



Lisbon School  
of Economics  
& Management  
Universidade de Lisboa

**MASTER**  
**MANAGEMENT AND INDUSTRIAL STRATEGY**

**MASTER'S FINAL WORK**  
**DISSERTATION REPORT**

**THE SINO-US TECHNOLOGICAL COLD WAR AND GLOBAL VALUE  
CHAIN RESTRUCTURING: EVIDENCE FROM CHINESE LISTED FIRMS**

**MENGYU ZHANG**  
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**JUNE 2026**



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**JUNE 2026**

*To all my master's students  
that started a dissertation  
under my supervision, but  
were abducted by extra-  
terrestrials or crossed to  
another dimension*

## ABSTRACT AND KEYWORDS

This study examines how the Sino–U.S. technological cold war affects Chinese firms’ positions in global value chains. The existing research still focuses more on macro-level analysis (e.g., Amiti et al., 2019; Alfaro & Chor, 2023) with a few studies that began to explore firm-level responses (e.g., Amiti et al., 2019; Bonadio et al., 2021). However, these studies still primarily rely on customs data or proprietary datasets. It remains unclear whether publicly disclosed firm-level information can systematically capture value chain adjustments.

This study uses panel data from 211 Chinese listed firms from 2017 to 2024. The study constructs multiple GVC embedding indicators from annual reports. These indicators include customer concentration, supplier concentration, foreign revenue share, geographic diversification, and overseas subsidiary ratio. A difference-in-differences approach compares firms with different exposure to the technological conflict.

The results show that instead of starting right from the initial phase of trade tensions in 2018, the main structural changes occur after 2020. The significant adjustment is observed in customer concentration, which increases for firms in more exposed industries to the US, particularly in the Battery sector. In contrast, it does not show any significant changes occur in supplier concentration, foreign revenue, or overseas subsidiary deployment.

The study further suggests that downstream relationships adjustments is the core response for Chinese firms to deal with the geopolitical uncertainty. These findings indicate that global value chain restructuring is slow and gradual. It is not a broad, quick withdrawal from international markets.

This study contributes to the literature by providing firm-level evidence from Chinese listed firms using only publicly disclosed data. It also highlights the importance of demand-side relationships in shaping firms’ responses to geopolitical shocks.

**KEYWORDS:** geopolitical tensions; global value chains; Chinese firms; supply chain restructuring; difference-in-differences.

**JEL CODES:** C33; F14; F23; F51; L14; M16.

## RESUMO

Este estudo analisa de que forma a Guerra Fria Tecnológica entre a China e os Estados Unidos afeta o posicionamento das empresas chinesas nas cadeias de valor globais. A investigação existente continua a centrar-se predominantemente em análises ao nível macroeconómico (por exemplo, Amiti et al., 2019; Alfaro & Chor, 2023), embora alguns estudos tenham começado a explorar as respostas ao nível empresarial (por exemplo, Amiti et al., 2019; Bonadio et al., 2021). No entanto, estes estudos continuam a basear-se principalmente em dados aduaneiros ou em bases de dados proprietárias. Permanece, assim, por esclarecer se a informação empresarial divulgada publicamente permite captar, de forma sistemática, os ajustamentos nas cadeias de valor.

Este estudo utiliza dados em painel de 211 empresas chinesas cotadas em bolsa, relativos ao período compreendido entre 2017 e 2024. Com base nos relatórios anuais, são construídos diversos indicadores de integração nas cadeias de valor globais. Estes indicadores incluem a concentração de clientes, a concentração de fornecedores, a proporção das receitas provenientes do estrangeiro, a diversificação geográfica e o rácio de subsidiárias no estrangeiro. Através de uma abordagem de diferenças-em-diferenças, são comparadas empresas com diferentes níveis de exposição ao conflito tecnológico.

Os resultados demonstram que as principais alterações estruturais não começaram logo na fase inicial das tensões comerciais, em 2018, tendo ocorrido sobretudo após 2020. O ajustamento significativo verifica-se na concentração de clientes, que aumenta entre as empresas pertencentes a setores mais expostos aos Estados Unidos, particularmente no setor das baterias. Em contrapartida, não se observam alterações significativas na concentração de fornecedores, nas receitas provenientes do estrangeiro ou na implantação de subsidiárias no estrangeiro.

O estudo sugere ainda que o ajustamento das relações a jusante constitui a principal resposta das empresas chinesas à incerteza geopolítica. Estes resultados indicam que a reestruturação das cadeias de valor globais é um processo lento e gradual, não correspondendo a uma retirada generalizada e rápida dos mercados internacionais.

Este estudo contribui para a literatura ao apresentar evidência ao nível empresarial relativa a empresas chinesas cotadas em bolsa, utilizando exclusivamente dados

divulgados publicamente. Destaca igualmente a importância das relações do lado da procura na definição das respostas das empresas aos choques geopolíticos.

PALAVRAS-CHAVE: tensões geopolíticas; cadeias de valor globais; empresas chinesas; reestruturação da cadeia de abastecimento; diferença nas diferenças.

CÓDIGOS JEL: C33; F14; F23; F51; L14; M16.

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## ACKNOWLEDGMENTS

The completion of this master's thesis marks the culmination of my studies at ISEG Lisbon School of Economics and Management. I would like to express my sincere gratitude to those who have supported me throughout this journey.

First and foremost, I am deeply grateful to my supervisor, Professor Nuno Fernandes Crespo, for his patient guidance and continuous support. His insightful feedback and academic rigor have been invaluable to the development of this research.

I also thank the faculty members at ISEG for providing the knowledge and critical perspectives that laid the foundation for this work. I am equally grateful to my classmates and friends for their support and for the stimulating discussions we shared.

Finally, I would like to express my deepest appreciation to my family for their unwavering encouragement and support throughout this process.

## 1. INTRODUCTION

In recent years, the rising geopolitical tensions have increasing effect on the global economic restructure. The Sino-US tension started from traditional trade conflict to broader strategic competition, including tariff barriers, expanded export controls, entity lists growth, and restrictions on advanced technologies (e.g., Bown, 2021; Alfaro & Chor, 2023; U.S. Department of Commerce, 2022; Miller, 2022).

There are numerous studies that assessed the impact of these tensions on trade flows, investment, and firm performance (e.g., Airaudo et al., 2025; D’Orazio et al., 2024; Alfaro & Chor, 2023). There is growing number of research on firm-level responses, but still limited (e.g., Qiu et al., 2023; Liu et al., 2024; Bourany et al., 2025). Most existing studies still rely on customs data, survey data, or proprietary datasets. It is also unclear whether the officially disclosed firm-level data can identify the global value chain adjustments. Moreover, most of the existing literature mainly focuses on macro-level measures of global value chain participation (e.g., Antràs, 2020; Borin et al., 2025). These measures are unable to fully capture how firms restructure their supply chain relationships and international operations.

Within this background, this study is focusing on whether the official disclosures in firms’ annual reports can provide meaningful evidence of changes in their position within global value chains. The annual report contains standardized information about key data, such as customers, suppliers, and overseas operations. This information can serve as an observable indicator of a firm's position within the global production network. Thus, the core research question of this study is: **Do Chinese firms adjust their supply chain relationships and international activities in response to geopolitical shocks?**

To answer this question, this study uses panel data from Chinese listed firms from 2017 to 2024 and applies a difference-in-differences (DID) method to compare firms affected by Sino-U.S. technological competition at different levels. Additionally, this study shows how firms change their position in global value chains under geopolitical pressure at the firm-level, through changes in customer concentration, supplier concentration, international market exposure, and overseas organizational structure.

The findings show that the adjustment process is more focusing on selective changes in firm-level relationships, especially on the demand side, rather than a broad withdrawal

from global markets. This suggests that geopolitical shocks reshape global value chains in a gradual manner, which can be partially observed through firm-level disclosed data.

## 2. LITERATURE REVIEW

### *2.1. Trade wars & geopolitical conflicts*

In recent years, geopolitical tensions and conflicts between countries have greater impact on international business. In the past, globalization was mainly driven by economic factors which include profit maximization, efficiency improvement and market expansion. However, the global environment has become much more political and less predictable. Beugelsdijk and Luo (2024) point out that government actions, national security concerns and political interests now have a strong impact on international business. Luo and Tung (2025) also suggest that firms now operate in a more fragmented and multipolar world. Therefore, geopolitical alignment is important for business decisions.

Geopolitical risk is an important concept for understands this change. Caldara and Iacoviello (2022) define it as uncertainty and threat associated with war, terrorist activities, and tensions between countries. Their study finds that the higher the geopolitical risk, the less investment and economic activity there are. Therefore, geopolitical conflicts are not occasional events. They're more like factors that continuously influence economic decisions and corporate behavior.

Trade war is a typical example of geopolitical tensions effects. It normally includes tariffs and other type of trade barriers between countries, and those measures are often linked to political or strategic demands. For instance, Amiti et al. (2019) pointed out that the additional tariff policy implemented by the U.S. in 2018 not only raised the prices of imported goods and weakened market competitiveness but also harmed public welfare. This shows that trade wars cause real economic loses for both firms and consumers and may also disrupt the existing international trade order.

Uncertainty is another major effect of trade wars. Since it is difficult to predict future trends, firms often adjust their business decisions before the relevant policies are formally implemented. Research by Handley and Limão (2022) confirms that trade policy uncertainty alone can reduce firms' willingness to invest, enter new markets, or reorganize production. For example, predicting changes in tariffs could be a typical trigger. As a result, firms may postpone their relevant strategic decisions and proactively avoid high-risk cross-border activities. This shows that the impact of the trade war comes

not only from tariffs themselves, policy risks, uncertainty and market expectations may also have far-reaching effects.

According to the International Monetary Fund (IMF, 2023a), geopolitical conflicts changed the flow and distribution of foreign direct investment across countries. At the same time, such effects are differentiated across different industries. Industries and firms with high levels of globalization and strategic importance are more affected than the other industries (IMF, 2023b). This suggests that geopolitical conflicts have heterogeneous impacts across firms and industries.

At the firm-level, external environment changes also bring new challenges to international business. Firms are facing with continuously rising uncertainty, rising operating costs, and increased risks related to international businesses. According to Luo and Tung (2025), the strategic adjustments are necessary to deal with the changes of protectionism and increasing political tensions. The measures may include changes in key market dependence, supply chains diversification, and international operating models.

## *2.2. Sino-US technological cold war*

Bilateral relations between China and the U.S. have changed from a traditional trade war to broader technological competitions since 2018 (e.g., Bown, 2021; Alfaro & Chor, 2023). Under the background of the growing strategical position of technology, high-end industries like semiconductors and artificial intelligence are gradually becoming the core of the game (Selwyn et al., 2025; see also Miller, 2022). Currently, it is not only the core driving force of a nation's economic development but also closely bond with national security. Therefore, the game between the two countries is generally described as a strategic technological competition rather than a simple trade dispute (Farrell & Newman, 2019; Bown, 2020).

One important feature of this technological competition is that the policy tools are no longer limited to tariff measures. Governments have adopted export controls, investment restrictions, and other regulatory measures to control the critical technologies. For example, the US imposed export restrictions on Chinese firms and added multiple firms to the Entity List, limiting their access to the core technology. These measures show that the conflict between the two sides has gone beyond the scope of trade. The core shift is to the dominance over key technologies and the global innovation system (Bown, 2020).

"Weaponization of interdependence" is another important perspective to interpret this competition. Farrell and Newman (2019) point out that countries can use their advantageous position in global economic networks to form a bargaining power. Under the Sino-US conflict, both sides are trying to control key links in global supply chains such as semiconductors and digital infrastructure. This distinguishes this competition from traditional trade wars as it extends to strategic competition over key technologies and reshaping global production networks.

