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When Structure Takes Over: The Autonomy of Global Supply Chain Networks Beyond Firm Capacity and Institutional Constraints

By

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Abstract

Building on research that highlights the role of governance, institutional, and network structures in shaping global value chains (Gereffi et al., 2005; Coe & Yeung, 2015; Coleman, 1998), this study investigates why firms in the semiconductor industry continued to outsource production after the 2020–2023 chip shortage, despite significant shifts in risk and cost (Miller, 2022; European Commission, 2022). I analyze how persistent outsourcing patterns are produced not only by firm capabilities or national policies, but also by the autonomous effects of supply chain network structure itself (Coleman, 1988; Granovetter, 1985).

Using an original dataset of 160 publicly traded semiconductor firms and 517 buyer-supplier ties, I apply Social Network Analysis (e.g., descriptive measures, Quadratic Assignment Procedure, and Exponential Random Graph Models) to disentangle the influence of governance (firm capacity), institutional (state and role similarity), and network (triadic closure) structures on the formation of long-term supplier relationships. While prior research has emphasized the explanatory power of firm resources and state intervention (Williamson, 1981; Goldberg et al., 2024), my results show that institutional similarity—such as shared supply chain role or headquarters country—strongly predicts tie formation within a network, whereas differences in market capitalization and R&D spending do not.

Most crucially, the analysis reveals that network structure—specifically, the prevalence of triadic closure—exerts an independent and statistically significant effect on the persistence of outsourcing ties, even after accounting for institutional similarity. This suggests that global supply chain networks can partially decouple from both firm-level capacity and institutional arrangements, sustaining legacy patterns through path-dependent network effects. I argue that, following the chip shortage crisis, the supply chain network itself has become a stabilizing force, locking firms into enduring hybrid relationships and limiting the impact of policy or market interventions.

Keywords: semiconductor industry; chip shortage; social network analysis; supply chain resilience; global value chain; global production network; computational social science; network modelling; quadratic assignment procedure; exponential random graph models

1 Introduction

When a firm needs to acquire supplies—whether it's parts, labor, or services—it generally faces a choice between two options: make it internally or buy it from the market. This decision is commonly explained by transaction cost economics (TCE), which argues that firms aim to minimize the overall cost and risk of economic exchanges (Williamson, 1981; 1991; 1993). According to TCE, firms purchase goods or services from external suppliers when doing so is cheaper, more efficient, and involves little risk. When outsourcing is too risky or too expensive, firms will internalize production through vertical integration of their suppliers and perform the tasks internally instead.

However, in a highly interconnected global economy, where vertical integration is impractical and constrained, many firms don't rely solely on internal production or outsourcing. Instead, firms work out in-between solutions—like long-term supplier relationships or contracted manufacturing—where two firms stay independent but work closely together. Inter-firm coordinations with such characteristics are called hybrid relationships (what Williamson [1981; 1991; 1993] refers to as "hybrid forms"). Hybrid relationships are especially common in high-tech industries like semiconductors, where production is fragmented across multiple highly specialized stages that no single firm can efficiently handle alone. Furthermore, the rapid pace of innovation, high capital intensity, and the presence of significant technological and institutional barriers, often reinforced by decades of state-led industrial policy and national security considerations, making hybrid form a more flexible and efficient solution in semiconductor production (Williamson, 1981; Gereffi et al., 2005). Therefore, the semiconductor industry is a perfect case for thinking about the persistence of inter-firm relationships in hybrid form.

On the individual level—which focuses on the behavior and psychological needs of decision-makers—firms are viewed as independent units operated by humans with limited information (Simon, 1955; Vaughan, 1998; Feduzi, Runde, & Schwarz, 2022). In such a context, decision-makers face bounded rationality, a condition in which individuals cannot make fully rational decisions because the human mind is incapable of knowing and processing all available information. In addition, decision-makers frequently engage in opportunism, making risky decisions driven by self-interest and often at the expense of their partners. Bounded rationality and opportunism give firms a natural tendency to dissolve their hybrid relationships (Williamson, 1981; 1991; 1993). However, in practice, many of these relationships persist for years or even decades (Miller, 2022). This durability cannot be explained by individual decision making alone. Instead, it points to the function of structure in shaping and stabilizing inter-firm relationship outcomes. Therefore, examining the structures surrounding firms offers the most direct lens for explaining the persistence of hybrid relationships, especially in industries where complexity and interdependence are high.

Structure is one of the most widely used, constantly debated, and yet inconsistently defined concepts in sociology. In this paper, I adopt Giddens' (1984) definition of structure as the broader relational, institutional, and network environment, made up of rules, resource asymmetries, and role expectations that both enable and constrain action (Giddens, 1984). Structures provide options for actions to be carried out, and different structures can interact when drawn upon simultaneously. Therefore, with the action being the persisting of a hybrid relationship, I categorize the factors enabling and constraining this action into three types: governance structures, institutional structures, and network structures.

I define governance structures as the power asymmetries that emerge from differences in firm capacity, which constrain and enable action by encouraging alignment with the leading firms. Firms with scaled access to consumer markets or production technologies with high entry barriers hold asymmetric power within their value chains (Gereffi 1994; Gereffi et al., 2005). These firms become difficult to replace, and smaller firms depend on them to access customers, secure contracts, and stay in business. Therefore, governance structures shape firm behavior not through direct control, but by facilitating dependency on the dominating firms.

I define institutional structures as formal rules and state-led interventions that constrain and enable action by making certain arrangements of inter-firm collaboration more feasible than others. The state in which a firm is embedded plays a critical role in determining which partners are willing to transfer technology, who is available for collaboration, and what kinds of inter-firm relationships are possible (Miller, 2022; Goldberg et al., 2024; Whetsell et al., 2020). Therefore, institutional structures shape firm behavior not through direct control, but by regulating the opportunities and constraints for collaboration.

Lastly, I define network structures as the specific characteristics of the network itself—such as triadic closure, a network property where two firms are more likely to trust and cooperate if they both share a connection with a third firm—that constrain and enable action by suppressing opportunism, fostering trust, and providing an informal channel of information exchange (Coleman, 1988; Granovetter, 1985; Podolny, 1994; Podolny & Page, 1998; Neilson, Pritchard, & Yeung, 2014). In environments with high uncertainty, where firms cannot easily evaluate the quality, reliability, or intentions of potential partners, decisions about who to cooperate or exchange are heavily shaped by the resources and obligations arising from being embedded in a network, collectively known as social capital (Coleman, 1988). Therefore, networks influence firm behavior not through direct control, but by clearly signaling which partners are reliable, guiding firms toward cooperation with partners embedded in the same network structures (Granovetter, 1985; Podolny, 1994).

It is noticeable, however, while governance, institutional, and network structures have strong theoretical foundations based on observable social exchanges between individuals, prior studies have largely relied on qualitative methods to identify these patterns. This limits the ability to statistically test how micro-level interactions aggregate to produce stable macro-level structures (Hedström & Swedberg, 1998; Coleman, 1990; Blau, 1964). In other words, while each of these structures can explain the persistence of a single hybrid relationship, what explains the persistence of an entire global supply chain network—build with multiple relationships accumulated—requires the interplay among governance, institutional, and network structures to be disentangled, and their relative contributions measured and compared. To address this, I plan to use quantitative data and statistical models to empirically examine the micro-to-macro processes that are consistent with the theoretical explanations underlying these structures. The 2020–2023 global chip shortage and subsequent crisis-driven state interventions created a unique turning point that makes this study possible. This period introduced new uncertainty, forcing firms to actively decide whether to maintain their hybrid relationships. Meanwhile, the governance and institutional structures that had supported these hybrid relationships were loosened by policy changes in response to the crisis. With resistance to large-scale dissolution of hybrid relationships lifted, widespread internalization or breakup might have been expected. Instead, both the number and magnitude of hybrid relationships increased (European Commission, 2022; SIA, 2022; Goldberg et al., 2024; Whetsell et al., 2020).

Therefore, I argue that the dominant factor explaining the persistence of hybrid relationships within a global supply chain network is the network structure itself, which has become a stabilizing force that shapes how firms respond to uncertainty and disruption. To test this, I operationalized key structural concepts into measurable variables. Governance structure is measured by inter-firm differences in market capitalization and R&D expenses, representing disparities in market access and technology. Institutional structure is measured by inter-firm similarities in their headquarters' country location and their specific supply chain role (e.g., "Chip Makers" vs. "Chip Users"), representing shared state environments and production specializations. These measures allow me to account for alternative explanations when evaluating whether the network structure itself plays an independent role (Gereffi, 1994; 2018; Williamson, 1981; 1991; Yeung and Coe, 2015; De Marchi and Alford, 2022).

My analysis uses an original dataset of 160 publicly traded firms in the semiconductor industry and the 517 buyer-supplier ties connecting them. The sample was constructed using a snowball method, starting with firms subsidized by the U.S. CHIPS and Science Act and expanding by tracing their relationships using data from the London Stock Exchange Group (LSEG). An inter-firm relationship is recorded as an undirected network tie if it has a confidence score of 50

I first conducted a descriptive analysis by creating network graphs and a triadic census. The graphs of institutional structure (country and supply chain role) showed clear clustering, indicating that firms were more likely to be connected if they belonged to the same country or production stage. In contrast, the graphs of governance structure (market capitalization and R&D spending) revealed no obvious patterns based on firm size or R&D investment. This led to the first hypothesis:

- **H1: Firms that share similarity in institutional structure have a higher probability of forming a tie compared to firms that share similarity in relational structure.**

Furthermore, the triadic census showed an unusually high number of open triads (where two firms are connected to a common third firm but not to each other). In a low-density network, this pattern suggests a structural tendency toward connection. This led to the second hypothesis:

- **H2: Firms that share a common partner have a higher probability of forming a tie, even after controlling for institutional structure similarity.**

To test these hypotheses, I used two statistical methods. I tested H1 using the Quadratic Assignment Procedure (QAP), a matrix-based regression model suited for network data. I tested H2 using Exponential Random Graph Modeling (ERGM), which models tie formation based on both firm attributes and network configurations. My findings provide strong evidence supporting both hypotheses, demonstrating that while institutional similarity is a significant predictor of inter-firm ties, the underlying network structure exerts an even greater influence on tie formation.

2 Literature Review

Transaction cost economics (TCE) offers one of the earliest and most influential frameworks for explaining how firms choose between outsourcing and internalizing production. Williamson (1981; 1991) argues that when assets—tools, equipment, or processes used in production—are not specific to any one buyer or supplier, meaning either side can easily switch partners, firms will tend to rely on the open market to reduce costs. However, when production involves highly specific assets, long-term commitments, or difficult-to-monitor quality, the costs of switching partners rise. Under these conditions, firms are more likely to internalize production through hierarchical control, or enter hybrid relationships such as long-term contracts (Williamson, 1981). This shift toward internalization or stable partnerships gives the firm more control over the production process, including full access to information and better coordination when resolving disputes. In his 1991 work, Williamson explains that in industries with strong legal protections and clear property rights, the decision of whether to ”make or buy” typically results in one of three inter-firm relationships: open market transactions (market), full internal control (hierarchy), or a mix of both (hybrid).

While Williamson recognizes that hybrid relationships can exist, his attitude toward their long-term stability is not optimistic. In his view, these relationships are constantly at risk because the decision makers running firms face two key limitations: bounded rationality and opportunism. Because of these psychological limitations, it is impossible to write contracts that cover every situation, and enforcing them depends on trust, which is especially fragile. As a result, Williamson argues that hybrid relationships are naturally fragile and will tend to break down unless strong safeguards are in place.

However, this view overlooks the fact that these relationships are not just economic exchanges but also social ones, which are shaped and stabilized by social structures. As Blau (1964) argues, repeated social exchanges—which depend on informal understandings, trust, and long-term commitments—generate social structures. These structures, in turn, influence the action of exchanging by providing certain options for how it is carried out, while constraining other possible choices (Giddens, 1984). Johnson (2014) further illustrates this by arguing that among the available options, some become “the path of the least resistance”—the easiest, most expected ways to act in a given situation. Firms tend to follow these paths not because they are forced to, but because they are built into the system and feel natural or obvious. By choosing these paths, their actions in turn reshape and reinforce the very structure that guides them. In summary, the persistence of inter-firm relationships are not just the result of individual decisions, but are continuously stabilized by broader structural forces.

