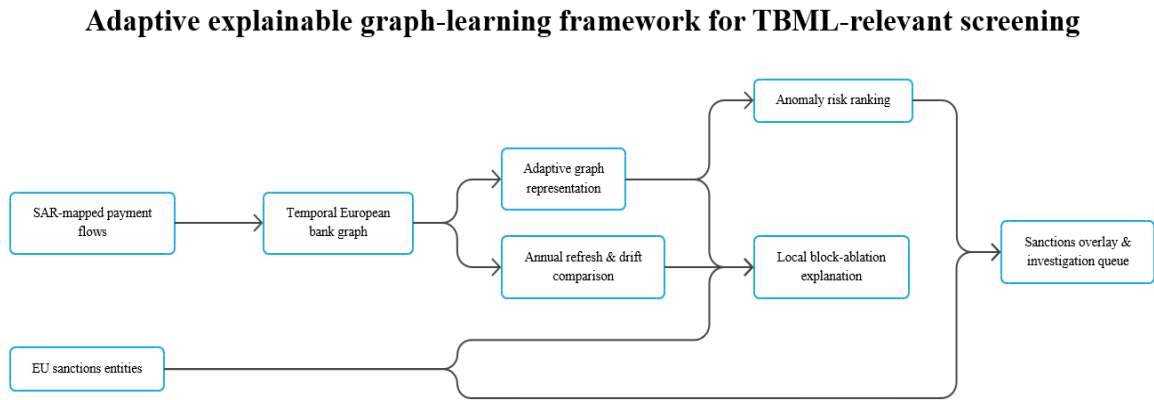


**Figure 1 Integrated conceptual and technical framework for adaptive TBML-oriented graph-risk prioritization.**

Explicit evolving payment relationships change the geometry of the graph; changing geometry changes learned representations and anomaly scores, high anomaly scores elicit explanation; and changing the relevance of compliance without re-labeling historical payments. The framework makes the assumption that SARs mapped information would be suspicious reported flows, and not necessarily a count of banking activity. It also makes the assumption that the terms sanction and laundering are analytically different and also legal terms. The latter is advantageous because it enhances the credibility of the causal interpretation, while the former is disadvantageous because it narrows the scope of causal interpretation. The resulting design considers the possibility of improving the ranking of the network positions that are relevant to the compliance and still maintain the raw flow to the reason for the alert transparency.

**4. Methodology**

**4.1 Research design and empirical setting**

A computational network design was explored longitudinally for relationships between suspicious payments that happened within Europe. The design was observational and unsupervised with no attempt to estimate the prevalence of laundering; there was no attempt to call suspicious activity reports as offences. Identifiers of banks created nodes and edges were the mapped suspicious flows between originator and beneficiary banks. Temporal (annual) adaptation was assessed by annual snapshots. A frozen 2011 model was used as a comparator, which is a model without accumulations but with representations.

**4.2 Data sources, scope, and entity resolution**

The transaction layer used the public FinCEN Files transaction-map release assembled by the International Consortium of Investigative Journalists. It contains suspicious activity report (SAR)-derived payment groupings with bank identifiers, countries, dates, transaction counts, and reported amounts. The full file contained 4,507 records. Primary analysis retained records with both endpoints in a broad European banking geography covering sovereign European states and listed financial territories, yielding 2,126 records. A wider graph with at least one European endpoint supported scope sensitivity. The sanctions layer used the European Union Consolidated List of Financial Sanctions Targets generated on 5 August 2026. Enterprise aliases were separated from person records. Primary matching removed Unicode accents, lower-cased text, replaced punctuation with spaces, and collapsed repeated whitespace. It neither deleted legal-form terms nor used fuzzy matching. A secondary resolver removed common bank and corporate legal-form terms for sensitivity analysis.

Table 2 summarizes data provenance and graph schema, distinguishing historical suspicious-flow structure from current sanctions status.

Table 2 Data provenance, analytical scope, and graph schema.

| Data layer                               | Analytical role                                                      | Scope                                                                       | Core fields                                                              | Use in study                                          |
|------------------------------------------|----------------------------------------------------------------------|-----------------------------------------------------------------------------|--------------------------------------------------------------------------|-------------------------------------------------------|
| ICIJ FinCEN Files transaction map        | Historical SAR-mapped suspicious payment groupings                   | 4,507 full records; 2,126 European-internal records                         | Bank IDs, countries, begin/end transaction dates, count, reported amount | Temporal graph construction                           |
| ICIJ FinCEN Files bank connections       | SAR filer-counterparty connection context                            | 5,498 records                                                               | Filer bank, entity/counterparty, countries                               | Provenance and scope check                            |
| EU Consolidated Financial Sanctions List | Current designated persons and enterprises                           | 43,851 denormalized rows; 1,772 unique enterprise IDs                       | Enterprise aliases, logical IDs, sanctions programme                     | Post-hoc relevance assessment and operational overlay |
| Derived European-internal banking graph  | Both payment endpoints located in defined European banking geography | 2,126 records; 878 banks; 1,035 unique bank pairs; 46 countries/territories | Log1p amount edge weight; topology and learned representation            | Primary model input                                   |

Table 2 confirms separate roles: transaction records generate temporal network structure, whereas sanctions data remain outside model fitting and enter during external relevance assessment.

