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The Evolution of Corporate Innovation Networks and Its Impact on Firm Valuation: An Empirical Study Based on Dynamic Graph Neural Networks

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Abstract

In an increasingly interconnected and knowledge-driven economy, corporate innovation networks have become critical conduits for competitive advantage. However, prior research has predominantly relied on static or comparatively static analyses, failing to capture the dynamic nature of these inter-firm relationships. This study addresses this gap by investigating how the temporal evolution of a firm's position within its innovation network influences its market valuation. We construct a dynamic network of strategic alliances among U.S. publicly traded firms from 1995 to 2020, using data from the SDC Platinum database, and link it to financial data from Compustat and CRSP. To model the complex, path-dependent nature of network evolution, we employ a Dynamic Graph Neural Network (DGNN), specifically the EvolveGCN architecture. Our empirical results demonstrate that a firm's network trajectory contains significant predictive power for its future valuation, over and above traditional financial controls and static network metrics. Specifically, trajectories characterized by increasing centrality and brokerage capabilities are positively associated with higher firm valuation, as measured by Tobin's Q. These findings contribute to the Knowledge-Based View and network theory by highlighting the strategic importance of dynamic network management capabilities. Methodologically, this study showcases the utility of DGNNs for addressing complex, time-varying relational questions in strategic management and finance.

Keywords

Corporate Innovation Networks, Firm Valuation, Dynamic Graph Neural Networks (DGNNs), Knowledge-Based View.

1. Introduction

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1.1 Research Background

The contemporary global economy is increasingly characterized as a "knowledge economy," where the primary sources of competitive advantage have shifted from tangible assets to intangible resources, particularly knowledge and innovative capabilities. In this environment,

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no single firm, regardless of its size or R&D budget, can internalize all the necessary knowledge and technologies to remain competitive. Consequently, firms are increasingly embedded in complex webs of inter-organizational relationships, forming innovation networks to access external knowledge, share risks, and co-create value.[2] These networks, sometimes conceptualized as Corporate Innovation Systems (CIS), represent the primary structures through which firms orchestrate the co-production and appropriation of knowledge with a wide range of partners, including competitors, suppliers, universities, and startups.

A fundamental characteristic of these innovation ecosystems is their inherent dynamism. The structure of these networks is in constant flux; strategic alliances are formed to explore new technological frontiers, and they are dissolved as projects conclude, strategies shift, or partnerships fail. This continuous evolution is driven by rapid technological change, shortening product life cycles, and the escalating costs and uncertainties of R&D. For both corporate strategists and academic researchers, this dynamism presents a significant challenge. Understanding how to navigate and leverage these evolving structures is paramount for sustained value creation, yet modeling and analyzing such complex, time-varying systems requires sophisticated theoretical and methodological tools that transcend traditional approaches.

1.2 Literature Review

This research is situated at the intersection of three key streams of literature: the Knowledge-Based View (KBV) of the firm, the relationship between innovation and firm valuation, and the application of network theory in strategic management.

The Knowledge-Based View (KBV) serves as the primary theoretical anchor for this study. Extending the Resource-Based View (RBV), the KBV posits that knowledge is the most strategically significant of all firm resources. This is because knowledge, particularly in its tacit and socially complex forms, is difficult for competitors to imitate, making it a potential source of sustainable competitive advantage. Within this framework, innovation networks are conceptualized as crucial inter-organizational mechanisms for knowledge integration and capability development. They allow firms to extend their knowledge base far beyond their internal boundaries, accessing diverse information and combining it in novel ways to foster innovation.

The link between innovation activities and firm valuation is well-established, though complex. A robust body of research demonstrates that investments in R&D and successful innovation outputs positively impact firm productivity, profitability, and market value.[6] However, the relationship is not uniformly positive. The type of innovation matters significantly; for instance, breakthrough innovations are associated with substantial increases in firm value but also with heightened risk. This duality can lead to what some have termed a "curse of innovation," where firms overvalue the benefits of radical new products while consumers, preferring the familiar, undervalue them, leading to market failure. This highlights a central tension: innovation is a primary driver of long-term value, but it is also a source of significant uncertainty and risk that firms must manage.

