



**Politecnico  
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# **Reshoring trajectories after firms offshoring decisions**

**Empirical analysis conducted on a sample of Italian  
manufacturing firms**

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## **Abstract**

This thesis investigates the phenomenon of reshoring among Italian manufacturing firms, examining whether and under what conditions firms that had previously relocated production stages abroad subsequently reversed those decisions. Over recent decades, the fragmentation of production across global value chains became a dominant strategy for firms seeking to exploit international cost differentials. Yet the accumulation of experience, the emergence of hidden operational costs, and a series of major supply chain shocks — most notably the COVID-19 pandemic — have increasingly led firms to reconsider the sustainability of highly dispersed sourcing strategies. Despite growing interest in reshoring, the empirical literature remains largely based on surveys and aggregate data, leaving a gap in the systematic measurement of reshoring at the firm level from observable trade flows. A central contribution of this thesis is therefore the construction of a firm-level binary reshoring measure derived exclusively from transaction-level import and export data, providing a replicable and objective alternative to survey-based identification strategies. Building on this measure, the study then investigates what distinguishes firms that reshore from those that do not, with particular attention to the history of their offshoring engagement, the type of goods they primarily trade, and the geographic composition of their international sourcing. The empirical analysis draws on a panel of Italian manufacturing firms observed over a fourteen-year period, offering a longitudinal perspective on the dynamics of production relocation in one of Europe’s most diversified manufacturing economies.



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# Chapter 1

## Introduction

In 2025, the Italian swimwear company Arena signed a ten-year agreement to bring the production of its swimming goggles back from China to a plant in the province of Modena [1]. A few years earlier, Artsana — the group behind the childcare brand Chicco — had reversed part of its production of infant goods from China to Italy, and Benetton had launched a programme it called “Return to Made in Italy,” repatriating key stages of its textile chain [2]. Other firms followed the same path: Wayel, an Emilian producer of electric bicycles, moved its manufacturing from China back to Bologna [3]. The phenomenon is not only Italian. In late 2025 Whirlpool announced that it would shift part of its production from China back to the United States, while Apple pledged one of the largest domestic-manufacturing commitments in its history [4, 5]. Individually, these are ordinary business decisions. Together, they hint at something larger: after three decades spent moving production abroad, some firms are moving it back.

For most of that period, the direction of travel was one-way. The logic of manufacturing was to divide production into stages and place each one where it cost least. Firms in high-wage countries increasingly stopped making goods themselves and began coordinating their production elsewhere, importing components and finished items and adding value at home. China stood at the centre of this system. For Italian producers of clothing, leather goods, electrical equipment and machinery, the appeal was straightforward: a Chinese wage, a small fraction of the domestic one, turned offshoring into a condition of survival in international markets.

That logic has been weakening for years. The wage gap on which it rested has narrowed steadily, as Chinese manufacturing pay, rising since the early 2000s, nearly tripled again over the period this thesis examines. To higher costs were added higher risks. The COVID-19 pandemic left goods stranded in ports; the blockage of the Red Sea routes and the war in Ukraine reinforced the lesson; and trade policy itself became a source of instability. The Bank of Italy noted that new trade restrictions in 2023 were three times as numerous as in 2019, and warned that the

era of rapid global integration had paused [6]. In the United States, the sweeping tariffs introduced in 2025 were designed to make importing costly enough to force production home [7]. A new vocabulary — reshoring, nearshoring, friendshoring — moved from trade journals into the language of industrial policy.

Governments have tried to accelerate the shift rather than merely observe it. Italy has been unusually active. The 2024 reform of international taxation introduced a reshoring regime that halves the corporate tax base for activities returned from outside the European Union, while the “Made in Italy 2030” strategy tied industrial policy to the return of critical production [8, 9]. Dedicated measures followed for the sectors most exposed to foreign competition, including a 250 million euros package for the fashion supply chain [10]. Surveys added to the sense of momentum, with roughly a fifth of firms that had once offshored reporting that they had brought at least part of their production home [11].

