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The Return "Home": Nearshoring as a Strategic Response to Globalization in Italian Firms

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*"Dreams do come true;
without that possibility,
nature would not incite
us to have them."*
~ John Updike

Summary

This thesis addresses the phenomenon of nearshoring in the current context, in which the governments of many countries are implementing policies to bring the production of their companies back to the country of origin. The main objective of this study, through the analysis of data from multiple Italian firms, is to determine whether nearshoring has actually taken place and what impact it has had on the performance of companies that have decided to adopt this strategy. The analysis aims to assess whether this decision has been a smart move for these firms making them more profitable, taking into account various external factors: rising wages in the countries where production had previously been relocated, or the potential effects of protectionist trade policies. Looking at these dynamics, the industry provides an overview of how is adjusting its efforts to face the new challenges the are upcoming and, through the analysis of financial statements, offers insight into which strategies are more effective. Is it better to maintain production in a foreign country or to relocate it to a nearby country that offers advantages compared to the country of origin?

Acknowledgements

If I had been able to reach this milestone in my life, it would be dishonest of me to claim that the achievement is my sole own. I have received unconditional support from my family, who, through their sacrifices, allowed me to study, often giving up small comforts just to see me succeed. The help I am referring to was not merely financial; what allowed me to fully focus on my studies was the care and attention I received. Whenever I needed it, a warm meal was waiting for me, prepared to help me rest and regain strength, and a comforting gesture to lift my spirits when I was exhausted. I found a family willing to give everything just to make me happy.

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Chapter 1

Introduction

In the new century, offshoring has emerged as a distinctive feature of corporate strategies, particularly for high-productivity firms. By transferring production abroad to access low cost inputs (for instance labor), firms have benefited from reduced costs and increased productivity, impacting the home country's economy [1]. However, having to adapt to disruptive events, including trade wars, the COVID-19 pandemic, and rising geopolitical tensions, policymakers are increasingly supporting production reshoring as a strategic move to mitigate supply chain vulnerabilities and boost domestic economic growth.
This thesis investigates this phenomenon by applying it to Italian data to highlight manufacturers that reorganized their production over the 2010–2022 period. The analysis is conducted using an Italian administrative dataset that links firm-level trade statistics (ISTAT-COEWEB) with balance sheet data (AIDA - Bureau van Dijk). This rich dataset enables a comprehensive portrait of these firms and provides evidence on the economic consequences of such reorganization for firms and their performance.
But how is it possible to formalize the concept of returning production? Reliance is initially placed on the established measure of narrow" offshoring, defined as the total imported inputs within the firm's production industry.
As explained by D'Ambrosio et al. [2], the existing literature typically defines strict reshoring as an event occurring when four criteria apply: *(i) a negative change occurs in "narrow offshoring" to a specific partner country; (ii) this negative change persists over time; (iii) the negative change is not offset by an increase in offshoring by the same firm to any other country; and (iii) the firm increases domestic capital or labor.* However, this thesis proposes a methodological shift to investigate two distinct relocation strategies: Nearshoring and Friend-shoring. To this end, the third restrictive hypothesis mentioned above is relaxed. It is assumed that, if a firm wants to mitigate its risk exposure, it does not necessarily have to bring production back strictly within national borders; rather, it may involve relocating production to countries that are geographically closer (Nearshoring) or geopolitically aligned (Friendshoring). A reorganization event is considered valid if the reduction in offshoring to a distant or hostile partner is offset by an increase to another country, provided that the new destination satisfies specific proximity criteria. To quantify these dimensions, two distinct metrics are employed: geographic distance for Nearshoring and a geopolitical alignment index based on United Nations General Assembly voting

patterns [3, 4] for Friendshoring. Investigating these strategies is driven not only by risk mitigation but also by involving economic fundamentals. It is hypothesized that the traditional cost advantages of offshoring are eroding. Wages and other inputs in countries where production was previously offshored are no longer as low as they once were, making it more convenient to bring production closer to home.
The ultimate objective of this thesis is to evaluate whether these phenomena have occurred and, if so, to assess the specific impact they have had on the performance of the firms involved. The econometric analysis applied in this study, based on a Difference-in-Differences approach, reveals that there is no significant decrease in firms' profitability and that, given the sample at our disposal, we cannot even claim statistical significance. Productivity increases slightly, but again no statistical significance is found. What seems to persist is that the decision to relocate production to a nearby or friendly country is therefore driven more by stability and security considerations, aimed at ensuring business continuity, than by purely economic motives centered on profit.

Chapter 2

The Pendolum of Global Strategies: From Offshoring to Nearshoring

2.1 The Era of Offshoring: Rationale and Drivers

Over the last few decades, globalization has driven firms to restructure their operations internationally. The traditional model of centralized production has been replaced by Global Value Chains (GVCs). This framework implies that different stages of the production process are located across different countries. Through the outsourcing and offshoring of activities, companies have leveraged comparative advantages and reduced operational costs. [5] The landscape of offshoring is currently evolving. With levels of remote work remaining high after the pandemic, new dynamics are emerging. If tasks can be performed from home, they can theoretically be performed from anywhere. This shift provides employers with access to a global talent pool, creating opportunities to offshore not just manufacturing but also service based jobs at a fraction of the cost. To fully grasp the scope and understand the implications of these dynamics, it is important to begin with a precise definition of the phenomenon and an analysis of its historical evolution.

2.1.1 Definitions

- **Offshoring:** *Offshoring refers to the total or partial transfer of an industrial activity (manufacturing or services) abroad, either to an existing or new affiliate, or through subcontracting to non-affiliated companies. The portion of the activity sent offshore that had been intended for the domestic market is then imported [6]*

Although frequently used interchangeably in public discourse, the concepts of offshoring and outsourcing describe distinct dimensions of corporate reorganization. To avoid conceptual ambiguity, a definition of outsourcing is provided in order to distinguish between the geographical location where a task is performed (domestic versus abroad) and the ownership structure of the unit performing the task (in-house versus external).

- **Outsourcing:** *is defined as the strategic decision to contract out specific segments of business operations to a third-party provider [7]*

2.1.2 The Historical Evolution of Offshoring

After having clarified the conceptual distinctions between offshoring and outsourcing is taken into account how these strategies have unfolded empirically over time. The global reorganization of production has not been a static phenomenon. The scope and nature of offshoring have evolved significantly over the last half century. This historical evolution can be examined through four distinct waves [5], reflecting changing economic incentives, technological improvements, and the changing geopolitical landscape.

- **1960s – 1990s (First Wave):** *the initial phase impacted mostly the manufacturing sector. Firms operating in consumer electronics, relocated physical production plants to low cost countries.*
- **Late 1990s (Second Wave):** *the second phase expanded to Information Technology (IT). Firms began offshoring routine and non core tasks (coding, testing, and data entry), which could be easily separated from central business operations.*
- **2005 – 2015 (Third Wave):** *the third shift occurred as offshoring extended to the service sector and knowledge intensive activities. Driven by globalization and falling costs, firms relocated core functions (R&D, product design, and engineering).*
- **Post-2015 (Fourth Wave):** *the last and current phase is characterized by a decline in offshoring and a rise in reshoring. Triggered by political nationalism and consolidated by the COVID-19 pandemic and geopolitical instability, this wave reflects a growing trend towards repatriating manufacturing and services to mitigate risk.*

Following the analysis of these historical waves, it's now clear how to identify the specific attributes that render a job susceptible to relocation. It is possible thanks to the literature to identify the three main characteristics that make an occupation offshorable: *i) a lack of or low degree of face-to-face interaction; ii) a high usage of ICT technologies; and iii) a low requirement for specific local, cultural, or social knowledge.*
As higlighted in the four waves previously mentioned, the evolution of these criteria point out a significant shift: there is no longer a strict correlation between an occupation's offshorability and the skill level of the workers. As the "Third Wave" demonstrated, high-skilled tasks are now just as vulnerable as routine ones if they meet the criteria above.
Due to these evolving definitions, attempts to quantify the impact on the labor market have shown mixed results. Over time and in several different studies, the share of jobs estimated to be offshorable has ranged significantly, from a conservative 11% of all US jobs[8] to as high as 38% [9].

2.1.3 Unpacking the Determinants of Offshoring

The predominant reason for offshoring identified in the literature is undeniably cost reduction. In the early waves, firms mainly sought to lower wages and leverage reduced trade barriers and transportation costs. For instance, 80% of German manufacturing companies cited personnel cost reduction as a decisive factor [10].
Another key factor, aside from lowering labor cost, is the regulatory environment that played a significant role. Firms may offshore to bypass stringent domestic labor market regulations or to escape collective bargaining requirements. This systemic tendency to exploit regulatory differentials creates what Nobel laureate Joseph Stiglitz describes as a *"race to the bottom"*, where economic rules are skewed in favor of corporate mobility:

> «Globalization is not just about moving goods... It is about the rules of the game. The rules have been written by corporations, for corporations. To attract [these] companies, countries lower taxes, lower labor standards, and lower environmental standards. It is a race to the bottom.»

The logic of cost efficiency also involves digital offshoring. A huge labor cost reductions for teleworkable jobs in France and the UK and opportunities to work from home have been correlated to an increase in offshoring to cut costs.
Another driver is related to the shortage of labor and skills in the domestic market. The inability to find qualified personnel at home is a major determinant for medium and large companies, which identify this cause as the primary driver (approximately 13% of companies) [11]. In the context of remote work, this consideration can be translated as the strategic need to access a global talent pool.
Moving away from cost efficiency and labor shortages, firms are also driven by strategic market considerations. Offshoring facilitates *New Product Development (NPD)* particularly when deep knowledge of local needs and habits is necessary to successfully penetrate foreign markets [12]. Offshoring is not only about cost reduction, it can also be a strategy to improve the quality of goods. By relocating, firms can access specialized local skills and knowledge (specialized districts or clusters of production) that may not be available at home, upgrading their production standards rather than lowering them [13]. Finally, the decision to relocate is often influenced by external "pull" factors, such as specific government incentives offered by host countries, and (particularly for SMEs) the pursuit of economies of scale.

2.1.4 Bucking the Trend: Reasons for Avoiding Offshoring

Although lower costs and labor shortages at home encourage companies to move abroad, there are significant obstacles to consider. One of the drawbacks, contrary to what was mentioned above, could be finding skilled workers in the new location, communication difficulties caused by language and cultural differences and risks with respect to sustainability and weak intellectual property protection [14, 15].
With regard to digital offshoring, the substitution between domestic and foreign labor is often imperfect. Many remote jobs still require specific soft skills that are difficult to replicate abroad, limiting the extent to which these roles can be effectively offshored.

Digital offshoring is further obstructed by complex regulatory uncertainties. The involvement of different national jurisdictions and labor standards laws due to the nature of remote work creates significant legal ambiguities [16]. Despite the fact that technology can eventually reduce some friction, the combined effect of these obstacles may have led to a turning point.
A significant drawback often realized ex-post concerns operational flexibility. Firms might offshore with the expectation of increasing agility, but they frequently experience the opposite. Extended supply chains often lead to reduced operational flexibility, making it difficult to react quickly to market changes. A critical aspect is that relying on external drivers, such as foreign government incentives or temporary wage differentials, exposes firms to volatility, creating a fragile strategic foundation that crumbles when the global economic environment changes [17].
These operational problems and hidden costs were already making companies question the value of offshoring, but the real change came with recent global crises. Combining the systemic shocks of the COVID-19 pandemic and the growing geopolitical tensions, these factors have altered the global landscape, modifying the initial cost-benefit analysis and possibly driving to a strategic shift away from offshoring toward nearshoring or friend-shoring.
This mix of internal challenges and external instability could mark the beginning of a new era, where the priority is bringing production back home to ensure safety and stability.

2.2 The Turning Point: Rising Protectionism and Supply Chain Disruptions

2.2.1 Criticalities Exposed by COVID-19 Due to Offshoring

A disruptive event of the magnitude of the COVID-19 pandemic acted as a brutal *awakening*, exposing the limits and criticalities of a supply chain model that was heavily dependent on offshoring. By prioritizing cost reduction and lean efficiency over resilience, this globalized structure left nations dangerously exposed during the crisis.
With the beginning of the health emergency, various countries were unable to cope with skyrocketing demand for critical goods. Due to a lack of domestic manufacturing capabilities and a rigid reliance on foreign imports, countries were paralyzed in a situation of harsh conditions for international logistic.
The pandemic revealed the fundamental weaknesses of a global supply chain model that had, for a long time, prioritized cost reduction and *just-in-time* efficiency over resilience. Standard forecasting strategies were inadequate, since they failed to account for disruptions of such scale. This fragility was exacerbated by a heavy reliance on foreign sources, particularly China, for critical medical products, including *Personal Protective Equipment (PPE)* and pharmaceuticals. With the virus bringing China to its knees, the country restricted exports to manage its own domestic emergency, resulting in immediate shortages in all Western economies. Looking at the United States, with domestic manufacturing capacity previously offshored, a chaotic scenario arose where the federal government, state

authorities, and individual healthcare facilities found themselves in a *bidding war*, competing against one another to secure medical limited supplies. This unfortunate situation was not limited only to healthcare. The crisis exposed a broader loss of critical industrial capabilities in other strategic sectors: semiconductors, communications, and IT hardware [18].