While structure is essential for explaining the persistence of inter-firm relationships, most of the existing literature on supply chains and outsourcing stops short of theorizing structure itself. Instead, what is commonly offered are observable patterns or mechanisms at the micro level, such as how firms with certain capabilities dominate value chains (Gereffi, 1994; Gereffi et al., 2005), how government policies influence firm strategies (Henderson et al., 2002; Miller, 2022; De Marchi and Alford, 2022), and how network positions and triadic closure shape trust and cooperation (Coe & Yeung, 2015; Coleman, 1988; Granovetter, 1985). Although these studies reveal important dynamics in firm behavior and interaction, they do not show how such patterns add up to stable, system-wide structures.

Therefore, to bridge this gap between micro-level observation and macro-level explanation, I revisit the main strands of existing literature. My goal is to systematically categorize the key mechanisms identified in these studies into distinctive types of structure and offer operationalizable definitions based on their micro-level insights. Following what GPN 2.0 theory (Coe & Yeung, 2015) advocates, I organize the existing literature into three main categories—governance, institutional, and network structures. These categories provide a framework for interpreting how previous research has explained the persistence of inter-firm relationships from different perspectives, and set the stage for qualitative conceptualization and empirical testing on network data.

2.1 Governance Structure

While Williamson's (1981; 1991) framework focuses on how firms respond to risk and asset specificity, it assumes that all firms have equal flexibility to switch suppliers or internalize production. However, this assumption does not always hold in complex global industries. Gereffi (1994) argued that firms with scaled access to markets or control over technologies with high entry barriers hold more power and influence in the supply chain, making them difficult or impossible to replace. So when relying solely on market trading becomes too risky, and internalizing production is not feasible, firms tend to establish closer and more coordinated relationships with their regular trade partners. These relationships—often based on repeated transactions, trust, or technical interdependence—allow firms to secure their buyer-supplier ties without full ownership or integration (Gereffi 2005). Furthermore, governance structure also includes the principle of homophily—the tendency for firms to form ties with others that share similar characteristics, such as organizational size, technological capability, or institutional background (McPherson et al., 2001). This means that both inter-frim differences and similarities influence which firms are likely to form and sustain hybrid relationships. In practice, the focus of governance structure is not just on which firms possess certain attributes or capacities, but also on how differences or similarities in those attributes between two firms affect the likelihood and stability of their connection.

2.2 Institutional Structure

The concept of institutional structure is deeply embedded in the Global Production Networks (GPN) literature, from its original formulation (Henderson et al., 2002) to its more recent theoretical refinements (Coe & Yeung, 2015). This series of work has consistently emphasized the multi-actor nature of the global economy. GPN 1.0 (Henderson et al., 2002) argues that the organization of global industries cannot be explained by firm strategies or market forces alone, but are instead deeply embedded in the social and political contexts of specific territories. GPN 2.0 (Coe & Yeung, 2015) builds on this by more systematically analyzing how these non-firm actors, especially states, both enable and constrain firms. Despite the growing influence of international and non-state actors, the practical reality remains that state power is still most clearly observed and measured. Therefore, for my purpose of analysis, it is necessary to focus on states and their policy environments as the primary units shaping institutional structure.

State support is crucial to the growth of the high-tech industry, especially in the initial phases, by providing protection and directing resources (Miller, 2022; Goldberg et al., 2024; Whetsell et al., 2020). Such support is widely adopted by countries at different stages of development—those at the leading edge of technology (Taiwan and South Korea), those seeking to advance their position (the United States, China, and Japan), and those attempting to enter the industry (India) (Goldberg et al., 2024). These state-led interventions take many forms. De Marchi and Alford (2022) offered a systematic typology of how states intervene in global production, arguing that states play four distinct roles—facilitator, regulator, producer, and buyer—each shaping firm behavior in different ways. As facilitators, states may provide R&D subsidies or tax incentives; as regulators, they may enforce labor or quality standards; as producers, they may operate state-owned enterprises; and as buyers, they may use public procurement to shape domestic industrial development. However, beyond the general support provided through these four roles, more specialized supports like international technology transfer and state-provided platforms were more decisive for securing long-term inter-firm collaboration.

Historically, the semiconductor industry offers a clear example of this dynamic. In the United States, massive state support—such as funding from the Department of Defense and DARPA—played a pivotal role in launching companies like Fairchild Semiconductor and Texas Instruments, while building an ecosystem that connected firms and diffused knowledge. Similarly, governments in East Asia, especially Taiwan, actively recruited American engineers from major U.S. firms and supported technology transfer to local institutions such as the Industrial Technology Research Institute (ITRI). Then, ITRI helped set up a series of private companies, offering production technology, and securing foreign and domestic customers for them . This state-led approach enabled the rapid development of a localized chip manufacturing community while securing foreign connections, eventually supporting the rise of global leaders like TSMC (Miller, 2022). This means that both the specific interventions and the state environment as a whole have concrete effects on what most firms specialize in, how they achieve technological upgrading, and most importantly, who they are collaborating with in the international market. Therefore, the focus of institutional structures should be on the state environment in which a firm is embedded—typically marked by its headquarters location—and the specific production role it specializes in. Examining whether two firms share the same state environment or similar specialized role within the global supply chain network can help demonstrate how similarities or differences in institutional context affect the likelihood and stability of their long-term connections.

2.3 Network Structure

GPN theories also stress the importance of network structure (Coe & Yeung, 2015), especially how it constrains and enables the flow of resources and information between members of the network. While the previous sections focused on how structural factors shape inter-firm relationship outcomes, these outcomes—when aggregated across many firms—constitute the broader network structure itself. A network is not merely the accumulation of relationships. Members of a network use it to access information about other members' reputations, allowing reputational consequences to travel quickly and expectations to be enforced. The explanation for the persistence of hybrid relationships would therefore be incomplete without accounting for the role of the network as both context and outcome.

Both Williamson (1981, 1991) and Gereffi et al. (2005) conceptualized supply chains as linear sequences, in which each firm interacts with only one or two adjacent partners. However, Yeung and Coe (2015) argue that linear-shaped production processes are an oversimplification of a complicated global economy. They propose that by modeling all inter-firm relationships as a web, the networked structure of global production can better reveal the complexity of how firms in different roles and locations are connected across the supply chain. This shift from a linear to a networked understanding of supply chains also highlights the different factors that sustain long-term relationships. While Gereffi et al. (2005) emphasized that some lead firms are irreplaceable and can govern global value chains through long-term contracting, network theorists (Coleman, 1988; Granovetter, 1985; Podolny and Page, 1998; Jarillo, 1988; Thorelli, 1986) argue that long-term relationships can also be sustained through trust, reputation, and interdependence. These mechanisms suppress opportunism even in the absence of formal integration, providing theoretical grounding to conceptualize inter-firm relationships as stable network ties: if one firm trusts another enough to list it as a major or exclusive supplier, that relationship can be understood as long-term, even without a written agreement.

Furthermore, a critical insight from network theory is that the stability and persistence of inter-firm relationships cannot be fully understood by looking only at dyadic connections. Instead, higher-order structures—especially triads—must also be considered. Triadic closure is the property that if individual A is closely connected to individual B, and B is closely connected to individual C, then there is an increased likelihood that A and C will also form a direct relationship. Triadic closure captures the underlying social power of trust, reputation, social capital, and risk mitigation. Therefore, when two firms share a common partner, they have indirect pathways for information and verification, which reduces uncertainty and encourages further cooperation (Granovetter, 1985; Coleman, 1988).

Network researchers have demonstrated that real-world networks—including global production and supply chain networks—are highly non-random because of triadic closure effects (Wasserman & Faust, 1994). The more closed triads there are in a network, the less likely new connections will form between individuals who don't already have a mutual acquaintance. This concentration of ties within triads reinforces clustering, making the network more stable and less prone to random new connections. Therefore, the focus of the network structure should be on triadic closure. Examining the prevalence and role of triads helps demonstrate how network structure affects the likelihood and stability of long-term connections between firms, beyond what can be explained by governance or institutional structures alone.

2.4 From Theory to Practice

The literature on governance, institutional, and network structures provides essential frameworks for understanding why hybrid relationships persist. However, the 2020-2023 semiconductor shortage presents a puzzle that these theories, in isolation, cannot fully resolve. The global supply chain network—constituted of numerous hybrid relationships—was maintained even when the crisis created strong incentives for firms to internalize production while new state policies actively loosened the structural constraints to do so. For example, R&D subsidies reduced market access and technology asymmetries between firms (governance structure), and new regulations eased the process of relocating across borders (institutional structure). The persistence of the status quo despite these shifts suggests that the structure of the network itself plays a crucial, independent role in holding these relationships together.

To empirically test this argument, the following section serves as a crucial bridge connecting the aforementioned theoretical frameworks to concrete measurements. Each structure is operationalized into observable and quantifiable variables to build a model capable of assessing their relative influence on the persistence of a hybrid relationship network.

3 Data and Methods

To examine how relational and institutional structure influence long-term supplier relationship outcomes, I organize them into two sets of explanatory variables. I then construct inter-firm ties using buyer-supplier relationships, which serve as the network outcome that my analysis seeks to explain. I operationalize each of these elements—explanatory variables and network ties—using publicly available firm-level data.

3.1 Operationalization of Core Concepts

3.1.1 Operationalization of Governance Structure

To measure the differences in firm capacity that define governance structure, I use two key financial indicators: market capitalization and research and development (R&D) spending. These serve as proxies for the two sources of firm capacity-led asymmetric power identified by Gereffi (1994) in the literature review.

- **Market Capitalization:** This numerical indicator, representing the total value of a company's shares, is used to capture a firm's scaled market access and its overall influence within the supply chain. As established previously, firms with significant advantages in market reach hold asymmetric power and are more difficult for their partners to replace.
- **R&D Spending:** This numerical indicator, representing a firm's investment in innovation, is used to measure its control over proprietary production technologies. As discussed in the literature, control over technology protected by high entry barriers is a primary source of influence and creates dependencies within the supply chain.

3.1.2 Operationalization of Institutional Structure

To capture the similarity in institutional embeddedness that shapes long-term relationships, I measure two key indicators. These proxies represent a firm's dependencies on other firms and its embeddedness in a particular state environment.

- **Supply Chain Role:** A firm's designated role in the production process is used to measure inter-firm dependencies. In this study, firms are categorized based on their official industry sub-category: those listed as "Semiconductors" or "Semiconductor Equipment & Testing" are classified as 'Chip Makers,' while all others in the network are classified as 'Chip Users.' This binary distinction is made to simplify the analysis by focusing on the fundamental division between the producers of core semiconductor technology and the consumers of that technology. As established in the literature, such specialization locks firms into specific long-term partnerships and often reflects the influence of state industrial planning (Gereffi, 2005; Miller, 2022).
- **Headquarters Location:** The country where a firm is headquartered is used to measure territorial embeddedness. This proxy reflects the fact that firms within the same national system are exposed to similar forms of state support, regulatory environments, and historical path dependencies (Miller, 2022; De Marchi and Alford, 2022).

3.1.3 Operationalization of Network Ties

In this study, network ties are operationalized using publicly disclosed, long-term buyer-supplier relationships. This approach is grounded in network theory, which proposes that a formal, public acknowledgment of a major trading partner reflects a stable relationship built on trust, reputation, and interdependence (Granovetter, 1985; Coleman, 1988; Knoke, 1993). This proxy was selected over other measures, such as interlocking directorates or joint ventures, due to its superior data availability and its relevance for capturing durable, meaningful ties in a global industrial context.

To identify these relationships, I used data compiled by the London Stock Exchange Group (LSEG). LSEG systematically aggregates and cross-references corporate disclosures from sources like U.S. Securities and Exchange Commission (SEC) filings and verified news reports to map firm value chains. To ensure a standard of reliability, only buyer-supplier relationships with an LSEG-assigned confidence score of 50% or higher are included in this study's dataset.

Although buyer-supplier relationships are inherently directional (from supplier to buyer), the ties in this network are treated as undirected. This decision was made because the primary focus of the analysis is on the existence and persistence of a stable relationship between two firms, not on the specific flow of resources or payments between them. This approach simplifies the analysis and is better suited for modeling structural effects like triadic closure.

3.1.4 Operationalization of Network Structure

Lastly, with network ties constructed, network structure is captured by measuring the prevalence of triadic closure. As established in the literature review, network characteristic is a key mechanism for generating the trust and reputational effects that stabilize relationships within a network (Granovetter, 1985; Coleman, 1988).

I measured this structural tendency using the Geometrically Weighted Edgewise Shared Partner (GWESP) statistic in the Exponential Random Graph Model (ERGM) (Luke, 2015). Due to computational limitations associated with a large network, GWESP is used as the sole indicator of higher-order triadic structures, and its decay parameter (α) is fixed at 0.25.

