Mapping upstream supply chain changes under geopolitical uncertainties: The case of three global lithium-ion manufacturers

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Abstract: Geopolitical tensions, trade war between China and the US, combined with factors like the COVID-19 pandemic, have intensified the uncertainty of the global supply chain (Roscoe et al., 2020). There has been growing attention to the relocation of the global supply chain from China to other countries, such as South Korea and Japan (Alfaro & Chor, 2023). However, there has not been strong empirical evidence or measurements of decoupling, especially in critical industries where upstream suppliers' information is hard to obtain from the firm level. Scholars are growing interest in supply chain transparency and visibility (Bridge & Faigen, 2022; Gualandris et al., 2021; T. Liu & Meidani, 2024). This research tries to examine the effect of geopolitical uncertainties on upstream suppliers' networks in the lithium-ion battery industry. By conducting a longitudinal network analysis of three leading global battery manufacturers' (CATL, TESLA, PANASONIC) supply chain maps from 2018 to 2024, this research finds that (1) the number of first-tier suppliers and types of supply become more diverse; (2) the supply chain network density increases; (3) deep-tier suppliers are anchored because of geographical limitation; (4) nexus suppliers constrains supply chain relocation by anchoring network dependencies and limiting substitutability.

Keywords: Supply chain map, sourcing strategies, nexus suppliers, geopolitical uncertainties

1. Introduction

The global-level exchanges of raw materials, manufactured goods, and information are highly intertwined (Fan et al., 2024). Multiple factors, including the rapid development of emerging technologies and digital technologies, geopolitical uncertainties (e.g. trade protectionism and nationalism), natural disasters (e.g. earthquakes and tsunamis), and large-scale outbreaks such as the COVID-19 pandemic, result in supply chain disruptions (Cajal-Grossi et al., 2023). Supply chain disruptions, such as semiconductors and some critical raw materials, happen from time to time, combined with demand adjustments in different periods. Such disruptions raise both scholars' and enterprises' attention to the effective management of inventory and suppliers (MacCarthy et al., 2022).

Therefore, knowing what happened and what is changing in the global supply chain is a prerequisite for multinational corporations and governments to discover the potential supply chain risks and improve industrial practice. The main objective of this research is to improve the understanding of changes in the global supply chain by integrating the efficient supply chain information among the upstream and downstream suppliers to generate supply chain maps based on different time points using the supply chain mapping method. However, research related to drawing a supply chain map mainly focused on particular companies or

products on a small scale, such as in a short period of time or only obtaining first-tier suppliers (Culot et al., 2022). The large-scale buyer-supplier relationship network is limited in access and presence because of the difficulty of obtaining multi-tier supplier relationship data (Culot et al., 2022; Dong et al., 2024; C.-L. (Eunice) Liu & Zhang, 2014). Another characteristic that troubles researchers in mapping the global supply chain is that today's global supply chain is more transient and intricate, which increases the difficulty of constructing a supply chain map and updating such a map regularly.

While past research related to the supply chain level could only present a static supply chain map by a certain time, this research addresses this gap by presenting the dynamic supply network using the buyer-supplier relationship data from the FactSet Supply Chain Relationships, with the starting date and ending date of the relationship, over a period of years, from 2018 to 2024. Despite the high unavailability of the multi-tier buyer-supplier relationship data, this study aims to improve the accuracy of the buyer-supplier network by the material/good flow to enhance supply chain transparency and visibility and to propose a method to construct a dynamic global supply chain network in a particular industry.

The research question is: What is the effect of geopolitical uncertainties on upstream suppliers' networks in the lithium-ion battery industry? In this research, I will mainly investigate the multi-tier buyer-supplier relationships of focal companies, especially upstream suppliers of focal companies.

This research is mainly making empirical contributions. While the vast majority of existing empirical scholarship is limited to Tier 1 or Tier 2 visibility (often relying on Bloomberg SPLC data), this study explores the supply chain by leveraging a granular dataset penetrating up to the multi-tier suppliers. We provide some of the deepest empirical evidence to date on multi-tier supply networks, exposing a critical disconnect between allied Tier 1 partners and entrenched rival dependencies at Tier N. Besides, based on the research result, we verify that even if geopolitical uncertainties become common, the supply chain remains stable in the deep tier.

The rest of the sections of this paper are as follows. In the second section, we will talk about supply chain mapping, supply chain networks and the four hypotheses. Then, in the third section, I will detail the focal industry and dataset we use. In the fourth section, I will present how to construct supply chain maps in different firms and in different years. In the fifth section, I will show the results of supply chain changes. In the sixth section, I will discuss the main contributions, limitations, and future directions of upstream supply chain changes to supply chain management.

2. Literature Review

2.1 Supply Chain Mapping Method

Supply chain mapping is defined as the linking of activities and actors in the supply chain. Supply chain mapping looks at the whole chain as a whole, including the flow of products and other information such as transaction volume, the starting and ending date of the buyer-supplier relationship, the company's geographical location, etc. (Ivanov & Dolgui, 2020; Kusi-Sarpong et al., 2022). It is a simplified yet accurate map, in which supply network relationships, flows, and dynamics are captured (Theodore Farris, 2010). In short, supply chain mapping provides visibility of the network that links suppliers and customers together and helps organisations make operational decisions.

Supply chain mapping method is used to improve integration and identify and solve some critical issues (Mubarik et al., 2023). Supply chain mapping includes three streams: upstream, midstream, and downstream. The upstream supply chain refers to the network of a firm's suppliers and sub-suppliers. The midstream supply chain represents all activities and processes that a company uses to convert the raw material into a value-added product. Whereas the downstream supply chain points to the coordination of the flow of information and goods with clients and customers. This research is limited to the upstream supply chain mapping and the upstream supply chain network. In the following content, the supply chain network refers to the upstream supply chain network.

This research uses the supply chain mapping method to integrate information from the supply chain and then constructs the supply chain network for further analysis.

2.2 Supply Chain Network

2.2.1 The Definition of Supply Chain Network

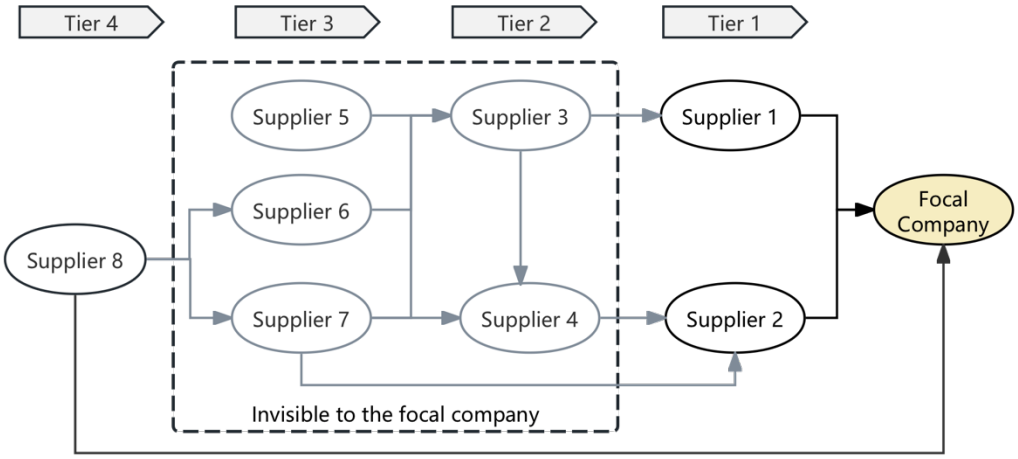
Supply chain networks are interconnected between organisations and their links rest on goods and services flows from suppliers to customers (Harland et al., 2001). Kim et al. (2011) points out that a firm's supply network includes both ties to its direct suppliers and customers, and tiers between them and their direct suppliers and customers. Choi and Hong (2002) concluded a supply network that engages firms from the manufacturing and assembly of parts to the final product. In my research, I will follow Choi and Hong's concept and choose three lithium-ion battery manufacturers. In this way, these three focal companies are regarded as downstream customers, and I could focus on the upstream supply network. Besides, my research will not collect data from focal companies' customers and related products.

Lamming et al. (2000) pointed out that the supply chain network uses the focal firm as the point of reference. Supply chain networks concentrate on the complex characteristics of the supply chain, describing lateral links, reverse loops, and two-way exchanges of the upstream and downstream activities. The participants or organisations in a network vary for a given product and over time (Choi & Hong, 2002). In conclusion, supply chain networks can be regarded from a higher strategic perspective.

A supply chain network is made up of a focal firm, having multiple tiers of suppliers. In the network, the suppliers serve as nodes, and the relationships between suppliers and customers serve as links. The direct suppliers, also called first-tier suppliers, of the focal

company, are called the supply base (Choi & Hong, 2002; Yan et al., 2015). Suppliers who produce essential influence on the focal buying company's profit and supply chain function are called strategic suppliers (Kraljic, 1983). However, there are also some suppliers that are valuable

In particular, multi-tier buyer-supplier relations/relationships refer to the combination of a relationship network of sub-suppliers of direct suppliers of a focal company. From Pic 1, the degree of distinction from sub-supplier to direct up to the focal company is named as Tier 1, Tier 2, and so on. The multi-tier buyer-supplier relationship is very complex because of the long chain and numerous suppliers. For example, supplier 8 in Tier 4 may supply to the focal company. Supplier 3 in Tier 2 may supply Supplier 4 in Tier 2 (Rauch et al., 2024).



Pic 1. The illustration of multi-tier buyer-supplier relationships

The Lithium-ion battery supply chain can mainly be divided into five stages: mining, raw material processing, cell component production, battery production, and battery recycling (International Energy Agency, 2023).

Mining refers to the process of extracting raw ores or materials, such as lithium, nickel, cobalt, graphite, and manganese, from mines. Raw material processing is after mining.

Raw materials need to be purified and refined into a form that can be used in the battery.

For cell production, the processed materials are manufactured into specialised battery components, including cathode, anode, electrolytes, separators, and packing. This process requires advanced materials chemistry and engineering.

Battery production is based on a specific proportion. Battery components are assembled into the battery pack. It includes two stages: electrode manufacturing and cell fabrication.

Recycling is at the end of the batteries' life. They are recycled and reused as raw materials.

2.1.2 Network Analysis Method

This research applies the network analysis method to analyse the multi-tier supply network (Freeman, 1987). Previously, network analysis was generally used to study the structure of communities and organisations. Then, Kim et al. (2011) deftly used network analysis on the supply network to identify the characteristics and structure of the social network. This method has been adopted more frequently under the supply chain disruption era. COVID-19, trade war, and unexpected natural disasters intensified the supply risks in the global supply chain, where network analysis could explain such phenomena by identifying core actors in the network and the interrelationships in the supply chain. For example, (Welburn et al., 2020) constructed a firm-level linkages network to analyse the systemic risk in the global economy.

This research continues the tradition of the social network analysis approach for the supply network. There are two ways to build the key network metrics: node-level metrics and network-level metrics. Kim et al. (2011) proposed that the node-level metrics pay attention to the relative importance of individual nodes in a network. For the multi-tier supply network, individual nodes refer to the firms that participate in the global supply chain, while the edge refers to the firms that have a supply relationship.

To formalise a network analysis model for a multi-tier supply network, this research begins by constructing a firm-level weighted adjacency $W = [w_{ij}]_{i,j} \in R^{n \times n}$, where $w_{ij} \in R^n$ refers to the material flows from firm i to firm j. w_{ij} = 0 if there is no material flow, while w_{ij} = 1 if there is a material flow from firm i to firm j.

There are four core centrality metrics for supply network analysis. First, degree centrality. This indicator measures how many direct connections a node has. Nodes with higher degrees represent that they are more important in terms of information dissemination or resource exchange. In supply chain management, it represents the extent to which one firm controls and manages the movement of materials in a supply network (Kim et al., 2011). The formula could be presented as:

$$C_D(v) = \sum_j w_{ij}$$

Second, betweenness centrality. This indicator quantifies how often a node appears on the shortest paths between other nodes. Nodes with high betweenness centrality act as bridges or brokers, controlling the flow of information across the network. For the supply chain network, they are more likely to influence the stability of the supply. The formula of betweenness centrality could be presented as:

$$C_B(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}$$

where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(i)$ is the number of those paths that pass through node i.

Third, closeness centrality. This indicator reflects how close a node is to all other nodes in the network. Nodes with high closeness centrality can spread information effectively as they are close to other nodes on average. The formula could be presented as:

$$C(i) = \frac{1}{\sum_{j \neq i} d(i,j)}$$

Fourthly, network density. To characterise the overall connectedness of the supply network, we calculate **network density**. Network density measures the extent to which the observed ties in a network approach the maximum number of ties that could theoretically exist among all nodes. In the context of a directed buyer–supplier network, density captures how densely firms are connected through supplier-to-buyer relationships.

Formally, for a directed network with N nodes and E observed directed edges, network density is defined as:

$$Network\ Density = \frac{E}{N(N-1)}$$

where N(N-1) is the maximum possible number of directed ties when self-loops are excluded. Here, N denotes the total number of firms in the network, and E denotes the total number of observed supplier-to-buyer links.

A higher density indicates that a larger proportion of all possible directed ties is realised, suggesting a more tightly connected network. Conversely, a lower density indicates a sparser structure in which only a small share of potential inter-firm ties is present. Because supply chain networks are typically selective rather than fully connected, density values are often relatively low in empirical settings.

In this study, we use density as an aggregate structural indicator of network connectedness. However, given that density is sensitive to network size, it is interpreted together with other structural measures, such as the number of nodes, the number of ties, and centrality-based indicators.

In the third section, this research will combine the following indicators with the supply chain mapping method.

2.2 Supply Chain Changes

Past literature proved that supply chain structure tends to minor change in the short term (Osadchiy et al., 2016). However, when and how the supply chain changes are still in the early stages of supply chain management literature. Therefore, this research tends to explore global supply chain changes from a dynamic perspective. Based on the above research question, a theoretical framework for changes in the global supply chain is presented below.

Based on the previous studies, this research identified global supply chain changes in five different aspects, including geographical changes (Alfaro & Chor, 2023; Braun et al., 2023; Goldberg & Reed, 2023; Gong, Hassink, Foster, et al., 2022), network changes (Durach et al., 2024; Fan et al., 2024), ownership changes (Antràs, 2020), technological and knowledge changes (Barrientos et al., 2011; Gereffi et al., 2019), and structural changes (Antràs & Chor, 2018).

External changes			
No.	Types of Change	Possible manifestations	Measurements
1.	Geographical Changes	Reshoring, nearshoring, friendshoring, FDI flows at a country level	The whole chain suppliers' country distribution in different years; the change in FDI flows from National Bureau of Statistics
2.	Network Changes	Companies in the supply chain may have different suppliers and customers	The number and density of the network; the duration of buyer-supplier relationship
Internal changes			
3.	Ownership Changes	The change in company's ownership from one country to another	The ownership changes from one country to another
4.	Structural Changes	Vertical integration	The length of supply chain related to the company
5.	Technological/ knowledge Changes	Upgrading and downgrading	The comparison position in the global supply chains
		FDI flows at a firm level	FDI flows got from financial statements
		Research output	R&D output got from financial statements
		Patent (number, forward citation)	The application date and forward citations from the Worldwide Patent Statistical Database (Patstat)

Table 1. The theoretical framework of the global supply chain changes

This research tries to identify the difference between external and internal changes. External changes refer to the supply chain changes outside the organisation. Therefore, the measurement of the external changes will focus on the upstream and downstream suppliers of the focal company to get an overview of the transformation of the supply chain in one specific industry. Internal changes refer to the supply chain changes within the organisation. It will focus on the ownership changes, upgrading, and vertical integration.

(1) Geographical Changes

In recent years, the geographical location of manufacturers has changed frequently. Past scholars have classified these phenomena into three dimensions: reshoring, nearshoring, and friendshoring. Reshoring refers to the supply chain returning to the consumer countries instead of outsourcing to other countries. Based on the research of Gong et al. (2022), the US reshored their core industries, such as the aerospace and medical industry, from China to the

US to decrease the trade dependency of China and guard its supply chain safety. Nearshoring refers to companies moving their suppliers to countries near the mainland (Braun et al., 2023). Based on the survey of IBM Global Locations Trends 2020, they found that 40% of respondents thought that the trend of nearshoring would increase. Accordingly, Alfaro & Chor (2024) discovered that the US moved its supply chain from China to Mexico based on the export trade data. Friendshoring refers to the change of manufacturers to places near the consumer country. For example, the US moved its supply chain from China to Mexico after 2021 (Alfaro & Chor, 2023).

Geographical changes are mainly influenced by market demand, political environment, local institutions and trade policy (Alfaro & Chor, 2023; Gereffi et al., 2019). However, most of the past research was based on the research on the tendency of executives of multinational enterprises by researchers' surveys. There is no actual evidence to show such migration in the supply chain and why they change. Besides, researchers know little about the period for enterprises to adjust their suppliers and the adjustment of geopolitical range. Are they adjust within a country level or choosing other countries' suppliers?

This study will base on three focal companies to collect lists of upstream and downstream companies in the battery industry, along with their suppliers, to determine the geographical changes of suppliers across the entire industry from a macro perspective. Besides, country-level inward and outward foreign domestic investment (FDI) flows could help learn the degree of geographical changes as building factories locally is highly related to FDI (Alfaro & Chor, 2023; Antràs, 2020). FDI can be observed in the outward and inward FDI data of every country (Antràs, 2020; Goldberg & Reed, 2023).

(2) Network Changes

Buyers and suppliers are interdependent to acquire critical resources to ensure business continuity and long-term survival. The supply chain uncertainty happens when an external party exerts huge control over the resources and there are limited alternatives available. The supplier-buyer network changes refer to the adjustment of industrial upstream and downstream supplier relationships. Network changes could reflect the cooperation level between companies and the duration of the network. Scholars used the network analysis method to know what are the critical nodes, that is suppliers, in the global supply chain and whether such critical suppliers change in different years or keep stable. Another application of network changes is using the number of suppliers to estimate its supply chain heterogeneity.

Previous scholars have proved that the supplier's network change has a positive relationship with technological level, cost, local policy and institute, policy environment, and market demand (BRINZA et al., 2024; Gong, Hassink, Foster, et al., 2022; Gong, Hassink, & Wang, 2022).

This study will use three focal companies' supplier networks as the main network, measuring the number of links to the focal company, the core of the network, and the density of the network in different years to investigate the cooperation level and degree among

companies and countries. Also, I will measure the duration of the supply chain relationship to measure the resilience of the supply chain.

(3) Ownership Changes

The change in a company's ownership from one country to another may be led by the trade policy, policy environment, and the strategy of the company (Carbonara et al., 2002). For example, after the trade war between China and the US, the trade barrier was increased between China and the US. In 2019, Ningbo Jifeng Auto Parts Co., a Chinese automotive parts manufacturer, acquired a controlling stake in Grammer AG, a German company specializing in automotive interior components. This acquisition allowed Ningbo Jifeng to expand its market in North America and learn the latest European technologies simultaneously. Therefore, understanding the change in ownership could help investigate the company's development direction, including where it decides to develop. In this study, I will collect the ownership change from the official website of the company.

(4) Structural Changes

The structural change inside the company that could influence the supply chain is vertical integration. Vertical integration is defined as a list of decisions on whether the company should manufacture inside or buy outside the company (Guan & Rehme, 2012). For some automotive companies, they decided to integrate upstream and downstream chains together and produce in-house (Sturgeon et al., 2008). In the real world, enterprises may choose to have larger production units within the company and decrease the number of suppliers (Abrahamsson & Brege, 1997). In some other cases, the situation is totally different. The reasons for structural changes are multiple, including costs, the consideration of strategy, price advantage, and uncertainty in cost/product/price. Under the influence of the current political instability, the main consideration of enterprises is how to solve the problem of uncertainty. In this study, I will measure whether the company does vertical integration in different years.

(5) Technological/Knowledge Changes

The change in technology and knowledge is highly related to geographical change, ownership change, and network change because knowledge and technology are intangible, accompanied by people and particular products. Therefore, when other changes happen, technological and knowledge changes occur as well.

Technological/ knowledge changes have several forms in the supply chain. The first one is upgrading and downgrading. Upgrading refers to the process of economic actors moving from low-value to relatively high-value activities. Downgrading refers to the process of economic actors lowering their rank, value, or quality in economic activities (Gereffi et al., 2005). Incremental upgrading may be realized through learning by doing or the allocation of new tasks by the chain's lead firm, which reflects knowledge/technology changes (Humphrey & Schmitz, 2002). Humphrey and Schmitz (2002) identified four types of upgrading: (1) product upgrading, which refers to increased unit values; (2) process upgrading, which refers to making the input-output process more efficient by introducing better technology or adjusting the production process; (3) functional upgrading, which refers to applying new functions or abandoning old functions to increase the overall skill content of activities; (4)

inter-sectoral upgrading, which refers to firms move from one product line to another product line by acquired competence. Although there are four types of upgrading, it is hard to identify the boundary between different types of upgrading in the real world. Also, supplying a whole range of goods in one place does not fit the concept of upgrading (Gereffi, 2019). For example, Antràs & Chor (2018) and Frederick (2019) also used the World Input-Output Database (WIOD) to trace the countries' GVC positioning (upstream, midstream, and downstream) and the changes in different years. In this study, I will use the suppliers' comparison positions (upstream or downstream), and the change in the length covered in the chain to measure upgrading and downgrading.

The second one is the FDI flows at a firm level. This indicator could reflect the change in companies' collaboration level with other companies. Typically, a high FDI amount reflects the high level of knowledge/technology transfer (Isaksson et al., 2016). This data could be collected from the firm's financial statements.

The third one is the R&D output. Dohse et al. (2024) found that research output could reflect firms' supply chain constraints. Therefore, research output could be seen as an indicator to measure technological/knowledge changes. This data could be also collected from the firm's financial statements.

The fourth one is patent. Patents reflect the change in technology/knowledge level in the company. Although previous research proved that it is not accurate to use patents to measure technology transfer, it does indicate communication between the two sides(Jaffe et al., 2000). Isaksson et al. (2016) suggested that the buyer-supplier relationship produces knowledge spillover, which can be measured by patents. Therefore, in this paper, I choose to collect the date of patent application and patents' forward citation from suppliers. The patent application date could reflect the time that knowledge/technology was created, and the forward citation could reflect the quality of the patent, which indirectly proves the change in the supply chain.

2.4 Theoretical Development and Hypothesis

2.4.1 Geopolitical risks and supplier diversification

Geopolitical tensions have caused supply chain uncertainties on a global scale (Cajal-Grossi et al., 2023). In response, firms are motivated to enhance supply chain resilience by strategies such as supplier diversification, redundancy, and flexibility (Fan et al., 2022). From a risk management perspective, reliance on a limited number of suppliers exposes firms to supply disruptions, particularly when suppliers are geographically concentrated in politically sensitive regions. Consequently, firms tend to expand their supplier base to reduce dependency on any single source and to improve substitutability (Bednarski et al., 2025).

This logic is consistent with the resilience literature, which emphasises that increasing the number and heterogeneity of suppliers enhances robustness against exogenous shocks (Yang et al., 2024). Under heightened geopolitical uncertainty, such diversification becomes not only desirable but necessary.

Son et al. (2021) talk about the length of uncertainties to the supply chain. Studies of sudden, localised shocks, such as the 2011 Japanese earthquake, find that firms do not necessarily expand their supplier base following disruption. This contrast suggests that the impact of disruption on supply network restructuring depends critically on the nature and temporal horizon of the disruption. While short-term catastrophic events emphasise recovery and stability, prolonged geopolitical uncertainty creates incentives for strategic reconfiguration over time. In such contexts, firms are more likely to proactively diversify their supplier base as part of a long-term risk mitigation strategy.

Therefore, we expect that firms will expand their direct supplier base in response to geopolitical risk.

P1: *Under long-term geopolitical uncertainty, firms will increase the number and diversity of direct suppliers to mitigate supply risk.*

2.4.2 Network densification as a multi-tier resilience result

While prior research has primarily focused on direct (tier-1) suppliers, global supply chains are inherently multi-tiered and interconnected (Gong et al., 2026). Disruptions often propagate through upstream tiers, making deeper layers of the supply network equally critical (Ren et al., 2024).

To address such systemic risks, firms may not only diversify their direct suppliers but also indirectly influence the structure of upstream networks. One outcome of such efforts is an increase in network density, as more suppliers are incorporated across multiple tiers, creating overlapping ties and redundant pathways (Luo et al., 2024).

From a network perspective, higher density enhances resilience by enabling alternative sourcing paths and reducing the likelihood that a single node failure disrupts the entire system. Thus, firms' responses to geopolitical risk extend beyond dyadic relationships and manifest as structural changes in the broader supply network. Accordingly, firms are expected to see an increase in the density of their multi-tier supply networks.

P2: *Firms respond to long-term geopolitical risks by increasing supply network density across multiple tiers to enhance redundancy.*

2.4.3 Structural embeddedness and the limits of relocation

Despite the expectation that firms will reconfigure supply chains under geopolitical pressure, such adjustments are not unconstrained. Global value chains are deeply embedded in historical, institutional, and geographical contexts, resulting in path dependence and structural inertia (Selwyn et al., 2025; Gültekin, 2025). In particular, upstream supply networks, especially in capital-intensive and technologically complex industries such as lithium-ion batteries, are characterised by high levels of specialisation, co-location, and accumulated capabilities. These features make deep-tier suppliers difficult to substitute or relocate.

As a result, while firms may attempt to relocate or "de-risk" their supply chains, such efforts are likely to be uneven across tiers. Adjustments are more feasible at the surface level (e.g., direct suppliers), whereas deeper layers remain anchored in their original locations due to embedded structural constraints. This suggests that supply chain relocation will be partial rather than complete, with persistence of deep-tier dependencies.

H3: *Despite efforts to relocate supply chains, deep-tier supply networks will remain geographically anchored due to structural embeddedness.*

2.4.4 Nexus suppliers and network-level constraints

While structural embeddedness explains the persistence of supply networks at a system level, nexus suppliers provide a node-level mechanism through which such constraints are enacted. A network perspective further refines our understanding of why deep-tier supply networks resist relocation. Prior research has traditionally emphasised "strategic suppliers," typically defined at the dyadic level. However, Yan et al. (2015) introduce the concept of the nexus supplier, defined as a critical supplier whose importance arises from its position within a multi-tier network rather than its direct relationship with a focal firm.

Nexus suppliers occupy structurally central positions and maintain extensive interorganizational ties, enabling them to influence the flow of materials, information, and capabilities across the network. Importantly, such suppliers can exist at any tier and are often deeply embedded within upstream networks.

Due to their centrality and the concentration of capabilities, nexus suppliers are difficult to replace. Their removal or relocation would require substantial reconfiguration of the entire network, making supply chains structurally "locked in." Consequently, even when firms seek to relocate their supply chains, the presence of nexus suppliers imposes significant constraints on such efforts. Thus, network-level dependencies centred on nexus suppliers limit the extent of supply chain relocation.

H4: *The presence of nexus suppliers in deep-tier supply networks will constrain relocation by anchoring network dependencies and limiting substitutability.*

3. Research Design and Sample

In this research, we chose the FactSet Supply Chain Relationship Database to collect buyer-supplier relationships. The FactSet Supply Chain Relationship Database was a commercial supply chain database that covers business relationship interconnections among companies globally. FactSet analysts systematically collect companies' relationship information exclusively from primary public sources such as SEC 10-K annual filings, investor presentations, and press releases, and classify them through normalised relationship types. Company information is fully reviewed annually, and changes based on corporate actions are monitored daily. The result is a comprehensive, detailed and up-to-date dataset of material intercompany relationships.

FactSet Supply Chain Relationships currently covers more than 25,000 publicly

traded companies around the world, comprising over 270,000 business relationships, normalised into 4 main categories and 13 types, with historical data going back as far as 2003. Percentage revenues between suppliers and customers are disclosed, as available. In addition, supply keywords are captured where available to provide meaningful context to the nature of the relationship between companies. As for the data Maintenance, FactSet Supply Chain Relationships is maintained and updated on an ongoing basis as companies release their annual financial filings throughout the calendar year. Relationships information for IPOs is derived from the prospectus.

This study will choose the global supply chain of the lithium-ion industry as the main study object. Reasons to choose the lithium-ion battery industry are multiple. First, the production of lithium-ion batteries is highly dependent on critical materials, such as cobalt, lithium, and nickel. Supply chain mapping could reveal the geographical information of the main suppliers and potential supply risks of these raw materials and help manufacturers predict and mitigate supply disruptions due to political instability, trade policies or natural disasters. Second, mapping the supply chain helps increase transparency in the industry, allowing companies to more accurately understand every link in their supply chain. This is particularly important for ensuring compliance with ESG standards, as the extraction and manufacturing of lithium-ion batteries can involve environmental damage and labour rights issues. Third, lithium-ion batteries have a long production chain all over the world, which is a proper industry for observing changes in the global supply chain.