2.2.2 Policy Strategies and Interventions to Promote Reshoring

To reduce risks and encourage the return of manufacturing, policymakers have adopted a mix of short-term and long-term strategies. One of the approaches is guaranteed public procurement, which consists of the government promising to buy products from firms, reducing the financial risk for those companies that invest in domestic production. This is also supported by tax breaks and incentives to lower the cost of building new factories. In addition, the state provides direct financial aid through grants and loans to help businesses expand in critical sectors. The direction of future policies focuses on sustainability through technological upgrades. Funding automation and Industry 4.0, governments aim to help domestic firms compete globally based on high productivity rather than low wages.
Empirical studies show that trade-related economic shocks can cause greater political polarization and increase support for isolationist parties in Western democracies [19, 20]. Governments have increasingly resorted to aggressive trade interventions, such as the unilateral tariff escalations seen in the U.S.-China trade war, to incentivize the return of production. However, the effectiveness of these measures in triggering actual reshoring is heavily dependent on the reduction of policy uncertainty. Firms tend to be cautious and avoid to incur the sunk costs necessary to restructure their supply chains unless they perceive these protectionist shifts as permanent rather than transitory [21, 22]. In any case, research suggests that crude protectionism often results in welfare losses [23] and that a more sustainable policy strategy to manage globalization's side effects. This would mean strengthening domestic welfare programs and making taxes more progressive, rather than reducing international trade integration[24].

2.3 Reshoring and Nearshoring: An Established Trend or an Emerging Wave?

2.3.1 Antràs' Model on the Profitability of Offshoring

In his paper *De-Globalisation? Global Value Chains in the Post-COVID-19 Age*, Pol Antràs presents a stylized model to determine when a firm finds it profitable to relocate (offshore) its production. The decision is decomposed into two levels of analysis. The first evaluation regards marginal costs, the second is an assessment of total profits that also accounts for fixed costs.

The Marginal Cost Condition

From the perspective of variable costs alone, offshoring is profitable if the total unit cost of production abroad is lower than the domestic cost.
This condition is expressed by the following inequality:

$$z^* w^* c^* t^* \tau^* < w \tag{2.1}$$

The variables in this equation are defined as follows:

- w: *wage of a domestic worker (in the home country, e.g., "the West");*
- w^*: *wage of a foreign worker (in the host country, e.g., "the East"), assuming $w^* < w$;*
- z^*: *inverse measure of foreign worker productivity ($z^* \geq 1$), indicating how many foreign workers are needed to match one domestic worker (the term $z^* w^*$ represents the productivity adjusted to the wage);*
- c^*: *communication and coordination costs related to remote management ($c^* > 1$);*
- t^*: *customs tariffs and trade barriers ($t^* > 1$);*
- τ^*: *cost of logistic in form of physical transportation and shipping costs ($\tau^* > 1$).*

The Total Profit Condition (with Fixed Costs)

Antràs shows that a marginal cost advantage alone is not sufficient. Offshoring entails higher fixed costs compared to domestic production. Thus, the firm must determine if the operating profits from offshoring exceed those from domestic sourcing.
This trade-off is described with the following inequality:

$$\underbrace{B\left(a_h p_h + a_m z^* w^* c^* \tau^* t^*\right)^{1-\sigma} - f_O}_{\text{Offshoring Profits}} > \underbrace{B\left(a_h p_h + a_m w\right)^{1-\sigma} - f_D}_{\text{Domestic Profits}} \tag{2.2}$$

In addition to the cost variables defined above, this equation introduces other parameters characterizing the firm and the market:

- B: *a term capturing the level of residual demand faced by the firm; it acts as a proxy for the firm's scale and market size (a higher B implies larger sales volume, so it's easier for the firm to amortize fixed costs);*
- σ: *the price elasticity of demand (where $\sigma > 1$); it determines how sensitive the firm's revenues are to changes in marginal costs;*
- a_h, a_m: *the units of headquarter services (h) and manufacturing labor (m) required to produce one unit of final output (reflecting the firm's production technology);*
- p_h: *the marginal cost of headquarter services (assumed to always be produced domestically);*

- f_D, f_O: *the fixed costs of domestic production and offshoring, respectively (with* $f_O > f_D$*, since the company has to face the relocation of the production).*

This condition clearly demonstrates the role of firm scale: even if the marginal cost condition is met, if the fixed cost differential $(f_O - f_D)$ is large, only firms with a sufficiently high demand (B), will find it profitable to offshore.

2.3.2 Shifting Parameters and the Case for Friendshoring and Nearshoring

Considering how the parameters of the inequality in Equation 2.2 have evolved compared to the period of "hyper-globalization" (1986-2008), underscore the importance of examining phenomena like friendshoring and nearshoring. Keeping production abroad and repurchasing the final final product remains a rational choice only if the left-hand side of the equation (offshore profits) continues to exceed the right-hand side (domestic profits). In the literature review it has been shown that with an uncertain environment, in which policy makers are pulling companies back home and the global pandemic exposed many issues in case of disruptive events, these variables are changed.

Labor Costs (w^*) and Productivity (z^*)

During the hyper-globalization era, the wage differential between the West (w) and the East (w^*) was significant. Lately has been observed a significant wage convergence. Labor costs in key hubs like China and other Asian Countries have risen faster than in advanced economies, eroding the main cost advantage of offshoring. Although foreign productivity has improved (reducing z^*), the rise of automation in advanced economies is altering the equation. Automation and offshoring as underlined by Antràs appear to be substitutes, so given that reliance on labor decreases, the low cost of w^* becomes less important. However, as noted by Rodrik [25], the situation can become tricky because nothing can stop multinational enterprises to simply design production processes involving large amounts of automation within their host countries, potentially maintaining the same amount of offshore despite rising wages.

Communication and Technology (c^*)

The ICT revolution was the main driver that lowered c^*, facilitating the initial unbundling of production. However, there are signs that this revolution may be slowing down, or at least that the marginal returns to remote coordination are diminishing. The pandemic, indeed, highlighted that many interactions require face-to-face contact to transfer complex know-how and build trust. During the pandemic given the travel difficulties and with extremely expensive tickets, the effective c^* raised, discouraging geographic distance. Additionally, western concerns regarding technology transfer, specifically China's *"quid pro quo"* policy and weak intellectual property (IP) protection, have increased the perceived risks of sharing proprietary technology abroad, acting as a barrier to fluid and transparent coordination.

Transport (τ^*) and Trade Policy (t^*)

These are the most volatile drivers of the current shift.

- τ^* **(Transport):** Shipping costs have become unpredictable due to supply chain disruptions (e.g., port congestion, container shortages). In the model, unreliability translates into a higher effective cost, damaging offshore profitability.

- t^* **(Tariffs):** The political parameter has shifted drastically. The U.S.-China trade war, Brexit, and rising nationalism have increased tariffs and uncertainty. With a massive increase in t^* revenues decline for firms that have adopted offshoring.

Fixed Costs (f_O) vs. Domestic Investment (f_D)

The decision to nearshore or friendshore is significantly influenced by the nature of fixed costs. Antràs, in his paper, emphasizes that f_O is high *ex-ante* but becomes a sunk cost *ex-post*. Firms that have already offshored do not return immediately when costs rise because they have already incurred the setup expenses. The current climate of geopolitical uncertainty increases the risk of relying on foreign cash flows. Firms are evaluating whether to incur new domestic fixed costs (f_D) to gain resilience and security, prioritizing supply chain stability over marginal efficiency.

2.3.3 Optimizing the Trade-offs: The Rise of Friend-shoring

Recent empirical literature largely reinforces the shifts in parameters identified by Antràs's model. The erosion of the cost differential, which is the key component of the offshoring equation, has been the main driver of relocation [26]. An evident example is provided by Gur and Dilek [27], who noted that labor costs in China have surpassed those in Mexico in recent years. American companies no longer view China as the ultimate low-cost manufacturing hub, but now they have a really close alternative with the same perks of having the production in China. This aligns perfectly with the model's prediction that as foreign wages (w^*) rise, the profitability of offshoring declines. Another important aspect to consider is that technological progress and process innovation in automation, have lowered domestic production costs (w), making domestic production even more profitable [28].

As previously discussed the decision to reshore is often driven by factors that extend beyond simple cost minimization. As Di Mauro et al. [17] emphasizes, reshoring should not be viewed merely as the mirror image of offshoring, but it frequently reflects a shift in strategic goals. For instance, while offshoring is predominantly driven by inputs cost, reshoring is often aimed at increasing the value perceived by the customer, allowing companies to capitalize on the *"Made in"* effect. In the British textile industry, the *Made in Britain* label has been assessed as a critical asset for brand differentiation [29].

Another purpose of reshoring is acting as a corrective mechanism for what Wiesmann et al. [30] describe as *"poor and hasty"* initial offshoring decisions. Firms often discover *ex-post* hidden costs, quality issues, or a lack of flexibility that was underestimated during the planning phase. Having observed this, bringing production home allows companies to

recover control, reduce lead times, and facilitate the co-location of R&D and manufacturing [29], fostering innovation cycles that are difficult to maintain across fragmented global chains. Thus, reshoring is driven by the willingness of firms to correct past estimation errors and pursuing new, value added strategies that prioritize quality and agility over pure cost efficiency.
It can be stated that, while reshoring remains the primary choice for enhancing perceived quality and brand reputation, *nearshoring* (and its politically driven variant, *friend-shoring*) emerges as a superior strategic equilibrium. This approach allows firms to preserve the labor cost advantage ($w^* < w$) that originally justified offshoring, leveraging lower wages compared to those in the home country, but within a perimeter of geopolitical proximity that reduces the risk profile of having distant production hub. By relocating production to neighboring or allied nations, companies can effectively neutralize the protectionist threat, evading tariffs (t^*) and trade barriers that afflict relations with distant geopolitical rivals. In addition, geographic proximity decreases the physical distance (τ^*), ensuring faster lead times and lower logistical volatility. Perhaps most importantly, nearshoring bridges the gap between innovation and execution: it facilitates the frequent interaction required between domestic R&D centers and manufacturing units, solving the coordination problems (c^*) of remote offshoring without necessitating a full and costly return to the home country.
As long as wage convergence between the domestic economy and these friendly nations remains incomplete, the economic incentive will strongly favor nearshoring over full reshoring. Since the labor cost arbitrage continues to be a decisive factor for competitiveness, pure reshoring is often economically unsustainable for tasks very labor intensive. This difference in inputs costs, combined with the security of geopolitical alignment, makes the empirical analysis of nearshoring particularly relevant in the current global landscape.

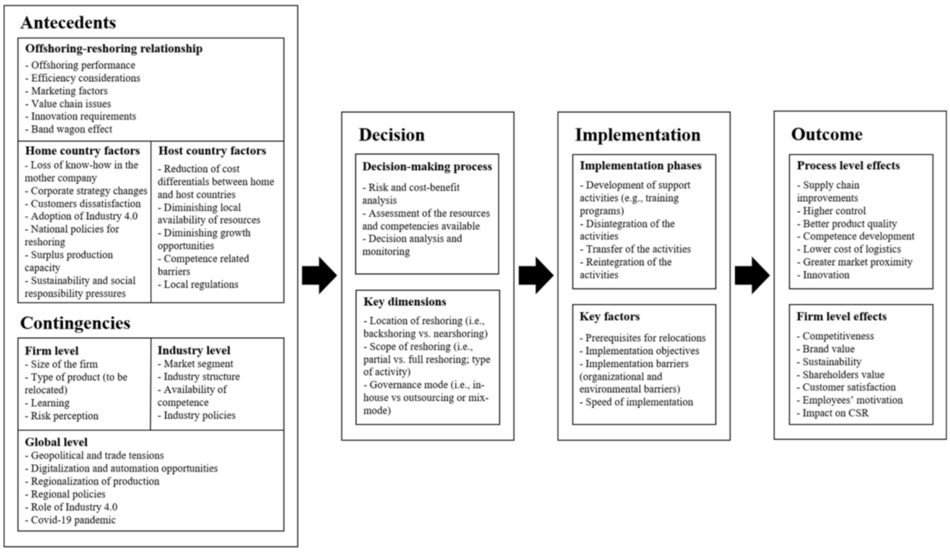

Figure 2.1. Reshoring process framework. [31]

Chapter 3

Empirical Strategy: Data and Methodology for Measuring Nearshoring

3.1 Operationalizing Offshoring

To operationalize the concept of offshoring, reference is made to the measurement approach developed by D'Ambrosio et al. [2]. Before identifying any relocation activity (whether frienshoring or its variant nearshoring), it is essential to define the standard condition of offshoring. Building on previous research, the specific concept of *narrow offshoring* is adopted as the measure for identifying production fragmentation [1, 2].
In line with this framework, offshoring is treated initially as a continuous variable rather than a simple dichotomy. This granularity is essential to detect not only the complete cessation of imports but also reductions in imported volumes, which constitutes the first condition to identify a relocation event. The operationalization proceeds by distinguishing between broad and narrow measures and is formalized in two steps.

3.1.1 Identification of Narrow Imports

Narrow offshoring focuses specifically on imports of intermediate goods that fall within the same industry classification as the firm's final output. As the authors argue, this distinction is crucial for identifying genuine production fragmentation, as opposed to general input purchasing.
Consider, for example, a firm in the automotive industry: if it imports raw steel, this represents a generic input purchase (broad measure). However, if it imports engines or braking systems (goods classified within the same ATECO/NACE code as the car itself) it signals that the firm is offshoring a specific production phase that it could have performed internally. This restriction enables the identification of the relevant pool of firms potentially eligible for nearshoring.
Formally, let Imp_{ict}^{k} denote the import flow of product k by firm i from country c at time

t, and let j denote the main activity sector of firm i. The relevant *narrow import value* is calculated by aggregating only those flows where the product code matches the firm's sector:

$$Imp_{ict}^{Narrow} = \sum_k Imp_{ict}^k \quad \text{such that} \quad k \in j \tag{3.1}$$

The components of this aggregation are defined as follows:

- Imp_{ict}^k**:** *the value of imports of product k by firm i from partner country c in year t;*
- j**:** *the main industry classification code (ATECO/NACE) of firm i;*
- $k \in j$**:** *the matching condition restricting the sum to products k that fall within the same industry category as the firm's output j (at the 4-digit level).*

In the empirical analysis conducted to identify firms engaging in offshoring, the specific variable import was selected as the numerator for the intensity calculation. This choice was driven by the necessity to capture the precise geographical origin of sourcing activities. Unlike aggregate measures available in the dataset (such as the total annual import value per firm), the import variable provides the monetary value of individual transactions. Using the import value allows the decomposition of trade flows by partner country, which is key to detect the subsequent strategic shifts (e.g., the redirection of production from far to close nations) that define the nearshoring and friend-shoring phenomena.