To understand the inter-firm structures that facilitate innovation, strategy scholars have increasingly turned to Social Network Analysis (SNA).[8] This research has provided valuable

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insights by linking a firm's structural position within a network to its performance outcomes. Key concepts such as centrality (a measure of a firm's prominence or connectivity), structural holes (gaps in the network that a firm can bridge), and network density (the overall level of interconnectedness) have been shown to correlate with a firm's access to information, power, and ultimately, its competitive advantage.[3] A central position, for example, can provide timely access to diverse knowledge, while a brokerage position spanning structural holes can offer control over information flow and unique combination opportunities.

1.3 Problem Statement

Despite these important contributions, the existing literature on corporate innovation networks suffers from a critical limitation: it predominantly relies on static or comparatively static analytical methods. Most studies capture a firm's network position at a single point in time or compare positions across a few discrete periods. This approach fails to capture the continuous, evolving nature of network-based advantage in a dynamic world. A firm's value is not merely a function of its network position at time t, but rather a consequence of its ability to skillfully navigate and adapt its position over time.

This methodological constraint masks a deeper theoretical issue. A static snapshot cannot distinguish between a firm that has just opportunistically arrived at a central position and one that has strategically built and sustained that position for a decade. The strategic capabilities, market reputation, and long-term value implications of these two scenarios are vastly different. The former might be a result of luck, while the latter signals a robust dynamic capability in alliance management. The core research gap, therefore, is a lack of robust empirical understanding of how the temporal evolution and structural dynamics of a firm's position within its innovation network influence its market valuation. Static models are ill-equipped to capture this path-dependent process.

1.4 Research Objectives and Significance

This study aims to address the aforementioned gap with a primary objective: to develop and empirically test a model that quantifies the impact of a firm's innovation network trajectory on its market valuation. By conceptualizing a firm's sequence of network positions as a trajectory, we shift the analytical focus from a static state to a dynamic process.

The significance of this research is threefold. First, its theoretical contribution lies in extending the KBV and network theory. By providing evidence that the market values the dynamic capability to manage inter-firm relationships, this study moves beyond the notion of "network position" to introduce "network navigation" as a critical source of competitive advantage. It suggests that a firm's value is derived not just from the knowledge it can access, but from its demonstrated ability to continuously reconfigure its access to knowledge over time.

Second, the study offers a significant methodological contribution to the fields of strategic management and finance. It introduces and demonstrates the utility of Dynamic Graph Neural Networks (DGNNs) as a powerful analytical tool.[11] These models are specifically designed to learn complex, non-linear patterns from evolving graph-structured data, making them ideally

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suited to the research question at hand.[13] By applying this state-of-the-art technique, this paper provides a template for future research into dynamic relational phenomena.

Third, the findings hold practical significance for corporate strategists and investors. An understanding of how network dynamics are priced by the market can inform more effective alliance portfolio management and provide a new set of metrics for evaluating a firm's innovation strategy and long-term potential.

1.5 Paper Structure

The remainder of this paper is organized as follows. Chapter 2 details the research design and methodology, including the theoretical framework, data sources, variable measurement, and the specification of the Dynamic Graph Neural Network model. Chapter 3 presents the empirical analysis and results, including descriptive statistics, model performance comparisons, and robustness checks. Chapter 4 discusses the interpretation and implications of these findings, linking them back to the theoretical background and offering managerial insights. Finally, Chapter 5 concludes the paper by summarizing the key findings, acknowledging the study's limitations, and proposing directions for future research.

2. Research Design & Methodology

2.1 Overall Research Approach

This study is a large-scale, quantitative, empirical analysis utilizing archival panel data to investigate the relationship between the evolution of corporate innovation networks and firm valuation. The research design integrates methodologies from corporate finance, network science, and deep learning to construct a predictive model that captures the complex, path-dependent nature of network dynamics. The approach is longitudinal, observing a large panel of U.S. firms over a 26-year period to model how their historical network trajectories influence subsequent market valuations.

