ESSAYS ON MANAGING MANUFACTURING AND SERVICE NETWORKS

By

Seongwon Park

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ABSTRACT

This dissertation investigates how network structures and relational dynamics shape environmental and operational outcomes, with a focus on supply chain systems in manufacturing and service industries. The first two essays examine manufacturing supply networks, emphasizing the role of interfirm relationships in influencing environmental performance and transparency. The first essay explores the impact of downstream firms on the environmental efficiency of upstream suppliers across multi-tier supply chains. Drawing on FactSet Revere and Trucost data from six manufacturing sectors, the analysis reveals that downstream firms' environmental efficiency positively influences that of upstream partners – a relationship that intensifies under higher levels of financial dependence.

The second essay examines the effect of buyer environmental disclosure on supplier disclosure, addressing concerns about potential supply chain leakage. Using data from FactSet Revere and Bloomberg environmental, social, and governance (ESG) covering the materials and pharmaceuticals sectors, the study finds no consistent evidence of a broad negative effect, suggesting that leakage may not be prevalent under voluntary disclosure regimes. However, the findings highlight key moderating dynamics. Structural social capital, reflected in shared network ties, plays a significant role: buyer–supplier pairs with weaker structural overlap are more likely to exhibit negative effects, while stronger overlap mitigates this risk. Similarly, cultural similarity moderates outcomes – greater cultural dissimilarity correlates with negative effects on supplier disclosure, whereas culturally aligned pairs show no significant effect.

The third essay turns to service networks, specifically examining how airline network configurations influence the management of operational disruptions. Using data from the U.S. Bureau of Transportation Statistics across seven major U.S. airlines, the analysis demonstrates that the network structure of an airline plays a critical role in managing delays, cancellations, and baggage handling issues. Together, these three essays contribute to a deeper theoretical and practical understanding of how varying network contexts – across both manufacturing and service domains – affect firms' environmental and operational performance.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

With the global expansion of business across manufacturing and service sectors, firms are increasingly expected not only to manage their own performance but also to engage with a diverse set of partners throughout the supply chain. As inter-firm relationships become more complex and interconnected, the scope of organizational responsibility extends beyond direct interactions to encompass indirect network influences. Paradoxically, increasing interdependence within global business networks often places greater operational and relational demands on the firms involved. This dissertation examines how both inter-organizational and intra-organizational networks affect firm performance, with a specific focus on corporate sustainability practices and operational disruptions in the service industry. By integrating insights from supply chain management, sustainability, and service operations, this work contributes to the growing literature on how network structure and relational dynamics shape organizational outcomes in both manufacturing and service sectors.

Spanning three empirical essays, this dissertation addresses underexplored but critical questions surrounding environmental management, corporate sustainability reporting, and operational reliability in networked contexts. The first essay investigates how downstream firms in multi-tier supply chains (MSCs) affect the environmental efficiency of their upstream partners. Using FactSet Revere supply chain relationship data and Trucost environmental performance data across six manufacturing industries, the study constructs firm-level environmental efficiency scores with network data envelopment analysis (NDEA). It further examines how suppliers' revenue dependence on downstream buyers moderates this cross-tier environmental effect. Drawing on 259 triadic relationships from 2014 to 2018, the analysis applies nonlinear models to explore the environmental influence across supply chain tiers. Given the lack of prior studies on cross-tier sustainability activities using secondary data, this study will provide useful insights into the dynamic interplay between firms in managing cross-tier environmental efficiency based on the use of a mixed-methods approach and the unique panel data set.

The second essay explores environmental disclosure behavior within buyer–supplier relationships (BSRs), particularly in the context of the supply chain leakage phenomenon and the pollution haven hypothesis. Using dyadic relationship data from FactSet Revere and Bloomberg environmental, social, and governance (ESG) data covering two manufacturing sectors over a five-year panel (2015–2019), the study finds no broad evidence of a negative influence of buyer disclosure on supplier environmental disclosure. However, the findings reveal important moderating effects. Structural social capital, represented by network overlap between buyers and their suppliers, and cultural similarity influence the extent to which buyers shape their suppliers' environmental disclosure behavior. To be specific, weak structural overlap or cultural dissimilarity amplifies the negative effect, while strong overlap or similarity mitigates it. Relationship duration, by contrast, does not significantly moderate the effect. Taken together, these findings enhance theoretical and managerial understanding by illustrating how different dimensions of social capital can differentially influence environmental practices within supply networks.

The third essay shifts the focus from supply chains to service networks, examining how different airline network configurations, hub-and-spoke versus point-to-point, affect service quality in the U.S. domestic market. Although network structure is widely recognized as a key determinant of airline performance, prior research has not systematically investigated its role in shaping operational resilience during disruptions. Using flight-level data from the U.S. Bureau of Transportation Statistics (BTS), this study compares the performance of full-service carriers (FSCs) and low-cost carriers (LCCs) through both linear and nonlinear modeling approaches. The results indicate that FSCs, which primarily operate hub-and-spoke networks, outperform LCCs in managing delays, reducing cancellations, and maintaining higher on-time performance. By contrast, LCCs demonstrate stronger performance in baggage handling. The analysis also reveals notable variation within the LCC group. In particular, Southwest Airlines, despite following a point-to-point model, performs well in reducing delays and baggage incidents but exhibits a higher rate of flight cancellations. These findings offer important insights into how network configurations shape operational outcomes in service industries.

Collectively, the three essays provide both theoretical and empirical insights into how network structures and relational dynamics shape firm behavior and performance. Rather than focusing solely on dyadic relationships, this dissertation examines the broader systemic and cross-tier interactions that define modern supply chains. It further extends this perspective to service operations by analyzing how network configurations influence operational performance and service reliability in the airline industry. By leveraging large-scale secondary data and applying a combination of linear and nonlinear modeling techniques, the dissertation highlights the importance of designing and managing networks not only to improve efficiency but also to enhance resilience and support sustainability.

CHAPTER 2

DYNAMICS OF ENVIRONMENTAL MANAGEMENT IN MULTI-TIER SUPPLY CHAINS

2.1 Introduction

In recent years, several countries have entered into international environmental treaties, such as the Kyoto Protocol, the Montreal Protocol, and the Paris Agreement, to help reduce the adverse impact caused by humans on the environment. Additionally, government bodies, such as the Environmental Protection Agency (EPA) of the United States, establish sustainability initiatives that assist firms in enhancing the sustainability of their supply chains through assessment, benchmarking, and enhancement of operational efficacy. SmartWay is an example of a voluntary public-private program introduced by the EPA in 2004 that has helped firms advance supply chain sustainability by reducing freight emissions. In addition to governments, non-profit organizations such as the Carbon Disclosure Project (CDP) help firms disclose their environmental impact and develop carbon emissions reduction strategies. According to a 2019 report (CDP, 2019) by the CDP, the collaborative action between the CDP Supply Chain program members and their suppliers reduced 8 million tonnes of carbon emissions.

With the rising demand for transparency in supply chains, focal companies and their suppliers are being held responsible for sustainability challenges within their supply chains (Wilhelm et al., 2016a; Awaysheh and Klassen, 2010). Accordingly, businesses are striving to reduce their environmental and social impacts (Bové and Swartz, 2016). Many multinational corporations have set social and environmental standards to manage suppliers in addition to pursuing social and environmental goals of their own (Villena and Gioia, 2020). However, from the viewpoint of focal companies in multi-tier supply chains (MSCs), managing the risk of environmental and social breaches caused by lower-tier suppliers located beyond direct suppliers is more challenging (Wilhelm and Villena, 2021; Villena and Gioia, 2018). This is because focal firms' control over lower-tier suppliers tends to be lower given the lack of information on their sustainability activities, the global nature of the supply chain (Wilhelm et al., 2016b), and distant relationships (Bellamy et al., 2020; Awaysheh and Klassen, 2010). According to a 2022 survey by Ernst and Young (Ernst & Young, 2022), over 60% of supply chain managers report no year-over-year enhancements in the comprehensive visibility of their supply chains. Thus, lower-tier suppliers are more passive in addressing social and environmental sustainability challenges as they perceive a low risk of being penalized for not attending to these challenges (Villena and Gioia, 2018). Although numerous global conglomerates have been incorporating sustainability practices into their business operations, the impact of these practices on the sustainable operations of upstream partners remains unclear and warrants further investigation (Hartmann and Moeller, 2014).

In this paper, our primary research question is to examine the cross-tier environmental impact on firms in MSCs resulting from the environmentally responsible actions of their downstream partners. Answering this question is challenging due to the lack of available data on upstream suppliers and the shortage of related studies in the literature (Villena and Gioia, 2018). To address this, we primarily use FactSet Revere supply chain relationships data in this study. Under an open triadic configuration, we consider numerous triadic relationships from the viewpoint of focal companies engaged in the general category of manufacturing. We augment the FactSet data using Trucost environmental data, which provides information on hundreds of key environmental performance indicators across 500 distinct industry sectors. Since MSCs involve multiple firms at each tier, we aggregate the environmental performance data and create comprehensive measures for each triadic configuration using network data envelopment analysis (NDEA). The environmental efficiency scores derived from NDEA provide a holistic approach to assessing firms' environmental performance across supply chains, as it uses multiple input and output factors based on both desirable and undesirable outcomes. Moreover, using NDEA in studies involving diverse supply chain activities is practical because it captures both the internal and external activities of firms that comprise the supply chains. This procedure helps us address whether the environmental efficiency of downstream firms positively influences the efficiency of not only their neighboring suppliers but also distant suppliers.

Our second research question is to enhance the understanding of how the cross-tier environmental impact in buyer-supplier relationships (BSRs) is strengthened by supplier revenue dependence. To achieve this, we revisit power-dependence relations from a supplier's perspective in the context of sustainable supply chain management (SSCM). While organizational performance is contingent on that of its partner, a firm often encounters a dilemma as its dependence on another organization becomes more interlocked (Pfeffer and Nowak, 1976). Thus, the performance benefits of relational dependence between firms may vary depending on the degree of the actual involvement in the relationship. Furthermore, addressing environmental concerns within supply chains is a shared priority, which, in turn, enables supply chain partners to support each other's operations and enhance their environmental sustainability (Hajmohammad et al., 2024; Kim and Henderson, 2015; Kim and Wemmerlöv, 2015; Hoejmose et al., 2013; Gimenez and Sierra, 2013). Consequently, in light of the environmental impact stemming from neighboring downstream partners on an upstream partner's environmental efficiency, we also address the moderating effect of supplier revenue dependence on the environmental association.

2.1.1 Contributions and Results

Our research contributes to the SSCM literature in three important ways as discussed below.

(i) **Impact beyond first-tier:** A majority of the research in SSCM concentrates on investigating the impact of focal firms on first-tier suppliers, and vice versa (Diebel et al., 2024; Song et al., 2024, 2023; Jira and Toffel, 2013). This perspective inherently assumes that the first-tier suppliers will oversee the lower tiers of supply chains in a manner aligned with and conducive to the objectives of the focal company. However, there is evidence indicating the ineffectiveness of this approach, as it puts the focal company at risk of dealing with and controlling adverse impacts resulting from the actions of the upstream members of their supply chains (Choi and Linton, 2011). Thus, to investigate the environmental impact of downstream firms on both the closest and distant suppliers, it is essential to adopt a holistic approach that evaluates performance beyond a dyadic level. Hence, in our study, we consider triadic relationships to precisely capture the internal dynamics in MSCs.

(ii) **Multiple criteria and network impact in measuring environmental efficiency:** Many studies in the SSCM literature consider only a single criterion to capture environmental performance (De Stefano and Montes-Sancho, 2024; Song et al., 2024; Adhikary et al., 2020). However, industrial production and business operations require diverse input resources and generate multiple negative environmental externalities. Thus, from a managerial viewpoint, it is necessary to consider a comprehensive measure that accounts for multiple desirable and undesirable environmental outcomes. We address this using an NDEA model, which creates a comprehensive measure of environmental efficiency considering multiple inputs and outputs of firms' operations that impact the environment. Moreover, our study contributes to the literature by employing a network DEA model that effectively captures the interrelationships between different entities within supply chains. This approach allows us to compute environmental efficiency scores that reflect the network interrelationships of firms.

(iii) **Time-varying impact and revenue dependence:** Many studies in the literature examine the environmental impact between members of MSCs over a limited time period. However, it is important to note that inter-firm environmental impact may vary over time. In our study, we utilize a unique panel dataset that allows us to conduct a robust analysis by capturing time-dependent measures of environmental efficiency. This enables us to test the inter-firm environmental impact not only across multiple firms but also over different periods. Moreover, our study contributes to the literature on power-dependence relations within SSCM by examining the effect of the revenue dependence of upstream suppliers (on their downstream firms) on the environmental impact between members of MSCs.

We employ a mixed methods approach, integrating the environmental efficiency scores derived from our NDEA model as variables into our econometric models to test our research hypotheses. Our main findings are as follows: (i) The environmental efficiency of focal firms positively influences the efficiency of their first-tier suppliers. (ii) The environmental efficiency of second-tier suppliers is impacted by the first-tier suppliers but not directly by the focal firms, suggesting that second-tier suppliers are more likely to align with their closest downstream partners. (iii) At any level of environmental efficiency, the downstream firms have a similar influence on the efficiency of their upstream partners. Moreover, the environmental influence of focal firms on first-tier suppliers is greater than the influence of first-tier suppliers on second-tier suppliers. (iv) Supplier revenue dependence enhances the positive relationship between the environmental efficiencies of MSC members, suggesting that higher revenue dependence of upstream partners on downstream firms in BSRs improves the impact of downstream firms on upstream partners' environmental efficiency.

2.1.2 Organization

The rest of our paper is structured as follows. In the next section, we review the related literature on environmental management in the context of MSCs and develop our hypotheses. Based on a thorough investigation of the contextual background, Section 3 presents our research design, including details on supply network configurations, data and sources, our NDEA model developed using diverse environmental performance measures, and the definitions of our variables. We present our estimation models and a discussion of our results in the fourth section. In Section 5, we offer additional insights through sensitivity analyses based on the results of nonlinear fractional probit models. Finally, in Section 6, we discuss the implications of our findings and provide directions for future research.

2.2 Background and Hypotheses

In this section, we discuss the relevant literature in SSCM and develop our hypotheses. We first develop our hypotheses related to cross-tier environmental impact in MSCs, followed by our hypotheses on the moderating effect of supplier revenue dependence on this impact.

2.2.1 Relational Dynamics in Multi-tier Supply Chains

Sustainability has been subsumed in the literature of diverse business disciplines, including operations and supply chain management (SCM) (Kleindorfer et al., 2005). Environmental accountability and transparency in supply chains are becoming increasingly important for firms (Song et al., 2024, 2023; Gualandris et al., 2021). Researchers, however, indicate a lack of knowledge regarding the tracing and measuring of social and environmental impacts and their externalized costs from global production and consumption systems (O'Rourke, 2014). This is because global supply chains have become more complex than ever due to the expansion of supply chain boundaries, in addition to firms being challenged with managing the depth and quality of BSRs and partners' malpractices that might harm their operations and reputation. Further, despite the increase in transparency and accountability in globalized supply chains, consumers do not differentiate the efforts made by members in MSCs and attribute the unsustainable behavior of suppliers to focal firms; this is referred to as "chain liability" (Hartmann and Moeller, 2014; Tachizawa and Wong, 2014). Therefore, understanding cross-tier environmental impact in MSCs is essential.

Given the nature of MSCs, member firms inevitably affect each other. Firms can enhance their productivity when they collaborate with productive partners by adopting their partners' efficient practices. Thus, a strong and productive partner's knowledge spills over through different channels across the supply chains (Serpa and Krishnan, 2018). This indicates that the environmental efficiency of productive partners could potentially transfer to the other members of the supply chain. In addition, when focal firms establish direct and contractual relationships with first-tier suppliers, they sometimes enforce compliance with sustainability measures in the contractual arrangements to control their own sustainability performance (Saunders et al., 2020; Hartmann and Moeller, 2014). To promote the environmental stewardship of supply networks, some focal firms also leverage a mimetic mechanism (Diebel et al., 2024) in which the suppliers mimic the sustainable practices of the focal firm. Consequently, it is highly likely that first-tier suppliers in MSCs are more receptive to the sustainability practices of focal firms. Hence, we hypothesize the following:

Hypothesis 1A (H1A). The environmental efficiency of focal firms positively influences the environmental efficiency of first-tier suppliers.

Previous studies have shown environmental influence not only between a focal firm and first-tier suppliers but also between first-tier suppliers and lower-tier suppliers; see e.g., Jamalnia et al. (2023), Wilhelm et al. (2016b), Tachizawa and Wong (2014), Touboulic et al. (2014). First-tier suppliers often serve as a boundary-spanner to improve sustainability performance across supply chains (De Stefano and Montes-Sancho, 2024; Grimm et al., 2014; Touboulic et al., 2014). Moreover, first-tier suppliers often monitor the sustainability performance criteria of second-tier suppliers and require them to meet these criteria to mitigate potential social and environmental risks (Wilhelm and Villena, 2021; Wilhelm et al., 2016b). Thus, we posit the following:

Hypothesis 1B (H1B). The environmental efficiency of first-tier suppliers positively influences the environmental efficiency of second-tier suppliers.

The impact of focal firms on the sustainable practices of suppliers beyond the first tier is not straightforward. Lower-tier suppliers often proactively adopt environmentally conscious practices when they are more exposed to the actions of their downstream customers who are sustainability leaders conscious of environmental issues. They tend to actively participate in their customers' industry organizations and imitate their sustainability initiatives (Villena and Gioia, 2018). Additionally, the intermediaries who oversee lower-tier suppliers' operations on behalf of the focal firms adopt helpful procedures to aid lower-tier suppliers in fulfilling their sustainability obligations (Jamalnia et al., 2023).

In contrast, studies in the literature also argue that the sustainable actions of focal firms may not impact suppliers beyond the first tier. Since focal firms can directly monitor the first-tier suppliers, the closest partners strive to meet sustainability standards, whereas lower-tier suppliers are sometimes too passive to engage in environmental and social issues. Managing the sustainability of distant partners is more complex and less controllable since they often have no direct and contractual relationship with focal firms. Instead, they indirectly communicate with focal firms with the help of intermediaries (Jamalnia et al., 2023; Hartmann and Moeller, 2014). Although focal firms delegate their responsibility to intermediaries for overseeing lower-tier suppliers and managing sustainability considerations of their upstream processes (Wilhelm et al., 2016a,b), lower-tier suppliers are still less likely to engage in social and sustainability obligations imposed by focal firms (Jamalnia et al., 2023; Villena and Gioia, 2018). Thus, in the absence of a contractually binding force, it is difficult for focal firms to regulate lower-tier suppliers and oversee their violations of sustainability requirements. This leads to lower-tier suppliers' perception that they are less likely to be penalized for not addressing environmental issues (Villena and Gioia, 2018), potentially leading to negative environmental consequences and stakeholder reactions for the focal firms (Jamalnia et al., 2023). Moreover, as the physical and organizational separation between focal firms and upstream partners expands, the focal firms experience difficulties in closely interacting with lower-tier suppliers, leading to challenges in data gathering, which results in a lack of visibility (Garcia-Torres et al., 2019; Wilhelm et al., 2016a; Awaysheh and Klassen, 2010). Despite focal firms becoming equipped with the ability to track and address social and environmental issues across supply chains due to technological advancements (Garcia-Torres et al., 2019), their awareness of the identities of lower-tier suppliers and their ability to directly influence them remain limited (Grimm et al., 2014). Thus, we hypothesize the following:

Hypothesis 2 (H2). The environmental efficiency of focal firms directly influences the environmental efficiency of second-tier suppliers.

2.2.2 Moderating Effects of Supplier Financial Dependence on Environmental Performance

Inter-organizational relationships have often been conceptualized via the resource dependence theory (RDT), which takes into account inter-relational issues such as dependence, uncertainty, power, and scarcity of resources (Hajmohammad et al., 2024; Tate et al., 2022). From a resource-dependence perspective, despite reducing external reliance leading to greater success, firms are typically not self-sufficient and rely on their partners to acquire necessary resources (Elking et al., 2017; Pfeffer and Salancik, 1978). Thus, inter-organizational relationships can be configured differently based on the diverse power dynamics of the partners involved. In SCM, supply networks comprise numerous organizations that are intricately connected and engaged in operational activities. Consequently, in MSCs, interdependence can serve as a driving force for fostering cooperative sustainable relationships among involved entities (Tate et al., 2022).

Dependence in relationships can also be found in the context of sustainability. The diffusion of environmentally conscious business practices among suppliers is fostered by greater relational interdependence (Tate et al., 2013). Managing sustainability in BSRs is essentially a reciprocal concern (Chen et al., 2017), and the adoption and implementation of sustainability practices are particularly active when buyers can exert coercive power (Sancha et al., 2019; Touboulic et al., 2014). Thus, it is also conceivable that suppliers might adhere to the sustainability standards set by the buying firm to preserve relationships and secure business opportunities with them. At the same time, the level of supplier dependence determines the buying firms' ability to monitor and encourage cooperation to facilitate each other and improve their environmental performance (Hajmohammad et al., 2024; Kim and Henderson, 2015; Kim and Wemmerlöv, 2015; Hoejmose et al., 2013; Gimenez and Sierra, 2013). Therefore, the greater the supplier's dependence on the buyer, the greater the benefits the supplier obtains by implementing collaborative practices to enhance the sustainability of their operations (Sancha et al., 2019; Touboulic et al., 2014). To summarize, supplier dependence has been considered in the literature as a key contingency factor that influences the effectiveness of sustainability practices among suppliers. Thus, we hypothesize the following:

Hypothesis 3A (H3A). The positive relationship between the environmental efficiency of the first-tier suppliers and that of the focal firms is strengthened by the financial dependence of first-tier suppliers on focal firms.

Hypothesis 3B (H3B). The positive relationship between the environmental efficiency of the second-tier suppliers and that of the first-tier suppliers is strengthened by the financial dependence of second-tier suppliers on first-tier suppliers.

2.3 Research Design

In this section, we first discuss the structure of MSCs used in our analysis. Next, we explain our data collection procedure and the sources of our data. We then develop our NDEA model to compute comprehensive measures of environmental efficiency. Finally, we define the variables used to test our hypotheses.

2.3.1 Triads

Different structural arrangements imply different business connections and outcomes between member firms in supply chains. In the context of MSCs, structural arrangements involve different combinations of member firms. As such, triads, the fundamental elements of supply chains, can be formed in various ways (Choi and Wu, 2009). Based on the structural, contextual, and relational characteristics, previous work has predominantly presented two major forms of triads: open and closed triadic structures (Vedel et al., 2016; Tachizawa and Wong, 2014; Mena et al., 2013). Specifically, groups of three interconnected firms create either an open triad where the three firms are indirectly linked through one of them, as shown in Figure 2.1, or a closed triad where all firms are directly linked to each other (Vedel et al., 2016).

Figure 2.1 Open Triad

Based on diverse methods, such as surveys, case studies, and conceptual and statistical analyses, previous studies have used different forms of triadic relationships (Vedel et al., 2016; Wu et al., 2010; McFarland et al., 2008). Drawing upon field interviews and institutional theory, the propagation of interfirm behaviors using two adjacent dyads (that is, manufacturer, dealer, and customer triads) is examined (McFarland et al., 2008), while supplier-supplier co-opetition using triadic data (that is, buyer-supplier-supplier triads) is also empirically investigated (Ried et al., 2021; Wu et al., 2010). Since our study aims to understand the cross-tier environmental impact in MSCs beyond the first-tier suppliers, using open triadic relationships is more appropriate. Focusing on open triadic relationships allows us to aggregate and compute tier-level metrics across the three tiers of MSCs. We note that closed triadic relationships are not appropriate for our study because, in those relationships, the supplier's supplier is also a direct supplier of the focal firm since they can establish a direct connection with each other. Thus, our study takes advantage of open triadic relationships to isolate second-tier suppliers, which do not have a direct and contract-based relationship with the focal firm, from focal companies (Jamalnia et al., 2023; Osadchiy et al., 2021; Wilhelm et al., 2016a; Grimm et al., 2014). Further, considering open triadic relationships allows us to utilize the NDEA model to compute tier-level environmental efficiency scores.

Figure 2.2 Data Collection and Processing

Step 1

1. Identify buyer-supplier relationships using revenue percentage data (FactSet).
    a) Among the different types of normalized relationships captured by FactSet Revere, select customer relationships with percentage revenues.
2. Merge buyer-supplier relationship data (FactSet) with environmental performance data (Trucost), spanning 2014 to 2018 (12,231 dyads), using International Securities Identification Number (ISIN).

Step 2

1. Remove duplicate buyer-supplier relationships (8,222 dyads).
    a) Remove duplicate buyer-supplier relationships with the same unique identifier for the relationship record in a year between 2014 and 2018 (8,675 dyads).
    b) Remove duplicate reporting of 451 buyer-supplier relationships with the same buyer and supplier but different relationship identifiers based on two criteria (8,224 dyads).
        i. Remove redundant buyer-supplier relationships with different unique identifiers for the relationship record but the same duration and percentage revenues.
        ii. Remove redundant buyer-supplier relationships with relatively small percentage revenues.
    c) Remove buyer-supplier relationships with the same start/end date and zero percentage revenue (8,222 dyads).

Step 3

1. Create triadic relationships using the multiple dyadic relationships established in Step 3 (1,067 triads).
    a) Remove triads with missing environmental performance data (1,911 triads).
    b) Remove triads where a focal firm's ISIN is equivalent to the second-tier supplier's ISIN (1,851 triads).
    c) Select focal firms operating in 10 four-digit Global Industry Classification Standard (GICS) groups, all within the manufacturing category (1,202 triads).
    d) Remove focal firms with less than $1 billion annual revenues (1,195 triads).
    e) Remove triads that have direct business connections between second-tier suppliers and focal firms (to sift out closed triadic relationships, we extensively examined 637,313 FactSet Revere supply chain relationships data beyond 2014) (1,067 triads).
2. Aggregating the triadic relationships established in the previous step, create triads with unique focal firm and year combinations (289 firm-level observations).

Step 4

1. Drop 30 observations due to NDEA empirical rules (259 firm-level observations).

2.3.2 Data

In this section, we discuss our data collection procedure and the sources of our data set. An overview of our data collection and processing procedure is provided in Figure 2.2.

Our empirical analysis is based on multiple buyer-supplier-supplier triads in MSCs. To construct these triadic relationships, we utilize firm-level BSR data provided by FactSet Revere. The effectiveness of FactSet Revere's supply chain relationships data has been highlighted within the context of SCM (Osadchiy et al., 2021; Wang et al., 2021) and environmental management (Cole et al., 2023; Modi and Cantor, 2021). According to FactSet Revere, their global business relationship data is hand-collected and verified from various public sources, including annual filings, investor presentations, and press releases (Agca et al., 2022; Wu et al., 2022). The established BSRs are also tracked daily based on public releases and corporate actions, ensuring that inter-company relationships are up-to-date. Prior research using FactSet Revere supply chain relationships data has utilized the start and end dates of BSRs to create variables and construct either time series or panel data for their studies (Pankratz and Schiller, 2024; Ağca et al., 2023; Crosignani et al., 2023; Culot et al., 2023; Gofman and Wu, 2022; Wu et al., 2022; Osadchiy et al., 2021; Wang et al., 2021; Chae et al., 2020; Gofman et al., 2020; Schiller, 2018). In particular, Gofman and Wu (2022) uses the start and end dates to create a snapshot of the BSRs observed at the end of each calendar year, enabling the formation of a series of production networks at an annual frequency. Crosignani et al. (2023) also discusses the superiority and granularity of FactSet Revere supply chain relationships data, mentioning that it offers an adequately frequent occurrence of the start and end dates of supply chain relationships. Culot et al. (2023) specifically mentions that start dates of BSRs are determined by the date when the information on BSRs is processed, whereas end dates are decided by the announcement of source companies and verified over time. In this study, we use this unique feature of FactSet Revere to set up a panel data structure comprising multiple buyer-supplier-supplier triads for our empirical analysis.

The second distinctive feature of FactSet Revere supply chain relationships data is that it provides information on revenue dependence in BSRs. According to FactSet Revere, their revenue percent data indicates the percentage of revenue a supplier derives from their relationship with each downstream member between the start and end dates. We use this revenue percent data not only to test the moderating effect of supplier revenue dependence on cross-tier environmental impact but also to compute the environmental efficiency scores of the member firms in all the triads in our data using our NDEA model (Pankratz and Schiller, 2024; Hyun and Kim, 2018; Schiller, 2018).

Another data set used in this study is Trucost environmental data (De Stefano and Montes-Sancho, 2024; Cole et al., 2023). Trucost provides data on hundreds of key environmental performance indicators across 500 distinct industry sectors via a four-step research process: mapping, estimating, collecting, and engaging with companies. This data set also relies on diverse sources, such as direct corporate disclosure of more than 15,000 corporations, scientific literature, and global-level and national-level databases, to collect a variety of information on pollutants, water dependency, natural resource consumption, waste disposal, corporate disclosure, and annual revenue. Based on prior research in SSCM (as shown in Table 2.1), to compute environmental efficiency scores, we collect data from the Trucost database on four different environmental performance indicators, in addition to revenue data, for each member of the triadic relationships we develop using FactSet data.

In our analysis, to control for heterogeneity in our hypotheses tests, we include several variables in our econometrics models, such as industry similarity and geographical distance between neighboring partners. We also include the economic freedom score of the country to which the firm under study belongs. Prior research has considered economic freedom as a driver of social and environmental responsibility (Graafland, 2019; Hartmann and Uhlenbruck, 2015), and hence, we include the economic freedom data from the Heritage Foundation as a control variable in our analysis. This data provides economic freedom scores for a country based on the rule of law, government size, regulatory efficiency, and market openness. We obtain the geographical distance data from the open-source website Geodatos[1].

Using the FactSet and Trucost datasets, we first identify BSRs with revenue percentage data

[1]https://www.geodatos.net/en

from 2014 to 2018. Next, we utilize these multiple dyadic relationships to form various triadic relationships. Finally, as in prior research (Song et al., 2023; Barker et al., 2022; Osadchiy et al., 2021; Dong et al., 2020), we aggregate these triadic relationships to create triads with unique focal firm and year combinations, resulting in 259 firm-level observations spanning from 2014 to 2018. The details of this procedure are explained step-by-step in Figure 2.2. In our dataset, for the observation of a focal firm's triad in a given year, we compute every variable related to tier-level performance or characteristic by appropriately aggregating or averaging the metric across different firms in that tier. We explain the details in the next sections. Our final dataset with 259 observations is an unbalanced panel with observations for each focal firm ranging from 2014 to 2018. Note that some focal firms may lack observations in specific years due to the unavailability of revenue percentage data for the dyadic relationships within their triads during those years.

2.3.3 Computing Environmental Efficiency Scores using NDEA

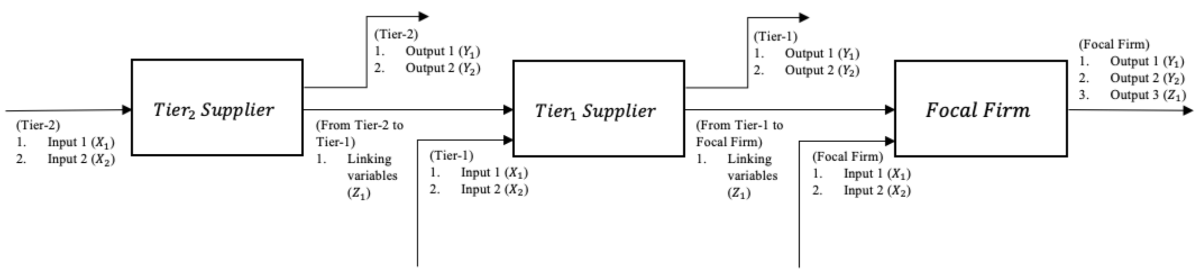
In this study, we use the data envelopment analysis (DEA) technique to compute the environmental efficiency scores of firms at different tiers of MSCs. DEA is a method used for assessing the relative efficiency of peer decision-making units (DMUs), and this technique is frequently used in SCM research to analyze and compare performance across business units. Efficiency scores obtained through DEA methods are commonly used as variables in subsequent empirical studies, thereby extending the applicability and insights provided by DEA (Dreyfus et al., 2020; Kao et al., 2017; Jacobs et al., 2016).

DEA requires an assumption of a homogeneous set of units. Therefore, we categorize our DMUs according to the Global Industry Classification Standard (GICS) industry taxonomy to enable a comparison between homogeneous DMUs. Furthermore, for our analysis in this study, we consider the aggregated triadic relationship for each focal firm within a given year. To reflect this, we treat the (aggregated) triad[2] of a focal company as a DMU (Tavana et al., 2013; Chen and Yan, 2011); Figure 2.3 illustrates the DMU of our analysis, which is a triad comprising three different tiers: focal firm, first-tier suppliers, and second-tier suppliers. A limitation of the DEA method is that it

[2]Henceforth, whenever we mention the triad of focal firm i in year t, we are referring to the aggregated triad of focal firm i in year t.

treats each DMU as a black box, relying solely on the initial inputs and final outputs consumed and produced by the DMU, respectively, and does not capture the internal and linking activities between divisions of DMUs. For our study, including the linking activities of DMUs is essential to capture the network interrelationships between member firms. Hence, to overcome the drawback of DEA and to capture the internal linking activities between divisions of DMUs, we use a NDEA model by introducing the concept of intermediate variables that link two consecutive divisions so that parts of the outputs from the preceding division can be used as inputs to the subsequent division (Tone and Tsutsui, 2009).