This research intends to collect three leading MNCs of lithium-ion batteries: Contemporary Amperex Technology Co. Limited (CATL), Tesla, Inc. (Tesla), and Panasonic Energy Co., Ltd. (Panasonic Energy), to construct the global supply chain.

In particular, CATL is a global leader in lithium battery manufacturing, specialising in EV and energy storage batteries, with advanced technology and large-scale production for major global automakers.

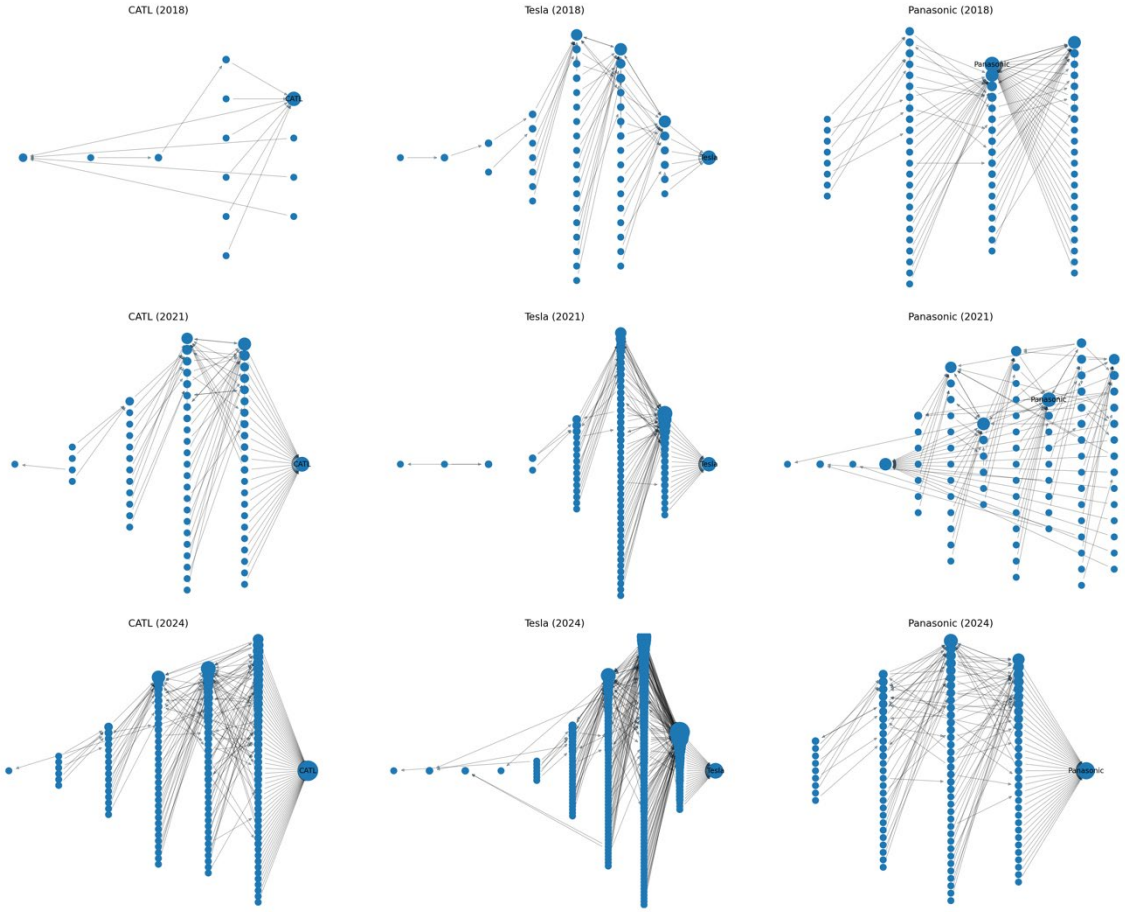
Tesla is a major player in the lithium-battery ecosystem, developing and manufacturing battery cells, battery packs, electric vehicles, and large-scale energy storage systems.

Panasonic Energy is a leading producer of lithium-ion batteries, specialising in high-performance cylindrical cells for electric vehicles and other mobility applications. The company supplies major EV customers and has expanded large-scale battery production in North America.

4. Supply Chain Network Construction

This research uses the three focal companies and constructs the supply chain networks separately. 9 supply chain networks have been mapped (CATL-2018, CATL-2021, CATL-2024; TESLA-2018, TESLA-2021, TESLA-2024; PANASONIC-2018, PANASONIC-2021, PANASONIC-2024).

Therefore, this research follows the method of Wichmann et al. (2020) to construct a supply chain map. Starting with the focal company, we search for suppliers that have the core business with the focal company (Direct supplier is Tier-1 supplier, direct supplier of Tier-1 supplier is Tier-2, ... Tier N). We will end searching if there are no more suppliers in the upstream supply chain. Then, we will construct a multi-tier supply chain map for each company.



Pic 2. 9 supply chain maps in different years

5. Results

5.1 Supply chain changes in three focal companies

Across all three firms, CATL, Panasonic, and Tesla, we observe a consistent expansion and increasing complexity of multi-tier supply networks over time. From 2018 to 2024, both the number of suppliers (nodes) and inter-firm relationships (edges) grow substantially, indicating a clear trend toward network densification and structural elaboration.

The extent of this expansion varies across firms. CATL exhibits a rapid scaling of its supply network, with the number of nodes increasing from 14 in 2018 to 141 in 2024,

accompanied by a corresponding rise in interorganizational ties. Tesla shows an even more pronounced expansion, with its network growing from 53 to 221 nodes and from 62 to 416 connections, reflecting an aggressive diversification and deepening of its supply base. In contrast, Panasonic demonstrates a more gradual but steady increase, with nodes rising from 79 to 110 and edges nearly doubling over the same period.

Importantly, this expansion is not limited to direct suppliers. The number of tiers involved and the connectivity within upstream layers also increase over time, suggesting that firms are not only adding suppliers but also developing more interconnected and multi-layered supply structures.

In addition to the expansion in nodes and connections, we observe a substantial increase in network density across all three firms over time. Network density, calculated based on observed inter-firm ties within the estimated multi-tier supply networks, shows a consistent upward trend from 2018 to 2024.

For CATL, density increases sharply from 2.17 in 2018 to 4.15 in 2021, and further to 11.90 in 2024, indicating a rapid intensification of interconnections within its supply network. Tesla exhibits an even more pronounced pattern, with density rising from 3.10 in 2018 to 6.15 in 2021, and reaching 20.80 in 2024, suggesting a highly interconnected and increasingly complex network structure. In contrast, Panasonic shows a more moderate but steady increase in density, from 3.10 to 5.35 and 6.60 over the same period.

Overall, these results indicate that supply networks are not only expanding in size but also becoming significantly more interconnected, reflecting a shift toward denser and more tightly coupled multi-tier structures. This pattern suggests that firms are not merely adding suppliers, but are actively reinforcing interdependencies within the network, leading to increasingly dense and structurally complex configurations.

Firm	2018	2021	2024
CATL	2.17	4.15	11.90
Tesla	3.10	6.15	20.80
Panasonic	3.10	5.35	6.60

Table 2. Network density of focal companies in different years

5.2 Main findings

5.2.1 Evidence for supplier diversification (H1)

Hypothesis 1 predicts that firms increase the number and diversity of direct suppliers in response to geopolitical uncertainty.

The empirical evidence strongly aligns with this expectation. Across all three firms, we observe a substantial increase in the number of direct suppliers over time. For instance, Tesla's supplier base expands markedly from 53 nodes in 2018 to 221 in 2024, while CATL shows a rapid increase from 14 to 141 nodes over the same period. Panasonic also demonstrates a steady expansion, with its supplier base growing from 79 to 110 nodes.

Beyond sheer numbers, the expansion also reflects increasing diversity and substitutability within the supplier base, as firms incorporate a broader range of suppliers across categories and tiers. This pattern suggests that firms actively reduce reliance on individual suppliers by distributing sourcing across a wider set of partners.

Taken together, these findings are consistent with H1 and indicate that supplier diversification serves as a key response to heightened geopolitical risk in the long term.

5.2.2 Evidence for network densification (H2)

H2 suggests that firms respond to geopolitical risks by increasing the density of their multi-tier supply networks.

The data provide clear evidence of such densification. As reported earlier, network density increases consistently across all three firms between 2018 and 2024. CATL's network density rises sharply from 2.17 to 11.90, while Tesla exhibits an even more pronounced increase from 3.10 to 20.80. Panasonic shows a more moderate but steady rise from 3.10 to 6.60.

Importantly, this increase in density is not merely a byproduct of network expansion. Rather, it reflects a growing number of interconnections among suppliers across multiple tiers, indicating the formation of more tightly coupled and interconnected structures. Upstream layers become increasingly populated and interlinked, suggesting that firms are reinforcing supply network connectivity rather than simply adding isolated nodes.

These findings are consistent with H2 and suggest that firms enhance resilience not only by expanding their supplier base but also by increasing the interconnectedness of their supply networks.

5.2.3 Evidence for uneven relocation and structural embeddedness (H3)

H3 predicts that supply chain relocation under geopolitical pressure will be uneven across tiers, with deep-tier networks remaining geographically anchored due to structural embeddedness. The empirical patterns strongly support this proposition. While we observe notable changes in the geographical composition of direct suppliers, particularly a shift away from concentrated reliance on specific regions, such adjustments are primarily confined to the surface level of the supply network.

In contrast, deeper tiers of the network exhibit a high degree of geographical persistence. A substantial proportion of upstream suppliers remain located in their original

regions, especially in China, despite increasing geopolitical tensions and policy pressures aimed at supply chain relocation. This persistence is observed consistently across all three firms. Taking Tesla 2024 as an example, most of the suppliers are concentrated in China. There is no sign of moving the supply chain from China to Other countries.

Pic 3. Supply chain map of Tesla in 2024

This divergence between surface-level adaptation and deep-tier stability suggests that supply chain restructuring is constrained by underlying structural factors. Deep-tier suppliers are often embedded in long-standing industrial ecosystems characterised by specialised capabilities, co-location advantages, and accumulated relational ties, making them difficult to substitute or relocate.

Overall, these findings provide strong support for H3 and indicate that supply chain relocation is inherently partial, resulting in a pattern of surface-level adjustment coupled with persistent deep-tier dependence.

5.2.4 Evidence for nexus suppliers and network constraints (H4)

H4 posits that the presence of nexus suppliers constrains supply chain relocation by anchoring network dependencies and limiting substitutability. Our network analysis provides strong evidence consistent with this proposition. Across the multi-tier supply networks of the focal firms, we identify a set of suppliers that occupy structurally influential positions, as indicated by their relatively high betweenness centrality, reflecting their role as brokers

connecting different parts of the network. Notable examples include CNGR Advanced Material, Amperex Technology, BASF, GEM, Ganfeng Lithium, Ningbo Ronbay, and Zhejiang Huayou Cobalt.

These suppliers are not merely prominent due to size or direct transactional importance; rather, they function as bridging nodes that link multiple tiers and coordinate flows across otherwise loosely connected segments of the supply network. Their high betweenness centrality indicates that a significant proportion of supply paths pass through them, making them critical intermediaries in the network structure.

This empirical pattern closely aligns with the concept of the nexus supplier proposed by Yan et al. (2015), who argue that certain suppliers become critical not because of their dyadic importance, but because of their network position and portfolio of interorganizational ties. Importantly, nexus suppliers can emerge at different tiers of a multi-tier supply network and exert influence that extends far beyond their direct relationships with focal firms (Yan et al., 2015).

The suppliers identified in our analysis share several common characteristics. First, they are concentrated in strategically important upstream segments of the battery value chain, such as lithium extraction, cathode and precursor materials, and key chemical processing stages. Second, they exhibit high brokerage positions, connecting multiple downstream manufacturers with upstream resource providers. Third, they possess specialised capabilities and scale advantages that are difficult to replicate in alternative locations within a short time frame.

These shared features make nexus suppliers particularly consequential for supply chain restructuring. Because they connect multiple tiers and embody critical capabilities, their presence creates structural dependencies that cannot be easily bypassed. As a result, even when firms diversify their direct suppliers or attempt to relocate parts of their supply chains, they remain indirectly dependent on these central nodes. In many cases, these nexus suppliers are geographically concentrated, further reinforcing the persistence of deep-tier dependencies.

In this sense, nexus suppliers represent a node-level mechanism through which broader structural embeddedness is enacted. They translate network-level constraints into concrete limitations on firms' ability to reconfigure supply chains.

Taken together, these findings provide strong support for H4 and highlight the critical role of nexus suppliers in constraining supply chain relocation.

6. Conclusion

6.1 Managerial Suggestions

1. Managing supply chain risk beyond direct suppliers

For managers, our findings highlight the importance of moving beyond a narrow focus on direct suppliers. While firms often prioritise diversification at the surface level, our results show that critical dependencies frequently reside in deeper tiers of the supply network. Managers should therefore invest in greater visibility across multi-tier supply chains and develop capabilities to monitor and manage upstream risks.

2. Rethinking relocation strategies

The findings also suggest that supply chain relocation strategies should be approached with caution. Although relocating direct suppliers may create an appearance of reduced geopolitical exposure, such efforts may have a limited impact if deep-tier dependencies remain unchanged. Managers should recognise that full relocation is often constrained by structural factors and should instead adopt a more realistic approach that combines partial relocation with risk mitigation strategies.

3. Identifying and managing nexus suppliers

A key managerial implication of this study is the need to identify and manage nexus suppliers. These suppliers, due to their central position within the network, play a critical role in shaping supply chain resilience and flexibility. Managers should prioritise mapping network centrality and assessing the substitutability of such suppliers, as disruptions at these nodes can have cascading effects across the entire supply chain.

4. Building resilient yet feasible supply networks

Rather than pursuing full decoupling, managers should focus on building resilient yet feasible supply networks. This includes balancing diversification with the realities of embedded supply structures, developing strategic partnerships with critical upstream suppliers, and investing in long-term capability development to gradually reduce structural dependencies.

6.2 Discussion

This study advances the literature on global supply chains under geopolitical uncertainty by offering a mechanism-based explanation for the limits of supply chain relocation. While prior research has emphasised firms' efforts to enhance resilience through diversification, redundancy, and reshoring, our findings reveal a more nuanced pattern of supply chain restructuring.

First, this study contributes to the supply chain resilience literature by demonstrating that firms respond to geopolitical risks not only by increasing the number of suppliers but also by fundamentally reshaping the structure of their supply networks. The observed increase in both supplier diversity and network density suggests that resilience strategies operate at a network level rather than solely through dyadic relationships. This extends existing research, which has largely focused on firm–supplier interactions, by highlighting the importance of multi-tier network configurations.

Second, this study contributes to the global value chain (GVC) and global production network (GPN) literature by revealing the structural limits of supply chain relocation. While much of the existing literature implicitly assumes that firms can reconfigure supply chains in response to external shocks, our findings show that such reconfiguration is uneven across tiers. Specifically, we identify a pattern of surface-level relocation coupled with persistent deep-tier dependence, suggesting that global supply chains are more deeply embedded and path-dependent than previously assumed.

Third, this study introduces and empirically extends the concept of the nexus supplier (Yan et al., 2015) in the context of geopolitical disruptions. We show that certain highly central suppliers exert a disproportionate influence on the structure and evolution of supply networks, effectively anchoring them in specific geographical regions. By integrating network theory with supply chain resilience and GVC perspectives, we provide a novel explanation for why deep-tier supply networks remain resistant to relocation.

Taken together, this study shifts the focus from whether supply chains can be relocated to how and why relocation is structurally constrained, offering a more realistic understanding of supply chain adaptation under geopolitical pressure.

6.3 Limitations

This research lacks data on the cost and the size of the order. Therefore, even though some suppliers seem essential in the supply chain network, they are still trivial for the supply chain resilience. *Vice versa*. Even if some suppliers seem to have a low centrality and are inconspicuous in the supply chain network, they may still play an important role in the whole network due to the size of the order or the low cost to the customer. Follow-up research could further explore such data and integrate it with the existing supply chain network.

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Recalibrating Corporate Philanthropy under Political Animosity and Geopolitical Volatility

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1. INTRODUCTION OF PHD RESEARCH QUESTION

Navigating the complex landscape of global business, multinational enterprises (MNEs) frequently encounter significant challenges, particularly in identifying and mitigating risks (Dang, Jasovska & Rammal, 2020). The early 21st century has been characterized as an age of global uncertainty, as numerous firms are facing increasing socio-political risks, ranging from uncontrollable external events to direct challenges from social and political stakeholders (Sun, Doh, Rajwani, Werner & Luo, 2024). Early literature focused primarily on political risks and tended to consider social risks as a subset of these risks (Simon, 1984), but social risks are becoming prominent and scholars now call for a more comprehensive approach to socio-political risks (Lawton, De Villa & Santamaria-Alvarez, 2024). In this paper, we look at socio-political risks, defined as a wide range of unpredictable and adverse changes arising from both political and social spheres (Puhr & Müllner, 2024; Shen, Giroud & Han, 2025). Previous literature has demonstrated that socio-political risks not only escalate economic and transaction costs (North, 1990), but also threaten corporate survival, competitiveness, and overall firm performance of MNEs (Hillman & Hitt, 1999). In this context, nonmarket strategy, which is defined as "a firm's concerted pattern of actions to improve its performance by managing the institutional or societal context of economic competition" (Mellahi, Frynas, Sun & Siegel, 2016, p. 144), emerges as a critical tool for MNEs to reduce their vulnerability to socio-political risks (De Villa, Rajwani, Lawton & Mellahi, 2019; White, Hemphill, Joplin & Marsh, 2014).

Therefore, my PhD study is guided by an overarching question:

> **How do MNEs employ nonmarket strategies to maintain competitiveness within the context of socio-political risks?**

Guided by this overarching research question, the study is structured around three sub-questions, each of which is addressed in a separate chapter of the PhD thesis. Chapter 1 lays the foundation by providing a comprehensive framework on MNEs, nonmarket strategies, and socio-political risks. Chapter 2 conducts a systematic literature review to explore how and why do MNEs adopt different types of nonmarket strategies to navigate the variety of existing and

novel socio-political risks in today's ever changing and turbulent world, which has been published on International Business Review (Shen et al., 2025).

Based on this literature review, we reveal that while substantial research has examined how political risks – primarily those weak institutional environments within a single country (within-country) and characterized by persistence and gradual development (ongoing) – can be managed or mitigated through nonmarket strategies, far less is known about how MNEs respond to cross-border geopolitical risks that are shaped by interstate political relations and may evolve abruptly and unpredictably (Shen et al., 2025; Shirodkar, Liedong, Rajwani, & Lawton, 2024). Addressing this gap, this study focuses on two distinct but relevant dimensions of interstate political relations, political animosity, which reflects the degree of hostility and misalignment between home and host countries (Hasija, Liou & Ellstrand, 2020), while volatility of political affinity, which refers to the propensity of sudden and unpredictable shifts in interstate relations (Adarkwah et al., 2024). Although both dimensions are manifestations of interstate relations, they create legitimacy challenges for MNEs through different mechanisms. Political animosity intensifies legitimacy concerns by increasing perceptions of foreign threat, thereby exacerbating the liability of origin and exposing firms to greater risks of interference and discrimination from host-country stakeholders (Liou, Brown, & Hasija, 2021). In contrast, volatility of political affinity increases uncertainty by generating fluctuating and potentially conflicting stakeholder expectations, making it more difficult for firms to anticipate and satisfy legitimacy demands (Adarkwah et al., 2024). These differences suggest that the two dimensions may prompt different nonmarket strategic responses as firms seek to manage legitimacy challenges in politically hostile and volatile environments.

A promising yet underexplored tool for managing these legitimacy challenges is corporate philanthropy (CP), which is defined as the voluntary and unconditional transfer of financial or in-kind resources to social causes (Gautier & Pache, 2015; Godfrey, 2005). CP has traditionally been conceptualized as an altruistic practice that demonstrates a firm's care for the surrounding society (Freeman, 1984; Gautier & Pache, 2015), and as a voluntary and discretionary component of Carroll's (1979) "pyramid of CSR" that lies beyond economic, legal, and ethical obligations (Carroll, 1991; Hemingway & Maclagan, 2004).

In contrast, a growing body of literature has regarded CP as a strategic tool, employed to secure or repair political legitimacy (Sanchez, 2000; Wang & Qian, 2011; Zheng, Ni & Crilly, 2019), manage stakeholder perceptions (Dai, Yin, Liao & Arndt, 2023; Parhankangas & Ehrlich, 2014),

gain competitive advantages (Lev, Petrovits & Radhakrishnan, 2010; Porter & Kramer, 2002), and buffer against reputational damage (Du, 2015; Luo, Kaul & Seo, 2018). In the international business (IB) field, this strategic philanthropy perspective has gained prominence. Prior studies have shown that MNEs strategically deploy CP to mitigate the liability of foreignness (Mithani, 2017), manage institutional distance (Campbell, Eden & Miller, 2012), respond to institutional disruption triggered by external shocks (Ballesteros & Magelssen, 2022), and buffer against reputational threat spillovers (Zhou & Wang, 2020). Despite these important insights, little is known about how do MNEs adopt CP as a strategic response to increasing geopolitical risks.

To address this gap, the purpose of this study is to explore *how do MNEs adopt cross-border corporate philanthropic strategy in response to political animosity and volatility of political affinity between home and host countries*. Drawing upon the strategic philanthropic perspective and the multilevel legitimacy framework (Bitektine & Haack, 2015), our study argues that in times of volatile geopolitical , CP of MNEs is not as a peripheral or purely altruistic activity, but as a nonmarket strategy, enabling them to strategically manage legitimacy judgments across individual-level propriety, nation-level validity, and supranational-level validity. To capture this complexity, we move beyond prevailing unidimensional focus on donation amounts and conceptualize MNEs' cross-border corporate philanthropic strategy as a multi-dimensional response by including channels of cross-border philanthropic giving. We argue that MNEs strategically recalibrate these two dimensions to manage multi-level legitimacy and navigate politically hostile and volatile geopolitical environments.

In particular, our study focuses on cross-border giving through U.S.-based corporate foundations. According to CECP (2024), 81% of survey U.S.-based companies had foundations or trust. Corporate foundations play a significant role in international giving (Hornstein & Zhao, 2018). 72% of the grants going from headquarters to international recipients go through the foundation (CECP, 2015). Using a sample of 213 U.S.-based MNEs' corporate foundation giving across countries from 2003 to 2023, we examine how two dimensions of MNEs' corporate philanthropic strategy are recalibrated in response to political animosity and volatility of political affinity.

2. THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1 Corporate Philanthropy as a Nonmarket Strategy

CP, a component of the domain of corporate social responsibility (Carroll, 1979), refers to the voluntary and unconditional transfer of financial or in-kind resources to social causes (Godfrey,

2005; Gautier & Pache, 2015). While traditionally perceived as an altruistic practice, an increasing body of literature has conceptualized CP as a nonmarket strategy employed by MNEs to build legitimacy, acquire resources, and protect reputation to navigate cross-border institutional complexity (Dai et al., 2023; Wang & Qian, 2011; Zhang, Tong & Qiao, 2024).

Firms engage in CP to construct a socially responsible public image that can spill over into how stakeholders evaluate other dimensions of the firm (Adams & Hardwick, 1998; Branco & Rodrigues, 2006). Beyond the direct beneficiaries of donations, CP can generate goodwill and enhance the firm's reputation among diverse stakeholder groups (Pek, Oh & Rivera, 2018), which can elicit favourable responses from them, such as positive evaluations from investors and journalists, increased appeal to prospective employees and business partners, and heightened customers' loyalty and demand (Lev et al., 2010; Porter & Kramer, 2002; Wang & Qian, 2011).

CP plays an important function in embedding MNEs within the local institutional environment. Contributions to post-disaster reconstruction or initiatives aligned with national development goals can strengthen local ties, build trust among local community, reduce the social and cultural barriers associated with the liability of foreignness, and enhance the perceived legitimacy of the firm (Dickson, 2003; Mithani, 2017; Qian, Gao & Tsang, 2015). This enhanced legitimacy, in turn, can facilitate access to critical resources and opportunities, such as favourable treatment by authorities and smoother regulatory approval (Saiia, Carroll & Buchholtz, 2003; Zimmerman & Zeitz, 2002).

Additionally, CP is also strategically leveraged by firms as a form of insurance (Godfrey, 2005). The moral capital and relationship-based intangible assets accumulated through philanthropic engagement can buffer firms against reputational damage in the face of adverse events occur or negative publicity (Godfrey, 2005; Shou, Shan, Shao, Lai & Zhou, 2024). For example, Luo et al. (2018) analysed firms in the U.S. petroleum industry and found that those engaging in CP accrued moral capital that buffered them from negative stock market reactions following oil spills. However, the same study also revealed a positive association between a firm's philanthropic donations and both the frequency and severity of subsequent oil spills (Luo et al., 2018). This finding suggests that CP is employed by some less socially responsible firms as a pre-emptive effort aimed at diverting public attention, obscuring irresponsible or unethical business practices, and mitigating the public criticism (Luo et al., 2018; Du, 2015; Wu, Jin, Monfort & Hua, 2021).

While cross-border CP can occur through various channels, such as direct cash donations or volunteer programs by local subsidiaries (Ballesteros, 2018), this study specifically focuses on cross-border giving through corporate foundations, which are legally distinct, nonprofit entities established and funded by for-profit firms with the stated mission of advancing social good (Roza, Bethmann, Meijs & von Schnurbein, 2020). Despite their nonprofit nature, corporate foundations frequently serve as strategic instruments for the funding firms (Brown, Helland & Smith, 2006). These foundations provide a centralized, formalized, and sustained mechanisms for managing philanthropic initiatives across borders (Gardberg, Zyglidopoulos, Symeou & Schepers, 2019), which not only enhances the visibility of the funding firm's philanthropic effort (Bertrand et al., 2020) but also ensures the strategic alignment of their giving strategies with the firms' global footprints (Hornstein & Zhao, 2018).

2.2 Political Animosity and Volatility of Political Affinity

Political animosity refers to the degree of misalignment between two countries' national interests (Hasija et al., 2020; Liou et al., 2021), reflecting "remnants of antipathy related to previous or ongoing military, political or economic events" toward a particular country (Klein et al., 1998, p. 90). Such animosity, if not reconciled, can persist over time, becoming embedded in collective memory and reinforced through societal and media narratives. It can be easily provoked by new sets of antagonistic intergovernmental acts and gradually institutionalized as part of a country's shared beliefs and culture, shaping judgments and attitudes toward foreign actors (Gao, Wang, & Che, 2018).

A growing body of research in marketing and IB has examined the consequences of political animosity across different levels of analysis. Early studies in the marketing literature showed that animosity influences consumer behaviour, leading individuals to avoid products from countries perceived as hostile even when these products are comparable or superior in quality to alternatives from other countries (Klein et al., 1998; Leong et al., 2008). Building on this insight, studies in IB show that the effects of political animosity extend beyond consumers to influence firm-level behaviour and performance. For example, Arikan and Shenkar (2013) demonstrated that hostility between nation pairs increases perceived opportunism and dyadic-specific risk, which in turn significantly reduces both the likelihood and the number of cross-border alliances. In addition, MNEs, frequently perceived as representatives of their home countries' political interests (Bucheli & DeBerge, 2024), are subject to varying levels of legitimacy and treatment in host countries based on the degree of political misalignment

between their home and host countries. When political animosity is high, MNEs are more likely to be perceived as potential threats to host country's interests, which leads to the heightened risks of interference and discrimination from local governments and societal actors (Bertrand et al., 2016; Li et al., 2018). As a result, foreign acquirers from politically misaligned countries tend to face regulatory opposition to acquisition deals, resulting in higher acquisition costs and weaker post-acquisition performance due to legitimacy concerns during post-acquisition integration (Bertrand et al., 2016; Hasija et al., 2020).