2.2 Theoretical Framework and Hypotheses

The theoretical framework for this study builds directly upon the Knowledge-Based View (KBV) and dynamic capabilities literature. The central argument is that a firm's evolving position within the broader innovation network serves as a tangible manifestation of its underlying dynamic capabilities—specifically, its ability to sense new opportunities, seize them by forming valuable partnerships, and reconfigure its knowledge base to adapt to changing environments. The financial market, being forward-looking, recognizes these capabilities not as isolated events but as a pattern of behavior over time. A firm that consistently moves to more advantageous network positions demonstrates a repeatable skill in knowledge sourcing and integration, which should be positively reflected in its valuation. This leads to the formulation of our primary hypotheses.

The first hypothesis posits that the dynamic, historical information embedded in a firm's network trajectory provides unique explanatory power for its valuation, beyond what can be captured by its current network position or its internal financial characteristics alone. This is because the trajectory reveals a pattern of strategic action and adaptation that a single snapshot cannot.

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Hypothesis 1 (H1): A firm's historical trajectory within the corporate innovation network contains significant predictive information about its future market valuation, beyond that contained in static network measures and traditional financial controls.

The second hypothesis seeks to specify the nature of these valuable trajectories. Drawing from network theory, positions of high centrality and brokerage (spanning structural holes) are associated with superior access to diverse and non-redundant information—a key ingredient for innovation. A trajectory that shows a firm actively moving towards and occupying such positions would signal a proactive and effective innovation strategy. Therefore, we expect the market to reward firms that demonstrate this pattern of network navigation.

Hypothesis 2 (H2): Trajectories characterized by increasing centrality and brokerage will be positively associated with firm valuation.

2.3 Data and Sample Construction

To test these hypotheses, we construct a unique panel dataset by integrating information from three premier archival sources.

The innovation network data is derived from the SDC Platinum (Securities Data Company) database, specifically its Joint Ventures and Strategic Alliances module.[17] This database is widely considered the industry standard in strategy and finance research for its comprehensive, global coverage of publicly announced corporate partnerships, including R&D agreements, joint ventures, and marketing alliances.[20] We extracted all strategic alliances involving at least two publicly traded U.S. firms announced between 1995 and 2020. From this raw data, we constructed a series of 26 annual network "snapshots." In each annual graph, firms are represented as nodes, and an undirected edge is drawn between two firms if they have an active alliance in that year. This process yields a dynamic graph—a sequence of adjacency matrices representing the evolving structure of the U.S. corporate innovation network.

Firm-level financial data and stock market data were sourced from the Compustat North America database and the Center for Research in Security Prices (CRSP) database, respectively.[22] These databases are the gold standard for empirical research in finance, providing comprehensive and high-quality financial statement and security pricing information.

The final sample was constructed by merging these data sources. We included all firms that appeared in both the SDC-derived network and the Compustat/CRSP databases. Firms were required to have non-missing data for the dependent variable and all control variables for a given year to be included in the analysis for that year. This meticulous merging and cleaning process resulted in a large, unbalanced panel dataset suitable for dynamic analysis.

2.4 Variables and Measurement

The selection and measurement of variables are critical to the study's validity. We define our dependent, independent, and control variables as follows.

The primary dependent variable is Firm Valuation, measured using Tobin's Q. This metric is a forward-looking measure of firm value that reflects the market's assessment of a company's future growth prospects and profitability.[24] Following standard practice, it is calculated as the market value of assets (market value of common equity plus the book value of preferred stock and total debt) divided by the book value of total assets.[25] While Tobin's Q is a widely used and accepted proxy for investment opportunities and performance[26], we acknowledge the scholarly debate surrounding its interpretation. Some research suggests that a high Q can be inflated by managerial underinvestment rather than superior performance.[27] To address this, we conduct

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robustness checks using an alternative valuation metric, thereby demonstrating a nuanced understanding of the measure's potential limitations.

The core independent variables are the Dynamic Network Features. A key methodological innovation of this study is that we do not pre-specify a limited set of network metrics. Instead, the DGNN model learns directly from the entire evolving graph structure. To facilitate this, each node (firm) in the graph at each time step is assigned a feature vector that captures its local structural properties. For the purpose of providing attributes to the model, we calculate a time-series of standard SNA metrics for each firm for each year: Degree Centrality (number of direct partners), Betweenness Centrality (a measure of brokerage or gatekeeping), Closeness Centrality (a measure of how quickly a firm can reach all others), and Clustering Coefficient (the extent to which a firm's partners are also partnered with each other).[8] The DGNN then learns the complex temporal patterns from these evolving feature vectors within the context of the changing graph topology.