Core Concepts Measurements Used In This Study

Theoretical Concept	Measure	Definition
Governance Structure	Market Capitalization	The total market value of a company's shares, used as a proxy for a firm's scaled market access and overall influence.
Governance Structure	R&D Expenses	A firm's total annual investment in innovation, used as a proxy for its control over proprietary technologies with high entry barriers.
Institutional Structure	Supply Chain Role	A categorical classification of a firm as either a 'Chip Maker' or 'Chip User' based on its industry sub-category, used to measure dependencies arising from specialization.
Institutional Structure	Headquarters' country	The country where a firm is headquartered, used as a proxy for its embeddedness within a specific national regulatory and state-support environment.
Network Ties	Buyer-Supplier Relationship	An undirected tie representing a stable supplier-buyer relationship, identified through public disclosures, and included only if it has an LSEG-assigned confidence score of 50% or higher.
Network Structure	Prevalence of Triads	A statistical term (GWESP) in an ERGM that measures the network's tendency for triadic closure (α=0.25), used as a proxy for structural effects like trust and information flow.

Table 1: Core Concepts Measurements Used in This Study

3.2 Data Collection

I started my collection process with 25 firms subsidized by the U.S. CHIPS Act (SIA, 2024). The CHIPS Act—short for Creating Helpful Incentives to Produce Semiconductors—was passed by the U.S. government in 2022 to strengthen the domestic semiconductor supply chain and reduce reliance on foreign production. Companies that received CHIPS Act subsidies were selected by the U.S. Department of Commerce based on their strategic role in chip manufacturing, packaging, and research. These firms serve as a strong starting point because their activities are influenced by firm capabilities and structural constraints—making them ideal cases to study how network ties and firm decisions interact.

Based on the subsidized list semiconductor supply chain (SIA, 2022), the system boundaries—with publicly traded firms as units of analysis—would be specified as the following: First, a preliminary list of key-suppliers would be defined as the companies subsidized by the U.S. CHIPS Act, for their significance in the industry had attracted direct state involvement (SIA, 2024). Their RIC, which is a unique identifier commonly used in stock market and business databases to identify companies when company names were recorded in various forms, will be matched to each firm with a Python API collector with Refinitiv library package.

Once I completed the preliminary list of names, I applied a snowball sampling technique. I added additional firms based on the buyer-supplier relationships of the existing firms until I reached a sufficient number of firms. This method was bidirectional, as I added both the buyers and the suppliers of every existing firm. I collected buyer-supplier relationship data from LSEG (previously Refinitiv and Thomson ONE), a database with records on supplier and buyer relations. I then filtered the inter-firm trade data by selecting only those with a confidence score above 50% in the legitimacy of the relationship to improve accuracy.

For each firm included in the final dataset, I collect four main attributes: market capitalization (to capture firm size as reflected in financial markets), R&D spending (to capture innovation effort), headquarters country (to reflect geographical base), and industrial subcategory. The sub-category is based on the Refinitiv Business Classification (TRBC), which categorizes firms into a five-tier industry hierarchy. Each firm is assigned an industry subcategory based on its main line of business as reported in global financial disclosures. This classification helps clarify whether a firm operates in areas like chip design, foundries, electronic components, or testing and packaging, which are important distinctions within the semiconductor supply chain. The dataset I collected includes 31 industrial sub-categories, but to simplify the analysis and focus on the core dynamics of the semiconductor supply chain, I group firms into two roles: chip makers (if they belong to either the "Semiconductors" or "Semiconductor Equipment & Testing" categories), and chip users (for all other categories). The data, sources, and tools used for this research are summarized below:

- **Dataset:** A proprietary network dataset of publicly traded firms in the global semiconductor industry. The data was collected on May 13, 2024. Due to the commercial nature of the source data, the dataset itself cannot be publicly disclosed.

- **Primary Data Source:** The LSEG Refinitiv Eikon Database was used to collect all firm-level financial data and to identify buyer-supplier relationships.
- **Tools & Replication:**
  - Self-made Python algorithms utilizing the Refinitiv Eikon Data API were used for data collection and processing.
  - All code used for data cleaning, network analysis, and statistical modeling is available for replication at the following GitHub repository: https://github.com/Cosmo280/organizational-network-analysis.git

3.3 Methodology

To test how firm attributes and network structure influence the persistence of hybrid relationships, I employ a two-step modeling approach. First, I use the Quadratic Assignment Procedure (QAP) to test which firm-level characteristics are significantly correlated with the presence of a tie, while controlling for the inherent dependencies in network data. Second, I use Exponential Random Graph Models (ERGM) to test whether the network's own structural properties, such as the tendency for triadic closure, have an independent effect on tie formation beyond what can be explained by firm attributes alone.

3.3.1 Quadratic Assignment Procedure (QAP)

Purpose and Justification

The first step is to determine which firm characteristics—such as market capitalization size, R&D spending, supply chain role, and country—are significantly associated with the formation of a long-term supplier tie. A standard regression model—like OLS or logistic regression—is not appropriate for this task. Standard models assume that each observation is independent, but in a network, observations are inherently interdependent; a tie between firm A and B may be influenced by their ties to firm C. As Krackhardt (1987) explains, this interdependence violates a core assumption of standard statistical tests, making them inapplicable for network data.

The Quadratic Assignment Procedure (QAP) is a non-parametric, permutation-based test designed specifically to handle this issue (Krackhardt, 1988). Instead of assuming independence, QAP evaluates the correlation between two matrices (e.g., a network matrix and an attribute-similarity matrix) by comparing the observed correlation to a distribution of correlations generated from thousands of random permutations of the original network.

This process determines whether the observed relationship between firm attributes and network ties is statistically significant or merely the result of random chance or the network's underlying structure.

QAP Regression Model

Model 1: Governance Structure (Numerical Variables)

This model tests whether the magnitude of difference in firms' financial capacities is significantly correlated with the presence of a supplier tie. It is implemented using the netlm() function in R.

$$\text{NetworkTies}_{ij} = \beta_0 + \beta_1(\text{Diff}_{\text{MarketCap}_{ij}}) + \beta_2(\text{Diff}_{\text{R\&D}_{ij}}) + \epsilon$$

Model 2: Institutional Structure (Categorical Variables) This model uses logistic regression to test whether firms sharing the same institutional context are more likely to have a supplier tie. It is implemented using the netlogit() function in R.

$$\text{NetworkTies}_{ij} = \beta_0 + \beta_1(\text{Same\_Role}_{ij}) + \beta_2(\text{Same\_Country}_{ij}) + \epsilon$$

Where:

- $NetworkTies_{ij}$ is the dependent variable matrix. It has a value of 1 if a tie exists between firm i and firm j, and 0 otherwise.
- $Diff_{MarketCap_{ij}}$ and $Diff_{R\&D_{ij}}$ are numerical matrices. They represent the absolute difference in market capitalization and R&D spending between firms i and j.
- $Same\_Role_{ij}$ and $Same\_Country_{ij}$ are binary matrices. Their value is 1 if firms i and j share the same attribute (e.g., role or country), and 0 otherwise.
- The β coefficients represent the strength and direction of the associations. Their statistical significance is determined by a Quadratic Assignment Procedure (QAP) permutation test.

3.3.2 Exponential Random Graph Models (ERGM)

Purpose and Justification

After QAP identifies which firm attributes are significant predictors of ties, I use Exponential Random Graph Models (ERGMs) to answer a deeper question: Does the structure of the network itself exert an independent influence on tie formation? ERGMs—also known as p* models—are statistical models that allow me to understand how local network patterns, or "configurations," contribute to the overall structure of the observed network (Kuskova & Wasserman, 2021; Robins et al., 2007).

While QAP is excellent for testing the role of firm-level attributes, ERGMs are designed to simultaneously model both these attributes and the network's self-organizing tendencies, which I focused on triadic closure in this study. This is crucial for my research question, as it allows me to statistically distinguish between firms forming ties because they are similar (homophily) versus because of their position within the network (Robins et al., 2007).

ERGM Model

An ERGM estimates the probability of observing a specific network configuration (y) as a function of a set of network statistics. The general form of the model is:

$$\Pr(\mathbf{Y} = \mathbf{y}) = \left(\frac{1}{\kappa}\right) \exp\left\{\sum_{A} \eta_A g_A(\mathbf{y})\right\}$$

Where:

- $P(Y = y)$ represents the probability of observing a specific network configuration y.
- κ is a normalizing constant, ensuring that the sum of all probabilities equals 1.
- The summation is performed over a set of network configurations, which could include elements like edges, node attributes, or triangles.
- $g_A(y)$ is the network statistic for a given configuration, such as the total count of edges or triangles in the network.
- η_A is the parameter estimate. It quantifies the strength and direction of the effect that a specific configuration has on the likelihood of a connection or "tie" forming.

Model Building

I build the ERGM in the following steps to isolate the effects of network structure and firm attributes.

1. **Null Model (Baseline)**: I begin with a baseline model that includes only an `edges()` term. This term represents the fundamental probability of a tie forming at random within the network, which is comparable to the intercept in a conventional regression analysis (Luke, 2015).

2. **Structural Model (Model 3)**: To this model, I incorporate the `gwesp()` (Geometrically Weighted Edgewise Shared Partner) term. This term is used to measure the tendency for **triadic closure**. I have chosen to use only this term with a low decay parameter (0.25) as it provides a balance between theoretical complexity and computational feasibility, which serves as a practical compromise when analyzing complex networks (Kuskova & Wasserman, 2021; Luke, 2015).

3. **Full Model (Model 4)**: Lastly, I include the significant firm attributes that were identified through the QAP analysis as control variables. Categorical variables, such as role and country, are integrated using `nodematch()` terms. Numerical variables, like market capitalization and R&D spending, are added using `absdiff()` terms (Luke, 2015).

By comparing these nested models, ERGM allows me to determine if the network structure (GWESP) remains a significant predictor even after controlling for firm similarity. This directly tests whether the persistence of supplier relationships is driven by firm attributes, the architecture of the network itself, or a combination of both.

4 Results

4.1 Descriptive Analysis

4.1.1 Governance Structure

To explore whether differences in firm capacity are correlated with the probability of forming a tie, I visualized the network with node sizes representing Market Capitalization and R&D Expenses across all percentile groups, which would later be divided into top 25%, middle 50%, and bottom 25%.

Table 2 displays the network with all percentile groups using Market Capitalization for all firms, while Table 3 does the same using R&D Expenses. In both visualizations, there is no recognizable pattern indicating that firms with similar or very different levels of resources are more likely to be connected. Ties appear scattered regardless of resource level.

To examine whether resource concentration at the upper end might influence network structure, I then focused on firms in the top 25% of Market Capitalization (see Appendix 1) and R&D Expenses (see Appendix 4). Once again, no clear pattern of tie formation emerges. Highly resourced firms do not appear to cluster together through direct ties, nor are they locking in firms with very little resources.

For further clarity, I repeated the analysis for the middle 50% and bottom 25% of firms by Market Capitalization (see Appendix 2 and 3) and R&D Expenses (see Appendix 4 and 5). In all these subgroups, ties are generally scarce, and there are still no visible patterns linking relational differences in resources to tie formation.

In summary, across every percentile group, whether among the largest, middle, or smallest firms, the network visualizations reveal no systematic association between numerical differences in Market Capitalization or R&D Expenses and the presence or absence of ties. This initial exploration suggests that neither extreme similarity nor large differences in firm resources are driving the formation of inter-firm relationships in the observed network, highlighting the need for more formal statistical testing in subsequent analysis.

4.1.2 Institutional Structure

Next, I examine whether similarity or differences in structural constraints—specifically, headquarters (HQ) country and supply chain role—are potentially correlated with the presence of network ties. Appendix 7 presents a contingency table of HQ country by supply chain role, showing that while the split between chip makers and chip users is nearly even, firm headquarters are highly concentrated in just a few countries. To understand whether this concentration creates homophily effects, I proceed to visualize the network by these structural attributes.

Table 4 shows a highly visible clustering pattern based on supply chain role: chip users tend to form ties with other chip users, and chip makers with other chip makers, indicating a strong homophily effect in role specialization. Table 5 visualizes the network by HQ country and reveals clear clustering among U.S. firms, suggesting that state proximity or shared institutional environments may play a role in tie formation. To test how far this country-based homophily effect extends, Appendix 8 removes all U.S. firms and finds that new, similarly strong clustering patterns emerge among Taiwanese, Japanese, and South Korean firms. Appendix 9, which further removes Taiwanese, Japanese, and Korean firms, shows that clustering based on country largely disappears, implying that institutional homophily is driven by dominant countries in the dataset.