3.1.2 Computing Offshoring Intensity

To distinguish strategic sourcing decisions from general fluctuations in firm performance, the value of narrow imports must be normalized. Following the specification by D'Ambrosio et al. [2], the offshoring intensity O_{ict} for firm i importing from country c at time t is defined as:

$$O_{ict} = \frac{Imp_{ict}^{Narrow}}{T_{it}} \tag{3.2}$$

The variables and parameters in this equation are defined as follows:

- Imp_{ict}^{Narrow}**:** *the cumulative value of narrow imports by firm i from partner country c in year t, restricted to products belonging to sector k that matches the firm's main production sector j;*
- T_{it}**:** *the total turnover of firm i in year t, serving as the denominator for normalization;*
- O_{ict}**:** *the normalized offshoring intensity; a positive value ($O_{ict} > 0$) identifies the firm as an active offshorer towards country c.*

The normalization by turnover (T_{it}) is highlighted as a methodological necessity to guarantee the internal validity of the measure [2]. Looking only at raw import values could be misleading: a reduction in imports might simply reflect a contraction in the firm's overall activity (e.g., financial distress or a drop in sales) rather than a strategic decision to reorganize the supply chain. By using this ratio, the model spots changes in the sourcing strategy from general fluctuations in firm performance.
This continuous metric O_{ict} serves as the foundation for the subsequent identification strategy. In the next section, this framework will be adapted to define nearshoring by observing a persistent negative variation in O_{ict} (e.g., stopping imports from a distant partner c) that is simultaneously offset by an increase in O_{ijt} towards a new partner j, provided that country j satisfies specific criteria of geographical proximity.

3.2 Operationalizing Nearshoring and Friend-shoring

Having defined the measure of offshoring intensity, the identification strategy proceeds to detect relocation events. To do so, this thesis builds upon the strict definition of reshoring provided by D'Ambrosio et al. [2] and proposes an extension to capture the phenomena of nearshoring and friendshoring.

3.2.1 Relaxing the Reshoring Constraints

To state that a reshoring event has occurred, the identification strategy requires four simultaneous conditions: *(i) a reduction in offshoring towards a partner, (ii) persistence over time, (iii) no substitution with other foreign partners, and (iiii) an increase in domestic inputs* [2].
To identify nearshoring or friendshoring, this framework is adapted by specifically relaxing the third hypothesis and clearly not taking into account the fourth given that this paper is not aimed at investigating a return back to the home country. The logic implies that firms do not necessarily repatriate production within national borders (as in strict reshoring), but rather relocate it from a "hostile" or distant partner. Therefore, the third condition of absence of substitution is modified. A nearshoring or friendshoring event is identified when the reduction of offshoring from a partner c is compensated by an increase in offshoring towards a new partner j, provided that partner j satisfies a condition of geographical or geopolitical proximity to the home country.

3.3 Disentangling Relocation Strategies: Nearshoring vs. Friend-shoring

While the literature often combines geographical proximity and political alignment, in this thesis the two driving forces are distinguished. Building on the relaxed reshoring framework established in the previous section, two distinct identification strategies are proposed.
The first model identifies *Nearshoring*, driven by the reduction of physical distance and

transport volatility. The second model identifies *Friend-shoring*, driven by the reduction of geopolitical distance and institutional friction. In both cases, the identification relies on observing a divestment from a distant/hostile partner that is simultaneously compensated by an investment in a partner satisfying specific proximity criteria.

3.3.1 Model 1: Identification of Nearshoring (Geographic Proximity)

A binary indicator, denoted as $NS_{i,t}$, is defined to take the value of 1 if firm i engages in nearshoring in year t. This strategy captures relocation towards countries that are physically close to the home country (Italy), prioritizing geographical proximity in favor of logistics and lead times.
The formal condition is expressed as follows:

$$NS_{i,t} = \begin{cases} 1 & \text{if } \Delta O_{ict} < 0 \quad \text{AND} \quad \Delta O_{ijt} > 0 \quad \text{AND} \quad GeoD_{ITA,j} \leq \bar{\delta} \\ 0 & \text{otherwise} \end{cases} \tag{3.3}$$

The variables governing the nearshoring strategy are defined as follows:

- $\Delta O_{ict} = O_{ict} - O_{ic,t-1} < 0$**:** *Divestment condition.* A negative variation in offshoring intensity towards the "source" country c, to capture the decoupling decision from the original partner.
- $\Delta O_{ijt} = O_{ijt} - O_{ij,t-1} > 0$**:** *Substitution condition.* A positive variation in offshoring intensity towards a "destination" country j. Unlike strict reshoring, the firm shifts the sourcing volume to a new international location.
- $GeoD_{ITA,j}$**:** *The Geographic Distance.* This variable represents the physical distance (in km) between Italy and the destination country j. The variable is computed using the distances among the capital of Italy and those of the other countries.
- $\bar{\delta}$**:** *The Nearshoring threshold.* This parameter represents the first quartile of the distribution of geographic distances between Italy and all potential global trading partners. Relocation is classified as nearshoring only if the destination country j is geographically closer than 75% of other potential partners ($GeoD \leq \bar{\delta}$).

3.3.2 Model 2: Identification of Friend-shoring (Geopolitical Alignment)

A separate binary indicator, denoted as $FS_{i,t}$, is defined to take the value of 1 if firm i engages in friendshoring. This strategy captures relocation towards countries that share political values and diplomatic alignment with Italy, prioritizing security and institutional stability.
The formal condition relies on the geopolitical metrics discussed by Bosone and Stamato [4]:

$$FS_{i,t} = \begin{cases} 1 & \text{if } \Delta O_{ict} < 0 \quad \text{AND} \quad GD_{ITA,c,t} > \text{Median} \\ & \text{AND } \Delta O_{ijt} > 0 \quad \text{AND} \quad GD_{ITA,j,t} \leq Q1 \\ 0 & \text{otherwise} \end{cases} \tag{3.4}$$

The variables specific to the friendshoring strategy are defined as follows:

- $\Delta O_{ict} = O_{ict} - O_{ic,t-1} < 0$**:** *Divestment condition.* As in the previous model, this captures the reduction in reliance on the original partner c. To identify friendshoring, this partner must belong to the "Rival" category ($GD >$ Median).
- $\Delta O_{ijt} = O_{ijt} - O_{ij,t-1} > 0$**:** *Substitution condition.* The compensating increase in sourcing from the new partner j. This partner must belong to the "Friend" category ($GD \leq Q1$).
- $GD_{ITA,(\cdot),t}$**:** *The Geopolitical Distance index.* To quantify the alignment between the home country (Italy) and potential destination partners, Bosone and Stamato [4] metric is employed, since they consider geopolitical distance a significant trade friction since 2018. This measure is based on the “Ideal Point Distance” originally proposed by Bailey, Strezhnev, and Voeten [3]. It is constructed using voting records from the United Nations General Assembly (UNGA), mapping countries’ foreign policy preferences. The bilateral distance reflects the disagreement between two nations in their voting behavior: a value close to 0 indicates high alignment (“Friends”), while higher values indicate divergence (“Rivals”).
- **Geopolitical Classification ($\bar{\theta}$):** To rigorously classify trading partners, the distribution of geopolitical distances is segmented into three distinct zones based on statistical quartiles:
  - **Friends ($GD \leq Q1$):** Countries falling within the first quartile represent the target destinations for friendshoring.
  - **Neutral ($Q1 < GD \leq Median$):** Countries falling between the first quartile and the median are excluded from the friendshoring definition to isolate clear strategic shifts.
  - **Rivals ($GD > Median$):** Countries with a distance above the median represent the geopolitical counterparts from which strategic divestment must originates.

By excluding the “Neutral” zone, this identification strategy filters out routine relocation between geopolitically similar nations, isolating only those events that represent a substantial reduction in geopolitical risk exposure (e.g., shifting from a Rival to a Friend).

3.3.3 Consistency and Temporal Persistence

For both identification strategies ($NS_{i,t}$ and $FS_{i,t}$), discriminating between structural strategic shifts and temporary fluctuations in trade volumes is critical. To ensure the robustness of the measure, a persistence condition is applied to the observed variations over a validation window of two years ($t + 2$).
In the analysis it is required that the divestment from the source country c ($\Delta O_{ict} < 0$) and the concurrent investment in the destination country j ($\Delta O_{ijt} > 0$) are not reversed in the subsequent two periods. This methodological choice has the purpose of filtering out short-term noise and volatility and of maximizing the inclusion of recent relocation episodes without being overly constrained by data availability for the most recent observations. By implementing this persistence constraint alongside the respective geographic ($\bar{\delta}$) and geopolitical ($\bar{\theta}$) thresholds, the models rigorously distinguish firms that strategically consolidate their supply chains from those that simply engage in short-term supplier switching.

3.4 Data Sources

To operationalize the identification strategies described above, the empirical analysis utilizes three distinct datasets: firm-level microdata for trade and production, geographical data for physical distance, and political data for geopolitical alignment.

3.4.1 Firm-Level Trade and Financial Data

The core analysis is constructed by merging transaction-level trade data with firm-level balance sheet information. This integration is crucial to calculate the offshoring intensity O_{ict} and then observe the firm-specific relocation patterns ($NS_{i,t}$ and $FS_{i,t}$).

- **Trade Data:** Information on imports and exports is sourced from the anonymized *ISTAT-COEWEB* database. This dataset provides information on the value of flows (Imp_{ict}) by firm, partner country, and product code, allowing tracking for each year the purchasing decision of each company. This granularity is required to filter *narrow imports* matching the firm's activity.

- **Balance Sheet Data:** To normalize trade flows and control for firm characteristics, trade data are merged with the *AIDA - Bureau van Dijk* database. This database provides the annual turnover (T_{it}), the main industry classification code (NACE/ATECO), and other precious information about Italian SMEs.

The matching between trade and financial data is performed using as a key the unique firm identifier provided in the dataset (specifically the variable n_firm), which serves to merge transaction-level with firm-level data.

3.4.2 Geographic Distance Data

To develop the nearshoring model and compute the geographic threshold $\bar{\delta}$, the database which is used is *CEPII GeoDist* [32].
The variable utilized to measure the geodesic distance in kilometers between Rome (Italy) and the capital city of the partner country j is the *distcap* (the distance between capitals). The approach applied for geographical distance is to look at the distribution of these bilateral distances to determine the first quartile. Countries falling within this geographic radius are considered eligible destinations for nearshoring, those outside it are considered too far. Thanks to this distinction, these closer countries tend to offer reduced logistical coordination and lower transport volatility compared to the global average.

3.4.3 Geopolitical Distance Data

In this thesis to quantify the geopolitical alignment between Italy and its trading partners, the *United Nations General Assembly Ideal Points* database is utilized [33]. This file provides an aggregate estimate of each country's foreign policy preference, denoted as the "Ideal Point", which is mapped onto a one single variable. These scores help to track cross-temporal and cross-country political closeness.

Calculation Method and Time Horizon

Since the database provides individual country scores rather than bilateral distances, the variable $GD_{ITA,j,t}$ is computed during the data processing phase. For each year t, the Ideal Point of the home country (Italy), denoted as $IP_{ITA,t}$, is confronted with the Ideal Point of the potential destination partner j, denoted as $IP_{j,t}$. The bilateral *Geopolitical Distance* is calculated as the absolute difference between these two values:

$$GD_{ITA,j,t} = |IP_{ITA,t} - IP_{j,t}| \tag{3.5}$$

A value close to 0 indicates that the partner country votes almost identically to Italy in the UN Assembly, signaling strong diplomatic alignment ("Friend"), in contrast, high values indicate political divergence.
In the classification thresholds introduced in the friendshoring model, short term political fluctuations are filtered out. Using the temporal coverage of the firm-level and transaction-level datasets utilized in this study, the analysis focuses on the period from 2010 to 2022. For this reason, the classification of a partner country j as a "Friend", "Neutral", or "Rival" is determined by the average geopolitical distance over this 12-year interval:

$$\overline{GD}_{ITA,j} = \frac{1}{T} \sum_{t=2010}^{2022} |IP_{ITA,t} - IP_{j,t}| \tag{3.6}$$

Consistent with the concept of friend-shoring, a partner j is classified as a valid destination for relocation only if its average distance $\overline{GD}_{ITA,j}$ falls within the first quartile of the global distribution. This captures the fact that the condition of the model ($\Delta O_{ijt} > 0$) is restricted exclusively to countries that have demonstrated consistent geopolitical alignment with Italy.

Chapter 4

Descriptive Evidence: Mapping the Relocation Zones

4.1 The Geographic Perimeter: Nearshoring

As anticipated in the previous chapters, to verify if firms applied a nearshoring strategy, physical distances between Rome and partner capitals were analyzed. The distribution reveals a clear concentration of trading partners within the European and Mediterranean area. Based on the first quartile of the distribution, the threshold for nearshoring is identified at $\bar{\delta} \approx 3{,}033$ km. As shown in Figure 4.1 visualizes this radius: countries falling within the green zone (including the entire EU, North Africa, and parts of the Middle East) represent eligible destinations for nearshoring relocation.