Yet the closer one looks, the less certain the picture becomes. Much of the enthusiasm rests on individual stories and voluntary surveys, which capture firms willing to announce a return but say little about the wider population, and still less about the conditions under which a reversal actually happens. The aggregate evidence is more sober. Consultancies that track the phenomenon reported their reshoring indices slipping backward in 2025, as imports from low-cost Asia kept growing [12]. Even in fashion, the sector most associated with the return of the Made in Italy, McKinsey estimated that apparel imports from China into Europe fell only modestly between 2019 and 2023 [10]. The result is a striking gap between how loudly reshoring is discussed and how little is firmly known about who is doing it.

## **1.1 Structure of the Thesis**

This thesis addresses that gap by studying behaviour rather than intentions. Rather than asking managers whether they have reshored, it infers reshoring from the actual trade flows of Italian firms, observed at the level of individual customs transactions between 2010 and 2023. The remainder of this section outlines how the argument is built, chapter by chapter.

### **1.1.1 Literature Review**

The next chapter situates the study within the existing research on offshoring and reshoring. It reviews the economic rationale for the international fragmentation of production and the more recent, and still unsettled, literature on its partial reversal. Particular attention is paid to how reshoring has been defined and measured, since the diversity of definitions — and the reliance on surveys and hand-collected case studies — is one of the reasons the aggregate evidence remains inconclusive.

### **1.1.2 Data and Construction of the Panel**

The following chapter presents the data. It describes the transaction-level customs records that underpin the analysis and the procedure used to transform them into a firm-year panel of roughly 64,000 observations. This behavioural, longitudinal design is what allows the study to observe reshoring directly, rather than relying on firms' own declarations.

### **1.1.3 Offshoring Trajectory, Intensity and Reshoring measurement**

A dedicated chapter defines the central variables. It classifies each firm according to the depth, intensity and stability of its engagement with foreign sourcing — its offshoring trajectory — and sets out the criteria by which a genuine contraction of that engagement is identified as reshoring. These measures form the backbone of the empirical analysis.

### **1.1.4 Conceptual Framework and Objectives**

Building on the literature and the measures, the study then develops its conceptual framework. Its overarching objective is to understand not whether reshoring is occurring in the aggregate — a question the macro data answer only ambiguously — but which firms reverse course, and under what conditions. Concretely, the analysis investigates whether the decision to bring production back depends on a firm's own history of offshoring rather than on the macroeconomic mood of a given year; whether the nature of the traded good makes reshoring more or less likely; whether the COVID-19 shock acted as a genuine catalyst, and in which parts of the economy; and whether the specific retreat from China can be traced, at the level of the individual firm, to the erosion of the cost advantage that had drawn firms there in the first place.

### **1.1.5 Empirical Model, Results and Conclusions**

The empirical chapter presents the model and its estimates, and the final chapter draws out the implications. Two results may be anticipated here, lightly. Reshoring, in these data, is not a general homecoming: it is concentrated among firms whose offshoring was unstable and discontinuous, while those tied to low-cost origins by deep, settled relationships rarely abandon them. And where firms do retreat from China, the move tracks the rising cost of Chinese labour. Taken together, the findings suggest that the return of production is real but selective — shaped by firm-level history and shifting relative costs more than by political enthusiasm —

with direct implications for the reshoring incentives now debated in Rome and Brussels.

## Chapter 2

# Literature Review

### 2.1 Global Value Chains, fragmentation of production and offshoring

Over the past decades, the world markets have become increasingly integrated, and this openness has entailed a disintegration of the production process. In fact, contrary to the well-established vertically integrated production structure, where production is carried out within a single country or firm, companies are now finding it profitable to fragment the process into a sequence of distinct stages performed either at home or abroad, resulting in complex international production networks, today referred to as Global Value Chains (GVCs).

To further investigate the drivers of this new paradigm, Feenstra [13] emphasizes that the expansion of international trade observed since the late twentieth century reflects not only increased demand for final goods, but it has as its core improvements in transportation and communication technologies, alongside trade barriers reductions, which have considerably reduced the costs and effort to coordinate production activities across different countries, allowing firms to decide which stages of production to be kept in the domestic country and which to be carried out offshore and leading them to a more efficient division of labor. Also in more recent time, these three factors are widely recognized as the real drivers to the period of globalization the world has been living since the late '80s, as emerges in Antràs [14].