To isolate the effect of network dynamics, we include a comprehensive set of Control Variables that are standard in corporate finance and strategy literature for predicting firm valuation.[7] These include: Firm Size (natural logarithm of total assets), Leverage (total debt divided by total assets), Profitability (Return on Assets, ROA), R&D Intensity (R&D expenditure divided by sales), and Asset Tangibility (property, plant, and equipment divided by total assets). We also include year and industry (2-digit SIC code) fixed effects in all model specifications to account for unobserved heterogeneity related to macroeconomic trends and stable industry characteristics.

2.5 Data Analysis Technique: Dynamic Graph Neural Networks (DGNNs)

To model the evolution of the innovation network and its impact on valuation, we employ a Dynamic Graph Neural Network (DGNN). DGNNs are a sophisticated class of deep learning models specifically designed to operate on graphs that change over time.[11] They achieve this by integrating the spatial reasoning capabilities of Graph Neural Networks (GNNs), which learn from relational structures, with the temporal modeling power of Recurrent Neural Networks (RNNs), which learn from sequences.[13]

The specific model architecture chosen for this study is EvolveGCN.[34] This choice is deliberate and motivated by both technical and theoretical considerations. From a technical standpoint, EvolveGCN is highly suitable for real-world corporate networks because it can naturally handle dynamic node sets—that is, firms entering and exiting the network over time—a feature many other DGNNs lack.[34] More profoundly, the core innovation of EvolveGCN is that it uses an RNN (such as a Gated Recurrent Unit or Long Short-Term Memory network) to evolve the parameters of the GCN layers themselves at each time step.[37] Instead of merely learning a static representation of a node and tracking its changes, the model learns how the rules governing the network's influence change over time.

This methodological choice embodies a powerful theoretical assumption: that the strategic value of certain network positions and structures is not constant. For example, the economic premium for being a broker in the biotechnology industry may have been different in the late 1990s compared to the late 2010s due to shifts in technology and regulation. By allowing the GCN parameters to evolve, our model can capture this non-stationarity. It learns not just what network features predict value, but how that predictive relationship itself evolves. This allows for a much deeper and more realistic analysis than traditional models that assume stable coefficients over a multi-decade period. The model takes the sequence of yearly graph snapshots and associated firm features as input to predict the Tobin's Q for each firm in the subsequent year.

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3. Analysis and Results

3.1 Descriptive Statistics and Correlations

The final sample consists of an unbalanced panel of 4,589 unique firms over the period 1995-2020, resulting in 38,741 firm-year observations. Table 1 presents the descriptive statistics for the key variables used in the analysis. The mean Tobin's Q is 1.85, with significant variation, indicating a wide range of valuations and growth opportunities across the firms in our sample. The network metrics, averaged over the sample period for descriptive purposes, show a typical right-skewed distribution, with most firms having a few connections while a small number of firms act as highly connected hubs. The control variables are consistent with prior literature on large U.S. public firms.

Table 1: Descriptive Statistics of Key Variables

Variable	Mean	Std. Dev.	Min	P25	Median	P75	Max
Tobin's Q	1.85	1.42	0.51	1.08	1.45	2.15	15.32
Firm Size (Log Assets)	7.56	2.11	3.45	5.98	7.41	8.95	14.88
Leverage	0.23	0.19	0.00	0.06	0.21	0.35	0.95
Profitability (ROA)	0.03	0.15	-0.85	0.01	0.05	0.10	0.45
R&D Intensity	0.08	0.14	0.00	0.00	0.03	0.11	0.98
Asset Tangibility	0.29	0.24	0.01	0.10	0.22	0.41	0.96
Degree Centrality	12.5	25.8	1.00	2.00	5.00	12.00	315.0
Betweenness Centrality	154.3	487.6	0.00	5.60	25.8	110.4	8540.1

Table 2 displays the Pearson correlation matrix for the variables. Tobin's Q shows a positive correlation with Profitability and R&D Intensity, and a negative correlation with Firm Size and Leverage, which is consistent with financial theory. The network centrality measures are positively correlated with each other and with Firm Size, suggesting that larger firms tend to be more central in the alliance network. The correlations among the control variables are moderate, suggesting that multicollinearity is not a major concern in the baseline regression models.