### 4.3 Graph construction and feature engineering

Each year, an undirected bank graph was generated, with a weight of 1 being placed on all of the records that were at least the year specified. The two directions in opposite directions were merged for structural learning, and the ones without instructions were left for descriptive learning. This was achieved by using edge weight (equal to the natural log of one plus accumulated reported amount). The node universe remained unchanged from the European-internal data, with all the identifiers in the data being included in the node universe. Five interpretable measures were computed: degree, weighted strength, PageRank, betweenness centrality and cross-border relationship ratio. The variables of strength and degree were log transformed. The learned graph representations were obtained from a 16-dimensional Truncated Singular Value Decomposition (TSVD) of the weighted adjacency matrix given. The sparse, modest public network proved it was possible to do as much as spectral embedding and without making claims that involved a very well-parameterized supervised architecture.

### 4.4 Adaptive anomaly model and frozen comparator

The adaptive detector was the combination of 16 embedding dimensions and 5 structural measures. The 'standardization' was added between active nodes within each snapshot. An unsupervised anomaly score was obtained with the Isolation Forest model using 500 trees and the same seed number for the random numbers. The values were higher, the more the structure deviated from the active network. The updating of the embedding basis and anomaly geometry has been done annually, as part of the refitting. They used the same embedding basis, scaler and Isolation Forest for the frozen comparator as in 2011. Subsequent adjacency matrices were projected using the 2011 basis, and scored without refitting. Since adaptation is the main model comparison, the specification and logic for validation is presented in Table 3.

Table 3 Adaptive graph-learning specification and frozen comparator.

| <i>Element</i>                | <i>Adaptive model</i>                                                                | <i>Frozen comparator</i>                                           | <i>Governance role</i>                                |
|-------------------------------|--------------------------------------------------------------------------------------|--------------------------------------------------------------------|-------------------------------------------------------|
| <i>Graph horizon</i>          | Cumulative through graph year y                                                      | 2011 representation basis retained for later years                 | Tests representation refresh                          |
| <i>Graph representation</i>   | 16-dimensional Truncated SVD refitted annually                                       | 2011 Truncated SVD basis fixed                                     | Captures evolving relational geometry                 |
| <i>Interpretable features</i> | Log degree, log strength, PageRank, betweenness, cross-border ratio updated annually | Same annual structural inputs projected into frozen model pipeline | Separates relational signals from embedding structure |
| <i>Anomaly learner</i>        | Isolation Forest, 500 trees, refitted annually                                       | 2011 scaler and Isolation Forest fixed                             | Unsupervised risk prioritization                      |
| <i>Sanctions labels</i>       | Excluded from fitting                                                                | Excluded from fitting                                              | Prevents label leakage                                |
| <i>Evaluation</i>             | Post-hoc strict sanctions linkage: ROC AUC, AP, review-depth lift                    | Same external criteria                                             | Compares ranking relevance                            |
| <i>Local explanation</i>      | Median block ablation of learned and interpretable feature groups                    | Not the principal explanation comparator                           | Produces reviewable alert reasons                     |

Sanctions labels are excluded from both model-fitting pipelines and enter only during post-hoc relevance assessment. Table 3 shows that refresh behavior is the key difference between models, preserving a controlled comparison.

#### 4.5 External relevance assessment and local explanation

Sanctions labels were excluded from training. After anomaly scores were produced, exact sanctions linkage supplied a post-hoc relevance check. Ranking discrimination used ROC AUC and average precision. Review efficiency used sanctions-match lift within the highest-ranked 5, 10, 20, and 30 percent of active identifiers relative to network prevalence.

Local explanations used block ablation. For each selected bank, one feature block was replaced with the active-network median while other inputs remained unchanged. Positive decreases in anomaly scores were normalized to 100 percent across embedding structure, degree, weighted strength, PageRank, betweenness, and cross-border ratio. The resulting shares provided case-specific reasons tied directly to model behavior.

#### 4.6 Robustness, bias control, and ethics

For the robustness tests, the number of embedding dimensions was varied between 8, 16 and 32 while the three following random seeds were used for Isolation Forest. It recalculated the linkage to sanctions based on strict and legal-form normalized matching and scope statistics were verified against the broader network linked to Europe. To control the temporal leakage, sanctions were not included as a source of the 2026 list, but rather kept as a post-hoc source. Results are focused on screening properties and public records based on SARs are sensitive. If dates, bank identifiers or amounts were not present, that was excluded only for calculations that need those data elements and no synthetic observations of the financial data were created. The amounts of transactions reported were retained in the nominal source currency value that were standardized to United States dollars with the released map. In addition to the manuscript, the sensitivity outputs, the diagnostic information for the model and the chart source tables were exported, thus ensuring that all numerical statements reported in the Results section are traceable back to a calculation. All calculations were done using a deterministic python script for preprocessing the data and keeping the data in source tables. The temporal protocol also maintained an active-node mask specific to each year, in order to avoid the activity of inactive identifiers from affecting annual scaling or ranking. The aggregation of edges, calculation of centralities, transformation to embedding, scoring anomalies and conversion to percentile were done in the following order for each graph year. Intermediate node level outputs were preserved prior to the sanctions matching process so that it was possible to verify that no external list information was used to change the construction of features and estimation of anomalies.

## 5. Results

### 5.1 Network scale, sparsity, and concentration

Network size and concentration analysis is the focus of this sub-section since screening effectiveness is contingent upon whether these suspicious flows are dispersed or concentrated within a relational core. This is shown in Table 4 which gives the numbers of records, banks involved, pairs per bank, connectivity, and flow concentration.