As a result of this dislocation, countries belonging to a specific GVC have started to highly specialize themselves not in producing entire goods, but in performing specific tasks or stages of whole production chain. Therefore, today international trade is no longer limited to final goods exchanges, but increasingly accounts for intermediate inputs that cross borders multiple times before reaching the final consumer. In this context, Hummels et al. [15] provide a formal framework to

capture the growing international fragmentation of production through the concept of vertical specialization. According to their definition, vertical specialization occurs when a country imports intermediate inputs that are subsequently embodied in goods exported to foreign markets. This framework highlights how exports increasingly rely on foreign value added, emphasizing the interconnected nature of modern production systems.

More broadly, the concept of vertical specialization introduced by Hummels et al. [15] highlights the growing interdependence among countries within global value chains. Moreover, a logical deduction of this strong relationship is that changes in sourcing strategies, trade costs or production technologies in one country can propagate and affect production decisions and trade flows of the other countries. This perspective is essential for understanding the expansion of offshoring activities and the potential challenges associated with reorganizing production structures, including the reversal of offshoring decisions which will be discussed later as the center of discussion.

However, this transformation should not be seen as an autonomous phenomenon at the macro level. Rather, it is the aggregate result of firms' decisions regarding how to fragment and locate production stages across countries. Understanding these firm-level decisions is therefore essential to explain both the expansion and the persistence of global value chains.

### **2.1.1 Firms' offshoring decisions and the organization of production**

Looking at the global fragmentation of production described above, it can be described at firms' level as their deliberate choices regarding how and where to perform production activities. In the economics literature, the term offshoring refers to relocating specific stages or tasks of the production process from the home country to foreign locations. Therefore, offshoring does not necessarily imply a complete relocation of production abroad, but rather an efficient reorganization of tasks along the production chain.

Grossman and Rossi-Hansberg [16] provide us with a conceptualization of this phenomenon. Adopting their framework, offshoring occurs when tasks previously performed at home are now carried out abroad, regardless of whether this takes place within firm boundaries or through arm's-length agreements with foreign suppliers. In other words, both production carried out by foreign affiliates of multinational firms and production sourced from external suppliers located abroad are encompassed when speaking about offshoring.

As has been described in the previous section, firms engagement in the offshoring process is aimed to exploit differences in production costs around the world while taking advantage of technological progress that has reduced the costs of coordinating

geographically dispersed activities. In this regard, cost-based explanations of offshoring were already emphasized by Feenstra and Hanson [17], who link offshoring with the import of intermediate inputs embodying foreign labor. In this view, firms offshore specific production stages to take advantage of cross-country differences in factor prices, particularly labor costs, while retaining more skill-intensive or strategic activities domestically.

However, the decision whether to go offshore or not is not only driven by cost considerations. A crucial role in shaping firms' strategies is also played by organizational friction and governance issues. In this view, Antràs and Chor [18] analyze how firms' production setup along a sequential value chain is relevantly impacted by the presence of incomplete contracts and relationship-specific investments. In fact, what stands out from their framework is that concerns related to control, incentives, and potential hold-up problems influence firms' choices between alternative organizational arrangements, affecting the structure and stability of global production networks.

## **2.2 Section 2: Reshoring and backshoring: definitions, drivers and limitations**

According to what has been discussed in the previous section, past decades and modern days have been characterized by a global production process setting, where firms fragment activities across countries to exploit international cost differentials. In this view, offshoring strategies have been widely adopted as a response to competitive forces and trade liberalization, and for a long time they were regarded as an efficient way to reduce production costs. However, with the accumulation of experience and the emergence of new economic conditions, the limits of such strategies have progressively become more evident. In this regard, several studies have highlighted highlighting an increasingly common behavior from both large multinational companies (MNCs), such as Apple, General Electric, NCR, Ford Company, Caterpillar, and numerous small-to-medium size enterprises operating in different industries, who have been bringing production back to the domestic country [19, 20].