Additionally, the technological cold war impacts are unevenly exposed to different industries. High-tech industries like semiconductors, electronics and new energy technologies are especially more affected than the other industries. These industries heavily rely on global supply chains and cross-border knowledge exchanges. Once export controls restrict and investment barriers rise, businesses will easily fall into a disadvantage (Evenett & Fritz, 2019).

At the firm-level, the tech-war also presents severe challenges to international firms. It becomes much more difficult for them to acquire foreign technology, maintain international partnerships and develop in key markets. These challenges are forcing them to replan and adjust their business strategies which goes beyond the short-term profits. They also reflect that geopolitical competition is gradually reshaping firms' global operational systems (Bown, 2020; Evenett & Fritz, 2019; Antràs, 2020).

Research related to the Sino-US conflict (tech cold war) is steadily increasing in recent years. However, most studies still focus on trade volumes, innovation outcomes, and overall firm performance (Benguria, 2023; Hu et al., 2024; Huang et al., 2024; Xu et al., 2022). Study in how this technological rivalry affects firm-level supply chain structures remains relatively limited (Qiu et al., 2023). There is also lack of systematic exploration of how firms adjust their observable supplier and customer relationships in response to geopolitical tensions. Although it is impossible to fully capture the entire value chain network, this research direction is highly valuable, since changes in corporate partnerships can intuitively reflect deep transformations in global value chains (e.g., Antràs, 2020; Alfaro & Chor, 2023).

### *2.3. Geopolitical Shocks and Institutional Theory*

Institutional theory provides a useful perspective for understanding firm-level reaction to geopolitical shocks. The main idea is that firms operate in a broader institutional environment with regulations, political pressures, and social expectations rather than only rely on efficiency or market opportunities (North, 1990; DiMaggio & Powell, 1983; Scott, 1995). Firms must seek legitimacy and stability by following to these institutional arrangements (Peng et al., 2008). However, the institutional environment is subject to change. When it shifts, firms may need to adjust their operating strategies and organizational structures in order to reduce uncertainty and maintain stable operation.

Geopolitical conflicts change the institutional environment in which enterprises survive essentially, giving the institutional theory strong practical meanings. Various geopolitical shocks, such as tariffs, export controls, investment restrictions, technology-related regulations, etc., directly change the institutional environments where the firms operate. Such shocks increase uncertainty and restrict firms' access to foreign markets, technologies, and supply chains (both suppliers and customers sides). From the perspective of institutional theory, such changes can be seen as external pressures on firms' strategic choices (Peng et al., 2008; Luo & Tung, 2025).

In case of the Sino-U.S. tech cold war, firms are exposed to long-term political changing and regulatory constraints (Miller, 2022; U.S. Department of Commerce, 2022). Within this background, firms did adjustments in their relationships with customers and suppliers, deployment to certain overseas markets, and their international operating strategies (Antràs, 2020). These are firms' proactive adaptations to changes in the external institutional environment (Luo & Tung, 2025).

On the other hand, institutional theory can also explain the internal logic of behavioral differences among firms under geopolitical shocks. As North (1990), Scott (1995) and Peng et al. (2008) argued, the impact of institutional pressure depends on firms' industry, resources, degree of internationalization, and position within global production networks. Luo and Tung (2025) further point out that firms in strategically sensitive sectors may face stronger institutional pressures than firms in less exposed industries. Therefore, their responses may be more visible in supply chain relationships or international business structures (Alfaro & Chor, 2023; Antràs, 2020).

In this study, Institutional Theory provides theoretical support to connect geopolitical shocks with firm-level adjustments in global value chains. This study treats geopolitical tensions as changes in the external institutional environment, and considers changes in customer concentration, supplier concentration, foreign sales, and overseas subsidiaries as observable firm-level responses. Based on this theoretical logic, it is expected that when geopolitical uncertainty and regulatory pressure increase, firms may adjust their global value chain positions accordingly (North, 1990; Scott, 1995; Peng et al., 2008).

#### *2.4. Impact on Global Value Chains*

Global value chains (GVCs) link production stages across countries through upstream and downstream relationships and foreign subsidiaries. When the international environment is stable, the core principle for building a firm's value chain is to pursue efficiency. Firms choose their corporate partners and production locations to minimize costs and maximize productivity. However, this logic can be easily destroyed by geopolitical shock. The international operations and partnerships are highly sensitive to the negative impact brought by political tensions. To avoid this, firms adjust their positions within global value chains to avoid uncertainty and maintain operational stability (Antràs, 2020; Baldwin & Freeman, 2022).

The existing research shows that geopolitical risks increase the importance of partner selection and reshape supply chain relationships under uncertainty (Antràs, 2020; Baldwin & Freeman, 2022; Alfaro & Chor, 2023; OECD, 2020). One core method that firms use to respond to geopolitical risk, is to adjust their upstream and downstream partnership structures. Some firms may reduce dependence on single core partners and diversify their supply chains to lower disruption risk. Others increase concentration and shift toward more reliable or politically aligned partners. For example, Doan et al. (2025) find that firms react with geopolitical shocks by diversifying their supply chains, shifting capacity and cooperation focus toward politically stable regions. Conversely, changes in network concentration can be used as observable indicators of how firms adjust their positions within global value chains.

Another important adjustment is related to international market exposure. The firms with heavy dependence on overseas revenue present higher sensitivity to trade policy fluctuations and political uncertainty. In order to avoid this risky environment, they

choose to reduce the reliance on overseas business, shift the operating focus back to domestic markets, or reallocate sales across different regions. We can capture this adjustment through changes in the share of foreign sales, which commonly used as an indicator to measure a firm's degree of internationalization (Sullivan, 1994; Hitt et al., 1997; Helpman et al., 2003).

On the production side, firms also adjust their global production networks in response to geopolitical tensions. A common strategy is to establish or expand overseas subsidiaries in different regions (Alfaro & Chen, 2012). Moving production closer to final customers allows the firm to make profit in the overseas markets and avoid the negative impact of trade restrictions. In this case, changes of the number or share of overseas subsidiaries are important criteria for observing how firms reorganize their global operations in response to geopolitical risks (Helpman et al., 2003; OECD, 2020).

In addition, geographic diversification can further reveal a firm's business strategy from the market structure perspective. Firms may optimize revenue structures in different regions even with the overall share of foreign sales does not change significantly. They may reduce exposure to politically sensitive markets and increase investment in markets with stable political environments. Using the entropy method to estimate the level of geographic diversification can capture whether firms' sales become more concentrated or more dispersed across regions. This approach has been widely applied in international diversification-related research (Jacquemin and Berry, 1979; Hitt et al., 1997).

The existing studies point toward a clear pattern. Geopolitical shocks are the cause of adaptive adjustments across global value chains. These adjustments occur in supplier and customer relationship concentration, market exposure and international production structures (e.g., Antràs, 2020; Baldwin & Freeman, 2022; Alfaro and Chor, 2023). However, most of the existing studies mainly focus on the macro-level changes (e.g., Antràs, 2020; Borin et al., 2025). Although some recent studies have used survey data for firm-level analysis (e.g., Qiu et al., 2023), there is still a gap in identifying such adjustments based on publicly disclosed firm-level data.

It is worth noting that several foundational references in our review, such as Antras (2020) and Baldwin & Freeman (2022), are circulated as NBER working papers rather than peer-reviewed journal articles. Given the fast-moving nature of geopolitical shocks,

we rely on these for real-time conceptual framing, but our empirical inferences are primarily benchmarked against peer-reviewed studies on trade policy (e.g., Amiti et al., 2019; Autor et al., 2013).

### *2.5. Hypotheses Development*

Building on the discussion above, this study develops three research hypotheses to analyze the impact of geopolitical shocks on firms' positions within global value chains. The hypotheses cover three main dimensions of firm-level GVC embedding: supply chain relationships, international market exposure, and international production structures.

First, geopolitical shocks may affect firms' suppliers and customers relationships. When geopolitical uncertainty rises, they begin to reconsider the stability and reliability of their partners rather than pure efficiency considerations. From an institutional theory perspective, external political and regulatory environment changes push firms to adjust their organizational relationships to reduce uncertainty (North, 1990; Scott, 1995; Peng et al., 2008). Within global value chains, changes in supplier and customer concentration clearly reflect these adjustments. Firms may diversify their relationships to reduce dependence on a few key partners or increase concentration by choosing more stable or politically aligned partners. The existing studies confirm that geopolitical risks and supply chain disruptions can lead firms to reorganize their network relationships and partner selection criteria (Antràs, 2020; Baldwin & Freeman, 2022; Alfaro and Chor, 2023). Therefore, this study proposes the first hypothesis:

***Hypothesis 1:*** *Geopolitical shocks lead firms to adjust their supply chain relationships, namely changing:*

- a) The customers' concentration;*
- b) The suppliers' concentration.*

Second, geopolitical shocks may affect firms' international markets exposure. It brings bigger negative impact on firms with higher share of foreign sales. In response, firms may reduce their reliance on foreign markets, move toward domestic demand, or reallocate sales across regions. Previous studies on internationalization suggest that foreign sales is an important indicator for measuring firms' international involvement and market exposure (Sullivan, 1994; Hitt et al., 1997). In the context of the Sino-U.S. tech

war, firms in highly internationalized industries show higher motivation to adjust their internationalization layouts. Therefore, this study proposes the second hypothesis:

***Hypothesis 2:*** *Geopolitical shocks reduce firms' exposure to international markets, as reflected in a decline in the share of foreign sales.*

Third, geopolitical shocks may influence firms' international organizational structures. Facing trade barriers and technology controls, firms may reallocate their production location, subsidiaries, and operational activities. This helps them reduce exposure to trade restrictions and maintain access to foreign customers. The existing studies suggest that overseas subsidiary deployments are important part of firms' global production strategies (Helpman et al., 2003; Lu and Beamish, 2004; Alfaro and Chen, 2012). From the institutional theory perspective, geopolitical pressure encourages firms to optimize their overseas organizational structures, even though reorganizing subsidiaries requires time, costs, and long-term strategic planning consideration. Therefore, this study proposes the third hypothesis:

***Hypothesis 3:*** *Geopolitical shocks lead firms to reorganize their international production structures, reflected in changes in overseas subsidiaries.*

## *2.6. Conceptual Framework*

Building on the work summarized above, this study develops a simple conceptual framework. Figure I presents the conceptual framework of this study. The framework links the Sino-U.S. geopolitical shock to firms' strategic adjustments within global value chains.

The left side of the framework represents the geopolitical shock, measured in this study through the escalation of the Sino-U.S. technological conflict. From an institutional theory perspective, this shock changes the external environment faced by firms by increasing uncertainty and regulatory pressure.

The right side of the framework presents the main firm-level adjustment outcomes examined in this study. H1a focuses on downstream supply chain adjustment, measured by the top five customer sales ratio. H1b focuses on upstream supply chain adjustment, measured by the top five supplier purchase ratio. H2 examines changes in international

market exposure, measured by the foreign revenue share (FSTS). H3 examines changes in international production structure, measured by the overseas subsidiary ratio.