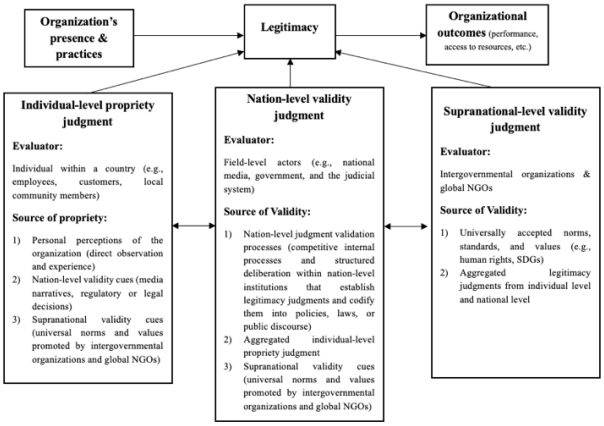
Political relations between two countries are inherently dynamic, subject to fluctuations driven by evolving domestic political values and shifting geopolitics (Amenta, Caren, Chiarello & Su, 2010; Cohen, 2014). Recognizing this, Adarkwah et al. (2024) introduce the concept of "volatility of political affinity", defined as "the propensity for sudden and unpredictable shifts in political relations between countries" (p. 2279). This definition emphasizes two critical dimensions, unpredictability and abrupt change (Adarkwah et al., 2024). Unpredictability refers to the transformation of previously stable bilateral relationships into volatile ones. The 2025 trade conflict between the United States and Canada exemplifies this shift. Despite a longstanding alliance, President Trump's imposition of sweeping tariffs on Canadian imports, citing national security concerns and border enforcement issues, led to a deterioration in relations (Mena, 2025). Canda's retaliatory tariffs on U.S. goods further escalated tensions (Saltman, Klein & Goldman, 2025), highlighting the volatility of political affinity between historically allied nations. This unpredictability complicates the ability of MNEs to anticipate shifts in the political landscape and make informed investment decisions. Abrupt change denotes the rapidity with which these shifts can occur, often within short time frames. A pertinent example is the 2022 Russia-Ukraine war, which swiftly transformed the political landscape of Europe. The war not only led to immediate international condemnation and the imposition of extensive sanctions on Russia but also prompted sudden shifts in alliances and defence policies, such as Finland and Sweden's applications to join NATO (Izzeldin, Muradoglu, Pappas, Petropoulou & Sivaprasad, 2023). Such sudden change makes it challenging for MNEs to monitor and adjust their strategies promptly (Darendeli, Hill, Rajwani & Cheng, 2021). As a result, prior research has demonstrated that the high volatility of political affinity impedes firms' ability to form expectations about stakeholder behaviour (Adarkwah et al., 2024).

2.3 Multilevel Legitimacy Framework

Building on Suchman's (1995, p. 574) widely accepted definition of legitimacy as "a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions", we adopt an evaluator-centric perspective (Bitektine & Haack, 2015) that conceptualize it as a dynamic judgment rendered by evaluators at multiple, interacting levels. Bitektine and Haack (2015) distinguish between micro-level propriety, which captures individual evaluators' assessments of whether an organization's actions are desirable and appropriate (Dornbusch & Scott, 1975), and macro-level validity, which refers to the general consensus among field-level actors, such as national media, regulatory bodies, and judicial institutions, regarding whether the entity is appropriate within a specific social context (Tost, 2011). These two levels are not independent: macro-level validity influences individual propriety judgments, while repeated individual propriety judgments, in turn, can reinforce or challenge the consensus at the collective level (Bitektine & Haack, 2015).

Given the complexity faced by MNEs when they engage in continuous interactions with sociopolitical stakeholders across their home, host, and supranational environments (Sun et al., 2021), we extend this two-level legitimacy framework by introducing a third, supranational level, supranational-level validity, which is rendered by intergovernmental organizations and global non-governmental organizations (NGOs) and captures the extent to which an organization's actions align with transnational or universal norms of corporate behaviour (Matten & Moon, 2008). These supranational validity judgments create powerful legitimacy cues that can cascade downwards, influencing both nation-level validity and individual propriety judgment. This expanded framework (see Figure 1) underscores that legitimacy is not determined by the judgments of a single level but emerges from dynamic interactions across individual, nation, and supranational levels. In this context, MNEs must navigate this multilevel legitimacy landscape, striving to operate within the accepted and proper bounds and norms defined by diverse evaluators. Any misalignment can result in delegitimating, leading to marginalization, public backlash, and penalties (Chadee, Roxas & Kouznetsov, 2021; Dowling & Pfeffer, 1975).

Figure 1. Multilevel Legitimacy Framework



2.4 Political Animosity, Volatility of Political Affinity, Corporate Philanthropy, and Legitimacy

Drawing on the multilevel legitimacy framework (Bitektine & Haack, 2015), we conceptualize political animosity and volatility of political affinity as two dimensions of geopolitical risks that shape legitimacy judgments across supranational, nation-level, and individual evaluators.

In contexts of high political animosity, nation-level validity judgments toward firms from politically misaligned home countries tend to become unfavourable, which are codified in legal documents and media narratives that frame these MNEs as security threats or unwelcome outsiders (Bitektine & Haack, 2015). The legitimacy concerns at the nation level can also exert a top-down influence on individual evaluators' propriety judgments, shaping how local customers and business partners perceive and assess foreign MNEs' presence and conduct (Bitektine & Haack, 2015). For instance, the sudden escalation of geopolitical tensions between China and U.S. fractured the macrolevel validity surrounding Huawei's legitimacy in several Western markets. In Sweden, Huawei faced not only an administrative ban imposed by the government (nation-level validity judgment) but also the termination of partnerships by local business actors (individual-level propriety judgment) (Fjellström, Bai, Oliveira, & Fang, 2023).

Under institutional stability, legitimacy judgments reinforce one another through a "stability loop" that enables firms to sustain legitimacy by adhering to widely accepted norms (Bitektine & Haack, 2015). However, in contexts of geopolitical volatility, the institutional environment becomes unstable (Adarkwah et al., 2024), consequently, the institutional stability loop no longer operates effectively (Bitektine & Haack, 2015). Volatility in political affinity between home and host countries can trigger abrupt and dramatic shifts in nation-level validity judgments, as key field-level actors, like regulatory bodies, national media, and business associations, suddenly reframe the status and acceptability of foreign MNEs in light of new

geopolitical dynamics (Bitektine & Haack, 2015), making it difficult for MNEs to anticipate the behaviours and values that will be deemed acceptable and to align their operations accordingly (Adarkwah et al., 2024; Suchman, 1995). Additionally, in the absence of collective legitimacy judgments at the macro level, individual evaluators become less likely to trust contradictory validity cues from the environment and instead rely more heavily on, and more openly express, their own independent propriety assessments (Bitektine & Haack, 2015). Consequently, MNEs might face fragmented and potentially conflicting legitimacy norms across different stakeholder groups (Lamin & Zaheer, 2011), significantly increasing the challenges and costs associated with achieving and maintaining sociopolitical legitimacy in the host country.

Jeong and Kim (2019) argue that corporations could strategically allocate resources to "doing good" as a means to secure legitimacy. In the face of legitimacy challenges arising from political animosity and volatility of political affinity, MNEs could implement cross-border CP purposefully to gain or reinforce legitimacy across all three levels (Dai et al., 2023). At the individual level, by delivering tangible benefits to beneficiaries like local employees or community members, MNEs can shape individual evaluators' propriety judgments, establishing or protecting perceptions that their actions are desirable and appropriate (Zhang et al., 2024). These repeated individual-level judgments can gradually reshape the broader collective consensus within the host-country context (Bitektine & Haack, 2015). At the nation level, CP can ease fiscal burdens on host governments and be perceived as a socially responsible behaviour that addresses pressing societal issues and promotes local social welfare, thereby strengthening the MNEs' validity in the eyes of host regulatory bodies and media (Wang & Qian, 2011; Mithani, 2017). At the supranational level, MNEs can strengthen global validity by aligning with internationally recognized norms and values and by demonstrating their commitment to addressing global challenges and fostering a more sustainable future. For instance, when MNEs support gender equality (Agenda 2030 Sustainable Development Goal 5) by investing in women's education in underdeveloped regions (Minefee & Yue, 2025), they reinforce global legitimacy. These supranational endorsements can, in turn, positively influence national-level validity and shape how individual stakeholders in host countries perceive the organization, ultimately helping to mitigate legitimacy risks and navigate the complex and volatile geopolitical environment.

As CP becomes a nonmarket strategy for MNEs to secure legitimacy under conditions of geopolitical volatility, the effectiveness of this strategy depends not only on whether firms

engage in cross-border philanthropy, but how they do so. MNEs must make choices regarding how much to give and through which channels to deliver their donations. The following section examines these two dimensions of CP as key levers through which MNEs respond to political animosity and volatility of political affinity.

2.4.1 Donation amount

Although CP is discretionary and voluntary in nature, MNEs cannot determine the amount of their donations solely based on internal efficiency considerations (Jeong & Kim, 2019). To maintain or enhance legitimacy in the eyes of host-country stakeholders, firms must meet or exceed an externally constructed baseline of philanthropic engagement (Zheng, Luo & Maksimov, 2015). This threshold is shaped by societal expectations, which often presume that for-profit organizations, particularly foreign ones, should contribute generously to local welfare (Jeong & Kim, 2019). In the context of high political animosity between home and host countries, MNEs from politically misaligned home countries often face heightened scrutiny of their philanthropic activities. Contributions below the minimum level of social acceptance are more likely to be interpreted by regulators and the media as signs of weak commitment or strategic indifference to local communities, thereby undermining nation-level validity (Jeong & Kim, 2019). This negative framing at the nation level can trickle down to individual-level propriety judgments. Local individual evaluators may perceive such donations as evidence of opportunism rather than genuine social concern, particularly when they appear modest compared to those made by local competitors or companies from countries with high and stable political affinity with the host country, which might lead to the public backlash (Zhang et al., 2024).

In response, MNEs may strategically increase their philanthropic donations to signal commitment to the host society and mitigate legitimacy concerns across multiple levels. Higher levels of giving can demonstrate alignment with host-country priorities, improve evaluations by regulators and media at the nation level, and enhance perceptions of sincerity among local stakeholders. In addition, visible philanthropic engagement may align firms with global norms of responsible corporate behaviour, thereby reinforcing supranational-level legitimacy. Thus, we propose the following hypothesis:

Hypothesis 1: MNEs' corporate foundations are more likely to increase cross-border philanthropic donations to the host country in response to the higher political animosity between home and host country.

Under conditions of high volatility of political affinity, MNEs face rapidly shifting and sometimes conflicting nation-level validity judgments, as well as fragmented and diverse legitimacy expectations across different individuals (Adarkwah et al., 2024; Bitektine & Haack, 2015). The absence of stable and dominant legitimacy cues makes it challenging for MNEs to anticipate which behaviours will be perceived as appropriate and legitimate in the host country and to align their strategies with the expectations of different stakeholder groups. In such environments, philanthropic donations are more likely to be misinterpreted or contested, increasing the risk that donations fail to gain the intended legitimacy. Consequently, MNEs may adopt a more cautious approach to philanthropic engagement, reducing their donation amounts in response to volatile geopolitical conditions. Accordingly, we propose the following hypothesis:

Hypothesis 2: MNEs' corporate foundations are more likely to decrease cross-border philanthropic donations to the host country in response to the higher volatility of political affinity between home and host country.

2.4.2 Channels of cross-border philanthropic giving

In addition to decisions regarding the amount of donation, choosing the appropriate channels through which CP is delivered also constitutes a strategic consideration for gaining legitimacy and mitigating risks amid geopolitical volatility. Hornstein & Zhao (2018) categorize cross-border philanthropic giving into two broad categories: direct local giving and intermediated giving. Direct local giving involves grants made to recipient organizations that are located in the beneficiary country and primarily implement philanthropic activities for local beneficiaries (Hornstein & Zhao, 2018). Intermediary giving refers to donations channelled through intermediary organizations that coordinate and channel cross-border philanthropic giving across national boundaries, such as Red Cross / Red Cresent and the World Wide Fund for Nature (Hornstein & Zhao, 2018).

In contexts characterized by high political animosity, MNEs from politically misaligned home countries are subject to heightened scrutiny and scepticism regarding both their intentions and their contributions to local society. To mitigate these legitimacy challenges, MNEs' corporate foundations tend to rely on direct local giving. By partnering with local recipient organizations, MNEs can leverage their local knowledge, enabling a more locally tailored, context-sensitive allocation of resources that aligns with the specific needs and expectations of the host community (Hornstein & Zhao, 2018). Direct local giving allows firms to deliver tangible and

visible benefits to local stakeholders and signal their commitment to the host society, thereby influencing individual-level propriety judgments. At the nation level, visible contributions through local organizations may be interpreted by governments and media as evidence of responsiveness to local priorities, helping to soften negative narratives and reduce regulatory obstacles (Wang & Qian, 2011; Mithani, 2017). Compared to donations through intermediary organizations, direct local giving more directly targets host-country evaluators and strengthens nation-level legitimacy by addressing the specific concerns arising from national animosity. Therefore, we propose:

Hypothesis 3: MNEs' corporate foundations' cross-border philanthropic donations are more likely to rely on direct local giving channels in response to higher political animosity between home and host country.

Volatility of political affinity can destabilize the perceived consensus at the nation level and fragment propriety judgments at the individual level (Adarkwah et al., 2024; Bitektine & Haack, 2015). These conditions pose particular challenges for direct local giving, as firms struggle to formulate and implement a cohesive set of locally tailored philanthropic practices that can satisfy diverse and often conflicting stakeholder expectations and keep pace with rapidly evolving legitimacy standards, especially for MNEs operating across multiple institutional contexts (Marano & Tashman, 2012). Moreover, MNEs operating in host countries often lack adequate local information and knowledge (Makino & Delios, 1996), making it difficult to identify well-aligned local recipient organizations. Misalignment in partner selection and limited monitoring capabilities can undermine the intended impact of CP.

In response to these challenges, MNEs may turn to intermediary giving as a more viable approach. Partnering with established organizations with international credentials can lend credibility to the MNE's philanthropic activities. These organizations are endowed with in-depth knowledge of global social norms, cultural patterns, and governance expectations, enabling them to implement charitable initiatives in ways that align with widely accepted and relatively stable global standards (Marano & Tashman, 2012). The cross-border philanthropic giving of MNEs through these intermediaries are therefore more likely to be regarded as adhering to global norms (Matten & Moon, 2008), thereby enhancing MNE's supranational validity, which can cascade downward to reinforce or even recalibrate nation-level and individual-level legitimacy perceptions. Additionally, intermediary organizations typically possess more infrastructure and implementation expertise (Marano & Tashman, 2012),

allowing MNEs to execute cross-border philanthropy more effectively and achieve higher legitimacy in the beneficiary country (Porter & Kramer, 2002). Thus:

Hypothesis 4: MNEs' corporate foundations' cross-border philanthropic donations are less likely to rely on direct local giving channels in response to higher volatility of political affinity between home and host country.

3. RESEARCH METHODS

3.1 Sample and Data

To test our hypotheses, we assembled a panel dataset at the firm–host country–year level spanning the years 2003 to 2023. We obtained data on philanthropic donations by U.S.-based corporate to foreign recipients from the Foundation Directory Online (FDO), a database curated by Candid (formerly the Foundation Center) and widely used in previous academic research (Hornsterin & Zhao, 2018; Pek et al., 2018; Seo et al., 2021). The FDO contains all reported grants made by U.S. company-sponsored foundations and corporate giving programs. These data are primarily drawn from IRS Form 990 fillings (Returns of Organization Exempt from Income Tax), which all 501(c) 3 nonprofit organizations such as corporate foundations are legally required to submit annually. This database provides grant-level information including the donor organization's name and location, the recipient organization's name and location, grant amount, and the cause area classification (Seo et al., 2021). Follow previous research (Hornstein & Zhao, 2018), we restrict our sample to corporate foundations affiliated with publicly listed U.S.-headquartered MNEs in non-financial industries, identified using a combination of foundation names, IRS Employer Identification Numbers (EINs), and parent-firm matching through Orbis and Compustat. We then manually collected grant records to identify CP made to non-U.S. recipients by the selected corporate foundations. Aiming to explore philanthropic strategy, we exclude grants that lack information on donation amounts, cause classifications, or recipient locations, as well as grants allocated to multiple countries or anonymous individual recipients. The final dataset consists of 5,057 firm-host country-year observations across 213 U.S.-based publicly listed non-financial MNEs.

In terms of the variables related to political affinity between the home and host countries, we use the voting decisions of the home country (the U.S.) and host country made in the UN General Assembly. According to the previous IR literature, these votes capture the extent to which the U.S. and a given host country align or diverge in their positions on global affairs,

with higher similarity indicating higher level of political affinity between the two states (Gartzke, 1998; Liou et al., 2021). Despite the common concerns of UN roll-call voting as a proxy for political affinity between states, such as its symbolic nature and limited reflection of substantial and costly state commitments (Gartzke, 2000), it remains a valuable indicator in the IR studies due to its temporal and spatial coverage (Gartzke, 1998). Its consistency across diverse dyads and issue areas allows for comparison of preference similarity, thereby providing valuable insights into the explanation of different phenomena, such as military conflicts, aid allocation, and trade patterns (Bertrand et al., 2016). In this study, we draw on the updated UN voting dataset provided by Voeten, Strezhnev and Bailey (2009), which provides voting data on all UN-member-country dyads from 1946-2023 and has been used in prior studies in the strategy literature (Adarkwah et al., 2024; Bertrand et al., 2016; Hasija et al., 2020).

We also integrate the data on host country characteristics from World Bank Development Indicators and Worldwide Governance Indicators database. Data on natural disasters are obtained from the Emergency Events Database (EM-DAT), the most widely used global database of hazard events. EM-DAT compiles information on more than 27,000 disaster events reported worldwide since 1988. A disaster is recorded if causing at least 10 fatalities, 100 affected people, a request for international humanitarian assistance, or a declaration of a state of emergency. Disaster reports are collected from a variety of sources, including United Nations agencies, national governments, and the International Federation of Red Cross and Red Crescent Societies (EM-DAT CRED/UCLouvain, 2026; Lesk, Rowhani, & Ramankutty, 2016).

3.2 Variables and Measurements

3.2.1 Dependent variables

Donation amount

Consistent with previous research (Hornstein & Zhao, 2018; Wang & Qian, 2011; Zolotoy, O'Sullivan, Seo & Veeraraghavan, 2021), we measure *Donation Amount* as the amount of a corporate foundation's philanthropic donations (in U.S. Dollar) to non-U.S. beneficiaries in a host country in a year. Given the highly skewed nature of the donation data, we apply a log transformation by computing the natural logarithm of one plus the donation amount.

Direct local giving percentage

Following prior research (Hornstein & Zhao, 2018), we construct *the Direct Local Giving Percentage* as our dependent variable to capture the corporate foundation's strategic choice in

channels of cross-border philanthropic giving. This variable is measured as the proportion of a corporate foundation's philanthropic donations (in U.S. Dollar) to non-U.S. beneficiaries in a host country in a year that were granted directly to recipient organizations located within the host country and primarily serving local beneficiaries, such as local hospitals, schools, and charities.

3.2.2 Independent variables

Political animosity

We measure *Political Animosity* using the voting decisions of the home country (the U.S.) and host country made in the UN General Assembly in a given year. Following previous literature (Bertrand et al., 2016; Hasija et al., 2020; Liou et al., 2021), we first calculate political affinity, which captures, in a given year t, the similarity in country i and country j's voting portfolios made in the UN General Assembly. The affinity data are coded with the "S" indicator. "S" is calculated as $1 - 2\frac{D_t\left(V_t^i, V_t^j\right)}{D_t^{max}}$, where D_t is the sum of absolute metric distances between votes in the voting portfolio V_t^i and V_t^j and D_t^{max} reflects the maximum possible distance for these votes (Gartzke, 2006).

To capture political animosity, we reverse the affinity score. The political animosity score ranges from -1 to 1, where a value of 1 indicates completely opposite voting pattern in a given year and a score of -1 reflects identical voting behaviour (Hasija et al., 2020).

Volatility of political affinity

Another independent variable is *Volatility of Political Affinity*, which is measured as the moving standard deviation of absolute political affinity between the home country and the host country for the past five years (Adarkwah et al., 2024). The use of a five-year window to estimate volatility is standard in economics and finance (Engle, 2004).

Using these annual affinity scores, we compute the five-year moving average (MA) and corresponding standard deviation (δ) for each U.S. – host country dyad (Adarkwah et al., 2024). The resulting standard deviation serves as our measure of *Volatility of Political Affinity*, with higher values indicating greater fluctuation in bilateral political alignment over time.

$$MA = \frac{absolute\ political\ affinity_1 + \cdots + absolute\ political\ affinity_n}{n}$$

$$\delta = \sqrt{\frac{(absolute\ political\ affinity_1 - MA)^2 + \cdots + (absolute\ political\ affinity_n - MA)^2}{n}}$$

3.2.3 Control variables

We controlled for a number of firm-level attributes that may influence the cross-border philanthropic strategies of MNEs through their corporate foundations. These controls are drawn from previous literature and sourced from DCA (Brown et al., 2006; Seifert, Morris & Bartkus, 2004; Udayasankar, 2008). These controls include a firm's *Size*, measured as the natural logarithm of the number of employees at the firm's global headquarters, and firm's *Slack Resources*, measured as the ratio of current assets to current liabilities at the parent-company level (Seo et al., 2021). In addition, we construct a control variable, *Foreign Investment Activities*, to capture the extent of the firm's international footprint. Thie variable is measured by 1) the total number of countries in which the firm has FDIs, and 2) the total number of FDIs in which the parent firm holds an equity share of 10 percent or more (Lu & Beamish, 2001). A wider global footprint may increase both the range of alternative donation locations competing for philanthropic resources and complicate decisions regarding how much and how to allocate cross-border philanthropic giving (Hornstein & Zhao, 2018). Furthermore, local embeddedness could enhance knowledge of demands of local stakeholders and reduce liability of foreignness (Halaszovich & Lundan, 2016), potentially influencing the strategic choice of CP. Therefore, we also include *Local Experience* as a control variable, which is measured as the number of years a firm has operated subsidiaries in the focal host country (Mithani, 2017).

At the industry level, we control for *Local Competitors*, measured as the number of firms operating in the same four-digit SIC code within the same host country and year, based on DCA data (Hornstein & Zhao, 2018). A higher number of local competitors may increase peer pressure, motivating firms to engage more actively in philanthropic giving to enhance legitimacy (Marquis, Glynn & Davis, 2007; Zhang et al., 2024).

Further, at the country level, since prior research has shown that firms often use philanthropic giving as a strategic response to weak or opaque institutional environments in host countries (Hornstein & Zhao, 2018), we include *Institutional Quality* as a control variable, which is sourced from the World Bank's Worldwide Governance Indicators (WGI) database (Hearn, 2015). Moreover, given that stronger economic growth may signal a more attractive and expanding market, potentially motivating higher levels of CP, we include the *annual Change*

in GDP per capita as a control variable (Hornstein & Zhao, 2018). Furthermore, natural disasters often trigger urgent humanitarian needs and can prompt spikes in corporate giving in the affected regions (Ballesteros, 2018; Mithani, 2017). To control for this effect, we include *Natural Disaster*, measured as the total number of people affected by natural hazards in host country-year. This measurement captures individuals requiring immediate assistance (e.g., those injured or rendered homeless) following disaster events such as floods, earthquakes, and tsunamis (EM-DAT CRED/UCLouvain, 2026; Nohrstedt et al., 2021).

3.3 Empirical Model

To test our hypotheses, we use fixed-effects ordinary least squares (FE OLS) models. Hence, our main regressions models are represented as follows:

$$CP_{ict} = \beta_0 + \beta_1 Political\ Animosity_{ct-1} + \beta_2 Volatility_{ct-1} + \gamma' X_{ict-1} + \alpha_{ic} + \lambda_t + \varepsilon_{ict}$$

where CP_{ict} represents the corporate philanthropic strategy of a MNE in the host country during the given year, operationalized through two separate dependent variables: the natural logarithm of the donation amount, and direct local giving percentage; β_0 is the intercept; β_1 is coefficient of political animosity between the home and host country ($Political\ Animosity_{ct-1}$); β_2 is coefficient of volatility of political affinity between the home and host country ($Volatility_{ct-1}$); $\gamma'$is a vector of coefficients of control variables; α_{ic} is firm-country fixed effect; λ_t denotes the year fixed effect; and ε_{ict} is the error term. Subscripts i, c, and t represent firm, country, and year. Consistent with previous literature (Adarkwah et al., 2024), in order to mitigate concerns regarding endogeneity and reverse causality, we lag both the independent variable and control variables by one year. The exception is the *Natural Disaster* control variable, as corporate philanthropic responses to such events typically occur within the same fiscal year.

4. PRELIMINARY FINDINGS

To date, we have conducted preliminary regression analyses to test Hypotheses 1–4 without including control variables. The results provide initial insights into how political animosity and geopolitical volatility shape MNEs' cross-border CP.

Consistent with our theoretical expectations, higher levels of political animosity between the home and host country in the previous year are associated with an increase in firms' cross-border philanthropic donation amounts to the host country in the focal year ($\beta = 0.088$, $p <$

0.001). However, higher volatility in political affinity is negatively associated with donation amounts ($\beta = -0.053$, $p < 0.001$), suggesting that MNEs scale back their philanthropic engagement in more uncertain geopolitical environments.

We further examine how firms adjust the channels through which cross-border philanthropy is delivered. The results indicate that higher levels of political animosity are associated with a greater proportion of donations delivered through local recipient organizations ($\beta = 0.101$, $p < 0.001$). In contrast, higher volatility in political affinity is associated with a lower proportion of donations delivered through local organizations ($\beta = -0.047$, $p < 0.001$), suggesting that firms rely less on direct local engagement under conditions of heightened uncertainty.

5. DISCUSSION AND IMPLICATIONS

Our study makes several potential contributions. First, prior research on MNEs' nonmarket strategies for managing socio-political risks has primarily focused on persistent, within-country risks, such as widespread corruption or judicial system incompleteness (e.g., Jean, Sinkovics & Zagelmeyer, 2018; Röell, Arndt, Benischke & Piekkarum 2024). These types of risks tend to be relatively stable and predictable, allowing firms to proactively adjust their strategies (Darendeli et al., 2021). However, this contrasts with today's volatile, uncertain, complex, and ambiguous (VUCA) global environment (Buckley, 2020). We advance this literature by examining how MNEs deploy nonmarket strategies to manage cross-border socio-political risks, conceptualized as both the level of political animosity between home and host countries and the volatility of these relationships.

Second, we contribute to the CP literature by conceptualizing it as a multidimensional strategic tool. Prior research has largely treated CP as a unidimensional construct, typically focusing on the total amount donated (e.g., Wang & Qian, 2011; Zhang et al., 2024). We extend this perspective by examining not only how much MNEs donate across borders but also how they donate through different giving channels in response to geopolitical risks. This offers a more comprehensive understanding of how CP is used not only to signal benevolence and humanity but also to strategically manage socio-political risk, advancing the literature on CP as a nonmarket strategy.

Third, this study enriches the multilevel legitimacy framework proposed by Bitektine and Haack (2015) by introducing the supranational-level validity judgments that MNEs face in the contemporary global landscape. MNEs are no longer evaluated solely by local stakeholders or nation-level validity institutions, and they are also judged against global norms of corporate

behaviour, such as sustainability, human rights, and development goals promoted by intergovernmental organizations and global NGOs. By applying the multilevel legitimacy framework to, our research conceptualizes CP as a multi-level, legitimacy-seeking mechanism that enables MNEs to strategically respond to and align with these complex and dynamic evaluative norms and expectations.

Fourth, this study offers practical guidance for managers seeking to navigate hostile and abrupt shift of geopolitical relationships through CP. By highlighting how political animosity and volatility of political affinity between home and host countries influence donation amount and the employment of giving channels, our findings help MNEs develop more responsive and context-sensitive cross-border giving strategies to align philanthropic activities with evolving stakeholder expectations and mitigate legitimacy risks.

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1. Introduction

Organisational innovation is widely understood as a process of recombining and reconfiguring knowledge, in which diverse expertise forms the basis of creative problem-solving and novel outcomes (Nonaka & Takeuchi, 1995). To manage the increasingly complex demands of innovation, contemporary organisations rely heavily on cross-functional collaboration. Cross-functional teams provide a central mechanism for integrating diverse knowledge, yet they also introduce new managerial challenges. Positioned between organisational-level expectations and team-level needs, these teams must navigate tensions that arise during the implementation of knowledge-intensive innovation.

The responsibility for managing these tensions often falls upon middle managers. Situated at the intersection of organisational systems and team practices, middle managers coordinate across functions, translate strategic intentions, and mobilise resources to support innovation. However, their actions are shaped—and frequently constrained—by the broader organisational environment. Because cross-functional teams are embedded within formal and informal control systems, middle managers' behaviours are influenced by organisational structure (e.g., decision authority, communication pathways) and organisational culture (e.g., norms of risk taking, trust, and cooperation).

To capture the combined influence of these control mechanisms, this study adopts the concept of **perceived managerial discretion**, defined as the latitude of action managers believe they possess under organisational constraints (Hambrick & Finkelstein, 1987). Prior research distinguishes formal, objectively granted discretion from the discretion managers *perceive* based on cultural expectations, trust relations, and risk tolerance (Gibson & Birkinshaw, 2004; Martinko & Gardner, 1982). Yet, in innovation contexts, scholars increasingly argue that granted discretion alone is insufficient. Successful innovation often requires middle managers to dynamically extend or reshape their initial boundaries of discretion (Maimone & Sinclair, 2015).