Before delving into the reasons underneath this trend, it is crucial to provide some definitions to set the terminology context, and this need was also shared by many scholars who felt the urge to overcome lack of uniformity and clarity surrounding the terminology related to this phenomenon. Over the course of the years, many authors started to refer to this behavior by adopting the term “reshoring”. According to several publications, researchers agree in defining reshoring as the relocation of value creation activities previously been offshored to geographically closer locations such as domestic or nearshore countries [21, 22].

In the literature, it is possible to find several contributions highlighting that reshoring cannot be described as a uniform process but rather encompasses a variety of production relocation strategies differing along key dimensions, with the aim of capturing the heterogeneity of firms' relocation choices and their underlying economic motivations.

An early and influential contribution is provided by Gray et al. [23], who conceptualize reshoring as a decision purely based on location, defining it as the relocation of manufacturing activities from offshore to onshore locations, independently of who performs those activities. Within this framework, facilities' ownership does not represent a separate decision dimension but rather serves to distinguish alternative manifestations of the same relocation choice. By combining the geographical location of production with whether manufacturing activities are performed internally by the firm or by external suppliers after relocation, Gray et al. identify four possible reshoring configurations:

- *in-house reshoring*, meaning that a firm relocates manufacturing activities previously performed in wholly owned offshore facilities back to wholly owned based facilities within the country.
- *reshoring for outsourcing*, meaning that a firm relocates manufacturing activities previously performed in wholly owned offshore facilities back to domestic country-based suppliers.
- *reshoring for insourcing*, meaning that a firm relocates manufacturing activities previously performed by offshore suppliers back to wholly owned based facilities in the domestic country.
- *outsourced reshoring*, meaning that a firm relocates manufacturing activities previously performed by offshore suppliers back to domestic country-based suppliers.

This approach is explicitly aimed at clarifying the heterogeneous interpretations of reshoring emerging in the popular press, while maintaining a narrow and precise conceptual definition.

Building on this perspective, Foerstl et al. [24] extend this classification of reshoring. On the geographical side, they distinguish between full returns to the home country, calling it backshoring, and relocations toward geographically closer countries, which are referred to as nearshoring, thereby relaxing the strict offshore–onshore dichotomy. On the organizational side, they allow for intermediate governance structures, such as long-term partnerships or collaborative arrangements, in addition to pure insourcing and outsourcing. By combining geographical scope and governance modes, their taxonomy captures a wider set of reshoring strategies.

Importantly, the literature emphasizes that reshoring does not imply a complete reversal of globalization or a return to fully domestic production structures, but rather a selective reconfiguration of specific stages of the production process within global value chains [21, 22].

Overall, the literature highlights that reshoring encompasses a heterogeneous set of relocation strategies, whose interpretation depends on both the geographical scope of production relocation and the organizational structure of manufacturing activities. Several studies emphasize that the lack of standardized definitions and classifications complicates empirical analysis and contributes to fragmented evidence across the reshoring literature [22, 20]. Building on these definitions, the following section examines the main drivers that have led firms to bring the production processes back home.

### **2.2.1 Drivers of reshoring**

Following the growing attention reshoring has captured in recent years, a growing body of literature has investigated the factors backing firms' decision to reconsider the geographical organization of their production activities. Rather than identifying a single dominant cause, existing studies emphasize that reshoring is driven by a heterogeneous set of economic, operational, and strategic considerations, whose relevance varies across firms, industries, and institutional contexts [20]. In particular, in Barbieri et al. [20] a comprehensive review of the literature is provided, showing that reshoring decisions can be traced back to a limited number of recurring drivers that operate at different levels. On top of them, as highlighted by De Backer et al. [22], the growing relevance of reshoring suggests that the relative attractiveness gap between advanced and emerging economies has reduced, making domestic production a viable option for certain manufacturing activities once again after decades of production relocated towards low-cost countries.