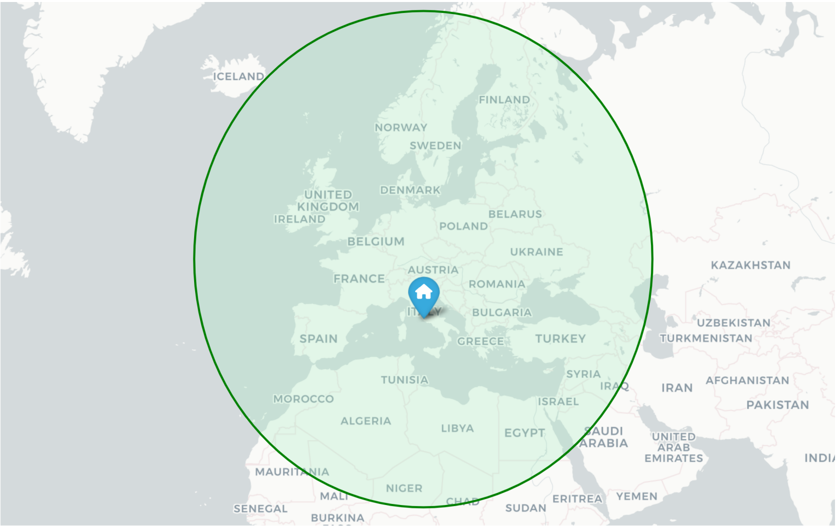

Figure 4.1. Nearshoring Zone centered in Italy. The map highlights countries whose distance from Rome falls within the first quartile of the global distribution ($\leq 3{,}033$ km).

Figure 4.2 shows the statistical distribution of distances. The data confirms that the chosen threshold (around 3,000 km, marked in green) effectively isolates a specific group of closer trading partners, distinguishing them from the rest of the world (average distance in red).

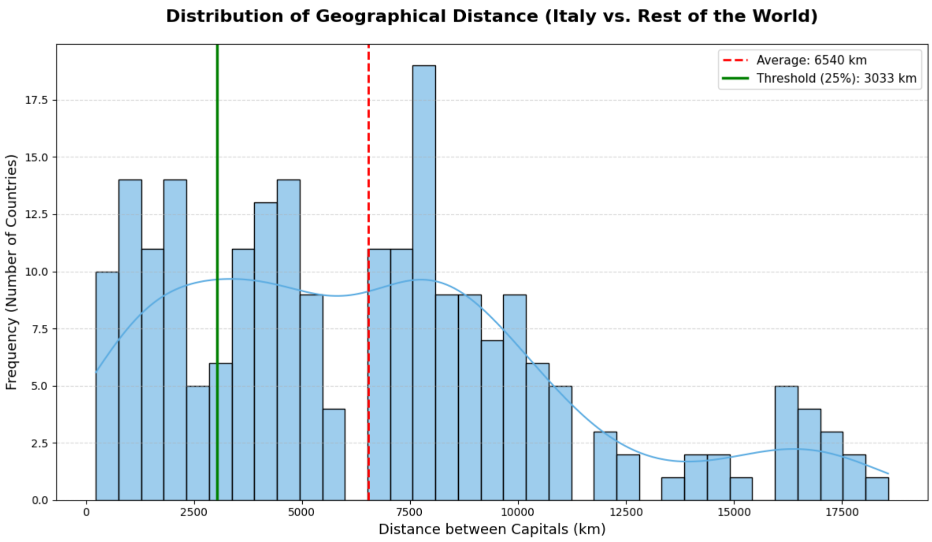

Figure 4.2. Distribution of Geographical Distance (Italy vs. Rest of the World). The vertical lines indicate the average distance (red) and the nearshoring threshold (green).

4.2 Geopolitical Alignment: Friendshoring

The analysis of the geopolitical landscape, based on the average Ideal Point Distance from Italy over the 2010–2022 period, reveals a clear polarization of international relations.
Figure 4.3 visualizes the global alignment with Italy. The Countries in green represent "Friendshoring Partners" ($GD \leq 0.61$) and they are heavily concentrated within the European continent. Almost the entire European Union falls into this category, reflecting a deep institutional and political alignment of these Nations. In Europe there are two notable exclusions, which are Russia and Belarus. These countries, classified as Rivals (red), make the analysis consistent with the escalating geopolitical tensions related to the start of the war observed in the latter part of the sample period.
Outside of continental Europe, the map highlights a select group of strategic allies. Global partners such as Canada, Japan, South Korea, and Australia are firmly located within the "Friend" zone, proving that political alignment goes beyond geographical proximity.
The United Kingdom is classified as a "Neutral" country (yellow). This result captures the divergence in voting patterns and political positioning likely driven by the Brexit, which dominated the diplomatic agenda for a significant portion of the observed time window. Even more surprisingly, the United States, traditionally considered the closest ally and

the geopolitical beacon of the West, falls into the "Rival" category ($GD > 1.43$) when observing the 2010–2022 median.
It is worth noting that an analysis restricted to the most recent data would likely reclassify the UK as a "Friend" and the US as "Neutral". In this thesis to ensure rigorous consistency with the firm-level and transaction-level dataset, which covers the 2010–2022 interval, the geopolitical classification must reflect the average alignment over the entire period of economic activity. For this reason, the identification strategy will adhere to the zoning depicted in Figure 4.3. Not even for UK an exception is made, which is located just above the threshold value and constantly in between the "Friend" and "Neutral" range.

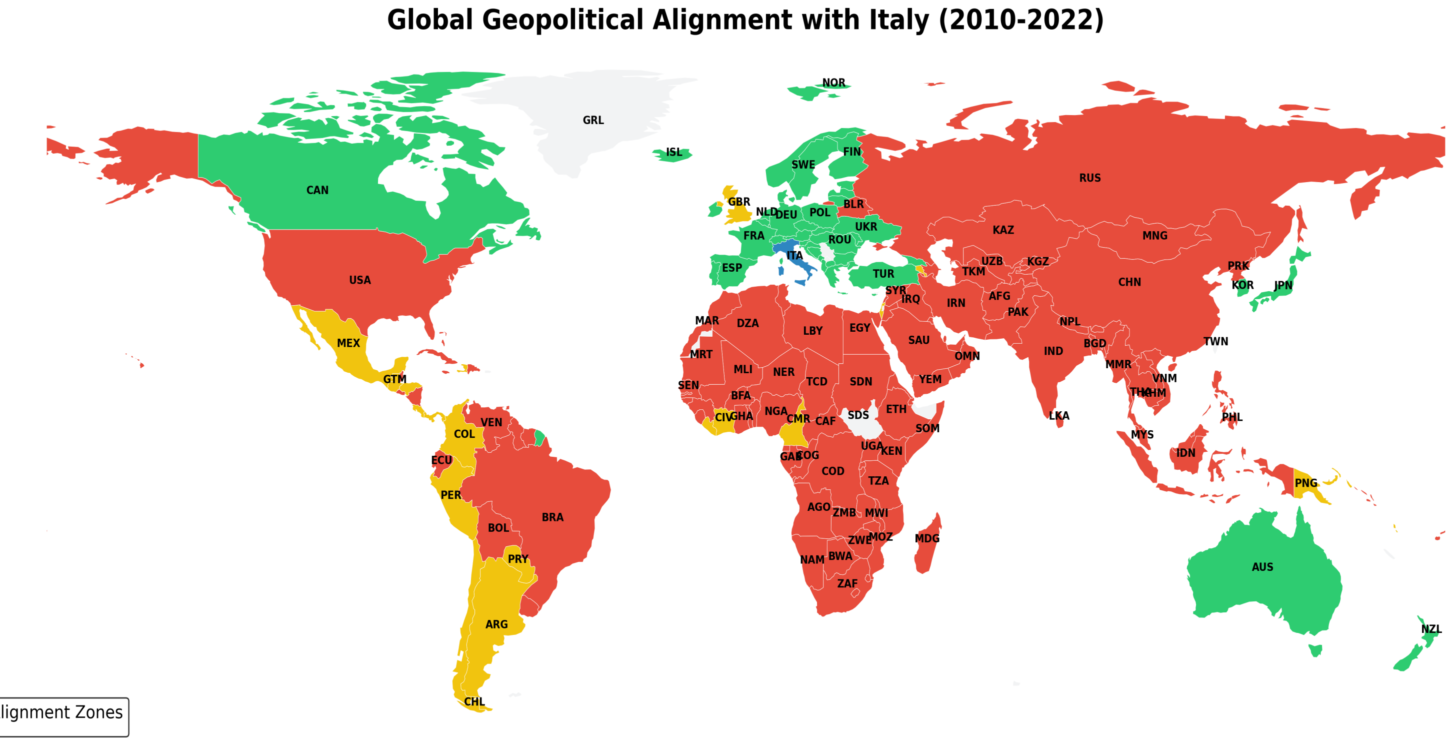

Figure 4.3. **Global Geopolitical Alignment with Italy (2010–2022).** Countries are classified based on the average Ideal Point Distance. Green: Friends ($GD \leq 0.61$); Yellow: Neutral; Red: Rivals ($GD > 1.43$).

Figure 4.4 presents the statistical distribution of the average geopolitical distances. From this distribution is possible to distinguish the nature of the global political landscape.
It is visible a distinct cluster of highly aligned countries (left tail) separated from the rest of the world. The vertical green line marks the Friend-shoring threshold (0.61), which effectively isolates the closest allies, while the black line indicates the global average distance (1.24).

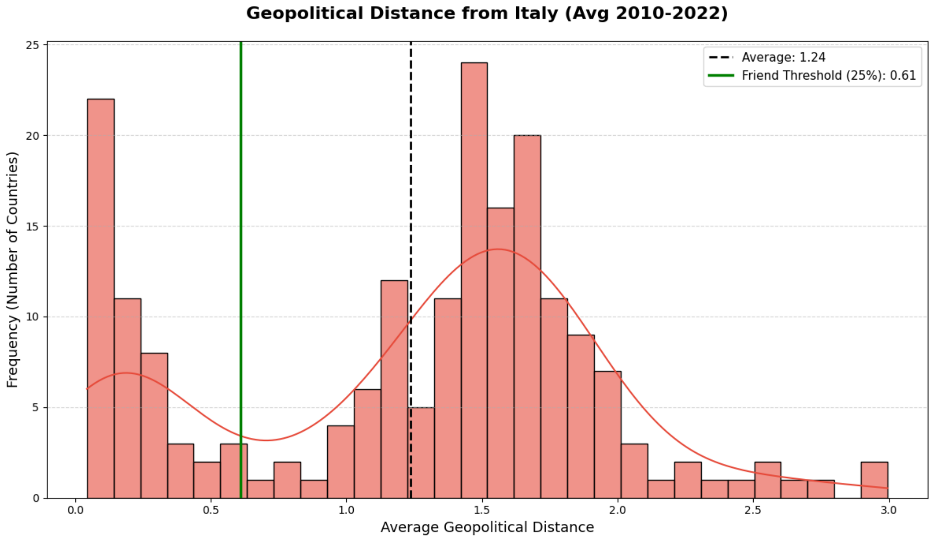

Figure 4.4. **Distribution of Geopolitical Distance (Italy vs. Rest of the World).** Green line: Friend-shoring threshold (1st Quartile); Black line: Global Average.

4.3 Temporal Dynamics of Geopolitical Distance

Traditional economic geography tends to treat distances between nations as fixed time-invariant parameters. Physical distance, measured in kilometers, remains constant regardless of economic cycles or political shifts. However, geopolitical proximity operates on an entirely different logic. Unlike geography, political alignment is highly volatile and sensitive to exogenous shocks.
Observing the evolution of the Ideal Point Distance over time (Figure 4.5), it becomes evident how critical events, such as the outbreak of conflicts, referendums, or shifts in presidential administrations, can rapidly alter the equilibrium of international alliances. This dynamic implies that a country classified as a "Friend" today might have been a "Rival" only a few years prior, highlighting the importance of using time-varying metrics rather than static indicators for identifying friendshoring opportunities.

4.3.1 Country-Specific Trajectories (2010–2022)

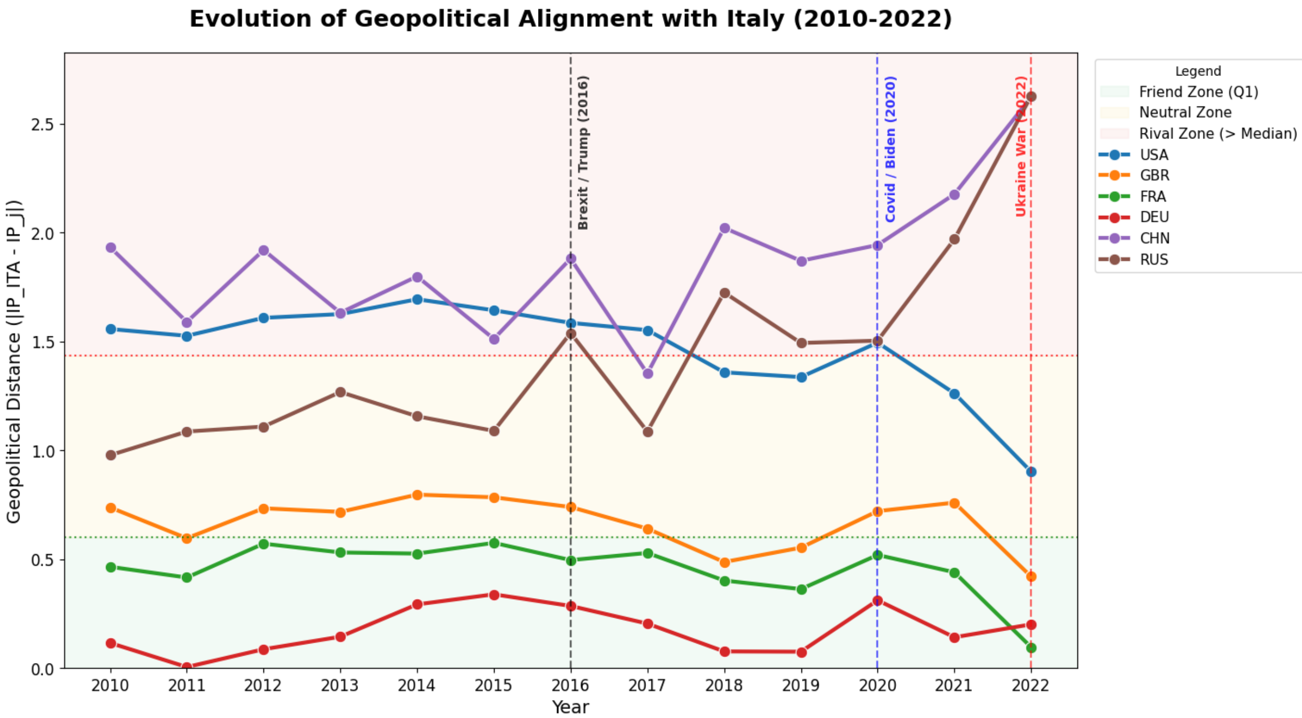

Figure 4.5. **Evolution of Geopolitical Alignment with Italy (2010–2022).** The chart tracks the Ideal Point Distance for key countries. Dotted lines indicate critical geopolitical events.