Figure 2.3 NDEA Configuration



Since industrial production and business operations require diverse input resources and generate multiple negative environmental outcomes, we develop an NDEA model that takes into account multiple desirable and undesirable environmental outcomes to compute environmental efficiency scores for members of MSCs. Table 2.1 presents the input and output factors used in our NDEA model. We now discuss how we operationalize the input, output, and intermediate factors at each tier of the triadic DMU. First, since the triadic relationships we study comprise only one focal firm, we directly use the focal firm's inputs and outputs as the corresponding inputs and outputs in the NDEA model. Let $Input_{it}$ (resp., $Output_{it}$) be an input (resp., output) of a focal firm i in year t. Then, in our NDEA model, for the triad formed by focal firm i in year t, we define the input and

Table 2.1 NDEA Variables

Name	Variable (Label)	Description	Reference
Water Purchased	Input (X_1)	The volume of water purchased from utility companies (cubic meter)	Cole et al. (2023); Fu and Jacobs (2022); Sodhi and Tang (2019)
Natural Resource Use	Input (X_2)	External cost of direct and indirect natural resource usage (USD mn)	Kalaitzi et al. (2018); Brandenburg et al. (2014); Tang and Zhou (2012)
Carbon-Scope 1 & 2 Emissions	Undesirable Output (Y_1)	Sum of the greenhouse gas (GHG) emissions from operations that are owned or controlled by the company and the GHG emissions from consumption of purchased electricity, heat or steam by the company (tonnes CO2e)	Song et al. (2024, 2023); Adhikary et al. (2020); Saunders et al. (2020); Sodhi and Tang (2019); Zhou et al. (2018); Wu et al. (2016)
Waste	Undesirable Output (Y_2)	External cost of hazardous and non-hazardous waste produced by the company (USD mn)	Wu et al. (2016); Tang and Zhou (2012); Kleindorfer et al. (2005)
Revenue	Intermediate (Z_1)	Annual revenue (USD mn)	An et al. (2016); Wu et al. (2016); Brandenburg et al. (2014)

output of focal firm i as follows:

$$Focal\ Firm\ Input_{it} = Input_{it} \tag{2.1}$$

$$Focal\ Firm\ Output_{it} = Output_{it} \tag{2.2}$$

Next, in year t, let $Input_{ijt}$ (resp., $Output_{ijt}$) be an input (resp., output) of a first-tier supplier j in the triad of firm i. Let J be the total number of first-tier suppliers of focal firm i in the triad. Then, to consider the impact of network interrelationships between the focal firm and its first-tier suppliers on cross-tier environmental influence, we aggregate the input and output of first-tier suppliers within the triad of focal firm i as follows:

$$Tier_1\ Input_{it} = \sum_{j=1}^{J} Input_{ijt} \tag{2.3}$$

$$Tier_1\ Output_{it} = \sum_{j=1}^{J} Output_{ijt} \tag{2.4}$$

Moreover, we capture the network interrelationships between the focal firm and its first-tier suppliers using the total amount of revenue of first-tier suppliers that is dependent on focal firm i as the linking variable (variable Z_1 as shown in Figure 2.3). In year t, for the triad of focal firm i, using the revenue of first-tier firm j ($Revenue_{ijt}$), the percentage of revenue dependence of first-tier supplier j on focal firm i (RP_{ijt}), the relationship duration (in days) between first-tier supplier j and focal firm i (RD_{ijt}), and the number of days in that year (N_t), we define the linking variable connecting the first tier of the triad to the focal firm as follows:

$$Tier_1\ Intermediate\ Measure_{it} = \sum_{j=1}^{J} \frac{RD_{ijt}}{N_t} \times RP_{ijt} \times Revenue_{ijt} \tag{2.5}$$

Note that since the focal firm i and first-tier supplier j may not always maintain a business relationship throughout the entire year t, we compute our linking variable based on the fraction of the year t during which their business relationship exists. Finally, to capture the network interrelationships between the second-tier suppliers and their downstream firms, we use a similar approach to the one discussed above. We define the input, output, and linking variables for the second tier of the triad of focal firm i as follows:

$$Tier_2\ Input_{it} = \sum_{k=1}^{K} \sum_{j=1}^{J} Input_{ijkt} \tag{2.6}$$

$$Tier_2\ Output_{it} = \sum_{k=1}^{K} \sum_{j=1}^{J} Output_{ijkt} \tag{2.7}$$

$$Tier_2\ Intermediate\ Measure_{it} = \sum_{k=1}^{K} \sum_{j=1}^{J} \frac{RD_{ijkt}}{N_t} \times RP_{ijkt} \times Revenue_{ijkt} \tag{2.8}$$

Here, in year t, $Input_{ijkt}$ (resp., $Output_{ijkt}$) denotes an input (resp., output) of a second-tier supplier k (which is the supplier of first-tier supplier j) in the triad of focal firm i. Further, in year

t, the variables $Revenue_{ijkt}$, RP_{ijkt}, and RD_{ijkt} represent the revenue of the second-tier supplier k, the percentage of revenue dependence of second-tier supplier k on first-tier supplier j, and the relationship duration (in days) between second-tier supplier k and first-tier supplier j, respectively.

Using all the inputs, outputs, and linking variables defined above for each tier of the triadic relationships, we run our NDEA model to compute the environmental efficiency scores for each tier. Based on the homogeneity assumption of NDEA, we run separate NDEA models by clustering all the triads of focal firms within the same industry, according to the GICS classification. In each NDEA model we run for a cluster of triads belonging to the same industry, we treat the triad of a focal firm in a given year as a separate DMU (Wang, 2019; Surroca et al., 2016). This procedure benchmarks all DMUs, enabling meaningful comparisons of their performance through efficiency scores (Wang, 2019). Further details of our NDEA model can be found in the Appendix.

For the triad of each focal firm i in a given year t, our NDEA models compute three environmental efficiency scores, one for each tier. We represent these as follows: $Focal\ Firm_{it}$, $Tier_1\ EE_{it}$, $Tier_2\ EE_{it}$, corresponding to the environmental efficiency score of focal firm i, the first-tier of focal firm i, and the second-tier of focal firm i, respectively, in year t.

2.3.4 Variables for Econometric Analysis

In this section, we first describe the dependent and independent variables, followed by the control variables we use in our econometric models.

2.3.4.1 Dependent Variables

To test the hypotheses of our study, we use two dependent variables: environmental efficiency scores of first- and second-tier suppliers. As discussed in the previous section, using NDEA analysis, we first compute the dependent variable $Tier_2\ EE_{it}$. This variable is a score that collectively measures the environmental efficiencies of all the second-tier suppliers in the triad of focal firm i in year t. Note that this score is based on multiple input, output, and intermediate measures in the upstream stage of Figure 2.3, and comprehensively mirrors the environmental footprint of second-tier suppliers. Similarly, we compute our second dependent variable $Tier_1\ EE_{it}$, a score that collectively measures the environmental efficiencies of all the first-tier suppliers in the triad of focal firm i in year t.

2.3.4.2 Independent Variables

Testing our hypotheses requires four main independent variables. To test the influence of the first-tier suppliers on the environmental efficiency of the second-tier suppliers, we use $Tier_1\ EE_{it}$ as the independent variable. Next, to test the influence of the focal firm on the environmental efficiency of the first-tier suppliers, we compute the independent variable $Focal\ Firm\ EE_{it}$ using our NDEA model.

To test H3A and H3B, we compute the following two independent variables: $Tier_1 Dependence_{it}$ and $Tier_2 Dependence_{it}$. The variable $Tier_1 Dependence_{it}$ (resp., $Tier_2 Dependence_{it}$) measures the degree of first-tier (resp., second-tier) suppliers' revenue dependence on the focal firm (resp., first-tier suppliers). Below, we describe the procedure used to compute these variables.

Consistent with prior studies (Pankratz and Schiller, 2024; Hyun and Kim, 2018; Schiller, 2018), using FactSet Revere, we obtain supplier revenue dependence data, which measures the percentage of a supplier's revenue derived from the relationship with their downstream partner. Consider focal firm i in year t. Let RP_{ijt} be the percentage revenue dependence of first-tier supplier j on the focal firm i in year t. Then, we compute $Tier_1\ Dependence_{it}$ – the overall revenue dependence of its first-tier suppliers on focal firm i in year t – as a weighted average of the revenue dependencies of all its first-tier suppliers as follows:

$$Tier_1\ Dependence_{it} = \sum_{j=1}^{J} \left(\frac{Revenue_{ijt}}{\sum_{j=1}^{J} Revenue_{ijt}} \right) \times \frac{RD_{ijt}}{N_t} \times RP_{ijt}. \tag{2.9}$$

The variables in the above equation are defined as in (2.5). Note that since a first-tier supplier does not always have a relationship with the focal firm throughout the year, our method uses the exact proportions of the relationship durations as weights to compute the average revenue dependence. Using a similar approach, we compute the overall revenue dependence of the second-tier suppliers (of firm i) on the first-tier suppliers (of firm i) as follows:

$$Tier_2\ Dependence_{it} = \sum_{j=1}^{J} \left(\frac{Revenue_{ijt}}{\sum_{j=1}^{J} Revenue_{ijt}} \right) \times \left(\sum_{k=1}^{K} \left(\frac{Revenue_{ijkt}}{\sum_{k=1}^{K} Revenue_{ijkt}} \right) \times \frac{RD_{ijkt}}{N_t} \times RP_{ijkt} \right) \tag{2.10}$$

The variables in the above equation are defined as in (2.8).

2.3.4.3 Control Variables

Several firm-level and country-level characteristics across different tiers in MSCs may influence the environmental efficiency scores of the member firms. To account for potential confounding effects and the impact of unobserved factors, we include a set of control variables in our empirical models. We discuss this below in detail.

Previous work shows that a firm's financial performance measure is associated with corporate willingness and ability to disclose environmental performance (Bellamy et al., 2020; Jira and Toffel, 2013; Al-Tuwaijri et al., 2004). Furthermore, a focal firm's size is often seen as an influential factor of environmental performance (Modi and Cantor, 2021) and used as a measure for a buyer's power (Jira and Toffel, 2013). Therefore, to account for a focal firm's size and power in its supply chains, we use its annual revenue as a control variable. In our models, we include the control variable $lnRevenue_{it}$, which is the natural logarithm of the annual revenue of a focal firm i in year t.

Since partnership success is contingent on sharing similarities in corporate strategies, structure, and cultural fit, companies take advantage of same-sector partnerships to increase efficiency (Gutiérrez et al., 2016). Previous work on managing corporate sustainability in the context of MSCs controls for information on suppliers' industry heterogeneity (Song et al., 2024, 2023; Bellamy et al., 2020; Jira and Toffel, 2013). Therefore, we include another set of control variables in our models that represent whether two firms in a dyad are included in the same industry. For the triad of focal firm i in year t, using Trucost data, we compute the control variable $Same\ Industry\ Downstream_{it}$ as the proportion of first-tier firms belonging to the same industry as the focal firm i. Similarly, for the triad of focal firm i in year t, we compute the control variable $Same\ Industry\ Upstream_{it}$ as the average of the variables $Same\ Industry\ Upstream_{ijt}$, where $Same\ Industry\ Upstream_{ijt}$ represents the proportion of second-tier firms of first-tier firm j belonging to the same industry as the first-tier firm j.

Geographical location and dispersion of partner firms are other decisive factors that determine the implementation of sustainability practices (Wilhelm et al., 2016b) and increase supply chain complexity (Wilhelm et al., 2016a; Awaysheh and Klassen, 2010; Bozarth et al., 2009). Hence, we also control for the average between-firm geographical distances across different tiers of supply networks. The control variable $lnUpstream\,Distance_{it}$ (resp., $lnDownstream\,Distance_{it}$) in our models represents the natural logarithm of the average geographical distances between second-tier suppliers and first-tier suppliers (resp., between first-tier suppliers and focal firm) of focal firm i in year t. The procedures used to compute these variables are detailed below.

Across multiple triadic relationships, we gather sets of cross-country distance data, comprising the distance between centroids of the two countries. Using Geodatos, these measurements are taken between the two countries where the headquarters of the two firms, engaged in a dyadic relationship within supply networks, are situated. For a triad formed with firm i as the focal firm, in year t, let D_{ijt} denote the distance between the centroids of the countries in which the focal firm i and its first-tier firm j are located. Then, to control for the effect of the geographical distance between focal firm i and its first-tier firms on their cross-tier environmental impact, we define the variable as follows:

$$lnDownstream\,Distance_{it} = \ln\left(\frac{1}{J}\sum_{j=1}^{J} D_{ijt} + 1\right) \tag{2.11}$$

Note that since distances between countries in our data follow a skewed distribution, we apply a natural logarithmic transformation to normalize the distances. Further, we add 1 to the average geographical distances before applying the logarithm to avoid any negative values. Similarly, to control for the effect of the geographical distance between the second-tier and first-tier of focal firm i on their cross-tier environmental impact, we define the variable as follows:

$$lnUpstream\,Distance_{it} = \ln\left(\frac{1}{J}\sum_{j=1}^{J}\frac{1}{K}\sum_{k=1}^{K} D_{ijkt} + 1\right) \tag{2.12}$$

Here, D_{ijkt} represents the distance between the centroids of the countries in which the second-tier firm k and the first-tier firm j (of the focal firm i) are located in year t.

Across various nations, economic freedom has been demonstrated to enhance the ability to innovate in environmentally sustainable ways. Significant advancements in clean energy utilization

Table 2.2 Descriptive Statistics and Correlations

N = 259	Mean	SD	Min	Max	1	2	3	4	5	6	7
1. *$Tier_2$ EE*	0.164	0.296	0.00	1.00	1.00						
2. *$Tier_1$ EE*	0.304	0.373	0.00	1.00	0.52*	1.00					
3. *Focal Firm EE*	0.678	0.348	0.03	1.00	0.14*	0.46*	1.00				
4. *$Tier_2$ Dependence (%)*	9.367	15.921	0.13	100	-0.05	-0.12	-0.04	1.00			
5. *$Tier_1$ Dependence (%)*	8.386	10.839	0.00	83.17	0.04	0.21*	0.10	-0.12*	1.00		
6. *Same Industry Upstream (%)*	47.881	39.917	0.00	100	-0.10	-0.13*	0.08	0.25*	-0.20*	1.00	
7. *Same Industry Downstream (%)*	46.416	47.593	0.00	100	-0.00	-0.11	0.02	0.03	0.12	0.06	1.00
8. *lnUpstream Distance*	5.189	4.000	0.00	9.41	0.01	0.07	0.18*	-0.07	0.10	0.14*	-0.01
9. *lnDownstream Distance*	4.472	4.294	0.00	9.45	0.14*	0.24*	0.23*	0.12	-0.01	-0.01	0.11
10. *Economic Freedom*	71.653	7.696	52.00	90.20	0.08	0.10	0.11	0.11	0.06	0.01	-0.05
11. *lnRevenue*	10.468	1.238	7.54	12.54	-0.08	0.07	0.23*	-0.04	0.29*	-0.16*	0.06

	Mean	SD	Min	Max	8	9	10	11
8. *lnUpstream Distance*	5.189	4.000	0.00	9.41	1.00			
9. *lnDownstream Distance*	4.472	4.294	0.00	9.45	0.11	1.00		
10. *Economic Freedom*	71.653	7.696	52.00	90.20	0.32*	0.29*	1.00	
11. *lnRevenue*	10.468	1.238	7.54	12.54	0.28*	0.38*	0.28*	1.00

Note: $*p < 0.05$.

and energy efficiency have predominantly arisen from improvements in economic freedom and expanded trade (Miller et al., 2022). Economic freedom is measured by multiple quantitative and qualitative factors in four broad categories, including rule of law, government size, regulatory efficiency, and open markets, and it is known to stimulate corporate environmental responsibility (Graafland, 2019). Thus, in our analysis, we control for the overall economic freedom of the country in which the focal firm is headquartered. We denote this control variable by $Economic\ Freedom_{it}$.

In summary, the final data set for our empirical analysis is panel data, ranging from 2014 to 2018. The descriptive statistics of all the variables in our study and their correlations are presented in Table 2.2.

2.4 Analysis and Results

In this section, we first discuss the results of our NDEA model. Next, we describe the models used for the empirical analysis to test our hypotheses. Finally, we present the results of our empirical models.

2.4.1 NDEA Results

Recall that for the triad of each focal firm in years ranging from 2014 to 2018 (i.e., for all the 259 unique focal firms and year combinations in our panel dataset), our NDEA model outputs three efficiency scores: one each for the focal firm, the first tier, and the second tier. Table 2.3 provides the averages and standard deviations of the environmental efficiency scores of focal firms, first-tier suppliers, and second-tier suppliers. As shown in the table, all focal firms in our dataset fall under the general category of manufacturing and are classified into six distinct GICS industry groups. Additionally, the first and second-tier suppliers belong to 15 different industry groups, each with its own industry composition, as detailed in Table 2.4.

Table 2.3 Sample Statistics of Focal Firms across 6 GICS Industries

		$Tier_2\ EE$		$Tier_1\ EE$		$Focal\ Firm\ EE$	
Industry (four-digit GICS code)	**Observations**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**
Automobiles & Components (2510)	54	0.114	0.243	0.283	0.346	0.747	0.273
Capital Goods (2010)	60	0.164	0.306	0.178	0.334	0.451	0.388
Health Care Equipment (3510)	31	0.161	0.275	0.474	0.362	0.843	0.208
Materials (1510)	55	0.093	0.263	0.339	0.402	0.666	0.387
Pharmaceuticals & Biotechnology (3520)	27	0.353	0.316	0.260	0.369	0.772	0.240
Technology Hardware & Equipment (4520)	32	0.210	0.353	0.385	0.381	0.772	0.306
Total	259	0.164	0.296	0.304	0.373	0.678	0.348

Table 2.4 Industry Composition of First- and Second-tier Suppliers

Second-tier Suppliers		***First-tier Suppliers***	
GICS Industry Classifications	Observations	GICS Industry Classifications	Observations
Automobiles & Components	114	Automobiles & Components	97
Capital Goods	59	Capital Goods	31
Commercial & Professional Services	2	Consumer Durables & Apparel	5
Consumer Durables & Apparel	1	Energy	37
Energy	63	Food & Staples Retailing	3
Food, Beverage & Tobacco	1	Food, Beverage & Tobacco	5
Health Care Equipment	3	Health Care Equipment	6
Materials	99	Materials	64
Pharmaceuticals & Biotechnology	275	Pharmaceuticals & Biotechnology	153
Real Estate	254	Real Estate	3
Semiconductors & Semiconductor Equipment	83	Semiconductors & Semiconductor Equipment	27
Software & Services	23	Software & Services	2
Technology Hardware & Equipment	19	Technology Hardware & Equipment	17
Transportation	3	Transportation	4
Utilities	18	Utilities	6

Note: Observations are reported based on the number of unique firms in a given year.

2.4.2 Empirical Strategy

We now discuss the empirical models we use to test our hypotheses. To test the influence of the focal firm's environmental efficiency on that of its first-tier suppliers (H1A) and if this influence is affected by the revenue dependence of the first-tier suppliers, we use the following model:

$$\begin{aligned} Tier_1\ EE_{it} &= \gamma_0 + \gamma_1 \times Focal\ Firm\ EE_{it} + \gamma_2 \times Tier_1\ Dependence_{it} \\ &+ \gamma_3 \times Focal\ Firm\ EE_{it} \times Tier_1\ Dependence_{it} + \boldsymbol{\gamma_4} \times \boldsymbol{\eta_{it}} + \alpha_i + \delta_t + \epsilon_{it}. \end{aligned} \tag{2.13}$$

In this model, $\boldsymbol{\eta_{it}}$ represents all the control variables such as revenue and the economic freedom of the focal firm (discussed in Section 2.3.4.3), whereas the variables α_i and δ_t control for the focal firm and year specific unobserved heterogeneity, respectively.

Next, to test the influence of the first-tier suppliers and focal firm on the environmental efficiency of the second-tier suppliers (H1B), and if this influence is affected by the revenue dependence of the second-tier suppliers, we use the following model:

$$\begin{aligned} Tier_2\ EE_{it} &= \beta_0 + \beta_1 \times Tier_1\ EE_{it} + \beta_2 \times Focal\ Firm\ EE_{it} + \beta_3 \times Tier_2\ Dependence_{it} \\ &+ \beta_4 \times Tier_1\ EE_{it} \times Tier_2\ Dependence_{it} + \boldsymbol{\beta_5} \times \boldsymbol{\mu_{it}} + \alpha_i + \delta_t + \epsilon_{it}. \end{aligned} \tag{2.14}$$

Here, $\boldsymbol{\mu_{it}}$ denotes the set of control variables, while α_i and δ_t account for unobserved heterogeneity at the focal firm and year levels, respectively.

Note that the efficiency score outputs from DEA models are typically numbers between 0 and 1. Therefore, for hypotheses tests on efficiency scores, we use a correlated random effects (CRE) approach via the use of Mundlak device (Mundlak, 1978) to estimate nonlinear and unbalanced panel data models in the presence of unobserved heterogeneity (Bates et al., 2024; Joshi and Wooldridge, 2019; Wooldridge, 2019). The fraction probit model we use is as follows:

$$E[Y_{it}|X_{it}, \bar{X}_i, T_i] = \Phi(\psi_t + X_{it}\beta + T_i\gamma + \bar{X}_i\delta) \tag{2.15}$$

In the equation above, Y_{it} denotes fractional dependent variables, whereas X_{it} collectively represents independent variables, control variables, and year dummies (as described in (2.13) and (2.14)). The variable $\bar{X}_i = T_i^{-1} \sum_{t=1}^{T_i} X_{it}$ refers to the time averages of each covariate, the parameter ψ_t represents year-specific intercepts, and $\Phi(\cdot)$ denotes the cumulative distribution function (CDF) of the standard normal distribution. Here, the time averages of explanatory variables serve as proxies for firm-level fixed effects. To account for our unbalanced panel data, similar to that in Bates et al. (2024), we employ indicators (T_i) that denote the number of time periods observed for a focal firm i. In the next section, we discuss the parameters estimated from these models and the corresponding results.

2.4.3 Main Results

Table 2.5 illustrates the results for all our hypotheses tests. The results for hypotheses H1A and H3A are presented in Models 1, 2, and 3 in Panel A, while the results for hypotheses H1B, H2, and H3B are presented in Models 4, 5, 6, and 7 in Panel B.

In the results of Models 2 and 3, the parameter estimate of $Focal\,Firm\,EE$ is statistically significant and positive supporting hypothesis H1A and indicating that the environmental efficiency of the focal firm positively influences the efficiency of its first-tier suppliers. The parameter estimate of $Tier_1\,EE$ across Models 5, 6, and 7 is statistically significant and positive supporting hypothesis H1B showing that the environmental efficiency of the first-tier suppliers positively influences the efficiency of the second-tier suppliers. However, the estimate of $Focal\,Firm\,EE$ in Models 6 and 7 is insignificant suggesting that focal firms do not directly influence the environmental efficiency of second-tier suppliers, but rather do so indirectly through first-tier suppliers. Thus, our hypothesis H2 is not supported.

Next, we examine the results of the hypothesis tests for H3A and H3B regarding the effect of supplier revenue dependence on environmental efficiencies. In Model 3, the parameter estimate of the interaction between $Tier_1\,Dependence$ and $Focal\,Firm\,EE$ is statistically significant and positive indicating that the revenue dependence of first-tier suppliers on the focal firm increases the influence of the focal firm on their environmental efficiency. Specifically, at the mean level of $Tier_1\,Dependence$, the marginal effect of $Focal\,Firm\,EE$ on $Tier_1\,EE$ is 0.502 ($s.e.$ = 0.095), and it is positive and statistically significant at the 0.1% level.

Similarly, the parameter estimate of the interaction between $Tier_2\,Dependence$ and $Tier_1\,EE$ in

Table 2.5 Coefficient Estimates (APEs) of Pooled Fractional Probit Models

	Panel A			*Panel B*			
Dependent variable:	$Tier_1\ EE$			$Tier_2\ EE$			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Independent variable:							
$Tier_1\ EE$					1.618***	1.687***	1.387***
					(0.257)	(0.271)	(0.340)
$Tier_1\ EE$ (APE)					0.303***	0.315***	0.325***
					(0.050)	(0.052)	(0.051)
$Focal\ Firm\ EE$		1.867***	-0.036			-0.280	-0.236
		(0.478)	(0.458)			(0.265)	(0.258)
$Focal\ Firm\ EE$ (APE)		0.518***	0.436***			-0.052	-0.043
		(0.130)	(0.094)			(0.049)	(0.047)
$Tier_2\ Dependence$							-0.011
							(0.009)
$Tier_2\ Dependence$ (APE)							0.003
							(0.002)
$Tier_2\ Dependence \times Tier_1\ EE$							0.052*
							(0.024)
$Tier_1\ Dependence$			-0.177***				
			(0.041)				
$Tier_1\ Dependence$ (APE)			0.004+				
			(0.002)				
$Tier_1\ Dependence \times Focal\ Firm\ EE$			0.240***				
			(0.052)				
$Same\ Industry\ Upstream$				-0.003	0.002	0.001	-0.000
				(0.006)	(0.005)	(0.005)	(0.006)
$Same\ Industry\ Downstream$	-0.002	-0.002	-0.001	-0.004	-0.004	-0.004	-0.004
	(0.004)	(0.005)	(0.004)	(0.006)	(0.006)	(0.006)	(0.005)
$lnUpstream\ Distance$				-0.053	-0.096**	-0.098**	-0.095+
				(0.035)	(0.031)	(0.031)	(0.054)
$lnDownstream\ Distance$	-0.039	-0.045	-0.022	0.051	0.090	0.089	0.080
	(0.065)	(0.070)	(0.063)	(0.035)	(0.061)	(0.062)	(0.073)
$Economic\ Freedom$	-0.023+	0.004	-0.002	-0.005	0.010	0.005	0.006
	(0.012)	(0.018)	(0.011)	(0.010)	(0.011)	(0.012)	(0.012)
$lnRevenue$	-0.133	0.017	-0.256	-1.132**	-1.250***	-1.293***	-1.097***
	(0.321)	(0.361)	(0.250)	(0.428)	(0.312)	(0.312)	(0.321)
Constant	-1.495	-1.313	-0.614	-1.191	-1.844	-1.897	-1.663
	(1.290)	(1.190)	(1.118)	(1.539)	(1.755)	(1.710)	(1.773)
Model Specification							
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	259	259	259	259	259	259	259
Number of Focal Firms	115	115	115	115	115	115	115
Pseudo R^2	0.184	0.351	0.464	0.204	0.386	0.399	0.420

Note: $+p < 0.1$, $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$ indicate statistical significance at the 10 percent, 5 percent, 1 percent, and 0.1 percent levels. Standard errors ($s.e.$) are clustered at the focal firm level and reported in parentheses below parameter estimates. We report both the coefficients and average partial effects (APEs) from the fractional probit models. In addition, we present the pseudo R^2 based on squared correlation for all model specifications. The pooled fractional probit models include the time averages of independent variables, control variables, and time dummies. For brevity, I do not report the APEs of control variables and the estimates of the time averages of independent variables, control variables, and time dummies here.

Model 7 is statistically significant and positive indicating that the revenue dependence of second-tier suppliers on first-tier suppliers increases the influence of the first-tier suppliers on their environmental efficiency. To be specific, at the mean level of $Tier_2\ Dependence$, the marginal effect of

$Tier_1\ EE$ on $Tier_2\ EE$ is 0.348 ($s.e.$ = 0.055), and it is positive and statistically significant at the 0.1% level. Consequently, both hypotheses H3A and H3B are supported.

Remark 1. ***(Note on Simultaneity Bias):*** *We note that the parameter estimates of our models, and consequently our results, are free from simultaneity bias. As discussed in Section 2.3.3, the inputs and outputs used to compute the environmental efficiency for each tier differ from those used for the other tiers not only, particularly due to differences in aggregation procedures and tier-specific characteristics. Additionally, the linking variable in our NDEA models is revenue, which is not a direct measure of environmental efficiency. Therefore, in any given triad, the environmental efficiency score computed for first-tier suppliers (resp., second-tier suppliers) is not directly related to the score computed for the focal firm (resp., first-tier suppliers), thereby eliminating concerns of reverse causality and simultaneity bias.*

2.5 Sensitivity Analysis

In this section, we explore how the influence of a downstream firm on its upstream partners varies with the firm's level of environmental efficiency. To this end, we build on the results from the previous section, which employed a CRE framework using a fractional probit model.

The advantage of using fractional probit models with a nonlinear functional form is that it enables the estimation of average partial effects (APEs) at different points along the distribution of explanatory variables (Bates et al., 2024; Papke and Wooldridge, 2008). We run a pooled fractional probit model with CRE estimation to estimate APEs at the 5th, 25th, 50th, 75th, and 95th percentiles of both $Tier_1\ EE$ and $Focal\ Firm\ EE$ distributions. Using Models 2 and 5 in Table 2.5, we examine how the influence of environmental efficiency changes at different percentiles of its distribution.

Figures 2.4 and 2.5 illustrate how the environmental efficiency of downstream firms, at different percentiles, affects the environmental efficiency of the upstream partners. Figure 2.4 shows the influence of the focal firm's environmental efficiency on first-tier suppliers, while Figure 2.5 shows the influence of first-tier suppliers on second-tier suppliers. Both figures demonstrate a consistent pattern of increasing influence at all percentiles of environmental efficiency. This suggests that at any value of the environmental efficiency of the downstream firm, an increase in the efficiency will continue to improve its impact on the upstream partner's efficiency. Notably, its increasing rate is the highest at intermediate levels of environmental efficiency in downstream firms. Additionally, the impact of the focal firm's environmental efficiency on first-tier suppliers is stronger compared to the influence of first-tier suppliers on second-tier suppliers. This indicates that downstream supply chain firms have a stronger influence on their upstream partners.

Figure 2.4 APEs of $Focal\ Firm\ EE$

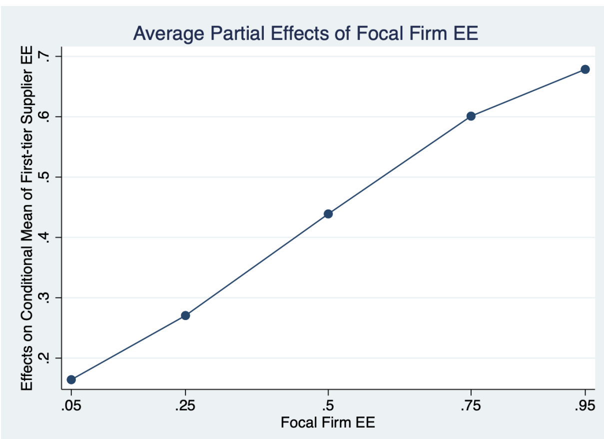
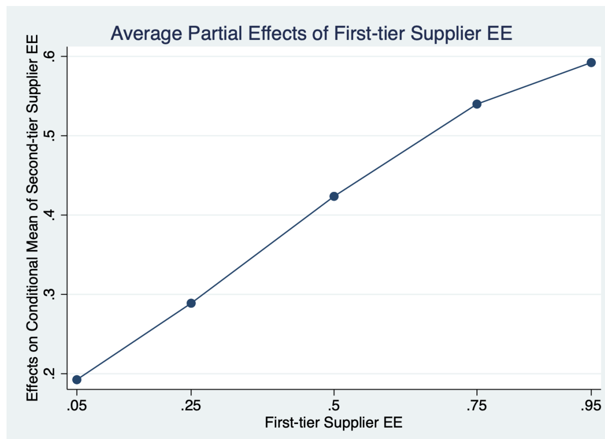


Figure 2.5 APEs of $Tier_1\ EE$



2.6 Discussion and Conclusion

2.6.1 Theoretical Implications

With increasing pressure to disclose firms' supply chain information and the collective efforts of supply chain members, significant progress has been made in reducing the social and environmental impacts caused by supply chain participants (Bové and Swartz, 2016). However, to our knowledge, previous studies seldom examine the dynamics of cross-tier environmental efficiency management between firms at different supply chain levels. Furthermore, while existing studies on SSCM predominantly focus on buying firms (Brandenburg et al., 2014), there is a growing need to assess and monitor the sustainability practices of upstream suppliers in MSCs. Research on SSCM that emphasizes the influence of downstream firms on upstream environmental outcomes remains limited.

In this study, we aim to expand the scope of existing research by examining how the environmental efficiency of downstream supply chain firms influences their upstream partners in an open triadic configuration, where direct business connections between focal firms and second-tier suppliers are nonexistent. We achieve this by aggregating firm-level environmental performance data and utilizing NDEA to compute tier-level environmental efficiency scores for each triad. Our empirical analyses reveal that downstream firms have a positive environmental influence on their immediate upstream members.

Physical distance, measured by geographical, cultural, and organizational dimensions, underpins the rationale behind information asymmetry and coordination efforts (Tachizawa and Wong, 2014; Awaysheh and Klassen, 2010). This physical distance increases the likelihood of suppliers' opportunistic behaviors and discretionary practices. Firms may adopt diverse social and environmental practices, leading to different approaches to addressing environmental issues, which in turn could provoke additional uncertainty due to limited access to information. Our empirical results indicate that while focal firms positively influence the environmental efficiency of first-tier suppliers, they do not have a significant impact on the environmental efficiency of second-tier suppliers. This finding suggests that, in the absence of direct business connections, lower-tier suppliers are more likely to align their environmental efficiency with their nearest partners rather than with entities further down the supply chain.