#### **Changes in the economic and technological conditions of offshoring**

A first group of drivers relates to changes in the economic and technological conditions that originally fueled offshoring practices. From a macroeconomic perspective, the rapid increase in labor costs in major offshoring destinations, together with rising transportation and energy costs, has progressively narrowed the cost differentials that motivated the relocation of production to low-cost countries. As documented by De Backer et al. [22], these developments have reduced the purely cost-based advantages of offshore manufacturing for a range of production activities.

At the same time, advances in automation and digital technologies have lowered the relative importance of labor costs in manufacturing, as they account for a

smaller share of the total costs. As a result, producing in advanced economies seems to be more competitive than in the past, as labor force is now less relevant in competitive advantage creation. Therefore, for certain stages of production, the location decision has become less sensitive to wage differentials and more closely linked to efficiency, reliability, and proximity to markets [22].

Beyond these observable cost changes, recent theoretical contributions stress that shifts in uncertainty, coordination requirements, and the complexity of global production networks can alter firms' optimal sourcing decisions even in the absence of large changes in factor prices. In this perspective, changes in the global economic environment may reduce the relative attractiveness of offshore production by increasing the costs associated with managing complex international supply chains.

### **The emergence of hidden and underestimated costs**

A second category of drivers refers to the reassessment of offshoring decisions that turned out to be suboptimal *ex post* due to the late emergence of hidden and underestimated costs. As emphasized by Barbieri et al. [20], many firms engaged in offshoring following dominant industry trends or focusing specifically on unit labor costs, without taking into consideration total production costs, assuming that lower wages would automatically translate into lower overall costs.

Coherently with this, scholars agree in highlighting that such assessments often failed to account for a broader set of cost components that become relevant once production is relocated across borders. In particular, Gray et al. [23] emphasize that manufacturing activities' coordination often requires substantially greater managerial effort, as firms must devote additional resources to monitoring suppliers, aligning production schedules, and resolving unexpected disruptions.

Logistics-related costs represent another important component of these hidden expenses. Offshore production typically comes with longer and more complex transportation routes, which increase exposure to delays, inventory holding costs, and uncertainty in delivery times. As a result, firms may be forced to keep higher inventory buffers to ensure continuity of production and on-time delivery to final markets, raising working capital requirements and reducing overall operational efficiency.

Quality management also plays a central role in the discussion of the true offshoring cost. Being able to ensure consistent product quality across distant production sites turned out to be more challenging than initially anticipated, particularly when production processes are based on tacit knowledge or require close interaction between engineering, manufacturing, and quality control functions. Therefore, additional resources must be allocated to training, supervision, and rework activities, which further reduce the expected cost advantages of offshore manufacturing. [25].

Moreover, offshore production can entail significant communication and coordination costs. Differences in language, time zones, and institutional environments complicate information flows between headquarters and production sites, slowing down decision-making processes and reducing firms' ability to respond rapidly to changes in demand or design specifications. Over time, these frictions can accumulate and negatively affect both cost performance and operational flexibility.

Finally, several studies point to risks related to the protection of proprietary knowledge and intellectual property. When production is carried out in distant or weakly regulated environments, firms may face increased exposure to knowledge leakage or imitation, generating potential long-term costs that are difficult to quantify *ex ante* but can have substantial strategic implications [23, 20].

### **Operational complexity, quality, and flexibility constraints**

In addition to cost considerations, operational factors have played a significant role in motivating reshoring decisions. Empirical evidence suggests that firms have faced increasing difficulties in maintaining flexibility and ensuring consistent product quality when production is carried out in distant locations. Long lead times, limited responsiveness to demand fluctuations, and challenges in transferring tacit production knowledge have often reduced the effectiveness of offshore manufacturing arrangements [25].

These operational constraints are particularly relevant in industries characterized by frequent design changes, customized production, or tight coordination between production and downstream activities. In such contexts, proximity between manufacturing, engineering, and final markets can represent a critical competitive advantage, strengthening the case for reshoring.