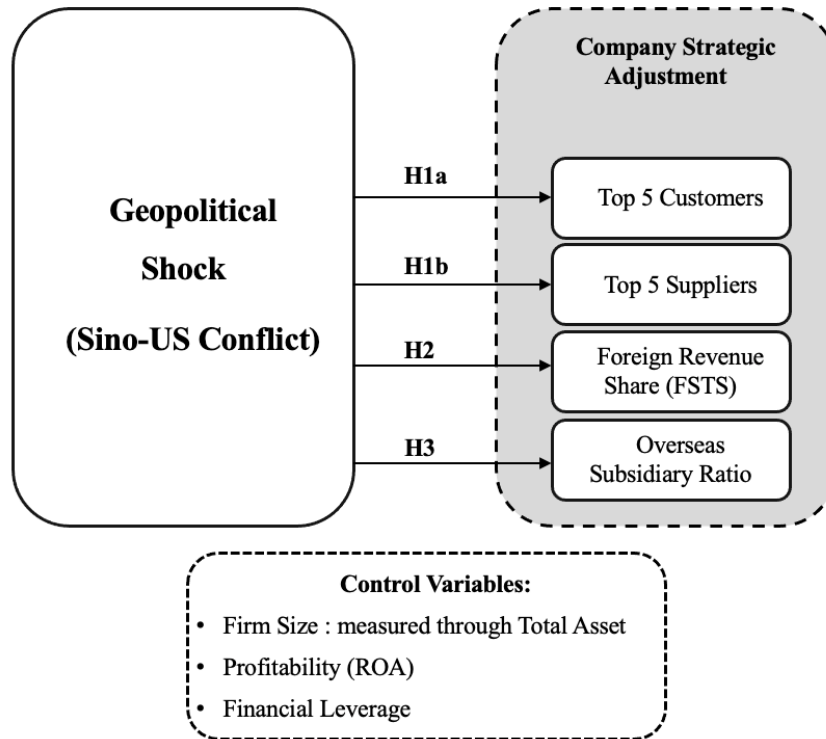


Figure I – Conceptual Framework

The framework also includes control variables that may affect firms' strategic adjustment, including firm size, profitability (ROA), and financial leverage. Overall, the framework presents how geopolitical shocks may lead to observable firm-level changes in global value chain embedding.

### 3. METHODOLOGY

#### *3.1. Research Design*

This study examines whether the escalation of US geopolitical rivalry has affected how Chinese firms are embedded in global value chains. The main objective is to use officially disclosed data (annual reports) to identify evidence of changes in global value chain embedding.

The empirical design adopts a quantitative panel-data approach based on firm-level annual report data. A difference in differences (DID) framework is used to estimate how GVC embedding changed among firms that were more directly exposed to the technological restrictions. The DID approach is widely used in empirical research to identify causal effects by comparing treated and control groups before and after a policy shock (Card and Krueger, 1994; Angrist and Pischke, 2009). For instance, Autor et al. (2013) employ a DID approach to identify the causal effects of import competition on local labor markets. This empirical strategy has since been widely extended to examine micro-level responses to trade and policy shocks (e.g. Flaaen and Pierce, 2019; Fajgelbaum et al., 2020).

The research design is based on the assumption of geopolitical tensions affect different industries in different ways. Industries closely related to technological competition are expected to be more strongly affected. In contrast, firms in less sensitive sectors may experience smaller changes. Therefore, the empirical strategy compares firms across different industry groups over time.

While these measures are based on disclosed major partners rather than complete supply networks, they provide meaningful proxies for firms' positioning within global value chains.

#### *3.2. Data and Sample*

This study uses firm-level data collected from publicly available annual reports of Chinese listed firms through the CSMAR database. The CSMAR (China Stock Market & Accounting Research) database is widely used in academic research and provides comprehensive financial and governance data on Chinese listed firms. The sample covers the period from 2017 to 2024 and includes firms from several industries with different

levels of exposure to U.S. technological competition. The main objective is to use these officially disclosed data to identify evidence of changes in firms' global value chain embedding.

The sample selection followed several steps. First, industries with different degrees of exposure to the Sino–U.S. technological rivalry were identified based on their strategic relevance. Battery and Semiconductor industries were selected as the primary treatment group because they have been directly affected by U.S. export controls and technology restrictions. Electronics and New Energy Vehicle (NEV) industries were included as comparison groups due to their close connections with advanced manufacturing but relatively lower direct exposure. In addition, a control group consisting of firms from industries with limited direct exposure to U.S. technology restrictions was constructed to provide a benchmark for comparison.

Second, all A-share listed firms belonging to these industries were retrieved from the CSMAR database. Firms were then screened according to several criteria. Firms that were delisted during the sample period, lacked continuous annual report disclosures, or had substantial missing information required to construct the main variables (e.g., foreign sales, major customers, major suppliers, or overseas subsidiaries) were excluded. To ensure a balanced panel, only firms with complete observations throughout the sample period (2017–2024) were retained.

Following this screening procedure, the final sample consists of 211 firms and 1,688 firm-year observations. Firms are categorized into five groups based on their industry characteristics: Battery (55 firms), Semiconductor (36 firms), Electronics (40 firms), NEV (40 firms), and a Control group (40 firms). These industries are selected to capture differences in strategic importance and exposure to geopolitical tensions.

The battery and semiconductor industries (91 firms total) are generally considered to be more sensitive in the context of technological competition between China and the United States, particularly due to their strategic importance and exposure to export controls and technology restrictions (e.g., U.S. Department of Commerce, 2022; see also Miller, 2022). In contrast, the other industries in the sample are expected to be less directly affected by technology restrictions and supply chain adjustments. This variation allows us to identify heterogeneous responses across industries.

The Control group consists of 40 listed firms exclusively operating in the general equipment manufacturing sector (e.g., pumps, valves, bearings, machine tools, and industrial instrumentation). These firms serve diversified industrial end-markets such as construction, petrochemicals, and infrastructure, and have minimal direct exposure to U.S. semiconductor or battery export controls. This composition ensures that the Control group is not inadvertently affected by the same technological restrictions, thereby preserving the exclusion restriction in our DID design.

All financial and operational data, including revenue by region, major customer and supplier information, and overseas subsidiary structures, are obtained from the CSMAR database, which compiles information disclosed in firms' annual reports. As these data are originally publicly disclosed, they ensure a certain level of transparency and consistency. These disclosures make it possible to construct several indicators that capture different aspects of firms' global value chain embedding.

### *3.3. Variable Construction*

#### *3.3.1. Dependent Variables: Global Value Chain Embedding*

Given the complexity of global value chain (GVC) participation, this study adopts a multi-indicator approach to capture different dimensions of firms' positions in GVCs (e.g., Antràs, 2020; OECD, 2020). The indicators are constructed from annual report disclosures and organized around the three hypotheses.

To test Hypothesis 1, two variables are used to capture supply chain concentration:

- The top five customer sales ratio measures downstream supply chain concentration. It captures the proportion of total sales accounted for by the five largest customers. This variable is commonly used to reflect customer concentration and dependence (e.g., Patatoukas, 2012).
- The top five supplier purchase ratio measures upstream supply chain concentration. It reflects firms' dependence on key suppliers and is widely adopted in studies on supply chain relationships (e.g., Cen et al., 2017).

To test Hypothesis 2, the foreign revenue share (FSTS) is used:

- The foreign revenue share (FSTS) measures internationalization. It's calculated by dividing overseas revenue by total revenue. It is widely used in the literature to capture firms' international involvement (e.g., Sullivan, 1994; Hitt et al., 1997).

To test Hypothesis 3, the overseas subsidiary ratio is used:

- The ratio calculates the share of overseas subsidiaries over the total number of subsidiaries. This is commonly used to capture firms' international expansion strategies (e.g., Lu & Beamish, 2004).

In addition, geographic diversification is included as a supplementary measure to provide a more detailed view of firms' international market structure:

- This index presents the distribution of revenue across regions (China, Asia, Europe, North America, and other regions). According to Hitt et al. (1997), the entropy measure is defined as:  $E = -\sum(P_i \times \ln P_i)$ , where  $P_i$  represents the share of revenue in region  $i$ . A higher value represents greater geographic diversification (Jacquemin and Berry, 1979; Hitt et al., 1997). This variable is not directly specified in a formal hypothesis. It's helpful to supplements Hypothesis 2 by observing how firms reallocate sales across regions even when the overall foreign sales share remains stable.

### 3.3.2. Key Independent Variables

To identify the impact of escalating Sino-U.S. technological rivalry, this study employs a difference-in-differences (DID) design.

The treatment variable, *Exposure*, equals “1” for firms in the Battery and Semiconductor industries and “0” for the other industries. These sectors are considered to be more directly affected by technological competition and supply chain adjustments.

The policy variable, *Post*, is set to “1” for years starting from 2018; it equals “0” for all earlier years. The study select year 2018 initially as a reference point because it marks the start of trade tensions between the United States and China. This year is commonly used in the literature as the starting point of intensified Sino-US trade and technology tensions (e.g., Amiti, Redding, & Weinstein, 2019; Bown, 2020). The validity of this timing choice will be further examined through break-year identification tests in subsequent analysis.

The DID interaction term is defined as:

$$\mathbf{DID}_{it} = \mathbf{Exposure}_i \times \mathbf{Post}_t$$

This interaction captures the differential change in GVC embedding outcomes for highly exposed firms after the escalation of technological restrictions.

### 3.3.3. Control Variables

Several firm-level control variables are included to account for differences in firm characteristics.

- Firm size is measured by the logarithm of total assets.
- Profitability is captured by return on assets (ROA), calculated as net profit divided by total assets.
- Financial leverage is measured as the ratio of total liabilities on total assets.

All continuous variables are limited at the 1st and 99th percentiles to mitigate the influence of extreme values.

## 3.4. Empirical Strategy

### 3.4.1. Break-year identification

Before estimating the baseline DID model, this study first identifies the most appropriate structural break year. This test is motivated by the fact that although trade tensions emerged in 2018, the technological conflict intensified substantially following the May 2020 expansion of the Foreign Direct Product Rule (FDPR), which restricted Huawei's access to semiconductors manufactured worldwide using U.S. technology. This event marked a qualitative escalation of technology controls and support the needs to clarify whether the initial 2018 trade shock affected firms or a later and more intensive phase of Sino–U.S. technological confrontation led to additional changes in firms' global value chain embedding.

Candidate break years include 2018, 2019, 2020, and 2021. These candidate years are selected based on major policy events and the timeline of escalating Sino–US technological tensions. For each candidate year, a two-way fixed effects model with firm and year fixed effects is estimated. This approach is commonly used in panel data analysis to control for unobserved heterogeneity across firms and over time (e.g., Wooldridge,

2010). The purpose is to compare which timing best captures structural changes in the main GVC embedding indicators.

This procedure allows the empirical design to distinguish between the earlier trade-war phase and the later technology-control phase, which are often discussed as different stages of Sino-U.S. economic tensions (e.g., Bown, 2020; Evenett & Fritz, 2021).

Furthermore, we acknowledge that testing multiple candidates break years may increase the probability of finding statistically significant results by chance. To mitigate this concern, we also conduct an event-study specification and placebo test for cross validation.

### 3.4.2. Baseline DID model

The baseline empirical model is specified as follows:

$$Y_{it} = \beta(\text{Exposure}_i \times \text{Post}_t) + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

where  $Y_{it}$  represents the outcome variables capturing different dimensions of global value chain (GVC) embedding for firm  $i$  in year  $t$ .  $X_{it}$  denotes the vector of control variables.  $\mu_i$  represents firm fixed effects, which control for time-invariant firm characteristics, and  $\lambda_t$  denotes year fixed effects, capturing common macroeconomic shocks. Standard errors are clustered at the firm level to account for within-firm correlation over time (e.g., Bertrand et al., 2004).

The coefficient of interest,  $\beta$ , captures the differential change in GVC embedding outcomes for firms in more exposed industries after the policy shock. In the baseline specification, the policy timing is initially set to 2018, and its validity is further examined in the break-year analysis.