**Table 4 Descriptive properties of the European-internal suspicious-flow network.**

| <b>Metric</b> | <b>Value</b> |
|---------------|--------------|
|---------------|--------------|

|                                                  |                     |
|--------------------------------------------------|---------------------|
| <i>SAR-mapped European-internal records</i>      | 2,126               |
| <i>Unique banks</i>                              | 878                 |
| <i>Unique bank pairs</i>                         | 1,035               |
| <i>European countries/territories</i>            | 46                  |
| <i>Reported flow amount (USD)</i>                | \$21,046,907,014.05 |
| <i>Network density</i>                           | 0.002688            |
| <i>Largest connected component</i>               | 708                 |
| <i>Mean degree</i>                               | 2.358               |
| <i>Global transitivity</i>                       | 0.001969            |
| <i>Top-10 bank flow share</i>                    | 44.18%              |
| <i>Strict sanctions-matched bank identifiers</i> | 29                  |
| <i>Distinct sanctions enterprise IDs</i>         | 9                   |

Amounts are reported mapped flows based on the transaction map of the public domain. Counted cases do not account for all transactions of European banking activity. The graph of internal European transactions included 2,126 SAR mapped instances, 878 banks, 1,035 unique bank pairings, and 46 countries or territories accounting for USD 21.05 billion of reported mapped flows. Density was 0.00269, mean degree was 2.36, and the largest connected component had 708 banks (80.6 percent of nodes). The global transitivity was 0.00197. In spite of low connectivity, ten banks with the highest flow amounted to 44.18 percent of mapped amount.

## 5.2 Temporal variation in suspicious-flow exposure

This dimension is concerned with changes in the recorded flow. It is relevant in establishing whether the frozen graph matches later relationships or not. Below is a graph of annual mapped amount of European internal from 2004 to 2017.

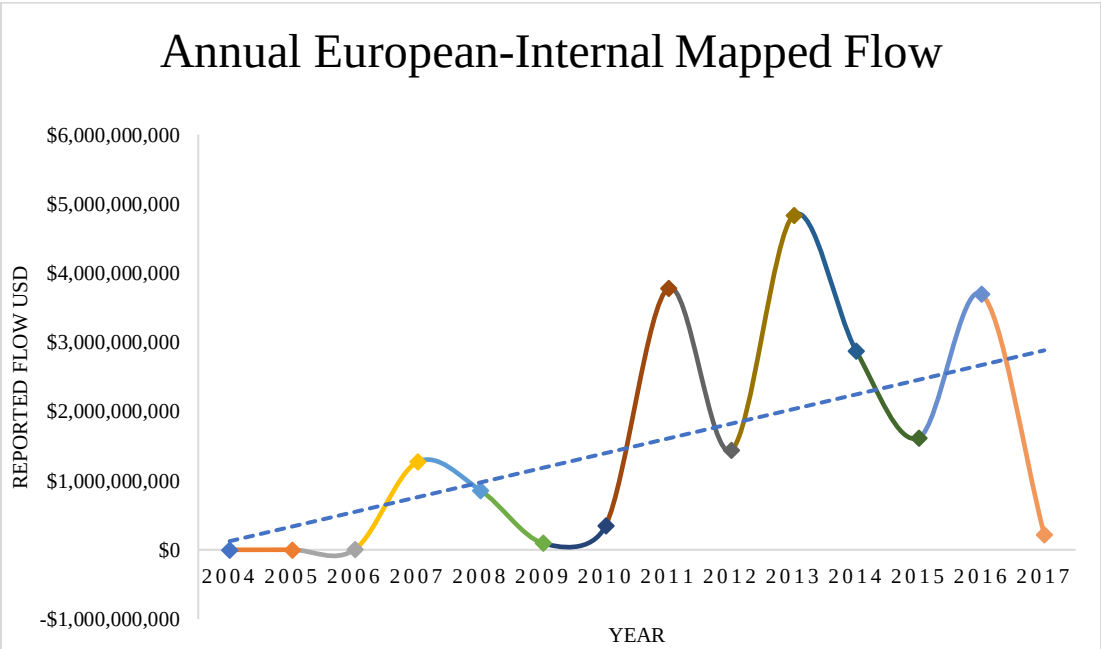


Figure 2 Annual European-internal SAR-mapped reported flow, 2004–2017.

The reported amount was increased to USD 1.27 billion in 2007 and attained USD 3.78 billion in 2011. The maximum amount recorded per year was USD 4.84 billion in 2013, while the following years saw amounts of USD 2.87 billion in 2014, USD 1.62 billion in 2015, and an increase back up to USD 3.69 billion in 2016. The significantly smaller amount of USD 0.22 billion in 2017 is attributed to the shorter tail of data records mapped out.

5.3 Corridor structure and network brokerage

The corridor concentration and brokerage section analyzes TBML settlement risk due to routing and amount. See Figure 3 for a comparison of the ten largest country-pair corridors based on mapped flow.