We also examine the role of supplier revenue dependence in influencing the positive impact of downstream firms on the environmental efficiency of upstream members. Power dynamics in BSRs are inherently complex, with power asymmetry shaping the gains or losses from relational dependence. However, the impact of dependency on the diffusion of environmentally friendly practices in MSCs remains under-explored (Tate et al., 2013). Therefore, we revisit power-dependence relations from a resource-dependence and sustainability perspective to better understand how a supplier's revenue dependence influences environmental efficiency in a dyadic context. Our empirical analysis reveals that supplier revenue dependence enhances the positive association between the environmental efficiencies of dyads in supply chains. Our findings build upon prior research on power-dependence relationships within SSCM, demonstrating that upstream partners' environmental efficiency improves with increased revenue dependence on downstream partners in BSRs.

2.6.2 Managerial Implications

The expansion of global supply chain networks and the growing financial and operational interdependence among member firms have heightened interest among scholars and practitioners in studying sustainability in SCM. Sustainability, represented by the confluence of the three main pillars, people, planet, and profit, in operations management, encompasses green product and process development, lean and green operations management, and remanufacturing and closed-loop supply chains (Kleindorfer et al., 2005). However, the lack of sufficient knowledge in tracing and measuring environmental externalities from global production and consumption systems adds complexity to the investigation and implementation of SSCM practices, rendering them often symbolic (Adhikary et al., 2020; O'Rourke, 2014). Addressing these limitations within the context of MSCs, our study provides several implications for practitioners.

First, we emphasize the importance of using a comprehensive measure to gauge environmental performance across supply chains. Operational features may vary depending on inherent and situational factors of supply chain entities, making it essential to utilize diverse environmental metrics such as GHG emissions, waste, and environmental costs resulting from operational outcomes to assess corporate environmental efficiency. A single measure of environmental performance can obscure these diverse aspects, whereas environmental efficiency scores based on multiple input and output environmental metrics provide a more accurate reflection of corporate environmental performance across various dimensions.

Next, we note that separate tier-level models do not consider the linking activities occurring at different stages of supply chains. Therefore, employing NDEA models in sustainable supply chain research is effective, as they account for both internal operations and the interconnected actions of companies within the supply chains. Unlike node-level performance evaluation, network-level performance evaluation that integrates multifaceted characteristics provides a comprehensive understanding of how firms at different stages of supply chains interact with members at other tiers. Therefore, using measures that capture multi-dimensional activities and consider cross-tier interactions will help managers obtain meaningful insights.

Among firms that share their environmental performance data with external stakeholders, our empirical evidence indicates a positive cross-tier environmental impact. However, the impact may vary depending on firms' positions within the supply chain and their business relationships. Specifically, while focal firms can influence the environmental efficiency of their immediate suppliers, they may not directly affect the sustainable practices of suppliers further upstream. In light of these findings, even in the absence of direct contractual relationships with upstream suppliers, managers of focal firms should closely monitor the upstream suppliers' sustainable practices and implement mechanisms to incentivize and enhance their environmental efficiency.

Finally, while we find a positive association in cross-tier environmental efficiency, this relationship varies based on the level of a supplier's financial dependence in dyadic relationships. Our empirical evidence indicates that a supplier's revenue dependence enhances the positive association between the environmental efficiencies of suppliers and their downstream partners. This indicates that managers should intensify their efforts to collaborate with suppliers who are less financially dependent on them to establish and pursue joint environmental goals, as these suppliers may be less inclined to align their practices with the firm's environmental standards.

2.6.3 Future Research and Conclusion

Our study has several limitations, giving rise to opportunities for future research. First, to analyze the impact of cross-tier interactions on tier-level environmental performance, we focus on open triadic relationships, exploring a specific form of triads. However, the governance mechanisms in MSCs may be more complex and diverse (Tachizawa and Wong, 2014; Mena et al., 2013; Choi and Wu, 2009). Therefore, considering other forms of triadic relationships could potentially offer a more nuanced understanding of the dynamics of environmental performance within MSCs.

Second, to consider the linking activities and revenue dependence between firms at different tiers of supply chains, we utilize revenue percentage data and relationship longevity of BSRs. In Section 2.3.2, we detail how the unique features of FactSet Revere supply chain relationships data, including the start and end dates of BSRs, have been handled in previous studies. Notably, these studies coarsen the start and end dates of BSRs. In contrast, we use the exact proportions of relationship durations within a given year. Both approaches may introduce some degree of noise. Using supply chain relationship data over more granular timespans, such as monthly or quarterly data, would enhance the robustness of our empirical analyses.

Next, the sample selected for our empirical analysis is exclusively drawn from six distinct manufacturing industries. While both second-tier and first-tier suppliers operate across a diverse range of industries, the focal firms in this study have been chosen solely from the manufacturing sector. As a result, the findings of this research may not be fully generalizable to other sectors.

In conclusion, prior research in SSCM has predominantly focused on managing the sustainability performance of direct suppliers. However, attention to levels beyond first-tier suppliers has been limited, often neglecting the dynamics and interactions involving sub-suppliers (Grimm et al., 2014). Despite certain limitations highlighted earlier, this study advances SSCM research by examining multiple triadic relationships and employing a unique panel data framework. Our work sheds light on the dynamics of cross-tier environmental management and highlights the significant role of supplier revenue dependence in influencing these dynamics.

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APPENDIX

MODELING RELATIVE ENVIRONMENTAL EFFICIENCY IN MSCS USING NDEA

NDEA is a highly effective method for evaluating the efficiencies of various tiers in supply chains, as it accounts for divisional efficiency at each stage as well as the overall efficiency within unified supply networks (Tone and Tsutsui, 2009). To comprehensively evaluate bilateral efficiency, encompassing both individual divisions and the overall system, this study employs a network slack-based measure (NSBM) approach. A DEA model based on the NSBM approach is suitable when input and output factors do not change proportionally. Due to the non-radial nature of the NSBM approach, a variable return-to-scale (VRS) method is used in this study to ensure that at least one fully efficient DMU is available to serve as a benchmark for other inefficient units (Tone and Tsutsui, 2009). Further, we employ a non-oriented DEA model because firms attempt to achieve a dual goal that simultaneously aims to decrease the input and increase the output to maximize efficiency (Keskin, 2021; Martínez-Campillo et al., 2020; Gharfalkar et al., 2015; Moreno and Lozano, 2014; Price and Joseph, 2000). In summary, we employ an NDEA model based on the non-oriented NSBM approach under the VRS assumption.

Building on previous studies that include undesirable outcomes in NDEA to compute efficiencies (Chen et al., 2021; Martínez-Campillo et al., 2020; Tone and Tsutsui, 2009), we develop an NDEA model to evaluate tier-level environmental efficiency scores across supply chains, along with the overall system-level environmental performance. To model the system-level efficiency analysis, we first describe the data matrices for each input, output, and intermediate linking factor.

In our NDEA model, let N be the total number of DMUs and S be the number of stages for each DMU. For the stage $s \in \{1, 2, ..., S\}$ of DMU $n \in \{1, 2, ..., N\}$, let x_n^s denote the vector of inputs and let m_s be the number of inputs. Then, we can write the input vector of stage s of DMU n as follows:

$$x_n^s := \left(x_{n,1}^s, x_{n,2}^s, ..., x_{n,m_s}^s \right). \tag{A.1}$$

Here, for any $n \in \{1, 2, ..., N\}$, $s \in \{1, 2, ..., S\}$, and $m \in \{1, 2, ..., m_s\}$, the input $x_{n,m}^s \in \mathbb{R}^+$.

Similarly, let y_n^s be the vector and r_s be the number of desirable outputs of stage s of DMU n, respectively. Then, we write the vector of desirable outputs of stage s of DMU n as follows:

$$y_n^s := \left(y_{n,1}^s, y_{n,2}^s, ..., y_{n,r_s}^s\right). \tag{A.2}$$

Next, let $\tilde{y}_n^s$ be the vector and t_s be the number of undesirable outputs of stage s of DMU n, respectively. Then, the vector of undesirable outputs of stage s of DMU n is:

$$\tilde{y}_n^s := \left(\tilde{y}_{n,1}^s, \tilde{y}_{n,2}^s, ..., \tilde{y}_{n,t_s}^s\right). \tag{A.3}$$

Finally, for any $s_1 \in \{1, 2, ..., S\}$ and $s_2 = (s_1 + 1)$, let $z_n^{(s_1,s_2)}$ be the vector and p_{s_1} be the number of intermediate variables linking stage s_1 to stage s_2 of DMU n, respectively. We then define the vector of intermediate variables linking stage s_1 to stage s_2 of DMU n as follows:

$$z_n^{(s_1,s_2)} := \left(z_{n,1}^{(s_1,s_2)}, z_{n,2}^{(s_1,s_2)}, ..., z_{n,p_{s_1}}^{(s_1,s_2)}\right). \tag{A.4}$$

Here, for any $n \in \{1, 2, ..., N\}$, $s \in \{1, 2, ..., S\}$, $r \in \{1, 2, ..., r_s\}$, $t \in \{1, 2, ..., t_s\}$, and $p \in \{1, 2, ..., p_{s_1}\}$, the variables $y_{n,r}^s$, $\tilde{y}_{n,t}^s$, and $z_{n,p}^{(s,s+1)}$ belong to the set of positive real numbers $\mathbb{R}^+$. Using these input, output, and intermediate linking factors, similar to Tone (2017); Tone and Tsutsui (2009), we build our NDEA optimization model as follows:

Observe that the model in (A.5) is an NSBM model with both desirable and undesirable outputs. The decision variables $\hat{\delta}^{s-}$, δ^s, and $\tilde{\delta}^s$ represent the amount of slack in the inputs, desirable outputs, and undesirable outputs, respectively. The decision variables λ^s refer to weights assigned to the DMUs corresponding to stage s (Tone, 2017). The parameter W^s represents the weight assigned to the efficiency of each stage. Consistent with previous studies (Chen et al., 2021; Martínez-Campillo et al., 2020; Tone and Tsutsui, 2009), we assign equal weight to this parameter in our model. We represent the optimal overall efficiency as ρ_o^*.

$$
\min_{\lambda^s,\hat{\delta}^{s-},\delta^s,\tilde{\delta}^s} \quad \rho_o^* = \frac{\sum_{s=1}^{S} W^s \left[1 - \frac{1}{m_s}\left(\sum_{m=1}^{m_s} \frac{\hat{\delta}_m^{s-}}{x_{m,o}^s}\right)\right]}{\sum_{s=1}^{S} W^s \left[1 + \left(\frac{1}{r_s+t_s}\right)\left(\sum_{r=1}^{r_s} \frac{\delta_r^s}{y_{r,o}^s} + \sum_{t=1}^{t_s} \frac{\tilde{\delta}_t^s}{\tilde{y}_{t,o}^s}\right)\right]}
$$

subject to

$$
\begin{aligned}
& x_{m,o}^s = \sum_{n=1}^{N} x_{n,m}^s \lambda_n^s + \hat{\delta}_m^{s-} \quad \forall 1 \le m \le m_s, 1 \le s \le S, \\
& y_{r,o}^s = \sum_{n=1}^{N} y_{n,r}^s \lambda_n^s - \delta_r^s \quad \forall 1 \le r \le r_s, 1 \le s \le S, \\
& \tilde{y}_{t,o}^s = \sum_{n=1}^{N} \tilde{y}_{n,t}^s \lambda_n^s + \tilde{\delta}_t^s \quad \forall 1 \le t \le t_s, 1 \le s \le S, \\
& \sum_{n=1}^{N} z_{n,p}^{(s,s+1)} \lambda_n^s = \sum_{n=1}^{N} z_{n,p}^{(s,s+1)} \lambda_n^{s+1} \quad \forall 1 \le p \le p_s, 1 \le s \le S, \\
& \sum_{n=1}^{N} \lambda_n^s = 1 \; \forall 1 \le s \le S, \quad \lambda_n^s \ge 0 \; \forall 1 \le s \le S, 1 \le n \le N, \\
& \sum_{s=1}^{S} W^s = 1, \\
& \hat{\delta}_m^{s-}, \delta_r^s, \tilde{\delta}_t^s, W^s \ge 0 \; \forall 1 \le s \le S, 1 \le m \le m_s, 1 \le r \le r_s, 1 \le t \le t_s.
\end{aligned}
\tag{A.5}
$$

CHAPTER 3

ENVIRONMENTAL DISCLOSURE IN SUPPLY NETWORKS

3.1 Introduction

In recent years, consumers have grown increasingly interested in how the products they use are sourced and produced. According to recent research, consumers may be inclined to spend an additional 2% to 10% on products from companies that offer enhanced transparency in their supply chains (Bateman and Bonanni, 2019; Kraft et al., 2018). Faced with increasing pressures from diverse stakeholders, firms tend to put in extra effort to shift the boundaries of supply chain information disclosure (Marshall et al., 2016). For example, Patagonia launched a Supply Chain Environmental Responsibility Program aimed at evaluating, reducing, and ultimately eliminating the environmental impact associated with the production of its products and materials. Patagonia routinely assesses the manufacturing facilities of current and prospective suppliers to form a shared supply chain, and an increasing number of companies participate in these initiatives to assess and disclose their environmental impacts.

Supplier sustainability actions can also be tracked and disclosed in compliance with government regulations. The Corporate Sustainability Reporting Directive (CSRD) took effect on January 5, 2023, updating and reinforcing the regulations regarding the reporting of social and environmental information by companies. Specifically, this European Union (EU) regulation mandates that all large and publicly listed small and midsize enterprises (SMEs) must report on perceived risks and opportunities related to social and environmental issues, as well as the effects of their operations on people and the environment. With the new rules, both large companies and SMEs, often upstream suppliers in supply chains, are required to regularly report on social and environmental risks. This enables investors and stakeholders to access data that evaluates the impact of companies on people and the environment, as well as to analyze the financial risks and opportunities related to climate change and other sustainability issues.

In the context of sustainable supply chain management (SSCM), previous literature has highlighted two key practices for information sharing within supply chains: supply chain transparency and supply chain visibility. Supply chain visibility is often defined as the degree to which a company can have access to the information within its supply chain (Oracle Corporation, 2023; Sodhi and Tang, 2019; Kraft et al., 2018; Basole and Bellamy, 2014). On the other hand, supply chain transparency means a company disclosing information to the external stakeholders, including consumers and investors, about upstream and downstream operations (Mollenkopf et al., 2022; Gualandris et al., 2021; Sodhi and Tang, 2019; Pagell and Wu, 2009). In other words, supply chain transparency requires companies to comprehend activities happening in their supply chain and to communicate this information internally within the organization as well as externally to stakeholders (Gualandris et al., 2021; Bateman and Bonanni, 2019). Although both concepts aim to convey information for supply chain management (SCM), firms disclose information to varying degrees based on their varying perceptions of the value of supply chain visibility and transparency.

Disclosure is often defined as a company's decision for the purpose of information sharing and communication with diverse stakeholders (Kraft et al., 2018; Gualandris et al., 2015). In general, firms are determined to disclose their information to the public to gain credibility and legitimacy, which is defined as "a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions (Delgado-Márquez et al., 2017; Haniffa and Cooke, 2005; Mitchell et al., 1997)." Therefore, both stakeholders (such as regulators, investors, and governments) and non-stakeholders (including the general public who may not have a direct interest) influence and are interested in the information that is disclosed to the public (Jira and Toffel, 2013).

Firms disclose their environmental efforts not only to comply with regulatory requirements but also to protect their reputation among increasingly environmentally conscious stakeholders. These disclosures serve as signals of internal sustainability commitments, shaping how investors, regulators, and consumers perceive a firm's social responsibility.

Environmental disclosure has garnered substantial attention in the context of SCM and buyer–supplier relationships (BSRs) (Bellamy et al., 2020; Gualandris et al., 2015; Jira and Toffel, 2013). Broadly defined, it reflects the extent to which a firm publicly reports its environmental impacts, policies, and practices (Diebel et al., 2024; Song et al., 2024; Bellamy et al., 2020). Amid increasing societal and regulatory scrutiny, stakeholders are demanding greater transparency regarding firms' environmental footprints, particularly as these affect communities embedded within global supply chains (Gualandris et al., 2021; Bellamy et al., 2020; Tate et al., 2010).

In response, firms' engagement in environmental, social, and governance (ESG) initiatives, particularly environmental disclosure, is shaped not only by internal strategic priorities but also by their network positions and inter-organizational relationships. Suppliers' willingness to disclose environmental information often hinges on the behavior and expectations of their buyers, including how buyers signal, request, or utilize such information in relational exchanges (Diebel et al., 2024; Villena and Dhanorkar, 2020; Jira and Toffel, 2013). Beyond these dyadic dynamics, a range of firm- and context-specific factors, such as environmental performance, administrative innovation, national institutional context, industry characteristics, and supply chain visibility, also influence disclosure practices across networked firms (Diebel et al., 2024; Gualandris et al., 2021; Kraft and Zheng, 2021; Bellamy et al., 2020; Pucheta-Martínez and Gallego-Álvarez, 2020; Jira and Toffel, 2013; Cho et al., 2012; Scholtens and Dam, 2007). Accordingly, supplier environmental disclosure emerges as a complex outcome shaped by both buyer influence and broader structural and relational dimensions within supply networks.

Buying firms often play a central role in shaping their suppliers' business strategies and influencing key operational decisions. While traditional supply chain research has focused on linear, dyadic relationships between buyers and suppliers (Cox et al., 2001; Zhu and Sarkis, 2004; Kim et al., 2011), this perspective overlooks the more complex and interconnected nature of buyer–supplier networks. In practice, corporate strategy and environmental decision-making are embedded in broader systems of interactions involving not just direct partners but also shared ties and indirect influences. As such, BSRs are frequently better conceptualized as dynamic networks rather than simple transactional links (Kim et al., 2011).

Applying a social capital perspective provides a more nuanced understanding of how the characteristics of these networked relationships moderate inter-firm dynamics. Social capital, defined as “the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by [...] a social unit” (Nahapiet and Ghoshal, 1998), facilitates the flow of information, trust, and norms across supply networks. Within the context of environmental disclosure, social capital embedded in BSRs plays a critical role in shaping how buyers exert influence and how suppliers respond. Building on prior research, we argue that three dimensions of social capital are especially salient in determining whether buyer influence encourages, discourages, or has no significant effect on supplier environmental disclosure, particularly in the manufacturing sector where environmental pressures and disclosure expectations are increasingly diffused across the network.

This paper first investigates how the environmental disclosure of buyers operating in the manufacturing industry influences the level of environmental disclosure among their suppliers. While conventional wisdom holds that greater transparency by buyers should encourage suppliers to follow suit, emerging evidence related to the supply chain leakage phenomenon and the pollution haven hypothesis (PHH) suggests an alternative possibility. Our second research question explores how the inherent network characteristics of BSRs enhance relational cohesion, thereby influencing the extent to which suppliers engage in voluntary environmental disclosure. That is, the negative influence proposed by the supply chain leakage phenomenon and the PHH may be either amplified or mitigated under specific conditions of structural equivalence, relationship duration, and cultural similarity, depending on the strength of supply chain visibility with suppliers. Further, we intend to explore potential disparities between the materials industry and the pharmaceutical and biotechnology industry, despite their joint classification under the manufacturing sector in prior research (Diebel et al., 2024; Gualandris et al., 2021).

3.1.1 Key Findings and Contributions

Our research contributes to the environmental management and SCM literature. This study emphasizes the role of social capital within BSRs in shaping supplier environmental disclosure, particularly in light of supply chain leakage concerns. In the manufacturing sector, many suppliers remain hesitant to disclose their environmental performance – a pattern we interpret through the lens of the PHH and supply chain leakage concepts.

We further explore how firm-level and network-level characteristics influence the link between buyer and supplier environmental disclosures. Grounded in social capital theory, we examine the moderating effects of three key dimensions – structural, relational, and cognitive dimensions – within BSRs in the materials and pharmaceutical industries. Using voluntary disclosure data from Bloomberg ESG, we assess the relationship between buyer and supplier environmental disclosure. We find no evidence supporting a negative influence, suggesting that the supply chain leakage effect may not be broadly applicable in the context of voluntary environmental disclosure. Our analysis shows that structural social capital, reflected in shared network ties, plays a key moderating role in this relationship. Buyer–supplier pairs with lower structural overlap experience a negative effect, whereas pairs with higher overlap show a mitigation of this negative influence. A similar conditional pattern emerges for cultural similarity: partnerships characterized by greater cultural dissimilarity demonstrate a negative effect on supplier disclosure, while those with higher cultural similarity show no significant effect. In contrast, the length of the BSR does not significantly moderate the relationship.

This study contributes to the theoretical understanding of how BSRs, shaped by dimensions of social capital, influence supplier environmental disclosure within manufacturing supply networks. While previous research has largely focused on buyer performance, we examine how supply chain leakage and the PHH relate to suppliers' disclosure behaviors. We also highlight how relational factors, such as structural equivalence and cultural similarity, positively moderate the influence between buyer and supplier environmental disclosures. This implies that network dynamics can offset the potential negative impacts of outsourcing. From a managerial perspective, our findings underscore the importance of fostering cooperative, strategically aligned partnerships with suppliers, particularly those that share common connections or cultural backgrounds, to enhance environmental transparency. Buyers should also be mindful of how their network positions influence supplier behavior and prioritize close collaboration, especially when working with culturally diverse partners. Policymakers, in turn, should recognize the heterogeneity of firms across industries and supply chains, and tailor sustainability initiatives that consider local contexts and relational dynamics. Together, these insights offer a more nuanced understanding of how environmental responsibility can be promoted across interconnected supply networks.

3.1.2 Organization

Our paper is organized as follows: We begin by reviewing the relevant literature on transparency within SSCM and the institutional factors emphasized in corporate social responsibility (CSR) in the upcoming section. Following this, Section 3 delves into our hypotheses, which we develop through a detailed examination of the contextual background and social capital literature. This section also introduces our conceptual framework for testing these hypotheses. In Section 4, we outline our research design, detailing the data sources, sample selection process, and the definitions of our variables. This section further explains our estimation models and discusses the findings. Section 5 extends our analysis with additional insights through comparisons across buyer industries and includes robustness checks that employ various empirical specifications. Finally, Section 7 wraps up the paper by discussing the implications of our findings and suggesting avenues for future research.

3.2 Literature Review

Scholars and practitioners are increasingly focusing on sustainability within supply chains, primarily driven by the escalating demand for transparency in supply chain practices. In this section, we will review existing literature on environmental management and disclosure within supply networks. In addition, we plan to explore the characteristics of supply networks within BSRs and their impact on firm-level environmental performances and actions. Following a comprehensive examination of sustainability in supply networks, we will shift our focus to the theoretical background and develop and test a series of hypotheses.

Evaluating sustainability performance often extends beyond the activities of any single tier or firm. This is because firms are intrinsically part of broader supply networks that include upstream suppliers and buying firms, facilitating the exchange of products, services, and information across diverse geographical locations. In addition, sustainability in supply chains not only measures traditional operational outcomes, such as profit and loss, but also encompasses an expanded conceptualization of performance that includes social and environmental dimensions (Koberg and Longoni, 2019; Pagell and Wu, 2009; Elkington and Rowlands, 1999). Environmental management in supply networks has often been addressed through the adoption of environmental management systems and practices, such as International Organization for Standardization (ISO) 14000 certifications and eco-management audit scheme, aiming to monitor and control the impact of firm operations on the natural environment (Hardcopf et al., 2019; González et al., 2008; Montabon et al., 2007). As such, environmental management falls within the wider scope of sustainability, which has garnered growing interest in supply chain and operations management (OM) in conjunction with the release of voluntary and international environmental standards (Hofer et al., 2012; Linton et al., 2007). Moreover, being environmentally proactive is closely associated with new business opportunities, efficient resource utilization, and an enhanced corporate image, all of which can yield significant benefits (Montabon et al., 2007).

Along with the growing interest in environmental management in supply chains, corporate environmental disclosure has long been the focus of scholarly research. Historically, corporate environmental reporting has served as a voluntary tool for companies to disclose their environmental impacts and potential risks, aimed at addressing the needs of their key stakeholders (Fallan, 2016; Gualandris et al., 2015). Such reporting has become more institutionalized, serving not only to monitor environmental impacts but also to achieve environmental goals that include enhancing accountability and transparency (Christensen et al., 2021). Nonetheless, disclosure often ranges from little information to comprehensive information on sustainability evaluation, verification processes, and outcomes (Gualandris et al., 2015).

Stakeholders and the public have pressurized firms to disclose the environmental impacts of their business operations on the communities across their supply chains (Gualandris et al., 2021; Bellamy et al., 2020; Tate et al., 2010). Firms often showcase their corporate responsibility performance as a means of enhancing the public image as well as achieving CSR goals. In the context of corporate environmental disclosure, socio-political theories like legitimacy theory and stakeholder theory have been used to explain how firms respond to institutional pressure by providing more comprehensive environmental information. Legitimacy theory provides the rationale behind corporate environmental disclosure in response to social and political pressure. To be specific, compared to economic legitimacy monitored through the marketplace, social legitimacy is more likely to be monitored via the policy process by actively participating in the public policy processes, one of which is disclosure (Patten, 2002). On the other hand, stakeholder theory can also be applied to the problems of CSR, and it also helps to identify the different situations in which stakeholders with varying degrees of power, legitimacy, and urgency are presented (Tate et al., 2022; Mitchell et al., 1997). Drawing on institutional theory, previous research has also considered the institutional pressures from buyers and industry peers that compel suppliers to disclose significant environmental impacts and risks in supply networks (Diebel et al., 2024; Villena and Dhanorkar, 2020).

As a contingency factor, the institutional context has been highlighted in prior studies that emphasize the disparities in CSR reporting between countries. These studies suggest that differences in national contextual factors could account for the variation in CSR disclosure. The reasons for social and environmental reporting requirements differ between these countries, influenced by external forces, key stakeholders, significant investments, and long-term commitments, leading to discrepancies (Luo et al., 2013). Cultural difference across countries also strongly affects ethics, CSR, organizational culture, and managerial practices (Pucheta-Martínez and Gallego-Álvarez, 2020; Scholtens and Dam, 2007). Along these lines, multinational corporations (MNCs) tend to exhibit greater environmental consciousness when operating in developed countries, where regulatory standards are typically more stringent. In contrast, operations in less-developed countries are often subject to more lenient environmental regulations (Hassan, 2023; Eskeland and Harrison, 2003) and are more prone to financial constraints that can hinder the implementation of sustainability initiatives (Luo et al., 2013). Thus, as part of corporate strategic decision-making, firms often choose to locate manufacturing facilities in countries with more lenient environmental regulations to minimize pollution abatement costs (Berry et al., 2021). For instance, strict regulatory frameworks in developed countries often incentivize the relocation of pollution-intensive industries to less developed regions, a dynamic commonly explained by the PHH (Levinson and Taylor, 2008; Eskeland and Harrison, 2003).

Along with the national context, industry characteristics are also commonly employed to elucidate the scope and content of social and environmental disclosure (Reverte, 2009; Brammer and Pavelin, 2008; Cowen et al., 1987). The influence of peers within the same industry on corporate decision-making has been discussed in previous studies (Zhao and Wang, 2024; Huang et al., 2023; Lin et al., 2018; Leary and Roberts, 2014). In the realm of CSR, it is recognized that managers within the same industry are incentivized to emulate the CSR decisions of their peers, highlighting the significant role industry peers play in enhancing firms' CSR performance (Zhao and Wang, 2024; Chen et al., 2023; Huang et al., 2023; Campbell, 2007). In addition, the average behavior of peer groups within the same industry influences corporate disclosure practices, leading to reduced environmental uncertainty and improved quality of managerial private information (Seo, 2021).

Our research examines the social capital factors embedded within supply networks in the context of environmental disclosure. In practice, MNCs that monitor and manage their suppliers are increasingly prioritizing sustainable operations. They pursue this by restructuring their supply chain architectures, redefining partnerships, and even collaborating with competitors to improve scale efficiency (Lee, 2010). Since corporate strategy and firms' network behavior are heavily shaped by the structure and complexity of supply networks, it is crucial to understand how suppliers, buyers, and customers are interconnected to fully capture the dynamics of their transactions (Kim et al., 2011). Moreover, the relationships between suppliers and buyers are plausibly influenced by the broader characteristics of the supply network, which can either constrain or enhance firm performance within these interconnected systems (Bellamy et al., 2020; Chae et al., 2020; Kumar et al., 2020; Sharma et al., 2020; Lu and Shang, 2017).

Over the past few decades, many MNCs have increasingly sought business partners across diverse geographic regions. Faced with evolving business environments and growing institutional pressures to operate sustainably, these firms have intensified efforts to strengthen relationships with their partners in pursuit of environmental objectives. Adopting a social capital perspective, this study examines how the negative influence of buyer environmental disclosure on supplier environmental disclosure is conditioned by supply chain visibility, which is often shaped by key dimensions of social capital. By examining how social capital embedded in buyer–supplier dyads either bridges or exacerbates information gaps within supply networks, this research contributes to the literature on BSRs and environmental management through a social capital lens.

3.3 Hypotheses Development and Conceptual Framework

In this section, we first formulate a hypothesis regarding corporate environmental disclosure in BSRs. Building on this foundational hypothesis, we proceed to examine the moderating influence of social capital dimensions, with a specific focus on the features embedded in BSRs within supply networks.

3.3.1 Buyer Environmental Disclosure and Its Impact on Supplier Environmental Disclosure

Companies often prioritize different dimensions of social, environmental, and economic responsibility within their supply chains, depending on institutional factors such as national and industry contexts (Tate et al., 2010; Van der Laan Smith et al., 2005). As part of their strategic decision-making, firms may choose to locate manufacturing facilities in countries with more lenient environmental regulations to reduce pollution abatement costs (Berry et al., 2021). For example, the stringent regulatory environment in developed countries prompts the relocation of polluting industries to less developed regions (Levinson and Taylor, 2008; Eskeland and Harrison, 2003). These outsourced operational activities often enable firms to leverage complementary resources, thereby enhancing operational efficiency and financial performance, while such benefits may also extend to improvements in the supply chain's environmental performance (Song et al., 2023). This phenomenon is succinctly captured by the PHH. The PHH illustrates a form of institutional or jurisdictional arbitrage, whereby firms strategically locate their operations in institutional environments that offer more lenient regulatory conditions (Berry et al., 2021).

Within the context of SCM, supply chain leakage manifests as a firm-level phenomenon, yet it bears a resemblance to the PHH (Song et al., 2023). Previous literature on environmental management within supply chains has explored the concept of supply chain leakage, particularly in terms of outsourcing emissions, commonly known as carbon leakage. Outsourcing emissions to the supply chain can occur when firms seek to preserve their reputation and social capital without making significant efforts to respond to pressures from local and national institutions (Song et al., 2024). This might lead to an escalation in suppliers' greenhouse gas (GHG) emissions, as certain customers might attempt to lower their own emissions at their suppliers' expense, a practice commonly known as carbon outsourcing or leakage. Consequently, enhanced environmental disclosure by customers could inadvertently lead to undesirable environmental performance among their suppliers, suggesting that environmental disclosure might prompt some opportunistic partners to engage in carbon outsourcing, which potentially creates a negative externality across supply chains (Song et al., 2024).

To delve deeper into how a firm's environmental actions, initiatives, efforts, or encouragement can influence environmental disclosure, and to explore the potential positive relationship between environmental performance and disclosure levels, we review existing literature on the interconnections between environmental disclosure and both environmental and economic performance. It has been demonstrated that more extensive disclosure of environmental information correlates positively with environmental performance, which may also significantly enhance economic performance (Al-Tuwaijri et al., 2004; Cormier and Magnan, 1999). Specifically, firms with higher performance levels are more likely to disclose pollution-related environmental information compared to their lower-performing counterparts (Clarkson et al., 2008; Al-Tuwaijri et al., 2004). This suggests that firms use environmental disclosure as a means to communicate with market participants, offering transparent, environment-related information as positive news, while also setting a rational baseline for future reference. Thus, in line with voluntary disclosure theory, firms that exhibit superior sustainability performance often opt for high-quality sustainability disclosures as a means to signal their exemplary sustainability achievements (Rezaee and Tuo, 2017; Hummel and Schlick, 2016).

Suppliers often disclose their environmental efforts not only to comply with regulatory mandates but also to protect their reputation among increasingly environmentally conscious stakeholders. In many cases, suppliers draw on information shared by their buyers to mirror the buyers' commitment to transparency, often driven by institutional pressure and stakeholder expectations (Diebel et al., 2024; Villena and Dhanorkar, 2020; Jira and Toffel, 2013). National culture and business environments also play a critical role in shaping communication between firms and stakeholders, as well as in defining the institutional context within which firms, governments, and civil society interact (Villena and Dhanorkar, 2020; Jira and Toffel, 2013; Van der Laan Smith et al., 2005).

Despite these dynamics, emerging evidence on the supply chain leakage phenomenon and the PHH points to a countervailing possibility. When a focal firm reduces its carbon emissions and promotes a favorable environmental image through disclosure, it may do so by shifting pollution-intensive operations upstream to suppliers. This leakage of carbon can place a disproportionate environmental burden on suppliers, raising their carbon footprints. Since firms tend to disclose environmental data when performance is strong, suppliers with higher emissions and wastes may become reluctant to report such information, resulting in lower levels of disclosure. Building on prior research into supply chain leakage, which shows that local environmental transparency or regulatory enforcement can produce unintended consequences, and considering the theoretical underpinnings of this dynamic, we propose the following hypothesis:

Hypothesis 1 (*H_1*) A buyer's environmental disclosure negatively influences its supplier's environmental disclosure.