### **Strategic and organizational considerations**

Finally, reshoring has also been driven by broader strategic and organizational considerations. Drawing on Transaction Cost Economics, several contributions emphasize that increased uncertainty, supplier opportunism, and coordination complexity can raise the governance costs of offshore sourcing arrangements. As a result, firms may find it optimal to reconfigure their production networks by relocating activities closer to the home country and, in some cases, by adjusting the governance structure of production [24].

## **2.2.2 Limitations to reshoring activities' spread**

Despite numerous reasons have been presented in support to the relocation of production back to the home country, empirical evidence shows that reshoring is still a limited and selective phenomenon, described as "a trickle rather than a flood"

[22, p. 25]. While firms increasingly reassess their global sourcing strategies, only a minority of them have performed a full reshoring process. A key explanation behind this behavior lies in the stickiness of global value chains, which will be now discussed.

In fact, a distinctive feature of global production networks is precisely that international sourcing relationships are resistant to reversal once they have been established. This stickiness is made up by the presence of fixed and sunk costs associated with joining global value chains. As emphasized in the survey by Pol Antràs [14], firms engaging in international production fragmentation must incur substantial upfront investments, which are largely irreversible. Among them, are included costs related to foreign suppliers' research and screening, production processes' adaptation to foreign regulatory and technological standards, building logistical and managerial capabilities, and developing the organizational know-how required to coordinate activities performed in different places. Once sustained, these investments cannot be fully recovered if firms decide to relocate production again, generating rigidity in firms' location and sourcing decisions.

As a result of GVCs stickiness, firms' responses to economic shocks are inherently asymmetric due to the presence of sunk costs. Even when offshore production becomes less attractive in terms of costs convenience, firms may continue to rely on existing global production networks, as dismantling them and rebuilding domestic capabilities would entail new fixed costs. In this sense, sunk costs generate the stickiness of global value chains highlighted by Antràs [14], making production structures highly resistant to change *ex post*.

Beyond these sunk cost considerations, reshoring diffusion is further limited by additional structural factors. From a macroeconomic perspective, De Backer et al. [22] explain that offshoring activities remain relevant not only for cost-related reasons, but also because emerging economies are increasingly becoming major final markets. As a result, firms often engage in onshoring—locating production close to local demand—within emerging countries rather than reshoring production to the home country. Additionally, international fragmentation practices over the past decades have weakened domestic industrial ecosystems in many advanced economies, leading to shortages of specialized suppliers and technical skills necessary to support complex manufacturing activities, representing a crucial issue in reshoring strategies.

Concerning this point, Barbieri et al. [20] and Bals et al. [21] document that reshoring manufacturing activities is considerably more complex than moving back services operations, as it often entails relocating heavy capital equipment, recreating supplier networks, and reintegrating production capabilities that firms may no longer possess internally. As a result, many firms lack the organizational readiness required to successfully implement reshoring, even when its potential benefits are recognized.

Finally, Gray et al. [23] caution that reshoring decisions are not necessarily optimal responses to changing conditions. Just as offshoring decisions were sometimes driven by an excessive focus on unit labor costs, reshoring may also be influenced by managerial biases or short-term reactions to disruptions, potentially leading firms to underestimate the costs associated with reversing established global production arrangements.

## 2.3 existing measures of offshoring

The empirical measurement of offshoring has evolved considerably over time, reflecting both the increasing fragmentation of production across borders and the progressive availability of more detailed datasets. Because offshoring is not directly observable in standard statistics, researchers have relied on a variety of indirect proxies based on trade flows, input-output relationships, firm-level surveys, and administrative microdata. Among these approaches, the framework discussed by Feenstra [26] represents the conceptual cornerstone of the literature, as it formalizes the idea that offshoring can be inferred from the import content of production.

### 2.3.1 Trade-Based Measures: Imported Intermediate Inputs as a Proxy for Offshoring

The most influential approach to measuring offshoring is based on the intuition that firms offshore production when they substitute domestically produced inputs with imported intermediates. In his review of the literature, Feenstra [26] highlights how the seminal contributions of Feenstra and Hanson [27, 17] established what has become the standard empirical approach to quantifying offshoring. Their methodology measures the extent to which domestic industries rely on imported intermediate goods, under the assumption that a growing share of imported inputs reflects a progressive relocation of production stages abroad.