In summary, these descriptive results provide strong evidence for homophily in institutional structure—both in supply chain role and HQ country—as a key factor shaping tie formation. This leads directly to the following hypothesis:

- **H1: Firms that share similarity in institutional structure have a higher probability of forming a tie compared to firms that share similarity in relational structure.**

4.1.3 Network Structure

Next, I examine whether the prevalence of different triad types is correlated with the presence and persistence of network ties. Table 6 reports the results of the undirected triadic census, summarizing the frequency of each of the four possible undirected triad types: 003 (no ties), 102 (one bidirectional tie), 201 (open triad with two bidirectional ties), and 300 (closed triad) (Wasserman, 1994). As expected in a sparse network, triads with no ties (003) are by far the most common, with more than 500,000 instances observed. The 102 triad, featuring a single tie between two firms, appears approximately 60,000 times, while the 201 triad—an open triad with two ties and one possible tie missing—appears about 5,000 times. In contrast, the fully closed triad (300), which would represent a tightly clustered group of three mutually connected firms, is nearly absent from the data.

These results suggest that while most firms are isolated or form only simple pairwise connections, a notable portion of the network consists of open triads (201), which are one step away from forming closed triangles. The scarcity of fully closed triads (300) is consistent with the overall sparseness of the network, but the presence of a substantial number of open triads suggests that the potential for triadic closure is significant. This pattern provides an initial insight to network structure's role in stabilizing or promoting the persistence of inter-firm relationships. Based on these observations, I propose the following hypothesis:

- **H2: Firms that share a common partner have a higher probability of forming a tie, even after controlling for institutional structure similarity.**

The descriptive analysis revealed a clear contrast: while firm-level governance attributes showed no visible patterns, institutional and network structures provided strong visual evidence for homophily (H1) and a potential for triadic closure (H2). However, these visual findings are only suggestive and require formal statistical testing to rule out spurious correlations and assess the relative importance of each effect.

Therefore, the following section will use Quadratic Assignment Procedure (QAP) and Exponential Random Graph Models (ERGM) to rigorously test these hypotheses.