3.3.2 The Impact of Social Capital on Environmental Disclosure in Supply Chains

In this section, we mainly explore how the different dimensions of social capital embedded in BSRs moderate the influence between buyer and supplier environmental disclosure. We begin by establishing the theoretical foundation of the study, drawing on social capital theory as the primary lens through which the research hypotheses are developed. Next, we examine how the structural, relational, and cognitive dimensions of social capital individually shape the relationship between buyer and supplier environmental disclosure levels. Subsequently, we review previous studies to formulate a series of hypotheses for empirical evaluation, examining how these three dimensions influence the relationship between a supplier's environmental disclosure and that of a buying firm.

Behaviors within a dyad ripple through the network, initiating a sequence of actions and responses that establish norms and expectations across the entire network (Ireland and Webb, 2007). Thus, cohesion within the network plays a vital role in supporting information exchange and fostering a common identity, leading to opportunities for joint learning and the adoption of sustainable and social initiatives across supply chains. Through this section, we, therefore, seek to deepen the understanding of how buying firms can strengthen cohesion with suppliers by leveraging the social capital embedded in buyer-supplier networks, thereby enhancing supplier engagement in sustainability practices, including environmental disclosure. Our theoretical framework proposes that suppliers' decisions to disclose non-financial information are shaped not only by the environmental disclosure practices of buyers in manufacturing industries but also by the degree of supply chain visibility operationalized through social capital factors embedded within BSRs. Specifically, we highlight how the diversity in buyers' disclosure levels within these networks shapes suppliers' disclosure strategies.

From a network perspective, social capital underscores how economic behavior is embedded in interpersonal relationships and structural positions within networks (Lin, 2017; Granovetter, 1985). It emphasizes the value of diverse connections that facilitate trust, cooperation, and the mobilization of resources through collaboration (Blount and Li, 2021; Kim, 2014; Autry and Griffis, 2008; Nahapiet and Ghoshal, 1998). Central to this concept are structural and relational embeddedness, where actors leverage their positions for anticipated returns (Burt, 2004). Positional advantages, such as occupying structural holes, enhance access to non-redundant information and resources (Lu and Shang, 2017; Podolny and Baron, 1997; Burt, 1992), while closed networks and strong ties foster cooperation, norm adherence, and overlapping inter-organizational connections (Moran, 2005; Granovetter, 1973).

In the context of social networks among individuals or social units, social capital has been discussed in terms of three primary aspects: structural, relational, and cognitive dimensions (Blount and Li, 2021; Chae et al., 2020; Nahapiet and Ghoshal, 1998). In previous literature, the structural dimension is primarily defined as the properties of the social system and overall patterns within network relations, whereas the relational dimension is referred to as the interpersonal or inter-organizational linkages that entities have developed through interactions. In addition, the cognitive dimension indicates "those resources providing shared representations, interpretations, and systems of meaning among parties (Nahapiet and Ghoshal, 1998, p.244)." In Table 3.1, we primarily focus on studies exploring the dimensions of social capital as the theoretical foundation for their analyses. Furthermore, Ravindran et al. (2015) extended the three dimensions of social capital to examine the impact of the four distinct levels of client and vendor firms' embeddedness of economic relationships in which firms' social capital in an inter-organizational network was operationalized by the four distinct measures of embeddedness: structural embeddedness at the node level, relational embeddedness at the dyad level, contractual embeddedness at the level of a neighborhood of contracts, and positional embeddedness at the level of the entire network (Ravindran et al., 2015). Social capital has often been used alongside both dyadic and network perspectives to evaluate how its various dimensions impact different aspects of corporate performance within supply networks (Kumar et al., 2020).

As corporate environmental reporting becomes institutionalized as a tool for promoting accountability and transparency, firms increasingly disclose their environmental performance in response to institutional pressures and stakeholder demand, as a signal of their commitment to sustainability (Bellamy et al., 2020; Jira and Toffel, 2013). In SCM, transparent buyer disclosure often encourages suppliers to follow suit, fostering shared sustainability goals. Building on this, the following section explores how social capital, through its interaction with network structures and its role in shaping supply chain visibility, moderates the relationship between buyers' and suppliers' environmental disclosures.

3.3.2.1 The Influence of Social Capital's Structural Dimension

Even though there is no clear consensus concerning how members in a social network pursue the values derived from social capital, the total values of structural components (e.g., relative social position, distance between members and existing connections) often represents the structural dimension of social capital in a social network (Autry and Griffis, 2008). In other words, the

Table 3.1 A Review of Previous Work and Their Use of Three Social Capital Dimensions

Reference	**Research Focus**	**Social Capital Dimensions**
Nahapiet and Ghoshal (1998)	The creation of intellectual capital	• Structural dimension • Relational dimension • Cognitive dimension
Tsai and Ghoshal (1998)	Patterns of resource exchange and product innovation	• Structural dimension • Relational dimension • Cognitive dimension
Autry and Griffis (2008)	Supply chain knowledge development and performance	• Structural dimension • Relational dimension
Villena et al. (2011)	Value creation in BSRs	• Structural dimension • Relational dimension • Cognitive dimension
Kim (2014)	A buying firm's operational and financial performance	• Structural dimension • Relational dimension
Claridge (2018)	Dimensions of social capital	• Structural dimension • Relational dimension • Cognitive dimension
Chae et al. (2020)	Supplier innovation value	• Structural dimension • Relational dimension • Cognitive dimension
Blount and Li (2021)	Buyers' procurement activities with ethnic minority businesses and supplier diversity	• Structural dimension • Relational dimension • Cognitive dimension
Wang et al. (2023)	Green innovation output	• Structural dimension • Relational dimension • Cognitive dimension

structural dimension of social capital mainly focuses on the relative positions within a network and the continuous formation of relationships among its members. For example, structural density (i.e., the extent to which possible connections are activated) and structural holes (i.e., less dense areas in which ties are missing; see e.g., Burt (1992)) are the two dominant forms of structural embeddedness within a network (Autry and Griffis, 2008). In particular, dense networks reduce information asymmetry and opportunism, allowing firms to better understand their partners' behavior. This not only fosters increased cooperation but also mitigates opportunistic behavior (Bellamy et al., 2020; Phelps, 2010). Information flow and knowledge spillovers can also be enhanced by locally dense interactions connected via a few bridging ties (i.e., small-world networks, Watts and Strogatz (1998)) (Fleming et al., 2007). Thus, structural components, such as a firm's network position and the configuration and distribution of embedded exchange relationships, play a crucial role in the economic actions of firms (Autry and Griffis, 2008; Uzzi, 1996).

Previous literature identifies several structural components in a network and the qualities of BSRs as influential factors in the willingness to disclose information by supply chain members. As a monumental study, Burt (1987) discussed how social structural circumstances make two individuals assimilated into one another when two individuals maintain structurally equivalent patterns in relation to all other individuals within the network. The identical pattern of relations with occupants of other positions in the network helps to manage uncertainty between the two actors. Also, structural equivalence between buying firms and suppliers uses the redundancy benefits in that the same source of information that two organizations share allows for the benefits of information redundancy (Burt, 1997). In other words, irrespective of how they feel about one another, structurally equivalent organizations will exhibit similar thoughts and behaviors due to their relationships with other actors in the network (Chae et al., 2020; Xiao et al., 2015; McPherson et al., 2001; Friedkin, 1998). Furthermore, if two organizations' relationships with other actors in a network become increasingly similar, their sentiments of collaboration get stronger, boosting the possibility of a link between them (Xiao et al., 2015; Burt, 1997).

In supply chains, the quality of BSRs and the structure of interorganizational networks are key components of social capital, significantly shaping supply chain transparency, visibility, and dependency (Melnyk et al., 2022; Gualandris et al., 2021; Cheung et al., 2020; Awaysheh and Klassen, 2010). Direct BSRs promote the exchange of information and resources and facilitate the diffusion of organizational practices (Pallotti and Lomi, 2011). Structurally equivalent actors, those embedded in similar social circles, tend to engage in more consistent knowledge sharing and experience lower levels of conflict and perceived risk (Cannizzaro, 2020). Such homophilic relationships, characterized by shared partners that reinforce prevailing norms and expectations, cultivate elevated levels of trust and reciprocity, particularly as environmental standards and consumer expectations diffuse through overlapping network ties. Consequently, in highly visible dyads marked by high structural equivalence, the negative influence of a buyer on its supplier's environmental disclosures is attenuated. In contrast, low structural equivalence, reflecting fewer overlapping connections, limits visibility, increasing the likelihood that suppliers in arm's length relationships will refrain from disclosure to avoid reputational or commercial risks. Given that structurally equivalent actors benefit from similar network patterns and visibility, we propose the following hypothesis:

Hypothesis 2A (H_{2A}) Structural equivalence between a buyer and its supplier diminishes the negative influence of the buyer on the supplier's environmental disclosures.

3.3.2.2 The Influence of Social Capital's Relational Dimension

The relational dimension of social capital that buying firms establish with their suppliers, on the other hand, indicates the assets that are inherent in a relationship and are built based upon mutual trust, respect, and friendship between two individuals through longstanding interactions (Chae et al., 2020; Villena and Craighead, 2017; Krause et al., 2007; Nahapiet and Ghoshal, 1998; Tsai and Ghoshal, 1998). Relational attributes in social networks, such as trust, trustworthiness, cooperation, and relationship duration, help to reduce the uncertainty in relationships and to create opportunities for the potential transactions (Squire et al., 2009; Uzzi and Lancaster, 2003; Uzzi, 1996). Based upon relationship-specific communication and coordination routines, multiple and repeated interactions could enhance cooperation and trust in the long run (Ravindran et al., 2015; Krause et al., 2007; Hoetker, 2005; Uzzi, 1996), which, in turn, ends up with reducing transactional uncertainty (Uzzi and Lancaster, 2003; Uzzi, 1996). Trust, as a pivotal element of social interactions, serves primarily as a governance mechanism for managing relationships (Uzzi, 1996), motivates partners to collaborate (Tsai and Ghoshal, 1998), and enhances the efficacy of information flows (Lee and Ha, 2018). Consequently, the risks associated with improper use of information and information asymmetry among involved parties can be substantially reduced through open and honest mutual information sharing, which is underpinned by trust (Lee and Ha, 2018).

The strength of ties has often been used as another representation of relational capital (Tate et al., 2013; Krause et al., 2007; Hansen, 1999; Granovetter, 1973). To be specific, Granovetter (1973) defines the strength of ties as "a combination of the amount of time, the emotional intensity, the intimacy, and the reciprocal services which characterize the tie (Granovetter, 1973, p.1361)." Rowley et al. (2000) also measures the strength of ties in two different ways: the frequency with which partners contact and their level of commitment to the relationship in terms of resources. In the context of SCM, previous studies have also conceptualized the strength of ties among members from a network perspective. Kim (2014) considers relational embeddedness as the strength of relationships between suppliers and buying firms, suggesting that a high degree of relational embeddedness promotes close observations and interactions, enabling firms to access specific information, tactical knowledge, and expertise. Krause et al. (2007) also highlights that direct involvement in supplier development, defined as activities initiated by buyers to enhance their suppliers' performance, creates an environment conducive to the transfer of tacit knowledge and fosters mutual learning between firms.

Relational embeddedness, defined by strong and enduring ties between actors, facilitates the exchange of information and the assimilation of organizational practices (Andersson et al., 2002; Uzzi, 1996). Relational capital helps mitigate opportunistic behavior by fostering trust and cooperation, whereas its absence may lead partners to withhold valuable resources, reduce collaborative behavior, and increase uncertainty (Villena et al., 2011). When firms maintain longstanding relationships characterized by trust, shared vision, and high asset specificity, they are more likely to share environmental information with supply chain partners (Kim and Henderson, 2015; Jira and Toffel, 2013; Tate et al., 2011; Locke et al., 2007). Within our research context, this suggests that in more visible dyads, characterized by longer relationship duration, the negative influence of buyer environmental disclosure on supplier disclosure tends to be attenuated. Conversely, when relationship duration is short and visibility is limited, suppliers may be more reluctant to disclose, particularly in arm's-length relationships. Given that the diffusion of sustainability practices, defined as efforts to enhance a firm's environmental responsibility, is closely tied to the relational embeddedness of partners within BSRs (Jira and Toffel, 2013; Tate et al., 2011), we propose the following hypothesis:

Hypothesis 2B (H_{2B}) Relationship duration between a buyer and its supplier diminishes the negative influence of the buyer on the supplier's environmental disclosures.

3.3.2.3 The Influence of Social Capital's Cognitive Dimension

Next, the cognitive dimension of social capital refers to shared languages or common cultures that help social units to agree on collective goals and proper behaviors (Chae et al., 2020; Nahapiet and Ghoshal, 1998; Tsai and Ghoshal, 1998). Corporations that align on common values are more likely to form partnerships, facilitated by the exchange of resources (Blount and Li, 2021; Nahapiet and Ghoshal, 1998; Tsai and Ghoshal, 1998). Social networks also keep evolving, facilitated by various factors, such as shared activities, affiliations of involved parties, and the similarity of individual attributes (Kossinets and Watts, 2006). As a foundational study, McPherson et al. (2001) defines homophily as the principle that social units prefer significant contact with others who share similar characteristics, resulting in more frequent interactions among similar entities. The study also highlights the several causes of homophily. In their analysis, they identify geographical location and organizational foci as primary motivators influencing the formation of homophilous ties. The prevalence of homogeneity among network members, stemming from these fundamental causes, is often considered a cognitive dimension of social capital, highlighting how the evolution of social networks is predominantly driven by the similarity of attributes shared by organizations.

Geographical and cultural distances are known to hinder collaboration and the formation of close relationships, making it difficult for firms to implement consistent monitoring and auditing systems across diverse markets (Adhikary et al., 2020; Awaysheh and Klassen, 2010). Cultural gaps between buyers and suppliers can disrupt cohesion, increase hold-up costs, and weaken collaboration and coordination. In contrast, BSRs are more likely to exhibit higher levels of cognitive social capital when both parties share similar political, economic, and cultural backgrounds (Chae et al., 2020; Bolino et al., 2002). In other words, shared values, such as institutional ownership and domain similarity, help connect entities within a network, facilitating task completion and fostering cooperation (Cheung et al., 2020; Van de Ven, 1976). Their connections can also be strengthened by shared physical time and space. Thus, while firms are obligated to disclose their environmental performance to effectively manage inter-firm environmental impacts, their responses to environmental reporting requirements vary based on situational factors. These factors are often determined by whether organizations share similar behaviors and attitudes, enabling them to actively participate in sustaining inter-organizational relationships and enhancing transparency in supply chains.

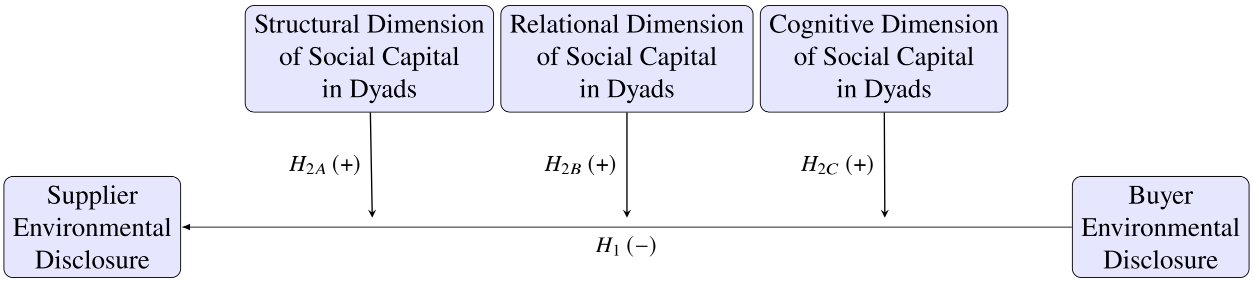
Hence, we expect that the cognitive dimension of social capital, cultural similarity, moderates the negative influence of a buyer on its supplier's environmental disclosures. Specifically, a supplier's disclosure tends to be lower when supply chain visibility is reduced due to low cultural similarity with the buyer. In such cases, the negative relationship is likely to be more pronounced, as suppliers in culturally distant, arm's length relationships may be more reluctant to disclose, possibly to avoid commercial or reputational risks. Conversely, in more visible dyads, characterized by high cultural similarity, the negative effect is attenuated. Taking these considerations into account, we further posit that:

Hypothesis 2C (H_{2C}) National cultural similarity between a buyer and its supplier diminishes the negative influence of the buyer on the supplier's environmental disclosures.

3.3.3 Conceptual Framework for Hypothesis Testing

In this study, we formulate hypotheses to test the direct influence (H_1) of a buyer on its supplier environmental disclosures. Figure 3.1 illustrates the conceptual framework, depicting the proposed direct influence between the supplier environmental disclosure and that of a buying firm. It also shows the moderating effects of different dimensions of social capital embedded in BSRs (resp., the structural dimension of social capital (H_{2A}), the relational dimension of social capital (H_{2B}), and the cognitive dimension of social capital (H_{2C})). In total, we test four hypotheses in this study.

Figure 3.1 Conceptual Framework



3.4 Data Source

3.4.1 Data

In this section, we first outline the multiple sources for collecting secondary data. Subsequently, we detail the variables utilized in our empirical models to test our hypotheses.

In this study, to establish BSRs, we use the dataset that comes from FactSet Revere. The FactSet Revere supply chain relationships data illuminates the interconnected commercial partnerships between organizations. Data about supply chain relationships provided by FactSet Revere is systemically collected through primary public sources, including U.S. Securities and Exchange Commission (SEC) 10-K annual reports, public announcements, and investor relations, and reverse-linked to non-disclosure parties (FactSet Revere, 2021). Regarding the scope of data, the FactSet supply chain relationships cover over 31,000 publicly traded companies globally, encompassing more than 450,000 business relationships (FactSet Revere, 2021). According to FactSet Revere, the collected supply chain relationships are predominantly categorized into four main types, resulting in 13 distinct sub-types of supply chain relationships to address varying levels of company disclosure. Specifically, inter-company relationships are organized and presented based on the nature of the relationship, competitors, strategic partners, suppliers, and customers, each further divided into 13 normalized sub-types for more precise categorization.

The FactSet Revere supply chain relationships data specifically includes unique data for this study in that it also provides information on the start date and end date of the business relationships and interconnections, with the history of data going all the way back to 2003. In addition to these data, the nature of a company's relationships is further detailed beyond the four categories and thirteen sub-types, and is summarized as relationship keywords within the dataset. In conclusion, FactSet Revere supply chain relationships data gives 360-degree visibility into a company's interconnected business ties, their nature, and their dependability. To operationalize social capital factors and to form supply networks of focal firms, FactSet Revere supply chain relationships data is primarily used in this study.

To examine the fundamental relationship between buyer and supplier environmental disclosures, we employ Bloomberg's ESG disclosure score from the Bloomberg ESG database, which compiles firm-level quantitative and policy-related environmental indicators from both public and private sources, as our primary measure of environmental disclosure (Diebel et al., 2024; Bellamy et al., 2020). Specifically, the database collects data on firms' internal ESG practices and performance through direct communications, such as meetings, phone interviews, and surveys, as well as from corporate sustainability reports, regulatory filings, websites, and news articles (Gualandris et al., 2021). Bloomberg's ESG data provides comprehensive data on over 9,000 companies from more than 70 countries, spanning over 900 fields related to ESG topics like air quality and governance, and offers up to a decade of historical data that supports quantitative analysis to identify ESG factors that may impact long-term company performance (Bloomberg Professional Services, 2018).

The Bloomberg ESG disclosure score provides investors with insights into how transparently companies report their ESG practices. It measures the quality of ESG disclosures based on over 120 data points across environmental, social, and governance factors but does not assess the actual performance of these practices. A firm's performance across each indicator is validated through multiple sources, including CSR reports, annual reports, company websites, Carbon Disclosure Project (CDP) data, and third-party research to guarantee accuracy and reliability (Bellamy et al., 2020; Bloomberg Professional Services, 2018). Hence, to operationalize a firm's extent of environmental disclosure, we utilize Bloomberg's environmental disclosure score, which quantifies the level of a firm's environmental reporting and assigns firms a numerical value based on the comprehensiveness of their environmental disclosures (Bellamy et al., 2020).

Third, we compile firm financial data from the Bloomberg Financial Analysis (FA) database

(Diebel et al., 2024; Gualandris et al., 2021; Bellamy et al., 2020; Sharma et al., 2020). This database serves as an extensive repository of financial data, offering both real-time and historical information on public and private companies. It encompasses market data, economic indicators, and sector-specific metrics, providing a holistic view of financial landscapes. To construct independent and control variables, we also augment our three primary data sources with additional private datasets. These include the base culture data encompassing Geert Hofstede's six dimensions of culture, and FactSet Revere's Company data, which provides general information about companies.

3.4.2 Sample Collection Procedure

In this section, we first outline the composition of our sample for empirical analysis. Following that, we elaborate on the procedure used to collect our dataset and proceed to describe the variables integrated into our empirical models for hypothesis testing.

3.4.2.1 Sample Selection

In this study, we hypothesize the impact of buyer environmental disclosure on supplier environmental disclosure. Accordingly, our primary unit of analysis is the supplier within a BSR. Since our objective is to investigate the primary relationship and the moderating effects from a network perspective, we have framed our sample, which encompasses a diverse array of buyers, to initiate our data collection. By referring to previous literature (Diebel et al., 2024; Gualandris et al., 2021), the Forbes 2000 list published in 2018 serves as our fundamental sample framework in this study because it offers an annual ranking of the world's largest firms across various sectors in both manufacturing and service industries. These firms are equally visible to external stakeholder groups, a factor crucial due to their significant business volumes (Gualandris et al., 2021).

In our industry selection process, we specifically focus on buying firms within the broader category of manufacturing. This choice is motivated by the fact that traditional manufacturing industries are significant contributors to negative environmental externalities (Hardcopf et al., 2021). In previous research, many papers focused on SCM tend to examine a single industry where buyers operate, such as the automotive (Chae et al., 2020; Potter and Wilhelm, 2020; Kim et al., 2011), electronics (Chedid et al., 2021; Wilhelm and Villena, 2021; Basole et al., 2017), and food industries (Bourlakis et al., 2014; Grimm et al., 2014). Conversely, some studies simultaneously explore multiple industries to facilitate comparisons (Diebel et al., 2024; Adhikary et al., 2020; Bellamy et al., 2020; Hardcopf et al., 2019; Villena, 2019; Villena and Gioia, 2018; Wilhelm et al., 2016). In this study, based on the Global Industry Classification Standard (GICS) industry classification, we examine the supply networks of buying firms between two distinct manufacturing sectors: Materials (four-digit GICS code: 1510) and Pharmaceuticals & Biotechnology industries (four-digit GICS code: 3520). In previous literature, the materials industry has often been classified as environmentally sensitive (see, for example, Cho et al. (2012), Reverte (2009), Cho and Patten (2007), Patten (2002), and Cowen et al. (1987)). Given this context, the industry is likely more attuned to concerns regarding safety, environmental impact, and sustainability. In contrast, the pharmaceutical industry is recognized for its significant investment in research and development (R&D). However, with an aging global population and advancements in healthcare systems fueling demand, this industry faces increasing pressure to achieve sustainable development while expanding its product offerings. Consequently, the environmental impact of its operations has become a focal point of scrutiny (Milanesi et al., 2020). To enrich our investigation, this study proposes examining two distinct manufacturing industries with respect to potential environmental stewardship. This approach provides a more substantial justification for focusing on specific sectors of interest.

In the sample collection procedure shown in Figure 3.2, we exclusively use supply chain relationships classified as “direct” (disclosed by the focal firm) and “reverse” (disclosed by the focal firm’s suppliers or customers). This approach enables us to construct a wide range of dyadic relationships across two distinct manufacturing industries (Culot et al., 2023). After organizing our data, we integrate this sample with other datasets described in Section 3.4.1. We then eliminate dyads lacking key independent and control variables in two steps: first, we exclude dyads with missing values for the moderators, resulting in 10,145 dyads, 1,608 unique suppliers, and 166 unique buyers; second, we remove dyads missing control variable data, involving 9,296 dyads, 1,459 unique suppliers, and 166 unique buyers.

Figure 3.2 Sample Selection Procedure

Step 1: Select Buyers

1. Download the 2018 Forbes Global 2000 firm list.
2. Select 208 manufacturing firms in Materials (GICS: 1510) and Pharmaceuticals (GICS: 3520).

Step 2: Construct Buyer-supplier Dyads

1. Download FactSet Revere BSRs data (2015–2019) for relationships identified as customers or suppliers, excluding dyads missing International Securities Identification Number (ISIN) codes for both buyers and suppliers (857,372 dyads).
2. Align the selected BSRs with buying firms featured in the 2018 Forbes Global 2000 rankings, specifically focusing on the two aforementioned distinct industries, both of which are included in the general category of manufacturing (32,413 dyads).
3. Consolidate the data by merging dyads according to relationship IDs and respective years, ensuring each unique ID corresponded to a single BSR within each year from 2015 to 2019 (23,416 dyads).
4. Exclude dyads that lack information on the suppliers' GICS sector and industry codes, as well as those classified under the service industry (18,040 dyads & 5,914 unique dyads).

Step 3: Merge Environmental Disclosure Data

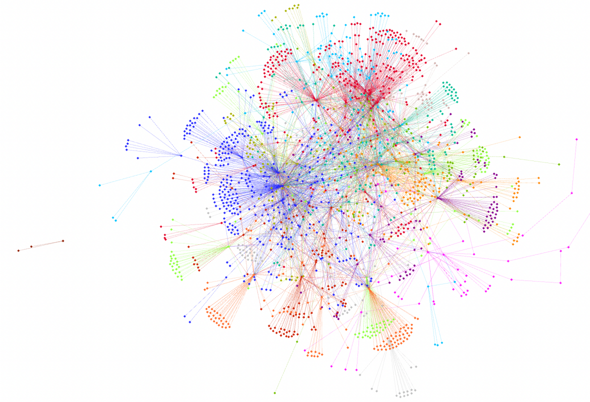
1. Collect environmental disclosure data for buyers and suppliers for the period from 2015 to 2019.
2. Exclude dyads with missing environmental disclosure data for buyers and suppliers 10,580 dyads & 1,664 unique suppliers & 169 unique buyers).

Step 4: Form Supply Networks of Buying Companies

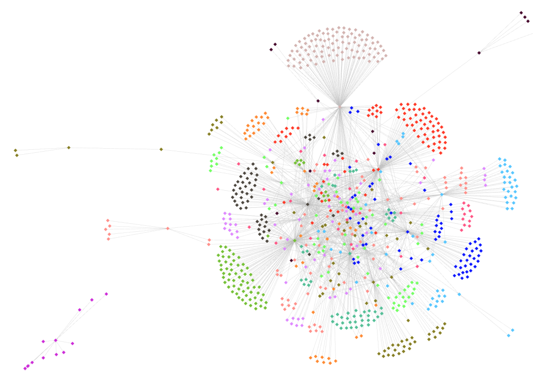
1. Separate lists of buyers and suppliers were created for each year within the period 2015 to 2019.
2. Remove duplicates, resulting in 857,872 buyer relationships and 356,824 supplier relationships.
3. Based on Step 4-2, retain any BSRs that were active at any point from 2015 to 2019.
4. Based on buyers and suppliers identified in Step 3-2, 30,117 (2015), 36,221 (2016), 43,481 (2017), 44,778 (2018), and 46,399 (2019) dyads were retained; structural equivalence was then computed.

3.4.2.2 Sample Description

Previous research has highlighted the crucial role of partner interconnectedness in enhancing information flows within a network (Bellamy et al., 2020). To better depict the unique structural features of supply networks across the chosen industries in 2019, as outlined in the fourth point of Step 2 in Figure 3.2, we employ Gephi 0.10.1. As one of the network mapping layouts provided by this visualization tool, we employ the Yifan Hu multilevel layout. This layout method integrates a force-directed model with a graph coarsening technique, effectively simplifying complex visualizations while preserving the integrity of the network. This approach is efficiently detailed by Hu (2005), highlighting its effectiveness in network analysis.



(a) Materials Industry in 2019



(b) Pharmaceutical Industry in 2019

Figure 3.3 Visualization of Supply Networks of Two Different Industries

Figure 3.3 clearly shows that the materials industry was denser compared to the pharmaceutical industry in 2019. In addition, Figures 3.3a and 3.3b use color-coded modularity to delineate firms into distinct communities, facilitating an intuitive understanding of network segmentation. Based on the color-coded modularity for community detection, the materials industry comprised 17 communities, while the pharmaceutical industry included 15 in 2019. Furthermore, the materials industry maintained a larger supply base compared to the pharmaceutical industry during the same period.

In summary, our final sample includes suppliers and buyers operating across diverse manufacturing sectors (see Table 3.2). Additionally, based on the location of the headquarters of the suppliers in our sample, Figure 3.4 demonstrates the global coverage of these suppliers. The numbers shown in Figure 3.4 represent the observed number of suppliers according to the location of their headquarters in Table 3.2.

3.4.3 Variables

In this section, we construct a set of variables for empirical analysis and hypothesis testing. These variables are detailed in Table 3.4, which presents their descriptions and applications in

Table 3.2 Sample Demographics

Unique Suppliers		Unique Buyers	
Industry	N	Industry	N
Automobiles & Components	27	Materials	128
Capital Goods	316	Pharmaceuticals & Biotechnology	38
Consumer Durables & Apparel	17		
Energy	130		
Food, Beverage & Tobacco	21		
Health Care Equipment	56		
Household & Personal Products	6		
Materials	420		
Pharmaceuticals & Biotechnology	321		
Semiconductors & Equipment	20		
Technology Hardware	43		
Utilities	82		
Total	1,459	Total	166

Country of Suppliers' Headquarters in Unique Dyads		Country of Buyers' Headquarters in Unique Dyads	
Country	N	Country	N
United States	1,161	United States	1,016
India	316	Japan	458
Japan	315	Germany	335
China	186	United Kingdom	238
Australia	177	South Korea	160
United Kingdom	166	France	156
Germany	157	India	156
South Korea	149	Australia	143
France	111	Canada	118
Canada	97	Luxembourg	115
Others	804	Others	744
Total	3,639	Total	3,639

the analysis. In addition, Table 3.3 provides the summary statistics and correlation matrices, which are crucial for understanding the interactions among the variables relevant to our empirical investigation.

Figure 3.4 The Distribution of Suppliers' Headquarters across the World

3.4.3.1 Dependent Variable

As a primary dependent variable, we utilize the voluntary environmental disclosure of supplier s, denoted as $S\_ED_{s,t+1}$, which is rated on a 100-point scale, for the subsequent year $t+1$ in this study. This rating draws upon 120 internal and external environmental impact indicators, each weighted according to the salience of industry-specific characteristics, such as emissions, energy use, water management, waste management, and other environmental operational categories (Diebel et al., 2024; Bellamy et al., 2020). Consistent with Diebel et al. (2024), Villena and Dhanorkar (2020), and Jira and Toffel (2013), this study explores the impact of buyers' sustainability attributes on the environmental transparency of suppliers. One key strength of Bloomberg's environmental disclosure score from the Bloomberg ESG database is its incorporation of both structured and unstructured data, with Bloomberg's Global Reporting Initiative (GRI)-based sustainability survey filling gaps in publicly available information (Bellamy et al., 2020). Therefore, Bloomberg's environmental disclosure score is ideal for our study, as it specifically measures a supplier environmental disclosure rather than actual environmental performance, while also accounting for the firm's industry context (Bellamy et al., 2020; Yu et al., 2018). Previous literature has also utilized Bloomberg's ESG disclosure score to assess firms' willingness to participate in sustainability activities and practices (Diebel et al., 2024; Adhikary et al., 2020; Bellamy et al., 2020).

3.4.3.2 Independent Variables

As the primary independent variable, we employ the voluntary environmental disclosure of the buyer b, denoted as $B\_ED_{b,t}$, which is rated on a 100-point scale, for the current period t in this study. Consistent with the dependent variable, we utilize Bloomberg's environmental disclosure score from the Bloomberg ESG database.

In addition, we utilize the three dimensions of social capital to examine the moderating effects of a buyer's influence on supplier environmental disclosure (resp., structural dimension of social capital (i.e., $SD_{s,b,t}$), relational dimension of social capital (i.e., $RD_{s,b,t}$), and cognitive dimension of social capital (i.e., $CD_{s,b,t}$)). To more accurately evaluate the impact of the structural dimension of social capital, denoted as $SD_{s,b,t}$, on the dyadic relationships between buyers and suppliers, it is crucial to examine structural equivalence from both parties' perspectives. This involves examining the patterns and configurations of relationships each party maintains within the network, thus offering insights into how similar their roles and influences are within their respective networks. Structural equivalence indicates how similar relations between two nodes in a network are (Xiao et al., 2015; Burt, 1997; Coleman, 1994). In a few previous studies, structural equivalence has been operationalized in a similar manner by assessing the shared connections of two separate nodes (Chae et al., 2020; Xiao et al., 2015; Kossinets and Watts, 2006). In this research context, structural equivalence will be measured by the proportion of shared suppliers or customers between the two firms in a BSR, relative to their total number of connections. This measure, commonly referred to as the Jaccard index, calculates the ratio of shared (or overlapping) connections to the total connections, reflecting the intersection of true and expected positive matches (Ebbes and Netzer, 2021). We compute this metric in the following manner:

$$J(B_i, S_j) = \frac{|N(B_i) \cap N(S_j)|}{|N(B_i) \cup N(S_j)|}$$

$$\text{where} \quad N(B_i) \text{ is the neighborhood nodes of } B_i, \qquad (3.1)$$

$$N(S_j) \text{ is the neighborhood nodes of } S_j.$$

In this study, we calculate $J(B_i, S_j)$ as defined in (3.1) using the Python *NetworkX* package, which is widely utilized in supply network research (Chae et al., 2022; Taghizadeh et al., 2021). Identifying these shared connections is crucial for assessing the structural equivalence between firms.

