

TradeGraph: Learning Global Semiconductor Market Dynamics from International Trade Networks using Hybrid Graph Neural Networks

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ABSTRACT

The global semiconductor industry has become a strategic pillar of the digital economy and mainly supports the artificial intelligence technology, cloud computing, advanced manufacturing, and modern electronic devices. Forecasting international semiconductor trade flows is therefore essential for governments, researchers, and policymakers. In this paper, we propose TradeGraph, a hybrid Graph Neural Network (GNN) architecture that combines Graph Attention Networks (GAT), Graph Convolutional Networks (GCN) and GraphSAGE through an adaptive gated fusion mechanism for bilateral trade flow prediction. This research used the BACI international trade database. First, we analyze the structural evolution of the global semiconductor trade network and identify its major trading communities. Then, we develop a hybrid GNN model that we compare with three baseline GNN architectures under a temporal train-validation-test split, to predict the semiconductor trade flow. Experimental results demonstrate that TradeGraph achieves the best predictive performance and exhibits lower variability across multiple independent runs. Our results reveal that the global semiconductor market is characterized by a limited number of major trade blocs and suggest an increasing importance of Asian economies in the global semiconductor trade network over the study period. These findings demonstrate the potential of hybrid Graph Neural Networks for analyzing and forecasting complex international trade networks.

Keywords: Semiconductor Market; Graph Neural Networks; Artificial Intelligence; International Trade; Economic Network Analysis; Trade Flow Prediction.

NOMENCLATURE

X_t	Node feature matrix at time t	$W^{(l)}$	Trainable weight matrix
E_t	Edge index (graph connectivity) at time t	h_v^l	Node embedding of node v at layer l
Y_t	Observed bilateral trade flow matrix at time t	$N(v)$	Neighborhood of node v
$\hat{Y}_t$	Predicted bilateral trade flow matrix at time t	α_{ij}	Attention coefficient between nodes i and j
t	Prediction year (time index)	a	Learnable attention vector
$\tilde{A}$	Adjacency matrix with self-loops	$\sigma(\cdot)$	Activation function
$\tilde{D}$	Degree matrix	$H^{(l)}$	Node embeddings at layer l

1 Introduction

Over the last few decades, people have increasingly relied on electronic devices, which has driven strong growth in demand for these products. The rapid development of artificial intelligence (AI) and other emerging technologies has also increased the need for the materials used to manufacture electronic devices. Semiconductors play a key role in this production. A semiconductor conducts electricity

differently from a conductor or an insulator because its electrical conductivity falls between that of a conductor and that of an insulator. This property makes semiconductors essential components of computers, integrated circuits, electronic devices, and many other digital technologies (1,3). Under specific physical conditions, semiconductors can either conduct or resist electricity, a property that enables virtually all modern electronic systems to operate.

Many countries now take part in semiconductor production and trade, linking their markets through a complex international supply chain. These connections give the international semiconductor market an important place in the global economy and support both technological innovation and economic growth. Researchers and policymakers need to understand how these trade relationships develop and change over time, but the large number of countries involved makes this task complex. We represent this system as a weighted and directed network, where each country corresponds to a node and each bilateral trade relationship corresponds to an edge. The trade value associated with a relationship determines the weight of its corresponding edge.

Graph-based methods provide another way to examine such interconnected systems. In particular, Graph Neural Networks (GNNs), introduced by Scarselli et al. (4), learn directly from the relationships represented in a graph. Since their introduction, researchers have developed several architectures, among them Graph Convolutional Networks (GCN) (5), Graph Isomorphism Networks (GIN) (6), Graph Attention Networks (GAT) (7), and GraphSAGE (8). Studies using these architectures have reported promising results for different network analysis tasks. In international trade research, however, many approaches still use one GNN architecture at a time or combine GNNs with gravity-based trade models (9). A single architecture may not capture all of the structural dependencies present in an international trade network, particularly when local and broader network interactions occur at different scales.

In this paper, we introduce a hybrid Graph Neural Network architecture called TradeGraph for forecasting bilateral semiconductor trade flows. TradeGraph combines GCN, GraphSAGE, and GAT through an adaptive gated fusion mechanism. This design allows the model to combine complementary structural information learned by the three architectures. In addition to forecasting future trade flows, we use the framework to represent the global semiconductor trade network, identify trade communities, and examine the dynamics of international semiconductor markets.

2 Related Work

The ability of Graph Neural Networks (GNNs) to model complex relational structures has encouraged their use in economic and financial applications. Recent studies have reported better performance from GNN-based models than from conventional machine learning techniques in tasks such as stock price prediction, financial risk assessment, fraud detection, and market forecasting. These models take advantage of the dependencies that exist among interconnected economic entities(10,11).

Researchers have also increasingly used GNNs to analyze international trade. Several studies have shown that graph-based learning can represent complex trade relationships and improve bilateral trade prediction. For example, Sellami et al. (12) showed that Graph Convolutional Networks (GCN) and Graph Attention Networks (GAT) significantly improve bilateral trade flow prediction on the UN Comtrade dataset compared with traditional machine learning approaches. Similarly, Rincon-Yanez, Mouakher, et al., 2023 (13) and Rincon-Yanez, Ounoughi, et al. (14) combined knowledge graphs with machine learning techniques to improve international trade prediction while providing richer semantic representations of trade relationships. Earlier studies using GCN, GAT, Graph Autoencoders (GAE), and Variational Graph Autoencoders (VGAE) also reported the effectiveness of graph learning for link prediction and country relationship modeling (13).

Researchers have extended graph-based approaches to several other applications related to bilateral trade prediction. Monken et al. (15) for example, used Graph Neural Networks to investigate causal relationships in international trade networks. Köse et al. (16) developed a GNN framework for HS6-level bilateral trade flow prediction, while Binsuwadan et al. (17) introduced a hybrid Graph Convolutional Recurrent Neural Network optimized with the Lion optimization algorithm for trade value prediction. Zhao et al. (18) used machine learning techniques to predict links in the global liquefied natural gas trade network. Shen (19) developed a Hybrid Graph Attention Network–Temporal Convolutional Network for global trade forecasting. Yi & Luo (20) combined knowledge graphs with reinforcement learning to analyze international trade behavior and predict economic trends. Lian et al. (21) used knowledge graph optimization for credit evaluation of international trade enterprises. Together, these studies show how researchers are applying graph learning and graph-based artificial intelligence to a wide range of problems in international trade.