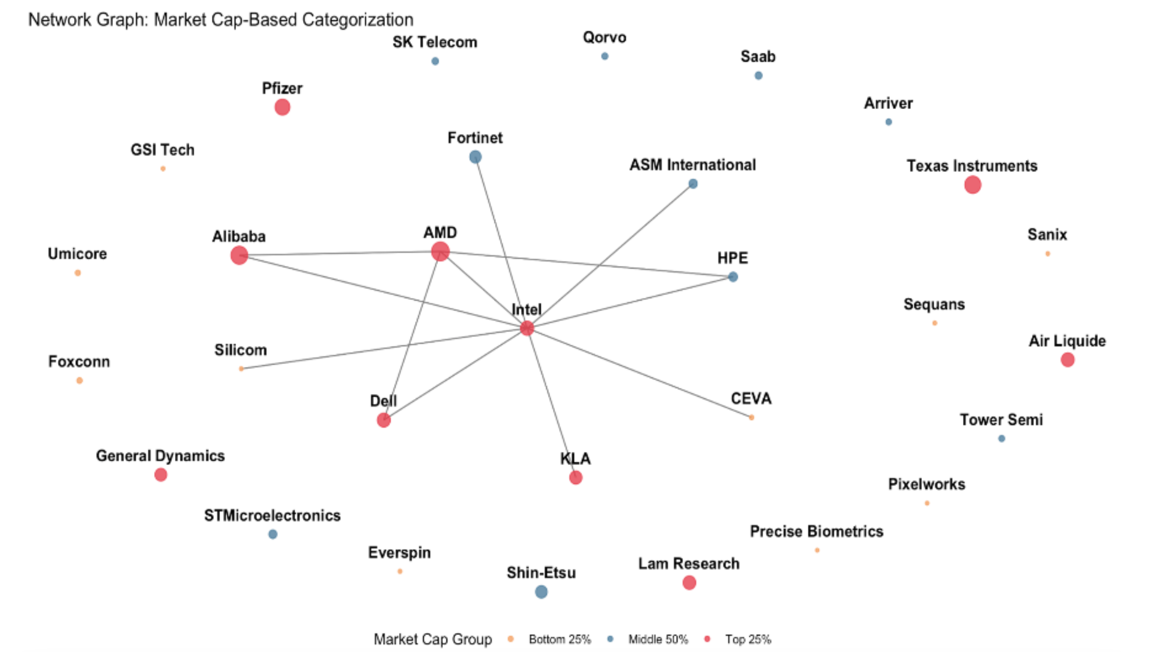

Table 2: Network Visualization of Market Capitalization Value on All Percentile

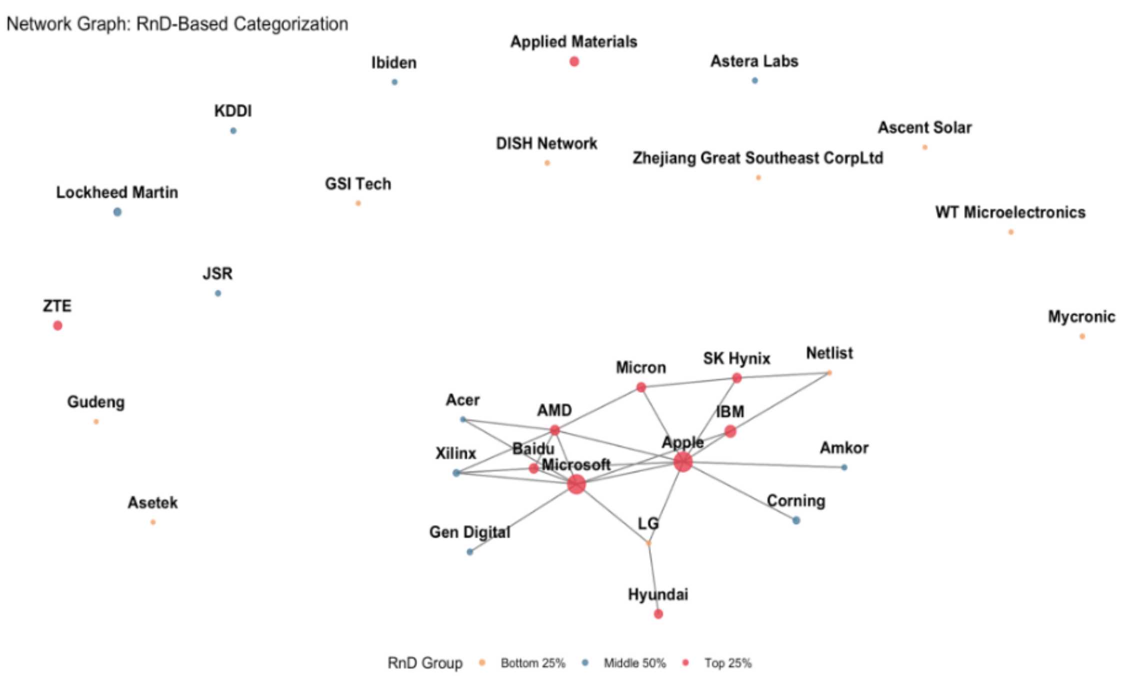

Table 3: Network Visualization of R&D Expenses on All Percentile

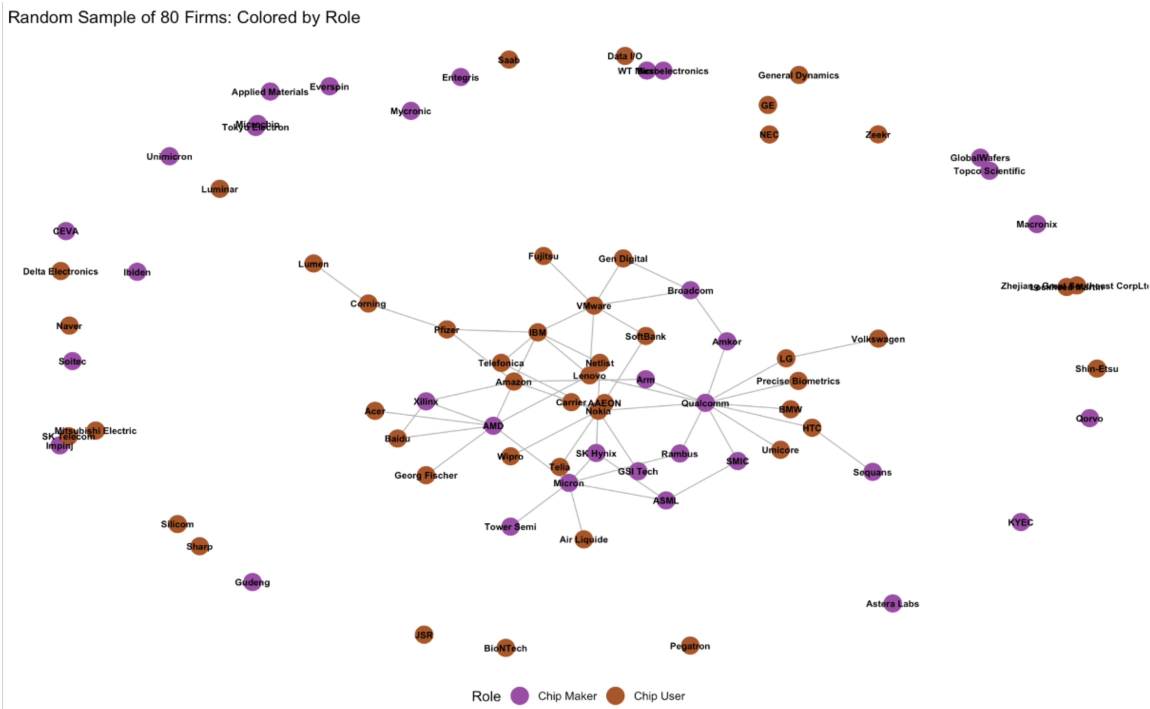

Table 4: Network Visualization of Supply Chain Role

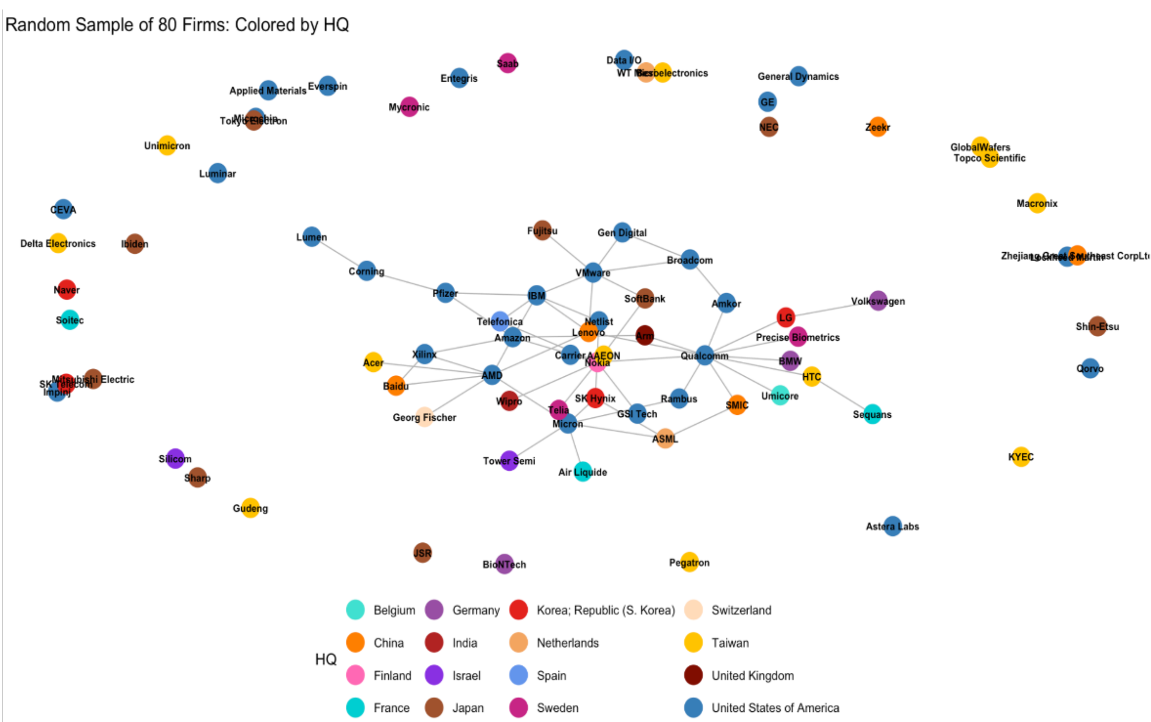

Table 5: Network Visualization of HQ Country

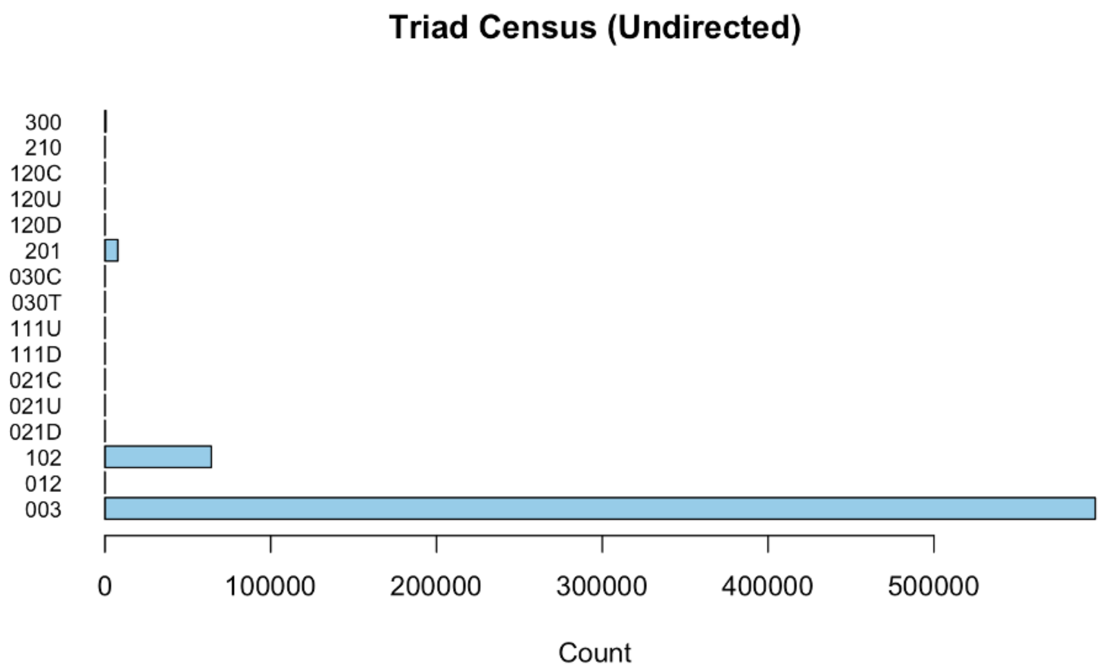

Table 6: Undirected Triadic Census—003 (no ties), 102 (one bidirectional tie), and 201 (open triad with two bidirectional ties)

4.2 Statistical Modeling and Hypothesis Testing

The statistical analysis was conducted in two main stages. First, QAP models were used to test Hypothesis 1 by assessing the relative importance of governance and institutional attributes. Second, the significant institutional attributes were carried forward into a series of nested ERGM models to test Hypothesis 2 and evaluate the independent effect of network structure. For all QAP and ERGM analyses, statistical significance is determined using two-tailed tests, with a significance level (α) set at 0.05.

4.2.1 QAP Results: The dominance of Institutional Structure (H1)

The results of the QAP analysis, summarized in Table 7, provide strong support for Hypothesis 1. The model for governance structure, which tested the effect of differences in market capitalization and R&D spending, was not a meaningful predictor of inter-firm ties, explaining very little of the variation in the network (Adjusted $R^2 \approx 0.05$). In drastic contrast, the model for institutional structure, which tested for similarity in supply chain role and headquarters country, was a powerful predictor of tie formation, with a very high Pseudo-R^2 (≈ 0.76) and classification accuracy.

This finding clearly indicates that the institutional context in which firms are embedded is a far more significant driver of relationship formation than their individual firm capacities. Due to the highest correlation coefficient and the higher clustering effect suggested in the descriptive analysis, Supply Chain Role was selected as the sole institutional control variable for the subsequent ERGM analysis. The detailed outputs for the QAP models can be found in Appendices 10, 11, and 12.

4.2.2 ERGM Results: The Independent Effect of Network Structure (H2)

The results of the nested ERGM analysis, summarized in Table 8, provide strong support for Hypothesis 2. The analysis proceeded in steps, starting from a null model (see Appendix 14) and progressively adding the term for institutional structure control.

The key finding comes from the final full model (Model 4), which included terms for both triadic closure (GWESP) and institutional homophily (Supply Chain Role). As shown in Table 8, the effect of triadic closure remained large, positive, and highly significant, with a coefficient substantially greater than that for role homophily. This demonstrates that the network's internal tendency to form triangles is a powerful and independent predictor of why relationships persist, even after controlling for the significant effect of institutional similarity. Further model diagnostics, including goodness-of-fit tests and network simulations, confirmed that this final model is stable and provides an excellent representation of the observed network's key features (see Appendices 20-26 for details).

Results of QAP

	Model 1 (Netlm)		Model 2 (Netlogit)	
Mechanism	Est	Sig	Est	Sig
Constant	0.0223		-3.674	***
Market Cap	4.93×10^{-14}	***		
R&D	2.31×10^{-12}	*		
Supply Chain Role			0.555	***
HQ Country			0.666	**
Adjusted R^2	0.052			
Adjusted Pseudo R^2			0.513	

*Notes: Two-Tailed p-value reported; *p-value < 0.05, **p-value < 0.01, ***p-value < 0.001; Replications: 1000 runs*

Table 7: Results of QAP

Results of ERGM

	Baseline			Model 3			Model 4		
Mechanism	Est.	S.E.	Sig.	Est.	S.E.	Sig.	Est.	S.E.	Sig.
Edges	-3.161	0.045	***	-5.109	0.130	***	-5.318	0.132	***
Transitivity[1]				1.735	0.106	***	1.726	0.103	***
Supply Chain Role							0.375	0.071	***

*Notes: *p-value < 0.05, **p-value < 0.01, ***p-value < 0.001.*
1. Transitivity is calculated with gewsp (decay = 0.25, fixed = TRUE).

Table 8: Results of ERGM

5 Conclusion

I set out to explain why firms continued to rely on outsourced semiconductor production after the 2020–2023 chip shortage, despite a major shift in cost and risk conditions. By combining descriptive statistics, QAP regression, and ERGM modeling, I tested whether governance, institutional, or network structures better explain the formation of hybrid relationships in the global semiconductor supply chain network.

The descriptive analysis revealed that there was no clear pattern linking governance structure measures—such as market capitalization or R&D spending—to the presence of hybrid relationships. Whether firms were large or small, or spent more or less on R&D, did not appear to determine whether they would form or maintain ties with each other. However, when I examined institutional structures—specifically, supply chain role and headquarter country—clear clustering patterns emerged. Firms with the same role or based in the same country were much more likely to form ties, indicating that institutional similarity plays a strong role in shaping these networks.

The QAP regression results confirmed and quantified these patterns. Differences in firm resources were statistically insignificant predictors of tie formation, with very low explanatory power. In contrast, institutional variables—particularly sharing the same supply chain role or being headquartered in the same country—were both highly significant and had much stronger effects on the likelihood of a tie. The QAP model showed that institutional structure, not governance structure, accounts for most of the variation in the network ties.

Using ERGM modeling, I found that triadic closure—the tendency for firms that share partners to form new ties—played an independent and highly significant role in shaping network structure. Firms with shared partners were much more likely to form additional ties, even after accounting for similarities in supply chain role. This confirms that network dynamics could independently and more significantly drive supply chain tie formation within a network.

Taken together, these results suggest that global supply chain networks themselves exhibit partial autonomy. While institutional structures continue to shape who connects with whom, the network itself—through mechanisms like triadic closure—has become a powerful force that locks firms into path-dependent relationships. Outsourcing decisions are no longer based solely on transaction cost calculations, differences in firm capabilities, or state embeddedness, but are increasingly shaped by the existing structure of the network.

These findings carry important implications. For policymakers aiming to build national supply chain resilience or reconfigure global production through efforts like the CHIPS Act or the European Chips Act, it is not enough to support individual firms through subsidies or innovation incentives. Such tools may boost a firm's internal capabilities, but they are unlikely to shift that firm's position within the larger network unless the surrounding network topology also changes. Strategic industrial policy must account for the inertia of legacy relationships and the cumulative interdependencies that reinforce them.

For researchers, my study highlights the importance of moving beyond firm- or state-level analysis to consider how network structure itself acts as an independent force. Future research should explore how relational patterns and embedded constraints jointly shape global production—especially in industries where coordination, trust, and technical interdependence are just as influential as market logic.

6 Discussion and Limitations

While I provide strong empirical evidence for the partial autonomy of network structure in shaping supply chain behavior, this study has several limitations that should be acknowledged.

First, my analysis is based on a cross-sectional dataset—a static snapshot of the supply chain at one point in time. As a result, I cannot observe how firms move into or out of central positions, or how network ties evolve in response to policy shocks, geopolitical events, or technological disruptions. Without temporal data, I cannot determine whether the decoupling between firm capabilities and network structure is a stable feature or a contingent outcome of the post-pandemic realignment. A longitudinal dataset would allow future researchers to examine how structural inertia interacts with shifting institutional environments over time.

Second, I rely on standardized and observable proxies for core concepts. While market capitalization and R&D expenses are useful indicators of firm capability, they cannot capture internal decision-making logic, political maneuvering, or informal forms of power. Similarly, although degree centrality serves as a reasonable proxy for network position, it does not capture more nuanced dimensions such as brokerage, betweenness, or multiplexity—each of which may play a critical role in strategic influence. Future work could incorporate more complex centrality measures or layer additional relational data, such as board interlocks or joint ventures.

Third, although ERGM allows me to statistically model the structural logic of tie formation, it cannot account for micro-political dynamics such as rent-seeking, informal alliances, or symbolic signaling—practices that often shape inter-organizational behavior beneath the surface of observed network patterns. A mixed-methods approach, combining quantitative modeling with interviews, fieldwork, or archival research, could better illuminate how firms interpret and respond to their positions within the network.

Fourth, my ERGM analysis faced practical limitations due to the complexity and size of the observed network, as well as the limited computational resources available. To manage these constraints, I set the decay parameter for triadic closure to a low value, which reduced the model's ability to capture fine-grained clustering and higher-order structural effects. As a result, some aspects of triadic closure and network clustering may be underrepresented in my results, and the simulated networks had difficulty reproducing high-degree nodes or accurately modeling local hub structures. Future studies with greater computational power, or using alternative modeling strategies, could address these limitations to provide even more robust insight into the effects of network structure on tie formation.

Finally, my study focuses exclusively on the semiconductor industry, which is highly technology and capital-intensive. These structural features make it especially prone to positional lock-in and relational asymmetry. Other industries may operate under different governance models, with more fluid entry/exit dynamics or less technical interdependence. Therefore, future studies should test whether similar forms of decoupling appear in other sectors—especially those undergoing digitalization, decarbonization, or geopolitical restructuring.

In summary, while this study provides strong support for the autonomy of supply chain network structure, it also opens the door for a broader research agenda that more fully integrates time, context, and institutional dynamics. By extending this framework across sectors, scales, and temporal horizons, I hope future research can develop a deeper and more dynamic understanding of how global production is not only coordinated by firms or shaped by states—but also governed by the evolving structure of the network itself.

AI Assistance

AI was used solely as a writing tool to assist with language, structure, and clarity. All ideas, arguments, and original content presented are entirely my own.