The analysis of the specific bilateral geopolitical relationships with Italy reveals distinct patterns of convergence and divergence:

- **United States (USA):** The trajectory of the US is perhaps the most interesting of all. Looking at the entire decade, particularly during the pre-2020 period, the US maintained a significant geopolitical distance from Italy, remaining within the "Rival" or high "Neutral" zone. This reflects structural divergences in UN voting patterns. Moving forward in time, a structural break is observable after 2020, coinciding with the election of the Biden administration, which triggered a rapid convergence towards the Italian position, bringing the US almost to the edge of the "Friend" zone by 2022.
- **Russia (RUS):** The Russian trajectory shows a dramatic decoupling trend. In the first period there was a relatively moderate distance (comparable to the US at the time), then the relationship deteriorated progressively. The curve shows a steep vertical explosion following 2016 and culminates in a maximum peak in 2022, confirming the total rupture of diplomatic alignment following the invasion of Ukraine.

- **United Kingdom (GBR):** The UK displays a unique pattern. Despite the Brexit referendum in 2016, which politically separated Britain from the EU, the geopolitical alignment with Italy on global issues remained relatively stable within the "Neutral" zone. In particular, the data shows a convergence in the very last years (2021–2022), suggesting that the strategic partnership remains robust despite the institutional separation from the EU.

- **China (CHN):** China represents the structural rival. The geopolitical distance metric remains consistently high throughout the entire period, so China firmly appears within the "Rival" zone. There are no significant fluctuations or periods of rapprochement (unlike the US or UK), confirming China as a consistent geopolitical antagonist to Italy.

- **France (FRA) and Germany (DEU):** For what regards France and Germany, the curves provide the benchmark for stability. Both countries exhibit a flat and low-distance trajectory that remains constantly within the "Friend" zone (below 0.602). This confirms a structural alignment of the core European Union members. Not even external shocks that reshaped relations with non-EU powers could affect this bond.

In concluding this descriptive analysis, it is important to acknowledge a limitation inherent in the metric utilized. The Ideal Point Distance aggregates voting behavior across many kinds UN resolutions without distinguishing between thematic areas. Consequently, significant divergences may arise from specific domains (e.g., resolutions regarding human rights or cultural values), where the US and Italy often are misaligned. While these disagreements inflate the calculated geopolitical distance, they do not necessarily translate into trade friction or affect commercial agreements. This distinction helps explain why a key economic ally like the United States can appear distant in the aggregate index, but since it is not the purpose of this thesis, which decisions affect trade relations will not be further investigated.

4.3.2 The U.S. Anomaly in the Friend-shoring Framework

Tables 4.1 and 4.2 report a robustness exercise in which the United States is mechanically included in the set of "friends" (i.e., its geopolitical distance is set to zero), and the friendshoring identification algorithm is re-run. The goal is to verify whether the baseline results are driven by the classification of the United States as non-friendly and to assess whether the data reveal a sizable reallocation of offshoring toward the United States once it is forced into the friend set.

Table 4.1. Robustness check: do USA-directed investments emerge when the United States is treated as a "friend"?

Item	Baseline	USA forced friend
Is the United States classified as a "friend"?	No	Yes
Any USA-directed investment links within friendshoring events?	No	Yes
USA investment links within friendshoring events (firm-year links)	0	27
Firms involved in USA investment links (unique firms)	0	21

Notes: Counts refer to USA-directed *investment* links observed among firm-years classified as friendshoring. In the baseline, the United States is not eligible to be counted as a friend destination by construction.

Table 4.2. USA investment links within friendshoring events, by year: baseline vs robustness.

Year	Baseline	USA forced friend
2011	0	1
2012	0	1
2013	0	1
2014	0	1
2015	0	6
2016	0	2
2018	0	1
2019	0	1
2020	0	1
2021	0	2
2022	0	10

Notes: Counts refer to the number of observed firm-year investment links to the United States among friendshoring events.

As highlighted in the text [34], there is a clear temporal misalignment between the United States and Europe in the process of distancing from China. Despite the frequent perception that Europe and the United States constitute a single, fully aligned geopolitical bloc, they appear to implement distinct strategies and to adjust their external economic

relations with different timing and intensity.
Consistent with this interpretation, the robustness exercise suggests that increases in offshoring links toward the United States become more visible once the U.S. is treated as a “friend” destination, and they are particularly concentrated in 2022. This timing is meaningful because 2022 coincides with the outbreak of the war in Ukraine, a shock that intensified geopolitical tensions and coincided with a closer alignment between Russia and China. In such a context, European firms faced stronger incentives to reconsider sourcing patterns and to shift part of their supply-chain exposure toward partners perceived as more reliable, including the United States.

4.4 Results of Nearshoring and Friendshoring Analysis

In the tables below are shown the “Top 10” divestment and investment destinations. This table are created from a merged database constructed at the firm–year level. Divestment observations and investment observations are matched using the keys (n_firm, $year$), so that each row in the resulting table reports, for the same firm and year, (i) the country from which the firm divests and (ii) the country in which it increases activity.
Because in the analysis the merge is many-to-many, a single divestment occurring in a given firm–year can be associated with multiple investment destinations in the same year. Therefore, the reported *count* should be interpreted as the number of observed divestment–investment *links* (firm–year country pairs), rather than the number of unique divestment events. It is better explained by an example: if a firm reduces exposure to one origin country and simultaneously increases exposure to three destination countries in the same year, that origin country contributes three times for each paired destination. This construction is useful to highlight the most frequent country connections associated with nearshoring/friendshoring activities, although it may yield larger counts.

Table 4.3. Nearshoring: Top 10 divestment and investment countries (counts of observed firm-year links).

country	divestment_count	country	investment_count
USA	168	DEU	151
CHN	161	GBR	85
IND	65	FRA	84
JPN	40	NLD	52
ARE	35	ESP	49
KOR	32	CHE	42
HKG	30	POL	41
MEX	26	TUR	36
CAN	26	BEL	29
AUS	26	AUT	28

Table 4.4. Friendshoring: Top 10 divestment and investment countries (counts of observed firm-year links).

country	divestment_count	country	investment_count
USA	171	DEU	113
CHN	167	FRA	64
IND	60	NLD	37
ARE	31	ESP	36
COG	17	KOR	35
MYS	13	TUR	30
EGY	13	POL	29
THA	12	BEL	26
SGP	11	JPN	23
SAU	10	CHE	20

As shown in Tables 4.4 and 4.3, firms' strategic choices display substantial similarities. Since several countries fall simultaneously into both the "Rivals" category and the group of geographically distant countries, a strong tendency to divest from the United States, China, and India emerges.
Surprisingly investment destinations are not primarily countries with the lowest labor costs. Although some lower-wage locations are present (e.g., Poland, Turkey, and the Czech Republic), the leading destinations are Germany, France, the Netherlands, the United Kingdom, and Spain. This pattern points to a preference for more stable and predictable environments, consistent with a consolidation of industrial alignment, in addition to political proximity and with the search for advantages related to logistical proximity.
Figure 4.6 complements the country-level evidence by showing how the sectoral composition of treated firms compares to the overall population of firms. The chart is built using ATECO 2-digit divisions [35] and reports the fraction of firms in each group belonging to a given sector.

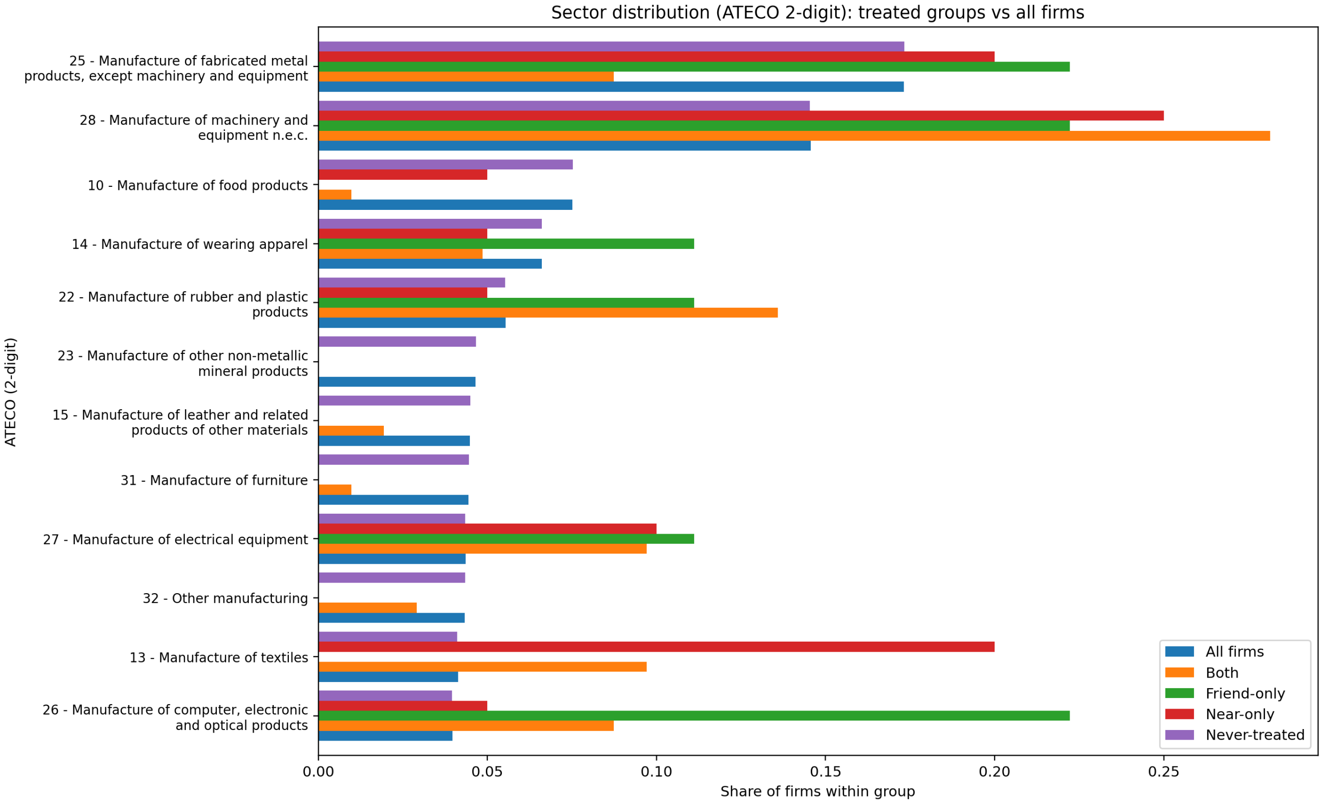

Figure 4.6. Sector distribution (ATECO 2-digit): treated groups vs all firms. Bars report the share of firms within each group falling into a given sector (within-group normalization).

The treated groups display a sectoral profile broadly aligned with the manufacturing core of the sample, with a strong concentration in manufacture of machinery and equipment (ATECO 28) and fabricated metal products (ATECO 25), which are also extremely present in the overall population. At the same time, some differences emerge across strategies: the *Near-only* group appears comparatively more concentrated in textiles (ATECO 13), while *Friend-only* firms show a stronger presence in computer, electronic and optical products (ATECO 26) and wearing apparel (ATECO 14). These patterns suggest that relocation strategies may reflect different exposure to the sourcing of inputs and supply-chain risks across industries.

Table 4.5 shows that nearshoring and friendshoring events are observed throughout the sample period, but they become more frequent toward the end of the window. After a gradual increase in the early years (2011–2016) and a relatively flatter phase between 2017 and 2020, the number of events rises again in 2021–2022, reaching a clear peak in 2022 (77 total events, split almost evenly between nearshoring and friend-shoring). This surge is consistent with a sharp deterioration in the geopolitical environment and a renewed emphasis on supply-chain security: Russia's invasion of Ukraine in 2022 amplified

Table 4.5. Number of nearshoring and friendshoring events by year (firm-year level).

Year	Nearshoring events	Friendshoring events	Total events
2011	6	6	12
2012	18	13	31
2013	16	13	29
2014	32	28	60
2015	30	27	57
2016	23	20	43
2017	19	17	36
2018	18	10	28
2019	26	22	48
2020	16	17	33
2021	28	21	49
2022	39	38	77

Notes: An event is defined at the firm-year level (each row corresponds to a firm-year in which the firm is classified as nearshoring or friendshoring).

perceived risks related to reliance on politically distant or unstable partners, strengthening incentives to relocate sourcing toward Europe and geopolitically aligned countries. At the same time, a wider rise in economic nationalism and strategic autonomy agendas across advanced economies, highlighted in particular by the 2022 Italian elections and the formation of the Meloni government, may have further reinforced firms' attention to resilience, encouraging relocation strategies toward nearby and "friendly" destinations.