These studies also leave two main gaps. First, most existing work deals with general international trade prediction, link prediction, or trade relationship modeling, while the global semiconductor trade market has received very limited attention despite its strategic importance in today's digital economy. To the best of our knowledge, no previous study has specifically examined bilateral semiconductor trade forecasting with Graph Neural Networks. Second, previous research has shown the effectiveness of individual GNN architectures, including GIN (6), GCN (5), GAT (7), and GraphSAGE (8), as well as hybrid models that combine GNNs with recurrent neural networks or optimization techniques. However, few studies have explored the combination of several complementary GNN architectures within a single framework. We consider that the different GNN architectures can capture different structural properties of a graph. Bringing these representations together may therefore provide more informative graph representations and improve predictive performance.

These gaps motivate the development of TradeGraph, a multi-branch hybrid Graph Neural Network architecture that combines GAT (7), GraphSAGE (8), and GCN (5) through an adaptive gated fusion mechanism for bilateral semiconductor trade flow forecasting. With this framework, we aim to complement the existing literature by developing a dedicated approach for the global semiconductor trade market and examining the benefits of combining multiple GNN architectures.

3 Methodology

The methodology adopted in this paper contains two main stages. First, we conduct an exploratory analysis of the global semiconductor trade network by identifying the major trade communities using the Louvain community detection algorithm (22,23). This first analysis provides insights into the structural organization of the global semiconductor market and highlights the principal trading blocs. Second, we forecast bilateral semiconductor trade flows using Graph Neural Networks (GNNs). In this study, all models perform a one-step-ahead prediction, where the bilateral trade flows for year t are predicted using only the graph observed at year $t - 1$ including its node features, graph connectivity, and edge weights.

3.1 Problem Formulation

The international semiconductor trade market can be naturally represented as a weighted and directed graph, where countries are represented as nodes and bilateral trade relationships as edges. The weight associated with each edge corresponds to the annual trade value between an exporting country and an importing country.

Given the graph observed at year $t - 1$, the objective is to predict the trade values for year t . The forecasting problem can therefore be formulated as follows:

$$(X_{t-1}, E_{t-1}, Y_{t-1}) \rightarrow \hat{Y}_t \quad (1)$$

Where X_{t-1} denotes the node features at year $t - 1$ (node features are generated from graph-theoretic centrality measures, whereas edge weights correspond to bilateral trade values.), E_{t-1} represents the graph connectivity (edge index), Y_{t-1} denotes the observed edge weights (bilateral trade flows), and $\hat{Y}_t$ is the predicted edge weight vector for year t .

For each target year t , the prediction edges are defined by the exporter-importer relationships with observed trade flows in year t . For each target edge, the bilateral trade value of the same exporter-importer pair in year $t - 1$ is used as the lagged trade feature. When a target relationship is not observed in year $t - 1$, its lagged trade value is set to zero. This allows newly formed trade relationships observed in year t to be included in the edge-weight regression. Trade relationships observed in year $t - 1$ but not in year t are not included in the target edge set and are therefore not predicted. No zero trade values are present in the original dataset that we used in this study; the zero value used for the lagged feature represents the absence of a previous-year observation for the corresponding exporter-importer pair.

To evaluate the proposed framework, we first implement three widely used baseline Graph Neural Network models, namely GCN, GraphSAGE, and GAT. We then compare their performance with our proposed hybrid architecture, TradeGraph.

3.2 The Proposed Hybrid Architecture: TradeGraph

TradeGraph is a hybrid multi-branch Graph Neural Network (GNN) designed for forecasting international semiconductor trade flows. Rather than relying on a single graph convolution operator, the proposed architecture is based on the assumption that different message-passing mechanisms capture complementary structural information from international trade networks. Consequently, the same input graph is processed simultaneously by three independent GNN branches before their learned representations are adaptively fused into a unified embedding for edge-weight prediction.

Our architecture consists of three complementary branches:

3.3 Graph Convolutional Networks (GCN)

GCN (5) is a semi-supervised graph learning framework that extends convolution operations to graph-structured data. At each layer, every node aggregates normalized information from its neighboring nodes, allowing the model to capture the global structural organization of the graph. In this study, the GCN branch is employed to learn the global topology of the global semiconductor trade network. Its propagation rule is defined as:

$$H^{(l+1)} = \sigma \left(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} W^{(l)} \right) \quad (2)$$

where $\tilde{A}$ denotes the adjacency matrix with self-loops, $\tilde{D}$ is the corresponding degree matrix, $H^{(l)}$ represents the node embeddings at layer l , $W^{(l)}$ is the trainable weight matrix, and $\sigma(\cdot)$ is the activation function.

3.4 GraphSAGE

Introduced by Hamilton et al. (8), GraphSAGE is an inductive Graph Neural Network that generates node representations by aggregating information from local neighborhoods. Unlike transductive methods, GraphSAGE can generalize to previously unseen nodes or graphs. Its aggregation rule is given by:

$$h_{N(v)}^{(l)} = \text{AGGREGATE}^{(l)} \left(\{h_u^{(l-1)}, u \in N(v)\} \right) \quad (3)$$

The node embedding is then updated as:

$$h_v^{(l)} = \sigma \left(W^{(l)} \cdot \text{CONCAT} \left(h_v^{(l-1)}, h_{N(v)}^{(l)} \right) \right) \quad (4)$$

Where $h_v^{(l-1)}$ denotes the embedding of node v at the previous layer, $N(v)$ is the neighborhood of node v , AGGREGATE is a neighborhood aggregation function (e.g., mean, max-pooling, or LSTM (Long Short-Term Memory (24,25))), and CONCAT denotes vector concatenation.

In our hybrid model, this branch captures local interactions among trading partners and learns neighborhood-aware node representations.

3.5 Graph Attention Networks (GAT)

GAT was introduced by Veličković et al. (7). It's a self-attention mechanism that assigns different importance weights to neighboring nodes during message passing. Instead of treating all neighbors equally, GAT automatically learns attention coefficients that quantify the influence of each neighboring node. We used this GNN to capture heterogeneous trade relationships by emphasizing the most influential trading partners.