The relational dimension of social capital, denoted as $RD_{s,b,t}$, which represents the second dimension of social capital, will be operationalized through the extent to which both the buyer and the supplier hinge on their relationship. In line with the previous work (Chae et al., 2020; Hoetker et al., 2007), the duration (in years) of BSRs is measured by the total number of years a buying firm has maintained relationships with its suppliers. In a recent and important advancement, Capaldo (2007) expands on prior relationship theories by conceptualizing inter-organizational relationship strength as a three-dimensional construct encompassing temporal, resource, and social dimensions. In the study, Capaldo (2007) identifies three key factors that interact to determine the strength of BSR ties: (1) the overall duration of the relationship, (2) the frequency of interaction, and (3) the intensity of interaction. In this framework, duration represents the temporal dimension, while all three factors collectively embody the resource-based and social dimensions. In essence, higher levels of these factors generally correspond to greater resource commitments and are prerequisites for the transfer of social content between firms (Autry and Golicic, 2010). Hence, the operationalization of the relational dimension of social capital is well justified.

To effectively measure the cultural gap between a buying firm and its suppliers, previous research has frequently employed the concept of national cultural distance (Chae et al., 2020; Morosini et al., 1998). In this study, we adapt the traditional national cultural distance measure to assess the cognitive dimension of social capital, denoted as $CD_{s,b,t}$. By reverse engineering this metric, we aim to capture the shared understanding evident in language, codes, and narratives

(Chae et al., 2020; Claridge, 2018; Morosini et al., 1998; Kogut and Singh, 1988). The measure of national cultural distance reflects the Euclidean distance between Hofstede's cultural dimensions for the countries where the buyer's and supplier's headquarters are located. Specifically, following the established framework of Beugelsdijk et al. (2018) and Hofstede (2011), this study incorporates six cultural dimensions: power distance, uncertainty avoidance, individualism versus collectivism, masculinity versus femininity, long-term versus short-term orientation, and indulgence versus restraint. To capture the shared understanding reflected in these cultural dimensions, we multiply it by a negative one to refine it into a more context-specific proxy for cognitive alignment or misalignment in international business relationships. Specifically, we compute this metric in the following manner:

$$CD_{s,b,t} = -1 \times (\text{The Euclidean distance between Hofstede's cultural dimensions})\,. \tag{3.2}$$

3.4.3.3 Control Variables

To avoid the confounding effects stemming from unobserved dyad and supplier heterogeneity, we utilize several factors that can address supplier-level and dyad-level heterogeneity in this study and might affect a supplier's level of environmental disclosure.

Corporate governance is primarily categorized into internal mechanisms, such as the board of directors, and external mechanisms, including ownership and pressure from other stakeholders (Velte, 2024). Given that corporate environmental disclosure is considered a high-level strategic decision for the firm, we control for the number of board members of supplier s in year t (i.e., $S\_BOARD\_SIZE_{s,t}$) (Velte, 2024; Lu and Shang, 2017). Furthermore, as a key aspect of corporate governance, we control for gender diversity at the executive level, measured by the number of female executives within a company (i.e., $S\_FEM\_EXECUTIVES_{s,t}$). Recognized as a crucial variable in sustainable corporate governance, gender diversity is predicated on the idea that female directors contribute diverse perspectives, promote a broader array of eco-friendly solutions, and influence the strategic and operational decisions of boards toward addressing environmental issues (Velte, 2024; Liu, 2018). Existing literature on SSCM has demonstrated that the gender composition of the workforce can significantly impact sustainability improvements, as well as environmental and social conditions (Villena et al., 2021; Wilhelm and Villena, 2021). Therefore, justifying the inclusion of the number of female executives within a company as a control variable in this study is well-supported.

A firm's financial performance may affect its willingness and ability to disclose environmental information (Bellamy et al., 2020). To account for this influence, we control for a financial metric that reflects firm financial performance, including net income after taxes (i.e., $S\_NET\_INCOME_{s,t}$). Next, we also control for supplier size, measured as the natural logarithm of the number of employees (i.e., $\ln S\_EMP_{s,t}$) (Villena et al., 2021; Wilhelm and Villena, 2021; Adhikary et al., 2020; Sharma et al., 2020), given its role as a well-established determinant of corporate environmental disclosure (D'Amico et al., 2016; Cho et al., 2012; Cormier and Magnan, 1999).

We incorporate ESG and socio-political factors to account for CSR activities. First, the presence of a dedicated committee (i.e., $S\_CSR\_COM_{s,t}$) overseeing CSR and sustainability initiatives offers key insights into a company's governance structure and commitment to sustainability (Velte, 2024). Another key environmental factor is a company's exposure to climate-related risks (i.e., $S\_CLI\_RISKS_{s,t}$), particularly whether it has identified inherent risks with the potential to significantly impact its financial or strategic operations. Corporate climate risks, goals, and related information are typically disclosed through environmental reporting (Wilhelm and Villena, 2021; Jira and Toffel, 2013). Moreover, firms often prioritize accountability to their workforce to gain or maintain corporate legitimacy, recognizing employees as key stakeholders (Parsa et al., 2018). As companies navigate public pressure within social and political environments, they strengthen their legitimacy when stakeholders perceive their value systems as acceptable. This social legitimacy is continuously assessed and reinforced through the public policy process (Parsa et al., 2018; Patten, 2002). In this regard, we also account for the presence of companies' human rights policies (i.e., $S\_HR\_POLICY_{s,t}$) as a control variable.

Lastly, organizations actively adapt to their evolving environments and contingency factors, such as technological advancements and government policies, to optimize performance (Sodhi and Tang, 2018). In OM, variables such as national context, culture, firm size, and strategic orientation are commonly recognized as contingencies shaping corporate best practices. In SSCM, in particular, industry-specific and national contexts serve as key contingency factors (Sodhi and Tang, 2018; Sousa and Voss, 2008). Within this framework, environmental disclosure in supply chains reflects a company's commitment to complying with environmental regulations and norms. However, these commitments may be compromised not only in the countries where suppliers operate but also in the buyer's market (Sodhi and Tang, 2019). Previous studies highlight industry type, country context, and peer effects as major contingency factors influencing the extent of corporate disclosure (Zhao and Wang, 2024; Seo, 2021; Bellamy et al., 2020; Sodhi and Tang, 2018; Jira and Toffel, 2013; Cowen et al., 1987).

In this study, due to the high correlation between the geographical proximity in BSRs and one of our independent variables, $CD_{s,b,t}$, we have opted to exclude the variable indicating whether the buying firm and supplier are headquartered in the same country from the main analysis. However, we retain this variable for robustness checks as an alternative metric for assessing the cognitive dimension of social capital. In addition, to control for industry alignment at the dyadic level, we include a dummy variable, $SAME\_IND_{s,b,t}$, which denotes whether the buying firm and supplier operate within the same industry, as determined by four-digit GICS industry classifications (Song et al., 2023). This methodological choice aids in demonstrating the consistency between our main findings and the robustness check results. The summary statistics and correlation matrix for the variables of interest are presented in Table 3.3.

3.5 Empirical Specification

In this section, we outline the models used for the empirical analysis to test our hypotheses and conclude with a presentation of the empirical results.

3.5.1 Empirical Models

To mitigate causal ambiguity, we measure each supplier's environmental disclosure at time t+1 ($S\_ED_{s,t+1}$), while the buyer's disclosure score ($B\_ED_{b,t}$), three social capital factors ($SD_{s,b,t}$,

Table 3.3 Descriptive Statistics and Correlations

Variable	N	Mean	SD	Min	Max	1	2	3	4	5	6	7
1. $S\_ED_{s,t+1}$	5,571	27.187	24.857	0	90.577	1.00						
2. $B\_ED_{b,t}$	9,296	52.819	19.347	0	90.577	0.03*	1.00					
3. $SD_{s,b,t}$	9,296	0.021	0.027	0	0.394	0.23*	-0.00	1.00				
4. $RD_{s,b,t}$	9,296	2.023	2.110	0	16	0.03	-0.01	0.10*	1.00			
5. $CD_{s,b,t}$	9,296	-45.836	38.061	-129.171	0	-0.16*	-0.10*	0.13*	0.06*	1.00		
6. $S\_BOARD\_SIZE_{s,t}$	9,296	9.271	3.020	3	22	0.39*	-0.02	0.20*	-0.02*	-0.02*	1.00	
7. $S\_FEM\_EXECUTIVES_{s,t}$	9,296	0.909	1.212	0	18	0.23*	0.03*	0.14*	0.05*	-0.08*	0.22*	1.00
8. $S\_NET\_INCOME_{s,t}$	9,296	580.128	2376.88	-22355	23352	0.30*	-0.02	0.19*	0.05*	-0.06*	0.22*	0.17*
9. $\ln S\_EMP_{s,t}$	9,296	8.322	2.027	0	13.348	0.63*	-0.02	0.18*	-0.02*	-0.13*	0.54*	0.20*
10. $S\_CSR\_COM_{s,t}$	9,296	0.300	0.458	0	1	0.24*	0.00	0.11*	-0.01	-0.00	0.30*	0.19*
11. $S\_CLI\_RISKS_{s,t}$	9,296	0.221	0.415	0	1	0.29*	0.05*	0.05*	0.10*	-0.02	0.24*	0.18*
12. $S\_HR\_POLICY_{s,t}$	9,296	0.610	0.488	0	1	0.65*	0.05*	0.17*	-0.02	-0.14*	0.31*	0.11*
13. $SAME\_IND_{s,b,t}$	9,296	0.512	0.500	0	1	0.02	-0.09*	0.18*	0.12*	-0.08*	-0.04*	-0.00
	N	Mean	SD	Min	Max	8	9	10	11	12	13	
8. $S\_NET\_INCOME_{s,t}$	9,296	580.128	2376.88	-22355	23352	1.00						
9. $\ln S\_EMP_{s,t}$	9,296	8.322	2.027	0	13.348	0.29*	1.00					
10. $S\_CSR\_COM_{s,t}$	9,296	0.300	0.458	0	1	0.17*	0.28*	1.00				
11. $S\_CLI\_RISKS_{s,t}$	9,296	0.221	0.415	0	1	0.15*	0.30*	0.23*	1.00			
12. $S\_HR\_POLICY_{s,t}$	9,296	0.610	0.488	0	1	0.17*	0.53*	0.25*	0.19*	1.00		
13. $SAME\_IND_{s,b,t}$	9,296	0.512	0.500	0	1	0.05*	-0.18*	-0.05*	-0.03*	-0.09*	1.00	

Note: $*p < 0.05$.

$RD_{s,b,t}$, and $CD_{s,b,t}$), the dummy variable ($SAME\_IND_{s,b,t}$) indicating whether buyers and suppliers share the same institutional context, and all other covariates ($\boldsymbol{\mu_{k,t}}$) are measured at time t (Diebel et al., 2024; Dai et al., 2021). As shown in Table 3.5, $\boldsymbol{FE_t}$ represents the fixed effects incorporated in the model, including supplier-country, supplier-industry, and year.

$$\begin{aligned} S\_ED_{s,t+1} = \beta_0 + \beta_1 B\_ED_{b,t} + \beta_2 SD_{s,b,t} \quad & \left(\text{or } RD_{s,b,t},\ \text{or } CD_{s,b,t}\right) \\ + \beta_3 SD_{s,b,t} \quad & \left(\text{or } RD_{s,b,t},\ \text{or } CD_{s,b,t}\right) \times B\_ED_{b,t} \\ + \sum_{k=1}^{K} \beta_k \boldsymbol{\mu_{k,t}} + \boldsymbol{FE_t} + \epsilon_{t+1}. & \end{aligned} \tag{3.3}$$

We utilize ordinary least squares (OLS) estimation with multi-way clustered standard errors at both the supplier-year and buyer-year levels to account for potential cross-sectional correlations among dyads that share the same suppliers and buyers within each period (Diebel et al., 2024; Cameron et al., 2011). We conduct our estimation using the $reghdfe$ command in Stata 17, which efficiently handles high-dimensional fixed effects and multi-way clustering.

Table 3.4 Variable Descriptions

Variable	Description	Database
Dependent Variable		
$S\_ED_{s,t+1}$	Supplier's environmental disclosure score (100-point scale), assessing voluntary environmental reporting. *Reference:* Diebel et al. (2024)	Bloomberg
Independent Variables		
$B\_ED_{b,t}$	Buyer's environmental disclosure score (100-point scale), measuring sustainability transparency. *Reference:* Diebel et al. (2024)	Bloomberg
$SD_{s,b,t}$	Structural dimension of social capital, measured using the Jaccard index of shared supplier/buyer ties. *Reference:* Xiao et al. (2015); Burt (1997)	FactSet
$RD_{s,b,t}$	Relational dimension, measured as the total duration of the buyer-supplier relationship. *Reference:* Capaldo (2007); Hoetker et al. (2007)	FactSet
$CD_{s,b,t}$	Cognitive dimension, measured as the negative value of national cultural distance using Hofstede's index. *Reference:* Beugelsdijk et al. (2018); Hofstede (2011)	Hofstede Index
Control Variables		
$S\_BOARD\_SIZE_{s,t}$	Number of board members in the supplier firm. *Reference:* Velte (2024); Lu and Shang (2017)	Bloomberg
$S\_FEM\_EXECUTIVES_{s,t}$	Number of female executives in the supplier firm. *Reference:* Velte (2024); Liu (2018)	Bloomberg
$S\_NET\_INCOME_{s,t}$	Supplier's net profit (losses) after expenses. *Reference:* Pekovic et al. (2018)	Bloomberg
$\ln S\_EMP_{s,t}$	Natural log of the number of employees. *Reference:* Villena et al. (2021); Wilhelm and Villena (2021)	Bloomberg
$S\_CSR\_COM_{s,t}$	Indicator for CSR or sustainability committee. *Reference:* Velte (2024)	Bloomberg
$S\_CLI\_RISKS_{s,t}$	Indicator for substantive climate-related risk disclosure. *Reference:* Wilhelm and Villena (2021); Jira and Toffel (2013)	Bloomberg
$S\_HR\_POLICY_{s,t}$	Indicator for formal human rights policy. *Reference:* Parsa et al. (2018)	Bloomberg
$SAME\_IND_{s,b,t}$	Dummy for buyer and supplier in the same 4-digit GICS industry. *Reference:* Song et al. (2023)	FactSet

3.5.2 Empirical Results

We present the results of the panel regression model in Table 3.5, estimating six different models across two industries: materials and pharmaceuticals. First, we report the baseline model (Model 1), which includes only control variables. Then, we sequentially introduce the main independent variables in Models 2 through 5. Finally, Model 6 presents the full specification, incorporating all independent and control variables.

Table 3.5 Estimates of Ordinary Least Square Methods

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
$B\_ED_{b,t}$		-0.017	-0.033*	-0.010	0.013	0.006
		(0.012)	(0.014)	(0.014)	(0.017)	(0.021)
$SD_{s,b,t}$			2.638			13.797
			(17.100)			(17.452)
$B\_ED \times SD$			0.722**			0.596*
			(0.273)			(0.279)
$RD_{s,b,t}$				0.209		0.289+
				(0.181)		(0.172)
$B\_ED \times RD$				-0.003		-0.005
				(0.004)		(0.004)
$CD_{s,b,t}$					-0.050**	-0.054**
					(0.016)	(0.017)
$B\_ED \times CD$					0.001**	0.001*
					(0.000)	(0.000)
$S\_BOARD\_SIZE_{s,t}$	0.382*	0.384*	0.362*	0.385*	0.397*	0.377*
	(0.180)	(0.180)	(0.179)	(0.179)	(0.180)	(0.179)
$S\_FEM\_EXECUTIVES_{s,t}$	0.480	0.475	0.416	0.477	0.483	0.419
	(0.319)	(0.319)	(0.311)	(0.319)	(0.318)	(0.311)
$S\_NET\_INCOME_{s,t}$	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln S\_EMP_{s,t}$	4.246***	4.234***	4.118***	4.228***	4.205***	4.057***
	(0.274)	(0.274)	(0.273)	(0.275)	(0.273)	(0.272)
$S\_CSR\_COM_{s,t}$	5.527***	5.528***	5.636***	5.534**	5.545**	5.652***
	(1.153)	(1.152)	(1.142)	(1.152)	(1.153)	(1.143)
$S\_CLI\_RISKS_{s,t}$	4.459***	4.447***	4.454***	4.431***	4.388***	4.352***
	(1.031)	(1.029)	(1.027)	(1.036)	(1.025)	(1.029)
$S\_HR\_POLICY_{s,t}$	16.911***	16.954***	16.762***	16.951***	16.895***	16.632***
	(1.034)	(1.032)	(1.038)	(1.035)	(1.031)	(1.043)
Constant	-24.281***	-23.314***	-21.637***	-23.680***	-25.069***	-23.988***
	(1.930)	(2.052)	(2.084)	(2.074)	(2.156)	(2.203)
Same Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Supplier Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Supplier Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,570	5,570	5,570	5,570	5,570	5,570
R^2	0.555	0.556	0.558	0.556	0.557	0.560

Note: Note: $+p < 0.1$, $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$ indicate statistical significance at the 10 percent, 5 percent, 1 percent, and 0.1 percent levels. Cluster-robust standard errors (s.e.) are reported in parentheses below parameter estimates. Multi-way clustered errors are estimated at the levels of supplier-year and buyer-year. Within R^2 is reported.

As our baseline hypothesis, we predict a negative influence of a buyer firm's environmental disclosure on its supplier's environmental disclosure. In Model 2, as presented in Table 3.5, our empirical findings suggest a negative influence ($\beta_{B\_ED_{b,t}}$ = -0.017, $s.e.$ = 0.012) between the forward environmental disclosure of a supplier ($S\_ED_{s,t+1}$) and the environmental disclosure of a buying firm at time t ($B\_ED_{b,t}$); however, this impact is not statistically significant, suggesting that H_1 is not supported.

In Hypothesis H_{2A}, we hypothesize that the structural equivalence between a buyer and its supplier weakens the negative influence of the buyer on its supplier's environmental disclosures. Model 3, as detailed in Table 3.5, provides empirical support for this hypothesis. Our findings indicate that structural equivalence between the buyer and supplier moderates the influence between the buyer's and supplier's environmental disclosures in a positive direction ($\beta_{B\_ED_{b,t} \times SD_{s,b,t}}$ = 0.722, $p < 0.01$), such that the negative influence becomes weaker at higher levels of structural equivalence ($\beta_{B\_ED_{b,t}}$ = -0.033, $p < 0.05$). In summary, the observed effect between the environmental disclosure of a supplier ($S\_ED_{s,t+1}$) and the environmental disclosure of a buying firm ($B\_ED_{b,t}$) supports the validity of the moderating effect of structural equivalence, as hypothesized in H_{2A}. To provide greater specificity, our calculations suggest that a one standard deviation increase in buyer environmental disclosure (equivalent to 19.347) is estimated to lead to a 51.379% increase in supplier environmental disclosure (equivalent to 13.969), on average. This relationship holds for dyads characterized by higher structural equivalence between the two entities. The percentage increase is derived from the calculation $51.379\% = \frac{19.347 \times 0.722}{27.187}$.

In Hypothesis H_{2B}, we posit that the duration of the relationship between a buyer and its supplier weakens the negative influence between a supplier's environmental disclosure at time $t+1$ and that of a buying firm at time t. However, the findings presented in Model 4, as detailed in Table 3.5, do not support this hypothesis. Our analysis reveals a non-significant and negative moderating effect of relationship duration ($\beta_{B\_ED_{b,t} \times RD_{s,b,t}} = -0.003$, $s.e.$ = 0.004) on the influence between the environmental disclosure of a supplier ($S\_ED_{s,t+1}$) and the environmental disclosure of a buying firm ($B\_ED_{b,t}$), indicating that H_{2B} lacks empirical support.

In Hypothesis H_{2C}, we hypothesize that the national cultural similarity between a buyer and its supplier weakens the negative influence of the buyer on its supplier's environmental disclosures. Model 5, as detailed in Table 3.5, provides empirical evidence supporting this hypothesis. Our results show that national cultural similarity between the buyer and supplier moderates the influence between the buyer's and supplier's environmental disclosures in a positive direction ($\beta_{B\_ED_{b,t} \times CD_{s,b,t}} = 0.001$, $p < 0.01$). In summary, the observed effect between the environmental disclosure of a supplier ($S\_ED_{s,t+1}$) and the environmental disclosure of a buying firm ($B\_ED_{b,t}$) provides empirical support for the moderating effect of national cultural similarity, as proposed in Hypothesis H_{2C}. To provide a more precise analysis, we estimate that a one standard deviation increase in buyer environmental disclosure (equivalent to 19.347) is associated with an average increase of 0.07% in supplier disclosure (equivalent to 0.020). This effect is observed in dyads exhibiting higher national cultural similarity between the two entities. The calculated percentage increase is determined by $0.07\% = \frac{19.347 \times 0.001}{27.187}$. In addition, we incorporate all interaction terms in a fully specified model to jointly test all proposed hypotheses. This comprehensive approach confirms that the results are consistent with the findings observed in Models 2 through 5.

Lastly, as shown in Figures 3.5 and 3.6, we present the interaction effects at high, middle, and low levels of the structural and cognitive dimensions of social capital. These levels are determined using -1 and $+1$ standard deviations from the mean, with the median representing the middle level. However, for the structural dimension of social capital, since its minimum value is 0, we designate 0 as the low level in Figure 3.5.

The interaction effect, illustrated by the estimated means of supplier environmental disclosure, suggests that the negative relationship between a supplier's environmental disclosure ($S\_ED_{s,t+1}$) and a buyer's environmental disclosure ($B\_ED_{b,t}$) is moderated by the level of structural equivalence. As shown in Figure 3.5, this moderating pattern is reflected in the differences in slopes across varying levels of structural equivalence. Using the *margins* command in Stata, we examine the slopes at low, median, and high levels of the structural dimension.

At the low level of structural equivalence (blue line), the slope is negative and statistically significant ($\beta = -0.033$, $p < 0.05$), indicating that as buyer environmental disclosure increases, supplier environmental disclosure significantly decreases when structural overlap is low. At the median level (red line), the slope remains negative and statistically significant ($\beta = -0.024$, $p < 0.1$), but it is flatter compared to the low level, suggesting a weaker negative effect. At the high level of structural equivalence (green line), the slope appears visually flat and is not statistically significant ($\beta = 0.002$, $p > 0.1$), based on margins testing. This pattern supports the existence of a significant moderating effect, implying that greater structural equivalence between buyers and suppliers can buffer or even neutralize the negative influence of buyer environmental disclosure on supplier environmental disclosure.

A similar moderating pattern is observed for national cultural similarity. As depicted in Figure 3.6, the interaction effect suggests that the negative relationship between a supplier's environmental disclosure ($S\_ED_{s,t+1}$) and a buyer's environmental disclosure ($B\_ED_{b,t}$) diminishes with increasing levels of cultural similarity. For buyer–supplier pairs with low national cultural similarity (blue line), the slope is strongly negative and statistically significant ($\beta = -0.055$, $p < 0.01$), indicating that as buyer disclosure increases, supplier disclosure significantly decreases under conditions of greater cultural dissimilarity. At the median level of cultural similarity (red line), the slope is still negative and statistically significant ($\beta = -0.032$, $p < 0.05$), although it is flatter compared to the low similarity group, reflecting a weakened negative effect. In contrast, at the high level of national cultural similarity (green line), the slope is visually flat and not statistically significant ($\beta = 0.007$, $p > 0.1$). This pattern further confirms the moderating role of national cultural similarity, indicating that greater cultural alignment between buyers and suppliers can mitigate or eliminate the negative impact of buyer environmental disclosure on supplier environmental disclosure.

3.6 Robustness Checks and Additional Analysis

3.6.1 Robustness Checks

In this section, drawing on previous literature that addresses potential concerns related to endogeneity and alternative empirical specifications, we aim to validate the consistency of our findings using the empirical setup outlined in Section 3.5.1.

Figure 3.5 Margins Plot of Estimated Supplier Environmental Disclosure in Model 3

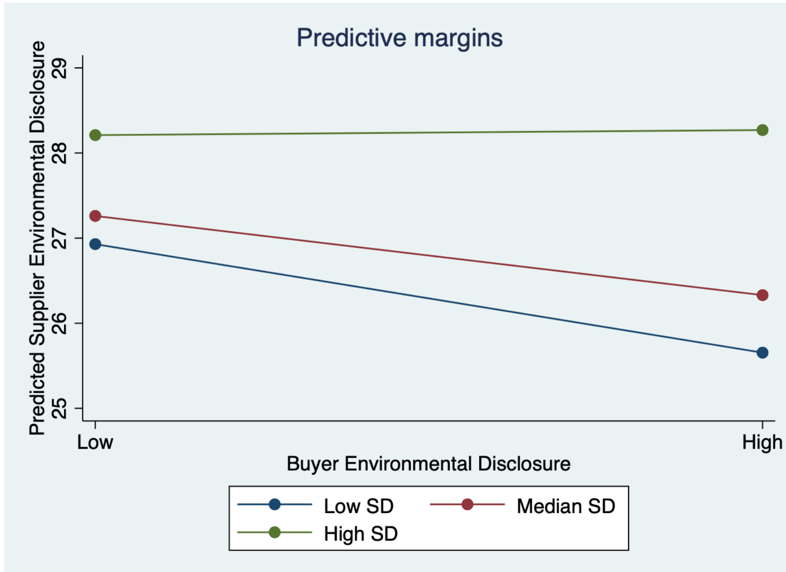
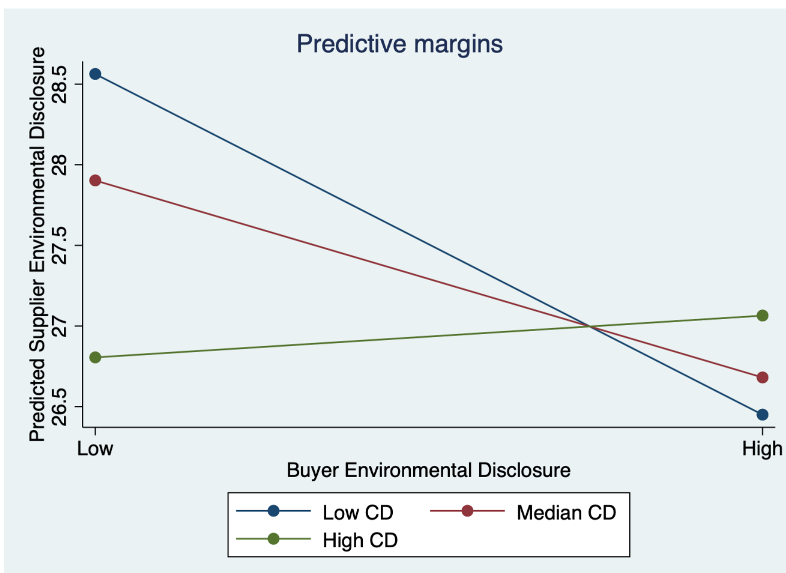


Figure 3.6 Margins Plot of Estimated Supplier Environmental Disclosure in Model 5



3.6.1.1 Endogeneity

In empirical research, obtaining reliable estimates of effect magnitudes is essential for practical relevance; however, achieving unbiased and efficient estimates is often challenged by a range of methodological issues (Ketokivi and McIntosh, 2017). Endogeneity occurs when explanatory variables are correlated with the error term in a regression model, which can lead to biased, inconsistent, and inefficient parameter estimates (Ketokivi and McIntosh, 2017). In this study, we take a closer look at the issue of endogeneity and discuss the strategies we employ to address it within our research design.

First, in our empirical specification, simultaneity is unlikely to be a source of endogeneity given our modeling approach and empirical context. To be specific, by employing a lagged structure, we model supplier environmental disclosure as a response to buyer environmental disclosure from the previous period, thereby reducing concerns about simultaneous determination (Diebel et al., 2024; Gualandris et al., 2021; Dong et al., 2020). Consistent with prior literature (Diebel et al., 2024; Villena and Dhanorkar, 2020; Jira and Toffel, 2013), our sample also reveals that buyers exhibited a significantly higher degree of disclosure than suppliers, suggesting that buyers have historically led by example in comparison to their suppliers.

Omitted variables pose a potential endogeneity concern, as unobserved factors may be correlated with both the dependent variable and the independent variables, leading to biased estimates (Ketokivi and McIntosh, 2017). First, our main model incorporates a range of fixed effects, including supplier-country, supplier-industry, and year, to account for both observable and unobservable time-invariant characteristics of suppliers, as well as potential temporal shocks. In addition, we include a comprehensive set of control variables to further mitigate confounding influences. Nevertheless, we take an additional step to address this issue by applying a two-step control function approach.

To implement a two-step control function approach, it is essential to select instruments that not only satisfy the relevance and exclusion conditions but are also supported by strong theoretical justification. Prior studies have commonly used lagged explanatory variables as instruments to address endogeneity concerns (Wang and Bellemare, 2019; Bellemare et al., 2017). In this study, we use lagged values as instruments for the corresponding independent variables. Drawing on prior literature (Cameron and Trivedi, 2022; Adhikary et al., 2020; Villena and Dhanorkar, 2020; Bellemare et al., 2017; Wooldridge, 2007), our instruments satisfy both the relevance and exclusion criteria and are grounded in strong theoretical justification. To be specific, with respect to the relevance condition, autocorrelation in the explanatory variables suggests that the endogenous variable is, to some extent, correlated with its own lag (Wang and Bellemare, 2019), and this condition can be tested in the first-stage regressions.

On the other hand, the exclusion restriction requires that the instruments influence the dependent variable solely through their effect on the suspected endogenous variables. In our study, this condition is plausibly satisfied by the use of lagged explanatory variables. To be specific, the past environmental disclosure of downstream partners, particularly in our context, where buyers in the manufacturing industries frequently outsource production to upstream suppliers, is unlikely to be directly relevant to suppliers' forward sustainability decision-making. Moreover, suppliers are unlikely to directly incorporate the prior structural and relational characteristics of buyers' supply networks into their own forward-looking environmental disclosure strategies. Further, considering the overall disclosure levels of both buyers and suppliers in our sample, much of this information is not fully observable to suppliers at the time of decision-making. Thus, there is little reason to believe that the lagged explanatory variables have a direct effect on the forward environmental disclosure of suppliers. Accordingly, we use these lagged explanatory variables as instruments for the potentially endogenous independent variables – $B\_ED_{b,t}$, $SD_{s,b,t}$, and $RD_{s,b,t}$ – in our analysis.

However, this approach cannot be applied to address the potential endogeneity of the third social capital dimension, $CD_{s,b,t}$, as it is time-invariant in our study. Thus, we opt for a proxy for cultural and institutional proximity. To operationalize geographical proximity at the dyadic level, we introduce the dummy variable $SAME\_HQ_{s,b,t}$, which equals 1 if the buying firm and supplier have headquarters in the same country and 0 otherwise. This metric explicitly captures whether buyer–supplier pairs share the same national context, serving as a proxy for cultural and institutional proximity. In this sense, it is both theoretically justified and empirically correlated with $CD_{s,b,t}$, while the co-location of headquarters is unlikely to be theoretically related to the error term in the supplier's environmental disclosure equation. In addition to the lagged explanatory variables, we employ $SAME\_HQ_{s,b,t}$ as an additional instrument for the final potentially endogenous independent variable, $CD_{s,b,t}$, in our analysis. Lastly, to test the moderating effects, our primary variables of interest are the interaction terms between buyer environmental disclosure and the three dimensions of social capital. To address potential endogeneity concerns, we treat these interaction terms as the third endogenous variable in each equation.

When we include the fitted residuals from the first-stage regressions as additional regressors in the second-stage models – where $S\_ED_{s,t+1}$ is the dependent variable – we find no substantial empirical differences compared to the results from our main specification with respect to hypothesis testing. Specifically, using the same empirical model specification as in Table 3.5, which incorporates control variables, fixed effects, and multi-way clustered robust standard errors, we report the key estimates in Table 3.6. Notably, across all four models, the fitted residuals from the first-stage reduced-form regressions are statistically insignificant in the second-stage regressions, with the exception of those associated with the interaction terms involving the structural and cognitive dimensions of social capital, both of which are marginally significant at the 10% level. Consequently, after addressing potential endogeneity using a two-step control function approach across all explanatory variables in our empirical models, the results suggest that endogeneity is unlikely to pose a significant threat to the validity of our analysis.