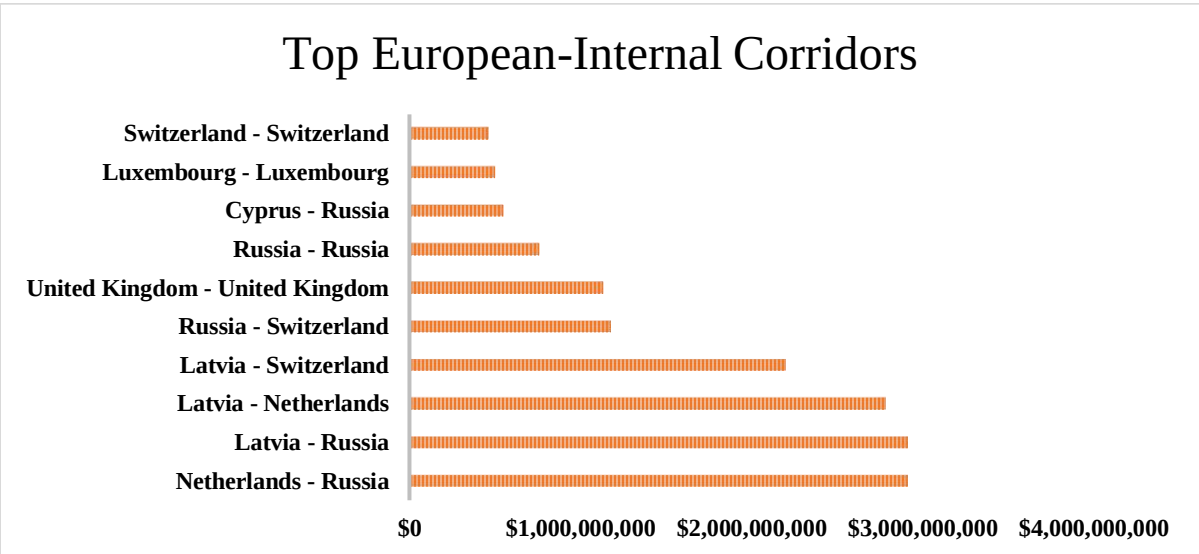


Figure 3 Ten largest European-internal country-pair corridors by mapped reported flow.

Netherlands-Russia and Latvia-Russia were both near USD 2.91 billion, followed by Latvia-Netherlands with USD 2.78 billion and Latvia-Switzerland with USD 2.20 billion. Switzerland-Switzerland was the smallest of the ten with USD 0.46 billion.

Latvia was present in four major corridors, whereas Russia was present in five, suggesting geographic clustering over multiple corridors rather than one bilateral corridor. To test if there was value clustering along structurally significant positions, Figure 4

shows 2016 incident flow against betweenness centrality, with degree shown via marker size and strict sanctions matches marked separately.

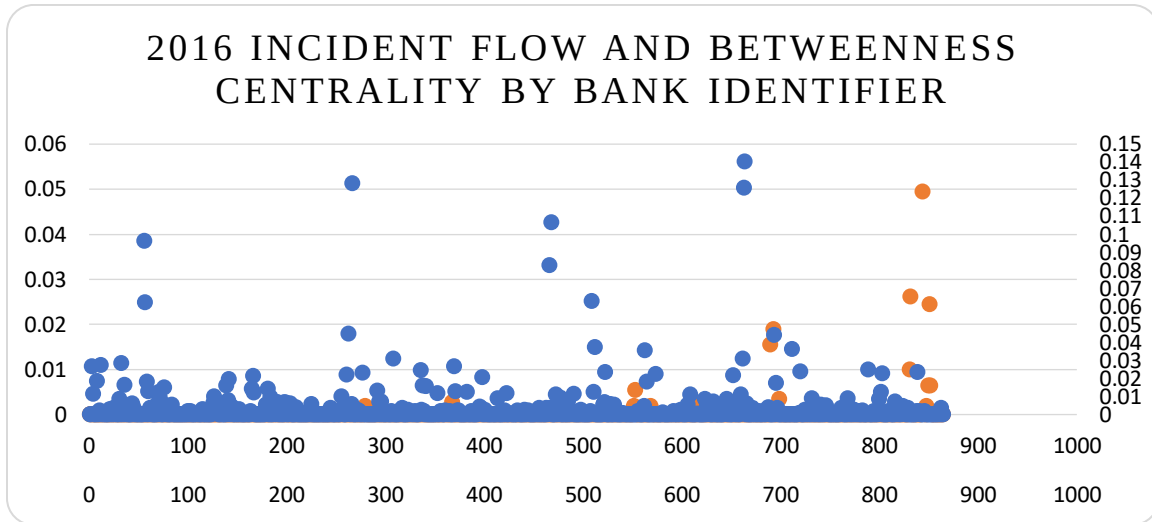


**Figure 4 2016 incident reported flow versus betweenness centrality, with strict sanctions matches identified.**

Active banks tended to group around the low end of betweenness scores, though there was considerable value variability. There were several that combined flow with good brokerage and became upper-right outliers. Sanctions match, on the other hand, were uniformly spread out without clustering, suggesting that the mere presence of sanctions failed to account for graph anomalies.

#### 5.4 Adaptive versus frozen graph-risk ranking

The performance aspect evaluates the impact of annually renewed representation on the ranking of the relevant identifiers for compliance purposes compared to a fixed model from 2011. The results in terms of average precision, top-10 percent sanctions matching, and node coverage are provided in Table 5.

**Table 5 Frozen and adaptive ranking performance under strict post-hoc sanctions linkage.**

| <i>Year</i> | <i>Active bank identifiers</i> | <i>Strict sanctions match</i> | <i>Frozen AP</i> | <i>Adaptive AP</i> | <i>Frozen top-10% lift</i> | <i>Adaptive top-10% lift</i> |
|-------------|--------------------------------|-------------------------------|------------------|--------------------|----------------------------|------------------------------|
| 2011        | 291                            | 17                            | 0.1145           | 0.1145             | 2.95                       | 2.95                         |
| 2012        | 385                            | 19                            | 0.0930           | 0.0988             | 2.67                       | 3.20                         |
| 2013        | 566                            | 25                            | 0.0762           | 0.0834             | 2.02                       | 2.83                         |
| 2014        | 698                            | 27                            | 0.0743           | 0.0797             | 1.87                       | 2.62                         |
| 2015        | 781                            | 28                            | 0.0780           | 0.0862             | 2.50                       | 2.86                         |
| 2016        | 865                            | 29                            | 0.0714           | 0.0810             | 2.77                       | 2.77                         |

AP = average precision. Lift is defined as the ratio of sanctions-match prevalence in the chosen set for review against prevalence of active bank identifiers. Coverage grew from 291 active banks in 2011 to 865 in 2016. Adaptive average precision was always higher than the frozen comparator, reaching 0.0810 and 0.0714 respectively by 2016. Adaptive Top-10 Percent lift was highest in 2012, when its value reached 3.20, and consistently exceeded 2.62 in all post-baseline years.