The attention coefficients are computed as follows:

$$\alpha_{ij} = \frac{\exp(\text{LeakyReLU}(a^T [Wh_i \| Wh_j]))}{\sum_{k \in N(i)} \exp(\text{LeakyReLU}(a^T [Wh_i \| Wh_k]))} \quad (5)$$

The node representation is then updated as :

$$h_i' = \sigma \left(\sum_{j \in N(i)} \alpha_{ij} Wh_j \right) \quad (6)$$

Where W is a learnable weight matrix, a is the attention vector, α_{ij} denotes the attention coefficient between nodes i and j , and $\sigma(\cdot)$ is the activation function.

The three branches first produce the node embeddings Z_{GCN} , Z_{SAGE} , and Z_{GAT} . We concatenate these embeddings to form a joint representation:

$$Z_{cat} = [Z_{GCN} \| Z_{SAGE} \| Z_{GAT}] \quad (7)$$

We then feed this representation into a gated fusion network composed of two fully connected layers, ReLU activation, dropout, and a Softmax function. The network produces three node-specific weights for the GCN, GraphSAGE, and GAT representations:

$$[\alpha, \beta, \gamma] = \text{Softmax}(W_2 \text{ReLU}(W_1 Z_{cat} + b_1) + b_2) \quad (8)$$

Where α, β , and γ represent the learned importance of the GCN, GraphSAGE, and GAT representations, respectively, for each node. The Softmax function constrains these weights to non-negative values and ensures that $\alpha + \beta + \gamma = 1$. We then combine the three branch representations through a weighted fusion:

$$Z_{fused} = \alpha Z_{GCN} + \beta Z_{SAGE} + \gamma Z_{GAT} \quad (9)$$

We further refine the fused representation using a fully connected network:

$$Z_{refined} = W_4 \text{ReLU}(W_3 Z_{fused} + b_3) + b_4 \quad (10)$$

The dropout layers are applied between the two fully connected layers according to the dropout rate selected during hyperparameter optimization. Finally, we add a residual connection that combines the refined representation with the average of the three branch representations:

$$Z_{final} = Z_{refined} + \frac{Z_{GCN} + Z_{SAGE} + Z_{GAT}}{3} \quad (11)$$

Where W_1 , W_2 , W_3 , and W_4 denote learnable weight matrices, while b_1 , b_2 , b_3 and b_4 denote the corresponding learnable bias vectors.

The directed trade structure is preserved throughout the GCN, GraphSAGE, and GAT layers by retaining the exporter-to-importer direction in the edge index. For each directed trade relationship, the final node embeddings are concatenated with the lagged bilateral trade value. The resulting edge representation is then passed to an MLP decoder to predict the bilateral trade flow for year t . Algorithm 1 presents the pseudo-code for the TradeGraph training process.

Algorithm 1. TradeGraph Training Process

Require:

Training graph $G = (V, E)$

Node feature matrix X

Ground-truth trade values Y

Learning rate

Number of epochs T

1: Initialize GCN, GraphSAGE and GAT branches

2: Initialize Gated Fusion Network

3: Initialize Prediction MLP (Multi-Layer Perceptron)

4: **for** epoch = 1 to T **do**

5: $H_{GCN} \leftarrow GCN(X, E)$

6: $H_{SAGE} \leftarrow GraphSAGE(X, E)$

7: $H_{GAT} \leftarrow GAT(X, E)$

8: $H \leftarrow Concatenate(H_{GCN}, H_{SAGE}, H_{GAT})$

9: $Z \leftarrow GatedFusion(H)$

10: Construct edge representations from source and target node embeddings
and lagged trade values

11: $\hat{Y} \leftarrow PredictionMLP(Z)$

12: Compute RMSE loss

13: Backpropagate gradients

14: Update all parameters

15: **end for**

16: **Return predicted bilateral trade values**

4 Experimental Setup

In this study, we analyze the international semiconductor trade market using the BACI International Trade Database (26,27). BACI provides harmonized annual bilateral trade flows covering approximately 200 countries and more than 5,000 products classified according to the six-digit Harmonized System (HS). We use the BACI 202601 release version, published on 22 January 2026, together with the HS92 revision, which provides a consistent product classification over the period of 1995–2024.

Following the World Customs Organization (WCO) Harmonized Commodity Description and Coding System (HS) (28,29), we identified semiconductor products using HS heading 8541, which includes semiconductor devices such as diodes, transistors, photosensitive semiconductor devices, and semiconductor-based transducers, and HS heading 8542, which covers electronic integrated circuits, including memories, processors, amplifiers, and other integrated electronic components. These two

product categories constitute the core of the international semiconductor industry and therefore define the trade network analyzed in this study.

4.1 Data Preprocessing

The BACI dataset is already extensively harmonized and cleaned, making it suitable for large-scale international trade analysis. During the preprocessing stage, we observed that approximately 2.56 % of the records contain missing values for the quantity variable. Since the proposed TradeGraph framework models trade relationships using monetary trade values rather than traded quantities, these observations were retained and no imputation was performed.

We then filtered the dataset to retain only semiconductor products corresponding to HS 8541 and HS 8542. For each year, bilateral trade flows between exporting and importing countries were aggregated to construct a weighted and directed trade network, where nodes represent countries and edge weights correspond to the total annual trade value between country pairs.

For each country and year, we constructed six node features: out degree, in degree, total degree, log exports, log imports, and log total trade. The degree features capture the number of outgoing and incoming trade relationships. We then standardized all six node features using the StandardScaler method before providing them to the GNN models.

Because international trade values span several orders of magnitude and exhibit a highly right-skewed distribution, we transformed the trade values using the natural logarithm, $\log(1 + Y_t)$, before model training. This transformation reduces the influence of extremely large trade flows, improves numerical stability during optimization, and facilitates the learning process. For evaluation, the predicted values were transformed back to the original monetary scale using the inverse exponential transformation ($e^{\hat{Y}_t} - 1$), and all performance metrics were calculated on this original scale.