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Appendix

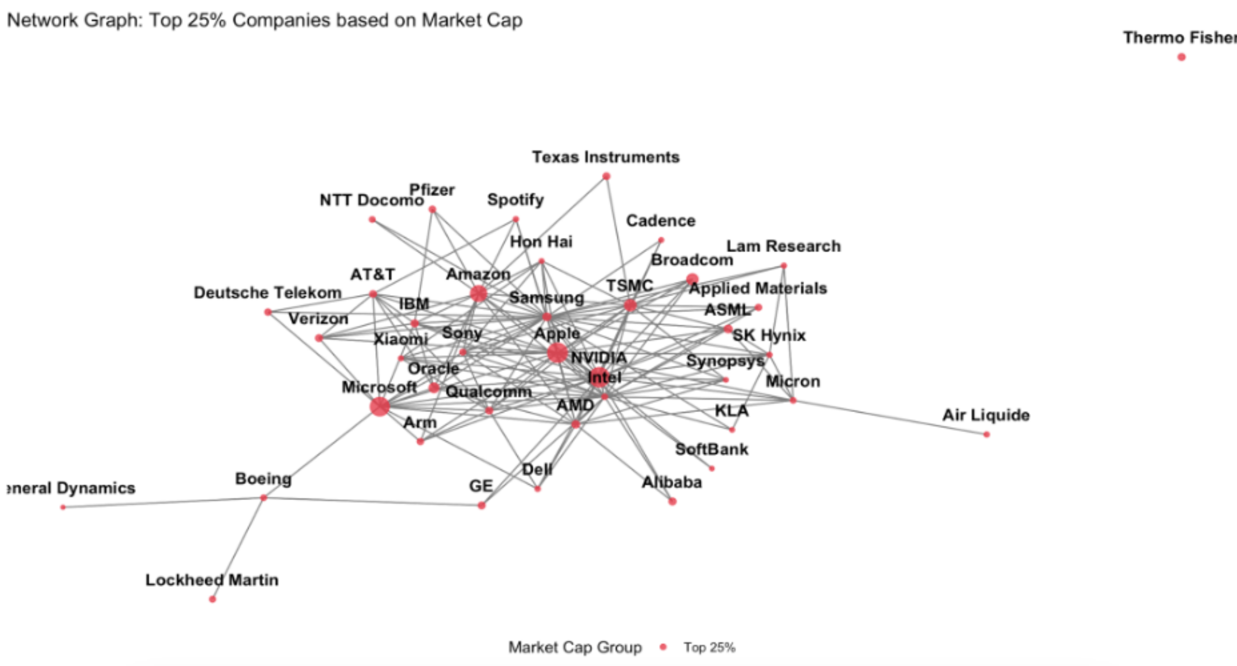

Figure 1: Network Visualization of Market Capitalization Value on Top 25%

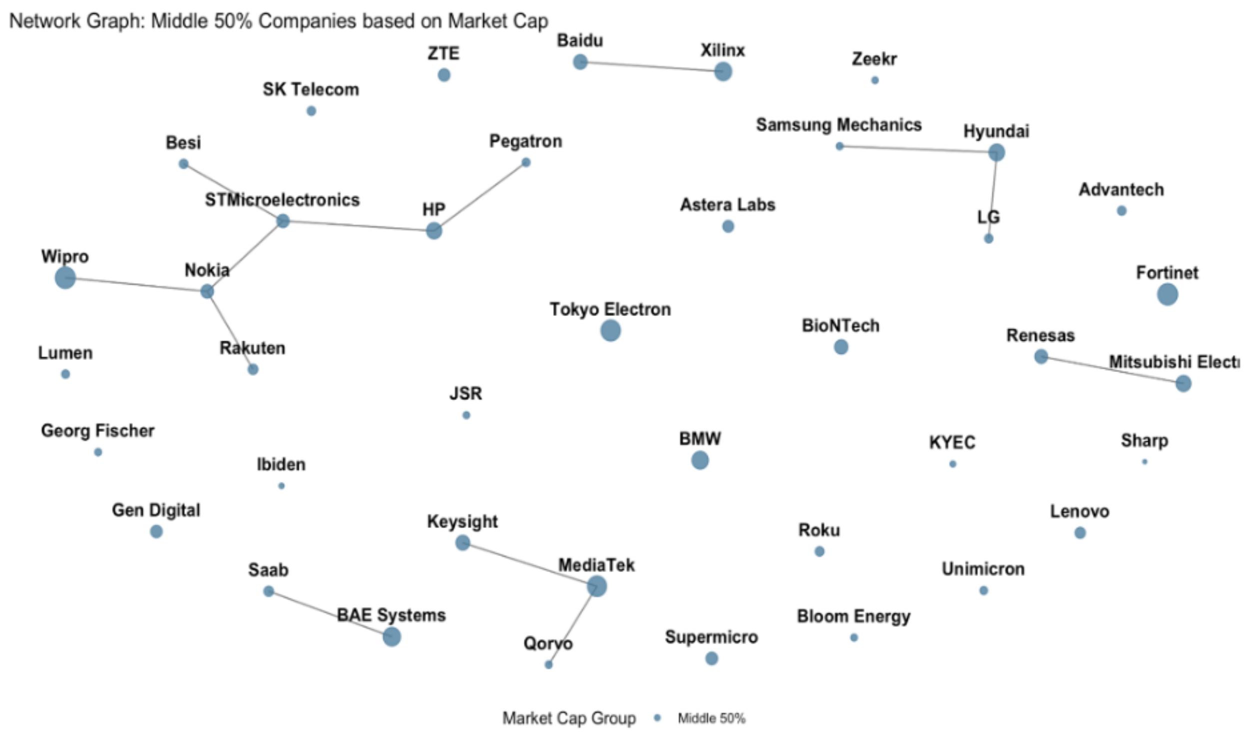

Figure 2: Network Visualization of Market Capitalization Value on Middle 50%

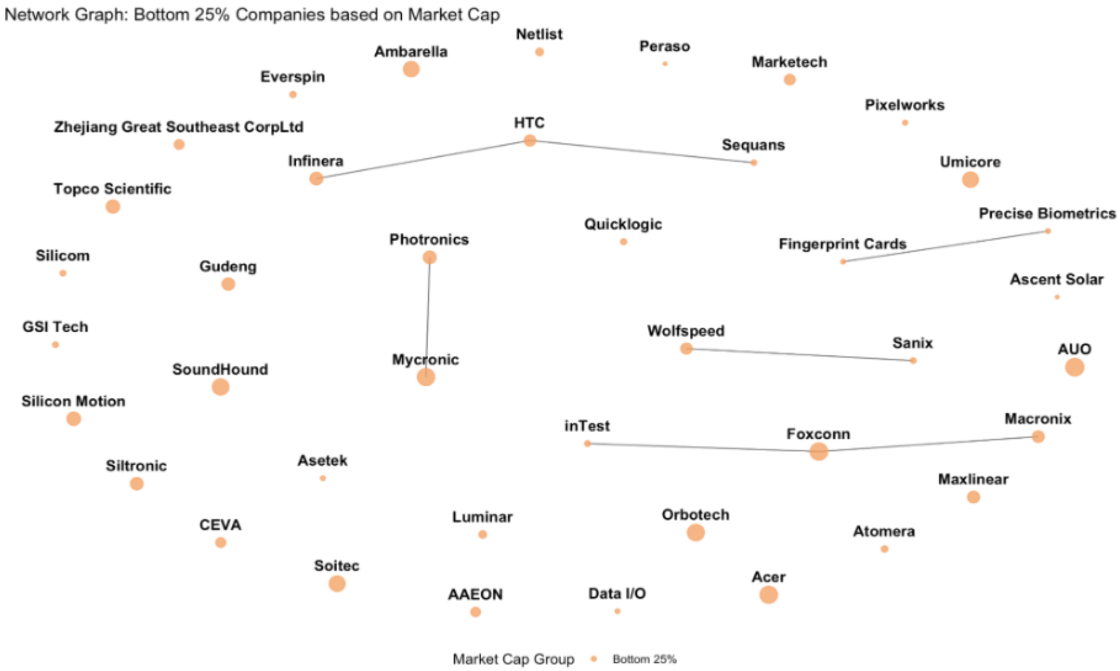

Figure 3: Network Visualization of Market Capitalization Value on Bottom 25%

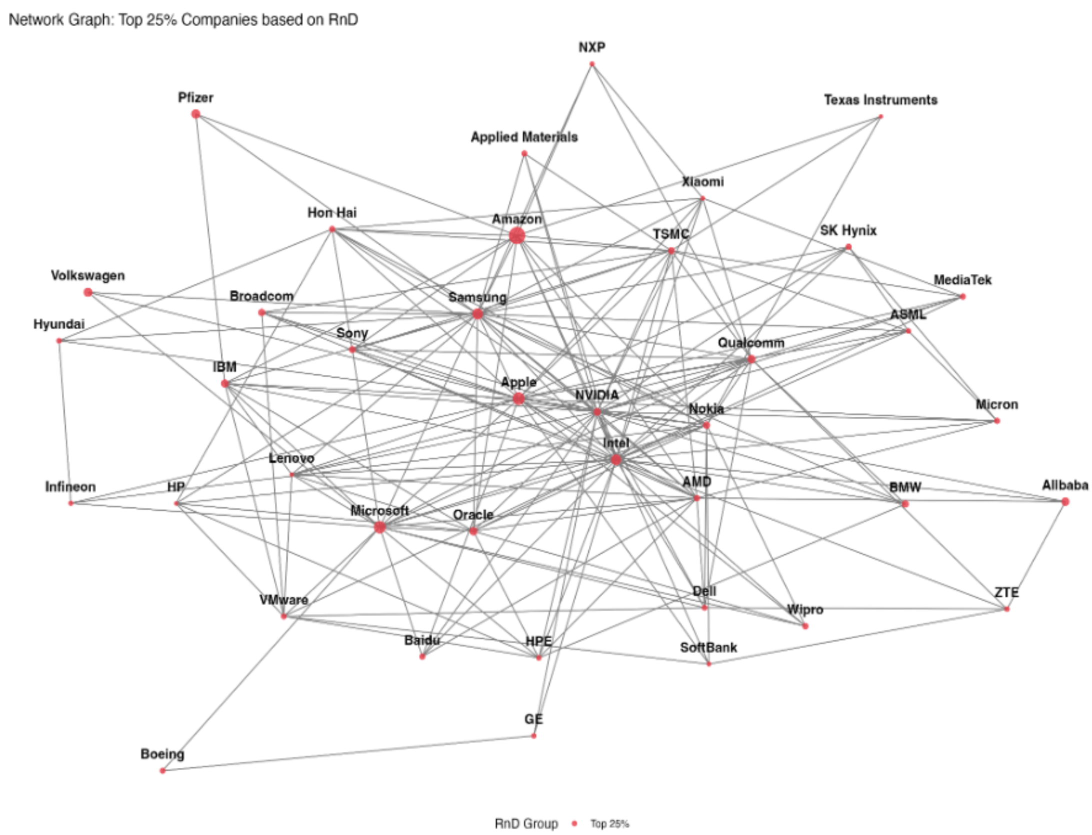

Figure 4: Network Visualization of R&D Expenses on Top 25%

Figure 5: Network Visualization of R&D Expenses on Middle 50%

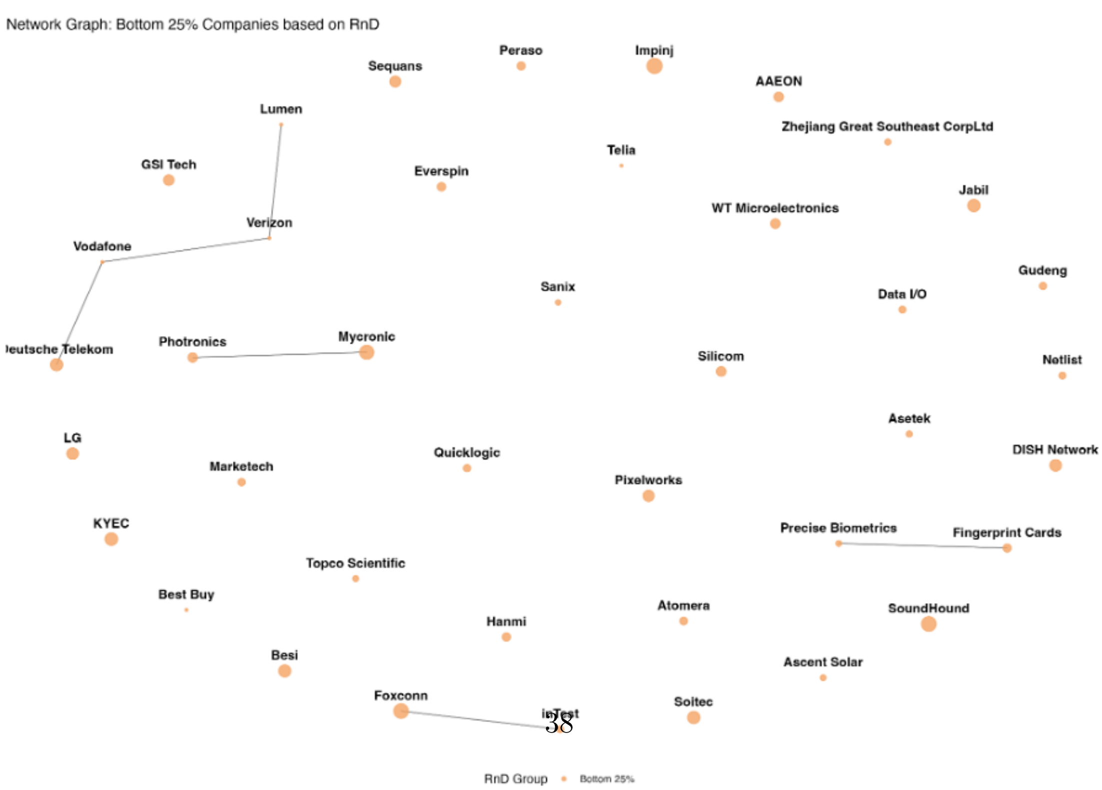

Figure 6: Network Visualization of R&D Expenses on Bottom 25%

	HQ	Chip_Makers	Chip_Users	Maker_%	User_%
1	United States of America	31	39	50.00	39.80
2	Taiwan	11	11	17.74	11.22
3	Netherlands	5	0	8.06	0.00
4	Japan	4	12	6.45	12.24
5	France	2	1	3.23	1.02
6	Germany	2	4	3.23	4.08
7	Korea; Republic (S. Korea)	2	6	3.23	6.12
8	China	1	7	1.61	7.14
9	Hong Kong	1	0	1.61	0.00
10	Israel	1	2	1.61	2.04
11	Sweden	1	5	1.61	5.10
12	United Kingdom	1	2	1.61	2.04
13	Belgium	0	1	0.00	1.02
14	Denmark	0	1	0.00	1.02
15	Finland	0	1	0.00	1.02
16	India	0	2	0.00	2.04
17	Ireland; Republic of	0	1	0.00	1.02
18	Luxembourg	0	1	0.00	1.02
19	Spain	0	1	0.00	1.02
20	Switzerland	0	1	0.00	1.02