The frozen series performed worse in enrichment in four out of five post-baseline periods.

Figure 5 illustrates ROC AUC by graph year to separate discrimination from review-depth efficiency.

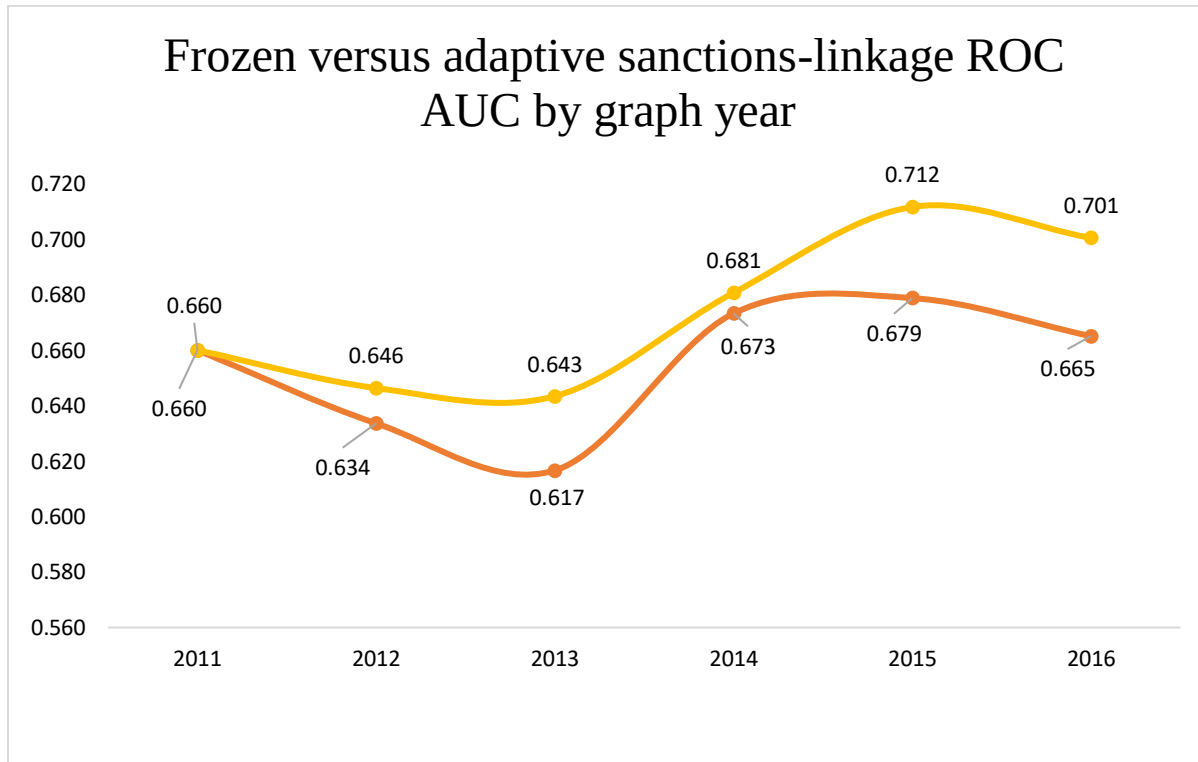


**Figure 5 Frozen versus adaptive sanctions-linkage ROC AUC by cumulative graph year.**

Both models began at 0.660 in 2011. The adaptive series then remained above the frozen series, reached 0.712 in 2015, and ended at 0.701 in 2016. The frozen model fell to 0.617 in 2013 and ended at 0.665. The final 0.035 AUC difference represents a modest, persistent benefit from graph refresh.

### **5.5 Alert composition, sanctions enrichment, and explanation**

This subsection examines the highest-ranked alerts because operational usefulness depends on reviewable cases rather than aggregate metrics alone. Table 6 presents the ten highest unique-name alerts with risk percentile, incident flow, degree, betweenness, cross-border ratio, and strict sanctions linkage.

**Table 6 Ten highest unique-name alerts under the 2016 adaptive model.**

| <b>Alert Bank</b>                            | <b>Country</b> | <b>Risk<br/>Percentile</b> | <b>Incident<br/>Reported    Flow<br/>(USD)</b> | <b>Degree</b> | <b>Betweenness</b> | <b>Cross-<br/>Border<br/>Ratio</b> | <b>Strict<br/>Sanctions<br/>Match</b> |
|----------------------------------------------|----------------|----------------------------|------------------------------------------------|---------------|--------------------|------------------------------------|---------------------------------------|
| AS Expobank                                  | Latvia         | 100.00                     | \$2,593,124,581                                | 28            | 0.096              | 0.992                              | No                                    |
| Rosbank                                      | Russia         | 99.88                      | \$1,154,761,181                                | 36            | 0.126              | 0.758                              | No                                    |
| Credit Suisse<br>Ag (Zurich,<br>Switzerland) | Switzerland    | 99.77                      | \$1,783,693,540                                | 30            | 0.128              | 0.961                              | No                                    |
| LTB Bank                                     | Latvia         | 99.54                      | \$570,579,261                                  | 35            | 0.063              | 1.000                              | No                                    |
| JSC Norvik<br>Banka                          | Latvia         | 99.42                      | \$454,135,064                                  | 41            | 0.107              | 1.000                              | No                                    |
| Credit Suisse<br>AG                          | Switzerland    | 99.19                      | \$634,607,118                                  | 19            | 0.045              | 0.846                              | No                                    |
| Norvik Banka<br>JSC                          | Latvia         | 98.96                      | \$718,026,898                                  | 20            | 0.036              | 1.000                              | No                                    |
| VTB Bank                                     | Russia         | 98.84                      | \$289,402,364                                  | 14            | 0.049              | 1.000                              | Yes                                   |
| SEB Bank                                     | Estonia        | 98.61                      | \$28,589,740                                   | 18            | 0.036              | 1.000                              | No                                    |
| Rigensis Bank<br>AS                          | Latvia         | 98.50                      | \$542,063,595                                  | 10            | 0.031              | 0.692                              | No                                    |