4.2 Graph neural networks evaluation metrics

Since the primary objective of this study is to forecast bilateral semiconductor trade flows, the proposed task is formulated as an edge weight regression problem. To evaluate the predictive performance of the proposed TradeGraph model and compare it with the baseline Graph Neural Network (GNN) models, we employed four widely used regression metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2), defined as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (13)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (14)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (15)$$

where:

y_i denotes the observed trade value;

$\hat{y}_i$ is the predicted trade value;

$\bar{y}$ represents the mean of the observed trade values;

n is the total number of observations.

Lower values of MSE, RMSE, and MAE indicate better predictions by measuring the magnitude of the prediction errors, and a higher R^2 value indicates that a larger proportion of the variance in the observed trade values is explained by the model.

5 Results and Discussion

5.1 Preliminary Network Analysis

This subsection presents a preliminary analysis of the global semiconductor trade market. In 2024, the market reached a total trade value of USD 1,130.48 billion, representing an annual growth of 6.76% compared with 2023. Figure 1 shows the evolution of the global semiconductor trade from 1995 to 2024. The market exhibits a strong long-term upward trend, growing from less than USD 200 billion in 1995 to more than USD 1.1 trillion in 2024. This sustained growth reflects the increasing global demand for semiconductor-based technologies.

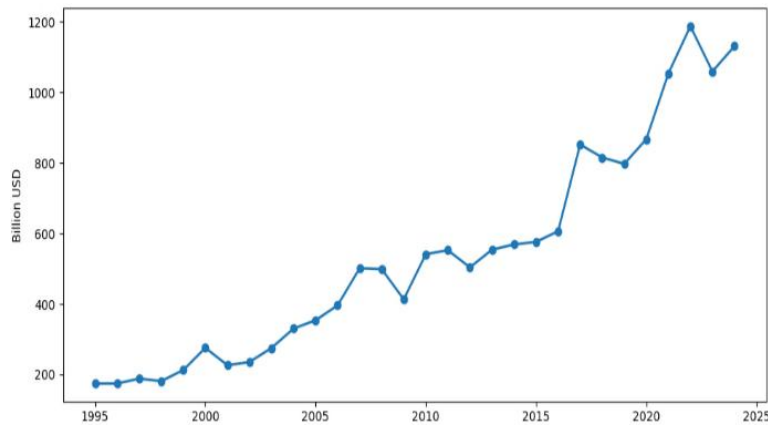


Figure 1. Evolution of global semiconductor trade. Source: Created by the authors based on BACI data.

Figure 2 presents the annual growth rate of the market. Although the overall trend is positive, the semiconductor industry experienced notable contractions in 2001 (-17.82%), in 2009 (-17.15%), and in 2023 (-10.78%), corresponding to major global economic disruptions. Nevertheless, the market rapidly recovered after each downturn, highlighting the resilience of the global semiconductor industry.

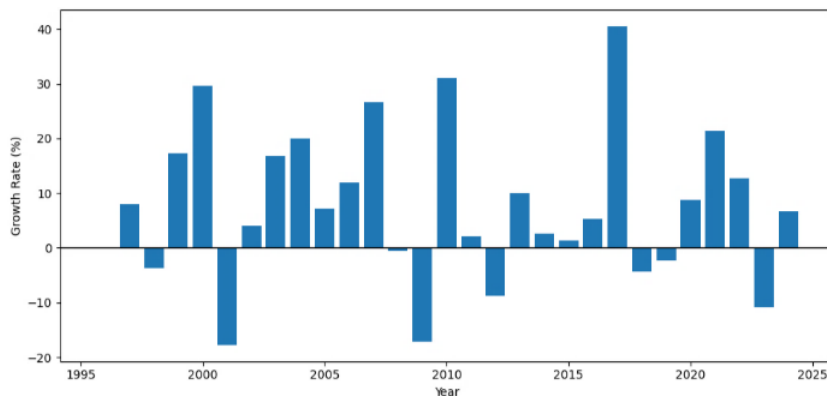


Figure 2. Annual growth rate of global semiconductor trade. Source: Created by the authors based on BACI data.

Table 1. Descriptive statistics of the global semiconductor trade network (1995-2024).

Year	Nodes (Country)	Edges	Density	Average Degree	Average Clustering	Connected Components
1995	208	4315	0.100	41.490	0.813	1
1996	210	4699	0.107	44.752	0.836	1
1997	207	5034	0.118	48.638	0.830	1
1998	207	5311	0.125	51.314	0.847	1
1999	212	5736	0.128	54.113	0.848	1
2000	222	6968	0.142	62.775	0.844	1
2001	222	7314	0.149	65.892	0.821	1
2002	222	7476	0.152	67.351	0.844	1
2003	222	7866	0.160	70.865	0.843	1
2004	222	8308	0.169	74.847	0.830	1
2005	222	8477	0.173	76.369	0.833	1
2006	223	8996	0.182	80.682	0.819	1
2007	223	9279	0.187	83.22	0.825	1
2008	223	9500	0.192	85.202	0.821	1
2009	223	9697	0.196	86.969	0.815	1
2010	223	9994	0.202	89.632	0.815	1
2011	224	10132	0.203	90.464	0.818	1
2012	225	10398	0.206	92.427	0.821	1
2013	227	10518	0.205	92.670	0.810	1
2014	226	10551	0.207	93.372	0.803	1
2015	226	10884	0.214	96.319	0.821	1
2016	226	11090	0.218	98.142	0.817	1
2017	226	11179	0.220	98.929	0.815	1
2018	226	11137	0.219	98.558	0.818	1
2019	226	11164	0.220	98.796	0.820	1
2020	226	10910	0.215	96.549	0.825	1
2021	226	11431	0.225	101.159	0.825	1
2022	226	11503	0.226	101.796	0.824	1
2023	226	11494	0.226	101.717	0.828	1
2024	226	10835	0.213	95.885	0.831	1

Table 1 summarizes the main structural characteristics of the global semiconductor trade network. In this table, nodes represent countries and directed weighted edges represent bilateral trade relationships. As illustrated in Figure 3, the number of edges increased from 4,315 in 1995 to more than 11,000 after 2016. This reflects the growing complexity and interconnectedness of the global semiconductor market.