Despite growing recognition of middle managers 'central role in innovation, important gaps remain. First, existing research largely examines how organisational systems enable or constrain innovation, but pays less attention to how middle managers **interpret** these systems and convert them into usable discretion within cross-functional collaboration. Second, although behaviours such as issue selling, championing and resource mobilisation have been well documented (Dutton & Ashford, 1993; Parker

et al., 2010), little is known about **how these behaviours emerge** when middle managers face limited authority, ambiguous responsibilities, and competing innovation demands.

These gaps lead to the central question guiding this study:
How do middle managers, operating within organisational structures and cultures that shape their initial discretion, actively leverage and reshape these constraints to lead cross-functional teams toward successful innovation?

Addressing this question offers new insight into the behavioural strategies of middle managers and clarifies the organisational conditions that enable or hinder innovation within cross-functional settings.

2. Background

2.1 The nature of organisational innovation

From a knowledge-based view, organisational innovation is defined as the create new knowledge by re-using and re-combining the existing knowledge, where the knowledge can be classified based on the nature of knowledge, including the explicit and implicit knowledge, and the functions of the knowledge, indulging three types of knowledge-based, analytical, symbolic and synthetic knowledge base. The difference between exploration and exploitation is rooted in the searching stage of knowledge, with the tension between the distance of searching for knowledge and the use direction of different types of knowledge (market-oriented and technology-oriented) (Cantarello, Martini & Nosella, 2012). However, both innovation requires the basic innovation process, which emerges before the final products (Crossan and Apaydin, 2010). Innovation received different research views, including the process and outcomes. In this research, we prefer the innovation process to cover all types of innovation with different results. For organisational innovation, the whole process of generation and implementation of innovation is a spiral process across different levels (Damanpour and Aravind, 2012). For a generation, it is the creative process that combines new and existing ideas in a creative way to produce new things, which usually starts with individuals or small groups, and then is distributed to the team and organisations. On the contrary, the implementation of innovation is downwards spiraling. After the generation of ideas, top managers at organisation level release the adoption and implementation of innovation goals based on their understanding of innovation. After the team level coordinate and organising related resources based on the goals, the individuals implement the innovation in their practices, and until the innovation becomes a regular activity in organisation (Damanpour and Aravind, 2012).

2.2 Why focusing the organisational innovation at the team level

In the whole complex innovation process, the team acts as the middle layer in the organisation, connecting the above-mentioned top-down and bottom-up innovation processes, which means the team level received the impacts from both top and bottom levels. From the top, the culture, structure, leadership, and strategies as characteristics constraints the teams' environment and their responses, including the set of team goals; meanwhile, the interactions, behaviors, and knowledge among team members also can impact the team performance, such as collective knowledge, routine and values (Kozlowski and Bell, 2013). Therefore, the team level is the connectors that deliver the team goal from the top and coordinate individuals at the bottom level to achieve goals. Meanwhile, from the knowledge-based view, the organisational innovation is the reusing and re-combination of organisational knowledge which is mostly stored in individuals (Nonaka and Takeuchi, 1995, Argyris and Schön, 1978, Grant, 1996), so that the team is the basic unit that aggregates individuals with different knowledge and coordinates them to achieve the organsitional innovation through the different knowledge sharing path (Argote and Fahrenkopf, 2016). Therefore, the team level is the proper level to observe the organisaional innovation. Here, we use the definition of the team developed by Kozlowski and Bell (2013), which refers to a team as a complex system within organisations that contains two or more people with team identity and spoiled interactions, and the main function of the team is to achieve the common goals by appropriate operation and coordination. When the team gathering the diverse knowledge that required in the innovation process, it is know as the cross-functional interface or cross-functional team.

2.3 the challenge in management of innovation in cross-functional team

Although the cross-functional interface is the appropriate place that cultivate the creativity and implement the innovation in the organisations, but there are challenge and requires good coordination:

Why gathering the diverse knowledge is not enough—-coordination challenges:

Cross-functional teams (CFTs) serve as a primary integration mechanism for mobilizing diverse individual expertise to achieve innovation outputs. These teams are typically responsible for managing the entire innovation lifecycle, from initial idea generation to final implementation (ref). Successfully navigating this process requires a balance between exploration and exploitation. While a diverse knowledge base is a fundamental prerequisite for both activities, achieving the necessary balancing depends on effective internal coordination within the CFT.

For generating the good ideas (achieving the exploring), the coordination and integration among diverse knowledge is required. The research of van Knippenberg & Schippers (2007) and van Knippenberg (2017) address the diverse knowledge can positively impact the team creativity, but also claims that sharing among different knowledge requires the proper mechanism, which imply as the innovation climate, for creating the psychological safety and improve the motivation of creating. Moreover, the research of Drach-Zahavy and Somech, (2001) studies the function of communication mechanism within divers knowledge team for team innovation is important, for supporting the knowledge sharing. When moving to achieving the implementation, the situation becomes more complex and the successful implementation of innovative idea also requires more coordination. Van Knippenberg (2017) mentioned that the transition from idea generation to implementation is the most risky phase, requiring support and cooperation from other departments and top management. Morover, the research of Love and Roper (2009) emphasized the importance of inputting different knowledge at different stages of innovation. Their research found that the cross-functional team is particularly effective in the technical aspects of the innovation process, but at some stages, such as the marketing strategy stage, a single discipline and department is required.

Tensions:

Therefore, to achieve innovation goals and successful innovation, cross-functional teams need to adjust their resource allocation at different stages (Marks et al., 2001) and match them with appropriate coordination mechanisms and management practices. However, because cross-functional teams are deeply embedded in the organisational environment, their access to resources, resource acquisition capabilities, and the operational space of their coordination systems are inherently limited by the organisational environment (ref and more explanation). Since the organisational system is not designed specifically for the phased needs of short-term innovation projects, there is a disconnect between the resources and coordination mechanisms provided by the organisational system and the actual needs of the innovation project at different stages (ref)---example studies: insufficient team authority, a lack of key resources, and inefficient communication due to the lack of appropriate coordination mechanisms.

3. The managers in the cross-functional team might be solutions

Middle managers or team leaders, situated at the intersection of organisational and team levels, may be key to resolving the aforementioned conflicts in team innovation. As the management interface directly confronting this tension, the research of Wooldridge et al. (2008) has already confirmed the importance of middle leaders in connecting strategy formulation and actual

operations, demonstrating their central role across different hierarchical boundaries within the organisation. When the resources and coordination mechanisms provided by the organisational environment are insufficient to support innovation projects, middle managers demonstrate flexibility through their actual management behaviour, undertaking "boundary expansion" within established organisational constraints, thereby securing the necessary implementation space for team innovation.

3.1 The default set of organisational context

Before exploring how middle managers flexibly navigate tensions between the organisation and their teams, it is essential to first analyse the initial power granted to them by the organisational system, as this directly determines their degree of behavioural freedom. As Osborn et al. (2002) emphasise, leadership research must be understood within its embedded environment; similarly, Wooldridge et al. (2008) argue that multi-level leadership research should examine the organisational context in which middle managers operate and explore how organisational antecedents shape individual behaviour (Hitt et al., 2007).

Gemünden et al. (2018) further highlight that middle managers often find themselves “caught” between the organisational and project levels. This dilemma largely stems from limited autonomy—high levels of accountability but insufficient decision-making power—while being tightly constrained by time, budget and scope. Only when organisations grant adequate autonomy can middle managers demonstrate the flexibility needed to address innovation-related barriers, such as conflicts between organisational demands and project needs.

Therefore, this study takes the degree of behavioural freedom provided by the organisational environment as the core contextual factor (including the basic structural, cultural and resource conditions granted by the organisation), regarding it as the logical starting point for understanding how middle managers resolve hierarchical tensions.

The original organisational context: a coordination system combining structure and culture

To be more specific, the original organisational context is conceptualised as the coordination system shaped jointly by organisational structure and organisational culture. These two components define the boundaries of power available to middle managers and influence how they interpret, navigate and balance tensions between the organisational level and the team level.

(1) Structure

The organisational structure affects the scope of leaders ’decision-making, including their ability to design and shape team processes. As Wageman (2011) notes, leaders ’choices regarding team design

vary depending on the organisational constraints they face. For instance, when leaders possess limited authority, they may either accept organisationally assigned arrangements or attempt to negotiate with peers and superiors to gain additional discretion. Thus, any analysis of leaders 'influence on their teams must consider the organisational environment and the formal power granted to them as critical background conditions.

A major structural characteristic is the degree of centralisation. Centralised organisations concentrate decision-making at higher levels, thereby limiting the autonomy of team leaders, whereas decentralised structures distribute authority more broadly (Mintzberg, 1989; Cosh et al., 2010). Another structural indicator is the communication pathway within the organisation. Organic structures enable informal, cross-departmental communication, while mechanistic structures rely on hierarchical, formalised communication channels (Burns & Stalker, 1961). Hence, both the degree of centralisation and the scope/formality of communication serve as key markers for assessing the structural environment that shapes middle managers 'room for action.

(2) Culture

Beyond structural characteristics, organisational culture—particularly risk preferences and coordination norms—also shapes how middle managers lead their teams. Culture, functioning as a system of social control, influences middle managers 'use and expression of power through shared values and behavioural expectations (Flynn & Chatman, 2001).

For example, in cultures that embrace risk-taking and tolerate failure, middle managers are more likely to adopt leadership behaviours that support innovation, such as providing resources and psychological safety for employee creativity (Amabile, 1996). Conversely, in cultures that emphasise stability and control, middle managers may prioritise adherence to rules and risk avoidance, which can restrict their willingness or ability to decentralise resources and empower employees (Schein, 2010).

Given their position between upper management and teams, middle managers often act as cultural translators, transmitting and reinforcing cultural preferences through their daily leadership practices. Thus, organisational culture not only shapes their behavioural freedom but also influences how they interpret their role when balancing competing demands across hierarchical levels.

3.2 literature review (the merge between the managerial discretion and team leader's practice: TBC)

To better capture the autonomy granted to team levels by organisational coordination systems (culture and structure), this study draws on the concept of managerial discretion from the field of Human Resource Management (HRM) to capture the degree of empowerment

that organisational systems impose on middle-level leaders. Managerial discretion refers to the freedom of managers to manage in the way they deem most appropriate (Hambrick & Finkelstein, 1987), encompassing both objective discretion and perceived discretion. First, objective discretion based on organisational structure is determined by the degree of decentralization and formalization of power, constructing "nominal rule boundaries and action space" for managers (ref). However, organisational culture (such as attitudes towards innovation and risk tolerance) acts as an informal control mechanism, influencing the actual action space by releasing encouraging or discouraging signals (ref, see Carpenter and Golden, 1997). Therefore, this study emphasizes perceived discretion, as it is a comprehensive mapping of an individual's perception of both formal (structural) and informal (cultural) control signals from the organisation.

To further explain this using the perspective of routine, the gap between objective discretion and perceived discretion is essentially parallel to the difference between the ostensive and performative aspects of routine: the former refers to the abstract concept or rules of routine, while the latter refers to the specific practices of specific individuals in specific times, places, and situations (Feldman & Pentland (2003). The reason of chose the concept of "perceived discretion" rather than "routine" is, although the routine perspective captures the gap between abstract rules and actual behaviour, its research scope is mainly limited to repetitive workflows. When discussing the behavioural freedom of cross-functional team managers, their behavioural logic not only includes the execution of existing routines but also encompasses the leader's proactive efforts to "construct a favorable space for innovative management" when facing the initial organisational environment.

3.3 the actual practice of discretion: How middle manager facing the original organisational context and create the “space” for managing innovation

The following are studies from different fields on how middle management can create favorable conditions for management innovation (balancing exploring and exploitation) through practical flexibility (interactions between middle managers and the organisational level). :

Proactive behaviours:

Early literature on how managers proactively alter the "initial environment" is fragmented, primarily focusing on specific managerial roles and behaviours, such as knowledge broker in social network area, information accessor in managerial role, and issue selling behaviours. Cross-functional interfaces facilitate team leaders' access to cross-departmental and external knowledge. Therefore, cross-functional team leaders can effectively broaden the team's knowledge boundaries by acting as

knowledge intermediaries and proactive resource seekers. Mom et al. (2007) indicated that when managers actively seek lateral knowledge inflows from peer functional departments, their exploratory behaviour significantly increases, thus helping leaders create the necessary resource space for team innovation…..

In contrast, the micro-foundational perspective of dynamic capabilities—namely, the dynamic managerial capabilities (DMC) practices of middle managers—and the perspective of adaptive leadership provide a more comprehensive framework for understanding how middle managers respond to the initial organisational environment and create adaptable space for team innovation.

From a micro-foundational perspective of dynamic capabilities, the dynamic managerial capabilities (DMC) of middle leaders are considered a core variable in reshaping the actual innovation space of a team. Research by Gullmark, Salvato, and Clausen (2025) reveals that middle leaders reshape the original innovation space through proactive adaptation behaviours, specifically including: leveraging their social capital networks to mobilize resources, actively promoting issues to gain upper management support, and bridging the communication gap by concretizing abstract upper-level goals through language translation.

Adaptive leadership/adaptability: TBC

It is noteworthy that the organisational environment and innovation needs are not always in conflict. When the organisational environment and innovation needs are highly aligned, specific behaviours of middle managers can amplify and enhance their impact. Research by Kim et al. (2024) shows that middle leaders, through proactive goal regulation, can effectively convey an organisational innovation climate, thereby significantly enhancing their positive influence on employee innovation behaviour.

4. Research design

4.1 Research philosophy

TBC

4.2 Research method

To understand how team leaders create space within organisational contexts to manage team innovation, this study employs a qualitative research approach, specifically a multiple case study design. Since the research question aims to explore how team innovation is managed across different

organisational contexts shaped by organisational culture, the multiple case study method is appropriate for two main reasons.

First, the central phenomenon we aim to capture is the practice of middle managers 'discretion in supporting team innovation, and how the innovation process unfolds across different organisational contexts. This shared focus across cases represents the 'quintain, 'which allows individual cases to be connected under a unified theme or issue (Stake, 2013). In this research, the quintain refers to how middle managers use their perceived discretion to navigate the organisational context when managing team innovation.

Second, this study aims to identify a general framework for supporting team innovation in different organisational environments. Cross-case analysis can help identify patterns and enable limited generalisation. In this way, the multiple case study approach helps offset the uniqueness of single case studies and supports comparison across cases to reveal both similarities and differences.

4.2.1 Empirical background

To understand the "how does manager face the organisational context for successful innovation", the empirical area is the sector of functional food and drinks in UK food and drinks is considered, for two reasons:

Why UK food industry:

1. In the UK, food and drink manufacturing is one of the important sources of national economic income which created and the £153.2bn gross value added and 4.2 million jobs in 2023 (GOV.UK, 2025b) and faces growth pressure(The Food & Drink Federation, 2025 & 2025b). Therefore, Innovation in the UK food and drink industry is an important focus in the UK market and is seen as a main driver for keeping up with market trends and contributing to the UK economy (The Food & Drink Federation, 2025; 2025b). In this industry, most innovation is market-oriented, meaning it focuses on market introduction and diffusion rather than large-scale R&D activities (Grunert et al., 1997). These innovations often take the form of small changes that shape the final product for the market. Therefore, the UK food and drink industry is a good place to observe innovation.

Moreover, innovation in the food and drink industry requires the involvement of diverse types of knowledge and is expressed in different ways, which makes it possible to observe a wide range of innovation types and the diverse team processes behind them. Product innovation includes new formulations and raw materials, such as functional foods (Bigliardi & Galati, 2013), alternative

proteins, and personalised nutrition (Hassoun et al., 2024). Packaging and sustainability innovation includes intelligent and sustainable packaging, upcycling, and zero-waste production (Mahalik & Nambiar, 2010; Hassoun et al., 2024). Supply chain and distribution innovation includes blockchain for food traceability and 3D food printing (Hassoun et al., 2024). On the production side, innovation focuses on improving processes and manufacturing for efficiency, food safety, and automation. This includes advanced processing technologies such as High-Pressure Processing (HPP), Ultrasound, Cold Plasma, and Pulsed Electric Fields (PEF); energy-efficient methods (Mahalik & Nambiar, 2010); AI and IoT for automation; and improved production equipment and modelling (Hassoun et al., 2024; Naila et al., 2024).

Why functional food and drink sector:

2. With the rising concern for health and the growing adoption of healthy lifestyles, the UK food industry is increasingly viewed as responsible for addressing social issues such as reducing obesity, increasing healthy life expectancy, and lowering sickness-related absence (GOV.UK, 2025a). Functional foods and drinks, as a possible solution, have become a fast-growing sector in the UK food and drink market (Mintel, 2024). However, as part of the fast-moving consumer goods (FMCG) sector, functional food and drink products must respond quickly to rapid market changes, which increases the time and cost pressure on innovation (Sables, 2025). These pressures can intensify tensions between organisational systems and teams, such as conflicts between growth targets and the costs of innovation. Therefore, successful innovation in the functional food industry requires a high level of coordination within the team's innovation process. This makes it an ideal environment for research on how team leaders manage the tensions between corporate systems and team needs to achieve successful innovation.

As part of the UK food and drink industry, functional food and drink products also require the coordination of diverse knowledge, from market-side knowledge to technical knowledge, to achieve innovation. Different types of innovation are involved in functional food and beverage manufacturing, including product innovation, packaging innovation, and process innovation. For product innovation, the mainstream focus is on adaptation and the development of new flavours and ingredient adjustments to keep up with market trends, such as peanut butter flavours, adding more fibre and protein, reducing HFSS (high fat, salt, and sugar), and addressing needs for low-processed, sustainable, and convenient products (Fryers, 2025; Santos, 2024; Santos, 2024b). Innovation in functional foods also involves changes in ingredients for health purposes by adding extra nutrients or replacing harmful elements (Bigliardi & Galati, 2013). For example, Innocent highlights the energising vitamins added to their smoothies (Mintel, 2025).

Product innovation is not limited to ingredients; packaging innovation also plays an important role. Packaging is used to attract consumers with different motivations, such as health, Film/TV tie-ins, and influencer-owned or supported products. For example, Linwoods and Quaker highlight the protein and energy content in their overnight oats (Fryers, 2024); Insane Grain launched the *Insane Kane Salt & Vinegoaaal Flavour Baked Knobbly Sticks* in collaboration with footballer Harry Kane, emphasising its health benefits—34% less fat and "loaded with gut-friendly bacteria" (Baker, 2024).

However, packaging innovation is not only for attracting consumers but also for improving sustainability and usability. For sustainability, Nestlé uses regenerated plastic packaging for KitKat, and Heinz collaborates with retailers and plastic companies to launch Heinz Beanz Snap Pots made with recycled soft plastic (Mintel, 2023). In terms of usability, consumers value convenience and reusability. For example, older consumers are concerned about whether packaging is easy to open, and QR codes on packages aim to engage consumers by offering additional brand-related experiences (Mintel, 2023; Baker, 2023). This shows that packaging innovation not only attracts consumers but also improves their experience of using the product, which can be viewed as a form of service provision.

4.2.2 Case Selection and Sampling

For keep the consistency, the case selection criteria is mad. Since the aim of this study is to understand team innovation within organisations, the unit of analysis includes both the company level and the team level. Therefore, the case selection criteria were defined for these two levels.

Company Level

For company selection, the firm must be a UK functional food and drink brand. This means the company should be owned, funded, and registered in the UK. It should also meet the definition of a functional food and drink company, namely: a company that markets products formulated to provide a specific, targeted physiological or psychological benefit beyond basic nutrition (ref). These products typically contain bioactive compounds—such as probiotics, adaptogens, nootropics, or plant sterols—designed to optimise health, improve performance, or reduce disease risk. For better understanding, common categories of functional food and drink products include protein bars, powders, drinks or gels, energy drinks, and foods or beverages with added nutrients such as probiotics, CBD, or trace elements.

Team Level

Challenge of Identifying the "Innovation Process" Before Entering the Case

Since this study focuses on understanding the "innovation process," it is difficult to identify specific innovation goals and outcomes in functional food and drink companies before entering the case. In addition, innovation processes may involve sub-innovation tasks that contribute to a larger innovation project. To address this issue, the study includes all types of innovation in functional food and drinks mentioned earlier. Projects that produce an innovative output—such as a completed packaging design or other sub-innovation within a larger project—are included, even if these outputs do not become the final product that enters the market. Such sub-projects are still treated as complete innovation projects for the purpose of this study.

Participants

This study focuses on middle managers, who act as a bridge between top-level vision and front-line execution, and team leaders who have direct responsibility for innovation work streams. Participants may work in cross-functional teams or departments, including but not limited to new product development (NPD), packaging, ingredient R&D, and service development. Employees working within cross-functional innovation teams may also qualify as participants.

4.2.3 Data collection

This study uses both primary and secondary data for the purpose of triangulation. The primary data at the team level will be collected through semi-structured interviews with team leaders, as these leaders use their subjective initiative to guide their teams to innovate within a limited organisational context. Based on research conducted on LinkedIn, the relevant team leader roles in practice include NPD Manager/Consultant/Controller, Senior Innovation Manager, Development Lead, Process Development Manager, and Project/Programme Manager/Director/Leader.

The semi-structured interview questions are designed based on the literature review. They cover topics related to the actual discretion of team managers (how they use their flexibility when facing organisational constraints), the formal discretion granted to them by the organisational structure and culture, and the performance of these organisational contexts.

In addition, published documents and company reports from each selected case will be collected to complement the understanding of organisational culture and structure. Relevant research, reports, news, and videos about the selected companies will also be used to support the understanding of management practices within innovation projects.

4.2.3 Data Analysis

Abductive Analytic Logic with iterative analysis

This study employs abductive reasoning as its core analytical logic. Unlike pure inductive or deductive reasoning, abductive reasoning allows researchers to dynamically cycle between existing theoretical frameworks (such as perceived discretion) and emerging phenomena in the data (Mantere and Ketokivi, 2013). During the analysis, this study continuously compares three dimensions: 1. Organisational environment (culture and structure), 2. The scope or degree of discretion granted to middle managers by the organisational environment, and 3. The actual behaviour of middle managers. Through this cyclical comparison, the study aims to reveal how the organisational environment shapes the perceived discretion of middle managers, and how this perceived discretion translates into concrete management practices.

Stage 1: Case Profiling and Contextual Mapping

The first stage of data analysis focuses on within-case profiling, aiming to establish a baseline for each case. By extracting descriptions of company background, team structure, and specific innovative projects (such as packaging innovation or ingredient development) from interview texts, the study constructed a cross-case matrix. This ensured that subsequent analysis could be anchored within a specific organisational context, thereby identifying which behaviours were constrained and supported by the organisational environment.

3.3 Stage 2: Dual-Coding Strategy and Thematic Synthesis

To accurately separate the organisational environment from the actual behaviour of middle managers, this study implemented a dual-coding strategy. This process followed the thematic analysis method proposed by Braun and Clarke (2021) and was adjusted to address the characteristics of perceived discretion:

Contextual Coding: This aims to identify the "given conditions" imposed by the organisation. By recording managers' descriptions of company structure (degree of decentralization and formality) and culture (attitudes towards innovation and tolerance for risk), the pre-set boundaries of the organisational environment were delineated.

Risk Response (Defining the Scope of discretion): The scope of discretion is not solely determined by the wording, but rather defined by analyzing managers' "subjective narratives" of the aforementioned structural and cultural dimensions. This coding captures the organisation's pre-

defined "permitted space," serving as a reference point for measuring whether subsequent actions exceed these boundaries.

Practice Coding: This aims to identify managers' "proactive practices." When respondents describe how they resolve internal resource conflicts or interdepartmental goal misalignment (Internal Misfit) through informal communication, strategic persuasion, or flexible interpretations of rules, this segment is coded as Discretionary Practice.

Logic Recognition (How to Capture Discretion Through Practice): Discretion is not directly visible but is captured through its "performance." Research reveals the actual degree of empowerment managers actually receive by recording their specific practices in the management process (such as cross-departmental coordination and seeking superior support).

Possible solution: At this stage, the research focuses specifically on “Trigger Point Analysis”. That is, how the perceived “freedom” of middle managers translates into concrete coordination behaviours when internal tensions arise (such as the conflict between the technical complexity of R&D and packaging cost control). This distinction effectively prevents the misinterpretation of routine job responsibilities as discretionary power: routine responsibilities manifest as compliance with SOPs, while discretionary power manifests as flexible handling of rules and resource reallocation in the face of internal tensions. This ensures the validity of the coding results.

Stage 3: comparison within and between cases

TBC

5. Results: Some patterns after rough coding

Innovation in companies of all sizes relies on middle management for cross-departmental alignment, information integration, and risk filtering; however, this workload is heavier in small companies because limited resources and a fast pace of innovation force middle management to ensure organisational consensus on the direction of innovation. In large companies, innovation relies more on formalized governance, such as stage-gate systems, hiring processes, and cross-departmental workflows, making processes more stable but reducing the freedom middle management has over team composition and process design. In particular, when leaders join a company with the task of “building a new system or team,” they often gain significantly greater discretion, enabling them to independently design team structures, meeting schedules, and decision-making mechanisms—a point

more pronounced in resource-constrained but highly flexible small and medium-sized enterprises (SMEs).

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Structural Characteristics and firm-level Performance of AI-Related Firms: Evidence from the UK

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1 Introduction

In recent decades, artificial intelligence (AI) has become an increasingly important general-purpose technology (Brynjolfsson et al., 2020; Tambe et al., 2020; Zhai & Liu, 2023), with applications spreading across a wide range of sectors (Mihet and Philippon, 2019; Zhai and Liu, 2023). According to McKinsey's State of AI Survey (2025), the share of organisations reporting the use of AI in at least one business function increased from 55% in 2023 to 72% in the first half of 2024, and further to 78% in the second half of 2024. The survey is based on a global sample of firms. This is also supported by Reuters (2024), reported that 83% of Chinese industry decision-makers use generative AI. Beyond its macroeconomic influence, AI has begun to transform firm-level activities more fundamentally. being embedded into strategic decision-making, innovation processes, organisational practices, and workforce management (Zhang and Liu, 2024). As a result, AI has increasingly become an intangible strategic resource for firms, closely associated not only with firms' productivity performance and competitive advantage, but also with firms' ability to adapt to uncertainty, sustain operations, and maintain financial resilience (Cockburn et al., 2018; Brynjolfsson and Syverson, 2021).

The current AI literature primarily investigates the economic impact of AI technologies at the firm, industry, and national levels (Dedrick,et al., 2013; Damioli et al., 2021; Salehnejad, 2023). At the firm level, these economic outcomes are typically reflected not only in labour productivity, but also in financial resilience, as implementation of AI may require substantial investment, which affect firms' liquidity needs, financing requirements, and ability to absorb short-run adjustment costs (Shiyyab et al., 2023).

Existing evidence on these firm-level effects is not fully uniform. While many studies report positive productivity effects associated with the development or use of AI technologies (e.g. Czarnitzki et al., 2023; Nucci et al., 2023), other contributions emphasise slower adjustment, delayed returns, and the persistence of a "Modern productivity paradox" (Brynjolfsson et al., 2019; Capello et al., 2022). A similar lack of uniformity can also be observed in the literature on financial outcomes, such as Mishra et al. (2022); Shiyyab et al. (2023); Kurter & Bhatti (2025). Taken together, these mixed findings suggest that the economic returns to AI are unlikely to be homogeneous across firms.

This raises a broader question: what kinds of firms develop or adopt AI technologies, and how do their structural characteristics relate to differences in firm performance? Although a growing literature examines the causal impact of AI implementation on firm-level outcomes, relatively little is known about the structural characteristics of AI-related firms themselves. In much of the existing literature, firm characteristics are primarily introduced to explain heterogeneous treatment effects after examining the causal impact (Gopalakrishnan & Bierly, 2006; Semrau & Sigmund, 2012; Brynjolfsson, 2017). As a result, the literature provides limited systematic evidence

on the broader structural profile of AI-related firms, including their size distribution, age structure, geographical locations, productivity levels, financial conditions, and growth dynamics. This limitation is particularly pronounced in the context of the United Kingdom, where firm-level evidence on AI-related firms remains limited due to the lack of comprehensive micro-level datasets (Seamans & Raj, 2018).

To address this gap, we construct a novel firm-level longitudinal panel dataset to identify AI-related firms in the UK and examines their structural characteristics in this paper. The dataset covers the period from 2018-2023 and provides detailed information on firms' profiles, financials, funding, employment, growth trajectories, and geographical information. By focusing on the structural characteristics of AI-related firms, this paper provides new descriptive evidence on the economic profile of AI-related companies in the UK.

We focus on documenting how firm performance varies across AI-related companies with different structural attributes. We examine firm performance along two key dimensions: labour productivity and financial resilience. To capture firm performance more comprehensively, we examine both performance levels and performance dynamics.

We are interested in examining the size distribution and age distribution of AI-related companies across different years and exploring whether these structural characteristics are associated with differences in firm performance. Why some firms outperform others within the same type of companies has long been a widely discussed and debated question in the strategic management literature (Barney, 1991; Dubey, 2019). We also examine whether geographical location, sectoral affiliation and gender of directors are associated with differences in firm performance among AI-related firms.