Risk percentile is computed based on active bank identifiers. When there is a shown sanctions match, it is an indication of a strict current-list entity resolution and does not constitute evidence of historical laundering. AS Expo bank topped with a mapped flow of \$2.59 billion and a cross-border ratio of 0.992. Rosbank was second with high brokerage, but only participated in the broader name-resolution sensitivity.

VTB Bank was among the top ten banks and was a shown strict sanctions match. SEB Bank had a high anomaly percentile together with a low incident amount, indicating that the model is not a simple value screen. Figure 6 illustrates the strict sanctions-match lift at alternative review depths in 2016.

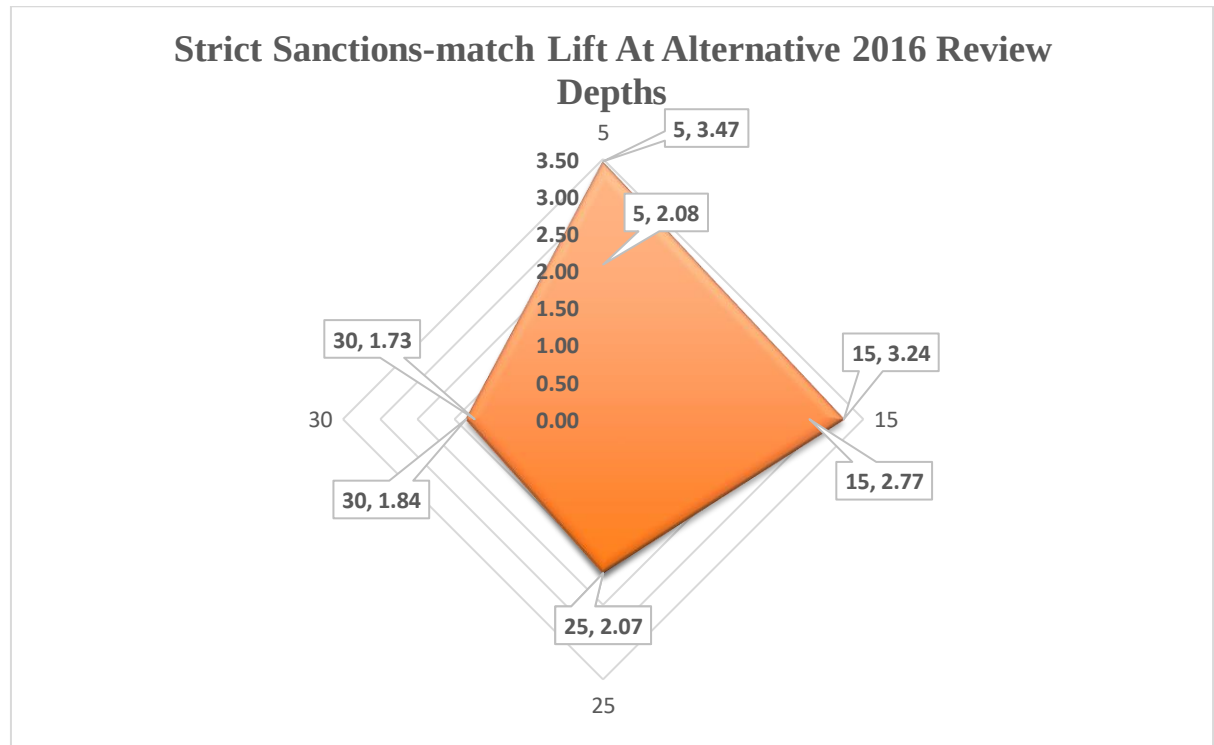


Figure 6 Strict sanctions-match lift at alternative 2016 review depths.

In the top 5 percent, the adaptive ranking system outperformed the frozen system by 3.47 times, compared to 2.08 times for the frozen system, yielding the greatest difference. In the 15 percent group, the lifts were 3.24 and 2.77 respectively. There was no difference between the models in the 25 percent group, where both systems had a 2.07-fold lift, whereas the adaptive ranking system had a small edge in the 30 percent group with a 1.84-fold lift, compared to 1.73 times for the frozen system.