### 3.4.3. Event-study specifications

This study further estimates an event-study specification to examine the dynamic effects of geopolitical shocks and assess the parallel trends assumption. This approach is used in DID settings commonly to analyze how treatment effects evolve over time and to validate the identification strategy (e.g., Angrist & Pischke, 2009).

In this specification, the single DID interaction term is replaced by a set of interactions between the treatment indicator and a series of event-time dummies defined relative to

the policy year. Each coefficient captures the difference between treated and control firms in a specific year relative to the policy shock. The year immediately preceding the policy shock is used as the reference period.

This setup allows us to trace the evolution of treatment effects both before and after the policy shock. In particular, the coefficients for the pre-treatment periods provide a direct test of the parallel trends assumption. If these coefficients are close to zero and not statistically significant, it suggests that treated and control firms followed similar trends before the shock.

For the post-treatment periods, the estimated coefficients show how the effects develop over time, indicating whether the impact of technological restrictions is immediate or gradual. This provides additional evidence on the timing and dynamics of firms' global value chain restructuring.

#### 3.4.4. Robustness, heterogeneity, and mechanism tests

To strengthen the credibility of the empirical results, this study conducts several additional analyses:

- Robustness checks are implemented by redefining the treatment group to examine whether the results are sensitive to alternative classifications of exposed industries. Such robustness analyses are commonly used to assess the stability of empirical findings (e.g., Bertrand et al., 2004; Cameron et al., 2008).
- Placebo tests are implemented by assigning false policy years to verify that the main findings are not driven by earlier shocks or pre-existing trends. It is widely used in DID studies to validate causal identification (e.g., Bertrand et al., 2004; Abadie et al., 2010).
- Industry heterogeneity is implemented by estimating treatment effects separately for the Battery, Semiconductor, Electronics, NEV, and Control groups. This allows to capture potential differences across industries with varying levels of exposure (e.g., Autor et al., 2013; Flaaen and Pierce, 2019).
- Mechanism analysis explores whether firms adjust their global value chain positions mainly through changes in customer-side concentration or supplier-side concentration (e.g., Flaaen and Pierce, 2019).

### *3.5. Feasibility and Ethical Considerations*

#### *3.5.1. Feasibility*

This study is feasible in terms of data availability, empirical methods, and research resources.

The data used in the analysis are publicly disclosed and easy to access via the CSMAR database. This database gathers information from firms' annual reports. Academic research frequently uses these data, as they provide reliable details on firms' financial performance, supply chain relationships and overseas operations.

Moreover, the study is feasible in terms of research resources. The data can be obtained by standard academic tools. The econometric analysis can be conducted with commonly used statistical software as well. Thus, the project does not depend on proprietary databases or highly specialized infrastructure.

#### *3.5.2. Ethical Considerations*

This study does not involve human participants, interviews, surveys, or experimental interventions of any kind. Instead, it only relies exclusively on publicly available corporate disclosures in annual reports and other related documents.

Because all data sources were public, the risk of confidentiality issues is very low. No personally identifiable information is included in the analysis. For this reason, there are few ethical concerns regarding privacy.

In addition, the study follows the principle of transparency. Data sources, sample selection procedures, variable construction and empirical models are all clearly documented. This allows the research process to be assessed and, when possible, replicated.

#### *3.5.3. AI-Assisted Literature and Data Screenings*

Artificial intelligence tools were used as an assistant throughout the research process. In particular, they supported the screening of relevant academic literature, including the search for related studies and the summarization of key findings. They also assisted in exploring appropriate empirical model specifications based on the research objectives, while the final model selection and research design decisions were made by the researcher.

In addition, AI tools were used to check variable consistency, support basic programming tasks, and improve grammar and writing clarity.

However, these tools did not replace academic judgment. All key decisions related to research design, literature selection, variable definition, sample construction, model specification, and result interpretation are made and validated by the researcher.

To ensure academic integrity, output generated with the help of AI was treated as preliminary support rather than as a final analytical product. While AI tools may assist with coding, all empirical results are generated, verified, and interpreted by the researcher. All final analytical decisions are based on publicly available sources, clearly defined coding procedures, and the researcher's own evaluation.

#### 4. EMPIRICAL RESULTS

This chapter presents the empirical findings in a structured and step-by-step manner. The analysis begins with a description of the sample, then identifies the most appropriate break year, followed by the estimation of the baseline DID model, and then proceeds to robustness, heterogeneity, and mechanism analyses.

The main empirical objective is to identify when key structural changes occur. In particular, the analysis distinguishes between the initial phase of the U.S.–China trade tensions and the later phase characterized by intensified technological controls. This distinction is important because the study aims not only to assess whether firms are affected by geopolitical tensions, but also to understand when these effects emerge and through which channels firms' global value chain embedding adjusts.

##### *4.1. Sample Description*

The final sample consists of 211 Chinese listed firms observed over the period 2017–2024, resulting in 1,688 observations. The sample period covers both the pre- and post-phases of Sino–U.S. technological tensions, allowing for a comparison of firm behaviors before and after the geopolitical shock.

The sample is constructed by selecting firms operating in industries relevant to technological competition, including Battery, Semiconductor, Electronics, New Energy Vehicles (NEV) and the control group. Firms that were delisted during the sample period are excluded to ensure data consistency. In addition, the sample contains firms with sufficient availability of financial and segment disclosure data only to ensuring the reliability of firm-level indicators.

In terms of industry composition (Table I), Battery firms account for the largest share of the sample, with 55 firms (26.1%), followed by Electronics, NEV, and Control firms with 40 firms each (19.0% each). Semiconductor firms account for 36 firms (17.1%). This distribution reflects the strategic importance of these industries in the context of Sino–U.S. technological competition. Particularly given on their central role in global value chains and their exposure to technological restrictions and export controls (U.S. Department of Commerce, 2022).

Table I - Industry Composition Summary

| Industry      | Number of firms | Percentage |
|---------------|-----------------|------------|
| Battery       | 55              | 26.1%      |
| Semiconductor | 36              | 17.1%      |
| Electronics   | 40              | 19.0%      |
| NEV           | 40              | 19.0%      |
| Control       | 40              | 19.0%      |
| Total         | 211             | 100.0%     |

Geographically, firms are concentrated in the economically developed provinces, with the top three all located in coastal regions (Table II). This regional distribution presents the heavy clustering of advanced manufacturing and high-technology industries in China's coastal regions.

Table II - Geographical Composition

| Provinces/City | Number of firms | Percentage |
|----------------|-----------------|------------|
| Guangdong      | 58              | 27.5%      |
| Zhejiang       | 29              | 13.7%      |
| Jiangsu        | 28              | 13.3%      |
| Shanghai       | 15              | 7.1%       |
| Shandong       | 13              | 6.2%       |
| Beijing        | 11              | 5.2%       |
| Hubei          | 7               | 3.3%       |
| Hunan          | 7               | 3.3%       |
| Fujian         | 6               | 2.8%       |
| Others         | 12              | 12.3%      |
| Total          | 211             | 100.0%     |

Descriptive statistics (Table III - V) reports the distribution of the key sample variables. The sample distribution is generally in line with the expected characteristics of Chinese listed firms engaged in global value chains. The tables display observable foreign market involvement, as reflected in the distribution of foreign sales intensity and geographic diversification. Meanwhile, the distributions of customer and supplier concentration suggest that the sample firms maintain established upstream and downstream supply chain relationships.

Table III - Distribution of FSTS

| FSTS          | Count       | Percentage  |
|---------------|-------------|-------------|
| 0.00%-9.99%   | 580         | 34.4%       |
| 10.00%-19.99% | 290         | 17.2%       |
| 20.00%-29.99% | 223         | 13.2%       |
| 30.00%-39.99% | 98          | 5.8%        |
| 40.00%-49.99% | 117         | 6.9%        |
| 50.00%-59.99% | 114         | 6.8%        |
| <b>Total</b>  | <b>1688</b> | <b>100%</b> |

(Detailed count in years could be found in appendix)

Table IV - Distribution of Top5\_Customer/Supplier\_Share

|                        | Top5_Customer_Share |             | Top5_Supplier_Share |             |
|------------------------|---------------------|-------------|---------------------|-------------|
|                        | Count               | Percentage  | Count               | Percentage  |
| <b>Less than 20%</b>   | 396                 | 23.5%       | 449                 | 26.6%       |
| <b>20.00%-39.99%</b>   | 531                 | 31.5%       | 738                 | 43.7%       |
| <b>40.00%-59.99%</b>   | 407                 | 24.1%       | 322                 | 19.1%       |
| <b>60.00%-79.99%</b>   | 270                 | 16.0%       | 136                 | 8.1%        |
| <b>80.00% or above</b> | 84                  | 5.0%        | 43                  | 2.6%        |
| <b>Total</b>           | <b>1688</b>         | <b>100%</b> | <b>1688</b>         | <b>100%</b> |

(Detailed count in years could be found in appendix)

Table V - Distribution of Geo\_entropy

| Geo_entropy                          | Count       | Percentage  |
|--------------------------------------|-------------|-------------|
| <b>No geographic diversification</b> | 172         | 10.2%       |
| <b>Low diversification</b>           | 758         | 45.2%       |
| <b>Moderate diversification</b>      | 713         | 42.5%       |
| <b>High diversification</b>          | 36          | 2.1%        |
| <b>Total</b>                         | <b>1679</b> | <b>100%</b> |

(Detailed count in years could be found in appendix)

In addition, firm age, total assets, and total revenue are included to describe the basic structure of the sample firms (Table VI – VII). Although the number of employees is not consistently available in the annual report data used in this study, financial indicators provide an alternative way to capture firm scale.

Table VI - Distribution of Firm Age

| Firm Age                  | Count | Percentage |
|---------------------------|-------|------------|
| Between 5 and 9.9 years   | 18    | 1.1%       |
| Between 10 and 14.9 years | 184   | 10.9%      |
| Between 15 and 19.9 years | 492   | 29.2%      |
| Between 20 and 24.9 years | 539   | 31.9%      |
| Between 25 and 29.9 years | 296   | 17.5%      |
| Between 30 and 34.9 years | 101   | 6.0%       |
| Between 35 and 39.9 years | 44    | 2.6%       |
| 40 or more than 40 years  | 14    | 0.8%       |
| Total                     | 1688  | 100%       |

(Detailed count in years could be found in appendix)

Table VII - Distribution of Financial Status

|                          | Total Revenue |            | Total Assets |            |
|--------------------------|---------------|------------|--------------|------------|
|                          | Count         | Percentage | Count        | Percentage |
| Less than 1 billion RMB  | 106           | 6.3%       | 223          | 13.2%      |
| 1-4.99 billion RMB       | 520           | 30.8%      | 684          | 40.5%      |
| 5-9.99 billion RMB       | 396           | 23.5%      | 307          | 18.2%      |
| 10-49.99 billion RMB     | 527           | 31.2%      | 364          | 21.6%      |
| 50-99.99 billion RMB     | 55            | 3.3%       | 42           | 2.5%       |
| 100 billion RMB or above | 84            | 5.0%       | 68           | 4.0%       |
| Total                    | 1688          | 100%       | 1688         | 100%       |

(Detailed count in years could be found in appendix)

Overall, the sample exhibits substantial variation across firm scale, industries, locations, international exposure, and supply chain structures. This variation provides a suitable basis for examining how geopolitical shocks affect firms' positions within global value chains.