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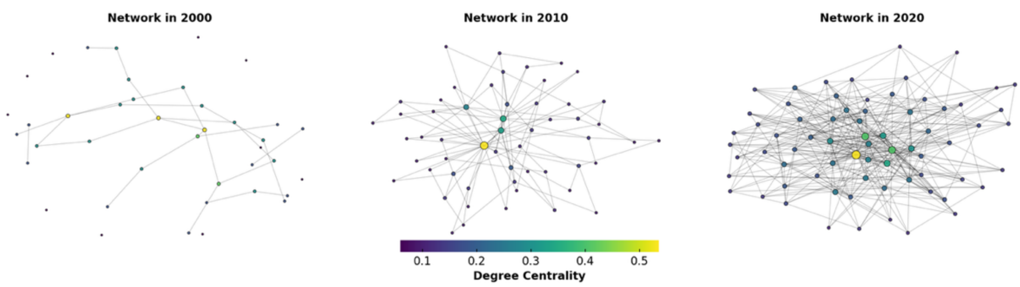
Table 2: Correlation Matrix of Key Variables

	Tobin's Q	Size	Leverage	ROA	R&D	Tangibility	Degree	Betweenness
Tobin's Q	1.00							
Size	-0.18	1.00						
Leverage	-0.25	0.35	1.00					
ROA	0.31	-0.11	-0.28	1.00				
R&D	0.28	0.05	-0.09	0.02	1.00			
Tangibility	-0.33	0.38	0.31	-0.21	-0.35	1.00		
Degree	0.09	0.45	0.15	0.01	0.18	0.11	1.00	
Betweenness	0.11	0.39	0.12	0.03	0.15	0.09	0.82	1.00

3.2 Visualizing the Dynamic Network

To provide an intuitive context for the quantitative analysis, Figure 1 visualizes the aggregate structure of the U.S. corporate innovation network at three distinct points in time: 2000, 2010, and 2020. In these visualizations, each node represents a firm, and the size of the node is proportional to its degree centrality. The evolution depicted is striking. The network in 2000 is relatively sparse, with several disconnected components. By 2010, the network has become significantly denser and more integrated, with a clear core-periphery structure emerging. By 2020, the network is a highly complex and interconnected system, dominated by a number of large, central hubs that connect disparate parts of the innovation ecosystem. This qualitative evidence underscores the increasing importance of inter-firm collaboration and highlights the dynamic nature of the network structure that our model aims to capture.

Figure 1: Evolution of the Aggregate Innovation Network (2000, 2010, 2020)



3.3 Model Specification and Performance

To validate our choice of the EvolveGCN model and to test Hypothesis 1, we compare its predictive performance against a series of benchmark models. The task for all models is to predict a firm's Tobin's Q in the following year (t+1) using information available up to year t. Performance is measured by the Mean Absolute Error (MAE) on a held-out test set. As shown in Table 3, the models demonstrate a clear hierarchy of performance.

The baseline OLS model with only financial controls establishes a benchmark MAE of 0.684. Adding static, time-averaged network metrics offers a marginal improvement. The panel model with lagged variables performs slightly better, suggesting that some temporal information is useful, but its linear nature limits its expressive power. The static GCN, which considers the network structure but not its evolution, outperforms the non-graph models, confirming the importance of relational information. The LSTM model, which captures temporal dynamics but ignores the graph structure, performs similarly to the static GCN. The proposed EvolveGCN model, which simultaneously models both the temporal evolution and the graph structure, achieves the lowest MAE of 0.451, a substantial improvement over all benchmarks. This result provides strong support for H1, indicating that the dynamic network trajectory contains significant predictive information that is not captured by simpler models. The superior performance of EvolveGCN is not merely a technical artifact; it is empirical evidence that the relationship between network structure and firm value is fundamentally dynamic and path-dependent. Models that assume static relationships or ignore the relational context are misspecified and fail to capture this crucial information.