Figure 7: Contingency Table of HQ Country by Supply Chain Role

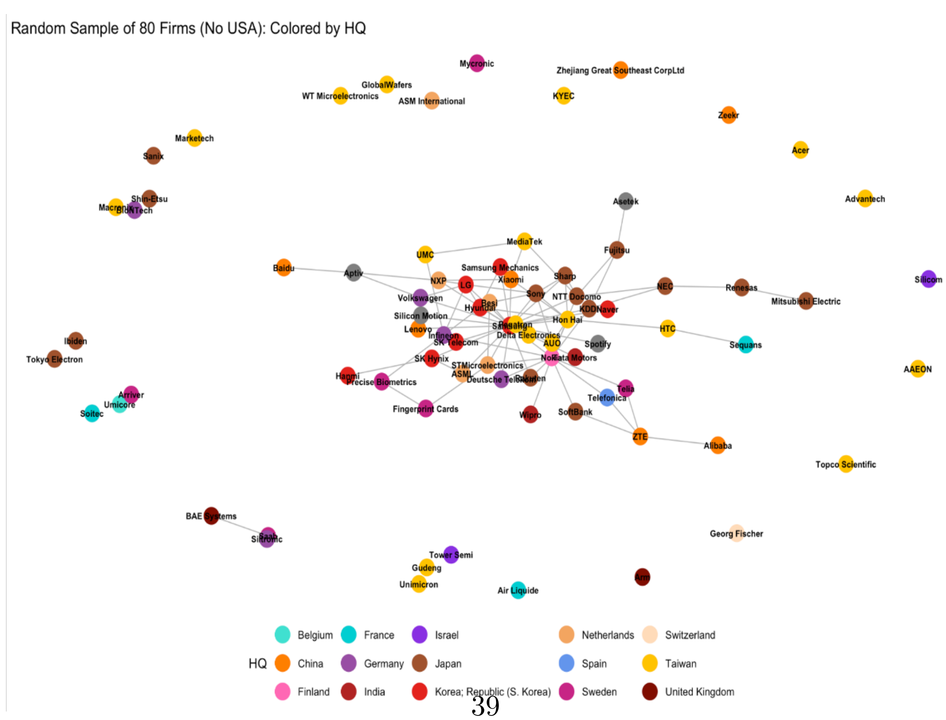

Figure 8: Network Visualization of HQ Country (without USA)

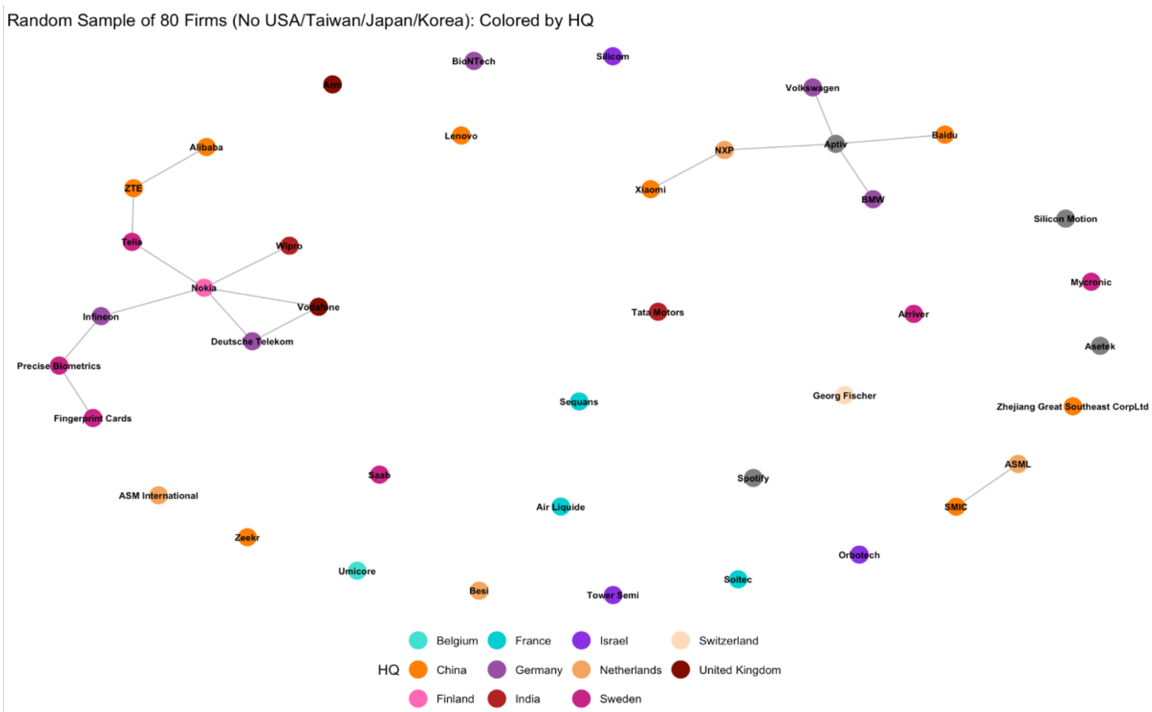

Figure 9: Network Visualization of HQ Country (without USA/Taiwan/South Korea/Japan)

```
OLS Network Model

Residuals:
         0%         25%         50%         75%        100% 
-0.25979212 -0.03264389 -0.02652431 -0.02345089  0.97768259 

Coefficients:
            Estimate             Pr(<=b) Pr(>=b) Pr(>=|b|)
(intercept) 0.022298956854863462 0.904   0.096   0.096    
x1          0.000000000000004928 0.999   0.001   0.001    
x2          0.000000000000230545 0.980   0.020   0.027    

Residual standard error: 0.1923 on 12717 degrees of freedom
Multiple R-squared: 0.05221     Adjusted R-squared: 0.05206 
F-statistic: 350.3 on 2 and 12717 degrees of freedom, p-value:     0 


Test Diagnostics:

        Null Hypothesis: qapspp 
        Replications: 1000 
        Coefficient Distribution Summary:

       (intercept)         x1         x2
Min       3.787938 -12.864250 -10.606370
1stQ     10.344107  -2.060118  -1.541569
Median   11.030573  -0.607751  -0.467800
Mean     10.804641   0.001392   0.076797
3rdQ     11.652269   1.083822   1.192745
Max      14.173294  14.690056  18.033443
```

Figure 10: QAP Netlm Results for numerical variables—Market Capitalization (x1) and R&D Expense (x2) on network ties

```
Network Logit Model

Coefficients:
             Estimate   Exp(b)     Pr(<=b) Pr(>=b) Pr(>=|b|)
(intercept) -3.6737481 0.02538116 0.000   1.000   0.000
x1           0.5549474 1.74184931 1.000   0.000   0.000
x2           0.6658480 1.94614016 0.997   0.003   0.003

Goodness of Fit Statistics:

Null deviance: 17633.66 on 12720 degrees of freedom
Residual deviance: 4243.837 on 12717 degrees of freedom
Chi-Squared test of fit improvement:
         13389.83 on 3 degrees of freedom, p-value 0
AIC: 4249.837   BIC: 4272.19
Pseudo-R^2 Measures:
        (Dn-Dr)/(Dn-Dr+dfn): 0.5128271
        (Dn-Dr)/Dn: 0.7593332
```

Figure 11: QAP Netlogit Results for categorical variables—Supply Chain Role (x1) and HQ State location (x2) on network ties

```
Contingency Table (predicted (rows) x actual (cols)):

        0      1
0   12203    517
1       0      0

        Total Fraction Correct: 0.9593553
        Fraction Predicted 1s Correct: NaN
        Fraction Predicted 0s Correct: 0.9593553
        False Negative Rate: 1
        False Positive Rate: 0

Test Diagnostics:

        Null Hypothesis: qapspp
        Replications: 1000
        Distribution Summary:

       (intercept)        x1        x2
Min      -36.69978  -4.25726  -6.84003
1stQ     -35.33550  -1.06827  -1.60475
Median   -34.92487  -0.12243   0.00403
Mean     -34.95903  -0.06127   0.08132
3rdQ     -34.57132   0.93208   1.67887
Max      -33.50234   4.93690   7.52517
```


Figure 12: QAP Netlogit Results for categorical variables—Supply Chain Role (x1) and HQ State location (x2) on network ties

```
Number of connected components:
3

Network density (gden):
0.04064465

Betweenness centralization:
0.2348957

Degree for each node (first 10 shown):
4 37 8 10 60 12 0 56 8 8

Unique roles in the network:
Chip Maker Chip User
```

Figure 13: Pre-ERGM Network Basic Information

```
Call:
ergm(formula = network_ug ~ edges, control = control.ergm(seed = 40))

Maximum Likelihood Results:

      Estimate Std. Error MCMC % z value Pr(>|z|)
edges  -3.1614     0.0449      0  -70.41   <1e-04 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

     Null Deviance: 17634  on 12720  degrees of freedom
 Residual Deviance:  4324  on 12719  degrees of freedom

AIC: 4326  BIC: 4334  (Smaller is better. MC Std. Err. = 0)
```

Figure 14: ERGM results for null model

```
Baseline probability of a tie (edges term only):
 0.04064465
```

Figure 15: Network tie probability derived from null model

```
Call:
ergm(formula = network_ug ~ edges + gwesp(0.25, fixed = TRUE))

Monte Carlo Maximum Likelihood Results:

                  Estimate Std. Error MCMC % z value Pr(>|z|)
edges              -5.1093     0.1302      0  -39.23  <0.0001 ***
gwesp.fixed.0.25    1.7346     0.1056      0   16.42  <0.0001 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

     Null Deviance: 17634  on 12720  degrees of freedom
 Residual Deviance:  3775  on 12718  degrees of freedom

AIC: 3779  BIC: 3794  (Smaller is better. MC Std. Err. = 0.9204)
```

Figure 16: ERGM results for model 1(triadic closure effect)

```r
edges <- -5.1093
gwesp <- 1.7346
decay <- 0.25
mean_shared <- 0.7643868
median_shared <- 0

logit_p_mean <- edges + gwesp * (decay^mean_shared)
logit_p_median <- edges + gwesp * (decay^median_shared)
```

```
Estimated probability of a tie given the average number of shared partners (triadic closure):
 0.01089888

Estimated probability of a tie with no shared partners (triadic closure):
 0.03309558
```

Figure 17: Network tie probability derived from model 1

```
Call:
ergm(formula = network_ug ~ edges + gwesp(0.25, fixed = TRUE) +
    nodematch("Role"), control = control.ergm(MCMC.burnin = 5000,
    MCMC.interval = 1000, MCMC.samplesize = 5000))

Monte Carlo Maximum Likelihood Results:

                 Estimate Std. Error MCMC % z value Pr(>|z|)
edges            -5.31800    0.13156      0 -40.422  <0.0001 ***
gwesp.fixed.0.25  1.72586    0.10272      0  16.801  <0.0001 ***
nodematch.Role    0.37540    0.07085      0   5.298  <0.0001 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

     Null Deviance: 17634  on 12720  degrees of freedom
 Residual Deviance:  3749  on 12717  degrees of freedom

AIC: 3755  BIC: 3778  (Smaller is better. MC Std. Err. = 0.8598)
```