Table VIII - Descriptive Statistics of Continuous Variables

| Firm Age            | MEAN  | SD   | MIN   | MAX   |
|---------------------|-------|------|-------|-------|
| FSTS                | 0.27  | 0.26 | -     | 0.96  |
| TOP5_CUSTOMER_SHARE | 0.39  | 0.22 | 0.01  | 1.00  |
| TOP5_SUPPLIER_SHARE | 0.33  | 0.19 | 0.04  | 1.00  |
| OVERSEAS_SUB_RATIO  | 0.15  | 0.17 | -     | 1.00  |
| LOG_ASSETS          | 22.80 | 1.40 | 18.09 | 27.64 |
| ROA                 | 0.04  | 0.06 | -0.71 | 0.43  |
| LEVERAGE            | 0.46  | 0.17 | 0.03  | 0.98  |

#### 4.2. Identifying the Break Year

The first empirical step is to compare alternative break years and identify the specific year of the structural change. The study takes years 2018, 2019, 2020, and 2021 into consideration and tests on three key factors: the magnitude of the DID coefficient ( $\beta$ ), its statistical significance (p-value), and the consistency of results across different GVC indicators.

The results (Table IX) show that earlier candidate years have small coefficients and are statistically not significant across all outcome variables. For 2018 and 2019, the estimated coefficients of FSTS remain around  $-0.02$  with p-value greater than 0.3. Both results are not statistically significant. Similarly, geographic diversification (Geo\_entropy) shows coefficients close to 0 with very high p-values which also indicates no detectable effect.

Table X – Results for Break Year Tests

|                     | Year | Count <sup>1</sup> | Coef_did     | SE_did | T_did  | P_did        | adj_R <sup>2</sup> |
|---------------------|------|--------------------|--------------|--------|--------|--------------|--------------------|
| FSTS                | 2018 | 1688               | -0.019       | 0.019  | -1.001 | 0.317        | 0.879              |
| FSTS                | 2019 | 1688               | -0.017       | 0.019  | -0.911 | 0.362        | 0.879              |
| FSTS                | 2020 | 1688               | -0.021       | 0.018  | -1.148 | 0.251        | 0.879              |
| FSTS                | 2021 | 1688               | -0.033       | 0.019  | -1.749 | 0.080        | 0.880              |
| Geo_entropy         | 2018 | 1679               | 0.000        | 0.022  | 0.018  | 0.986        | 0.845              |
| Geo_entropy         | 2019 | 1679               | 0.005        | 0.021  | 0.219  | 0.826        | 0.845              |
| Geo_entropy         | 2020 | 1679               | -0.003       | 0.021  | -0.149 | 0.881        | 0.845              |
| Geo_entropy         | 2021 | 1679               | -0.016       | 0.021  | -0.756 | 0.450        | 0.846              |
| Top5_Customer_Share | 2018 | 1688               | 0.022        | 0.017  | 1.258  | 0.209        | 0.862              |
| Top5_Customer_Share | 2019 | 1688               | 0.022        | 0.016  | 1.364  | 0.173        | 0.862              |
| Top5_Customer_Share | 2020 | 1688               | <b>0.029</b> | 0.016  | 1.795  | <b>0.073</b> | 0.863              |
| Top5_Customer_Share | 2021 | 1688               | <b>0.043</b> | 0.016  | 2.605  | <b>0.009</b> | 0.864              |
| Top5_Supplier_Share | 2018 | 1688               | 0.007        | 0.016  | 0.459  | 0.647        | 0.806              |
| Top5_Supplier_Share | 2019 | 1688               | 0.007        | 0.015  | 0.477  | 0.634        | 0.806              |
| Top5_Supplier_Share | 2020 | 1688               | 0.012        | 0.016  | 0.764  | 0.445        | 0.806              |

<sup>1</sup> The variation in the number of observations across regressions (1,688 for FSTS; 1,679 for Geo\_entropy; 1,641 for Overseas\_Sub\_Ratio) is due to missing disclosures in annual reports. Specifically, 9 firm-year observations lack geographical revenue breakdowns required for entropy calculation, and 47 observations lack subsidiary location details. These missing values are attributable to reporting heterogeneity rather than systematic firm selection, as all firms remain in the panel for other indicators.

|                            |      |      |        |       |        |       |       |
|----------------------------|------|------|--------|-------|--------|-------|-------|
| <b>Top5_Supplier_Share</b> | 2021 | 1688 | 0.021  | 0.016 | 1.332  | 0.183 | 0.807 |
| <b>Overseas_Sub_Ratio</b>  | 2018 | 1641 | -0.011 | 0.015 | -0.741 | 0.459 | 0.870 |
| <b>Overseas_Sub_Ratio</b>  | 2019 | 1641 | -0.014 | 0.013 | -1.096 | 0.273 | 0.870 |
| <b>Overseas_Sub_Ratio</b>  | 2020 | 1641 | -0.011 | 0.012 | -0.956 | 0.339 | 0.870 |
| <b>Overseas_Sub_Ratio</b>  | 2021 | 1641 | -0.011 | 0.011 | -0.953 | 0.340 | 0.870 |

The results become stronger when later break years are considered. This pattern is most evident in the customer concentration variable (*top5\_customer\_share*). Year 2020 coefficient increases to 0.029 with a p-value of 0.073, which is marginal significant compared to earlier years. The coefficient of year 2021 further increases to 0.043 and is statistically significant with a p-value of 0.009. By contrast, other variables do not show significant results.

Overall, year 2018 does not present clear effects on the GVC structural changes. Instead, year 2020 and 2021 show more noticeable results. Based on these results, the break-year analysis offers initial support for using a later policy timing in the baseline specification. This timing better captures the period when firms start to adjust their global value chain structures.

#### 4.3. Baseline Results

Table X reports the baseline DID estimates for the main GVC embedding indicators.

Table XI - Results for baseline DID estimates

|                            | N_Firms | Count | Coef_did     | SE_did | T_did        | P_did        | adj_R <sup>2</sup> |
|----------------------------|---------|-------|--------------|--------|--------------|--------------|--------------------|
| <b>FSTS</b>                | 211     | 1688  | -0.021       | 0.018  | -1.148       | 0.251        | 0.879              |
| <b>Geo_entropy</b>         | 211     | 1679  | -0.003       | 0.021  | -0.149       | 0.881        | 0.845              |
| <b>Top5_customer_share</b> | 211     | 1688  | <b>0.029</b> | 0.016  | <b>1.795</b> | <b>0.073</b> | 0.863              |
| <b>Top5_supplier_share</b> | 211     | 1688  | 0.012        | 0.016  | 0.764        | 0.445        | 0.806              |
| <b>Overseas_sub_ratio</b>  | 209     | 1641  | -0.011       | 0.012  | -0.956       | 0.339        | 0.870              |

The interaction term **Exposure** × **Post<sub>2020</sub>** of positive and marginally significant for the top five customer sales ratio. The estimated coefficient is 0.029 with a p-value equals to 0.073. This indicates that firms in more exposed industries increased their customer concentration by approximately 2.9 percentage points after the policy shock. Although the significance level is slightly above the standard 5% threshold, it is statistically significant at the 10% level. Given the sample mean of *Top5\_Customer\_Share* is approximately 39%, this represents a roughly 7.4% relative increase in customer

concentration, suggesting that the effect is economically meaningful despite being only marginally statistically significant. This finding indicates that firms in strategically exposed industries do not show a significant reduction in their overall international activities. Instead, they adjusted their downstream relationships to a smaller number of key customers. The pattern shows a shift toward more concentrated and possibly more stable demand-side connections.

In contrast, the other GVC indicators do not show statistically significant effects. For foreign revenue share (FSTS), the estimated coefficient is  $-0.021$  with a p-value of  $0.251$ , indicating that there is no significant change in firms' overall level of internationalization. Similarly, geographic diversification (*geo\_entropy*) shows a coefficient close to zero ( $-0.003$ ) with a very high p-value ( $0.881$ ), suggesting no statistically significant adjustment in the geographic distribution of sales.

On the supply side, top five supplier share has a positive coefficient ( $0.012$ ), but it is not statistically significant ( $p = 0.445$ ). It indicates there's no clear evidence of increased supplier concentration. In addition, the overseas subsidiary ratio shows a small negative coefficient ( $-0.011$ ) that is also not statistically significant ( $p = 0.339$ ). It suggests that firms did not implement large adjustments on their overseas organizational deployment in the short to medium term.

Overall, the baseline results lead to a pattern: rather than through a broad restructuring of international activities or supply chains, the main adjustment in response to geopolitical shocks occurs on the customer dimension. This pattern highlights that firms' global value chain embedding may become more concentrated on the demand side, while other dimensions remain relatively stable in the short run. This may reflect firms' short-term strategy of stabilizing demand relationships under increased uncertainty.

#### *4.4. Dynamic Effects: Event Study*

To further examine the timing and dynamics of the treatment effects, this study estimates an event-study specification. The interpretation focuses on the estimated coefficients in each period, their statistical significance, and the corresponding confidence intervals (Table XI).

Table XIII - Results for Dynamic Effects

|             | Event_Time | Coef         | SE    | T      | P            | CI_low | CI_high |
|-------------|------------|--------------|-------|--------|--------------|--------|---------|
| <b>2017</b> | -3         | -0.001       | 0.016 | -0.083 | 0.934        | -0.033 | 0.030   |
| <b>2018</b> | -2         | 0.004        | 0.011 | 0.334  | 0.738        | -0.018 | 0.026   |
| <b>2019</b> | -1         | -0.009       | 0.012 | -0.747 | 0.455        | -0.031 | 0.014   |
| <b>2020</b> | 0          | 0.018        | 0.014 | 1.234  | 0.217        | -0.011 | 0.046   |
| <b>2021</b> | 1          | <b>0.065</b> | 0.019 | 3.428  | <b>0.001</b> | 0.028  | 0.102   |
| <b>2022</b> | 2          | <b>0.046</b> | 0.021 | 2.244  | <b>0.025</b> | 0.006  | 0.087   |
| <b>2023</b> | 3          | <b>0.039</b> | 0.021 | 1.854  | <b>0.064</b> | -0.002 | 0.080   |

The pre-treatment coefficients provide support for the parallel trends' assumption. Specifically, the estimates for 2017 (event time = -3) and 2018 (event time = -2) are very close to zero (-0.001 and 0.004) and not statistically significant with p-value equals to 0.934 and 0.738. In addition, their confidence intervals include zero. These results suggest that there is no evidence of systematic differences in trends between treated and control firms before the policy shock.

As for the post-treatment periods, the estimated effects become positive gradually. The initial short-term response in 2020 (event time = 0) remains limited with a low coefficient of 0.018 and not significant p-value of 0.217. The effect becomes stronger starting from 2021 (event time = 1). The coefficient increases to 0.065 and is significant with p-value equals 0.001 and a confidence interval that is fully above zero. This suggests a clear and economically relevant increase in customer concentration.

The effect remains positive in following years and gradually stabilizes. The 2022 (event time = 2) coefficient is 0.046 and statistically significant with p-value of 0.025. By 2023 (event time = 3), it moderates to 0.039 and is only marginally significant with p-value equals to 0.064 and the confidence interval slightly overlaps with zero.

Overall, the dynamic pattern shows that the adjustment in firms' customer relationships does not occur immediately in the shock year. Instead, the effect appears slowly and only becomes clear around 2021. After that, it stays about the same.

This evidence reinforces what the break year and baseline DID analysis already suggested. The main structural change happens after 2020, and firms seem to adjust gradually rather than immediately change all at once. This gradual adjustment further

supports with the idea that firms need time to renegotiate contracts, reallocate demand and reorganize their customer networks.

#### 4.5. Robustness Tests

To examine whether the baseline results are sensitive to the definition of the treatment group, this study considers two alternative specifications (Table XII). The interpretation focuses on the estimated coefficients, their statistical significance (p-values), and the consistency of results across different outcome variables.