Chapter 5

Econometric Analysis: The Impact of Nearshoring and Friend-shoring on Firm Performance

This chapter presents the econometric analysis designed to quantify the impact of both Nearshoring and Friendshoring, on firms' performance. Having identified the firms that undertook these strategic decisions, the focus now turns to evaluating whether these strategic behaviors translated into tangible economic benefits.
To measure performance, the analysis primarily relies on the *Return on Assets (ROA)*, a key indicator of the efficiency with which a firm uses its assets to generate profit. In addition, two margin-based measures are considered: the *Return on Sales (ROS)*, which captures profitability relative to revenues, and the *Operating Margin*, which reflects operating profitability net of non-operating items. Finally, to capture operational efficiency, *Labor Productivity* is employed as a complementary dependent variable. The research question is whether firms that relocated production to geographically closer or geopolitically aligned countries experienced a statistically significant improvement in these indicators compared to firms that did not relocate.
To answer this question, a simple comparison between relocating and non relocating firms could provide misleading results due to selection bias [36]. Firms choosing to reorganize their supply chains might differ systematically from non-relocating firms in different ways (e.g., managerial quality, risk aversion, or pre-existing trends).
Therefore, to isolate the true treatment effect, in this thesis is adopted a *Difference-in-Differences (DiD)* approach with two way fixed effects. This methodology compares the change in performance over time for the treated group (firms undertaking nearshoring or friend-shoring) relative to the change for a control group (firms continuing traditional offshoring), thus simplifying out both time-invariant firm characteristics and common macroeconomic shocks.

5.1 Model Specification

The empirical analysis estimates a two-way fixed effects (TWFE) Difference-in-Differences model on firm-level panel data [37]:

$$Y_{it} = \alpha_i + \gamma_t + \beta \cdot DiD_{it} + \epsilon_{it} \tag{5.1}$$

where i indexes firms and t indexes years. The dependent variable Y_{it} represents firm performance and is operationalized through four distinct metrics:

- **ROA (Return on Assets):** a measure of profitability, calculated as:

$$ROA_{it} = \frac{\text{Net Profits}_{it}}{\text{Total Assets}_{it}}. \tag{5.2}$$

- **ROS (Return on Sales):** a measure of profit margin on sales, calculated as:

$$ROS_{it} = \frac{\text{Net Profits}_{it}}{\text{Revenues}_{it}}. \tag{5.3}$$

- **Operating Margin:** a measure of operating profitability, calculated as:

$$OM_{it} = \frac{\text{Operating Income}_{it}}{\text{Revenues}_{it}}. \tag{5.4}$$

- **Log Labor Productivity:** a measure of workforce efficiency, calculated as the natural logarithm of value added per employee:

$$\log(\text{Prod}_{it}) = \log\left(\frac{\text{Value Added}_{it}}{\text{Employees}_{it}}\right). \tag{5.5}$$

  The logarithmic transformation is commonly adopted to reduce skewness and allows interpreting the coefficient β as an approximate percentage change in productivity (semi-elasticity) [38].

The other components of the model are defined as follows:

- α_i**:** *Firm Fixed Effects.* These parameters capture unobserved, time-invariant heterogeneity specific to each firm (e.g., management quality, technological capabilities, size of the firm).

- γ_t**:** *Time Fixed Effects.* These parameters capture macroeconomic shocks common to all firms in a given year (e.g., business cycles, global supply chain disruptions, COVID pandemic).

- $\boldsymbol{DiD_{it}}$**:** the Difference-in-Differences regressor defined as:

$$DiD_{it} = Treated_i \times Post_{it}. \tag{5.6}$$

  In the empirical implementation are considered both Nearshoring and Friendshoring alternatives:

- **Nearshoring**: $DiD_{it} \equiv did\_near_{it}$;
- **Friendshoring**: $DiD_{it} \equiv did\_friend_{it}$.

The indicator $Treated_i$ equals 1 for firms that experience the corresponding relocation event within the sample period, and 0 for firms that have never been treated. The indicator $Post_{it}$ equals 1 for treated firms in years after the first treatment year (the *event year*), and 0 otherwise.

- β**:** the coefficient of interest. It measures the *Average Treatment Effect on the Treated* (ATT) under the assumptions of the DiD framework. It quantifies the average post-event change in performance for treated firms relative to the simultaneous change observed for never-treated firms, net of the firm fixed effects already discussed.

- ϵ_{it}**:** the idiosyncratic error.

The analysis is conducted using clustered standard errors at the firm level to consider serial correlation within firms over time.
Now the composition of the control group is defined. In the analysis treated firms are those that (i) reduce offshoring and (ii) simultaneously increase activity in at least one *near* or *friendly* destination (i.e., *nearshorers* and *friendshorers*). The control group instead includes firms that do not exhibit this reallocation pattern, in particular:

- firms that reduce offshoring but *do not* increase offshoring/investment in near or friendly countries (i.e., they downscale offshoring without near/friend substitution);

- firms that do not reduce offshoring and do not increase activity in near or friendly countries (i.e., no relevant reallocation over the sample period);

- firms whose adjustments (if any) are directed toward destinations that are neither classified as *near* nor *friendly*.

This definition clarifies that the counterfactual is built from firms that are either untreated or that adjust their international exposure without shifting production toward near or friendly locations.
Although this DiD framework features staggered adoption, the TWFE specification may implicitly use already treated firms as part of the control group for firms treated at later dates. In this setting, the concern is mitigated by the fact that the number of treated firms (friendshorers and nearshorers) is relatively small [39].

5.2 Theoretical Foundations of the Linear Estimation

5.2.1 The Geometry of the Linear Model

Following the classical statistical framework [40], the relationship between firm performance and relocation strategies is modeled as a linear system. In matrix notation, for a sample of size n, the general model is expressed as:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{5.7}$$

Where:

- $\mathbf{Y}$ is the vector of observations (ROA_{it}, ROS_{it}, OM_{it}, or $\log(\text{Prod}_{it})$);
- $\mathbf{X}$ is the *design matrix* collecting the intercept, the DiD regressor (DiD_{it}), and the fixed effects (firm and year);
- $\boldsymbol{\beta}$ is the vector of unknown coefficients to be estimated;
- $\boldsymbol{\varepsilon}$ is the vector of disturbances (errors).

5.2.2 Interpretation of the Coefficient with Binary Predictors

In this analysis, the key regressor is binary and equals 1 only for firms that have been treated in the post-event period ($DiD_{it} \in \{0,1\}$). This allows to interpret the coefficient β as a shift in expected outcomes.
As illustrated in Figure 5.1, when a regressor is binary, the regression line does not represent a continuous slope in the traditional sense, but rather a difference in means:

- When $DiD_{it} = 0$ (control firms and pre-event years), the expected value of Y_{it} is captured by the intercept and the fixed effects.
- When $DiD_{it} = 1$ (treated firms in post-event years), the expected value increases (or decreases) by β, ceteris paribus.

Consequently, β captures a differential in outcomes associated with treatment exposure. In the Difference-in-Differences setting, this differential is net of time-invariant firm characteristics (α_i) and common time shocks (γ_t), isolating the causal effect of the relocation strategy under the parallel trends assumption [37, 36].

5.2.3 Hypothesis Testing

The primary objective of the econometric analysis is to determine whether the adoption of nearshoring or friendshoring strategies generates a statistically significant shift in firm performance. This is formalized through the following hypothesis test on the coefficient β:

- **Null Hypothesis (H_0):** $\beta = 0$
  The relocation strategy has no impact on firm performance. Any observed variation is attributable to random noise or common trends affecting all firms.
- **Alternative Hypothesis (H_1):** $\beta \neq 0$
  The strategy has a significant impact (either positive or negative) on performance indicators.

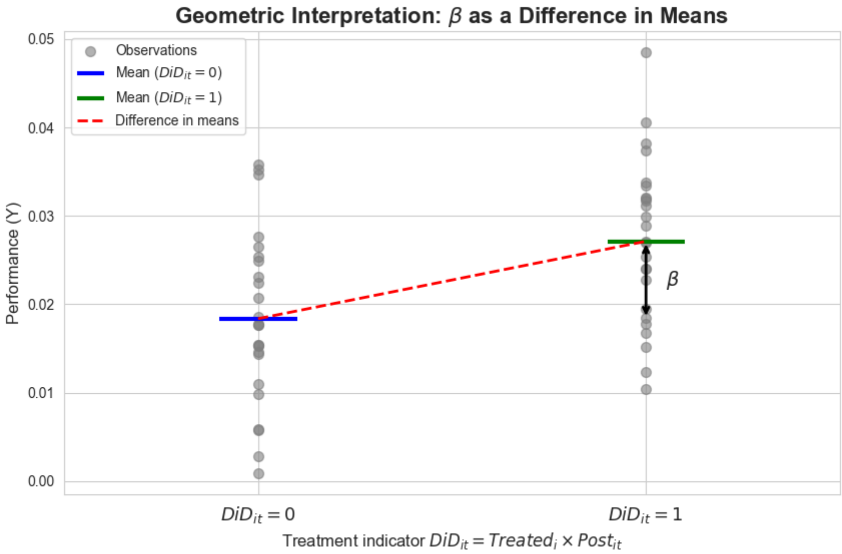

Figure 5.1. **Geometric intuition for the DiD regressor.**
Let $DiD_{it} = Treated_i \times Post_{it}$ be a binary indicator taking values in $\{0,1\}$. The coefficient β measures the average difference in the outcome between observations with $DiD_{it} = 1$ (treated firms after the event) and observations with $DiD_{it} = 0$ (never treated firms and pre-event years), conditional on firm and year fixed effects.

5.2.4 Visualizing the Causal Identification

The strength of the Difference-in-Differences approach lies in its ability to construct a credible counterfactual. As depicted in Figure 5.2, the coefficient β measures the change of treated firms with respect to the control group after the event.
The dashed line represents the counterfactual scenario: how treated firms would have performed in the absence of the relocation strategy, assuming they followed the same trend as the control group (Parallel Trends Assumption). The solid line represents the observed trajectory. The vertical distance between the observed and counterfactual outcomes in the post-event period identifies the causal effect β, net of time-invariant firm differences (α_i) and common shocks (γ_t).

5.2.5 Statistical Inference: t-statistic and P-Value

To determine whether the estimated coefficient β represents a genuine economic effect or merely a random fluctuation in the data, statistical inference relies on the t-statistic:

$$t = \frac{\hat{\beta}}{SE(\hat{\beta})} \tag{5.8}$$

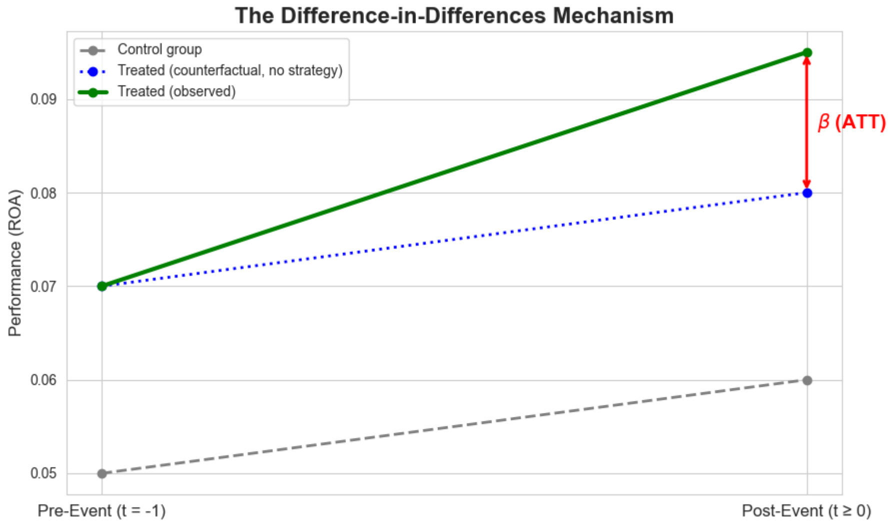

Figure 5.2. **The Difference-in-Differences Mechanism.** The chart illustrates the isolation of the Average Treatment Effect on the Treated (ATT). β captures the divergence of the treated group from its counterfactual trajectory.

where $\hat{\beta}$ is the estimated coefficient and $SE(\hat{\beta})$ is the firm clustered standard error. Under the null hypothesis ($H_0 : \beta = 0$), this statistic follows a Student's t-distribution. Consequently, for a large sample size, a value of $|t| > 1.96$ indicates that the coefficient is statistically different from zero at the 95% confidence level [38].
This condition is equivalently assessed through the P-Value, which represents the probability of observing such a t-statistic if the true effect were zero.

- If P-Value < 0.05, we reject the null hypothesis and conclude that the strategy has a significant causal impact on performance.
- If P-Value ≥ 0.05, the evidence is insufficient to claim an effect.

5.3 Descriptive Statistics

Table 5.1 reports descriptive statistics for the main outcome variables used in the econometric analysis: ROA, ROS, Operating Margin, and log labor productivity (computed on the sample of narrow offshorers over the 2010–2022 period). Firms are partitioned into four mutually exclusive groups: (i) firms that undertake both nearshoring and friend-shoring at least once, (ii) nearshoring-only firms, (iii) friend-shoring-only firms, and (iv) never-treated firms (i.e., firms that never experience either relocation strategy). To mitigate the influence of extreme observations, especially for profitability ratios that can become highly volatile when revenues are small, all the variables examined are winsorized at the 1st and 99th percentiles of the pooled sample.

Table 5.1. Descriptive statistics by treatment group (2010–2022)

Variable	Mean	Std. Dev.	Min	Max	N
Panel A: Both (Near & Friend) firms (Firms = 103)					
ROA	0.0250	0.0791	-0.3089	0.2881	1115
ROS	0.0150	0.1047	-0.5641	0.3024	1112
Operating margin	0.0413	0.1149	-0.5700	0.3636	1112
ln($Productivity$)	4.0781	0.5272	2.2119	5.4942	1096
Panel B: Near-only firms (Firms = 20)					
ROA	0.0515	0.0761	-0.3089	0.2881	208
ROS	0.0461	0.1133	-0.5641	0.3024	208
Operating margin	0.0747	0.1282	-0.5700	0.3636	208
ln($Productivity$)	4.1421	0.5535	2.2119	5.4638	197
Panel C: Friend-only firms (Firms = 9)					
ROA	0.0075	0.0752	-0.2778	0.2098	91
ROS	0.0044	0.0617	-0.2362	0.1731	91
Operating margin	0.0210	0.0739	-0.2283	0.2377	91
ln($Productivity$)	3.8033	0.5424	2.2119	4.8841	89
Panel D: Never-treated firms (Firms = 1568)					
ROA	0.0281	0.0765	-0.3089	0.2881	14238
ROS	0.0210	0.1022	-0.5641	0.3024	14219
Operating margin	0.0459	0.1124	-0.5700	0.3636	14219
ln($Productivity$)	4.0565	0.5487	2.2119	5.4942	13770

Notes: N is the number of firm-year observations. All outcomes are winsorized at the 1st and 99th percentiles of the pooled sample. Groups are mutually exclusive: Both (Near & Friend), Near-only, Friend-only, and Never-treated.