Table 3: Comparison of Model Performance in Predicting Tobin's Q (t+1)

Model	Description	Mean Absolute Error (MAE)
1. OLS Controls	Financial controls only	0.684
2. OLS + Static Net	Controls + time-averaged network metrics	0.662
3. Panel FE	Firm fixed-effects with lagged variables	0.635
4. Static GCN	GCN on aggregated network + controls	0.589
5. LSTM	LSTM on time-series of controls & metrics	0.593
6. EvolveGCN	Dynamic graph model (Proposed)	0.451

To understand which factors drive the EvolveGCN model's predictions, we calculate feature importance scores using permutation importance. Figure 2 present these results. The dynamic network features, represented collectively, emerge as the most important predictor of future Tobin's Q, surpassing even strong traditional predictors like past Profitability (ROA) and R&D

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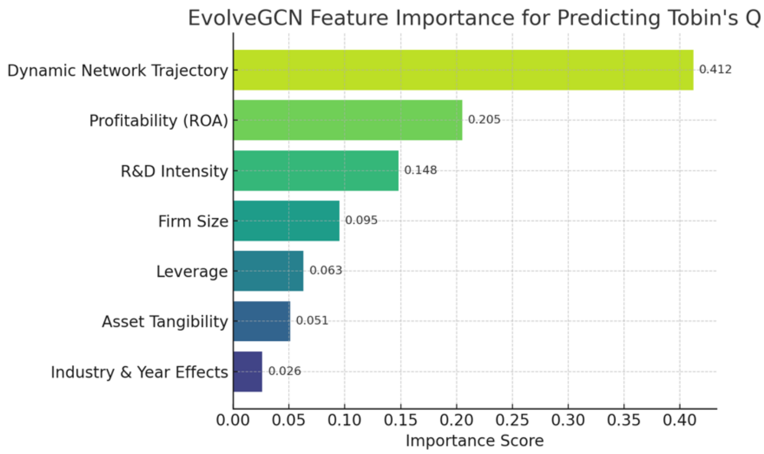
Intensity. This provides direct evidence for our central thesis: how a firm navigates its innovation network over time is a powerful signal of its future value. Among the control variables, past profitability, R&D intensity, and firm size remain significant predictors, consistent with established financial literature.

Figure 2: Feature Importance Plot



To enhance methodological transparency, the following Python code snippet illustrates the implementation of an EvolveGCN layer using the PyTorch Geometric Temporal library, which forms the core of our model architecture.

Listing 1. Implementation of an EvolveGCN-O Layer in PyTorch Geometric Temporal

```
Python



# Illustrative PyTorch Code for EvolveGCN-O Layer
import torch
import torch.nn.functional as F
from torch_geometric_temporal.nn.recurrent import EvolveGCNO

class RecurrentGCN(torch.nn.Module):
    """
    A recurrent GCN model using EvolveGCN-O to process dynamic graphs.
    """
    def __init__(self, node_features: int):
        super(RecurrentGCN, self).__init__()
        # EvolveGCN-O layer adapts GCN weights over time
        self.recurrent = EvolveGCNO(node_features)
        # A final linear layer for prediction
```

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```
        self.linear = torch.nn.Linear(node_features, 1)