Table XIII - Results for Robustness Tests

| Group   | Name                                        | Outcome             | N    | Coef   | P     | ADJ_R <sup>2</sup> |
|---------|---------------------------------------------|---------------------|------|--------|-------|--------------------|
| Treat_A | Battery +<br>Semiconductor                  | FSTS                | 1688 | -0.021 | 0.251 | 0.879              |
|         |                                             | Geo_Entropy         | 1679 | -0.003 | 0.881 | 0.845              |
|         |                                             | Top5_Customer_Share | 1688 | 0.029  | 0.073 | 0.863              |
|         |                                             | Top5_Supplier_Share | 1688 | 0.012  | 0.445 | 0.806              |
|         |                                             | Overseas_Sub_Ratio  | 1641 | -0.011 | 0.339 | 0.870              |
| Treat_B | Semiconductor<br>only                       | FSTS                | 1688 | -0.001 | 0.986 | 0.879              |
|         |                                             | Geo_Entropy         | 1679 | 0.012  | 0.718 | 0.845              |
|         |                                             | Top5_Customer_Share | 1688 | -0.015 | 0.490 | 0.862              |
|         |                                             | Top5_Supplier_Share | 1688 | 0.004  | 0.852 | 0.806              |
|         |                                             | Overseas_Sub_Ratio  | 1641 | -0.019 | 0.283 | 0.870              |
| Treat_C | Battery only                                | FSTS                | 1688 | -0.025 | 0.208 | 0.879              |
|         |                                             | Geo_Entropy         | 1679 | -0.012 | 0.611 | 0.845              |
|         |                                             | Top5_Customer_Share | 1688 | 0.045  | 0.020 | 0.864              |
|         |                                             | Top5_Supplier_Share | 1688 | 0.012  | 0.529 | 0.806              |
|         |                                             | Overseas_Sub_Ratio  | 1641 | 0.000  | 0.992 | 0.869              |
| Treat_D | Battery +<br>Semiconductor +<br>Electronics | FSTS                | 1688 | -0.018 | 0.327 | 0.879              |
|         |                                             | Geo_Entropy         | 1679 | -0.038 | 0.048 | 0.847              |
|         |                                             | Top5_Customer_Share | 1688 | 0.008  | 0.587 | 0.862              |
|         |                                             | Top5_Supplier_Share | 1688 | 0.019  | 0.172 | 0.807              |
|         |                                             | Overseas_Sub_Ratio  | 1641 | -0.012 | 0.346 | 0.870              |

(Detailed could be found in appendix)

In the baseline specification in Battery and Semiconductor industries, the main result is observed from customer concentration (`top5_customer_share`). The estimated coefficient is 0.029 with p-value equals to 0.073. It shows a positive and marginally significant effect. This suggests firms in battery and semiconductor industries increased their reliance on major customers after the policy shock. In contrast, other indicators such as FSTS, geographic diversification, supplier concentration, and overseas subsidiary ratio remain statistically not significant.

When the treatment group is restricted to Semiconductor firms only, the results become much weaker. The coefficient for customer concentration turns negative ( $-0.015$ ) and is statistically not significant ( $p = 0.490$ ). All other variables also remain not significant, with very small coefficients. This indicates that the baseline effect is not driven solely by semiconductor firms. One possible explanation is the smaller sample size, which may reduce statistical power, but it may also suggest that the adjustment is not uniform within this sector.

When samples are limited to Battery industry, the result for customer concentration increased significantly. The `top5_customer_share` estimated coefficient increases to 0.045 and becomes statistically significant at the 5% level ( $p = 0.020$ ). This suggests that Battery firms significantly increased their dependence on core major customers after the policy shock than the broader group. In contrast, the estimated results for FSTS, geographic diversification, supplier concentration, and overseas subsidiary ratio remain statistically not significant. Although the coefficient for supplier concentration is positive, the value is relatively low (0.012,  $p = 0.529$ ). This indicates that the strategic adjustments of sample firms are concentrated on downstream clients in the supply chain. In summary, the core empirical results of the baseline effect are mainly driven by firms in the Battery sector, which shows more sensitivity in geopolitical tensions and technological competition.

A different pattern appears when the treatment group is expanded to Battery, Semiconductor and Electronics firms. The effect on customer concentration becomes small (0.008) and not statistically significant ( $p = 0.587$ ). It indicates the baseline result becomes weaker. At the same time, geographic diversification (`geo_entropy`) becomes negative and statistically significant (coefficient =  $-0.038$ ,  $p = 0.048$ ). This suggests that firms in the broader high-technology sector didn't respond to external shocks by adjusting

the concentration of customer collaborations. Instead, they choose to shrink their sales regions and reduce the level of regional diversification of their business.

Overall, these results show that the baseline finding is sensitive to how the treatment group is defined. When the analysis focuses on Battery firms only, the increase in customer concentration becomes stronger and statistically significant. In contrast, the effect disappears when the treatment group is restricted to Semiconductor firms only and becomes weaker again when Electronics firms are included in the broader treatment group.

The results suggest that the value chain adjustments caused by geopolitical shocks are not common feature in high-technology industries. Instead, such effects are highly concentrated in the battery industry, where the impact of geopolitical tensions and strategic technological competition is more noticeable. Although the Battery-only specification shows the strongest effect, the full sample setting of the benchmark is still reasonable. The sample includes multiple strategic industries while still preserving the adjustment dynamics observed in Battery firms. Differences in sensitivity between industries further confirm that accurately defining the industry samples is crucial in geopolitical empirical analysis.

#### 4.6. Placebo Tests

To further check whether the identification strategy is reliable, this study carries out placebo tests. The policy shock timing is set to year 2018 and 2019. The observations focus on the estimated coefficients and their statistical significance of outcome variables (Table XIII).

Table XIV - Results for Placebo Tests

| Year | Event_time          | Coef   | P-value      |
|------|---------------------|--------|--------------|
| 2018 | FSTS                | -0.019 | 0.317        |
| 2018 | Top5_Customer_Share | 0.022  | <b>0.209</b> |
| 2018 | Top5_Supplier_Share | 0.007  | 0.647        |
| 2018 | Overseas_Sub_Ratio  | -0.011 | 0.459        |
| 2019 | FSTS                | -0.017 | 0.362        |
| 2019 | Top5_Customer_Share | 0.022  | <b>0.173</b> |
| 2019 | Top5_Supplier_Share | 0.007  | 0.634        |
| 2019 | Overseas_Sub_Ratio  | -0.014 | 0.273        |
| 2020 | FSTS                | -0.021 | 0.251        |

|      |                     |        |              |
|------|---------------------|--------|--------------|
| 2020 | Top5_Customer_Share | 0.029  | <b>0.073</b> |
| 2020 | Top5_Supplier_Share | 0.012  | 0.445        |
| 2020 | Overseas_Sub_Ratio  | -0.011 | 0.339        |

Setting the policy year to 2018 or 2019 shows no significant results across all variables. The customer concentration coefficient ( $\beta=0.022$ ) remains positive but still not significant in both years. These results confirm the absence of systematic adjustment during the initial tariff shock period.

In contrast, when setting to year 2020, the customer concentration coefficient increases to  $\beta=0.029$  and becomes marginally significant with p-value of 0.073. At the same time, the other outcome variables remain not statistically significant.

Overall, the placebo tests show that assigning earlier policy years does not generate statistically significant treatment effects. Only when the policy timing corresponds to 2020 does a meaningful effect emerge, and this effect is concentrated on the customer side.

This evidence supports the validity of the identification strategy. It shows that the main results are unlikely to be driven by pre-existing trends or earlier trade tensions. Instead, the evidence aligns better with the scenario that, after 2020, firms restructure their global value chain connections as a reaction to tightened technology controls. This result also aligns with the event-study as the significant effects only show after 2020.

#### 4.7. Industry Heterogeneity

The heterogeneity analysis further examines whether the baseline effect is different across industries. This part focuses specifically on customer concentration, measured by the top five customer sales ratio (top5\_customer\_share). In the heterogeneity test, each industry group is separately treated as the exposed group. The DID model is re-estimated using the same set of controls and fixed effects. The model includes firm and year fixed effects, with standard errors clustered at the firm level (Table XIV).

Table XVV - Results for Industry Heterogeneity

| Industry             | Coef         | P-value      |
|----------------------|--------------|--------------|
| <b>Battery</b>       | <b>0.045</b> | <b>0.020</b> |
| <b>Semiconductor</b> | -0.015       | 0.490        |
| <b>Electronics</b>   | -0.031       | 0.103        |

|         |        |       |
|---------|--------|-------|
| NEV     | -0.014 | 0.362 |
| Control | 0.003  | 0.881 |

The results show clear differences across industries. Among all groups, the Battery industry exhibits the strongest and only statistically significant effect among the groups. The estimated coefficient is  $\beta=0.045$  with a p-value of 0.020, indicating that battery firms increased their top five customer sales ratio by about 4.5 percentage points after 2020, relative to firms in the comparison group.

In contrast, the Semiconductor industry does not show a statistically significant effect. Its estimated coefficient is  $-0.015$  with a p-value of 0.490, suggesting no clear post-2020 increase in customer concentration. The NEV industry also shows a small and statistically not significant coefficient ( $\beta=-0.014$ ,  $p = 0.362$ ), while the Control group remains close to zero ( $\beta=0.003$ ,  $p = 0.881$ ).

The Electronics industry shows a negative coefficient ( $\beta=-0.031$ ) and is closer to significance ( $p = 0.103$ ), although it does not reach conventional significance levels. This pattern differs from the Battery sector and that firms in the Electronics sector do not show a clear increase in customer concentration.

Overall, the heterogeneity results indicate that the adjustment observed in the baseline model is mainly driven by the Battery industry which align with the robustness tests results. The change does not take place evenly across all exposed sectors. This finding suggests that geopolitical shocks affect customer-side GVC restructuring within a narrower group of strategically sensitive industries. One possible reason for this could be the deep global integration of the battery sector and its acute exposure to policy shifts. Supply chain adjustments in new energy technologies have placed this industry in an important position, and the data appear to reflect that pressure.

#### 4.8. Mechanism Analysis

The final empirical step explores the mechanism behind the observed changes. The analysis mainly focuses on the Battery industry, which is identified as the main driver in the heterogeneity analysis.

To explore the adjustment channels, two outcome variables are considered: customer concentration (top5\_customer\_share) and supplier concentration (top5\_supplier\_share).

Following the same DID framework, Battery firms are defined as the treated group, and the interaction term captures the change after 2020. The model includes firm and year fixed effects, along with standard control variables, and standard errors are clustered at the firm level (Table XV).

Table XVI - Results for Mechanism Analysis

| Battery Industry    | Coef  | P     |
|---------------------|-------|-------|
| Top5_customer_share | 0.045 | 0.020 |
| Top5_supplier_share | 0.012 | 0.529 |

The customer concentration, with the estimated coefficient of  $\beta=0.045$  and a p-value of 0.020, presents a positive and statistically significant effect at the 5% level. This implies that Battery firms increased their reliance on major customers by approximately 4.5 percentage points after 2020, relative to other firms. In contrast, for supplier concentration, the estimated coefficient is  $\beta=0.012$  and statistically not significant ( $p = 0.529$ ). Although the coefficient is positive, its magnitude is small and not distinguishable from zero, suggesting no systematic change in firms' dependence on major suppliers.

Taken together, these results indicate that the restructuring process is concentrated on the downstream side rather than the upstream side. The significance of the customer-side effect, combined with the absence of a supplier-side response, suggests that firms are more likely to adjust their demand relationships rather than their input sourcing strategies.