The network density and average degree also exhibit an overall upward trend, indicating that countries have progressively established more trade relationships over time. In contrast, the average clustering coefficient remains relatively stable (around 0.82), suggesting a persistent tendency of countries to form tightly connected trading groups. As shown in Table 1, the number of connected

components remains equal to one throughout the study period, indicating that the global semiconductor trade network forms a single connected graph in which every country is directly or indirectly linked to the others.

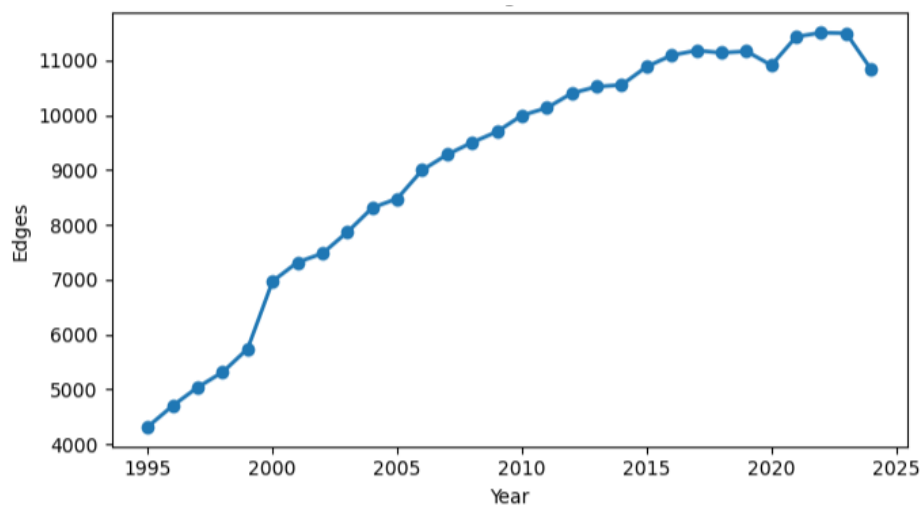


Figure 3. Evolution of bilateral trade relationships (edges) in the semiconductors network. Source: Created by the authors based on BACI data.

5.2 Community Detection

To identify the major trading communities in the global semiconductor network, we converted the directed trade network into an undirected weighted network while retaining the original trade-value weights. We then applied the Louvain community detection algorithm (22,23), using the trade-value weights in both community detection and modularity calculation. As summarized in Table 2, the network is consistently partitioned into three or four communities throughout the period of 1995–2024. The average community size ranges from approximately 56 to 75 countries, while the modularity remains relatively low (between 0.115 and 0.217), indicating that although distinct trading blocs exist, they remain highly interconnected. This finding reflects the globally integrated nature of the semiconductor supply chain, where countries maintain strong trade relationships across community boundaries.

Table 2. Summary of community detection statistics for the global semiconductor trade network (1995-2024).

Year	Number of Communities	Largest Community	Smallest Community	Average Community Size	Modularity
1995	3	113	47	69.333	0.162
1996	3	123	42	70.000	0.146
1997	3	124	40	69.000	0.143
1998	3	116	28	69.000	0.117
1999	3	109	51	70.667	0.142
2000	4	101	22	55.500	0.178
2001	4	108	22	55.500	0.164
2002	3	104	31	74.000	0.136
2003	3	129	38	74.000	0.174
2004	4	133	18	55.500	0.133
2005	3	185	17	74.000	0.155

2006	4	175	4	55.750	0.120
2007	4	155	17	55.75	0.151
2008	3	160	15	74.333	0.126
2009	4	120	15	55.750	0.178
2010	3	190	12	74.333	0.157
2011	3	124	50	74.667	0.136
2012	4	111	12	56.250	0.217
2013	4	91	20	56.750	0.145
2014	3	100	37	75.333	0.139
2015	3	148	31	75.333	0.116
2016	4	125	2	56.500	0.150
2017	3	180	13	75.333	0.131
2018	3	167	28	75.333	0.174
2019	4	123	5	56.500	0.172
2020	4	121	24	56.500	0.134
2021	4	133	8	56.500	0.162
2022	4	95	12	56.500	0.140
2023	3	101	42	75.333	0.160
2024	4	93	29	56.500	0.115

Figures 4, Figure 5, and Figure 6 illustrate the most influential countries in the global semiconductor trade network according to their trade-weighted PageRank. In 1995 (as shown in Figure 4), the network is centered around the United States, reflecting its dominant position in the early semiconductor industry. By 2010, Figure 5 shows that China and China, Hong Kong SAR emerge as major trade hubs, highlighting the growing importance of Asia in global semiconductor exchanges. In 2024 (Figure 6), China, Viet Nam, Malaysia, and Germany become the most influential hubs, suggesting an increasing importance of Asian economies in the global semiconductor trade network while maintaining strong interconnections with Europe.

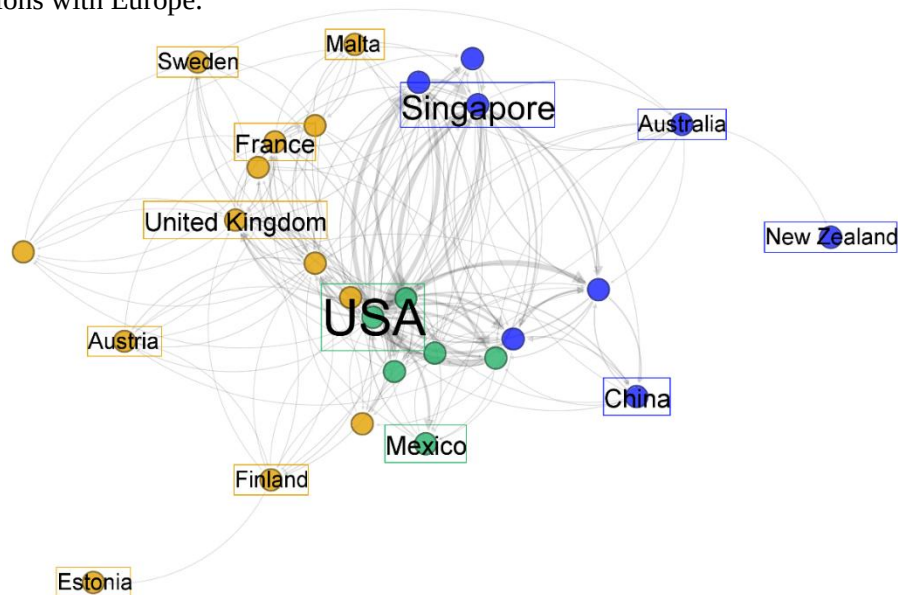


Figure 4. Most influential countries in the global semiconductor trade network in 1995. Source: Created by the authors based on BACI data.