Table 3.6 Estimates from Second-Stage Models

Estimated Coefficient	**Model A**	**Model B**	**Model C**	**Model D**
$\beta_{B\_ED_{b,t}}$	−0.017 (0.018)	−0.035 (0.022)	−0.017 (0.024)	−0.054 (0.038)
$\beta_{SD_{s,b,t}}$	–	−4.698 (26.280)	–	–
$\beta_{RD_{s,b,t}}$	–	–	0.079 (0.307)	–
$\beta_{CD_{s,b,t}}$	–	–	–	−0.058 (0.028)*
$\beta_{B\_ED_{b,t} \times SD_{s,b,t}}$	–	0.764 (0.437)+	–	–
$\beta_{B\_ED_{b,t} \times RD_{s,b,t}}$	–	–	0.000 (0.004)	–
$\beta_{B\_ED_{b,t} \times CD_{s,b,t}}$	–	–	–	0.001 (0.001)*
Observations	2,935	2,935	2,935	2,935
R^2	0.581	0.583	0.581	0.583

Note: $+p < 0.1$ and $*p < 0.05$ indicate statistical significance at the 10 percent and 5 percent levels. Cluster-robust standard errors (s.e.) are reported in parentheses to the right of the parameter estimates. Multi-way clustered errors are estimated at the levels of supplier-year and buyer-year. Within R^2 is reported.

3.6.1.2 Multi-way Clustered Robust Standard Errors

In Section 3.5.1, we employ OLS estimation with multi-way clustered standard errors at both the supplier-year and buyer-year levels to address potential cross-sectional correlations among dyads sharing the same suppliers and buyers within each period. In this section, we refine our estimation approach by implementing an empirical setup that utilizes different multi-way clustering strategies to further robustify our results. Diebel et al. (2024) suggests that clustering standard errors at the supplier's industry-country level enables accounting for correlations arising from three nested levels of analysis: the dyadic level (longitudinal correlations across the same dyad), the supplier level (both longitudinal and cross-sectional correlations among dyads sharing the same supplier), and the industry-country level (both longitudinal and cross-sectional correlations among dyads with suppliers operating within the same industry-country pair).

As shown in Table 3.7, although there are differences in the magnitudes of the coefficients and their cluster-robust standard errors, with respect to hypothesis testing, the findings remain consistent with those presented in Table 3.5. Therefore, in addition to clustering at the buyer-year level, further employing cluster-robust standard errors at the supplier's industry-country level effectively controls for correlations arising from three nested levels of analysis, thereby addressing more various forms of observational correlation within our dyadic panel data.

3.6.1.3 Alternative Measure for the Cognitive Dimension of Social Capital

In Section 3.5.1, we adapt the national cultural similarity measure to capture the cognitive dimension of social capital ($CD_{s,b,t}$). Specifically, we reverse-engineer the traditional national cultural distance metric, originally defined as the Euclidean distance between Hofstede's cultural dimensions of the buyer's and supplier's headquarters, to derive a measure of similarity rather than distance. Thus, to test the robustness of the newly introduced metric, this section incorporates an additional measure discussed in Section 3.6.1.1 to validate the reverse-engineered variable and reinforce the consistency and reliability of our empirical findings.

Prior studies frequently emphasize international variations in CSR reporting, attributing these differences primarily to national contextual factors. Variations in social and environmental reporting standards across countries are often driven by external pressures, stakeholder expectations, investment demands, and long-term strategic commitments, leading to notable discrepancies in CSR disclosure practices (Luo et al., 2013). Cultural differences across nations substantially

Table 3.7 Estimates of OLS Estimation with a Different Multi-way Clustering Strategy

Variable	**Model 2**	**Model 3**	**Model 4**	**Model 5**
$B\_ED_{b,t}$	-0.017	-0.033+	-0.010	0.013
	(0.016)	(0.019)	(0.018)	(0.023)
$SD_{s,b,t}$		2.638		
		(27.409)		
$B\_ED \times SD$		0.722+		
		(0.409)		
$RD_{s,b,t}$			0.209	
			(0.283)	
$B\_ED \times RD$			-0.003	
			(0.005)	
$CD_{s,b,t}$				-0.050*
				(0.023)
$B\_ED \times CD$				0.001*
				(0.000)
Constant	-23.314***	-21.637***	-23.680***	-25.069***
	(3.081)	(3.133)	(3.085)	(3.189)
Control Variables	Yes	Yes	Yes	Yes
Same Industry Dummies	Yes	Yes	Yes	Yes
Supplier Country FE	Yes	Yes	Yes	Yes
Supplier Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	5,570	5,570	5,570	5,570
R^2	0.556	0.558	0.556	0.557

Note: $+p < 0.1$, $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$ indicate statistical significance at the 10 percent, 5 percent, 1 percent, and 0.1 percent levels. Cluster-robust standard errors (s.e.) are reported in parentheses below parameter estimates. Multi-way clustered errors are estimated at the supplier's industry-country level. Within R^2 is reported

influence ethical standards, CSR orientations, organizational cultures, and managerial practices (Pucheta-Martínez and Gallego-Álvarez, 2020; Scholtens and Dam, 2007).

On top of that, firms are more likely to collaborate with and adopt practices aligned with peers in the same country, partly due to shared national norms, values, and institutional characteristics (Gualandris et al., 2021; Brandon-Jones et al., 2015). In addition, non-governmental organizations (NGOs) and other non-profit entities often monitor and publicize corporate activities concerning environmental and social responsibility within the regions where firms operate. Within this context, national culture and local institutional environments significantly influence communication patterns between firms and stakeholders, shaping the overall framework for interactions among companies, governments, and stakeholder groups.

Therefore, as a measure of geographical proximity at the dyadic level, we use the dummy variable $SAME\_HQ_{s,b,t}$, which equals 1 if the buyer and supplier are headquartered in the same country, and 0 otherwise, as part of this robustness check. Using the same empirical framework outlined in Section 3.5.1, we substitute $SAME\_HQ_{s,b,t}$ for $CD_{s,b,t}$ and find consistent results with the hypothesis testing presented in Section 3.5.2. To be specific, when supplier environmental disclosure ($S\_ED_{s,t+1}$) is used a dependent variable like in Section 3.5.1, our empirical results as given as follows: $\beta_{B\_ED_{b,t}} = -0.049$ ($p < 0.001$), $\beta_{SAME\_HQ_{s,b,t}} = -4.563$ ($p < 0.001$), and $\beta_{B\_ED_{b,t} \times SAME\_HQ_{s,b,t}} = 0.081$ ($p < 0.001$).

Under the empirical framework outlined in Section 3.5.1, we further validate our findings by introducing the alternative metric, $SAME\_HQ_{s,b,t}$. Specifically, we replace $CD_{s,b,t}$ with $SAME\_HQ_{s,b,t}$, an indicator of whether the buying firm and supplier are headquartered in the same country, and re-estimate Model 5 in Table 3.5 using supplier environmental disclosure ($S\_ED_{s,t+1}$) as the dependent variable. Despite differences in the magnitude of the coefficients, our empirical results in Section 3.5.2 remain consistent with those derived from $SAME\_HQ_{s,b,t}$, confirming robust and statistically significant relationships: $\beta_{B\_ED_{b,t}} = -0.049$ ($p < 0.001$), $\beta_{SAME\_HQ_{s,b,t}} = -4.563$ ($p < 0.001$), and $\beta_{B\_ED_{b,t} \times SAME\_HQ_{s,b,t}} = 0.081$ ($p < 0.001$). Put differently, cultural and institutional proximity between the buyer's and supplier's headquarters moderates the negative impact between their environmental disclosures in a positive direction, with the negative influence diminishing as the cultural and institutional proximity increases. In summary, although the magnitudes of the coefficients and their cluster-robust standard errors vary, the empirical findings for hypothesis testing remain consistent with those presented in Table 3.5.

3.6.2 Additional Analysis

In this section, we compare the levels of supplier environmental disclosure across two buyer industries – Materials and Pharmaceuticals – given that manufacturers in both sectors are particularly sensitive to environmental disclosures due to their focus on safety, environmental impact, and sustainability. Our goal is to determine whether there are differences in environmental disclosure among suppliers serving buyers across these distinct industry sectors.

3.6.2.1 Industry Comparison

When an analysis of variance (ANOVA) yields a significant result, it indicates that at least one group statistically differs from the others. To further explore these differences, ANOVA is typically followed by post hoc tests that focus on specific comparisons, commonly involving pairwise comparisons of means, which help to identify which specific groups differ from each other (Abdi and Williams, 2010).

When employing a one-way fixed-effects ANOVA to model data, we operate under four fundamental assumptions: 1. independence of observations, 2. additivity of effects, 3. normality of residuals, and 4. homogeneity of variances (Larson, 2008). Specifically, the fourth assumption mandates that the within-group random errors exhibit identical variance across all treatment groups. To verify this, Levene's test and Bartlett's test are commonly employed, with the choice of test depending on the normality of the data (Larson, 2008). Thus, we evaluate the homogeneity of variances using Levene's test and Bartlett's test, and determine that the assumption of equal variances across the buyers' industries is not met.

Given the results of Levene's test and Bartlett's test, we try the Kruskal-Wallis test (Kruskal and Wallis, 1952), Mann–Whitney test (Mann and Whitney, 1947), and Dunn's pairwise comparison test (Dunn, 1964) to check for any difference between supplier environmental disclosures of these two groups. The Kruskal-Wallis test is a non-parametric alternative to one-way ANOVA, extending the Mann-Whitney U test to compare differences among three or more independent groups on a continuous variable that does not follow a normal distribution (McKight and Najab, 2010). Given that the Kruskal-Wallis test is an omnibus test for median differences, rejecting the null hypothesis typically warrants conducting multiple pairwise comparisons to further examine the specific differences in medians (Dinno, 2015).

As shown in Table 3.8, the Kruskal-Wallis test provides evidence that rejects the null hypothesis, indicating that the samples do not come from the same population (χ^2 adjusted for ties = 496.882,

Table 3.8 Kruskal-Wallis and Wilcoxon Rank-Sum Test Results

Buyer Industry	Observations	Rank Sum
Materials Industry	6,331	32,107,891
Pharmaceutical Industry	2,965	11,104,566
Combined	**9,296**	**43,212,456**

$p < 0.001$) (Kruskal and Wallis, 1952), while the Mann-Whitney rank-sum test rejects the null hypothesis ($Z - statistic = 22.291$, $p < 0.001$) that two independent (unmatched) samples are drawn from populations with identical distributions (Mann and Whitney, 1947). In addition, Dunn's test of multiple comparisons using mean ranks also indicates a significant difference between the buyers' industries in terms of their supplier environmental disclosure, and this difference is highly significant ($Z - statistic = 22.291$, $p < 0.001$). In summary, based on the results in Table 3.8, the mean rank for the materials industry is significantly higher than that of the pharmaceutical industry, suggesting that the materials industry likely exhibits a larger supplier environmental disclosure.

3.7 Discussion and Conclusion

This study underscores the importance of social capital dimensions embedded within BSRs in shaping the level of supplier environmental disclosure, particularly in the context of supply chain leakage. In the manufacturing industry, not all suppliers within a network are equally willing to disclose their environmental performance. Such reluctance may arise from a range of factors, which we interpret through the lens of the PHH. Consequently, and somewhat counterintuitively, higher levels of buyer environmental disclosure may be associated with lower levels of supplier disclosure.

In addition, various firm-level and supply chain-level characteristics that shape visibility across supply chains may influence the negative impact between a buyer's and a supplier's environmental disclosures. Building on prior literature grounded in social capital theory, we examine the moderating effects of three key dimensions of social capital, structural equivalence, relationship duration, and cultural similarity, which capture essential relational attributes embedded within buyer–supplier dyads in the materials and pharmaceutical industries.

Drawing on voluntary environmental disclosure data from the Bloomberg ESG database, we first investigate the influence between a supplier's environmental disclosure and that of its buying firm across two manufacturing sectors. Our analysis reveals that, although the overall relationship is negative but not statistically significant, it becomes both negative and significant under conditions of low and median structural equivalence. In contrast, when structural equivalence is high, the negative effect is nullified and becomes non-significant, suggesting that the influence of a buyer's environmental disclosure on that of its suppliers is more likely to be voluntary when supply chain visibility is greater. However, we do not find evidence supporting a moderating effect of relationship duration. Lastly, we found that cultural and institutional proximity between the buyer's and supplier's headquarters moderates the negative influence of a buyer on its supplier's environmental disclosures in a positive direction, with the negative influence diminishing as the cultural and institutional proximity increases.

Our findings highlight the critical role of BSRs in shaping environmental disclosure within SSCM. For buyers seeking to promote comprehensive upstream transparency, rather than inadvertently shifting and obscuring environmental harm, it is essential to invest in building structural capital and shared cognitive frameworks with suppliers. In the absence of such alignment, a buyer's own environmental disclosure may paradoxically lead to reduced disclosure by suppliers. By examining this dynamic in the materials and pharmaceutical industries – both subject to heightened environmental scrutiny – we demonstrate that buyer-led transparency can, under certain conditions, contribute to hidden pollution upstream. However, when buyers and suppliers are well-aligned and supply chain visibility is high, this negative effect can be mitigated or even eliminated.

3.7.1 Theoretical Implications

To meet the growing and diverse demands of stakeholders, firms nowadays collaborate with members in supply networks to leverage partners' competency in key specialized areas. In supply networks, most of the buying firms tend to have many suppliers, enabling them to outsource some of their business functions, such as production, services, and finances, to external upstream partners. In many cases, buying firms engage proactively in these relationships to generate joint value, such as enhanced productivity and innovation, that can ultimately improve their operational performance

(Kim and Choi, 2018; Krause et al., 2007). At the same time, participants in supply networks are increasingly pressured to comply with the focal firm's initiatives related to production processes, material handling, and product distribution. From an environmental perspective, firms in the manufacturing industry often respond to these competing demands by strategically locating their production facilities in countries with more lenient environmental regulations, thereby minimizing pollution abatement costs (Berry et al., 2021). This contradicts the prevailing belief that increased environmental disclosure by a buying firm serves as a catalyst for similar behavior among its suppliers.

Our primary theoretical contributions examine whether the logic of the supply chain leakage effect, often associated with the PHH, can be extended to corporate environmental disclosures of buyers and suppliers. This is because supply chain leakage may be linked to a firm's efforts to optimize operations and manage environmental externalities through the outsourcing of operational activities, ultimately affecting the environmental performance of the entire supply chain (Song et al., 2023). Building on the underlying logic of supply chain leakage and the PHH, we propose a negative influence between a supplier's environmental disclosure and that of its buying firm in the manufacturing industry. This may occur when a focal firm reduces its own carbon emissions while promoting a pristine environmental image through disclosure, potentially masking the relocation or outsourcing of polluting activities to upstream suppliers. Such carbon leakage can impose a disproportionate environmental burden on suppliers, resulting in higher upstream carbon footprints. Our findings indicate that while the overall influence between a buyer's and a supplier's environmental disclosures is negative but statistically non-significant, it becomes both negative and significant under conditions of low and median structural equivalence. Although Song et al. (2023) provide evidence of supply chain leakage by documenting a negative relationship between a firm's internal GHG emissions intensity and that of its suppliers, empirically validating the direct application of the PHH remains particularly challenging in the context of voluntary corporate environmental disclosure (Berry et al., 2021).

Our additional theoretical contributions investigate how diverse social capital factors embedded within supply networks shape supplier environmental disclosure behavior. Despite the challenges posed by supply chain leakage, supply chains themselves can serve as valuable environmental assets by contributing to the mitigation of environmental issues across the broader network (Song et al., 2023). A substantial body of literature in SCM highlights that BSRs within supply networks, comprising numerous actors, can take various forms depending on how and why the relationships are established. From a strategic standpoint, firms often prefer to cultivate long-term, cooperative relationships with key suppliers, as purchasing is recognized as a critical lever for gaining competitive advantage (Carr and Pearson, 1999). However, BSRs can range from adversarial to cooperative in nature (Kim and Choi, 2015; Carr and Pearson, 1999; Carter et al., 1998). Adversarial BSRs are typically characterized by multiple sourcing strategies and shorter-term contracts (Carr and Pearson, 1999; Carter et al., 1998), whereas cooperative BSRs involve longer-term, closely integrated partnerships aimed at mutual benefit (Kim and Choi, 2015; Carter et al., 1998). Based on our analysis, suppliers engaged in more arm's length relationships characterized by lower social capital may be more reluctant to disclose, potentially to avoid reputational or commercial risks. In such cases, where suppliers have fewer overlapping partners and lower cultural similarity with the buyer, supply chain visibility tends to be weaker.

In today's hypercompetitive business environment and amid the evolving dynamics of BSRs, firms are increasingly adopting more nuanced and sophisticated relational strategies (Kim and Choi, 2015). Drawing on social capital theory, alongside the concepts of supply chain leakage and the PHH, this study extends prior research by examining how various dimensions of social capital influence the effect of buyer behavior on supplier disclosure. Our work complements existing studies on network effects in supply chains (Chae et al., 2022; Adhikary et al., 2020; Bellamy et al., 2020; Sharma et al., 2020) by showing that social capital embedded within BSRs shapes the influence between a buyer's and a supplier's environmental disclosures. In doing so, our findings help explain why suppliers may not necessarily mirror a buyer's public environmental commitments. Instead, strong buyer disclosure can, under certain conditions, lead to lower supplier disclosure – a manifestation of the supply chain leakage effect – depending on the structural and cognitive dimensions of social capital. Strengthening these dimensions within BSRs is thus essential for achieving authentic environmental progress across supply networks, rather than merely shifting emissions and obscuring upstream impacts.

Given the prevalence of firm-level studies, recent literature has increasingly called for more research focused on dyadic-level analysis in SSCM. Drawing on detailed data on buyer and supplier environmental disclosure, particularly within manufacturing supply networks, this study contributes to the literature by providing a granular understanding of the relational mechanisms through which buyers influence supplier behavior in the context of environmental disclosure. In doing so, it advances theoretical discussions on BSRs by integrating social capital theory with emerging concerns around sustainability and supply chain governance.

3.7.2 Managerial Implications

Our findings provide practical insights into corporate voluntary environmental disclosure from a network-based perspective. While prior literature often suggests that increased environmental disclosure by a buying firm encourages suppliers to follow suit, publicly signaling green objectives and fostering collective sustainability efforts across the supply chain, this assumption is not universally supported. Some studies argue that firms may strategically employ environmental disclosure as a form of greenwashing, shifting their environmental burdens upstream to suppliers in response to performance and disclosure pressures (Song et al., 2023; Dai et al., 2021; Kim and Lyon, 2011). Accordingly, and somewhat paradoxically, increased buyer environmental disclosure may correspond with reduced disclosure by suppliers.

Based on the PHH, buyers, particularly in the manufacturing industry, may outsource their operational and production activities, which can negatively impact suppliers' environmental performance. As a result, suppliers may be less inclined to publicly disclose their environmental performance. Therefore, given that strong environmental performers tend to disclose more information than their weaker counterparts (Al-Tuwaijri et al., 2004), we recommend that buyers in the manufacturing industry adopt a moral foundation to promote environmental transparency across their supply networks (Diebel et al., 2024). Buying firms often serve as catalysts for environmental responsibility, encouraging their suppliers to adopt sustainable practices in alignment with the firms' own expectations and demands (Jira and Toffel, 2013; Lee and Klassen, 2008).

We advise that buyers recognize the significant role their supply network structure and partner characteristics play in shaping supplier environmental disclosure. The configuration of a buyer's network relationships critically influences suppliers' motivation to engage in sustainability initiatives. Specifically, suppliers with a higher number of overlapping partners with the buyer are more likely to align with the buyer's environmental practices and participate in sustainability efforts. Moreover, collaboration with culturally similar suppliers tends to be more effective, as greater trust and shared understanding foster stronger relationships and enhance the likelihood of compliance with disclosure expectations. In such culturally aligned partnerships, buyers can anticipate greater willingness from suppliers to publicly disclose environmental performance, thereby strengthening collaborative efforts to address negative environmental externalities and improving overall supply chain visibility. However, in today's dynamic and competitive business landscape, buyers often pursue innovation by engaging with less familiar and culturally divergent suppliers (Chae et al., 2020). In these cases, buyers should be aware that such suppliers may be less inclined to conform to environmental disclosure expectations. To improve environmental outcomes, it is essential for buyers to invest in building trust and collaboration with these suppliers, enabling more effective management of upstream environmental risks.

Finally, as stakeholders increasingly demand that firms and their supply networks account for and publicly disclose their environmental impacts and associated risks, it becomes crucial for policymakers to understand the drivers that motivate suppliers to engage in environmental disclosure (Diebel et al., 2024). In general, firms are more likely to collaborate and adopt practices that align with those of peers who share similar values and characteristics (Gualandris et al., 2021; Brandon-Jones et al., 2015). This tendency is partly driven by the presence of shared traits among firms operating within similar industry or institutional contexts. Further, non-governmental organizations (NGOs) and other non-profit entities often monitor and publicize corporate environmental and social responsibility activities in the regions where companies operate. However, organizations focused on monitoring supply chain-related environmental and social practices often face limitations, as their efforts are constrained by local contexts, norms, and regulatory environments (Sodhi and Tang, 2019). Within this landscape, national culture and institutional environments play a pivotal role in shaping how firms communicate with stakeholders and in structuring the interactions among firms, governments, and civil society. Therefore, we encourage policymakers to consider the distinct characteristics of firms across various industry sectors and supply network configurations when formulating sustainability policies, as these firm-level and supply chain-level attributes, embedded within BSRs, are essential for fostering and sustaining meaningful environmental progress across the entire supply network.

3.7.3 Limitations and Future Research Directions

Although this study offers a detailed empirical research design and employs various precautions, such as robustness checks and supplementary analyses, it still has several limitations. First, since our analysis is limited to buyers within the materials and pharmaceutical industries, the findings may offer limited insights for other industry contexts. In other words, the empirical results may not be fully generalizable to buyers operating outside the manufacturing sector.

As highlighted by Chae et al. (2020), this study employs a relatively simple measure of the cognitive dimension of social capital. Specifically, we transform national cultural distance into national cultural similarity by multiplying it by negative one. This transformation allows for a more context-sensitive interpretation, enhancing the measure's ability to capture the nuances of cognitive alignment, or misalignment, in international business relationships. Nevertheless, the cognitive dimension of social capital remains a relatively simple and time-invariant construct within each BSR.

Third, our empirical analyses primarily rely on the FactSet Revere supply chain relationships dataset, complemented by the Bloomberg ESG dataset. As noted in Section 3.4.1, the FactSet Revere dataset covers over 31,000 publicly traded companies worldwide and includes more than 450,000 documented business relationships (FactSet Revere, 2021). However, regardless of the data source, mapping a firm's supply network is an ongoing process. As such, we acknowledge that certain supply chain relationships may be missing from our dataset or may have evolved over time (Song et al., 2023; Bellamy et al., 2020).

This study also opens several promising avenues for future research. In relation to the first and third limitations, the generalizability of our findings is constrained by the exclusive focus on two manufacturing industries and the incomplete nature of the network data. Future research could enhance external validity by expanding the industry scope and utilizing more comprehensive and dynamic supply network data.

Supply chains can fundamentally serve as strategic environmental assets by facilitating the mitigation of environmental issues across broader business networks (Song et al., 2023). Building on this perspective, future research could explore a wider range of firm performance dimensions within supply networks or dyadic relationships, extending beyond CSR activities to encompass innovation, economic outcomes, and operational efficiency (Bellamy et al., 2020; Chae et al., 2020; Sharma et al., 2020; Lu and Shang, 2017). In addition, although this study primarily focuses on manufacturing industries, where the supply chain leakage effect serves as a key mechanism, firms across sectors have increasingly advanced both internal and external environmental performance through collaboration with suppliers. Therefore, it would be valuable for future research to examine companies that emphasize integration, strategic partnerships, and collaborative practices as core mechanisms for fostering mutual benefits and achieving shared sustainability objectives between buyers and suppliers.

Conventional wisdom has long held that increased environmental disclosure by a buying firm should encourage its suppliers to follow suit. However, this study challenges that assumption by illustrating how suppliers may not mirror a buyer's public environmental commitments, particularly in the presence of the supply chain leakage effect, where strong buyer disclosure can, paradoxically, lead to lower supplier disclosure. In addition, by leveraging the reciprocal nature of BSRs, this research contributes to the relatively underexplored domain of social capital within BSRs. In summary, we extend the application of social capital theory to the context of SSCM, demonstrating that strengthening key social capital dimensions is essential for fostering authentic environmental progress across the supply network, rather than simply shifting emissions or obscuring upstream impacts.

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CHAPTER 4

EFFECTIVENESS OF ALTERNATIVE NETWORK CONFIGURATIONS IN THE AIRLINE INDUSTRY

4.1 Introduction

Operational disruptions, including flight delays, cancellations, and mishandled baggage incidents, can impose substantial costs on airlines and undermine customer satisfaction, ultimately leading to revenue loss. According to Airlines for America[1], delays also cost U.S. air travelers billions of dollars each year. The Federal Aviation Administration (FAA) estimated that the total annual cost of delays in the United States reached approximately $33 billion in 2019. This includes direct costs to airlines, such as increased operational expenses, compensation and assistance to passengers, as well as indirect costs stemming from lost demand, reputational damage, and broader economic impacts[2]. As airlines aim to balance profitability with service quality over the long term, they are increasingly motivated to improve flight punctuality and mitigate the effects of operational disruptions.

In today's fast-paced aviation industry, airlines aim to align with external conditions by strategically reallocating resources to optimize both revenue and operational efficiency (Girod and Whittington, 2017; Kohl et al., 2007; Miller, 1992). A variety of factors influence on-time performance (OTP) and overall service quality, many of which are tied to operational disruptions. Research highlights route characteristics and market competition as key drivers of delays and cancellations (Prince and Simon, 2015; Rupp and Holmes, 2006; Mazzeo, 2003), alongside operational and environmental factors such as weather, airport congestion, scheduled block time, and aircraft size (Deshpande and Arıkan, 2012). Additionally, studies emphasize the interconnected nature of operational failures, where initial disruptions can cascade and trigger further breakdowns across airline systems (Parast and Golmohammadi, 2020; Ramdas et al., 2013).

Airlines often improve OTP through various operational strategies, including adding time buffers to block times, adjusting network structures by adding or removing routes, and implementing

[1] https://www.airlines.org/dataset/u-s-passenger-carrier-delay-costs/
[2] https://travelradar.aero/a-data-driven-analysis-of-the-flight-delays-on-airline-profitability/

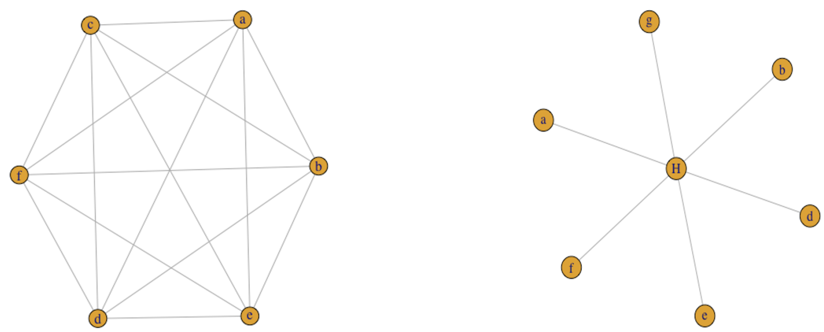
procedural enhancements such as streamlining boarding and reducing gate delays (Manchiraju et al., 2023). Airline-specific policies, such as baggage fees and boarding procedures, also play a significant role in shaping operational performance (Nicolae et al., 2017). Ultimately, effective operational strategies not only enhance efficiency but also support stronger financial performance (Alan and Lapré, 2018; Ramdas et al., 2013).

Despite the critical importance of managing operational disruptions and maintaining consistent service quality in the airline industry, prior research has not sufficiently addressed these challenges from a network perspective. Although preventive strategies to mitigate disruptions continue to evolve often shaped by the route structures airlines adopt, the impact of different network configurations on airlines' responses to disruptions remains underexplored. While prior studies have examined various operational performance metrics in aviation (Manchiraju et al., 2023; Alan and Lapré, 2018; Phillips and Sertsios, 2013; Tsikriktsis, 2007), comprehensive research linking multidimensional service quality outcomes to network strategies is still lacking.

The airline network is generally understood to comprise two fundamental components: airports and the routes that connect them (Ciliberto et al., 2019). Airlines route their flights between origin and destination airports and form their network structure to optimize their operations. The two major route systems are point-to-point and hub-and-spoke. In a point-to-point network (i.e., decentralized network), the passengers fly directly between airports, whereas, in a hub-and-spoke network (i.e., centralized network), passengers must make an additional stop through a hub when neither the origin nor destination airport is a hub (Brueckner, 2004). Figure 4.1 shows two simplified configurations of widely acknowledged airline networks. Previous studies have compared the two route systems based on various attributes, including connectivity, the scope of connecting services, flight frequency, and asset utilization (Zgodavová et al., 2018; Cook and Goodwin, 2008; Oum et al., 1995).

In response to intensified competition following the introduction of the Airline Deregulation Act in the U.S. in 1978, the airline industry underwent a major restructuring of carrier networks, shifting from predominantly linear configurations to the hub-and-spoke model (Mazzeo, 2003; Barla

Figure 4.1 Simplified Point-to-Point and Hub-and-Spoke Architectures



and Constantatos, 2000). This structure enables airlines to reallocate capacity more efficiently across markets by pooling passengers from multiple origins onto a single aircraft (Barla and Constantatos, 2000). In particular, the hub-and-spoke system offers a distinct operational advantage through its ability to reallocate capacity ex post under conditions of demand uncertainty (Barla and Constantatos, 2005, 2000).

While some airlines continue to adopt and invest in point-to-point networks, this structure is inherently more linear, offering fewer opportunities to consolidate passenger traffic and limiting the efficiency gains typically associated with hub-based operations. Nevertheless, a point-to-point network facilitates faster implementation of individual route and origin–destination options, and enhances organizational adaptability with fewer disruptions by supporting a broader and more flexible search strategy (Gualini et al., 2023).

U.S. airlines are commonly classified into four categories based on their operational and network characteristics: Full-Service Carriers (FSCs), Low-Cost Carriers (LCCs), Commuter/Subsidiary Carriers (CCs), and Leisure Carriers (LCs) (Deshpande and Arıkan, 2012). Among them, American Airlines, Delta Air Lines, and United Airlines, the three largest FSCs, operate primarily under hub-and-spoke networks centered around major hubs (Ciliberto et al., 2019; Deshpande and Arıkan, 2012; Tsikriktsis, 2007). In contrast, major LCCs such as Southwest Airlines, JetBlue Airways, Frontier Airlines, and Spirit Airlines typically adopt point-to-point networks, providing direct service between distinct city pairs (Zou and Yu, 2020; Ciliberto et al., 2019; Mellat-Parast et al., 2015; Tsikriktsis, 2007). Building on this classification, our study investigates how differences in network structures across these airline types shape operational performance and service quality management.

The hub-and-spoke structure commonly employed by FSCs is particularly effective in markets that demand high flight frequency, as it supports extensive service coverage while maintaining acceptable total travel times for connecting passengers (Brueckner, 2004; Mayer and Sinai, 2003). The superior rerouting capabilities of FSCs also enable them to mitigate the impact of delays by providing alternative flight paths, thereby illustrating how network design can improve key performance metrics through the strategic deployment of resources (Mellat-Parast et al., 2015). However, this model also entails high operational demands and increased vulnerability to congestion, particularly at major hub airports, rendering FSCs more susceptible to disruptions such as delays in the event of hub failures (Ding et al., 2023; Bauranov et al., 2021; Miller, 1992). Nonetheless, direct flights serving major airports tend to recover more swiftly from operational disruptions, owing to higher passenger demand, enhanced network connectivity, and greater availability of operational resources (Sugishita et al., 2024). In contrast, LCCs benefit from lower operating costs by avoiding complex connection schedules, utilizing less congested secondary airports with reduced fees, and achieving quicker aircraft turnaround times (Bitzan and Peoples, 2016). However, the point-to-point network structure typically employed by LCCs is more linear, offering limited opportunities for passenger pooling and thereby constraining the scale economies associated with hub-based operations. While LCCs are generally less susceptible to delays associated with hub airport disruptions and benefit from greater operational flexibility due to their standardized aircraft fleets, their low-cost model limits the availability of redundant resources, making recovery from disruptions more challenging.