Feenstra and Hanson distinguish between broad and narrow measures of offshoring. The broad measure includes all imported intermediate inputs used by an industry, regardless of their industrial origin, whereas the narrow measure focuses only on imported intermediates belonging to the same industry as the final product. As emphasized by Feenstra [26], the narrow measure provides a more precise proxy for fragmentation because it captures imported activities that are technologically closer to those that could be performed domestically. This distinction has become a benchmark in the empirical literature and remains the conceptual basis for many subsequent contributions.

The main strength of trade-based measures lies in their transparency and straightforward implementation using customs and input-output data. However,

they remain indirect indicators, since imported intermediates may increase not only because of offshoring, but also as a result of changes in product mix, supplier diversification, or fluctuations in final demand.

### **2.3.2 Input-Output Measures: Capturing Offshoring within Global Value Chains**

A second major strand of the literature extends the trade-based logic by using national and international input-output tables. These datasets make it possible to trace how foreign inputs are embodied in domestic production and exports, thereby capturing the role of countries within global value chains. Hummels et al. [15] introduced the concept of vertical specialization, defined as the imported content embodied in a country's exports. Building on this contribution, international databases such as WIOD and OECD TiVA have enabled researchers to construct indicators of foreign value added, backward participation, and forward participation in global value chains. De Backer and Miroudot [28] use these measures to assess the extent to which countries and industries rely on foreign production stages. Compared with simple trade-based indicators, input-output measures provide a more comprehensive macroeconomic perspective by accounting for indirect inter-industry linkages. Their main limitation, however, is the high level of aggregation, which makes it impossible to identify the specific firms driving the observed changes.

### **2.3.3 Firm-Level Survey Measures**

Another important approach relies on direct surveys of manufacturing firms. Rather than inferring offshoring from observed trade flows, these studies ask managers whether they have relocated production activities abroad and investigate the motivations behind such decisions. Kinkel and Maloca [25], using the German Manufacturing Survey, document the incidence of production offshoring among German firms and analyze how characteristics such as firm size, labor costs, and technological complexity affect relocation choices. Dachs and Zanker [29], drawing on the European Manufacturing Survey covering more than 3,000 firms across eleven European countries, provide further evidence on both offshoring and backshoring decisions and identify factors such as quality concerns, logistics costs, and proximity to customers as key determinants. Survey-based approaches offer a unique advantage in that they directly capture managerial intentions and strategic motivations. At the same time, they are subject to self-reporting bias and may be limited by sample size and representativeness.

### **2.3.4 Administrative and Customs Data**

Recent advances in data availability have led to a growing use of administrative and customs microdata. These datasets record actual import and export transactions by firm, year, country, and product, often at a highly detailed level such as HS or NC8 classifications. Recent advances in data availability have led to a growing use of administrative and customs microdata. These datasets record actual import and export transactions by firm, year, country, and product, often at a highly detailed level such as HS or NC8 classifications. Relative to survey-based methods, administrative data offer complete coverage of the population of firms and rely on observed behaviour rather than self-reported decisions. The methodology developed by the supervisor of this thesis belongs to this strand of the literature. By combining customs and firm-level administrative records, the authors construct indicators based on the joint evolution of imports and exports within detailed product categories, thereby allowing the identification of production relocation patterns at the firm-product level.

### **2.3.5 Measures Based on Multinational Enterprise Activity**

Another line of research measures offshoring by examining how multinational enterprises allocate production across domestic and foreign affiliates. In this framework, offshoring is interpreted as an expansion of productive capacity abroad relative to the home country. De Backer et al. [22] combine AMNE (Activities of Multinational Enterprises) data with firm-level information from ORBIS to assess whether increases in foreign employment or fixed assets are associated with slower growth or contraction of domestic operations. This approach is conceptually appealing because it focuses directly on the internal organization of multinational groups. However, it is applicable only to firms with foreign affiliates and requires detailed ownership information.