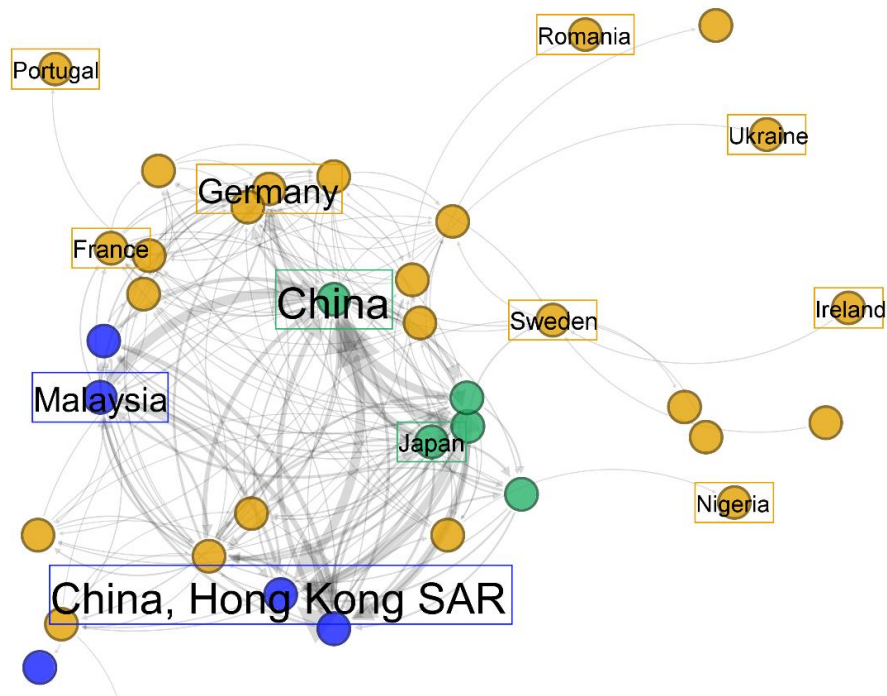


Figure 5. Most influential countries in the global semiconductor trade network in 2010. Source: Created by the authors based on BACI data.

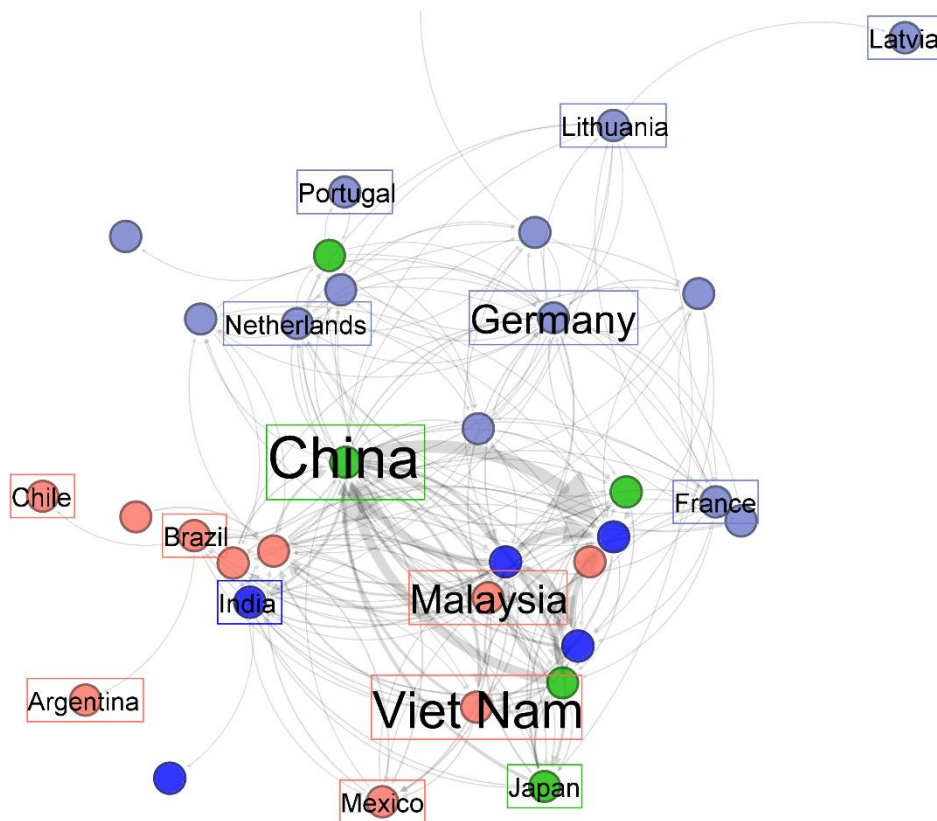


Figure 6. Most influential countries in the global semiconductor trade network in 2024. Source: Created by the authors based on BACI data.

5.3 Bilateral trade flow forecasting

This subsection evaluates the forecasting performance of the TradeGraph model against three widely used GNN architectures: GCN, GAT, and GraphSAGE. The results reported in Table 3 correspond to the mean $\pm$ standard deviation obtained over five independent runs with different random seeds (Run 1: Seed = 42, Run 2: Seed = 52, Run 3: Seed = 62, Run 4: Seed = 72, and Run 5: Seed = 82). To preserve the temporal dependency of trade data and avoid data leakage, the dataset was split sequentially according to the temporal order of the observations. The training set covers 1995–2018, the validation set covers 2019–2021, and the test set covers 2022–2024. RMSE and MAE are reported in this table in billion USD, and the MSE is expressed in billion USD².

We performed the hyperparameter optimization independently for each model using Optuna. We optimized TradeGraph, GCN, GAT, and GraphSAGE in separate experiments using their respective model-specific hyperparameter search spaces. For TradeGraph, we conducted 100 Optuna trials and used the validation RMSE on the log-transformed trade values as the objective metric. The optimization used a TPE sampler and a MedianPruner, with early stopping based on a patience of 20 epochs.