Figures 4.2 and 4.3 reveal clear distinctions between FSCs and LCCs in 2019 across two key operational metrics: OTP and the average number of mishandled bags per 1,000 enplaned bags. Specifically, Figure 4.2 shows that both carrier types follow similar seasonal trends in OTP, though FSCs consistently exhibit a slight performance advantage. In contrast, Figure 4.3 reveals that FSCs consistently underperform LCCs in minimizing mishandled baggage incidents. While these

Figure 4.2 On-time Performance in 2019

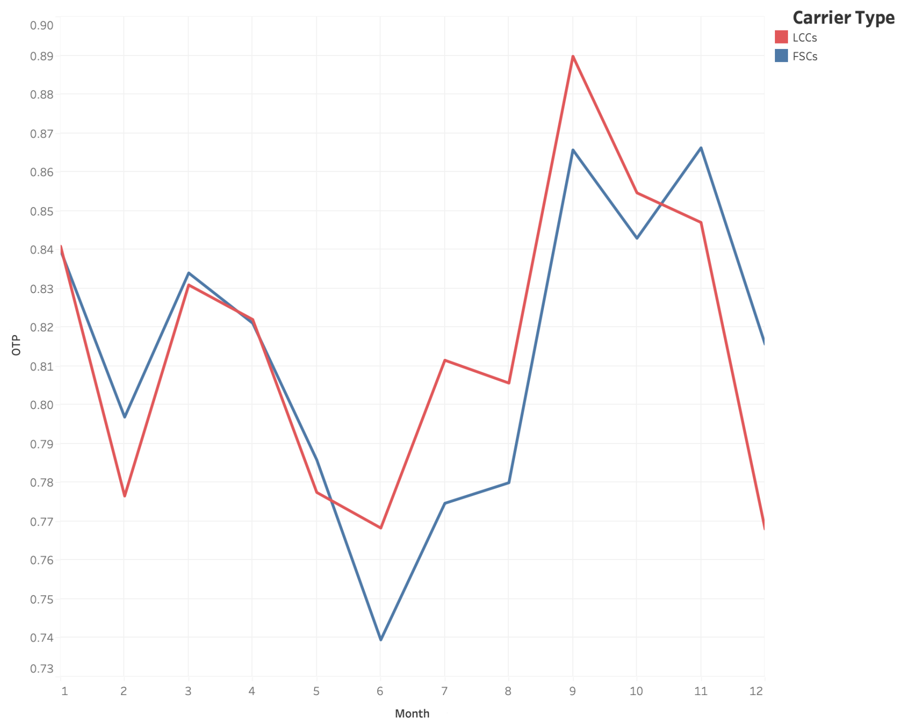
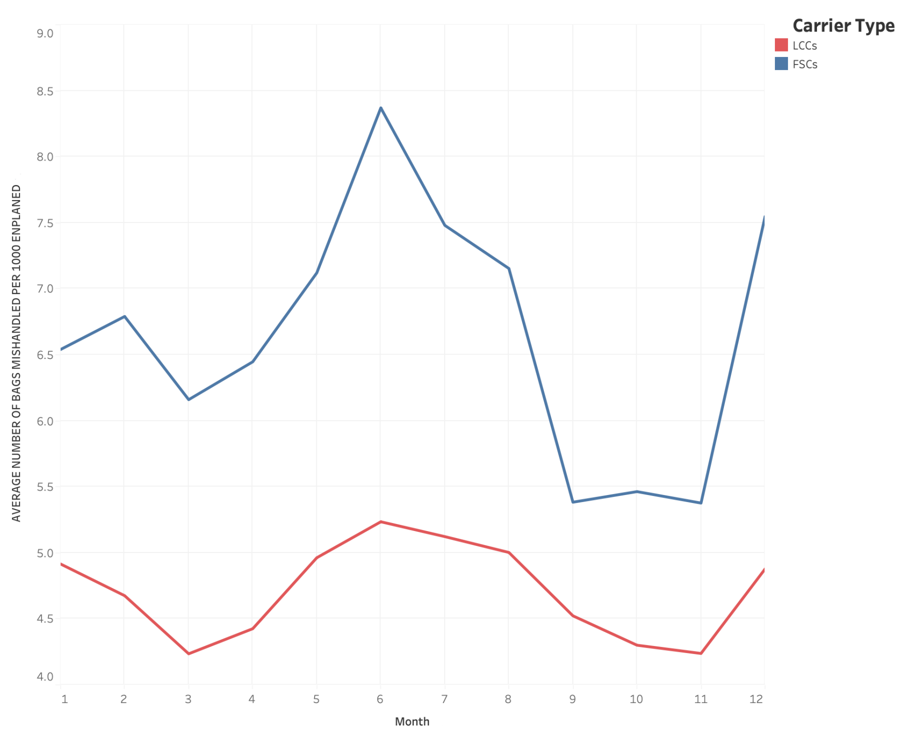


Figure 4.3 Average Reports per 1,000 Bags Enplaned in 2019



patterns suggest performance differences between network types, it remains unclear whether these differences are statistically significant or systematic across various metrics. Moreover, it is not immediately evident which carrier type performs better on which specific dimension of service quality. This ambiguity underscores the need for a systematic empirical investigation and forms the basis for the research questions addressed in this study.

4.1.1 Research Questions

The primary objective of this study is to investigate how airlines employing different network structures manage service quality, as evidenced by standard operational performance metrics widely used in the industry. Despite the importance of this topic, prior research has not adequately examined how service quality management practices vary across carriers with distinct network strategies. To address this gap, we conduct a comprehensive analysis and comparison of key performance indicators (KPIs) that quantify operational performance under disruptions in the airline industry. Specifically, we examine five metrics: (1) departure delays, (2) arrival delays, (3) OTP, (4) flight cancellations, and (5) baggage handling incidents, comparing outcomes between FSCs and LCCs. We assess whether operational and service quality outcomes systematically differ based on the network configuration adopted by an airline.

Moreover, we investigate whether there are significant differences in operational performance and service quality management among the group of LCCs. This question is particularly relevant in the context of Southwest Airlines, one of the largest U.S. carriers, which also operates a point-to-point network, albeit with a stronger presence and greater operational influence at specific airports within its network. Given both the operational scale and unique characteristics of Southwest, we seek to examine the extent to which variations in operations and service quality management exist within the broader LCC category.

4.1.2 Our Results and Contributions

Our empirical analysis draws on historical operational and service performance data from seven major U.S. domestic carriers, revealing systematic differences in performance across airline types based on five key metrics: departure and arrival delays, OTP, flight cancellations, and mishandled baggage incidents. First, we find that FSCs consistently outperform LCCs in minimizing both departure and arrival delays. Notably, within the LCC group, Southwest Airlines achieves lower arrival delays than its peers. Second, our findings indicate that FSCs are significantly more effective in maintaining high OTP and reducing cancellations. Specifically, FSCs have 53.9% higher odds of achieving on-time arrivals and 37% lower odds of cancellations compared to LCCs. While Southwest's OTP is statistically comparable to that of other LCCs, it performs worse than both FSCs and its LCC counterparts in managing cancellations. Finally, LCCs show better performance in baggage handling compared to FSCs, with Southwest outperforming all carriers in minimizing the number of mishandled bags per 1,000 enplaned bags.

Unlike prior studies that focus on a limited set of performance indicators, our study contributes to the literature by systematically comparing multiple dimensions of operational performance across different types of carriers. Using historical flight-level data from several U.S. airlines, we develop a comprehensive framework to assess how differences in network design influence service quality and operational reliability. Our findings suggest that network configuration plays a critical role in shaping performance outcomes, highlighting the strategic importance of network design decisions for airline operations. These insights underscore the need for airline managers to carefully consider their network structure when evaluating and benchmarking operational performance against competitors.

4.1.3 Organization

Our paper is organized as follows. Section 2 reviews the relevant literature on airline network structures and operational strategies, with particular attention to risk mitigation approaches discussed in both the aviation and supply chain management literatures. Section 3 presents our hypotheses, developed through a detailed examination of commonly used operational performance metrics, and introduces a set of competing hypotheses grounded in prior research. Section 4 outlines the research design, including data sources, summary statistics, and variable definitions. Section 5 describes the sample selection process, the matching procedure used to ensure comparable units of analysis, and the estimation models employed, followed by a discussion of the empirical results. In

Section 6, we conduct a separate analysis of Southwest Airlines, distinguishing it from other LCCs to explore within-group differences based on our network-based classification. Finally, Section 7 concludes by discussing the implications of our findings and offering directions for future research.

4.2 Literature Review

We position our study within the broader academic context by reviewing the existing literature related to airline operational performance and network configurations.

4.2.1 Managing Operational Disruptions and Performance in the Airline Industry

Understanding the implications of airline network structures is important when analyzing operational disruptions in the airline industry such as flight delays, flight cancellations, and mishandled baggage incidents. Among these, flight delays can be broadly categorized into two components: intrinsic delays, which arise from factors specific to the flight itself, and propagated delays, which result from spillover effects across an aircraft's rotation cycle (Nicolae et al., 2017; Arıkan et al., 2013). Intrinsic delay is typically measured by comparing the intrinsic duration of a flight (i.e., actual flight duration excluding spillover delays from previous flights) to its scheduled duration, calculated as the difference between scheduled departure and arrival times. The two critical dimensions of delays, intrinsic and propagated, play a central role in shaping overall service performance. Notably, flight arrival delays, a primary contributor to system-wide disruptions, are often influenced by a combination of intrinsic and propagated delays (Malladi and Sohoni, 2022). Accordingly, operational failures in the airline industry are frequently assessed using performance indicators such as flight delays, OTP, flight cancellations, and mishandled baggage rates, each of which serves as a proxy for service quality and reliability (Alan and Lapré, 2018; Deshpande and Arıkan, 2012; Tsikriktsis, 2007).

Prior studies have identified a range of factors contributing to operational disruptions, including adverse weather, airport congestion, aircraft utilization, market competition, and route characteristics (Deshpande and Arıkan, 2012; Rupp and Holmes, 2006; Mazzeo, 2003). These disruptions impose significant costs, such as crew overtime, increased fuel consumption, and passenger re-accommodation expenses, prompting airlines to continually refine their operational strategies to mitigate financial and reputational risks (Hassan et al., 2021). To improve OTP and reduce flight cancellations, airlines adopt strategic measures such as optimizing flight schedules, improving gate management, and adjusting network configurations (Prince and Simon, 2015, 2009). In addition, streamlined operations and efficient fleet utilization shaped by factors like flight demand, aircraft age, and maintenance capacity are closely linked to enhanced profitability and service quality (Tsikriktsis, 2007).

Despite advancements in the literature, several important limitations remain. Most existing studies focus on a single outcome variable, such as flight delays or cancellations, while rarely considering multiple dimensions of service quality in tandem. Furthermore, the influence of airline network structure, particularly the distinction between hub-and-spoke and point-to-point configurations, remains underexamined in relation to operational performance. Although prior research suggests that point-to-point networks reduce delay propagation due to route independence (Cook and Goodwin, 2008), there is limited empirical work that systematically compares how different network structures shape service outcomes. Furthermore, the choice and interpretation of operational metrics, such as measuring mishandled baggage per passenger versus per enplaned bag, can significantly influence assessments of airline performance. To address these gaps, this study jointly examines five key operational performance metrics: departure delays, arrival delays, OTP, flight cancellations, and mishandled baggage incidents. By adopting a multidimensional approach, this study provides a more comprehensive understanding of how network configurations and operational strategies affect airline service quality and reliability.

4.2.2 Airline Operations and Network Design

Most FSCs operate under a hub-and-spoke network model, channeling a substantial portion of passenger traffic through centralized hub airports. This configuration streamlines operations by enabling airlines to serve numerous destinations with fewer direct routes, while also enhancing resource efficiency through optimized aircraft deployment, crew scheduling, and airport utilization (Cook and Goodwin, 2008). The model improves connectivity across the network and allows airlines to adjust capacity more effectively, for instance, by deploying larger aircraft on high-

Table 4.1 Comparing Hub-and-Spoke and Point-to-Point Networks

Operational Metrics	**Hub-and-Spoke**	**Point-to-Point**
Number of routes needed to connect all nodes in a network	Lower number of routes	Higher number of routes
Market Size	Efficiently serves cities of widely varying sizes	Depends on high-density markets with one high-demand endpoint
Frequency of flights	Higher frequency	Lower frequency
Connectivity	Hub connections for continuing flights	No connecting flights
Size of aircraft fleet	Small aircraft fleet	Large aircraft fleet
Fleet type	Wide variation in seating capacity	Single fleet type
Total travel time	Longer travel time	Shorter travel time

demand routes between major hubs or international destinations, thereby minimizing the number of flights and total seat-kilometers offered (Zgodavová et al., 2018).

In contrast, LCCs favor point-to-point networks that offer direct service between origin and destination airports (Parast and Golmohammadi, 2020; Zou and Yu, 2020; Nicolae et al., 2017; Mellat-Parast et al., 2015; Lordan, 2014; Oum et al., 1995). Unlike the hub-and-spoke model, this approach requires a greater number of routes to expand network coverage. For instance, an airline operating from five airports would need 10 direct routes; adding a sixth destination would require five more routes to maintain full connectivity. While this model enhances flexibility and reduces reliance on centralized hubs, it often results in lower passenger load factors and demands significant investment in fleet size and personnel. Overall, each air transport network (ATN) exhibits distinct operational characteristics, as summarized in Table 4.1.

FSCs generally support longer aircraft turnaround times to coordinate feeder and trunk routes, thereby enhancing load factors and benefiting from economies of traffic density. This structure is particularly advantageous in markets requiring high flight frequency, as it maintains broad service coverage without significantly compromising total travel time for connecting passengers (Brueckner, 2004; Mayer and Sinai, 2003). Conversely, LCCs are designed for faster aircraft turnaround at the gate (Arıkan et al., 2013), allowing efficient operations even with smaller passenger volumes (Gualini et al., 2023). Thus, while hub-and-spoke networks optimize capacity through strategic hub placement, albeit with longer turnaround times, point-to-point networks are favored for their operational efficiency under tightly coupled schedules requiring minimal buffer time.

Although understanding the impact of the network structure of airlines on their operational performance is important, empirical evidence to understand network centrality and airline operational performance remains limited. This study, therefore, aims to understand the impact of different network structures on key operational performance metrics in the U.S. airline industry.

4.2.3 Flexibility vs. Redundancy

Our study also relates to the concept of resilience, which refers to the ability to recover from disruptions and is commonly examined within the risk management literature. In the context of supply chain risk management, potential risks include, but are not limited to, delays, disruptions, forecast inaccuracies, system breakdowns, and capacity issues (Sodhi and Chopra, 2004). When disruptions happen, firms implement diverse risk mitigation strategies to recover and restore operations. Previous literature suggests that firms can achieve resilience by either increasing flexibility or creating redundancy, leading to the identification of these two primary risk mitigation strategies, redundancy and flexibility, as key methods for strengthening organizational resilience (Talluri et al., 2013; Sheffi and Rice Jr, 2005).

Reducing vulnerability is basically a corporate strategic initiative aimed at increasing resilience, which can be achieved by either creating redundancy or enhancing flexibility (Sheffi and Rice Jr, 2005). While redundancy is a component of every resilience strategy, it often incurs substantial costs with limited benefits. In contrast, flexibility can provide a competitive advantage in daily operations (Sheffi and Rice Jr, 2005). Focusing on the manufacturing sector, Talluri et al. (2013) evaluate seven risk mitigation strategies across nine potential failure types and suggest that the most effective approaches do not necessarily involve shielding firms from disruptions (e.g., through redundancy), but rather emphasize enhancing recovery capabilities (e.g., through flexibility).

In the commercial aviation industry, a variety of factors shape airlines' ability to respond to disruptive events, as carriers continuously strive to improve recovery from operational disruptions (Park et al., 2018; Kohl et al., 2007). To maintain service quality amid uncertainty, airlines often reallocate internal resources to manage rising operational costs and volatility caused by such disruptions (Hassan et al., 2021). An airline's capacity to substitute aircraft and crew as needed plays a critical role in its ability to respond effectively, and this is largely determined by flight scheduling practices, aircraft assignments, and crew availability (Ramdas and Williams, 2006). Securing sufficient capacity enables more efficient resource reallocation, ultimately enhancing resilience in the face of service failures.

As shown in Table 4.1, the hub-and-spoke configuration, commonly used by FSCs, relies on centralized hubs and connecting flights, which complicates operational adjustments during disruptions and reduces flexibility. To support both international and domestic services, FSCs also operate diverse aircraft fleets, further increasing scheduling and maintenance complexity. However, this network structure enables more efficient resource allocation and operational efficiency, supported by economies of scale and greater resource availability. FSCs' superior rerouting capabilities allow them to minimize the impact of delays by offering alternative flight paths, highlighting how network design can enhance key performance metrics through effective resource deployment (Mellat-Parast et al., 2015).

In contrast to hub-and-spoke systems, point-to-point networks, commonly used by LCCs, offer greater operational flexibility, despite limited redundancy. Operating on tight schedules with minimal spare capacity, LCCs are less able to absorb disruptions. However, their network structure avoids intermediate stops and relies on more decentralized networks. Their point-to-point flights reduce total travel time while maintaining route independence (Cook and Goodwin, 2008). Further, as shown in Table 4.1, LCCs typically use homogeneous fleets, enabling more efficient crew assignments, streamlined maintenance, and enhanced flexibility.

In summary, FSCs excel in redundancy, offering multiple backup systems and service layers that help mitigate the impact of operational disruptions. In contrast, LCCs demonstrate superior flexibility, particularly in terms of operational and network responsiveness, enabling them to adapt more rapidly to disruptions or changing market and environmental conditions. Our study contributes to the risk management literature by evaluating the relative effectiveness of redundancy and flexibility in managing disruptions within service networks, with a particular emphasis on air transportation systems.

4.2.4 Organizational Structure

It has been acknowledged that the design and structure of an organization have a significant impact on the performance and effectiveness of the organization (Burton and Obel, 2018; Dalton et al., 1980; Van de Ven, 1976; Campbell et al., 1974). Organizational design prescribes the optimal structure for an organization to function effectively and efficiently (Burton and Obel, 2018; Dalton et al., 1980). Organizational structure is often defined as "the enduring characteristics of an organization, reflected in the arrangement of units and positions and their systematic relationships to one another" (James and Jones, 1976). It addresses various organizational attributes including specialization, centralization, standardization, and formalization (Campbell et al., 1974). The organizational structure serves two primary functions: 1) minimizing or regulating the impact of individual variations on the organization, and 2) exerting power to enable decision-making and the execution of organizational activities (Dalton et al., 1980).

The extensive academic literature explores the impact of organizational structure on organizational performance (Dalton et al., 1980; Van de Ven, 1976). Specifically, the extent of centralization, which reflects the concentration of decision-making authority among a few entities within an organization, is widely recognized as a critical factor influencing organizational performance. Previous literature suggests that learning spillover effects can be amplified through centralization by promoting the adoption of common practices (Chang and Harrington, 2000). On the other hand, it is frequently suggested that uncertainty, which affects decision-making processes, calls for the delegation of control through decentralization to ease the managerial workload (Miller, 1992). Nonetheless, empirical evidence on the relationship between centralization and organizational performance remains limited, particularly within the service sector.

4.3 Hypotheses Development

In this section, we develop hypotheses to assess the comparative performance of point-to-point and hub-and-spoke airline network structures across five key operational metrics that quantify performance under disruptions in the airline industry: departure delays, arrival delays, OTP, flight cancellations, and mishandled baggage incidents.

4.3.1 Departure and Arrival Delays

In service operations, departure and arrival delays serve as key indicators of service quality and operational consistency (Mellat-Parast et al., 2015; Ramdas et al., 2013; Tsikriktsis, 2007). Airlines can reduce delays by strategically balancing capacity and inventory, and by maintaining flexible excess capacity (Sodhi and Chopra, 2004). ATNs critically influence both service quality and operational profitability (Oum et al., 1995). Point-to-point networks, commonly used by LCCs, reduce reliance on hub airports by operating independent direct flights. This structure minimizes delay propagation, insulates the broader schedule from localized disruptions, and reduces total travel time by eliminating intermediate stops (Cook and Goodwin, 2008). Combined with fuel-efficient aircraft and operational simplicity, point-to-point systems are increasingly favored for their resilience and flexibility in handling disruptions (Kohl et al., 2007). Moreover, LCCs often operate homogeneous fleets, allowing for streamlined operations in which crew and aircraft can be easily reassigned, thereby enhancing scheduling efficiency, reducing maintenance complexity, and increasing overall flexibility.

In contrast, the hub-and-spoke model, typically adopted by FSCs, offers advantages in connectivity, market coverage, and capacity optimization. Despite greater vulnerability to systemic delays due to its centralized structure, this model supports higher flight frequencies and enables strategic capacity allocation through passenger pooling (Zgodavová et al., 2018; Cook and Goodwin, 2008). FSCs also maintain ample backup and slack resources to ensure smooth operations, operate diverse fleets, provide differentiated services, and achieve economies of scale by concentrating traffic on fewer, high-frequency routes (Parast and Golmohammadi, 2020; Tsikriktsis, 2007). While less robust to cascading disruptions, the model enhances operational efficiency on a larger scale.

As defined by the U.S. Bureau of Transportation Statistics (BTS), a departure delay refers to the number of minutes between a flight's scheduled and actual departure times, while an arrival delay captures the gap between scheduled and actual arrival times. These delays can propagate across an aircraft's rotation cycle, leading to spillover effects that disrupt subsequent flights (Nicolae et al., 2017; Arıkan et al., 2013). Although arrival delays frequently lead to departure delays, prior research highlights a gap in how airlines manage the two, owing to various operational and contingency factors such as the national aviation system, hub connectivity, weather conditions, and crew availability (Parast and Golmohammadi, 2020; Ramdas and Williams, 2006; Mayer and Sinai, 2003). While FSCs are often viewed as more capable of managing disruptions due to their ample and redundant resource base, LCCs may naturally reduce delay risks through simplified operations. These contrasting strengths and limitations in managing different types of delays motivate the following set of competing hypotheses for both departure and arrival delays.

Hypothesis 1A (H1A) Full-service carriers utilizing hub-and-spoke networks outperform low-cost carriers utilizing point-to-point networks in managing departure delays.

Hypothesis 1B (H1B) -competing. Low-cost carriers utilizing point-to-point networks outperform full-service carriers utilizing hub-and-spoke networks in managing departure delays.

Hypothesis 1C (H1C) Full-service carriers utilizing hub-and-spoke networks outperform low-cost carriers utilizing point-to-point networks in managing arrival delays.

Hypothesis 1D (H1D) -competing. Low-cost carriers utilizing point-to-point networks outperform full-service carriers utilizing hub-and-spoke networks in managing arrival delays.

4.3.2 On-time Performance

OTP is widely recognized as a key indicator of delivery reliability and overall service quality in the airline industry (Manchiraju et al., 2023; Alan and Lapré, 2018; Tsikriktsis, 2007). Airlines can improve OTP by strategically allocating critical resources, such as personnel, aircraft, and flight schedules, to manage disruptions and maintain punctuality (Manchiraju et al., 2023; Prince and

Simon, 2015, 2009). A key determinant of OTP is buffer time, which includes both block-time (the difference between scheduled and actual flight time) and ground-time buffers. These buffers help absorb operational variability and prevent delay propagation.

However, airlines face a trade-off: while longer buffers enhance schedule reliability and improve OTP, they reduce efficiency by lowering aircraft utilization and increasing turnaround times. This tension is particularly pronounced across different network structures. Point-to-point networks, which emphasize high utilization and direct services, minimize buffers and are therefore more susceptible to OTP deterioration under delays. In contrast, hub-and-spoke networks include more slack, especially around hub connections, offering greater resilience but exposing operations to congestion and coordination challenges.

Prior research shows that airline network structures significantly influence OTP outcomes by shaping buffer strategies and exposure to operational disruptions (Arıkan et al., 2013). Flights from major hubs often experience lower OTP due to congestion, connecting passenger coordination, and concentrated inbound traffic (Deshpande and Arıkan, 2012; Mayer and Sinai, 2003). However, other studies suggest that major hubs may offer more reliable connections than smaller airports due to superior infrastructure and resource availability (PeCoy and Redmond, 2023; Redmond et al., 2019). Airlines operating on less competitive routes may also have weaker incentives to maintain punctuality, regardless of network type (Prince and Simon, 2015, 2009; Mazzeo, 2003). While airlines attribute flight delays to factors beyond their control, research shows that they are shaped by strategic and operational decisions. Higher OTP among LCCs may reflect their reduced exposure to hub congestion, whereas FSCs often invest more heavily in mitigating delay-related costs to maintain schedule reliability. FSCs may therefore be better equipped to manage OTP under complex conditions, while LCCs benefit from streamlined operations and shorter turnaround times that naturally support punctuality. Taken together, these observations suggest that both FSCs and LCCs can achieve strong OTP performance, though through distinct mechanisms: FSCs leverage operational redundancy, resource efficiency, and built-in schedule buffers; LCCs operate through simplified, tightly scheduled, decentralized networks that emphasize flexibility. Based on this reasoning, we propose the following set of competing hypotheses:

Hypothesis 2A (H2A) Full-service carriers utilizing hub-and-spoke networks outperform low-cost carriers utilizing point-to-point networks in maintaining on-time performance.

Hypothesis 2B (H2B) -competing. Low-cost carriers utilizing point-to-point networks outperform full-service carriers utilizing hub-and-spoke networks in maintaining on-time performance.

4.3.3 Managing Flight Cancellations

According to the U.S. BTS, the primary causes of flight cancellations include extreme weather, operational issues (e.g., mechanical problems, crew shortages, late-arriving aircraft, and high traffic volume), and security concerns such as terminal evacuations or re-boarding after security breaches[3]. While cancellations can also result from low passenger demand or economic considerations, as airlines weigh the costs of operating a flight against canceling it (Alderighi and Gaggero, 2018; Rupp et al., 2006), they are often used strategically to minimize delays and contain irregular operations. Consequently, when faced with disruptions such as cancellations, congestion, or delays, airlines must adapt their operational strategies to maintain service quality and avoid financial strain.

Previous research shows that flight cancellations are shaped by both network structure and market conditions. Routes with high traffic concentration and operations at congested airports are more prone to delays and cancellations (Alderighi and Gaggero, 2018; Rupp et al., 2006; Mazzeo, 2003). LCCs, which rely on decentralized point-to-point networks with lower flight frequencies, generally report lower cancellation rates due to reduced dependency on individual airports and lower risk of cascading disruptions (Alderighi and Gaggero, 2018). Prior studies also suggest that routes with lower traffic concentration are less vulnerable to congestion, resulting in fewer delays and cancellations (Alderighi and Gaggero, 2018; Rupp et al., 2006; Mazzeo, 2003). Differing from this pattern, FSCs operating hub-and-spoke systems benefit from resource concentration at hubs, enabling faster recovery and aircraft substitution (Kohl et al., 2007; Rupp et al., 2006). Hub airlines are also less likely to cancel flights given the risk of disrupting multiple connections (Mayer and Sinai, 2003). However, alliance-affiliated FSCs often face higher cancellation rates overall,

[3] https://www.bts.gov/topics/airlines-and-airports/understanding-reporting-causes-flight-delays-and-cancellations

largely due to congestion and operational complexity at large hubs (Alderighi and Gaggero, 2018). Beyond network design, cancellation rates also rise with market concentration, reflecting reduced service quality under weaker competition (Alderighi and Gaggero, 2018; Cao et al., 2017; Rupp and Holmes, 2006), while flexible scheduling strategies, such as buffer times and idle capacity, can mitigate cancellations (Ramdas et al., 2013; Barnhart et al., 2012). These contrasting findings highlight that both FSCs and LCCs face distinct trade-offs in managing cancellations, motivating the following set of competing hypotheses.

Hypothesis 3A (H3A) Full-service carriers utilizing hub-and-spoke networks outperform low-cost carriers utilizing point-to-point networks in minimizing flight cancellations.

Hypothesis 3B (H3B) -competing. Low-cost carriers utilizing point-to-point networks outperform full-service carriers utilizing hub-and-spoke networks in minimizing flight cancellations.

4.3.4 Mishandled Baggage Incidents

In recent years, the rapid growth of the air travel industry and rising passenger volumes have led to an overall increase in the total number of mishandled bags, despite improvements in mishandled baggage rates. According to Société Internationale de Télécommunications Aéronautiques (SITA), more than 10 million additional bags were delayed, lost, misdirected, pilfered, or stolen in 2024 compared to previous years[4]. In the airline industry, average service quality is typically assessed using indicators such as OTP and mishandled baggage rates; the latter reflects an airlines' ability to recover lost items efficiently, which is a key component of service quality given the additional costs of locating and delivering delayed baggage, and customer dissatisfaction associated with baggage recovery (Alan and Lapré, 2018; Mellat-Parast et al., 2015; Phillips and Sertsios, 2013; Tsikriktsis, 2007).

Airports designated as hubs or focus cities introduce added operational complexity, largely due to the need to transfer baggage between connecting flights (Nicolae et al., 2017). This complexity is further amplified when airlines operate through large primary airports, such as Chicago O'Hare and Dallas/Fort Worth, compared to secondary airports like Chicago Midway or Dallas Love Field,

[4]https://www.sita.aero/resources/surveys-reports/sita-baggage-it-insights-2024/

which are less congested and typically expose airlines to fewer service failures (Alan and Lapré, 2018). From a network design perspective, these complexities are more pronounced for FSCs, which face tighter scheduling constraints and manage more diverse fleets than LCCs (Alan and Lapré, 2018). Moreover, FSCs facilitate a higher volume of connecting flights, increasing customer contact points and baggage handling requirements, thereby elevating the risk of service disruptions (Alan and Lapré, 2018). In contrast, the point-to-point network structure commonly adopted by LCCs reduces the likelihood of baggage mishandling, as passengers typically reclaim their luggage at each destination. Reflecting these operational differences, Parast and Golmohammadi (2020) find that FSCs, based on data from 1998 to 2009, report lower overall service quality, as measured by customer complaints, compared to LCCs.

When service failures occur, airlines must mobilize significant resources such as frontline staff time and compensation to manage disruptions (Alan and Lapré, 2018). While larger airlines face greater organizational complexity, they also benefit from more operational slack and resource availability, enabling more effective recovery (Hassan et al., 2021; Parast and Golmohammadi, 2020). FSCs, supported by greater operational slack and more robust baggage handling systems, may be better positioned to manage incidents such as mishandled baggage. Based on this reasoning, we propose the following set of competing hypotheses:

Hypothesis 4A (H4A) Full-service carriers utilizing hub-and-spoke networks outperform low-cost carriers utilizing point-to-point networks in reducing mishandled baggage incidents.

Hypothesis 4B (H4B) -competing. Low-cost carriers utilizing point-to-point networks outperform full-service carriers utilizing hub-and-spoke networks in reducing mishandled baggage incidents.

4.4 Data

In this section, we discuss the sources of our data sets and variables used for empirical analysis. An overview of our data sources and variables is provided in Table 4.2.

4.4.1 Databases

We obtained the data for our empirical analysis from the official websites of the BTS and the U.S. Department of Transportation (DOT). Consistent with prior research on operational performance in the U.S. airline industry (Manchiraju et al., 2023; Alan and Lapré, 2018; Nicolae et al., 2017; Deshpande and Arıkan, 2012), we primarily draw on the OTP dataset, which includes detailed flight-level records for all U.S. air carriers accounting for at least one percent of domestic scheduled passenger revenue. This dataset provides comprehensive operational information for each commercially scheduled flight operated by these carriers.

For the purpose of hypothesis testing, we focus on OTP data spanning from 2016 to 2019. This period offers comprehensive coverage of key variables used in our empirical models, including carrier identifiers, origin and destination airports, departure and arrival performance metrics, as well as flight cancellations and diversions. These variables form the foundation of both the dependent and independent constructs examined in this study. As such, the OTP dataset serves as a central resource for our analysis.

In addition, we collect mishandled baggage data from Air Travel Consumer Reports provided by U.S. DOT. This report is published monthly by the DOT's Office of Aviation Consumer Protection and is intended to provide consumers with information on the quality of services offered by airlines[5]. According to the U.S. DOT, baggage statistics are based on data reported by U.S. air carriers that account for at least one-half of one percent of total domestic scheduled-service passenger revenues, as determined by DOT's BTS. According to the monthly Air Travel Consumer Reports, the number of mishandled bags is defined as "the number of checked bags that are lost, damaged, delayed, or pilfered, as reported by or on behalf of the passenger."

Beginning in January 2019, the U.S. DOT revised its reporting criteria for mishandled baggage in the Air Travel Consumer Reports. Prior to this change, as noted in several previous studies (Alan and Lapré, 2018; Mellat-Parast et al., 2015; Tsikriktsis, 2007), mishandled baggage was reported as the number of lost, damaged, delayed, or pilfered bags per 1,000 passengers. However,

[5]https://www.transportation.gov/individuals/aviation-consumer-protection/air-travel-consumer-reports

since the revision, the metric has been updated to reflect the number of mishandled bags per 1,000 enplaned bags, which serves as a key indicator of airline service quality. To more accurately assess the relative performance of baggage handling across airlines, we adopt this updated metric in our analysis. Accordingly, we use mishandled baggage data covering the period from January 2019 to February 2020. This timeframe is selected to minimize the influence of external disruptions, concluding just prior to the World Health Organization's (WHO) declaration of COVID-19 as a global pandemic on March 11, 2020.[6]

4.4.2 Variables

We begin our empirical analysis by defining the dependent and independent variables used to test our hypotheses.

4.4.2.1 Dependent Variables

To test the first two sets of competing hypotheses, we use both departure and arrival delays in this study. Departure delays and arrival delays have been used to measure airline operational performance in previous studies (Nicolae et al., 2017; Deshpande and Arıkan, 2012; Ramdas and Williams, 2006). As defined by the BTS, a departure delay is defined as the difference in minutes between a flight's scheduled and actual departure times, whereas an arrival delay is defined as the difference in minutes between a flight's scheduled and actual arrival times. Thus, we define two dependent variables to test the first two sets of hypotheses: Dep_Delay_{itk} and Arr_Delay_{itk}. Specifically, Dep_Delay_{itk} (resp., Arr_Delay_{itk}) represents the departure (resp., arrival) delay of a flight operated by a carrier i, at time t, on route k.