Understanding the characteristics of firms that develop or adopt AI technologies is important for several reasons. First, it helps to clarify whether AI-related activities is concentrated among particular types of firms rather than being evenly distributed across the business population. Second, it provides new evidence on the structural heterogeneity underlying firm-level performance among AI-related firms. Third, in the UK context, such evidence is relevant to ongoing debates on innovation policy, industrial transformation, productivity growth, and the financial resilience of firms operating in emerging technology-intensive environments (OECD, 2023).

The paper is organised as follows. Section 2 reviews the relevant literature on AI and firm-level performance. Section 3 describes the data and methodology, including the construction of the sample and key variables. Section 4 presents the results. It first examines labour productivity across AI-related firms, before turning to financial resilience. Section 5 discusses the main findings and concludes.

2 Literature review

2.1 AI and firm-level performance

AI is increasingly regarded as a general-purpose technology with the potential to enhance firm-level productivity through innovation, automation, and augmentation (Leyer & Schneider, 2021; Lei & Kim, 2024). Accordingly, many current literature have the expectation that firms developing, adopting, or implementing AI are likely to achieve stronger productivity performance. Rodrigo (2021), Wang et al. (2021), Damioli et al. (2021), Lee et al. (2022), Grashof & Kopka (2022), Anderton et al. (2023), Kopka & Fornahl (2023), Nucci et al. (2023), Gao & Feng (2023), and Zhai & Liu (2023) provide empirical evidence consistent with this positive expectation. The findings suggest that AI-related activities may be associated with improved firm-level productivity performance.

However, an alternative perspective suggests that firms' investment in AI does not necessarily lead to immediate improvements in productivity. This phenomenon is often discussed in the literature as a "Modern productivity paradox", which has primarily been identified at the aggregate level, where increase in technological investments has not always been accompanied by increases in measured productivity. While this paradox is typically examined at the macro level, it also implies that productivity gains from AI-related activities at the firm level may be delayed, unevenly distributed, or difficult to observe in the short run (Brynjolfsson et al., 2019; Capello et al., 2022).

One possible explanation for these divergent findings is that the benefits of AI depend on firms' ability to make complementary investments and organisational adjustments (Brynjolfsson & Hitt, 2000; Arvanitis & Loukis, 2009; Dedrick et al., 2013). As Tambe et al. (2020) argue, AI adoption remains uneven across firms, with diffusion concentrated among those that possess strong complementary assets. As a result, firms that can integrate AI effectively into their operations are more likely to have productivity gains, while others may experience delayed or limited benefits.

A similar lack of uniformity can also be observed, albeit in a more limited body of work, in relation to AI and firms' financial outcomes. Existing studies have focused on indicators such as profitability, cost efficiency, or accounting performance. For example, Mishra et al. (2022) examine the relationship between AI-related activities and firms' profitability, while Shiyyab et al. (2023) provide evidence based on accounting measures such as return on assets (ROA), return on equity (ROE), and total expenses, both provide evidence that AI use is positively associated with financial performance and cost efficiency.

However, other studies suggest that this relationship may be more complex and conditional rather than uniformly positive. For instance, Chen et al. (2023) find that the effect of robot adoption on profit margins depends on the level of adoption, with lower levels of adoption associated with lower profit margins, while higher levels of

adoption are positively correlated with profit margins. This indicates that the financial effects of AI-related technologies may vary depending on the extent and intensity of adoption, rather than being consistently positive across all firms. One possible interpretation is that the financial effects of AI depend on the stage of adoption, with initial investment and adjustment costs potentially reducing financial performance in early stages, while efficiency gains may only materialise at later stages.

Taken together, the existing literature suggests that the relationship between AI and firm-level performance is not uniform across firms. While a large body of work documents positive effects of AI-related activities on productivity and financial outcomes, other studies point to delayed, uneven, or conditional effects. In this sense, the literature remains far from conclusive, with considerable variation in the observed outcomes across firms and contexts.

While existing studies mainly rely on broad financial indicators such as profitability or accounting performance (Mishra et al., 2022; Shiyyab et al., 2023), less attention has been paid to more direct measures of financial resilience—such as liquidity and leverage—which may be critical for understanding how firms absorb the costs and risks associated with AI use.

2.2 Previous empirical evidence on heterogeneous effects and hypothesis development.

Building on the heterogeneity in AI-related outcomes identified in the previous section, this section examines the firm characteristics that have been shown to shape the effects of AI across firms. Table 1 summarises the main firm-level characteristics that have been identified in the literature as sources of heterogeneity in the relationship between AI (or related digital technologies) and firm-level productivity.

The heterogeneous factors reported in Table 1 are derived from regression-based empirical frameworks, where firm characteristics are incorporated as control variables or interaction terms to explain heterogeneous treatment effects. In this approach, heterogeneity refers to variation in the magnitude of the impact of AI across firms, rather than differences in the underlying structure or composition of AI-related firms themselves.

With respect to firm age, the evidence remains mixed. Czarnitzki et al. (2023), Yang (2022), and Nucci et al. (2023) find that older firms tend to experience higher productivity gains from AI-related investments, which may reflect accumulated experience and stronger organisational capabilities. In contrast, Anderton et al. (2023) report that younger firms benefit more from digital technologies, consistent with the view that they are more flexible and better able to integrate new technologies without

legacy constraints, a pattern also observed by Borowiecki et al. (2021), particularly in the services sector.

Firm size is another key factor highlighted in the literature, although the findings are not fully consistent. Several studies suggest that larger firms experience stronger productivity gains due to their greater access to financial resources and complementary assets (Zhai & Liu, 2023; Yang, 2022; Nucci et al., 2023; Anderton et al., 2023). However, Kopka & Fornahl (2023) show that the role of firm size depends on the type of AI innovation, with different effects observed for AI methods and AI applications.

Industry characteristics and market conditions also play an important role. Anderton et al. (2023) find that firms operating in more concentrated markets tend to experience lower productivity gains, while Gao & Feng (2023) report a positive relationship between market concentration and productivity, suggesting that the effects may depend on institutional and policy contexts. In addition, sectoral differences—such as digital versus non-digital industries, labour-intensive versus capital-intensive sectors, and state-owned versus non-state-owned firms—have been shown to influence the extent to which firms benefit from AI-related investments (Zhai & Liu, 2023; Gao & Feng, 2023; Nucci et al., 2023).

Further evidence highlights the importance of firms' external engagement and initial conditions. Yang (2022) shows that firms with higher levels of foreign direct investment (FDI) and export intensity tend to experience greater productivity gains, consistent with the role of knowledge spillovers (Bloom et al., 2012). With respect to initial productivity, the evidence is more nuanced. Borowiecki et al. (2021) find that lower-productivity firms may benefit more from certain forms of digital adoption, particularly software-related technologies, suggesting potential convergence effects. In contrast, Anderton et al. (2023) show that only firms above a certain productivity threshold (the 30% of top-performing laggard firms) can benefit from digitalisation, highlighting the importance of pre-existing capabilities in shaping the returns to AI-related investments.

Compared to the extensive literature on productivity, empirical evidence on the heterogeneous financial effects of AI-related companies remains relatively limited. While some studies (Mishra et al., 2022; Shiyyab et al., 2023; Chen et al., 2023) examine the relationship between AI-related activities and firm-level financial performance, they focus on average effects rather than systematically exploring how these effects vary across firms with different characteristics. This suggests that the role of firm characteristics in shaping financial performance of AI-related companies has received relatively limited attention in the existing literature.

Author	Country	Year	Heterogenous factors

Czarnitzki et al.	Germany	2023	1. Firm age: higher productivity for older firms 2. 17 industry dummies: depend on the specific industry
Zhai & Liu	China	2023	1. Firm size: higher productivity for larger firms 2. State-owned enterprises: positive (gain more productivity from AI investments) 3. Labour-intensive industries: positive (gain more productivity from AI investments)
Anderton et al.	EU	2023	1. Firm size: higher productivity for larger firms 2. Firm age: lower productivity for older firms 3. Market concentration: negative (less productivity gains from AI investments) 4. Liquidity: negative (less productivity gains from AI investments) 5. Leverages: positive (more productivity gains from AI investments) 6. Digital sectors are more productive than non-digital sectors 7. Only the 30% of most productive lagged firms can benefit from digitalisation
Kopka & Fornahl	EU	2023	1. Types of AI patents: AI method patents vs. AI application patents - AI methods: greater positive effects of frontier firms, larger firms - AI applications: greater positive effect of latecomer firms, smaller firms
Gao & Feng	China	2023	1. Non-state-owned enterprises: positive (benefit more from technology investments) 1. Market concentration: higher productivity for higher market concentration 2. Capital-intensive: higher

			productivity for more capital-intensive firms. 3. Technology-intensive: higher productivity for more technology-intensive firms.
Yang	Taiwan	2022	1. Firm size: higher productivity for larger firms 2. Firm age: higher productivity for older firms 3. Foreign Direct Investment (FDI): engage in outward FDI, particularly through the establishment of foreign affiliates, tend to experience higher productivity gains. 4. Export intensity: higher proportion of firms' sales coming from exports tend to benefit more from AI investments.
Nucci et al.	Italy	2023	1. Firm size: higher productivity for larger firms 2. Firm age: older firms are more likely to rely extensively on digital technologies. 3. More labour-intensive: negative (less productivity gains from technology investments)
Borowiecki et al.	Netherlands	2021	1. Initial productivity levels: low-productivity firms benefit more from software development. 2. Firm age: productivity effects stronger for younger firms (in services)
Li et al.	China	2021	1. Operational efficiency (OE): measure OE using the stochastic frontier approach (SFA); Higher productivity for higher OE.

Table 1: The role of heterogeneous factors

Taken together, the existing evidence points to substantial heterogeneity in the effects of AI across firms, yet the findings remain fragmented and difficult to reconcile across different dimensions and contexts. Recent descriptive evidence based on UK firm-level survey data further suggests that the adoption of advanced digital technologies varies systematically with firm size, sector, and geographical location

(Massini et al., 2025), providing indicative evidence on the structural patterns underlying technology adoption. In particular, it remains unclear how firm characteristics are jointly distributed among AI-related firms and how such structural patterns are associated with variation in firm-level outcomes. Addressing this gap is essential for developing a more integrated understanding of both productivity differences and financial resilience in the context of AI-related firms.

Based on the above literature review, this study develops a set of hypotheses regarding how firm characteristics are associated with variation in firm-level performance (labour productivity and financial resilience) among AI-related firms:

H1: Firm size is associated with variation in labour productivity and financial resilience among AI-related firms.

H2: Firm age is associated with variation in labour productivity and financial resilience among AI-related firms.

H3: Sectoral differences, including the distinction between manufacturing and services as well as between high-, medium-, and low-technology industries, are associated with variation in labour productivity and financial resilience among AI-related firm.

H4: Differences between firms located in London and those located outside London are associated with variation in labour productivity and financial resilience among AI-related firms.

3 Data and method of analysis

This study constructs a firm-level panel dataset to identify AI-related firms in the UK and examine the association between structural firm characteristics and firm-level performance. The dataset is based on firm-level data obtained from TheDataCity, a commercial database that provides detailed information on UK firms. The sample is constructed in several steps. First, firm-level web content provided by TheDataCity is processed to extract relevant textual information. Second, a list of AI-related keywords (a text-based classification approach) is applied to firms' website information to identify AI-related firms. The keyword list is developed and iteratively refined to ensure that it accurately captures firms engaged in AI-related activities. To validate the relevance of each keyword, we manually inspect the firms returned by the platform's search engine and assess whether they are genuinely involved in AI-related technologies or applications. Keywords that generate a substantial number of non-AI-related firms are excluded from the final list. This validation procedure helps improve the precision of the classification and reduces the inclusion of irrelevant firms. The dataset covers the period from 2018 to 2023 and includes AI-related firms across a wide range of industries and sizes.

Firm performance is examined along two dimensions: labour productivity and financial resilience. Labour productivity is measured as total turnover divided by the number of employees, log-transformed to account for skewness in its distribution, and subsequently winsorised at the 1st and 99th percentiles. Financial resilience is captured using two indicators: liquidity and leverage. Liquidity is measured by the current ratio (current assets over current liabilities), and leverage is measured by the debt-to-equity ratio (total debt over shareholders' equity). The leverage measure is restricted to firms with positive debt-to-equity ratios. To mitigate the influence of extreme values, both liquidity and leverage are winsorised at the 1st and 99th percentiles.

Firm characteristics include firm size, firm age, sectoral affiliation, and geographical location. Firm size is measured by the number of employees. Firm age is defined as the number of years since establishment. Sectoral affiliation is based on firms' SIC (Standard Industrial Classification) codes, which are used to distinguish between manufacturing and services, and to classify firms into high-, medium-, and low-technology industries. Geographical location is defined using the ITL1 classification and is captured as a binary indicator distinguishing firms located in London from those located outside London. Where relevant, firm-level variables are constructed using both average values across years and the full panel structure to capture differences between overall firm-level patterns and variation over time.

The analysis documents the distribution of firm characteristics and examines differences in firm-level performance across groups of AI-related firms. Summary statistics are reported in Table 2. Differences across groups are further explored using statistical tests. For comparisons involving two groups, Welch's t-tests are employed. For comparisons across multiple groups, Welch's analysis of variance (ANOVA) is used, followed by Games–Howell post-hoc tests where appropriate.

Given that several firm-level variables are not normally distributed, non-parametric tests are also applied. In particular, Mann–Whitney U tests and Kruskal–Wallis tests are used to assess the robustness of the results.

4 Descriptive analysis and results

This section presents the descriptive statistics and main patterns for AI-related firms in the UK over the period 2018–2023. We begin by providing an overview of the sample and the key variables and then examine how firm performance varies across firms with different structural characteristics. In line with the focus of this paper, firm performance is analysed along two dimensions: labour productivity and financial resilience. The latter is captured through firms' liquidity and leverage positions. The analysis that follows focuses on documenting systematic differences across firm size, age, sector, location, and other structural attributes.

Table 2 reports the descriptive statistics of the main variables used in this study. The summary statistics show that, on average, firms differ across key dimensions of size, performance, and financial conditions. Firm size and turnover display relatively low mean values compared with their standard deviations, indicating variation across firms.

Variable	Obs	N firms	Mean	Std. Dev.	Min	Max
Productivity (£ thousand per employee)	353232	80802	107.265	179.956	7.441	1,396.333
Number of employees	358732	80834	31.805	115.751	1.000	916.000
Turnover (£ million)	367998	83842	6.966	31.683	0.005	261.077
Firm growth (2-year, %)	200051	71785	18.589	66.509	-70.000	400.000
Productivity growth (2-year, %)	194830	70712	4.063	28.259	-58.737	206.260
Firm age (average across 2018–2023)	96797	96797	10.522	11.126	0.000	61.000
Current ratio	406621	91993	5.692	19.066	0.000	158.847
Debt-to-equity ratio	438108	96195	19.352	120.059	-58.052	1,058.761

Table 2: pooled descriptive statistics

Notes:The statistics are reported for the 2018–2023 sample.
Continuous variables are winsorised at the 1st and 99th percentiles.
Total number of firms in sample = 96,802
Firm-year observations in 2018–2023 sample = 442,548

In terms of performance, firms exhibit positive average growth rates, while productivity growth appears more moderate. Financial indicators also show considerable variation, as reflected in the large standard deviations of both liquidity and leverage measures. We next examine whether these performance differences are systematically associated with firms' structural characteristics.

4.1 Labour productivity

In Figure 1, a clear pattern emerges in which the distribution shifts to the right as firm size increases, indicating higher productivity among larger AI-related firms. This pattern is highly consistent across years, with the overall shape of the distributions remaining stable over time. A similar pattern is observed in Figure 2,which presents the distribution of time-averaged labour productivity by firm size, further confirming the presence of a size–productivity gradient.

This visual evidence is supported by the statistical results. A Welch ANOVA indicates that labour productivity differs significantly across firm size groups within

AI-related firms. Post-hoc comparisons further show that productivity increases monotonically from micro to large firms, with all pairwise differences being statistically significant.

To examine whether a broader distinction between smaller and larger firms remains meaningful, firms are grouped into micro and small firms on the one hand, and medium and large firms on the other. Statistical tests indicate that larger AI-related firms have significantly higher labour productivity than smaller AI-related firms, and the difference is economically substantial.

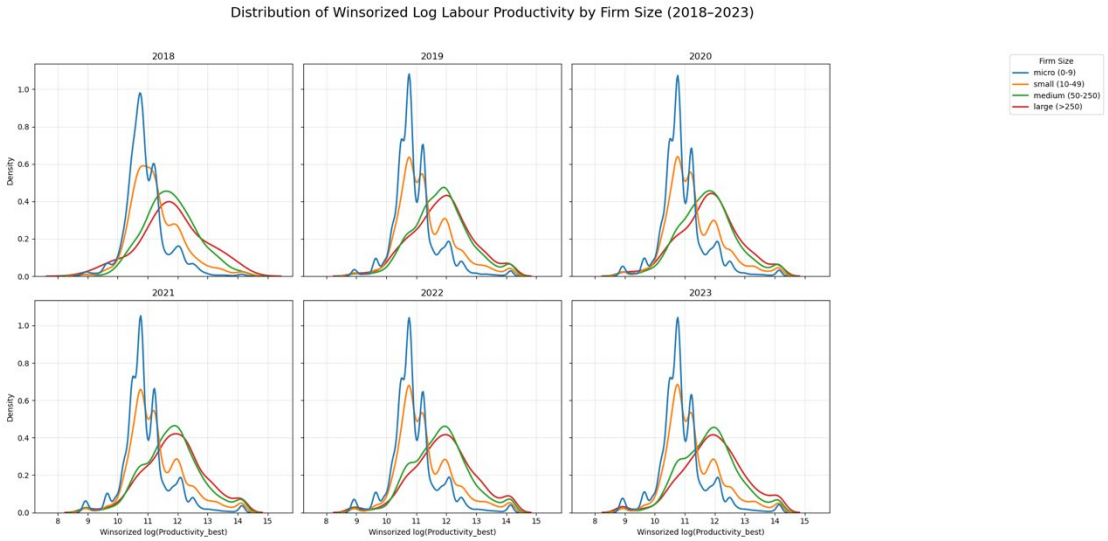


Figure 1: distribution of labour productivity level by firm size across years

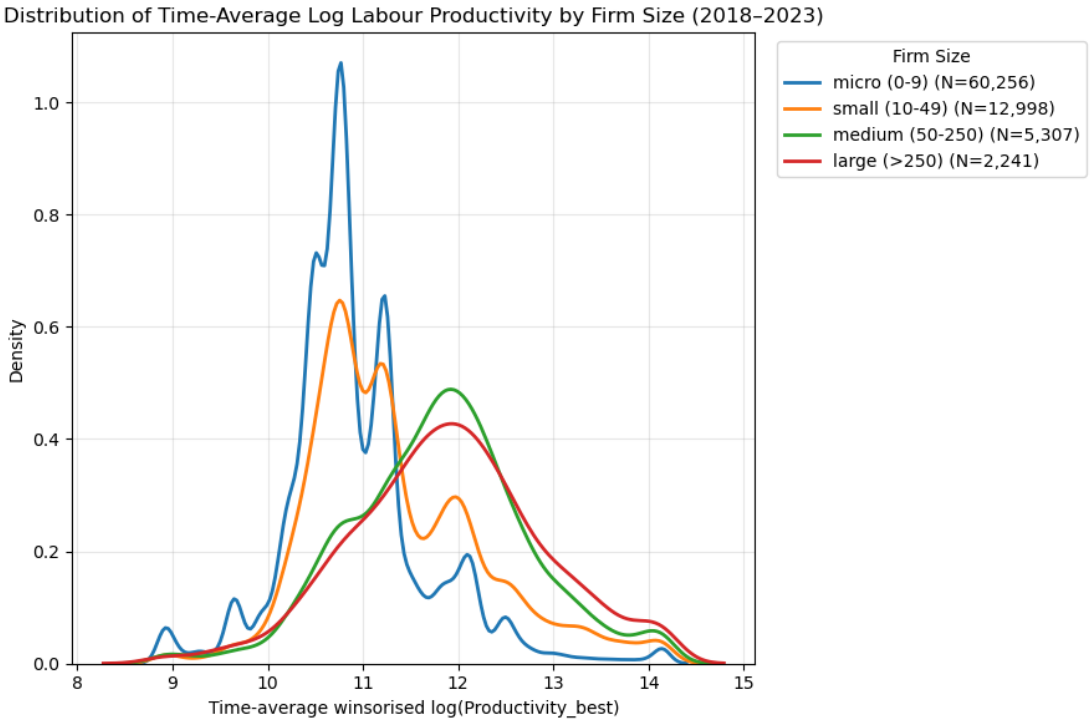


Figure 2: distribution of average labour productivity by average firm size

Figure 3 presents the distribution of two-year labour productivity growth across firm-size groups within AI-related companies. In contrast to the clear monotonic gradient observed for labour productivity levels, the size-related pattern in productivity growth appears less pronounced. The distributions still suggest higher productivity growth among larger AI-related firms, but the separation between groups is weaker, with particularly substantial overlap between medium and large firms. This is consistent with the statistical evidence: although two-year productivity growth differs significantly across firm-size groups overall, post-hoc tests indicate no statistically significant difference between medium and large firms. The main contrast therefore lies between smaller and larger firms, with micro and small firms showing weaker productivity growth performance than medium and large firms.

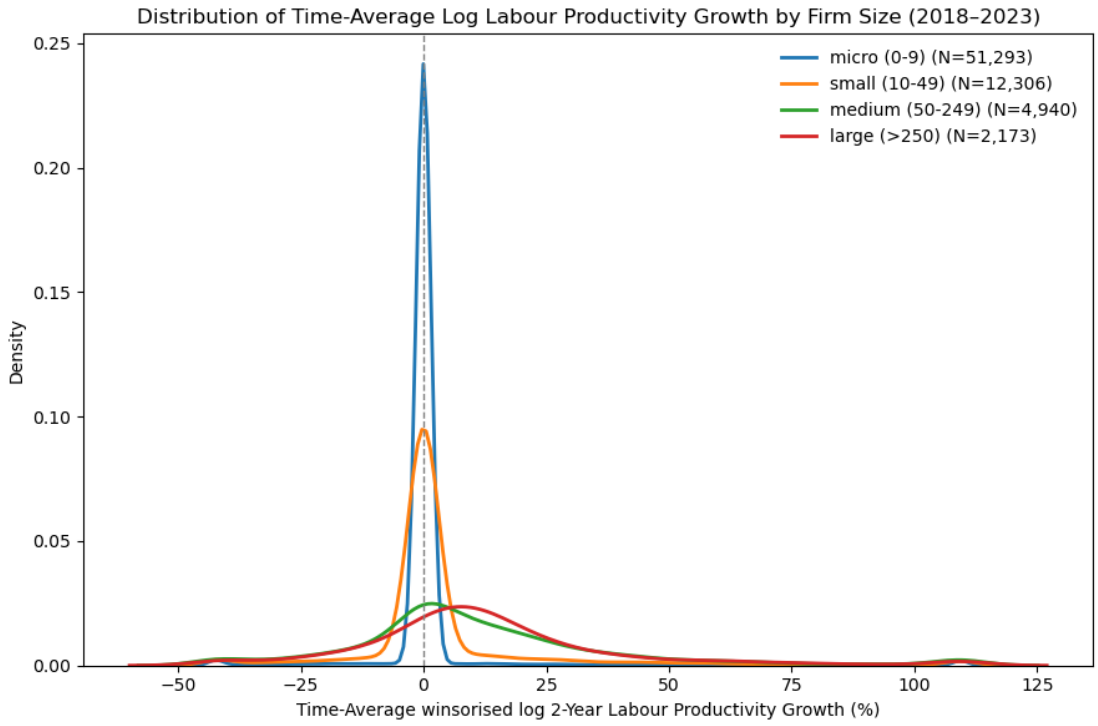


Figure 3: Distribution of 2-year labour productivity growth by firm size

A similar pattern is observed in Figure 4, where older AI-related firms exhibit higher labour productivity than younger firms throughout the sample period. This difference is highly consistent across years, with the two distributions maintaining a stable relative position over time. The same contrast is visible in Figure 5 for averaged labour productivity. This visual evidence is supported by the statistical results, which indicate that the difference in productivity levels between young and old firms is statistically significant and economically moderate. Compared with the size–productivity gradient, however, the magnitude of the age effect is noticeably smaller.

By contrast, the difference is much weaker for productivity growth. As shown in Figure 6, although older AI-related firms tend to exhibit slightly higher averaged productivity growth than younger firms, the two distributions overlap substantially. This is consistent with the statistical results, which indicate that the difference in productivity growth is statistically significant but economically small.

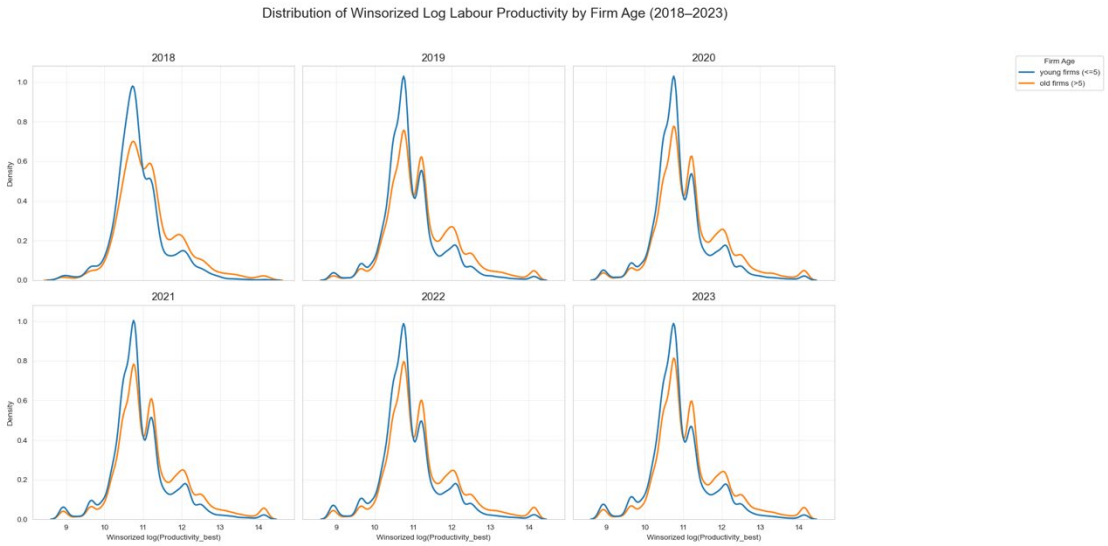


Figure 4: Distribution of labour productivity level by firm age across years

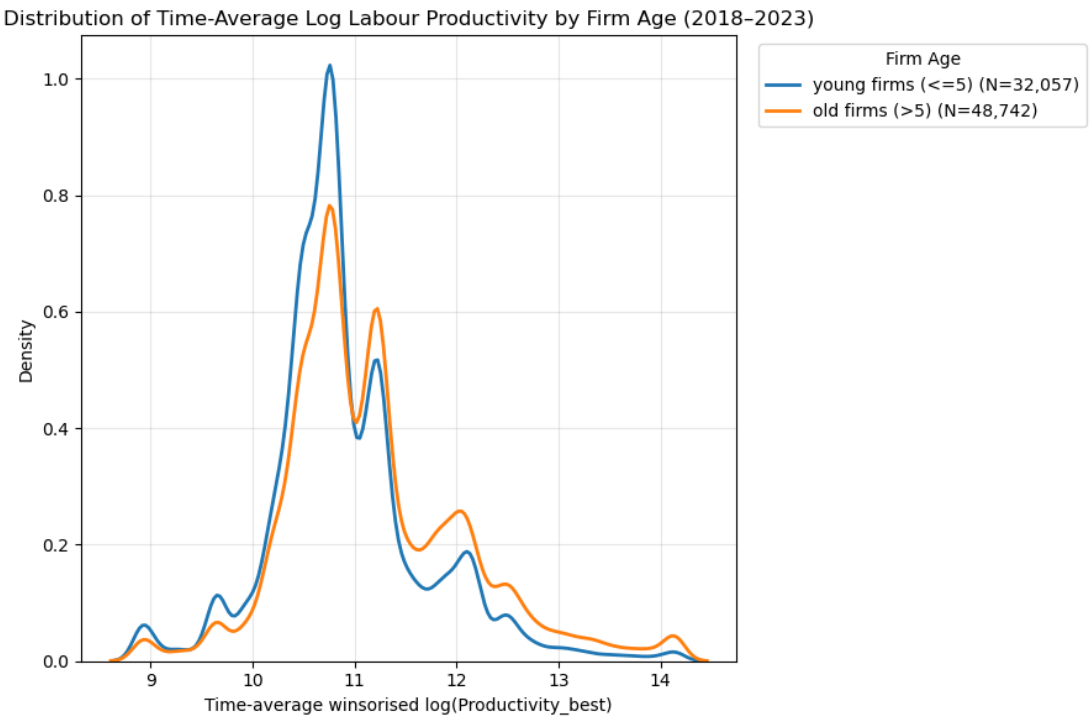


Figure 5: distribution of average labour productivity by average firm age

Figure 8 indicates that labour productivity differs slightly between London and non-London AI-related firms. Firms located in London exhibit marginally higher

productivity, as reflected in a modest rightward shift of the distribution. However, the two distributions largely overlap, suggesting that the magnitude of this difference is limited.