As shown in Table 3, TradeGraph achieves the best observed predictive performance across the reported evaluation metrics. On the test set, it obtains the highest coefficient of determination ($R^2 = 0.9482 \pm 0.0064$) together with the lowest RMSE (0.3404 ± 0.0209), MSE (0.1163 ± 0.0145), and MAE (0.0241 ± 0.0014). Furthermore, the relatively small standard deviations observed across the five tested random seeds indicate lower variability in the reported test metrics compared with the individual GCN, GAT, and GraphSAGE models.

Table 3. Forecasting performance of TradeGraph and baseline GNN models.

Model	Data Split	R^2	RMSE (Billion USD)	MSE (Billion USD ²)	MAE (Billion USD)
GCN	Training	0.8265 ± 0.0356	0.2643 ± 0.0260	0.0704 ± 0.0144	0.0173 ± 0.0018
	Validation	0.9338 ± 0.0123	0.3237 ± 0.0302	0.1055 ± 0.0197	0.0190 ± 0.0011
	Test	0.9434 ± 0.0306	0.3478 ± 0.0864	0.1270 ± 0.0688	0.0245 ± 0.0035
GAT	Training	0.7992 ± 0.0470	0.2839 ± 0.0327	0.0815 ± 0.0191	0.0182 ± 0.0030
	Validation	0.9190 ± 0.0360	0.3521 ± 0.0803	0.1291 ± 0.0573	0.0209 ± 0.0035
	Test	0.9266 ± 0.0302	0.3989 ± 0.0840	0.1648 ± 0.0679	0.0265 ± 0.0038
GraphSAGE	Training	0.6707 ± 0.3288	0.3392 ± 0.1520	0.1336 ± 0.1334	0.0228 ± 0.0112
	Validation	0.9254 ± 0.0493	0.3300 ± 0.1119	0.1189 ± 0.0785	0.0204 ± 0.0050
	Test	0.9197 ± 0.0516	0.4080 ± 0.1316	0.1803 ± 0.1159	0.0279 ± 0.0065
TradeGraph	Training	0.8523 ± 0.0305	0.2438 ± 0.0243	0.0599 ± 0.0124	0.0154 ± 0.0018
	Validation	0.9480 ± 0.0152	0.2852 ± 0.0446	0.0830 ± 0.0241	0.0179 ± 0.0015
	Test	0.9482 ± 0.0064	0.3404 ± 0.0209	0.1163 ± 0.0145	0.0241 ± 0.0014

Figure 7 presents the learning curves obtained in Run 5 (Seed = 82), one of the five independent runs performed to assess the stability of TradeGraph. As shown, the training and validation RMSE decrease rapidly during the first epochs before converging toward similar values, indicating stable optimization without noticeable overfitting during training. These results illustrate the potential of combining the complementary strengths of GCN, GraphSAGE, and GAT through an adaptive gated fusion mechanism for bilateral trade flow forecasting.

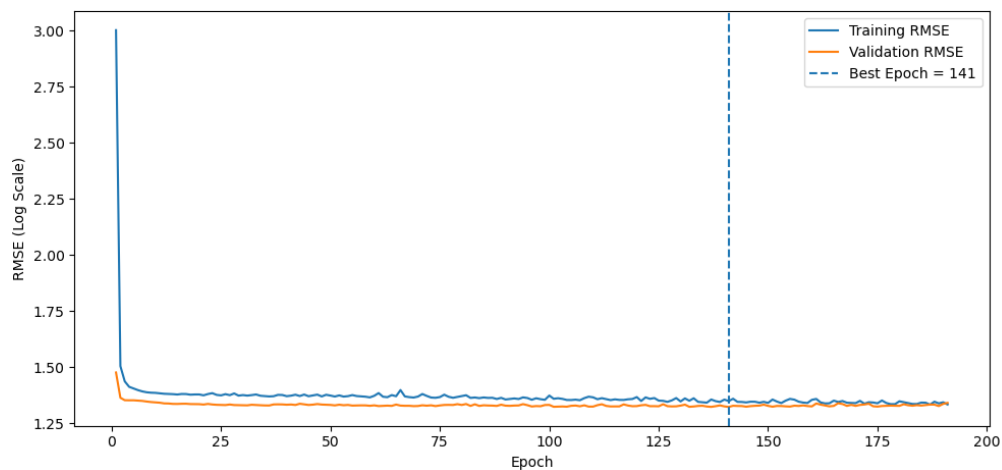


Figure 7. TradeGraph learning curves for Run 5 (Seed = 82). Source: Created by the authors.

Once the best-performing model was identified, we retrained TradeGraph on the complete dataset (1995–2024) using the optimal hyperparameters (in Table 4) and then, we used it to forecast bilateral semiconductor trade flows.

Table 4. Optimal hyperparameters of TradeGraph obtained using Optuna (Run 5, Seed = 82)

No.	Hyperparameter	Search range	Optimal value
1	Hidden dimension	64, 128, 256	256
2	Embedding dimension	32, 64, 128	32
3	Number of layers	2–4	2
4	Number of attention heads	2, 4, 8	8
5	Dropout	0–0.5	0.020027
6	Learning rate	10^{-4} – 5×10^{-3}	0.001564
7	Weight decay	10^{-7} – 10^{-3}	6.904961×10^{-6}
8	Optimizer	Adam	Adam
9	Number of epochs	—	141

Since the latest BACI release currently provides observations only up to 2024, the forecasts represent a one-year-ahead prediction (2025). Table 5 presents the fifteen largest predicted bilateral trade flows together with their observed 2024 values and estimated growth rates. The results indicate that China; China, Hong Kong SAR; Other Asia, nes (corresponding to Taiwan Province of China in recent BACI releases); Japan; Malaysia; and the Republic of Korea remain the dominant bilateral trading partners in the semiconductor market. While most of these major trade corridors are expected to continue growing, a few bilateral relationships are predicted to decline, suggesting a gradual reorganization of regional trade flows rather than a fundamental change in the global trade hierarchy. Since observed BACI data for 2025 are not yet available, these forecasts cannot currently be externally validated and should therefore be interpreted as model-based projections.