Several metrics are utilized in the airline industry to assess operational performance. Foremost among these are OTP and late arrivals, which are typically regarded as key internal measures of punctuality and service reliability (Manchiraju et al., 2023; Alan and Lapré, 2018; Tsikriktsis, 2007). According to the U.S. DOT, a flight is classified as delayed if it arrives at the destination gate 15 minutes or more after the scheduled arrival time (Ramdas et al., 2013; Deshpande and

[6] https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020

Arıkan, 2012). Similarly, OTP is defined as the proportion of flights of an airline that arrive within 15 minutes of their scheduled arrival time (Alan and Lapré, 2018). Based on this, to test the third set of competing hypotheses, we construct a dummy variable OTP_{itk} as follows:

$$OTP_{itk} = \begin{cases} 1, & \text{if the flight operated by airline } i\text{, at time } t\text{, on route } k\text{, arrives within} \\ & \text{15 minutes of its scheduled arrival time,} \\ 0, & \text{otherwise.} \end{cases}$$

We consider the proportion of flights canceled as the fourth dependent variable. Ramdas et al. (2013) suggest that cancelled flights often lead to prolonged delays and the added inconvenience of rebooking for travelers. Consequently, such extreme disruptions caused by cancellations are more likely to have a lasting negative impact on customers' perceptions of an airline and influence their future purchasing decisions (Ramdas et al., 2013). Accordingly, we incorporate flight cancellations as another indicator of service quality. We operationalize flight cancellations using the variable $Cancellation_{itk}$ as follows:

$$Cancellation_{itk} = \begin{cases} 1, & \text{if the flight operated by airline } i\text{, at time } t\text{, on route } k\text{, is cancelled,} \\ 0, & \text{otherwise.} \end{cases}$$

Finally, we use the number of mishandled bags per 1,000 bags enplaned as the last dependent variable in this study. Previous studies often rely on the number of mishandled baggage per 1,000 passengers to measure average service quality (Alan and Lapré, 2018; Nicolae et al., 2017; Mellat-Parast et al., 2015; Phillips and Sertsios, 2013). However, variations in free checked baggage policies may distort the evaluation of airline service quality. For instance, Southwest Airlines' "Bags Fly Free" policy is a central component of its marketing strategy and value proposition, but this policy may result in an increase in the volume of checked baggage (Nicolae et al., 2017). As a result, using the number of mishandled bags per 1,000 passengers as a service quality metric could disproportionately penalize Southwest, as the airline processes a higher volume of checked baggage, increasing the likelihood of baggage mishandling incidents. To account for potential distortions arising from differences in checked baggage policies across carriers, we use the number of mishandled bags per 1,000 enplaned bags as our dependent variable. Specifically, we define Bag_Issue_{jym} as the number of bags mishandled per 1000 bags enplaned by carrier j in month m of year y.

4.4.2.2 Explanatory Variables

In this study, we use two main independent variables to test our hypotheses. The first independent variable classifies each carrier as either an FSC or an LCC. First, we categorize American Airlines (AA), Delta Air Lines (DL), and United Airlines (UA) as FSCs, while JetBlue Airways (B6), Frontier Airlines (F9), Spirit Airlines (NK), and Southwest Airlines (WN) as LCCs[7]. We define the time-invariant dummy variable FSC_j to distinguish between FSCs and LCCs as follows:

$$FSC_j = \begin{cases} 1, & \text{if the airlines is a full-service carrier,} \\ 0, & \text{otherwise.} \end{cases}$$

Beyond the binary classification represented by FSC_j, we refine the carrier type variable into a categorical form by distinguishing Southwest Airlines as its own category in this study. Since Southwest Airlines operates a point-to-point network but with a stronger influence at specific airports within its network (e.g., DAL, HOU, and MDW airports), its network design allows it to achieve both flexibility and redundancy in responding to potential service disruptions. Thus, our study aims to understand any differential impact of Southwest Airlines compared to other LCCs. To do this, we define a categorical variable, $Category_j$, with three distinct categories as follows:

$$Category_j = \begin{cases} 2, & \text{if the airline is a full-service carrier} \\ 1, & \text{if the airlines is Southwest Airlines} \\ 0, & \text{otherwise} \end{cases}$$

[7]The International Air Transport Association (IATA) designator codes are provided within parentheses.

Following prior studies in airline research (Nicolae et al., 2017; Deshpande and Arıkan, 2012; Ramdas and Williams, 2006; Mayer and Sinai, 2003; Mazzeo, 2003), we account for fixed effects by including dummy variables for route, year, month, day of the week, carrier, and departure and arrival time blocks. First, the variable $Route_k$ captures fixed effects for all origin–destination airport pair combinations. The variable $Day\_of\_Week_t$ indicates the day of the week of the flight, accounting for fluctuations in flight volume throughout the week. $Dep\_Time\_Block_t$ and $Arr\_Time\_Block_t$ represent one-hour time intervals based on the scheduled departure and arrival times, respectively, to control for time-of-day effects. Finally, the variables $Year_t$ and $Month_t$ control for annual and seasonal variations, respectively. In the mishandled baggage analysis, the dataset is at the monthly level and the variables $Year_y$ and $Month_m$ are included to account for annual and seasonal variations, respectively. Table 4.2 presents a comprehensive overview of all variables used in this study, and Table 4.3 reports the associated descriptive statistics.

Table 4.2 Variable Descriptions

Variable	**Description**	**Database**
Dependent Variables		
Dep_Delay_{itk}	The difference in minutes between a flight's scheduled and actual departure times.	OTP Dataset
Arr_Delay_{itk}	The difference in minutes between a flight's scheduled and actual arrival times.	OTP Dataset
OTP_{itk}	A dummy variable coded as 1 if a flight arrives within 15 minutes of its scheduled arrival time, and 0 otherwise.	OTP Dataset
$Cancellation_{itk}$	A dummy variable coded as 1 if a flight is cancelled, and 0 otherwise.	OTP Dataset
Bag_Issue_{jym}	The number of mishandled bags per 1,000 bags enplaned.	Air Travel Consumer Report
Explanatory Variables		
FSC_j	A dummy variable coded as 1 for FSCs and 0 for LCCs.	OTP Dataset

Table 4.2 (cont'd)

Variable	Description	Database
$Category_j$	A categorical variable coded as 2 for FSCs, 1 for Southwest Airlines, and 0 for LCCs.	OTP Dataset
$Route_k$	An origin-destination airport pair combination.	OTP Dataset
$Day\_of\_Week_t$	The day of week of the flight.	OTP Dataset
$Dep\_Time\_Block_t$	One-hour time block based on the scheduled departure time of the flight.	OTP Dataset
$Arr\_Time\_Block_t$	One-hour time block based on the scheduled arrival time of the flight.	OTP Dataset
$Year_t$	The year of the flight.	OTP Dataset
$Month_t$	The month of the flight.	OTP Dataset
$Year_y$	The year in which the air carrier operated.	Air Travel Consumer Report
$Month_m$	The month in which the air carrier operated.	Air Travel Consumer Report

Table 4.3 Summary Statistics

Variable	Mean	Std. dev.	Min	Max	No. of obs.
Dependent Variable:					
Dep_Delay	8.855	37.889	-48	1930	3,023,984
Arr_Delay	3.899	40.681	-107	1910	3,023,984
OTP	0.818	0.386	0	1	3,023,984
$Cancellation$	0.014	0.119	0	1	3,104,887
Bag_Issue	5.451	1.628	3.240	11.300	98

Notes: Due to the number of observations available for flights with departure and arrival delays as well as OTP, our analysis focuses on flight records that include these performance metrics. As a result, gaps arise between this subset and the data that include cancelled flights.

4.5 Empirical Specification & Results

This section begins by outlining the sample composition used in the empirical analysis. We then describe the matching procedure used to identify and select comparable routes operated by multiple airlines with structurally different network models. Finally, we present the empirical models for hypothesis testing, which form the foundation of our analysis.

4.5.1 Sample

Consistent with prior studies (Manchiraju et al., 2023; Deshpande and Arıkan, 2012; Ramdas and Williams, 2006), we utilize individual flight-level data to test our hypotheses related to departure delays, arrival delays, OTP, and cancellations. For the period from January 1, 2016, to December 31, 2019, we draw on the OTP dataset, which contains detailed flight-level information for seven major U.S.-based carriers – AA, DL, UA, WN, NK, B6, and F9 – representing both full-service and low-cost carrier types. In contrast, our analysis of mishandled baggage is conducted at the carrier-month level due to the unavailability of more granular data. As discussed earlier, because of inconsistencies in the baggage-handling metric reported by the U.S. DOT, we restrict this analysis to the period from January 2019 to February 2020, during which the reporting metric is consistent and reliable.

4.5.2 Matching

Airlines typically operate distinct route networks, which can pose challenges for direct performance comparisons. For example, the Atlanta (ATL) – Orlando (MCO) route is predominantly served by Delta Air Lines, whereas JetBlue Airways does not operate on this route. Similarly, United Airlines frequently operates the Denver (DEN) – Minneapolis/St. Paul (MSP) route, while Spirit Airlines does not offer service along this route. Such network asymmetries introduce route-level heterogeneity, making direct comparisons of operational performance potentially biased. To address this issue, we implement a route-matching procedure designed to control for unobserved heterogeneity by focusing on routes that are either commonly served or closely comparable across carriers. This approach enables more valid comparisons of performance outcomes by aligning the analysis around operationally similar or equivalent routes.

The matching process proceeds as follows. First, we identify the top 10% of routes operated by the four LCCs based on flight frequency over the 2016–2019 period. These high-frequency LCC routes serve as the basis for comparative analysis. Next, we search for exact route matches between these LCC routes and those operated by FSCs. When exact matches are unavailable, we extend the matching criteria to include routes that connect geographically proximate airports within the same metropolitan area. For instance, JetBlue operates flights between Boston Logan International Airport (BOS) and Ronald Reagan Washington National Airport (DCA), while United operates between BOS and Washington Dulles International Airport (IAD). Although DCA and IAD differ in location and airport characteristics, both serve the Washington, D.C. metropolitan area and offer comparable route lengths and demand patterns. Thus, BOS–DCA and BOS–IAD are considered equivalent for the purpose of our analysis.

We further expand the matching framework to incorporate geographically aligned one-stop connecting routes operated by FSCs, corresponding to nonstop LCC routes. For example, while JetBlue offers direct service between John F. Kennedy International Airport (JFK) and Orlando International Airport (MCO), American Airlines provides a comparable one-stop service via Charlotte Douglas International Airport (CLT), flying JFK–CLT–MCO. Such connecting itineraries are treated as equivalent matches when they approximate the origin-destination pair served by LCCs. In summary, our final analysis of OTP data includes only those routes identified through the extended matching procedure, including exact matches, metropolitan-equivalent routes, and comparable one-stop connecting itineraries. This refined approach enables consistent and meaningful comparisons across the seven major carriers included in our study during the 2016–2019 period.

4.5.3 Empirical Models

To test H1A, H1B, H1C, and H1D, we employ the following ordinary least squares (OLS) linear regression models, as specified in Equations (4.1) and (4.2).

$$\begin{aligned} Dep\_Delay_{itk} = {} & \alpha_0 + \alpha_1 FSC_{itk} + \alpha_2 Route_k + \alpha_3 Day\_Of\_Week_t + \alpha_4 Dep\_Time\_Block_t \\ & + \alpha_5 Arr\_Time\_Block_t + \alpha_6 Year_t + \alpha_7 Month_t + \epsilon_{itk} \end{aligned} \tag{4.1}$$

$$\begin{aligned} Arr\_Delay_{itk} = {} & \beta_0 + \beta_1 FSC_{itk} + \beta_2 Route_k + \beta_3 Day\_Of\_Week_t + \beta_4 Dep\_Time\_Block_t \\ & + \beta_5 Arr\_Time\_Block_t + \beta_6 Year_t + \beta_7 Month_t + \omega_{itk} \end{aligned} \tag{4.2}$$

The coefficients α_1 and β_1 in Equations (4.1) and (4.2) capture the differences in departure and arrival delays between FSCs and LCCs, respectively.

We test H2A, H2B, H3A, and H3B using logistic regression models, as outlined in Equations (4.3) and (4.4). We use OTP_{itk} and $Cancellation_{itk}$ as the dependent variables for testing hypotheses H2A and H2B, and H3A and H3B, respectively.

$$\log\left(\frac{\Pr(OTP_{itk}=1)}{\Pr(OTP_{itk}=0)}\right) = \delta_0 + \delta_1 FSC_{itk} + \delta_2 Route_k + \delta_3 Day\_Of\_Week_t + \delta_4 Dep\_Time\_Block_t + \delta_5 Arr\_Time\_Block_t + \delta_6 Year_t + \delta_7 Month_t + \tau_{itk} \quad (4.3)$$

$$\log\left(\frac{\Pr(Cancellation_{itk}=1)}{\Pr(Cancellation_{itk}=0)}\right) = \theta_0 + \theta_1 FSC_{itk} + \theta_2 Route_k + \theta_3 Day\_Of\_Week_t + \theta_4 Dep\_Time\_Block_t + \theta_5 Arr\_Time\_Block_t + \theta_6 Year_t + \theta_7 Month_t + \eta_{itk} \quad (4.4)$$

In Equations (4.3) and (4.4), the parameters δ_1 and θ_1 estimate the differences in the odds of on-time arrivals and cancellations between FSCs and LCCs, respectively.

Lastly, we use Equation (4.5) to test Hypothesis H4A and H4B.

$$Bag\_Issue_{jym} = \gamma_0 + \gamma_1 FSC_{jym} + \gamma_2 Year_y + \gamma_3 Month_m + \zeta_{jym} \quad (4.5)$$

In the above equation, the parameter γ_1 identifies the difference in the baggage handling issues between FSCs and LCCs.

4.5.4 Results

In this section, we discuss the results of all our hypothesis tests. We provide the results for all models, both with and without fixed effects.

As shown in Table 4.4, there are substantial differences in the magnitude of both departure and arrival delays between FSCs and LCCs. To be specific, the estimated coefficients of FSC_{itk} in Model 1b ($\alpha_1 = -4.573$ minutes, $p < 0.001$) and Model 2b ($\beta_1 = -5.354$ minutes, $p < 0.001$) suggest that FSCs are significantly more effective than LCCs in managing flight delays. Accordingly, the findings support H1A and H1C, and they demonstrate that FSCs consistently outperform LCCs in mitigating both departure and arrival delays. Taken together, these findings indicate that FSCs enhance operational performance by strategically reallocating internal resources in response to disruptions, thereby enabling more rapid restoration of service quality during operational breakdowns. Given the additioanl availability of resources, such as aircraft and maintenance personnel, administrative and management staff, and specialized tools and equipment, FSCs are generally better equipped than their LCC counterparts to manage flight delays resulting from service failures in airline operations.

Table 4.4 OLS Regression Results: Departure and Arrival Delays

Dependent Variable:	Dep_Delay		Arr_Delay	
	Model 1a	Model 1b	Model 2a	Model 2b
FSC	-2.491***	-4.573***	-2.930***	-5.354***
	(0.045)	(0.079)	(0.049)	(0.084)
$Route$	No	Yes	No	Yes
Day_of_Week	No	Yes	No	Yes
Dep_Time_Block	No	Yes	No	Yes
Arr_Time_Block	No	Yes	No	Yes
$Year$	No	Yes	No	Yes
$Month$	No	Yes	No	Yes
No. of airlines	7	7	7	7
No. of obs.	3,023,984	3,023,984	3,023,984	3,023,984
Adj. R^2	0.001	0.037	0.001	0.036

Notes: $+p < 0.1$, $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$ indicate statistical significance at the 10 percent, 5 percent, 1 percent, and 0.1 percent levels. Robust standard errors are reported in parentheses below parameter estimates.

The results for the hypothesis tests of OTP and cancellations are similar. As shown in Table 4.5, the coefficient of FSC_{itk} in Model 3b of Table 4.5 ($\delta_1 = 0.431$, $p < 0.001$) is statistically significant at the 0.1% level. Consistent with the findings on departure and arrival delays, this result indicates that FSCs are more effective than LCCs in maintaining OTP, and therefore more capable of controlling longer delays. These findings provide empirical support for hypothesis H2A. To facilitate interpretation, we discuss the result in terms of log-odds, which appear on the left-hand side of Equation (4.3). In logistic regression, the log-odds of the event occurring, defined as $\log\left(\frac{p}{1-p}\right)$, where $p = \Pr(OTP_{itk} = 1)$, increases by the value of the estimated coefficient. Accordingly, transitioning from an LCC ($FSC_{itk} = 0$) to an FSC ($FSC_{itk} = 1$) results in a 0.431

increase in the log-odds of a flight arriving on time. To interpret this effect in terms of odds, we exponentiate the coefficient: $e^{0.431} = 1.539$. This implies that the odds of a flight arriving within 15 minutes of its scheduled arrival time are 53.9% higher for FSCs compared to LCCs.

Similarly, the coefficient of FSC_{itk} in Model 4b of Table 4.5 ($\theta_1 = -0.462$, $p < 0.001$) indicates that FSCs are significantly less likely to cancel scheduled flights compared to LCCs, further reinforcing their operational reliability. This finding provides empirical support for H3A. As with OTP_{itk}, we interpret this result in terms of log-odds, as shown on the left-hand side of Equation (4.4). Moving from an LCC ($FSC_{itk} = 0$) to an FSC ($FSC_{itk} = 1$) decreases the log-odds of flight cancellation by 0.462. Exponentiating this coefficient ($e^{-0.462} = 0.630$) implies that the odds of flight cancellation are 37.0% lower for FSCs relative to LCCs.

Table 4.5 Logistic Regression Results: OTP and Cancellations

Dependent Variable:	*OTP*		*Cancellation*	
	Model 3a	Model 3b	Model 4a	Model 4b
FSC	0.241***	0.431***	-0.651***	-0.462***
	(0.003)	(0.005)	(0.010)	(0.016)
Route	No	Yes	No	Yes
Day_of_Week	No	Yes	No	Yes
Dep_Time_Block	No	Yes	No	Yes
Arr_Time_Block	No	Yes	No	Yes
Year	No	Yes	No	Yes
Month	No	Yes	No	Yes
No. of airlines	7	7	7	7
No. of obs.	3,023,984	3,023,984	3,104,887	3,104,887
McFadden's Pseudo R^2	0.002	0.056	0.009	0.061

Notes: $+p < 0.1$, $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$ indicate statistical significance at the 10 percent, 5 percent, 1 percent, and 0.1 percent levels. Robust standard errors are reported in parentheses below parameter estimates.

Finally, we present the results related to our baggage handling analysis. As shown in Table 4.6, the estimated coefficient of FSC_{jym} in OLS regression Model 5b ($\gamma_1 = 1.954$, $p < 0.001$) suggests that LCCs handle baggage more effectively than FSCs, with approximately two fewer mishandled bags per 1,000 enplaned bags. These results provide empirical support for H4B. As discussed in Section 4.3.4, FSCs often operate through major hub airports where congestion increases the risk of service failures, particularly in baggage handling during connections. These inefficiencies are exacerbated by complex scheduling, frequent transfers, and greater fleet diversity (Alan and Lapré, 2018). In contrast, LCCs typically operate point-to-point networks with fewer connections, reducing baggage transfers. This streamlined process lowers the likelihood of baggage mishandling, as supported by our empirical findings.

Table 4.6 OLS Regression Results: Baggage Issues

Dependent Variable:	Bag_Issue	
	Model 5a	Model 5b
FSC	1.954***	1.954***
	(0.296)	(0.284)
$Year$	No	Yes
$Month$	No	Yes
No. of airlines	7	7
No. of obs.	98	98
Adj. R^2	0.350	0.401

Notes: $+p < 0.1$, $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$ indicate statistical significance at the 10 percent, 5 percent, 1 percent, and 0.1 percent levels. Robust standard errors are reported in parentheses below parameter estimates.

4.6 Additional Analysis

This section presents a distinct analysis of Southwest Airlines, considering it separately from the other LCCs.

4.6.1 Empirical Specification

As discussed in Section 4.4.2.2, given the scale of its operations, stronger operational control at select airports within its network, unique market positioning, distinctive implementation of its baggage policy, and notable influence on industry and market competition, analyzing Southwest Airlines separately allows for more nuanced insights into how its performance compares with both FSCs and other LCCs. To conduct this analysis, we use the same set of dependent variables introduced in Section 4.5.3 and apply the corresponding empirical specifications presented in Equations (4.1) through (4.5). However, instead of using FSC_{itk} as the primary independent variable of interest, we employ an alternative categorical variable, $Category_{itk}$, as defined in Section 4.4.2.2.

4.6.2 Results

As shown in Table 4.7, there are significant differences in both departure and arrival delay performance across carrier types. As expected, FSCs exhibit significantly lower departure and arrival delays compared to the other groups. The estimates from the model without fixed effects (Model 6a) indicate that Southwest Airlines has lower departure delays than other LCCs, but higher delays than FSCs. However, in the fixed-effects specification (Model 6b), the difference in departure delays between Southwest and other LCCs is no longer statistically significant. Further analysis suggests that this result is largely driven by the inclusion of route fixed effects, a finding that warrants additional investigation. Turning to arrival delays, the results from Models 7a and 7b show that Southwest performs significantly better than other LCCs, albeit worse than FSCs. One possible explanation is that Southwest's stronger operational presence and control at many of the airports in its network may enhance its ability to manage arrival delays more effectively.

The results from Models 8a and 8b presented in Table 4.8 indicate that Southwest Airlines performs worse than FSCs and is statistically indistinguishable from other LCCs in terms of OTP. Interestingly, the results from Models 9a and 9b reveal that Southwest performs worse not only than FSCs but also than other LCCs in managing flight cancellations. Based on the parameter estimates, a shift from another LCC to Southwest is associated with a 0.793 increase in the log-odds of cancellation. This indicates that the odds of cancellation are 121.0% higher for Southwest compared to other LCCs.

Southwest's comparatively higher cancellation rate among LCCs may stem from its operational scale and network complexity, which exceed those of most peer carriers. Unlike other LCCs that operate fewer flights and maintain simpler schedules, Southwest's dense point-to-point network leaves it more vulnerable to cascading disruptions. Additionally, its tight turnaround times limit flexibility during irregular operations. Southwest may also adopt a more proactive cancellation strategy, opting to cancel flights earlier to preserve schedule integrity, which can increase the

Table 4.7 Categorical Regression Results: Departure and Arrival Delays

Dependent Variable:	*Dep_Delay*		*Arr_Delay*	
	Model 6a	Model 6b	Model 7a	Model 7b
Category = FSC	-5.436***	-4.577***	-5.381***	-6.232***
	(0.086)	(0.102)	(0.092)	(0.109)
Category = Southwest	-4.615***	-0.011	-3.843***	-2.655***
	(0.088)	(0.131)	(0.094)	(0.140)
Route	No	Yes	No	Yes
Day_of_Week	No	Yes	No	Yes
Dep_Time_Block	No	Yes	No	Yes
Arr_Time_Block	No	Yes	No	Yes
Year	No	Yes	No	Yes
Month	No	Yes	No	Yes
No. of airlines	7	7	7	7
No. of obs.	3,023,984	3,023,984	3,023,984	3,023,984
Adj. R^2	0.002	0.037	0.002	0.036

Notes: $+p < 0.1$, $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$ indicate statistical significance at the 10 percent, 5 percent, 1 percent, and 0.1 percent levels. An ordinary least squares (OLS) linear regression model is used. Robust standard errors (s.e.) are reported in parentheses below parameter estimates.

number of cancellations even if it benefits downstream recovery.

Finally, we analyze the number of mishandled bags per 1,000 enplaned bags (Bag_Issue_{jym}). As reported in Table 4.9, the estimate of FSC in OLS regression Model 10b is 1.837 ($p < 0.001$), indicating that LCCs manage baggage handling more effectively than FSCs. Moreover, the estimate of $Southwest$ is –0.470 ($p < 0.01$), suggesting that Southwest Airlines outperforms both FSCs and other LCCs in minimizing baggage mishandling incidents.

Airlines that impose fees for checked baggage typically observe a decrease in the volume of checked bags, which can mitigate baggage handling complexity and, in turn, reduce the likelihood of departure delays. This suggests that fewer checked bags could benefit not only the operating carrier but also other airlines operating at the same airport (Nicolae et al., 2017). In contrast, Southwest Airlines has promoted its well-known "Bags Fly Free" campaign, which has led to a higher volume of checked baggage as a natural consequence. When evaluating the absolute number of mishandled baggage incidents, Southwest may appear more vulnerable to baggage-

Table 4.8 Categorical Regression Results: OTP and Cancellations

Dependent Variable:	*OTP*		*Cancellation*	
	Model 8a	Model 8b	Model 9a	Model 9b
Category = FSC	0.407***	0.427***	-0.420***	-0.274***
	(0.005)	(0.006)	(0.015)	(0.019)
Category = Southwest	0.267***	-0.014	0.342***	0.793***
	(0.005)	(0.009)	(0.016)	(0.035)
Route	No	Yes	No	Yes
Day_of_Week	No	Yes	No	Yes
Dep_Time_Block	No	Yes	No	Yes
Arr_Time_Block	No	Yes	No	Yes
Year	No	Yes	No	Yes
Month	No	Yes	No	Yes
No. of airlines	7	7	7	7
No. of obs.	3,023,984	3,023,984	3,104,887	3,104,887
McFadden's Pseudo R^2	0.003	0.056	0.011	0.063

Notes: $+p < 0.1$, $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$ indicate statistical significance at the 10 percent, 5 percent, 1 percent, and 0.1 percent levels. A logistic regression model is used. Robust standard errors (s.e.) are reported in parentheses below parameter estimates.

Table 4.9 Categorical Regression Results: Baggage Issues

Dependent Variable:	*Bag_Issue*	
	Model 10a	Model 10b
Category = FSC	1.837***	1.837***
	(0.304)	(0.294)
Category = Southwest	-0.470*	-0.470**
	(0.209)	(0.161)
Year	No	Yes
Month	No	Yes
No. of airlines	7	7
No. of obs.	98	98
Adj. R^2	0.352	0.405

Notes: $+p < 0.1$, $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$ indicate statistical significance at the 10 percent, 5 percent, 1 percent, and 0.1 percent levels. An ordinary least squares (OLS) linear regression model is used. Robust standard errors are reported in parentheses below parameter estimates.

related disruptions, which could contribute to increased departure delays and lower OTP. However, when mishandling is assessed in relative terms as the number of mishandled bags per 1,000 enplaned bags, the interpretation shifts, as demonstrated in our analysis. Based on the empirical evidence in Tables 4.7, 4.8, and 4.9, although Southwest Airlines does not exhibit a distinct advantage over other LCCs in managing departure delays or OTP, and even performs worse in managing flight cancellations, it significantly outperforms both FSCs and other LCCs in handling baggage issues when measured on a proportional basis. This suggests that, despite the perceived operational disadvantage introduced by its baggage fee policy, Southwest Airlines effectively manages baggage handling performance as evidenced by our results. This suggests that Southwest has developed highly efficient baggage handling processes that enable it to maintain superior performance even under heavier operational loads.

4.7 Discussion

In the airline industry, carriers design flight routes to optimize operational efficiency. Network strategies are typically shaped by key operational priorities such as cost efficiency, route flexibility, service coverage, and revenue. The two predominant network structures are the point-to-point and hub-and-spoke systems. In a point-to-point network, passengers travel directly between cities, while in a hub-and-spoke system, they often connect through a hub city when neither the origin nor destination is a hub. Most FSCs primarily operate under a hub-and-spoke model, whereas LCCs tend to rely more heavily on point-to-point networks (Mellat-Parast et al., 2015; Cook and Goodwin, 2008). These strategic choices are further influenced by broader considerations, including network configuration, product offerings, pricing models, and resource allocation decisions (Bourjade et al., 2017).

In this study, our first research question investigates how airlines operating under different network structures manage service quality. Prior research has not comprehensively examined how KPIs reflecting operational performance under disruptions capture the effectiveness of airline operations across different network structures. This study aims to demonstrate that service quality outcomes are closely linked to airlines' operational strategies, particularly as shaped by their network configurations. Building on this, we also examine Southwest Airlines separately, as it is widely recognized as one of the largest U.S. air carriers in terms of operational volume and capacity, despite being formally classified as an LCC. To test our hypotheses, we use historical data on operational and service performance for seven U.S. domestic airlines, drawing on OTP data and mishandled baggage records obtained from the official websites of the BTS and the U.S. DOT.

First, our results reveal significant differences between FSCs and LCCs in managing both departure and arrival delays, with FSCs consistently outperforming LCCs in minimizing overall delays. Additionally, while Southwest Airlines performs comparably to other LCCs – and worse than FSCs – in managing departure delays, it outperforms other LCCs in managing arrival delays. This pattern suggests that Southwest's stronger operational presence and control at several airports within its network may contribute to its improved performance in mitigating arrival delays. We also evaluate airline operational performance based on on-time arrival performance and flight cancellations. The results indicate that FSCs consistently outperform LCCs in both maintaining OTP and minimizing flight cancellations. Specifically, the odds of a flight arriving within 15 minutes of its scheduled arrival time are 53.9% higher for FSCs compared to LCCs and the odds of a flight being canceled are 37% lower for FSCs. Moreover, we find no statistically significant difference in the OTP of Southwest compared to other LCCs. However, Southwest performs substantially worse than both FSCs and its LCC peers in managing flight cancellations.

These findings highlight the structural advantages of the hub-and-spoke network used by FSCs, which includes built-in redundancy such as reserve crews, spare aircraft, and extensive rebooking options, all of which lead to greater schedule reliability, higher OTP, and lower delays and cancellations. In contrast, the leaner, point-to-point networks operated by LCCs, including Southwest, may lack sufficient slack to absorb disruptions, particularly when irregular operations arise. Southwest's notably poor performance on cancellations, despite having comparable OTP to other LCCs, suggests that its operational model, though efficient under normal conditions, may be more vulnerable when recovery resources are constrained. This highlights a critical trade-off in network design: while point-to-point structures can offer flexibility and efficiency, they may do so at the expense of robustness under strain.

These results have practical implications for both airline strategy and policy. As disruptions become more frequent and customer expectations for service reliability continue to rise, achieving an effective balance between efficiency and operational resilience is increasingly critical for airlines. For managers, investing in targeted buffers, operational contingencies, and selective redundancies, such as reserve crews or aircraft and increased operational control at key airports, can enhance operational performance without fundamentally altering the cost structure or compromising the efficiency advantages of a point-to-point model.

Another important operational performance metric examined in this study is the mishandled baggage rate, a key indicator of service failures in the airline industry. Mishandled baggage incidents not only reflect lapses in service quality but also impose additional operational costs on airlines, such as those related to locating lost items and arranging their timely return to passengers. These failures, defined as instances where the delivered service falls short of customers' expectations, can significantly erode customer satisfaction and, in turn, impact long-term loyalty (Mellat-Parast et al., 2015).

In this study, we investigate how airline network structure influences baggage-related service failures. Our empirical findings reveal that LCCs are generally more effective than FSCs in handling baggage, with LCCs reporting approximately two fewer mishandled bags per 1,000 enplaned bags. This advantage may stem from the leaner operational model of LCCs, characterized by direct routes, and fewer baggage transfers, which collectively reduce the likelihood of errors in baggage handling. Southwest Airlines, in particular, outperforms both other LCCs and FSCs in minimizing baggage-handling failures. A possible explanation is that, due to its no-fee checked baggage policy, Southwest handles a disproportionately high volume of checked bags, and this operational exposure may have led to the development of more efficient and experienced baggage handling processes.

These results offer important implications for airline operations. While FSCs offer higher schedule reliability, LCCs achieve superior outcomes in specific quality dimensions, such as baggage handling, through simplified logistics, higher process specialization, and operational focus.

For managers, these insights suggest that improving service reliability does not always require extensive redundancy; rather, it may be achieved through targeted process optimization aligned with the carrier's operating model.

We contribute to the existing literature by systematically comparing the performance of the two predominant airline network structures – hub-and-spoke versus point-to-point – across multiple operational metrics, including departure delays, arrival delays, OTP, flight cancellations, and mishandled baggage incidents. This multidimensional approach enables managers to evaluate whether meaningful differences in performance arise from the underlying network design itself. Furthermore, it provides a framework for benchmarking operational outcomes not only relative to competitors employing different network strategies but also across the various service dimensions within a firm's own operations.

While this study offers valuable insights, it also presents several limitations that suggest promising directions for future research. First, we use the number of mishandled bags per 1,000 bags enplaned as one of our service quality measures. Beginning in January 2019, the U.S. DOT revised its reporting in the Air Travel Consumer Reports to reflect the number of bags enplaned, rather than the number of enplaned passengers. Accordingly, we limit our analysis of mishandled baggage data to the period from January 2019 to February 2020 to minimize the influence of disruptions resulting from the COVID-19 pandemic. As a result, the number of observations related to mishandled baggage incidents is relatively small across the seven airlines included in this study. In summary, future research would benefit from identifying ways to expand the sample size, particularly for metrics related to mishandled baggage per enplaned bag, to strengthen the robustness of findings. Furthermore, this study does not focus exclusively on periods of extreme disruption to examine the influence of airlines' network strategies on operational performance metrics. However, given that the COVID-19 pandemic has been widely recognized as one of the most disruptive events in the service industry, future research could yield deeper insights by analyzing performance under both normal operating conditions and periods characterized by systemic disruption. Analyzing performance across different levels of disruptions would enable a more comprehensive assessment of how network structures influence operational outcomes under uncertainty. Finally, although our models include a wide range of fixed effects related to airline operations and scheduling, aimed at isolating the impact of the primary independent variables on service quality outcomes, it is important to acknowledge additional relevant factors. Consistent with prior research on airline operations (Nicolae et al., 2017; Prince and Simon, 2015; Ramdas et al., 2013), incorporating control variables such as weather conditions and load factors could enhance the explanatory power of the analysis, as these factors are closely linked to the overall success and reliability of airline operations. The aforementioned limitations raise important research questions and warrant further in-depth investigation in future studies.

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