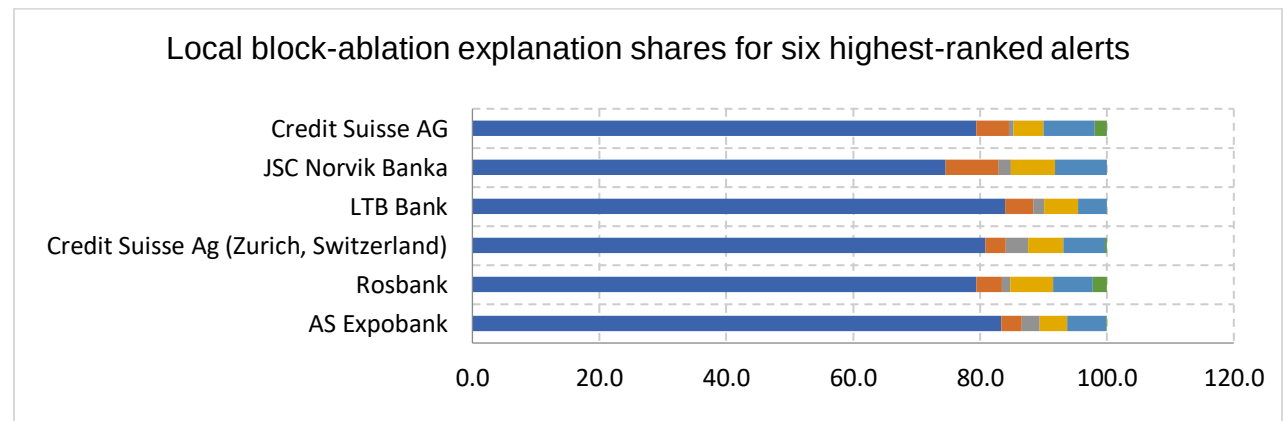


Figure 7 Local block-ablation explanation shares for six highest-ranked 2016 alerts.

Embedding structure dominated every displayed explanation, contributing roughly three quarters to more than four fifths of positive score reduction. Betweenness was generally the strongest non-embedding block, whereas degree and PageRank contributed smaller shares. Cross-border ratio rarely dominated despite extreme raw ratios. The alerts therefore reflected multivariate relational geometry rather than one geographic rule.

### 5.6 Robustness to representation and sanctions matching

The robustness dimension tests dependence on embedding size and entity-resolution rule. Table 7 presents mean results across three random seeds for 8-, 16-, and 32-dimensional embeddings under strict and legal-form-normalized matching.

**Table 7 Robustness across embedding dimensions and sanctions entity-resolution rules**

| <i><b>Embedding dimensions</b></i> | <i><b>Match rule</b></i> | <i><b>Matched bank IDs</b></i> | <i><b>active</b></i> | <i><b>ROC AUC</b></i> | <i><b>Average precision</b></i> | <i><b>Top-5% lift</b></i> |
|------------------------------------|--------------------------|--------------------------------|----------------------|-----------------------|---------------------------------|---------------------------|
| 8                                  | Legal-form normalized    | 42                             |                      | 0.6408                | 0.1339                          | 2.08                      |
| 8                                  | Strict                   | 29                             |                      | 0.7064                | 0.0763                          | 3.01                      |
| 16                                 | Legal-form normalized    | 42                             |                      | 0.6360                | 0.1215                          | 2.39                      |
| 16                                 | Strict                   | 29                             |                      | 0.7001                | 0.0809                          | 3.47                      |
| 32                                 | Legal-form normalized    | 42                             |                      | 0.6236                | 0.1022                          | 2.39                      |
| 32                                 | Strict                   | 29                             |                      | 0.6911                | 0.0754                          | 2.77                      |

The values are averaged across three Isolation Forest random seeds. Bigger normalization of the legal form raises the number of matched identifiers but yields lower AUCs. In strict matching, AUCs varied between 0.691 and 0.706, the 16-dimensional specification scored 0.700 and had a top-5-percent lift of 3.47. Bigger normalization raised the number of matched active identifiers from 29 to 42 but lowered AUCs to 0.624-0.641. Hence, looser entity resolution yields wider coverage but lower AUCs. The stricter specification is the more credible tool for checking the external validity, and the looser matching is proper for an analyst's analysis. Scope sensitivity yielded the same interpretation qualitatively. Expansion of the network to all records with at least one European endpoint yielded higher coverage up to 3,317 SAR-mapped records, 1,574 bank identifiers, 111 countries, 1,819 unique bank pairs, and USD 29.20 billion of reported flow. The scope widened international exposure greatly, but it did not change the key finding on sparsity and time variability of the network structure.

## 6. Discussion

The findings suggest that the key benefit of adaptive graph learning in the context is the prioritizing of the relational aspects of the learning, and not the direct classification of laundering. The European-internal suspicious-flow network was very sparse, but had a high concentration of value, and a large cluster with a significant number of high-value corridors. This is similar to earlier network-based studies of AML, where structural features of the network (brokerage and structural position) as well as relationships with counterparties, but not transaction characteristics, predict risk (Fan et al., 2026). An important structure in TBML-oriented monitoring is that a commercial settlement typically will travel through one or more intermediaries, called correspondent or intermediary chains, where each commercial settlement may look like an ordinary commercial settlement without regard to its context in the chain of commercial settlements. The other mechanism is the temporal results. The flow and number of active nodes mapped changed significantly, as well as the geometry of the graph, in the years that followed, creating a changing relational setting for a fixed representation that was created in 2011. The adaptive model yielded an increase in sanctions-linkage AUC for each graph year in the post baseline period and a higher mean AUC for the same period. In addition, the adaptive model had higher average precision scores in each of the graph years in the post baseline period. This finding corroborates the concept drift hypothesis in which a stable learner drifts away from the generating structure when it changes (Li et al., 2023). What was important is that the improvement was not very large, in other words not dramatic. The improvement made in external relevance was achieved by annual refitting, but did not result in a high certainty classifier for an existing suspicious-flow map that was only partially completed. The finding thus contributes to controlled refresh governance, including the use of a benchmark, the comparison of the frozen model. The sanctions analysis is also a means of understanding the concept of model performance. Even when the nodes were restricted to strict sanctions-linked bank IDs, these accounted for only a small percentage of the total number of nodes, but 3.47 times network prevalence of the highest 5 per cent of adaptive 2016 scores contained matches. The outcome, however, bolsters the argument for focusing on fewer investigations rather than pronouncing a verdict of guilt. Furthermore, sanctions research indicates that trade relations around the network change following the implementation of sanctions, as well as the routing of networks (Effendi & Chattopadhyay, 2024; Huong et al., 2024). Meanwhile, the overall name resolver improved the number of matched identifiers, but decreased the AUC. That trade-off is what makes it clear why it's a good idea to have a governed layer separate from model fitting in which to place the process of sanctions entity resolution. Use of a permissive alias rule enhances the recall of analysts searching for a person, but weakens the strength of the sanction's linkage as a quantitative measure. The embedding of the structure in the local explanation is a further differentiation from the threshold surveillance. The most important learned relational geometry and the most important betweenness-based interpretable structural contribution to high-ranked alerts were primarily related. High-ranked alerts were primarily driven by learned relational geometry and the betweenness-based interpretable structural contribution was the