Table 6 and Table 7 summarize respectively the predicted rankings of the fifteen largest semiconductor exporters and importers in 2025. As shown in Table 6, the forecasts indicate that Other Asia, nes, China, and the Republic of Korea remain the world's leading exporters, while China, China, Hong Kong SAR, and Singapore continue to dominate semiconductor imports according to Table 7. The projected rankings remain close to those observed in 2024, suggesting that the global semiconductor market is characterized by a relatively stable trade structure.

Several economies, including China, the United States, Malaysia, Japan, Singapore, and the Republic of Korea, appear among both the leading exporters and importers. This reflects the highly integrated nature of the semiconductor value chain, where countries simultaneously import chips, wafers, and intermediate components for processing or assembly before exporting higher-value semiconductor products to other markets.

Table 5. Top 15 predicted bilateral semiconductor trade flows in 2025.

No.	Exporter	Importer	Trade 2024 (Billion USD)	Forecast 2025 (Billion USD)	Growth (%)
1	China	China, Hong Kong SAR	83.604	96.638	+15.590
2	Other Asia, nes	China, Hong Kong SAR	50.593	72.926	+44.143
3	Other Asia, nes	China	64.410	68.179	+5.851
4	Rep. of Korea	China	47.770	63.938	+33.845
5	Other Asia, nes	Singapore	45.919	41.826	-8.913
6	Singapore	China, Hong Kong SAR	36.751	35.629	-3.053
7	China	Rep. of Korea	20.971	29.317	+39.801
8	China	Other Asia, nes	17.403	25.960	+49.169
9	Malaysia	China	21.010	24.589	+17.038
10	Japan	China	19.166	24.527	+27.972
11	Other Asia, nes	Japan	13.776	19.681	+42.858
12	Rep. of Korea	China, Hong Kong SAR	22.584	19.167	-15.131
13	Other Asia, nes	Rep. of Korea	22.765	18.293	-19.643
14	China	Viet Nam	28.971	16.486	-43.093
15	Rep. of Korea	Other Asia, nes	14.394	16.201	+12.550

Table 6. Top 15 predicted exporter semiconductor trade flows in 2025.

No.	Exporter	Exports 2024 (Billion USD)	Forecast Exports 2025 (Billion USD)
1	Other Asia, nes	241.744	284.186
2	China	228.876	282.083
3	Rep. of Korea	172.274	150.448
4	Malaysia	94.301	104.496
5	Japan	62.102	74.342
6	Singapore	75.895	73.300
7	USA	46.926	53.412
8	Viet Nam	40.021	41.744
9	Philippines	26.498	38.450
10	Germany	23.596	33.402
11	Thailand	21.785	30.140
12	Ireland	14.092	12.508
13	Netherlands	7.384	11.369
14	Israel	13.022	10.388
15	France	7.690	9.454

Table 7. Top 15 predicted importer semiconductor trade flows in 2025.

No.	Importer	Imports 2024 (Billion USD)	Forecast Imports 2025 (Billion USD)
1	China	214.839	272.215
2	China, Hong Kong SAR	238.928	267.095
3	Singapore	99.152	98.148
4	Other Asia, nes	78.767	71.655
5	USA	62.277	66.740
6	Rep. of Korea	64.363	64.472
7	Viet Nam	66.028	51.937
8	Malaysia	52.667	50.231
9	Germany	26.020	42.798
10	Japan	27.424	37.635
11	Mexico	28.168	31.860
12	India	28.985	28.174
13	Thailand	23.957	22.875
14	Philippines	14.521	16.691
15	Netherlands	7.919	13.631

6 Conclusion

This study introduced TradeGraph, a hybrid Graph Neural Network architecture for forecasting bilateral semiconductor trade flows. Instead of using a single graph learning operator, the model brings together GCN, GraphSAGE, and GAT through an adaptive gated fusion mechanism. Each branch contributes a different view of the network, covering global topology, local neighborhood structures, and attention-based trade relationships.

The analysis relied on the BACI international trade database for the period 1995–2024. We examined the evolution of the global semiconductor trade network and identified its principal trading communities. The network is organized around a limited number of major trade blocs, while Asian economies have taken on an increasingly important position within global semiconductor trade. TradeGraph achieved the best observed predictive performance across the reported evaluation metrics. The five independent runs, using different random seeds (Run 1: Seed = 42, Run 2: Seed = 52, Run 3: Seed = 62, Run 4: Seed = 72, and Run 5: Seed = 82), also showed lower variability. The one-step-ahead forecasts in Table 5 provide estimates of future bilateral semiconductor trade flows and indicate the countries expected to remain the leading exporters and importers in this strategic industry (Tables 6 and 7).

Beyond its methodological contribution, this study provides a graph-based perspective on the structure and future evolution of the global semiconductor market. The results obtained in this work indicate that hybrid GNN architectures can be useful for modeling complex international trade systems. Although this study focuses on semiconductors, the proposed framework can be extended to other strategic industries characterized by interconnected global supply chains. Future research may investigate the integration of temporal information, macroeconomic indicators, geopolitical factors, and dynamic Graph Neural Networks to further improve long-term trade forecasting performance. A limitation of the present study is the use of a single chronological train-validation-test partition. Although this protocol preserves temporal ordering and prevents data leakage, a rolling-origin or walk-

forward evaluation across multiple historical periods could provide additional evidence of temporal generalization.

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Data availability. The source code, Jupyter notebooks, scripts, processed datasets, and figures developed for this study are available in the authors' GitHub repository: <https://github.com/donalsonwilson-stack/TradeGraph-GNN-semiconductor-trade-forecasting>.

Author contributions.

Donalson Wilson: Conceptualization, methodology, data analysis, model development, experiments, manuscript writing, and visualization.

Salma Liichi: Data preprocessing, validation, literature review, and manuscript writing.

Chaimae Chouaa: Experimental validation, data analysis, and manuscript writing.

Abdellah Azmani: Supervision, research guidance, methodology validation, and manuscript review.

Mohamed Kounaidi: Supervision, research guidance, methodology validation, and manuscript review.

Use of artificial intelligence. The authors declare that no AI tools were used beyond language editing.

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