One possible interpretation is that in order to enhance stability and reduce demand-side risks from geopolitical uncertainty, firms consolidated sales toward fewer core customers. By contrast, adjusting supplier networks often brings higher switching costs, longer contract periods and more complex operational changes. Such adjustments are thus less likely to appear within the research time frame. This pattern also matches with the nature of disclosed data, which are more likely to capture stable customer relationships than complex supplier networks.

Overall, the mechanism analysis provides consistent evidence that the observed changes in global value chain embedding are driven by a shift toward more concentrated downstream relationships, rather than a broad reconfiguration of both upstream and downstream structures.

## 5. CONCLUSION

This study explores whether the escalation of Sino-US geopolitical competition is reshaping how Chinese firms are embedded in global value chains. More specifically, it responds to the core research question: Do Chinese firms adjust their supply chain relationships and international activities in response to geopolitical shocks? The answer provided by this study is that Chinese firms do adjust, but this adjustment is gradually selective rather than dramatically comprehensive.

Compared to previous studies in macro-level adjustments under geopolitical tensions (e.g., Amiti et al., 2019; Alfaro and Chor, 2023; Selwyn et al., 2025), this study uses annual report panel data from Chinese listed firms from 2017 to 2024 to construct firm-level GVC metrics. Indicators include foreign revenue share, geographic diversification, customer concentration, supplier concentration, and overseas subsidiary deployment. This study uses a difference-in-differences model method to compare companies in high-risk and low-risk industries.

The empirical results present several important findings.

First, the structural change did not occur during the earlier phase of trade tensions but occurs after 2020. This pattern supports the main adjustment of GVC is associated with the technological tension than the initial tariff shocks.

Second, the baseline DID results provide partial support for the Hypothesis 1 that geopolitical shocks alter supply chain relationships. The significant change occurs in customer concentration while the other indicators (foreign revenue share, geographic diversification, supplier concentration, and overseas subsidiary ratio) do not show statistically significant changes. This suggests that firms make selective downstream adjustments instead of reducing their international exposure nor reorganizing their production structures immediately.

Third, there is clear evidence of industry heterogeneity. The effect is concentrated in the Battery industry, which indicates that the observed adjustment is not common across all high-technology sectors but is driven by a more specific group of strategically exposed industries.

Finally, the mechanism analysis provides further support for Hypothesis 1 by showing the adjustment takes place mainly on the downstream side. It confirms that firms appear less motivated to adjust upstream supply chains in the short term. One possible explanation is that upstream supply chain relationships are more rigid and costly to reorganize in the short term. Therefore, firms choose to reorganize their demand-side connections instead.

In summary, the response to the research question is that Chinese firms do adjust their supply chain relationships in response to geopolitical shocks but the adjustment is limited, selective, and mainly concentrated on the customer side. Firms do not withdraw broadly from global markets under the context of intensified geopolitical tensions. Instead, they choose to reshape their embedment in global value chains. The most obvious adjustment comes from more concentrated customer relationships in certain strategically sensitive industries. These changes are partially observable through firm-level disclosed data, highlighting the usefulness of annual-report-based indicators for studying firm-level GVC adjustments under geopolitical uncertainty. This study contributes to the growing literature on the Sino-US technological cold war and global value chain restructuring by providing firm-level evidence from Chinese listed firms on how technological competition reshapes firms' embeddedness in international production networks.

### *5.1. Implications for Theory*

From a theoretical perspective, this study contributes to the literature on global value chains, international business, and geopolitical risk. It shows that firm-level network adjustments under geopolitical uncertainty are selective and incremental. While existing research emphasizes trade flows and macro-level restructuring (e.g., Antràs, 2020; Alfaro and Chor, 2023), our findings suggest that firms do not necessarily withdraw from global markets or drastically reorganize their international production structures in the short term. The clearest adjustment appears in downstream customer relationships. This pattern suggests a gradual and uneven GVC restructuring rather than rapid decoupling.

The findings also provide support the Institutional Theory. Under rising institutional uncertainty from geopolitical tensions and technological restrictions, firms adapt their organizational relationships and external network structures accordingly (North, 1990; Scott, 1995; Peng et al., 2008). These adjustments are not uniform across industries. The

stronger effect observed in the Battery sector confirms that firms' responses depend on their strategic exposure and position within global production networks. This result is consistent with recent studies emphasizing the uneven impact of geopolitical shocks across strategically important industries (e.g., Alfaro and Chor, 2023; Luo and Tung, 2025).

### *5.2. Implications for Managers*

From a managerial perspective, the study suggests that firms in high-exposed industries should pay more attention to geopolitical risk management. This management has growing importance in current international business practice (Luo and Tung, 2025). Compare to completely withdraw from international markets, managers should focus on strengthening and stabilizing key business relationships under uncertainty.

The customer concentration results show that firms choose to rely heavily on a smaller number of key customers to maintain stability and reduce market uncertainty. However, this also creates trade-offs. Greater short-term stability comes with greater dependence on a few partners with existing studies state this risk on customer-base composition (e.g., Patatoukas, 2012). Managers need to carefully balance the benefits of stable customer relationships against the risks of reduced diversification.

Supplier concentration does not change significantly. It suggests that upstream relationships may be relatively hard to transfer in the short term. This finding aligns with discussions on the inherent rigidity of global value chains said the reconstruction of upstream supply chain structures are slow and costly (Antràs, 2020; Baldwin & Freeman, 2022). Managers should treat supplier restructuring as a long-term strategic process through gradual diversification, long-term partnerships, and more flexible sourcing strategies.

### *5.3. Implications for Policies*

From a policy perspective, the geopolitical tensions reshape global production networks in more gradual and selective ways than the concept of "decoupling" often implies (Selwyn et al., 2025). Foreign revenue, geographic diversification, and overseas subsidiary deployment do not show significant changes. It means firms do not disengage from international markets immediately. Instead, they strengthen relationships with a smaller number of key customers.

This finding highlights a wider policy impact. Technological restrictions and export controls affect more than trade flows and also reshape firm-to-firm relationships within global value chains. As Farrell and Newman (2019) argue, state policies can reshape economic networks beyond direct trade effects. Policymakers should recognize that geopolitical policies may generate indirect effects on business networks and industrial organization.

The effects are concentrated in sectors such as the Battery industry. Industrial and trade policies need to take differences in sectoral exposure and supply chain dependence into account (IMF, 2023a). Policymakers may need to pay more attention in strategically exposed industries under geopolitical uncertainty.

#### *5.4. Limitations and Future Study*

This study has several limitations that need to be considered.

First, the analysis is based only on the data from Chinese listed firms. Listed firms are typically larger, more transparent, and more internationally engaged than smaller private firms. In this case, their responses to geopolitical shocks may be different. For example, larger firms may choose to increase customer concentration rather than reducing international exposure when facing uncertainty. This is consistent with evidence on heterogeneous firm responses to geoeconomic fragmentation (D'Orazio et al., 2024). Future research could extend the analysis to broader firm selection.

Second, the indicators are constrained by annual report disclosures. Customer and supplier concentration capture important aspects of firm-level networks. However, they provide only a partial view of the underlying structure. Indirect linkages, multi-tier supplier relationships, and informal network adjustments are not observable. Disclosed data may also have tiny difference across firms. It's because firms may use different definitions when reporting figures, and some information may not be fully disclosed. These factors may lead to inconsistent measurements and potential bias. Therefore, the observed results should be carefully interpreted. They reflect only the disclosed and measurable aspects of GVC relationships.

Third, the sample period ends in 2024. This limits the ability to capture longer-term effects. The event-study results show that customer relationship adjustments emerge with a lag. In later years, the effect gradually moderates. This indicates that global value chain

restructuring is a gradual process, and further changes may occur beyond the sample period. Future research could fix this issue by using longer time series data to examine whether the observed patterns persist over time.

Fourth, this study is also limited by the methodology. The DID model mainly identifies average net effects across firms. However, it may not fully capture different adjustment paths among firms. For example, some companies may increase customer or supplier concentration, while others may increase diversification simultaneously. These opposite responses may offset each other in the regression results, making the overall effect appear weak or statistically insignificant. Future research could complement DID analysis with methods that are more suitable for identifying multiple strategic configurations, such as fuzzy-set Qualitative Comparative Analysis (fsQCA) (Ragin, 2008). This approach could help examine how different combinations of firm characteristics, industry exposure, and geopolitical pressures lead to different patterns of GVC adjustment.

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# APPENDICES

**Table XI:** Results for robustness tests (full)

| Group   | Name                       | Outcome             | Firms | N    | Coef   | SE    | T      | P     | ADJ_R <sup>2</sup> | COEF_FMT | SE_FMT |
|---------|----------------------------|---------------------|-------|------|--------|-------|--------|-------|--------------------|----------|--------|
| Treat_A | Battery +<br>Semiconductor | FSTS                | 211   | 1688 | -0.021 | 0.018 | -1.148 | 0.251 | 0.879              | -0.021   | -0.018 |
|         |                            | Geo_Entropy         | 211   | 1679 | -0.003 | 0.021 | -0.149 | 0.881 | 0.845              | -0.003   | -0.021 |
|         |                            | Top5_Customer_Share | 211   | 1688 | 0.029  | 0.016 | 1.795  | 0.073 | 0.863              | 0.023*   | -0.016 |
|         |                            | Top5_Supplier_Share | 211   | 1688 | 0.012  | 0.016 | 0.764  | 0.445 | 0.806              | 0.012    | -0.016 |
|         |                            | Overseas_Sub_Ratio  | 209   | 1641 | -0.011 | 0.012 | -0.956 | 0.339 | 0.870              | -0.011   | -0.012 |
| Treat_B | Semiconductor<br>only      | FSTS                | 211   | 1688 | -0.001 | 0.033 | -0.018 | 0.986 | 0.879              | -0.001   | -0.033 |
|         |                            | Geo_Entropy         | 211   | 1679 | 0.012  | 0.032 | 0.361  | 0.718 | 0.845              | 0.012    | -0.032 |
|         |                            | Top5_Customer_Share | 211   | 1688 | -0.015 | 0.021 | -0.690 | 0.490 | 0.862              | -0.015   | -0.021 |
|         |                            | Top5_Supplier_Share | 211   | 1688 | 0.004  | 0.021 | 0.186  | 0.852 | 0.806              | 0.004    | -0.021 |
|         |                            | Overseas_Sub_Ratio  | 209   | 1641 | -0.019 | 0.018 | -1.073 | 0.283 | 0.870              | -0.019   | -0.018 |

**Table XI:** Results for robustness tests (full)

| Group          | Name                                        | Outcome             | Firms | N    | Coef   | SE    | T      | P     | ADJ_R <sup>2</sup> | COEF_FMT  | SE_FMT |
|----------------|---------------------------------------------|---------------------|-------|------|--------|-------|--------|-------|--------------------|-----------|--------|
| <b>Treat_C</b> | Battery only                                | FSTS                | 211   | 1688 | -0.025 | 0.020 | -1.258 | 0.208 | 0.879              | -0.025    | -0.020 |
|                |                                             | Geo_Entropy         | 211   | 1679 | -0.012 | 0.024 | -0.509 | 0.611 | 0.845              | -0.012    | -0.025 |
|                |                                             | Top5_Customer_Share | 211   | 1688 | 0.045  | 0.019 | 2.321  | 0.020 | 0.864              | 0.0452**  | -0.020 |
|                |                                             | Top5_Supplier_Share | 211   | 1688 | 0.012  | 0.018 | 0.630  | 0.529 | 0.806              | 0.012     | -0.018 |
|                |                                             | Overseas_Sub_Ratio  | 209   | 1641 | 0.000  | 0.012 | 0.011  | 0.992 | 0.869              | 0.000     | -0.013 |
| <b>Treat_D</b> | Battery +<br>Semiconductor<br>+ Electronics | FSTS                | 211   | 1688 | -0.018 | 0.018 | -0.980 | 0.327 | 0.879              | -0.018    | -0.019 |
|                |                                             | Geo_Entropy         | 211   | 1679 | -0.038 | 0.019 | -1.978 | 0.048 | 0.847              | -0.0376** | -0.019 |
|                |                                             | Top5_Customer_Share | 211   | 1688 | 0.008  | 0.015 | 0.543  | 0.587 | 0.862              | 0.008     | -0.015 |
|                |                                             | Top5_Supplier_Share | 211   | 1688 | 0.019  | 0.014 | 1.367  | 0.172 | 0.807              | 0.019     | -0.014 |
|                |                                             | Overseas_Sub_Ratio  | 209   | 1641 | -0.012 | 0.013 | -0.942 | 0.346 | 0.870              | -0.012    | -0.013 |