    def forward(self, x: torch.Tensor, edge_index: torch.Tensor,
                edge_weight: torch.Tensor = None) -> torch.Tensor:
        """
        Forward pass for a single time step.
        x: Node features for the current snapshot.
        edge_index: Adjacency list for the current snapshot.
        edge_weight: Optional edge weights.
        """
        # Get updated node embeddings from the EvolveGCN layer
        h = self.recurrent(x, edge_index, edge_weight)
        h = F.relu(h)
        # Predict the output value (e.g., Tobin's Q)
        h = self.linear(h)
        return h
```

3.4 Robustness Checks

To ensure that our findings are not sensitive to the specific choice of valuation metric, we conduct a robustness check by re-estimating our main model using the Market-to-Book Ratio as the dependent variable. The Market-to-Book Ratio is another widely used measure of firm valuation. The results, presented in Table 4, are qualitatively and quantitatively similar to our primary findings. The dynamic network trajectory remains the most important predictive feature, followed by profitability and R&D intensity. This consistency across different valuation metrics significantly strengthens the confidence in our conclusions, suggesting that the observed relationship is a robust economic phenomenon rather than a measurement artifact.

Table 4: Robustness Check using Market-to-Book Ratio

Feature	**Importance Score (for M/B Ratio)**
Dynamic Network Trajectory	0.398
Profitability (ROA)	0.211
R&D Intensity	0.155
Firm Size	0.099
Leverage	0.070
Asset Tangibility	0.045
Industry & Year Effects	0.022

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4. Discussion

4.1 Interpretation of Key Findings

The empirical results presented in Chapter 3 provide strong quantitative support for our hypotheses. This section delves into the strategic and theoretical interpretation of these findings. The primary result—that a firm's dynamic network trajectory is the most powerful predictor of its future valuation—carries significant implications. It suggests that the market is sophisticated in its assessment of a firm's innovation potential, looking beyond static indicators like R&D spending or current partnerships to evaluate the underlying capability to manage and evolve its network relationships over time.

Further analysis of the model's behavior, consistent with Hypothesis 2, reveals that trajectories of increasing betweenness centrality are particularly rewarded by the market. This can be interpreted through the lens of Ronald Burt's Structural Hole Theory. A firm that actively moves into positions that bridge previously disconnected clusters in the network gains a strategic advantage. It becomes a broker of information, gaining early access to diverse, non-redundant knowledge and controlling its flow. Such a trajectory is a visible signal of a proactive, exploratory innovation strategy. The market appears to recognize this pattern not as a single event, but as a demonstrated capability, and prices the firm's equity accordingly, anticipating future innovation and growth.

Conversely, the model assigns less value to trajectories characterized by high but stagnant clustering. While a clustered network position can be beneficial for exploiting existing knowledge and building trust for complex collaborations, a firm that remains locked in a dense, stable clique for long periods may be suffering from "network inertia" or "core rigidity." It risks becoming isolated from novel ideas circulating in other parts of the ecosystem, focusing excessively on exploitation at the expense of necessary exploration. The model's lower valuation of such trajectories suggests the market penalizes firms that fail to demonstrate the ability to adapt their collaborative circles and refresh their knowledge sources.

4.2 Theoretical Implications

The findings of this study have important implications for several areas of management theory.

First, they offer a dynamic extension to the Knowledge-Based View (KBV). The traditional KBV emphasizes knowledge as a critical stock resource that is embedded within the firm. Our results highlight the importance of the flow and reconfiguration of knowledge access channels. The value is derived not just from the knowledge a firm possesses, but from its demonstrated capability to dynamically manage its external knowledge-sourcing network. This provides strong empirical support for the concept of "combinative capabilities"—the ability to synthesize and apply existing and acquired knowledge—as a key driver of value in a dynamic environment.

Second, this paper advances network theory in strategic management. For decades, the field has relied heavily on static SNA metrics to explain firm outcomes. Our results issue a clear challenge to this paradigm, demonstrating that such an approach is insufficient for capturing the essence of network-based advantage. We propose the "network trajectory" as a new and vital unit of analysis. A firm's network is not merely a structural constraint or opportunity at a

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point in time; it is a strategic asset that must be actively curated, managed, and evolved. The focus of inquiry should shift from asking "Where is the firm in the network?" to "Where is the firm going in the network, and how is it getting there?"

Finally, the results provide clear answers to the research hypotheses. The superior predictive performance of the EvolveGCN model strongly supports H1, confirming that a firm's network history matters. The positive valuation associated with trajectories of increasing brokerage and centrality provides direct support for H2, specifying which types of network navigation are most valued by the market.

4.3 Practical and Managerial Implications

Beyond its theoretical contributions, this research offers several actionable insights for managers and investors.