5.4 Econometrics Results

This section reports the dynamic treatment effects.
Coefficients are interpreted relative to the omitted baseline period $k = -1$ (the year preceding the first relocation event). Each point in the figures represents the estimated effect at event time k (years relative to the first treatment), while vertical bars denote 95% confidence intervals.

5.4.1 Friendshoring

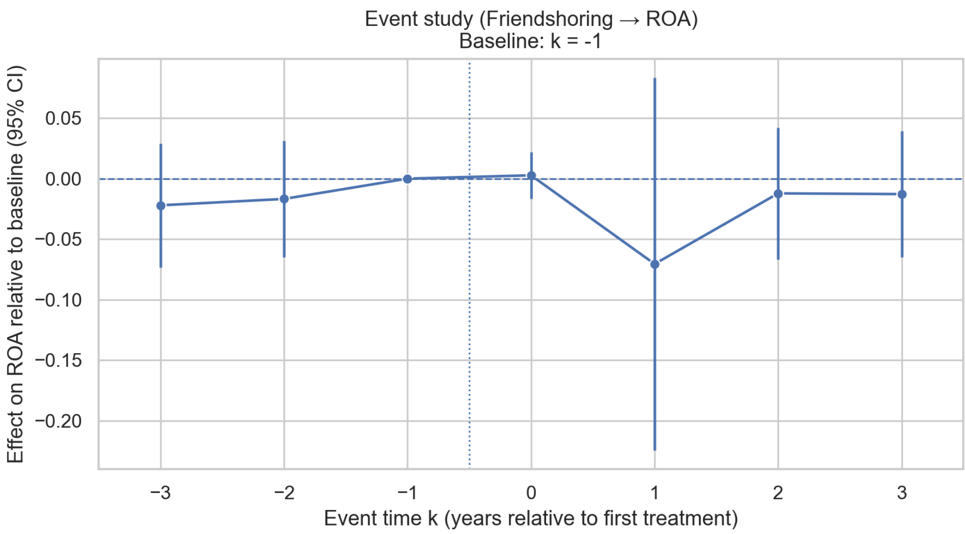

Figure 5.3. **Event study: Friendshoring → ROA.** Effects relative to the baseline period $k = -1$ with 95% confidence intervals.

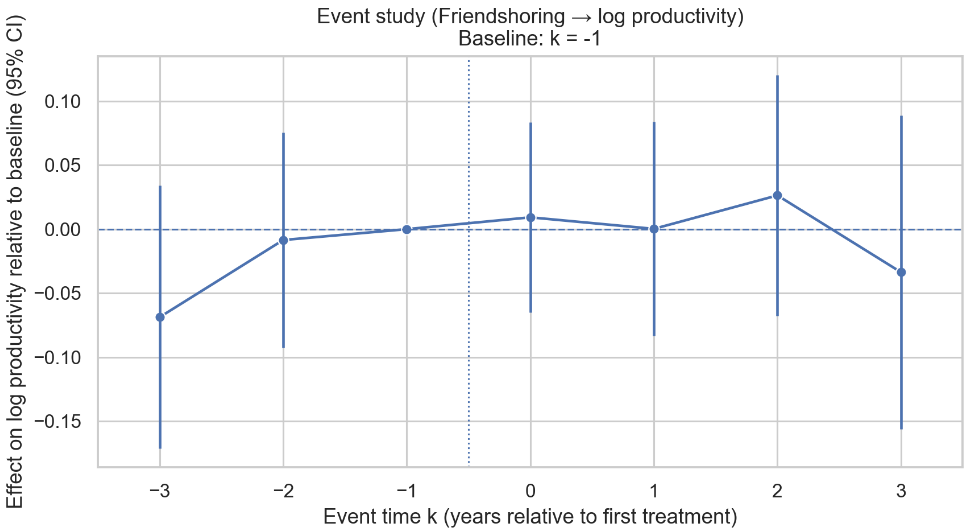

Figure 5.4. **Event study: Friendshoring → log labor productivity.** Effects relative to the baseline period $k = -1$ with 95% confidence intervals.

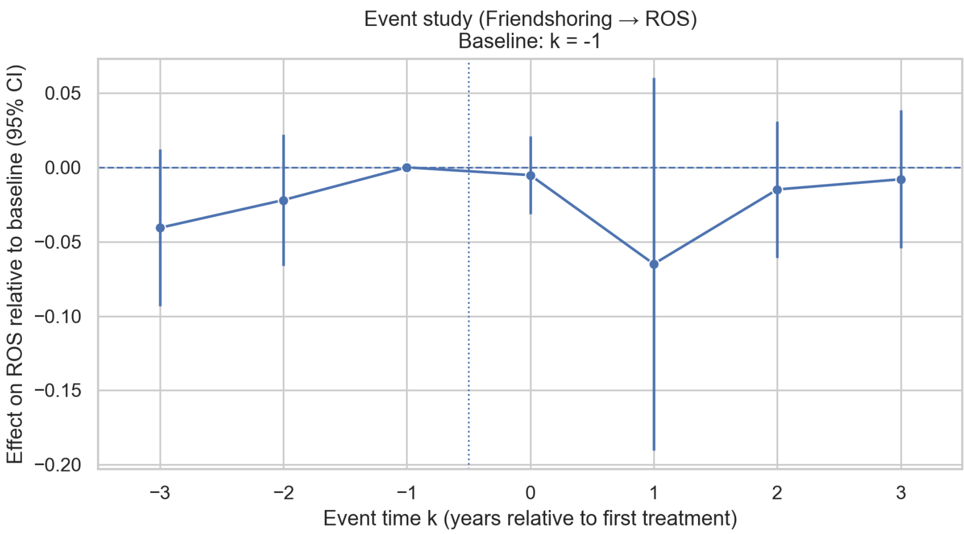

Figure 5.5. **Event study: Friendshoring → ROS.** Effects relative to the baseline period $k = -1$ with 95% confidence intervals.

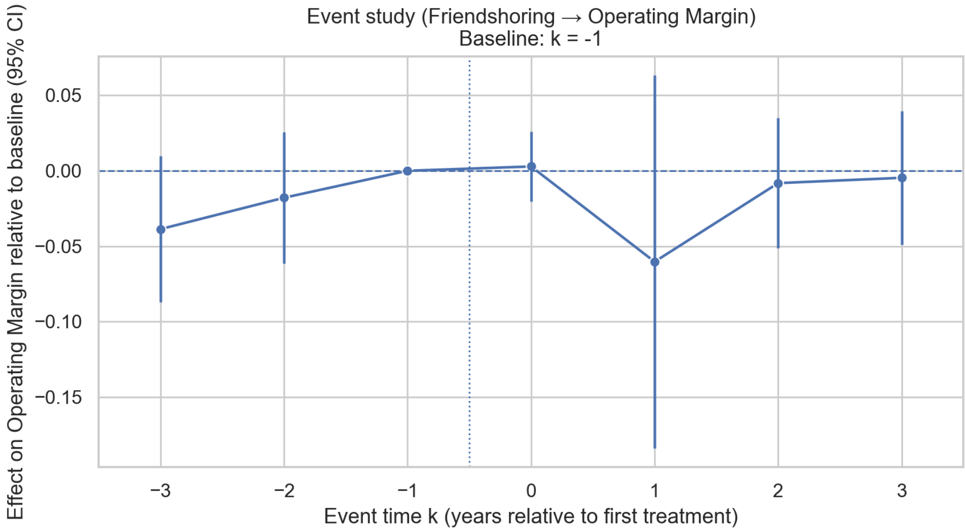

Figure 5.6. **Event study: Friendshoring → Operating Margin.** Effects relative to the baseline period $k = -1$ with 95% confidence intervals.

Figure 5.3 shows that the estimated pre-treatment coefficients $(k = -3, -2)$ are close to zero and their confidence intervals overlap with zero, providing supportive evidence for the *parallel trends* assumption in ROA. In the post-event period, point estimates for ROA tend to be negative, in particular around $k = 1$. However, these estimates remain statistically indistinguishable from zero given the wide confidence intervals. Overall, the pattern suggests a potential loss in profitability after the friendshoring event, but the data do not allow rejecting the null hypotesis.
Figure 5.4 reports the estimates for log labor productivity. Pre-treatment coefficients are once again close to zero confirming the parallel trend hypothesis. Post-treatment estimates appear slightly positive with a peak at $k = 2$), suggesting a possible productivity improvement after the relocation. However, the confidence intervals, as in the case analyzed before, are wide and include zero, implying that these dynamics are not statistically significant.
Figure 5.5 displays the event-study estimates for ROS. The pre-treatment coefficients $(k = -3, -2)$ are close to zero and their confidence intervals overlap with zero, providing additional support for parallel trends in sales-based profitability prior to the friendshoring event. After treatment, the point estimates become negative, with the largest drop around $k = 1$. Nonetheless, the confidence intervals remain wide and include zero, indicating that the post-event dynamics are not statistically significant.
Figure 5.6 reports the results for the operating margin. Pre-treatment coefficients are again small and statistically indistinguishable from zero, consistent with parallel trends in operating profitability. In the post-treatment period, estimates turn negative, particularly at $k = 1$, suggesting a potential deterioration in operating performance after

friendshoring. As in the previous outcomes, however, uncertainty is substantial and confidence intervals overlap with zero, so the effect cannot be distinguished from zero at conventional significance levels.

5.4.2 Nearshoring

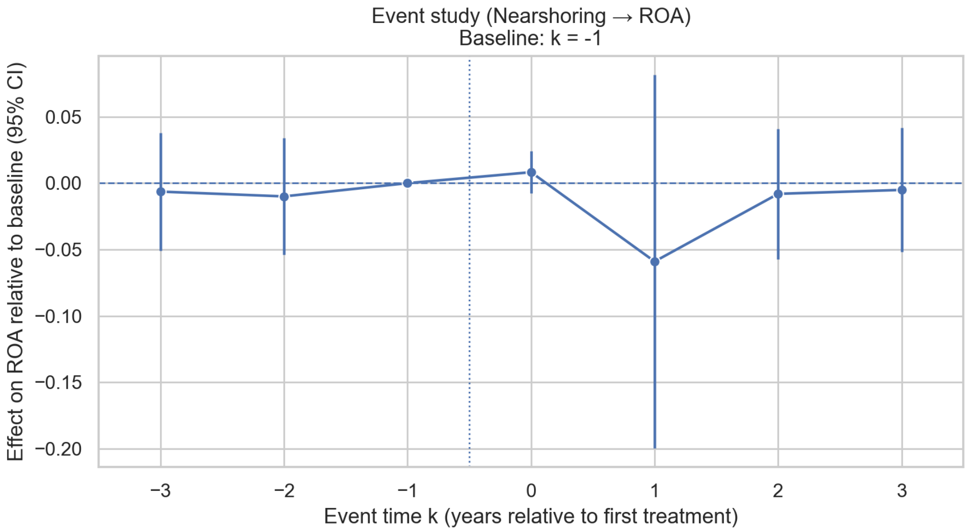

Figure 5.7. **Event study: Nearshoring → ROA.** Effects relative to the baseline period $k = -1$ with 95% confidence intervals.

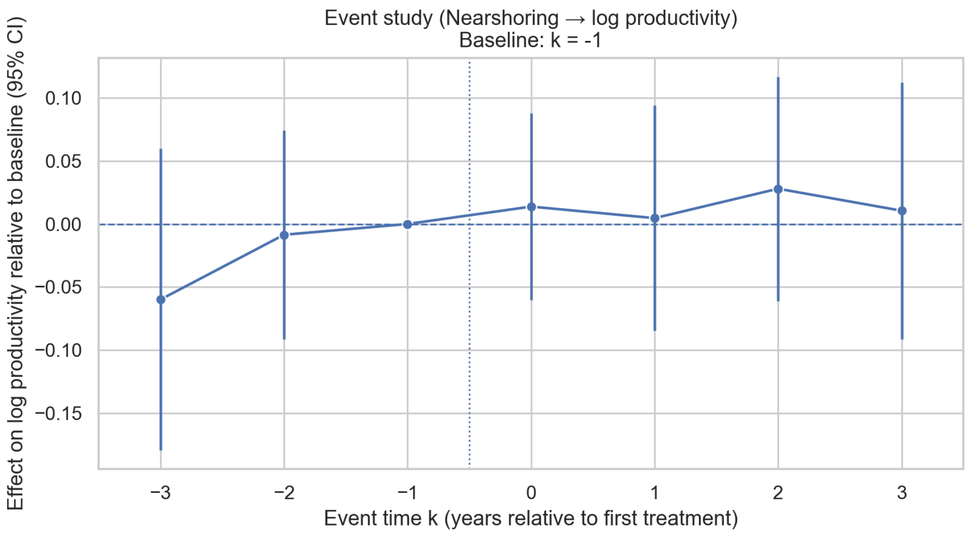

Figure 5.8. **Event study: Nearshoring → log labor productivity.** Effects relative to the baseline period $k = -1$ with 95% confidence intervals.