**Table XV:** Detailed sample distribution in years

| Years    |                 | 2017  |       | 2018  |       | 2019  |       | 2020  |       | 2021  |       | 2022  |       | 2023  |       | 2024  |       | Overall |       |
|----------|-----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|---------|-------|
|          | Distribution    | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms   | %     |
| FIRM_AGE | 5 - 9.9 years   | 9     | 4.3%  | 3     | 1.4%  | 2     | 1.0%  | 2     | 1.0%  | 2     | 1.0%  | 0     | 0.0%  | 0     | 0.0%  | 0     | 0.0%  | 18      | 1.1%  |
|          | 10 -14.9 years  | 50    | 23.7% | 46    | 21.8% | 34    | 16.1% | 26    | 12.3% | 14    | 6.6%  | 9     | 4.3%  | 3     | 1.4%  | 2     | 1.0%  | 184     | 10.9% |
|          | 15 - 19.9 years | 80    | 37.9% | 76    | 36.0% | 80    | 37.9% | 67    | 31.8% | 59    | 28.0% | 50    | 23.7% | 46    | 21.8% | 34    | 16.1% | 492     | 29.2% |
|          | 20 - 24.9 years | 47    | 22.3% | 53    | 25.1% | 55    | 26.1% | 67    | 31.8% | 81    | 38.4% | 80    | 37.9% | 76    | 36.0% | 80    | 37.9% | 539     | 31.9% |
|          | 25 - 29.9 years | 16    | 7.6%  | 22    | 10.4% | 28    | 13.3% | 35    | 16.6% | 40    | 19.0% | 47    | 22.3% | 53    | 25.1% | 55    | 26.1% | 296     | 17.5% |
|          | 30 - 34.9 years | 8     | 3.8%  | 8     | 3.8%  | 7     | 3.3%  | 6     | 2.8%  | 6     | 2.8%  | 16    | 7.6%  | 22    | 10.4% | 28    | 13.3% | 101     | 6.0%  |
|          | 35 - 39.9 years | 0     | 0.0%  | 2     | 1.0%  | 4     | 1.9%  | 7     | 3.3%  | 8     | 3.8%  | 8     | 3.8%  | 8     | 3.8%  | 7     | 3.3%  | 44      | 2.6%  |
|          | ≥ 40 years      | 1     | 0.5%  | 1     | 0.5%  | 1     | 0.5%  | 1     | 0.5%  | 1     | 0.5%  | 1     | 0.5%  | 3     | 1.4%  | 5     | 2.4%  | 14      | 0.8%  |
|          | Total           | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 1688    | 100%  |
| FSTS     | 0.00%-9.99%     | 80    | 37.9% | 76    | 36.0% | 75    | 35.6% | 76    | 36.0% | 74    | 35.1% | 68    | 32.2% | 66    | 31.3% | 65    | 30.8% | 580     | 34.4% |
|          | 10.00%-19.99%   | 34    | 16.1% | 35    | 16.6% | 33    | 15.6% | 34    | 16.1% | 35    | 16.6% | 40    | 19.0% | 39    | 18.5% | 40    | 19.0% | 290     | 17.2% |
|          | 20.00%-29.99%   | 26    | 12.3% | 27    | 12.8% | 28    | 13.3% | 26    | 12.3% | 32    | 15.2% | 25    | 11.9% | 28    | 13.3% | 31    | 14.7% | 223     | 13.2% |
|          | 30.00%-39.99%   | 11    | 5.2%  | 13    | 6.2%  | 14    | 6.6%  | 14    | 6.6%  | 11    | 5.2%  | 13    | 6.2%  | 14    | 6.6%  | 8     | 3.8%  | 98      | 5.8%  |
|          | 40.00%-49.99%   | 13    | 6.2%  | 15    | 7.1%  | 15    | 7.1%  | 13    | 6.2%  | 12    | 5.7%  | 13    | 6.2%  | 15    | 7.1%  | 21    | 10.0% | 117     | 6.9%  |
|          | 50.00%-59.99%   | 16    | 7.6%  | 16    | 7.6%  | 13    | 6.2%  | 14    | 6.6%  | 15    | 7.1%  | 15    | 7.1%  | 14    | 6.6%  | 11    | 5.2%  | 114     | 6.8%  |
|          | 60.00%+         | 31    | 14.7% | 29    | 13.7% | 33    | 15.6% | 34    | 16.1% | 32    | 15.2% | 37    | 17.5% | 35    | 16.6% | 35    | 16.6% | 266     | 15.8% |
|          | Total           | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 1688    | 100%  |

**Table XV:** Detailed sample distribution in years

| Years                       |                 | 2017  |       | 2018  |       | 2019  |       | 2020  |       | 2021  |       | 2022  |       | 2023  |       | 2024  |       | Overall |       |
|-----------------------------|-----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|---------|-------|
| GROUP                       | Distribution    | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms   | %     |
| TOP5_CU<br>STOMER_<br>SHARE | Less than 20%   | 57    | 27.0% | 52    | 24.6% | 53    | 25.1% | 44    | 20.9% | 46    | 21.8% | 46    | 21.8% | 52    | 24.6% | 46    | 21.8% | 396     | 23.5% |
|                             | 20.00%-39.99%   | 66    | 31.3% | 68    | 32.2% | 63    | 29.9% | 73    | 34.6% | 69    | 32.7% | 61    | 28.9% | 61    | 28.9% | 70    | 33.2% | 531     | 31.5% |
|                             | 40.00%-59.99%   | 46    | 21.8% | 46    | 21.8% | 51    | 24.2% | 54    | 25.6% | 53    | 25.1% | 55    | 26.1% | 50    | 23.7% | 52    | 24.6% | 407     | 24.1% |
|                             | 60.00%-79.99%   | 26    | 12.3% | 35    | 16.6% | 33    | 15.6% | 31    | 14.7% | 34    | 16.1% | 37    | 17.5% | 39    | 18.5% | 35    | 16.6% | 270     | 16.0% |
|                             | 80.00% or above | 16    | 7.6%  | 10    | 4.7%  | 11    | 5.2%  | 9     | 4.3%  | 9     | 4.3%  | 12    | 5.7%  | 9     | 4.3%  | 8     | 3.8%  | 84      | 5.0%  |
|                             | Total           | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 1688    | 100%  |
| TOP5_SUP<br>PLIER_SH<br>ARE | Less than 20%   | 52    | 24.6% | 53    | 25.1% | 55    | 26.1% | 58    | 27.5% | 54    | 25.6% | 60    | 28.4% | 57    | 27.0% | 60    | 28.4% | 449     | 26.6% |
|                             | 20.00%-39.99%   | 89    | 42.2% | 95    | 45.0% | 96    | 45.5% | 92    | 43.6% | 103   | 48.8% | 87    | 41.2% | 85    | 40.3% | 91    | 43.1% | 738     | 43.7% |
|                             | 40.00%-59.99%   | 44    | 20.9% | 36    | 17.1% | 40    | 19.0% | 43    | 20.4% | 33    | 15.6% | 39    | 18.5% | 48    | 22.8% | 39    | 18.5% | 322     | 19.1% |
|                             | 60.00%-79.99%   | 21    | 10.0% | 22    | 10.4% | 13    | 6.2%  | 13    | 6.2%  | 15    | 7.1%  | 19    | 9.0%  | 16    | 7.6%  | 17    | 8.1%  | 136     | 8.1%  |
|                             | 80.00% or above | 5     | 2.4%  | 5     | 2.4%  | 7     | 3.3%  | 5     | 2.4%  | 6     | 2.8%  | 6     | 2.8%  | 5     | 2.4%  | 4     | 1.9%  | 43      | 2.6%  |
|                             | Total           | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 1688    | 100%  |

**Table XV:** Detailed sample distribution in years

|                    | Years           | 2017  |       | 2018  |       | 2019  |       | 2020  |       | 2021  |       | 2022  |       | 2023  |       | 2024  |       | Overall |       |
|--------------------|-----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|---------|-------|
| GROUP              | Distribution    | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms | %     | Firms   | %     |
| OVERSEAS_SUB_RATIO | None            | 80    | 39.4% | 76    | 37.4% | 67    | 33.2% | 63    | 30.9% | 60    | 29.3% | 58    | 28.2% | 56    | 26.8% | 51    | 24.4% | 511     | 31.1% |
|                    | Less than 10%   | 31    | 15.3% | 32    | 15.8% | 33    | 16.3% | 36    | 17.7% | 41    | 20.0% | 45    | 21.8% | 37    | 17.7% | 49    | 23.4% | 304     | 18.5% |
|                    | 10.00%-24.99%   | 48    | 23.7% | 52    | 25.6% | 51    | 25.3% | 54    | 26.5% | 57    | 27.8% | 55    | 26.7% | 63    | 30.1% | 54    | 25.8% | 434     | 26.5% |
|                    | 25.00%-49.99%   | 37    | 18.2% | 34    | 16.8% | 40    | 19.8% | 37    | 18.1% | 36    | 17.6% | 37    | 18.0% | 43    | 20.6% | 47    | 22.5% | 311     | 19.0% |
|                    | 50.00% or above | 7     | 3.5%  | 9     | 4.4%  | 11    | 5.5%  | 14    | 6.9%  | 11    | 5.4%  | 11    | 5.3%  | 10    | 4.8%  | 8     | 3.8%  | 81      | 4.9%  |
|                    | Total           | 203   | 100%  | 203   | 100%  | 202   | 100%  | 204   | 100%  | 205   | 100%  | 206   | 100%  | 209   | 100%  | 209   | 100%  | 1641    | 100%  |
| GEO_ENTROPY        | None            | 29    | 14.1% | 24    | 11.5% | 22    | 10.4% | 25    | 11.9% | 21    | 10.0% | 18    | 8.5%  | 17    | 8.1%  | 16    | 7.6%  | 172     | 10.2% |
|                    | Low             | 91    | 44.2% | 91    | 43.8% | 94    | 44.6% | 89    | 42.2% | 97    | 46.0% | 100   | 47.4% | 98    | 46.5% | 98    | 46.7% | 758     | 45.2% |
|                    | Moderate        | 83    | 40.3% | 89    | 42.8% | 91    | 43.1% | 93    | 44.1% | 88    | 41.7% | 88    | 41.7% | 90    | 42.7% | 91    | 43.3% | 713     | 42.5% |
|                    | High            | 3     | 1.5%  | 4     | 1.9%  | 4     | 1.9%  | 4     | 1.9%  | 5     | 2.4%  | 5     | 2.4%  | 6     | 2.8%  | 5     | 2.4%  | 36      | 2.1%  |
|                    | Total           | 206   | 100%  | 208   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 211   | 100%  | 210   | 100%  | 1679    | 100%  |