This visual pattern is consistent with the statistical results, which indicate that the difference is statistically significant but economically small. The similarity in the distributions is also reflected in the median values, which are effectively identical across the two groups.

Figure 7 provides additional context by showing the spatial distribution of AI-related firms across UK regions. It highlights a strong concentration of firms in London and the South East. Despite this geographical concentration, the productivity advantage associated with London remains relatively modest, suggesting that location alone does not generate large differences in firm-level productivity within AI-related firms.

Figure 6: Distribution of 2-year labour productivity growth by firm age

Sectoral differences are particularly pronounced. Figure 9 indicates that AI-related firms in the manufacturing sector exhibit substantially higher labour productivity than AI-related firms in the services sector, with a clear rightward shift of the distribution and limited overlap between the two groups. This visual pattern is consistent with the statistical results, which indicate that the difference is statistically significant and large in magnitude. The separation is also reflected in both the mean and the median, suggesting that the productivity advantage of AI-related firms in the manufacturing sector is not driven solely by a small number of extreme observations.

Within the manufacturing sector, further differences emerge across technology groups. Figure 10 suggests that AI-related firms in low-technology manufacturing exhibit lower labour productivity than those in medium- and high-technology manufacturing, as reflected in a leftward shift of the distribution. By contrast, the distributions for medium- and high-technology manufacturing are broadly similar, with substantial overlap. The statistical evidence indicates that labour productivity differs significantly across manufacturing technology groups overall, but that the difference between medium- and high-technology groups is not statistically significant.

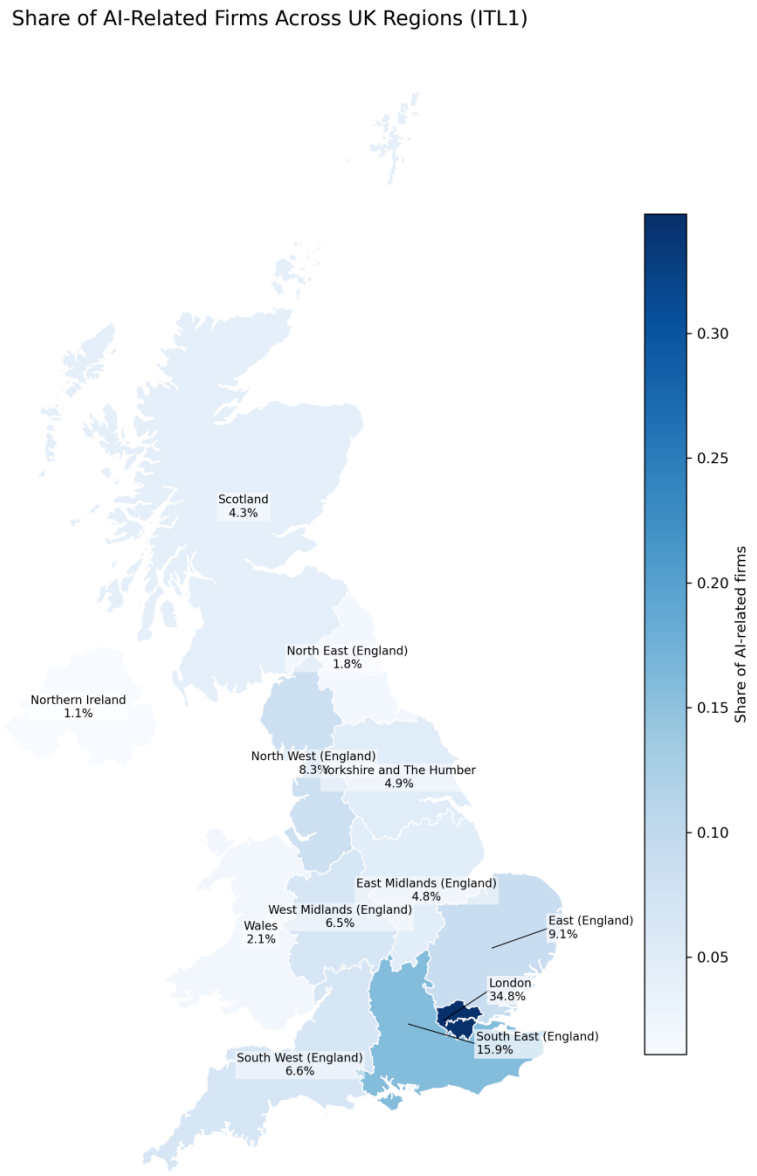


Figure 7: Share of AI-related firms across UK regions

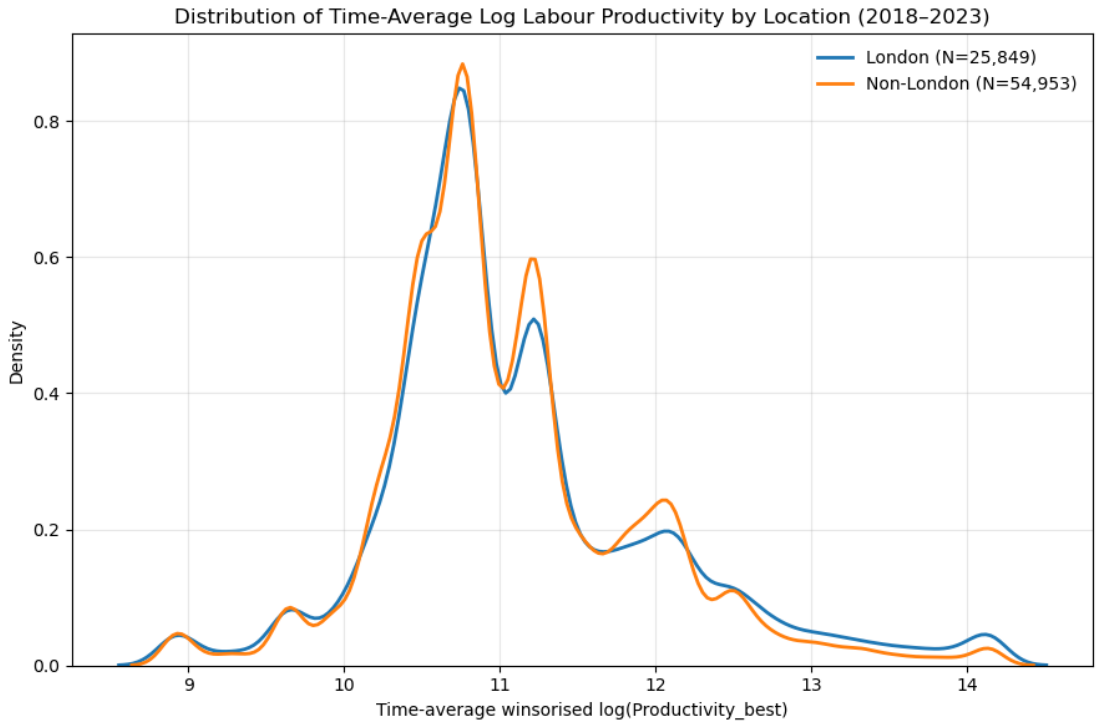


Figure 8: distribution of average labour productivity by location

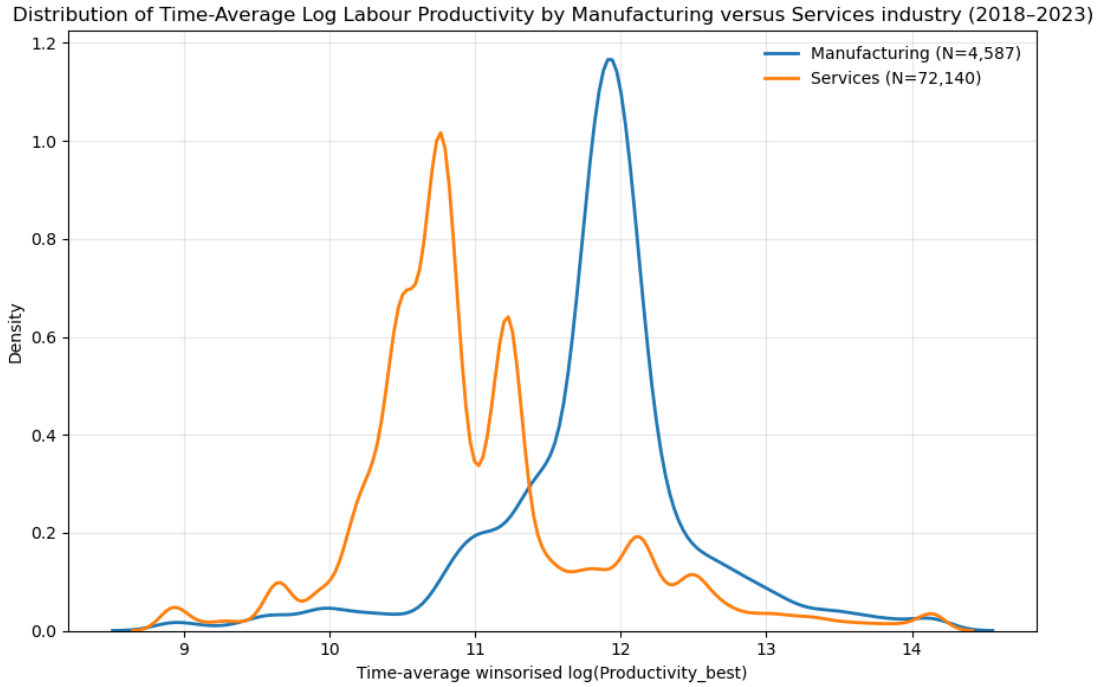


Figure 9: distribution of average labour productivity by manufacturing versus services sectors

Figure 10: distribution of average labour productivity by manufacturing high-tech, medium-tech, and low-tech industries

4.2 Financial resilience

In this section, we first examine AI-related firms' liquidity patterns across firm characteristics, before turning to leverage as a complementary indicator of financial resilience. Figures 11–14 collectively show that liquidity differs significantly across firm-size groups, although the size–liquidity pattern is not monotonic. In both manufacturing and services, small AI-related firms exhibit the highest median liquidity, while large AI-related firms consistently display the lowest, indicating that larger AI-related firms operate with tighter working capital positions. (see Figure 11).

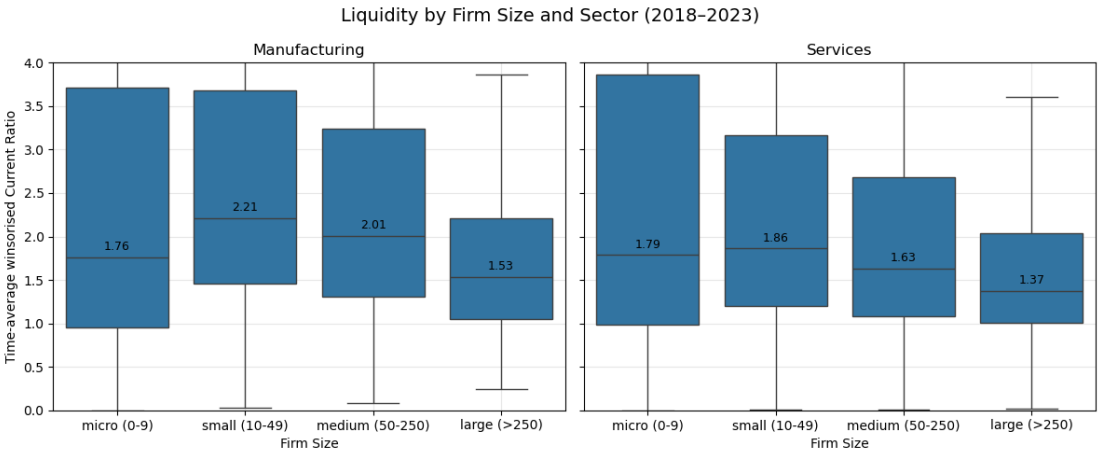


Figure 11: average liquidity by firm size and sector (manufacturing versus services)

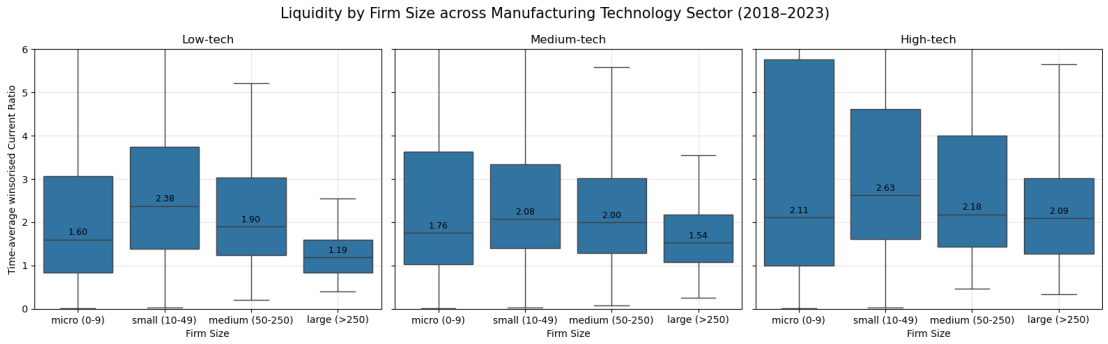


Figure 12: average liquidity by firm size and manufacturing technology sector

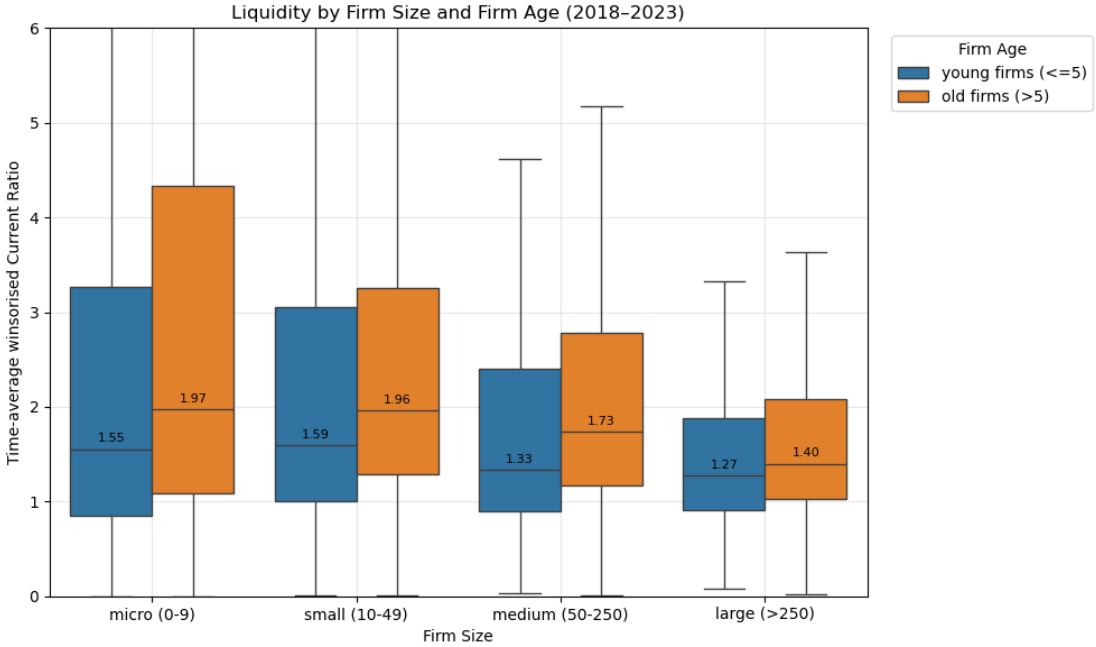


Figure 13: average liquidity by firm size and firm age

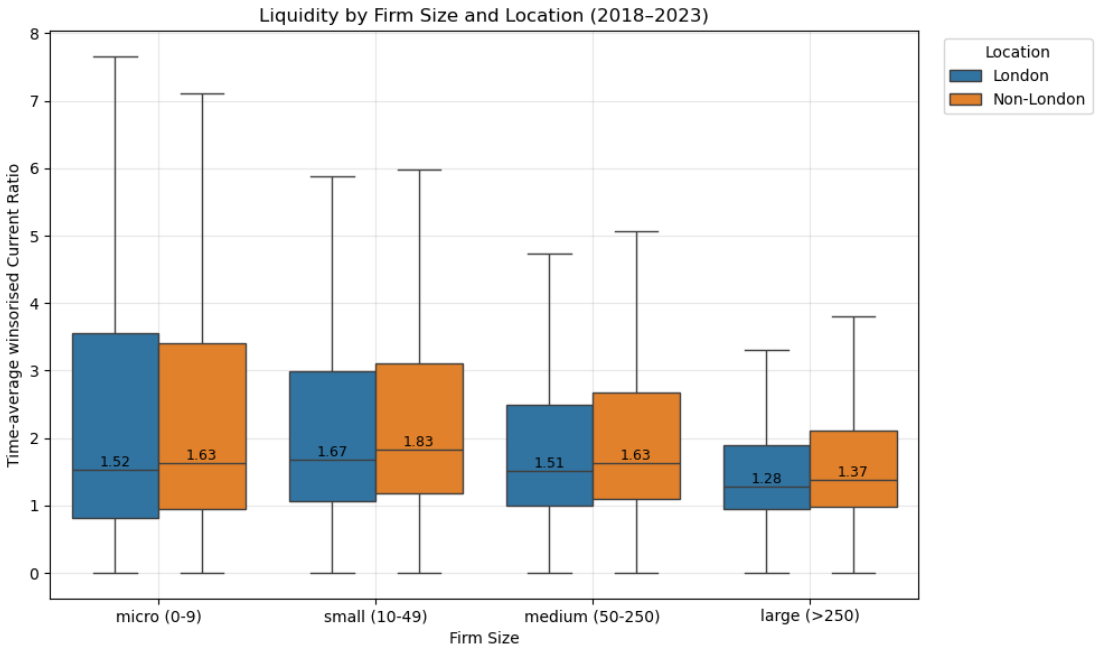


Figure 14: average liquidity by firm size and location

Despite these broadly similar size patterns, sectoral differences are concentrated in specific segments of the size distribution. Liquidity is significantly higher in AI-related firms in the manufacturing sector than in AI-related firms in the services sector among small and medium-sized firms, whereas no statistically significant difference is observed among micro or large firms after multiple-testing correction. This suggests that sectoral effects on liquidity are size-dependent rather than pervasive.

Within the manufacturing sector, liquidity among AI-related firms varies with technological intensity, but this pattern is heterogeneous across firm sizes. Differences across technology groups are evident for most size classes, particularly among micro, small, and large firms, while no statistically significant differences are observed among medium-sized firms. This indicates that the role of technology in shaping liquidity among AI-related firms is conditional on firm size (see Figure 12).

Firm age exhibits a consistent and economically meaningful effect. Older AI-related firms maintain significantly higher liquidity than younger AI-related firms across all size groups. Moreover, the size–liquidity gradient is more pronounced among older AI-related firms, indicating increasing differentiation in financial resilience as firms mature (see Figure 13).

Location-based differences display a clear pattern. Liquidity differs significantly across firm-size groups in both London and non-London AI-related firms, and non-London firms exhibit consistently and significantly higher liquidity than London firms within every size class. Despite this systematic level difference, the overall size–liquidity pattern remains similar across locations, with small AI-related firms showing

the highest liquidity and large AI-related firms the lowest. This suggests that location shifts the level of liquidity without fundamentally altering its relationship with firm size (see Figure 14).

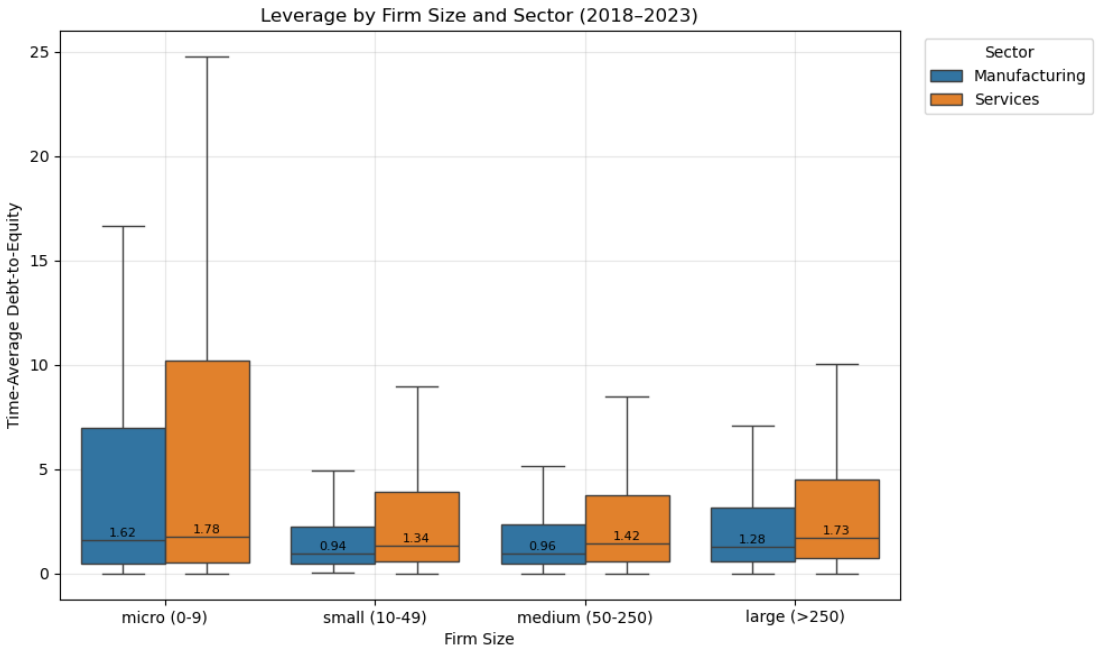


Figure 15: average leverage by firm size and sector (manufacturing versus services)

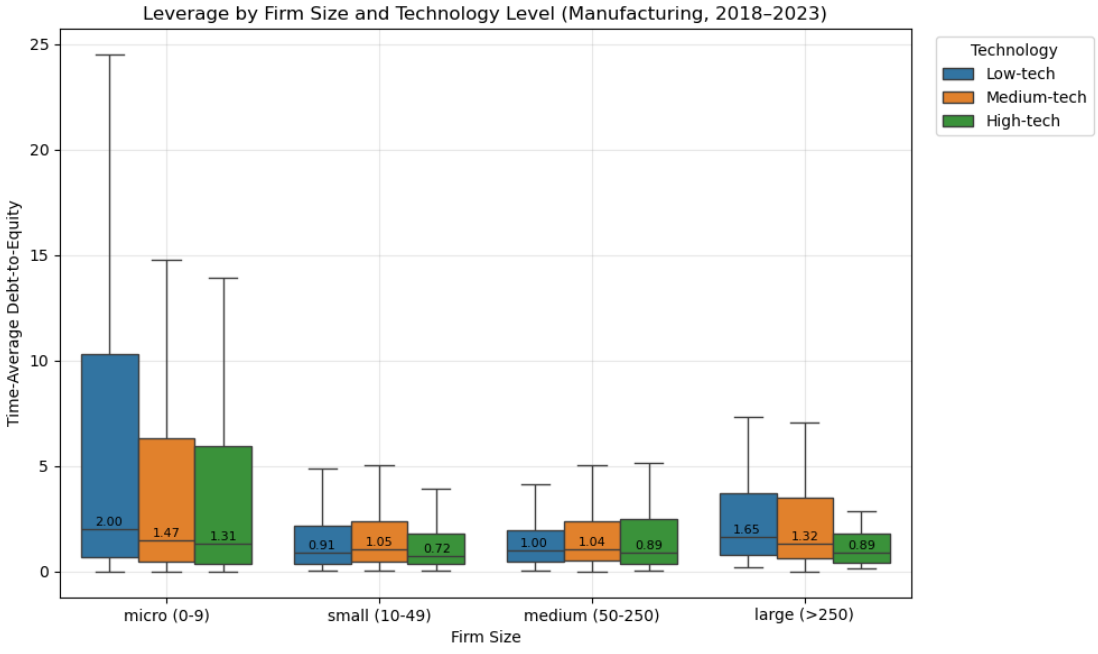


Figure 16: average leverage by firm size and manufacturing technology sector

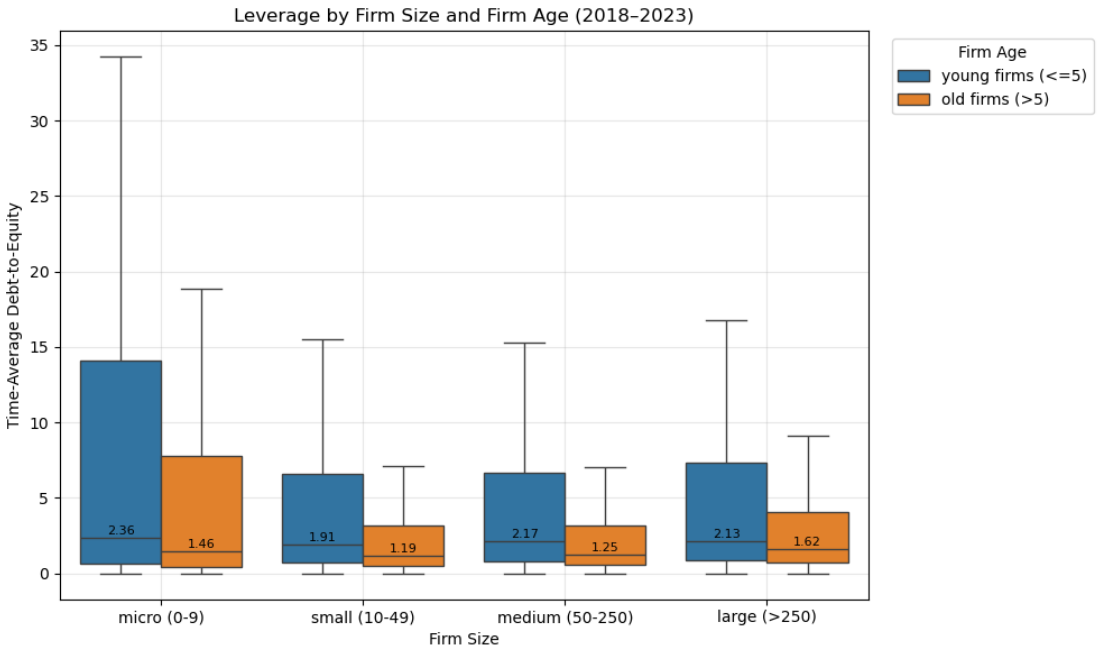


Figure 17: average leverage by firm size and firm age

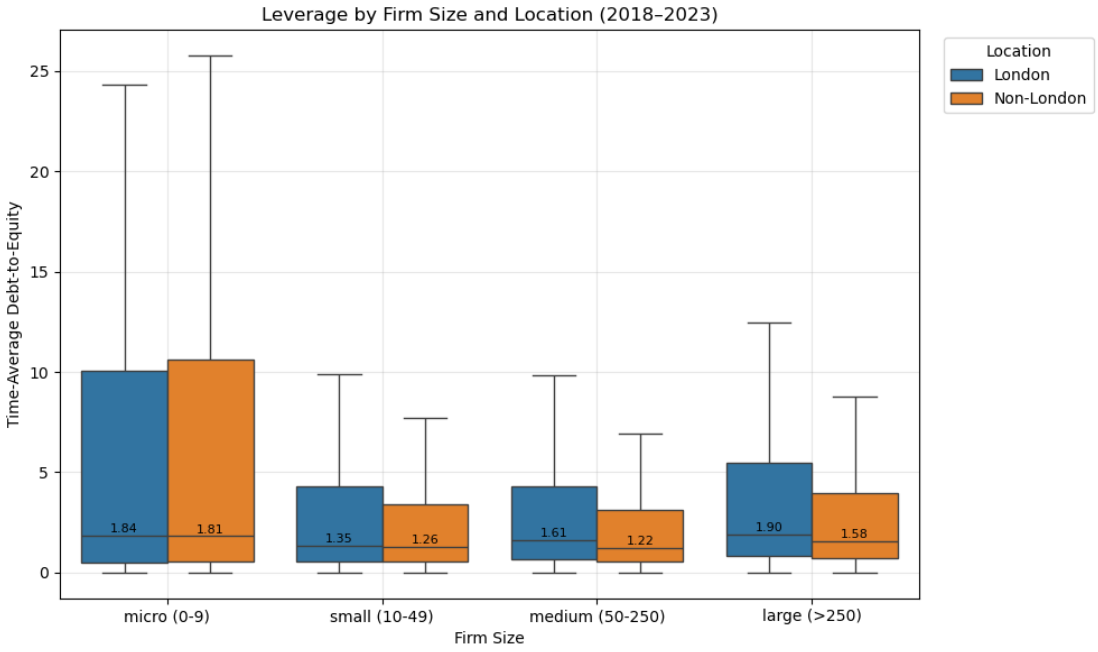


Figure 18: average leverage by firm size and location

Leverage, measured as the debt-to-equity ratio, provides a complementary dimension of financial resilience by capturing firms' reliance on external financing. While liquidity reflects short-term financial buffers, leverage reflects longer-term financing structures and risk exposure, allowing for a more comprehensive assessment of financial positions among AI-related firms.