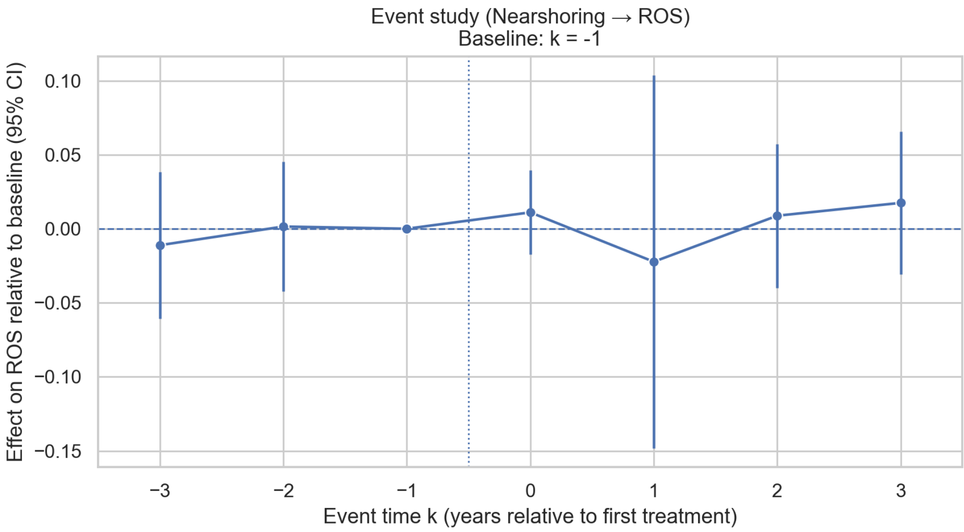

Figure 5.9. **Event study: Nearshoring → ROS.** Effects relative to the baseline period $k = -1$ with 95% confidence intervals.

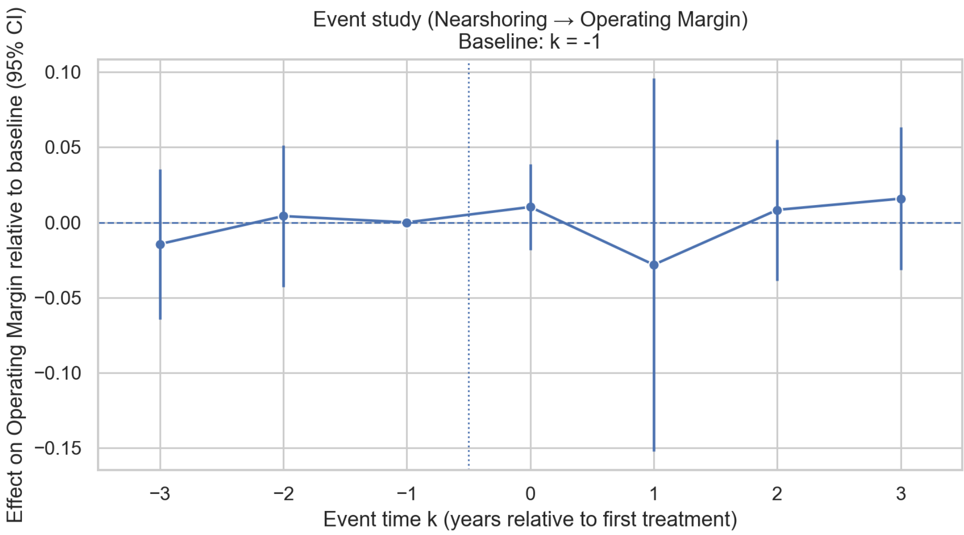

Figure 5.10. **Event study: Nearshoring → Operating Margin.** Effects relative to the baseline period $k = -1$ with 95% confidence intervals.

Figure 5.7 indicates that the pre-treatment coefficients are small and not statistically different from zero, which is consistent with parallel trends in profitability prior to the nearshoring event. Post-treatment point estimates for ROA are generally negative, with a drop around $k = 1$, suggesting that profitability may worsen after the relocation event.

Uncertainty remains still extremely high and the confidence intervals overlap with zero, so the evidence is a statistically insignificant effect.
Figure 5.8 suggests a different pattern for productivity. After nearshoring, estimated coefficients are mostly positive, suggesting a potential increase in labor productivity. As with friendshoring, however, the confidence intervals include zero at all event times.
Figure 5.9 reports the estimates for ROS. The pre-treatment coefficients are close to zero and statistically indistinguishable from zero, supporting parallel trends in sales-based profitability before treatment. After the nearshoring event, point estimates remain slightly positive at some horizons but dip around $k = 1$. Confidence intervals are wide and overlap with zero throughout, indicating that the evidence does not support a statistically significant effect on ROS.
Figure 5.10 shows the event-study estimates for operating margin. Pre-treatment coefficients are small and not statistically significant, consistent with parallel trends. Post-treatment estimates are generally close to zero, with a negative point estimate around $k = 1$ followed by a recovery in later periods. As for the other outcomes, the confidence intervals include zero at all horizons, so the implied dynamics are not valuable from a statistical point of view.

Chapter 6

Conclusions

This thesis investigated the phenomenon of nearshoring and friendshoring, which are recent supply chain reconfiguration strategies that satisfy particular criteria. The purpose of this research was to assess whether the firms that adopted this strategy obtained measurable improvements in economic performance. The analysis combined a theoretical discussion of the drivers of supply chain reorganization with an empirical strategy. In first place to identify relocation events offshoring intensity was measured, then the performance effects of nearshoring and friendshoring were analyzed through the Difference-in-Differences framework with two-way fixed effects.

6.1 What the data reveal about the prevalence of relocation strategies

An interesting first result concerns the rarity of these strategies in the data. Starting from a broad firm-level database (covering around 40,000 unique firms), the sample collapses to 1,700 firms once the focus is restricted to narrow offshorers (firms that systematically repurchase items strictly related to their specific sector in the period 2010–2022). Within this restricted population, relocation events remain uncommon: 112 firms are classified as adopting friendshoring at least once during the sample period, while 123 firms are classified as adopting nearshoring.

This evidence matters because it immediately suggests that nearshoring and friendshoring are not simple adjustments. These decisions appear to be strong strategic choices, potentially requiring non negligible reorganization costs, managerial attention, and operational redesign.

6.2 Reconciling theory and evidence: profits versus stability

The theoretical chapters highlighted a central trade-off: reorganizing production geographically (or geopolitically) may reduce coordination frictions, transport volatility, and exposure to policy risk, but it can also entail sizable fixed and sunk costs and disrupt established supplier networks. Under this perspective, it is not surprising that the empirical patterns point to a short-run profitability loss.

Consistent with this intuition, the event-study estimates for ROA show a negative pattern in the first post-event year (around $k = 1$) for both nearshoring and friendshoring. These estimates are not statistically different from zero given the width of the confidence intervals, but in any case the direction of the point estimates aligns with the idea that the immediate phase of relocation can be costly. Relocating production closer (or shifting to geopolitically aligned partners) can require efforts that may reduce margins in the short-run due to temporary duplication of capacity, renegotiation of contracts, training of new personnel, and adjustment of logistics.

At the same time, the dynamics for labor productivity suggest a somewhat different situation. For both strategies, the estimated coefficients for log labor productivity tend to be weakly positive in the post-event period, again without statistical significance but with a pattern that is economically plausible. Thanks to shortening distances and strengthening coordination with suppliers, companies can improve operational efficiency, reduce delays, and make problem-solving faster. Having key stages of the value chain closer to each other may facilitate knowledge transfer (without IP protection violation concerns) and tighter interaction between production and development functions, which can support productivity gains even if these gains are modest.

6.3 Dynamics over time: adjustment costs and partial re-stabilization

A further element emerging from the event-study graphs is that the negative profitability pattern does not appear to increase over time. After the initial post-event dip, ROA coefficients move back toward values closer to zero in the following years, suggesting that firms may partly absorb the adjustment costs and converge to a new operating regime in which profitability becomes broadly comparable to that of firms that continued traditional offshoring.

This is an important consideration because it witnesses that the decision to nearshore or friendshore may not be primarily aimed at boosting short-run profitability. Instead, it may reflect a strategic preference for business continuity and stability. In other words, firms might accept a temporary profitability sacrifice in exchange for lower exposure to extreme disruptions. To avoid high logistics volatility (e.g., transport-cost swings, supply bottlenecks, or policy shocks such as tariffs), firms have chosen to bring production sites closer to home, even at the expense of some cost advantages.

6.4 Why the 2010–2022 window matters

The sample period is a meaningful constraint. While 2010–2022 includes major disruptions (most notably the COVID-19 shock), it only partially captures the more recent acceleration of geopolitical fragmentation and policy activism observed in the last few years. As a consequence, the measured prevalence of nearshoring and friendshoring in this thesis may understate how widespread these strategies could become in a more recent setting. With post-2022 data, it may be observable a larger number of relocation events and clearer performance effects. In recent years firms have been given stronger incentives to redesign supply chains because of policy-driven shocks.

6.5 Final takeaway

Overall, the evidence depicted in this thesis tells that nearshoring and friendshoring are relatively rare strategic moves among narrow offshorers, and when they occur they seem to come with a short-run profitability cost, while potentially incresing operational efficiency as captured by the productivity indicator. Even though the estimated effects are not statistically significant in the available sample, the direction of the dynamics is consistent with the theoretical trade-off between cost minimization and resilience. In this sense, supply-chain reconfiguration appears less profitable (due to reduced margins) and safer as a long-run risk management choice aimed at preserving stability in an uncertain global environment.

Appendix A

Event-study regression tables

This appendix reports the full regression tables underlying the event-study figures presented in the main text. Each table shows the estimated coefficients $\hat{\beta}_k$ for event-time indicators, where k indicates the number of years relative to the first treatment year (nearshoring or friendshoring). The reference period $k = -1$ is reported in the tables as zero for convenience. All specifications include firm and year fixed effects, and standard errors are clustered at the firm level. Significance levels are denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table A.1. Event-study estimates (Nearshoring $\rightarrow$ ROA). Baseline: $k = -1$.

Event time k	Coefficient	Std. error
-3	-0.0064	(0.0227)
-2	-0.0100	(0.0224)
-1	0.0000	
0	0.0082	(0.0080)
1	-0.0590	(0.0718)
2	-0.0080	(0.0250)
3	-0.0051	(0.0239)

Notes: Firm and year fixed effects. Standard errors clustered at the firm level. Baseline category is $k = -1$ (omitted in the regression and shown here as 0). Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A.2. Event-study estimates (Nearshoring → ROS). Baseline: $k = -1$.

Event time k	Coefficient	Std. error
-3	-0.0111	(0.0253)
-2	0.0015	(0.0223)
-1	0.0000	
0	0.0110	(0.0145)
1	-0.0223	(0.0643)
2	0.0088	(0.0248)
3	0.0175	(0.0246)

Notes: Firm and year fixed effects. Standard errors clustered at the firm level. Baseline category is $k = -1$ (omitted in the regression and shown here as 0). Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A.3. Event-study estimates (Nearshoring → Operating margin). Baseline: $k = -1$.

Event time k	Coefficient	Std. error
-3	-0.0144	(0.0255)
-2	0.0042	(0.0241)
-1	0.0000	
0	0.0103	(0.0146)
1	-0.0282	(0.0634)
2	0.0083	(0.0240)
3	0.0158	(0.0242)

Notes: Firm and year fixed effects. Standard errors clustered at the firm level. Baseline category is $k = -1$ (omitted in the regression and shown here as 0). Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A.4. Event-study estimates (Nearshoring → log productivity). Baseline: $k = -1$.

Event time k	Coefficient	Std. error
-3	-0.0600	(0.0610)
-2	-0.0086	(0.0422)
-1	0.0000	
0	0.0138	(0.0377)
1	0.0046	(0.0456)
2	0.0280	(0.0454)
3	0.0105	(0.0519)

Notes: Firm and year fixed effects. Standard errors clustered at the firm level. Baseline category is $k = -1$ (omitted in the regression and shown here as 0). Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A.5. Event-study estimates (Friendshoring → ROA). Baseline: $k = -1$.

Event time k	Coefficient	Std. error
-3	-0.0164	(0.0300)
-2	-0.0171	(0.0288)
-1	0.0000	
0	0.0045	(0.0117)
1	-0.0801	(0.0915)
2	-0.0190	(0.0325)
3	-0.0173	(0.0322)

Notes: Firm and year fixed effects. Standard errors clustered at the firm level. Baseline category is $k = -1$ (omitted in the regression and shown here as 0). Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A.6. Event-study estimates (Friendshoring → ROS). Baseline: $k = -1$.

Event time k	Coefficient	Std. error
-3	-0.0565*	(0.0342)
-2	-0.0273	(0.0267)
-1	0.0000	
0	-0.0077	(0.0164)
1	-0.0831	(0.0742)
2	-0.0273	(0.0274)
3	-0.0324	(0.0369)

Notes: Firm and year fixed effects. Standard errors clustered at the firm level. Baseline category is $k = -1$ (omitted in the regression and shown here as 0). Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A.7. Event-study estimates (Friendshoring → Operating margin). Baseline: $k = -1$.

Event time k	Coefficient	Std. error
-3	-0.0453	(0.0313)
-2	-0.0190	(0.0262)
-1	0.0000	
0	0.0036	(0.0144)
1	-0.0758	(0.0732)
2	-0.0152	(0.0253)
3	-0.0226	(0.0365)

Notes: Firm and year fixed effects. Standard errors clustered at the firm level. Baseline category is $k = -1$ (omitted in the regression and shown here as 0). Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A.8. Event-study estimates (Friendshoring → log productivity). Baseline: $k = -1$.

Event time k	Coefficient	Std. error
-3	0.0071	(0.0578)
-2	0.0118	(0.0492)
-1	0.0000	
0	0.0171	(0.0435)
1	0.0170	(0.0510)
2	0.0628	(0.0594)
3	0.0015	(0.0739)

Notes: Firm and year fixed effects. Standard errors clustered at the firm level. Baseline category is $k = -1$ (omitted in the regression and shown here as 0). Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

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