Figure 18: ERGM results for model 4(triadic closure effect, with supply chain role as control)

```
# Coefficients from your ERGM model
edges <- -5.31800
gwesp <- 1.72586
decay <- 0.25
mean_shared <- 0.7643868
median_shared <- 0
nodematch_role <- 0.37540

# Calculations
decay_mean <- decay^mean_shared
decay_median <- decay^median_shared

# Mean shared partners, same role
logit_p_mean_rolematch <- edges + gwesp * decay_mean + nodematch_role
logit_p_median_rolematch <- edges + gwesp * decay_median + nodematch_role
```

```
Estimated probability of a tie (mean shared partners, same role): 0.01281216
Estimated probability of a tie (mean shared partners, different role): 0.008837579

Estimated probability of a tie (zero shared partners, same role): 0.0385406
Estimated probability of a tie (zero shared partners, different role): 0.02680124
```

Figure 19: Network tie probability derived from model 4

```
Goodness-of-fit for model statistics

                        obs      min     mean      max MC p-value
edges              517.0000 363.0000 522.8600 713.0000       0.92
gwesp.fixed.0.25   513.2934 317.4305 519.8987 766.7867       0.90
nodematch.Role     335.0000 249.0000 337.2900 477.0000       1.00
```

Figure 20: Goodness-to-fit scores of model 4 overall performance

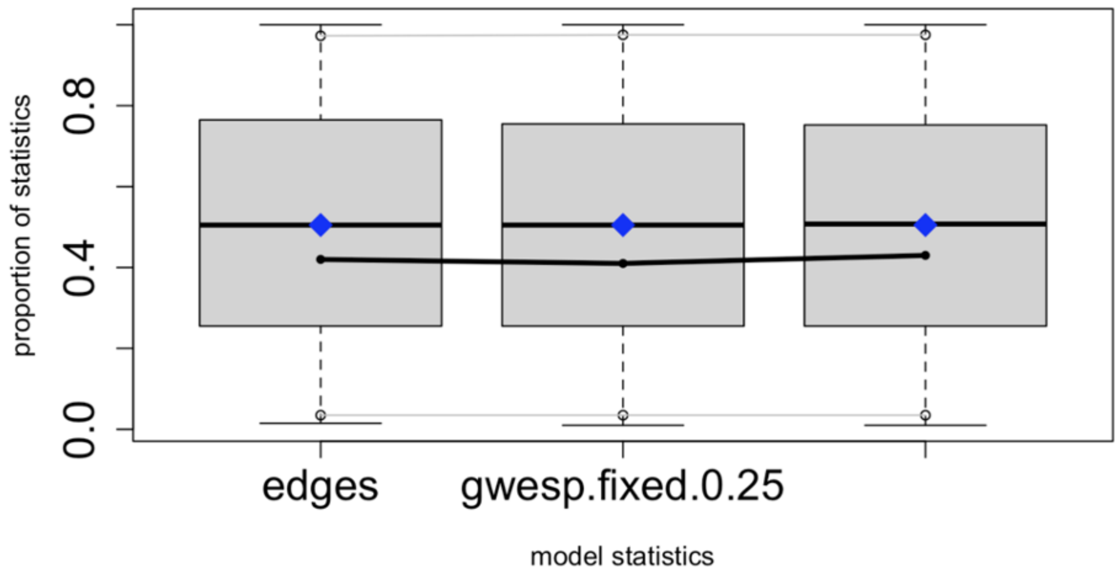

Figure 21: Goodness-to-fit plot of model 4 edges and gwesp performance

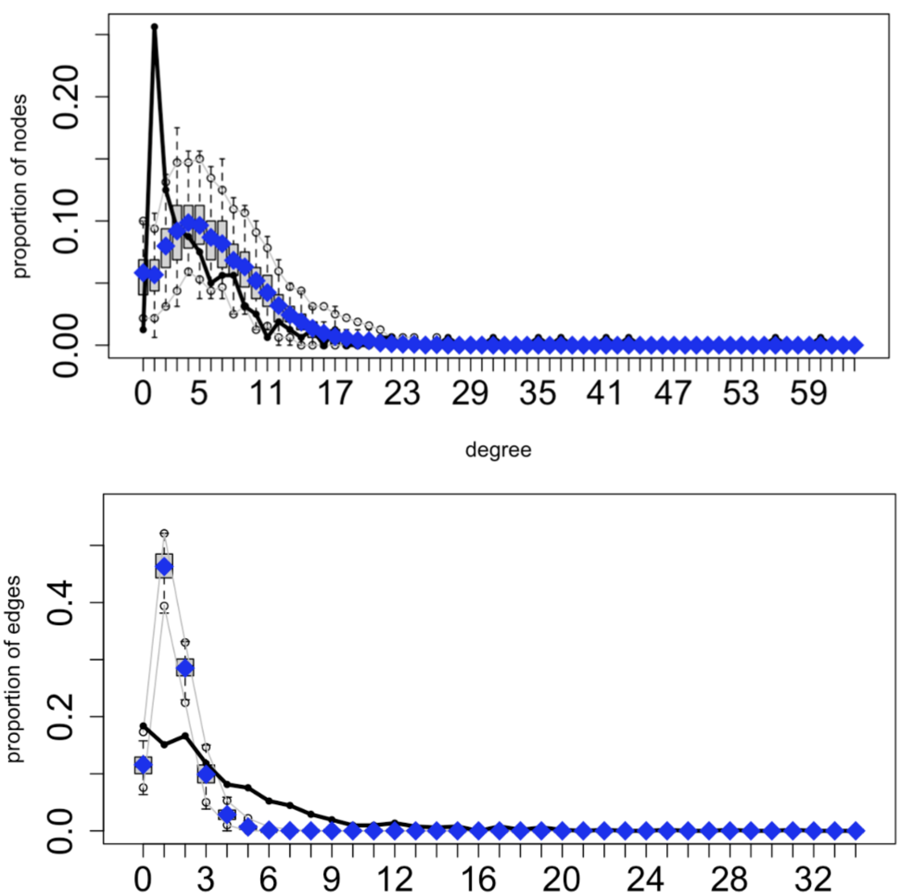

Figure 22: Goodness-to-fit plot of model 4 degree and edge-wise shared partners performance

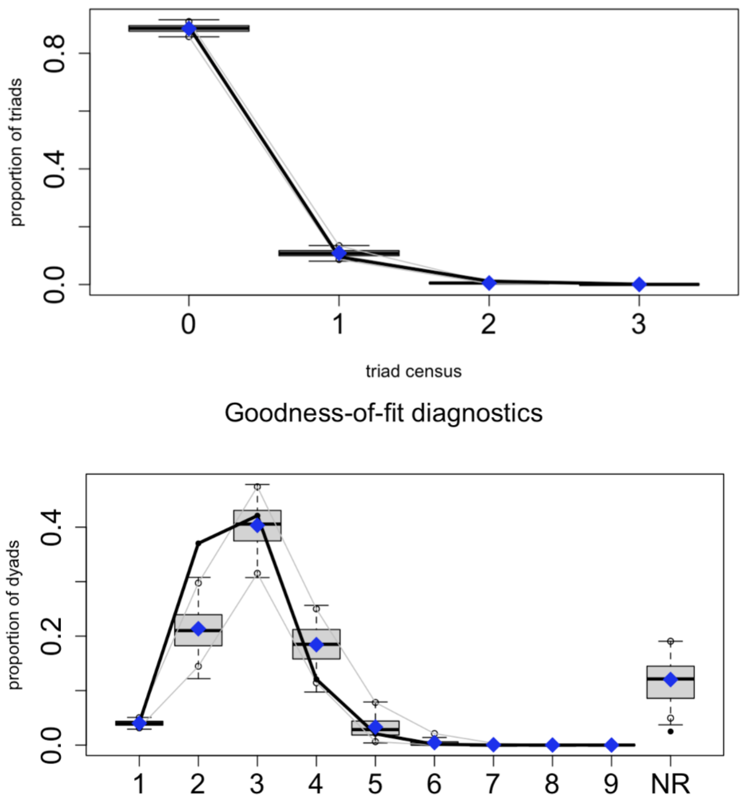

Figure 23: Goodness-to-fit plot of model 4 triadic census and minimum geodesic distance performance

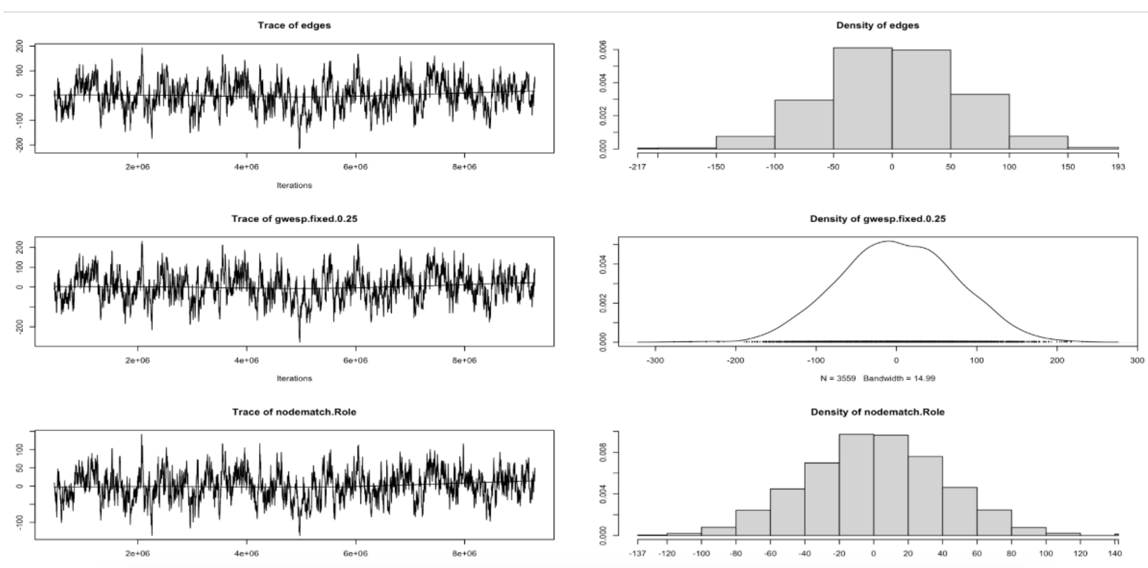

Figure 24: MCMC diagnostic of model 4

```
Network attributes:
  vertices = 160
  directed = FALSE
  hyper = FALSE
  loops = FALSE
  multiple = FALSE
  bipartite = FALSE
 total edges = 516
   missing edges = 0
   non-missing edges = 516
 density = 0.04056604

Number of connected components:
3

Network density (gden):
0.04064465

Betweenness centralization:
0.2348957

Degree for each node (first 10 shown):
4 37 8 10 60 12 0 56 8 8

Unique roles in the network:
Chip Maker Chip User
```

Figure 25: Characteristics of simulated network based on model 4

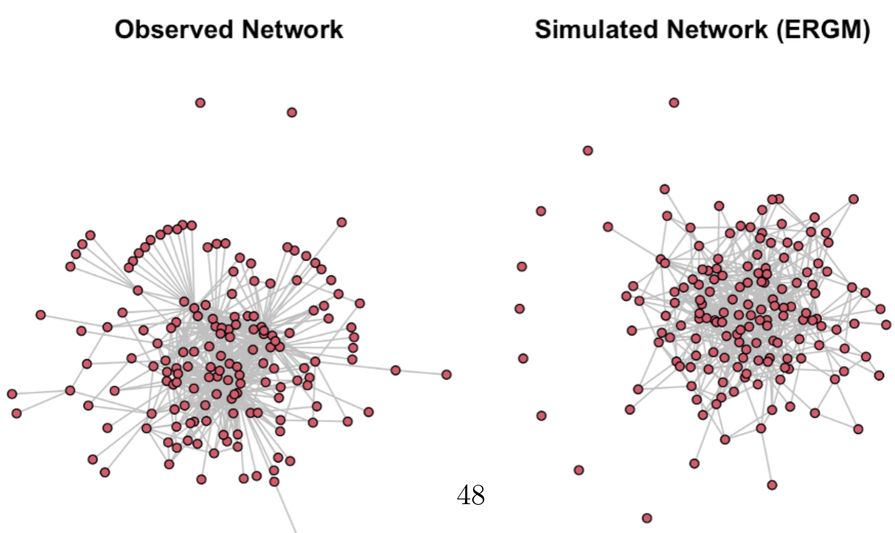

Figure 26: Network graph comparison of original network v. simulated network based on