Across sectors, leverage exhibits a clear size-dependent pattern among AI-related firms (see Figure 15). Leverage differs significantly across firm-size groups within

both AI-related firms in the manufacturing sector and AI-related firms in the services sector. In both sectors, micro AI-related firms exhibit significantly higher leverage than small and medium-sized firms, while differences between micro and large firms are not consistently significant after multiple-testing correction. In addition, AI-related firms in the services sector exhibit significantly higher leverage than those in the manufacturing sector within all size groups, indicating a systematically greater reliance on external financing in service-based AI activities.

Within manufacturing, leverage varies with technological intensity among AI-related firms, although this relationship is heterogeneous across firm sizes (see Figure 16). Differences across technology groups are statistically significant within micro, small, and large AI-related firms, but not among medium-sized firms. Pairwise comparisons indicate that low-technology AI-related firms tend to exhibit higher leverage than high-technology firms, particularly among micro firms, while differences between medium- and high-technology firms are less consistent. This suggests that reliance on debt financing declines with technological intensity, but only in specific segments of the size distribution.

Firm age exerts a strong and consistent effect on leverage among AI-related firms (see Figure 17). Leverage differs significantly across firm-size groups within both young and old AI-related firms. Moreover, young AI-related firms exhibit significantly higher leverage than old AI-related firms within every size group, indicating a systematic dependence on external financing at earlier stages of development. Within age groups, micro firms tend to display the highest leverage, although differences across larger size classes are less consistently significant. This pattern contrasts sharply with liquidity, where older AI-related firms maintain higher levels of financial buffers, highlighting a life-cycle dynamic in financial structure.

Location-based differences are more nuanced among AI-related firms (see Figure 18). Leverage differs significantly across firm-size groups within both AI-related firms located in London and those located outside London. However, differences between locations are size-dependent. AI-related firms in London exhibit significantly higher leverage than non-London firms among small, medium, and large firms, while no statistically significant difference is observed among micro firms. Within both location groups, micro firms tend to exhibit the highest leverage, although differences across larger size classes are not uniformly significant. This indicates that geographic differences in leverage are conditional on firm size.

5 Discussion and conclusion

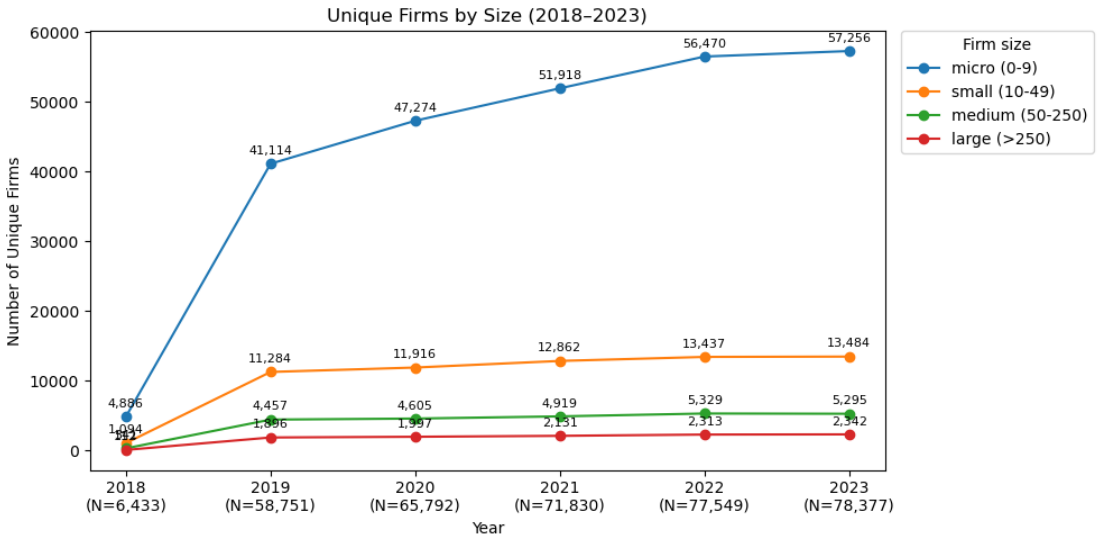
A key insight of this study is that financial resilience is inherently multidimensional. Liquidity and leverage do not move together, nor do they align mechanically with labour productivity. Instead, they reflect different aspects of firm behaviour: the accumulation of internal financial buffers versus reliance on external financing. The

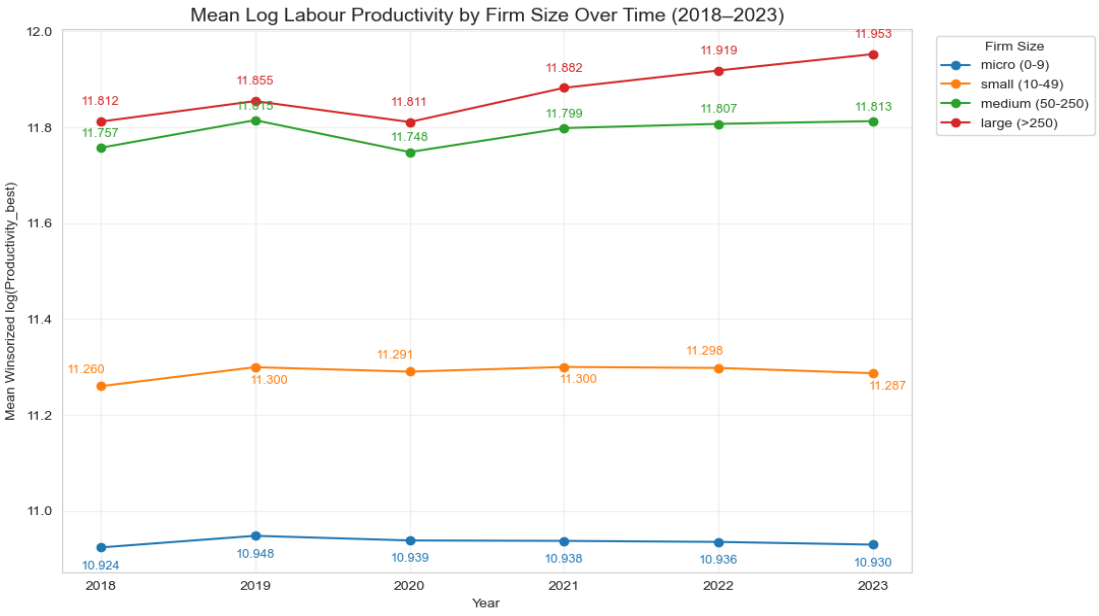
contrasting patterns observed across firm age are consistent with a life-cycle interpretation, whereby younger AI-related firms depend more heavily on debt financing, while mature firms gradually build internal reserves.

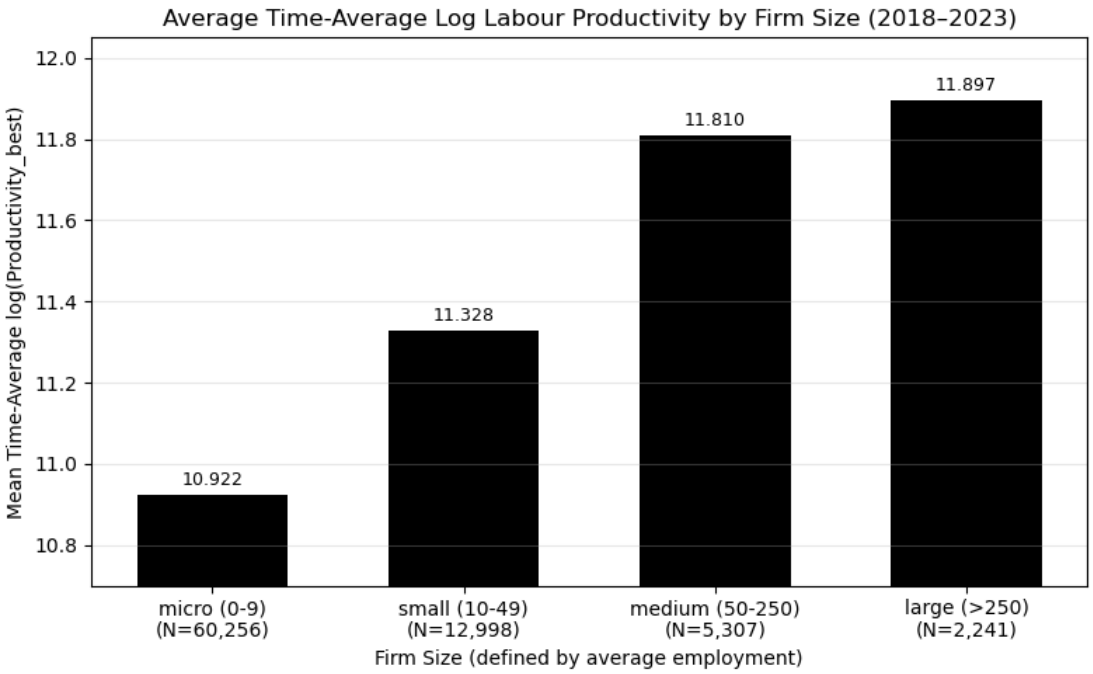
An additional finding concerns the relatively weak productivity advantage of AI-related firms located in London, which is somewhat surprising given the usual expectation that firms located in London benefit more strongly from agglomeration, finance, and knowledge spillovers.

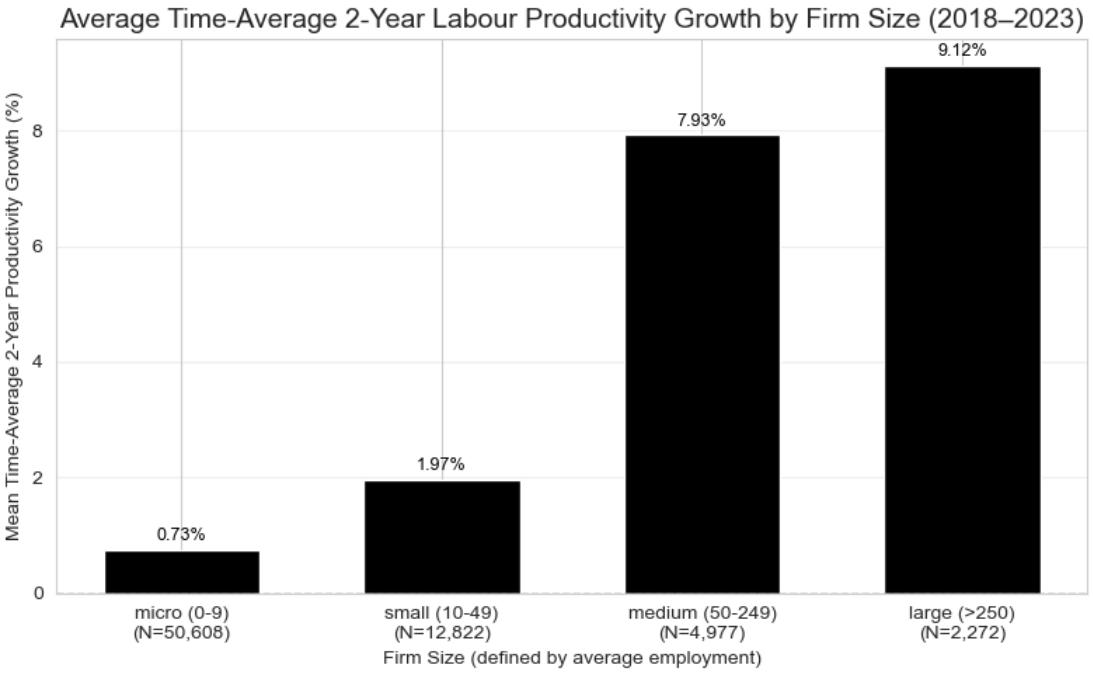
In conclusion, these findings suggest that AI-related firms in the UK do not form a homogeneous group. Their labour productivity, liquidity, and leverage vary systematically with size, age, sector, technology intensity, and location. At the same time, the descriptive nature of this paper means that the results should not be interpreted as causal. Rather, they provide a structured empirical profile of AI-related firms and a basis for future work on the mechanisms linking AI-related activity to firm performance and financial structure.

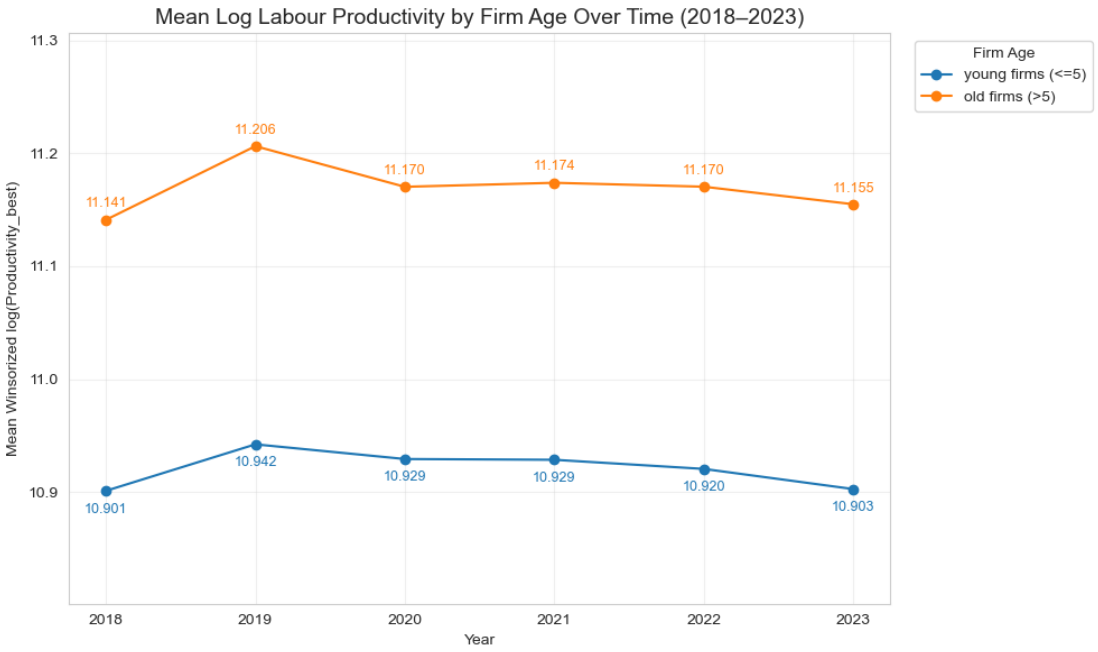
Appendix:

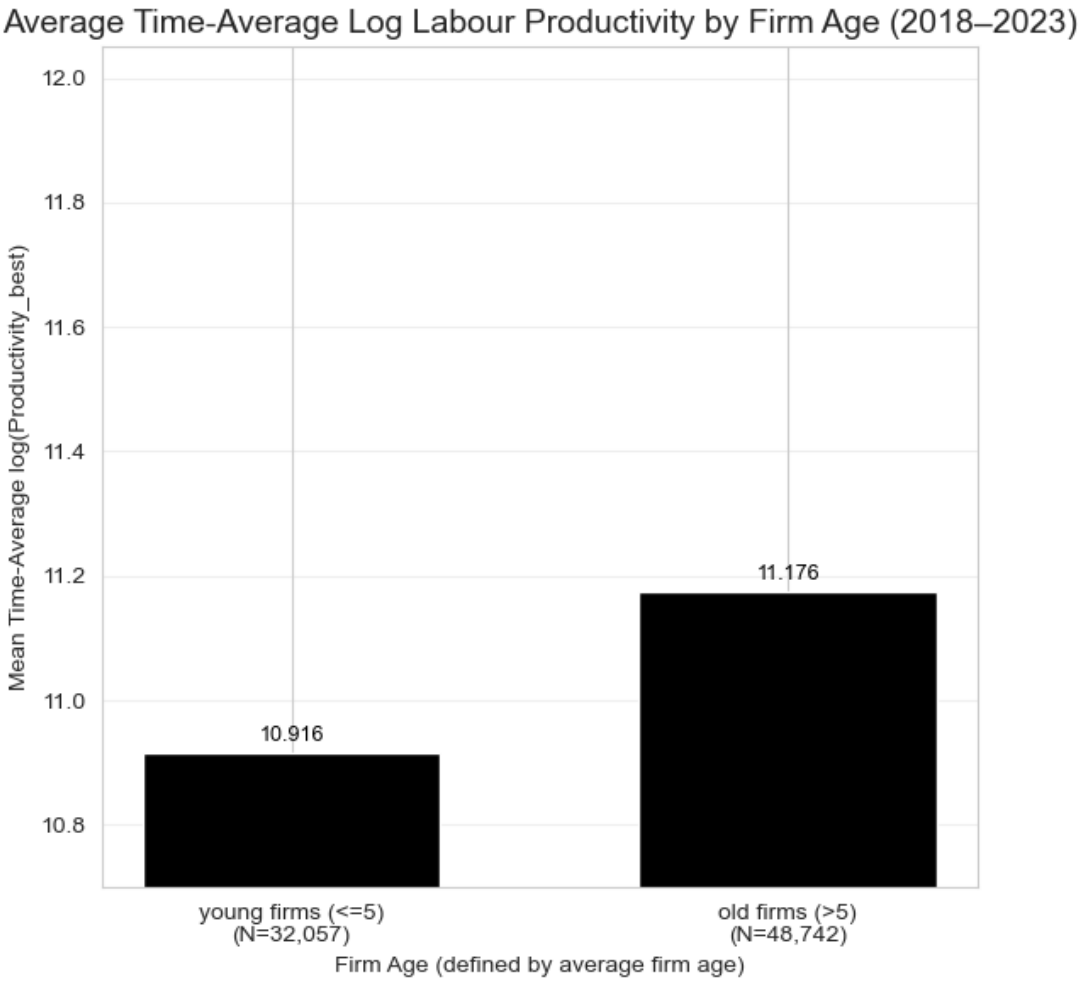

Unique Firms by Size (2018–2023)
Number of Unique Firms
Year
Firm size
micro (0-9)
small (10-49)
medium (50-250)
large (>250)
2018 (N=6,433)
2019 (N=58,751)
2020 (N=65,792)
2021 (N=71,830)
2022 (N=77,549)
2023 (N=78,377)
4,886
41,114
47,274
51,918
56,470
57,256
11,284
11,916
12,862
13,437
13,484
4,457
4,605
4,919
5,329
5,295
2,131
2,313
2,342


Mean Log Labour Productivity by Firm Size Over Time (2018–2023)
Mean Winsorized log(Productivity_best)
Year
Firm Size
micro (0-9)
small (10-49)
medium (50-250)
large (>250)
11.812
11.855
11.811
11.882
11.919
11.953
11.757
11.815
11.748
11.799
11.807
11.813
11.260
11.300
11.291
11.300
11.298
11.287
10.924
10.948
10.939
10.938
10.936
10.930

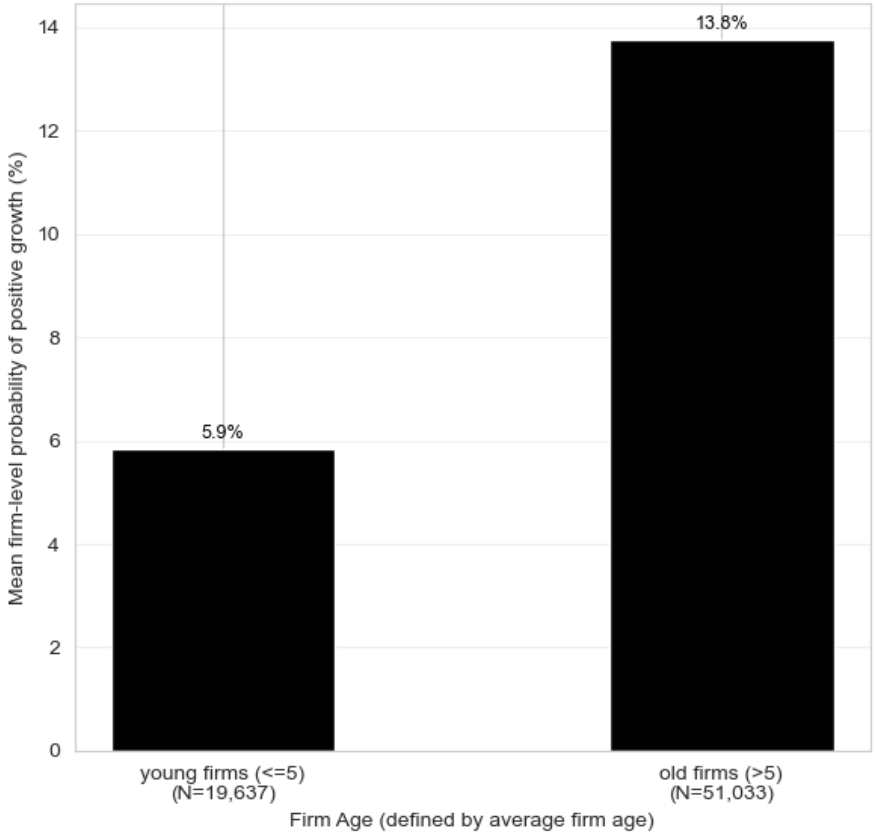

Average Time-Average Log Labour Productivity by Firm Size (2018–2023)
Mean Time-Average log(Productivity_best)
12.0
11.8
11.6
11.4
11.2
11.0
10.8
10.922
11.328
11.810
11.897
micro (0-9)
(N=60,256)
small (10-49)
(N=12,998)
medium (50-250)
(N=5,307)
large (>250)
(N=2,241)
Firm Size (defined by average employment)


Average Time-Average 2-Year Labour Productivity Growth by Firm Size (2018–2023)
Mean Time-Average 2-Year Productivity Growth (%)
8
6
4
2
0
0.73%
1.97%
7.93%
9.12%
micro (0-9)
(N=50,608)
small (10-49)
(N=12,822)
medium (50-249)
(N=4,977)
large (>250)
(N=2,272)
Firm Size (defined by average employment)

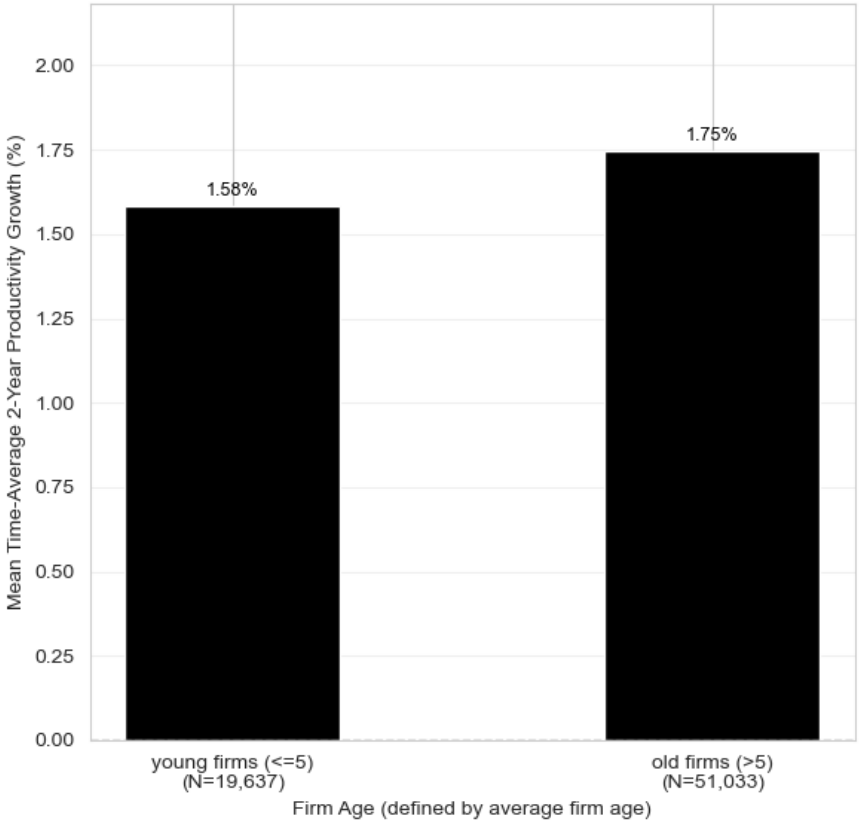

Mean Log Labour Productivity by Firm Age Over Time (2018–2023)
Mean Winsorized log(Productivity_best)
Year
Firm Age
young firms (<=5)
old firms (>5)
11.141
11.206
11.170
11.174
11.170
11.155
10.901
10.942
10.929
10.929
10.920
10.903

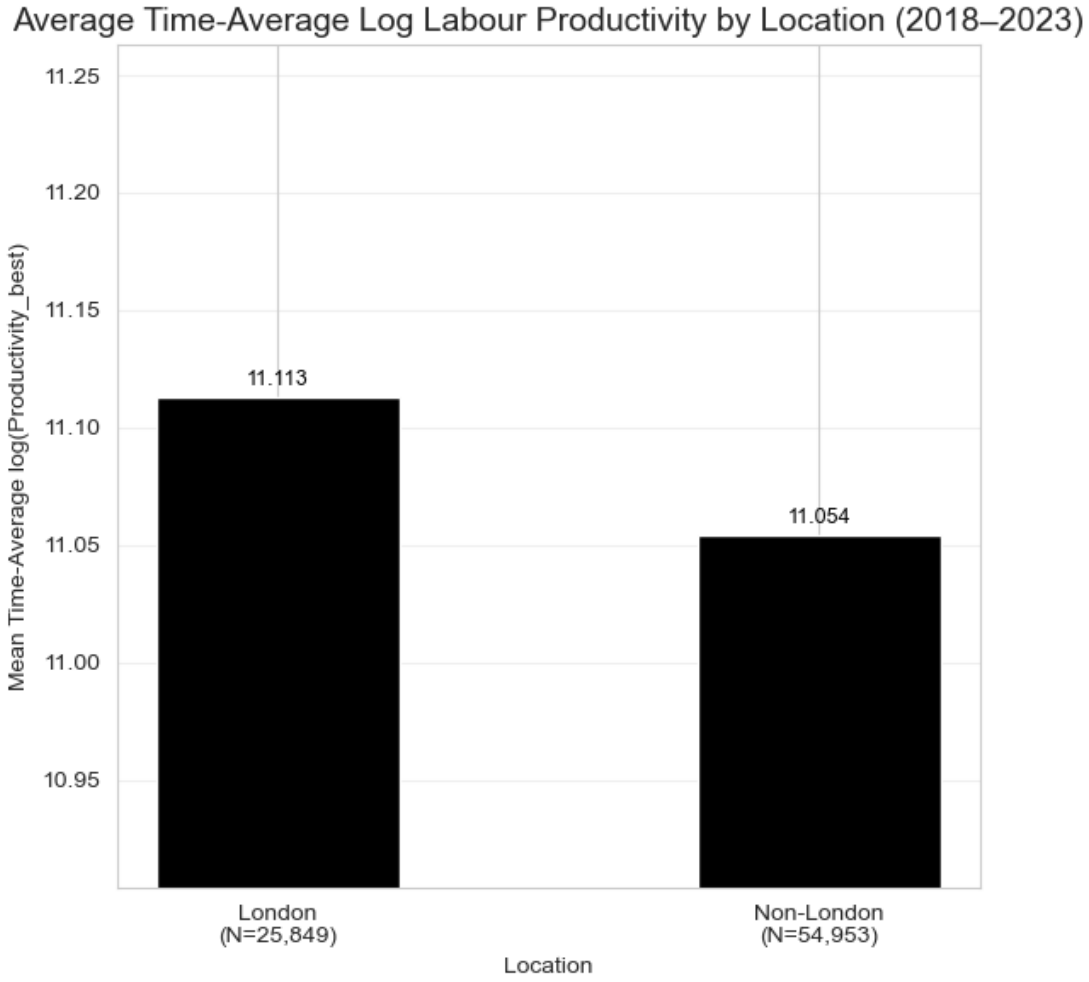

Average Time-Average Log Labour Productivity by Firm Age (2018–2023)
Mean Time-Average log(Productivity_best)
10.916
11.176
young firms (<=5)
(N=32,057)
old firms (>5)
(N=48,742)
Firm Age (defined by average firm age)