strongest recurring alert. This is consistent with temporal graph analysis results that demonstrate how neighborhood structure and sequence information is helpful in identifying illicit transaction patterns (Kute et al., 2021). It also establishes the graph-explainability perspective that relational structure is a crucial part of meaningful explanations, in addition to flat input attributes. The block-ablation design does that distinction too: Investigators can get a decomposition of abnormality, i.e., is it mostly due to the embedding, the brokerage, the connectivity, the flow strength, the centrality, or the cross-border exposure? Several implications follow. Methodologically, public suspicious-activity data can be used to conduct valuable experiments to test graph-risk, as long as claims are limited by provenance of the data. A SAR-off these maps are not the denominator of normal banking activity and a subsequent sanctions designation is not history laundering truth. Treating the relevance as being added to the end of the training set rather than as a training label is problematic in time series, but can be avoided if used as a post-hoc relevance. It is technically interesting that when there are few parameters to a graph, as in sparse public networks, and the graph is large but not well labeled, the results are in favor of adaptive learning of low parameters representation of the graph. Managerially, reviewing-depth lift is more tangible than just reviewing global discrimination – as there is limited capacity for reviewing analysts. Policy-wise, the segregation of risk scoring, explanation and sanctions overlay provides a better governance audit trail when it comes to model governance. The results also differ from the trend of increasingly sophisticated, supervised architectures for better AML technology. Heterogeneous graph learning on proprietary bank data has a definite upside thanks to extended richly typed relationships, but this will be contingent on a wealth of information about customers and business roles that can't be exposed in the public network. However, the present results reveal that this type of analytical power is preserved with sparse and imperfect data if the representation learning is restrained, data is refreshed annually, and the data is explicitly explained. The framework consequently provides a middle ground between rules-based and end-to-end classification which is defensible, but does not address the legal classification or case investigation.

## **7. Conclusion**

This research tackled the issue of identifying the TBML-relevant risk if there are suspicious payments spread out among the dynamic interbank connections and there are no definitive labels to provide for TBML. It has evolved a machine-learning approach that adapts to the graph and provides an explanation for its behavior, and applied it to the transaction-map records of the FinCEN Files, letting the European Union consolidated sanctions list as a separate entity to perform post-hoc relevance assessment. The empirical network consisted of 2126 SAR-mapped records, 878 bank identifiers, 1035 unique bank pairs, 46 countries/territories and USD 21.05 billion of reported mapped flows. It was a small structure and dense in a few institutional and corridors. Sanctions-linkage ranking has been enhanced each year since the graph was refreshed, compared to a 2011 representation. In 2016, adaptive ROC AUC was 0.701 versus 0.665 for the frozen comparator and the top 5 per cent had an enrichment of 3.47-fold in terms of sanctions-match. By ablation of blocks, it was found that the learned structure of the graph was the most prominent contribution in alert explanations while brokerage measures provided the most prominent interpretable contribution. What's unique about the contribution is that it brings together temporal adaptation, the relational anomaly detection, case-level explanation and conservative sanctions resolution without using sanctions status or SAR reporting as evidence of laundering. The design also establishes a reproducible distinction among historical suspicious-flow structure, present sanctions relevance, and investigator judgment. There are some constraints such as incomplete public transactions coverage, ambiguity of the bank names, lack of attributes on the invoice and customer and the lack of status of the sanctions on the past. Future research should be based on data at the institutional level, linkage of the trade documents, prospective temporal validation, testing of explanations by the analysts, and comparison with the results of the alerts on the operational level across different European banking environments.

## **8. Recommendations**

The European banking institutions and supervisory teams should have a multi-layered process for TBML screening not just a stand-alone transaction threshold. With graph representations, there should be a refresh schedule with a frozen benchmark for comparison with the model-risk during reviews and time series should show deterioration or improvement over the course of reviews. Entity-resolution rules are crucial for quantitative validation of sanctions data, and a more liberal alias normalization should be done in another analyst-search workflow and be manually validated and documented in order to ensure name-resolution decisions. If capacities are limited for investigations, operational queues should prioritize top percentile graphs with high graph-risk percentages as it is in the top 5 percentile that the greatest amount of enrichment took place. Every alert should include the following information: incident flow, brokerage, connectedness, cross-border exposure, and a local explanation of why the anomaly score has changed, due to a change in the feature blocks. Model outputs for explanation, entity-resolution logs, versioned source data, and model parameters are also needed for institutions to perform audit and challenge. To deploy the payment graphs for TBML, payment graphs need to be linked to attributes of invoices, commodity codes, quantities of the shipment, ownership, correspondent-bank roles, and attributes of the customers. At the end of the day, it is human judgement that is the deciding factor. Sanctions linkage continues to be a compliance-prioritization indicator rather than evidence of past crime and model outputs are dependent on documented escalation criteria prior to regulatory/investigative action.

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