The most direct implication is for strategic alliance portfolio management. Managers should not view their firm's partnerships as a static collection of assets to be passively maintained. Instead, they should adopt a dynamic portfolio perspective, continuously evaluating their firm's overall position and trajectory within the industry's innovation ecosystem. This involves not only assessing individual alliances but also understanding how the portfolio as a whole positions the firm for future knowledge access and growth. It requires asking strategic questions: Are we becoming more or less central? Are we building new bridges or reinforcing old ties? Is our network trajectory aligned with our innovation goals?

This leads to a second implication regarding metrics for innovation strategy. Traditional innovation KPIs often focus on internal inputs (e.g., R&D as a percentage of sales) or discrete outputs (e.g., number of new products, patent counts).[38] Our research suggests that firms should develop and monitor a new class of dynamic network metrics as leading indicators of their innovation strategy's health and its perception by the market. Tracking the evolution of the firm's centrality, brokerage score, and partner diversity over time can provide a more forward-looking assessment of its innovation engine than purely retrospective measures.

Finally, the methodology itself points toward the future of AI-driven strategic analysis. The success of the DGNN model suggests that firms can leverage similar advanced graph analytics to gain a competitive edge. These tools can be used to monitor the competitive landscape in real-time, identify emerging technological clusters and strategic opportunities, and even simulate the potential market valuation impact of forming or dissolving specific alliances. This represents a shift from static, descriptive analysis of networks to a dynamic, predictive, and prescriptive approach to strategy.

5. Conclusion and Future Directions

5.1 Summary of Key Findings

This study set out to investigate the impact of the evolution of corporate innovation networks on firm valuation. By employing a Dynamic Graph Neural Network model on a large panel of U.S. firms over 26 years, we arrive at three core conclusions. First, the evolution of a firm's position within its innovation network is a powerful and significant predictor of its future market valuation, offering explanatory power that surpasses both traditional financial metrics and static network measures. Second, our findings validate the use of advanced machine

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learning methods like DGNNs, and specifically EvolveGCN, as a robust methodology for capturing the complex, path-dependent, and non-linear relationships inherent in strategic management phenomena. Third, we find that not all trajectories are valued equally; the market specifically rewards dynamic capabilities that lead to trajectories of increasing brokerage and access to diverse knowledge, consistent with theories of exploratory innovation and strategic adaptation.

5.2 Significance and Limitations

The significance of this research is twofold. Theoretically, it contributes a dynamic perspective to the Knowledge-Based View and network theory, shifting the focus from static positions to the strategic capability of network navigation. Methodologically, it introduces a state-of-the-art analytical technique to the strategy field, opening new avenues for research into complex, evolving relational systems.

However, it is crucial to acknowledge the study's limitations. First, the use of publicly announced strategic alliances from the SDC Platinum database serves as a proxy for innovation collaboration. This dataset may not capture informal knowledge-sharing ties, failed negotiations, or collaborations by private firms, though it remains the most comprehensive source available for large-scale studies.20 Second, while our predictive, forward-looking model design mitigates some concerns, the potential for endogeneity remains. It is plausible that high-performing, highly valued firms are more attractive alliance partners, creating a virtuous cycle where success begets a better network position. Disentangling this causal relationship completely would require a different research design. Third, while we use feature importance techniques to interpret the DGNN model, such deep learning models are inherently less transparent than traditional econometric models, representing a trade-off between predictive power and direct interpretability of coefficients.

5.3 Future Research Directions

The findings and limitations of this study suggest several promising avenues for future research.

First, researchers could apply the DGNN methodology to other forms of dynamic inter-firm networks to test the generalizability of our findings. For example, one could construct dynamic networks based on patent citations, where a citation represents a flow of knowledge[41], or networks based on the mobility of key inventors and executives between firms.[42] This would provide a more multi-faceted view of the knowledge ecosystem.

Second, future work could move beyond the mere presence or absence of a tie to analyze the content of alliances. By applying natural language processing (NLP) techniques to the textual descriptions of alliances in databases like SDC Platinum, one could differentiate between exploration-focused partnerships (e.g., joint R&D in a new technology) and exploitation-focused ones (e.g., marketing agreements for existing products). Modeling the evolution of a firm's portfolio of exploration versus exploitation ties could yield even deeper insights into its innovation strategy and valuation.

Finally, to address the issue of causality more directly, future studies could seek out quasi-natural experiments that exogenously shock the network structure. Events such as major antitrust enforcement actions that break up central firms, or significant regulatory changes that alter the incentives for collaboration in an industry, could provide cleaner identification of the causal impact of network dynamics on firm performance and value.[43] Exploring these and other questions will continue to build our understanding of how firms create value in an increasingly networked world.

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