Probability of Positive 2-Year Labour Productivity Growth by Firm Age (2018–2023)

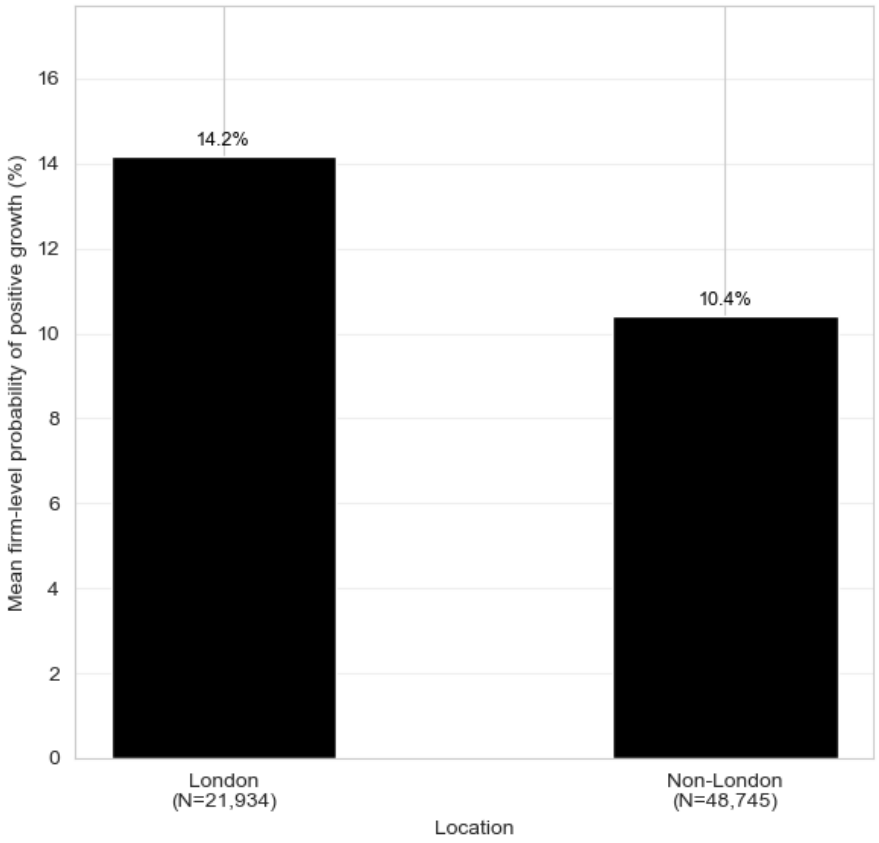


Average Time-Average 2-Year Labour Productivity Growth by Firm Age (2018–2023)

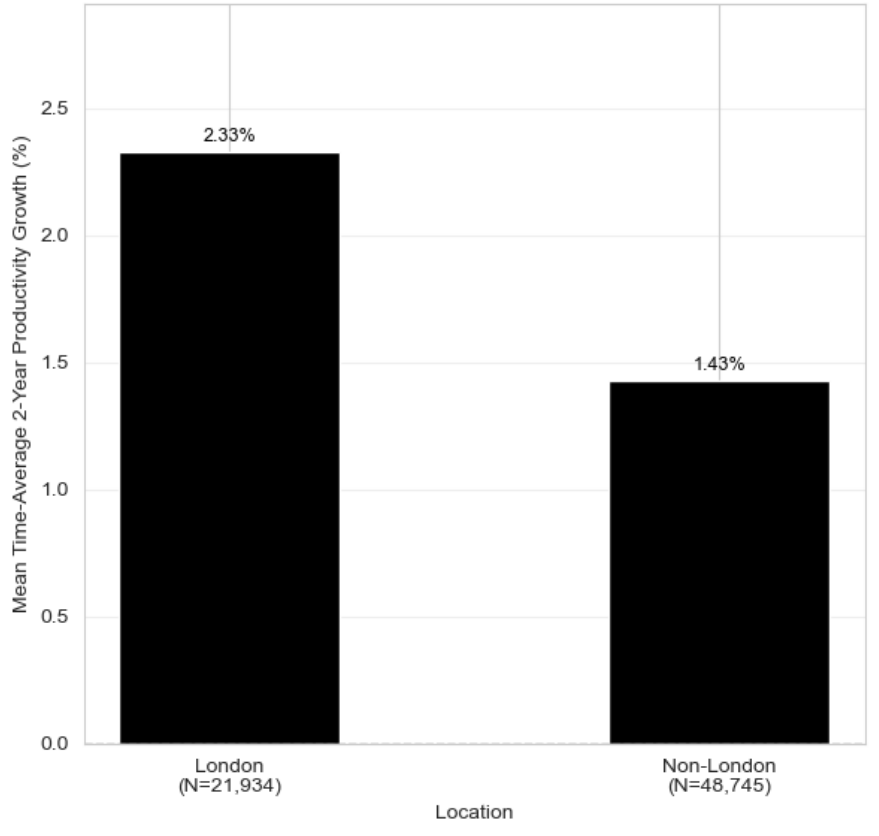


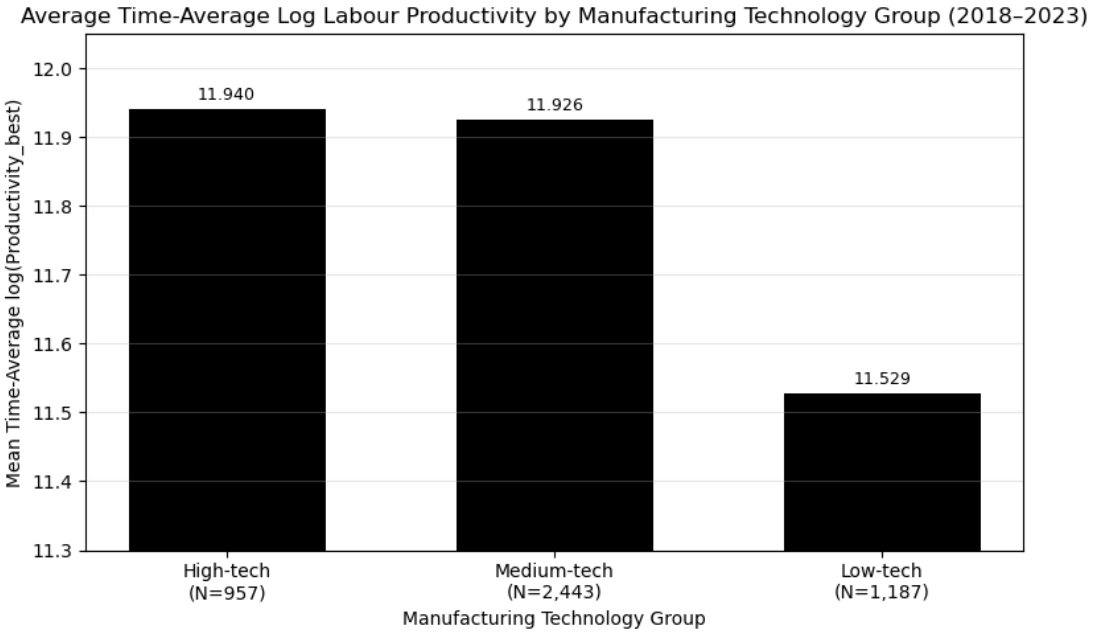

Average Time-Average Log Labour Productivity by Location (2018–2023)
Mean Time-Average log(Productivity_best)
11.25
11.20
11.15
11.10
11.05
11.00
10.95
11.113
11.054
London
(N=25,849)
Non-London
(N=54,953)
Location

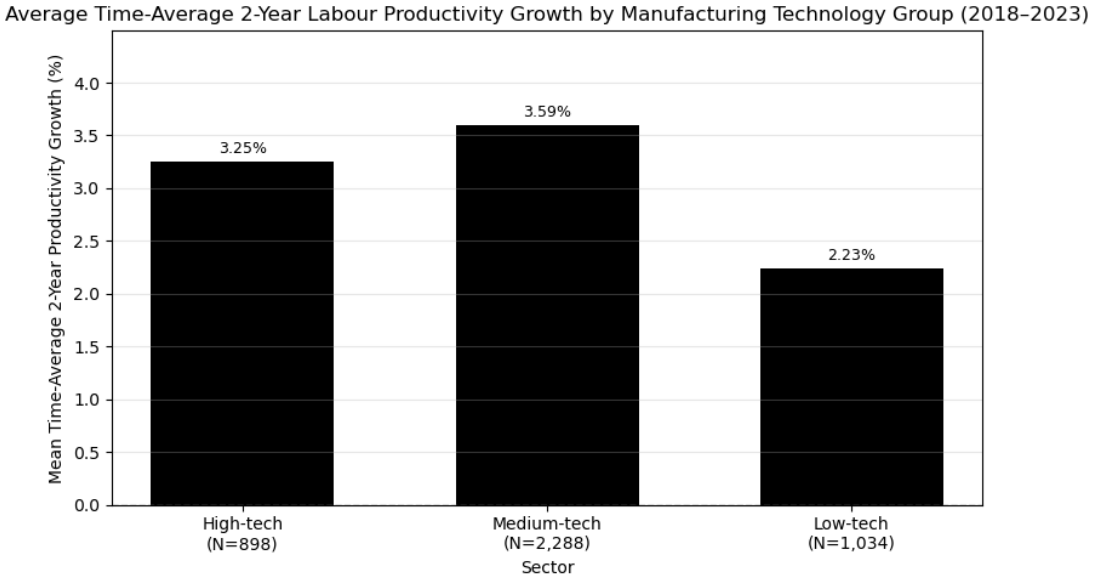
Probability of Positive 2-Year Labour Productivity Growth by Location (2018–2023)

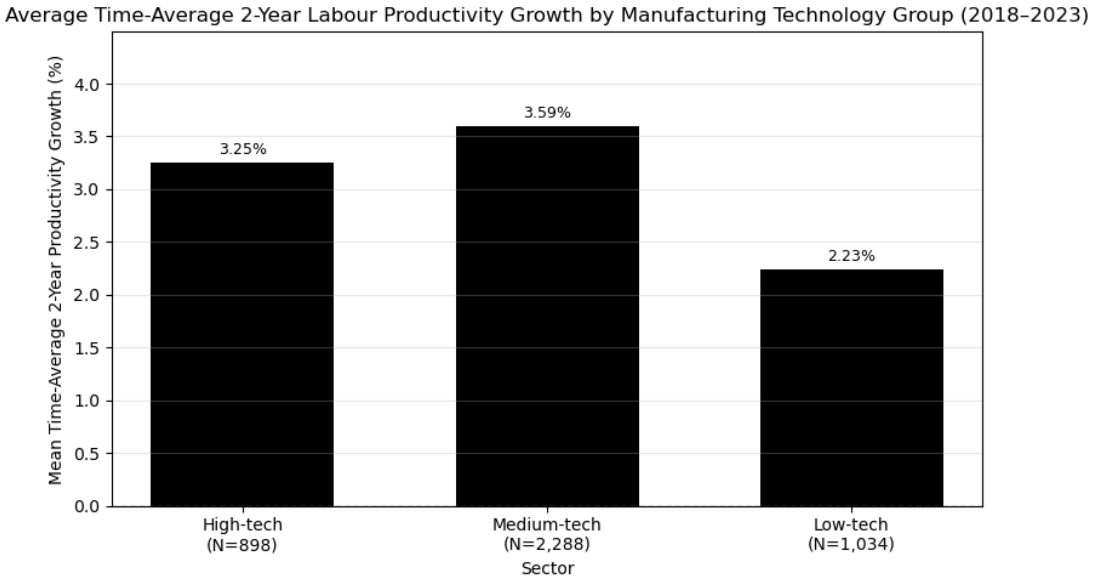


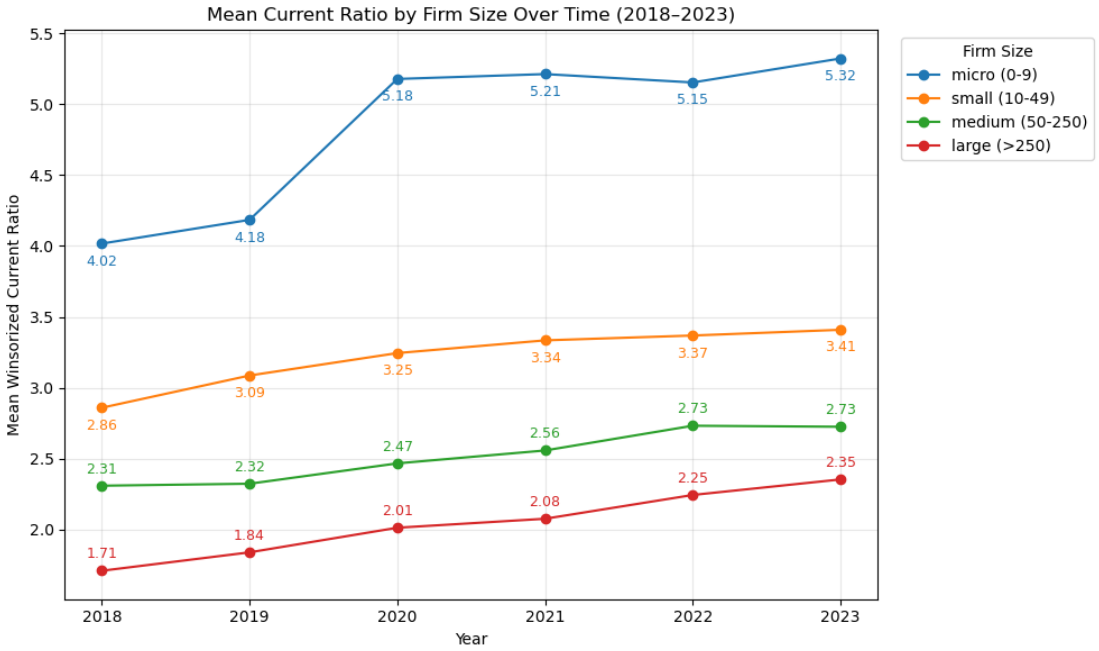
Average Time-Average 2-Year Labour Productivity Growth by Location (2018–2023)

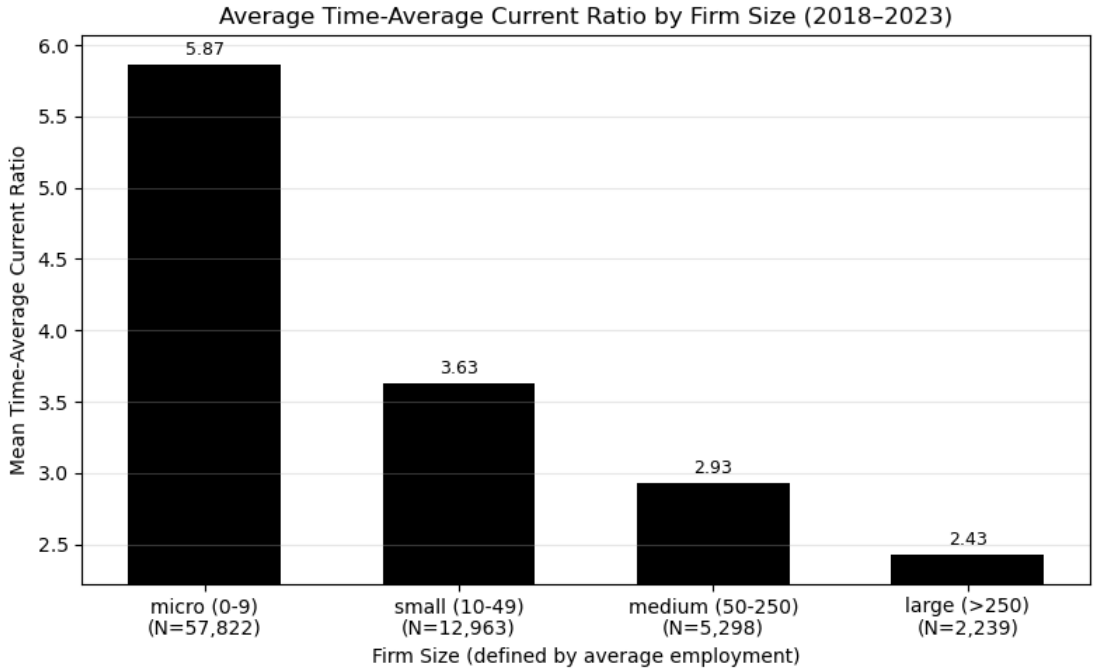


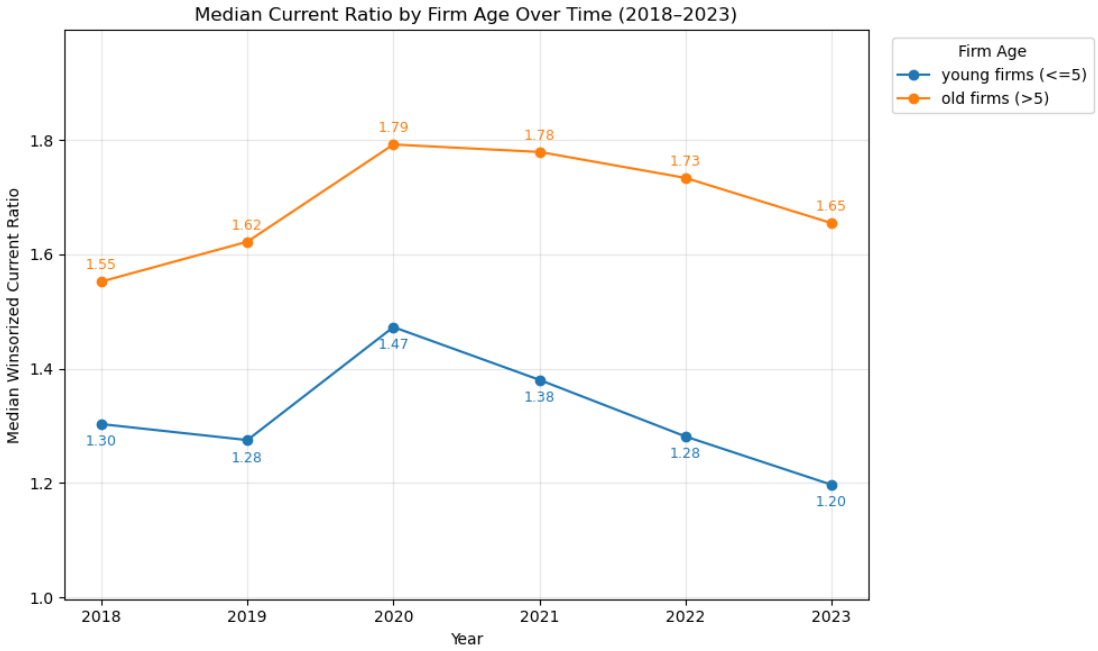

Average Time-Average Log Labour Productivity by Manufacturing Technology Group (2018–2023)
Mean Time-Average log(Productivity_best)
12.0
11.9
11.8
11.7
11.6
11.5
11.4
11.3
11.940
11.926
11.529
High-tech
(N=957)
Medium-tech
(N=2,443)
Low-tech
(N=1,187)
Manufacturing Technology Group

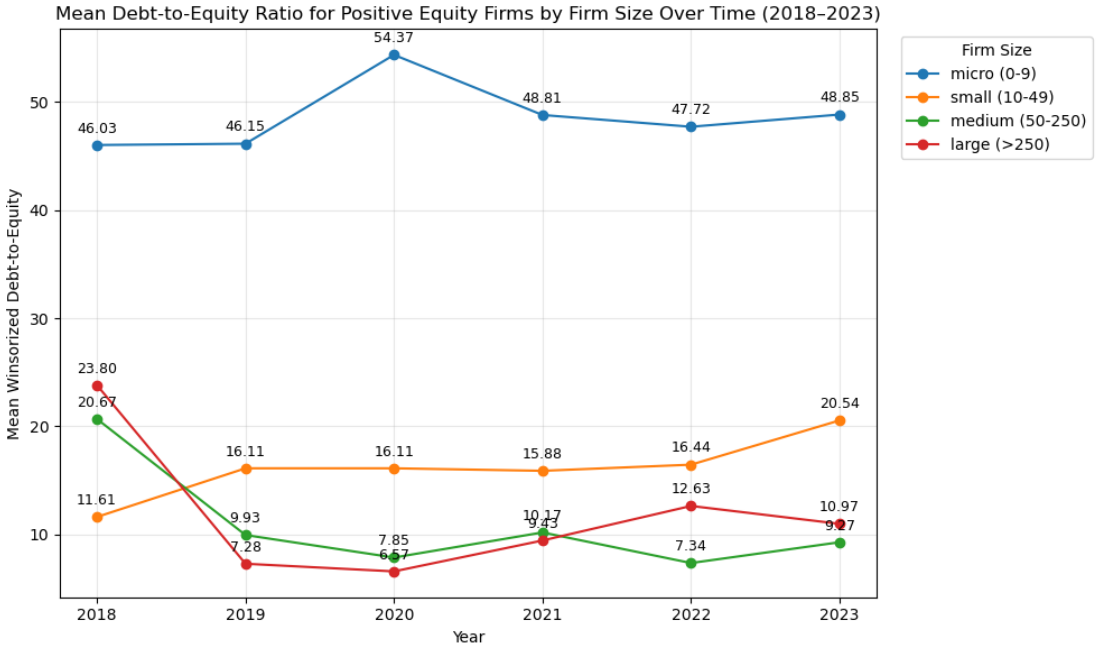

Average Time-Average 2-Year Labour Productivity Growth by Manufacturing Technology Group (2018–2023)
Mean Time-Average 2-Year Productivity Growth (%)
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
3.25%
3.59%
2.23%
High-tech
(N=898)
Medium-tech
(N=2,288)
Low-tech
(N=1,034)
Sector

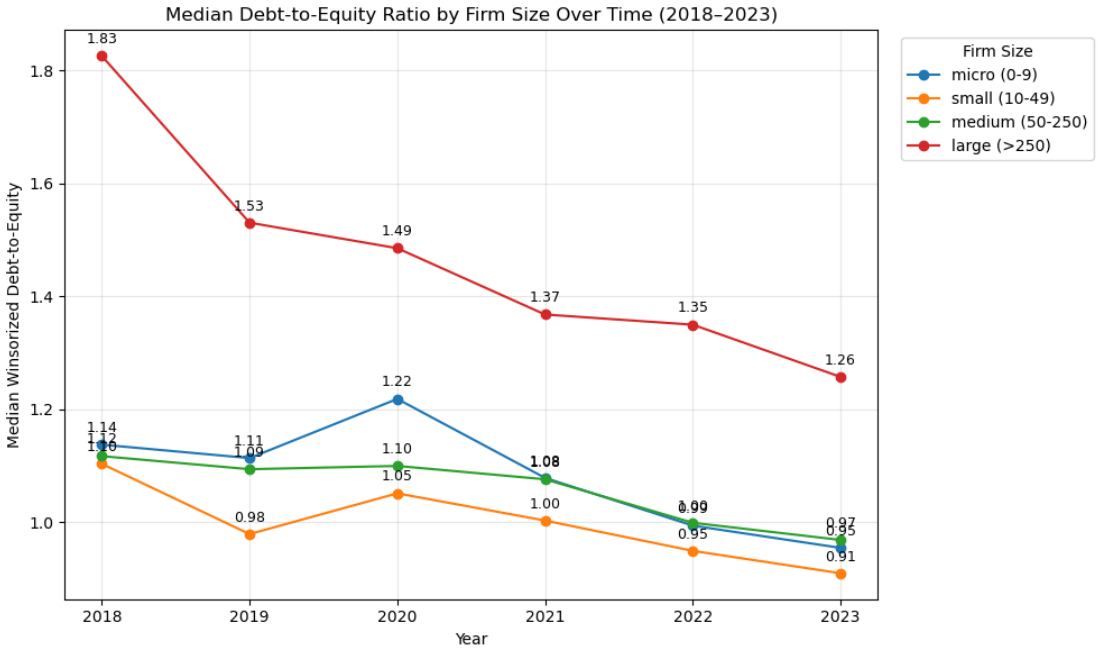

Average Time-Average 2-Year Labour Productivity Growth by Manufacturing Technology Group (2018–2023)
Mean Time-Average 2-Year Productivity Growth (%)
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
3.25%
3.59%
2.23%
High-tech
(N=898)
Medium-tech
(N=2,288)
Low-tech
(N=1,034)
Sector

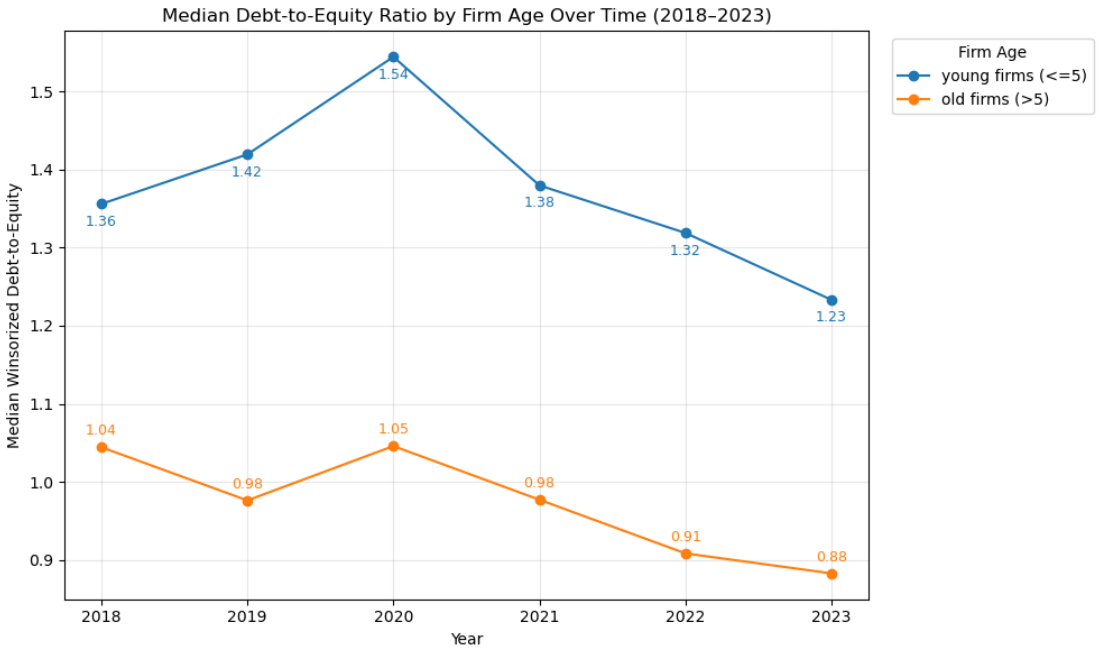

Mean Current Ratio by Firm Size Over Time (2018–2023)
Mean Winsorized Current Ratio
5.5
5.0
4.5
4.0
3.5
3.0
2.5
2.0
4.02
4.18
5.18
5.21
5.15
5.32
2.86
3.09
3.25
3.34
3.37
3.41
2.31
2.32
2.47
2.56
2.73
2.73
1.71
1.84
2.01
2.08
2.25
2.35
2018
2019
2020
2021
2022
2023
Year
Firm Size
micro (0-9)
small (10-49)
medium (50-250)
large (>250)


Average Time-Average Current Ratio by Firm Size (2018–2023)
Mean Time-Average Current Ratio
6.0
5.5
5.0
4.5
4.0
3.5
3.0
2.5
5.87
3.63
2.93
2.43
micro (0-9)
(N=57,822)
small (10-49)
(N=12,963)
medium (50-250)
(N=5,298)
large (>250)
(N=2,239)
Firm Size (defined by average employment)


Median Current Ratio by Firm Age Over Time (2018–2023)
Median Winsorized Current Ratio
1.8
1.6
1.4
1.2
1.0
1.55
1.62
1.79
1.78
1.73
1.65
1.30
1.28
1.47
1.38
1.28
1.20
2018
2019
2020
2021
2022
2023
Year
Firm Age
young firms (<=5)
old firms (>5)


Mean Debt-to-Equity Ratio for Positive Equity Firms by Firm Size Over Time (2018–2023)
Mean Winsorized Debt-to-Equity
Year
Firm Size
micro (0-9)
small (10-49)
medium (50-250)
large (>250)
46.03
46.15
54.37
48.81
47.72
48.85
11.61
16.11
16.11
15.88
16.44
20.54
20.67
9.93
7.85
10.17
7.34
9.27
23.80
7.28
6.57
9.43
12.63
10.97


Median Debt-to-Equity Ratio by Firm Size Over Time (2018–2023)
Median Winsorized Debt-to-Equity
Year
Firm Size
micro (0-9)
small (10-49)
medium (50-250)
large (>250)
1.83
1.53
1.49
1.37
1.35
1.26
1.14
1.12
1.10
1.11
1.09
1.22
1.08
1.08
1.10
1.05
1.00
0.98
0.95
0.91
0.97



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