### **2.3.6 Cross-Country and Sectoral Comparisons**

A broader strand of the literature adopts cross-country and sectoral comparisons to evaluate whether production systems are becoming more domestic, more regional, or increasingly global. These studies typically use aggregate indicators to assess structural changes in sourcing patterns over time. De Backer et al. [22] argue that reshoring should not be interpreted as a complete reversal of offshoring, but rather as a selective reconfiguration of global value chains. Their evidence suggests that firms may bring back some activities while continuing to offshore others, particularly when foreign markets remain strategically important. This approach is particularly useful for placing firm-level evidence within a broader macroeconomic

context, although it cannot identify the specific firms or products underlying the aggregate trends.

## **2.4 Existing measures of reshoring**

As highlighted by De Backer et al. [22] and Barbieri et al. [20], measuring reshoring empirically seems to represent a relevant methodological challenge, as the phenomenon is often linked to specific production stages and intermediate inputs that are not directly observable in aggregated trade or production figures [17, 30]. Furthermore, reshoring reflects internal organizational decisions within firms, which it is difficult to be traceable immediately in standard administrative datasets [23, 20]. As a result, numerous empirical approaches have been developed in the literature, differing in terms of the level of analysis, the type of data employed, and the identification strategy adopted.

### **2.4.1 Micro-level approaches based on surveys and firm questionnaires**

The first pillar comprehends firm-level surveys and case studies to identify reshoring decisions. By using structured questionnaires, these studies were addressed to managers in order to capture relocation decisions which are not recorded in official statements. Starting with Kinkel and Maloca [25], they used the German Manufacturing Survey (GMS) to estimate probit models explaining firms' propensity to reshore as a function of firm characteristics such as size, labor costs, and production complexity. Similarly, Dachs and Zanker [29, 31], based on the European Manufacturing Survey (EMS) covering several thousand firms across European countries, document that backshoring remains quantitatively limited and is mainly driven by quality problems, lack of flexibility, and high coordination and transport costs. While survey-based approaches allow researchers to directly observe reshoring decisions at the firm level by analyzing managerial motivations, they are often subject to self-reporting bias, limited representativeness, and reduced cross-country comparability, which limit their usefulness for systematic measurement.

### **2.4.2 Macro-level approaches based on aggregate and input–output data**

A second line of research follows a macroeconomic perspective, studying reshoring from aggregate indicators derived from trade, employment, and input–output data. In this framework, reshoring is typically interpreted as a reduction in foreign sourcing along global value chains. A very important contribution to this strategy is

the work by Krenz and Strulik [30], who proposed a continuous macro-level reshoring indicator based on changes in the ratio between domestic and foreign intermediate inputs, constructed using international input–output tables. They conceptualized reshoring not as a static process, but rather as a dynamic one, comparing data over time, and distinguished between a “broad” measure, capturing general increases in domestic sourcing, and a “narrow” one, whose objective is to isolate reshoring dynamics from changes in production scale or demand composition. Alongside this study, institutional studies by the OECD [22] adopt a similar approach, analyzing reshoring through the lens of indicators such as the share of imports in domestic demand and participation in global value chains. These contributions consistently found that reshoring remains a phenomenon limited in magnitude and still coexisting with ongoing offshoring dynamics.

### **2.4.3 Case-based databases and secondary data approaches**

A third empirical approach emerging from the literature is based on the systematic collection of publicly available information aimed at the construction of databases to track reshoring events. Fratocchi et al. [32, 33, 19] developed the UniAQ database, storing several hundred reshoring cases identified through press releases, media sources and company declarations. This approach allows for the geographical mapping of reshoring flows and highlights their sectoral distribution. However, case-based databases suffer from selection bias and incomplete coverage, as they rely on publicly reported events and tend to over-represent large firms or highly visible industries.

### **2.4.4 Micro-level production-based approaches using administrative firm data**

A more recent strand of the literature tries to identify reshoring by looking at linked administrative firm-level data through observable changes in both international sourcing and domestic production activity. Within this framework, reshoring is identified only when a reduction in offshoring—typically proxied by a decline in imports of intermediate inputs—occurs simultaneously to an increase in domestic production factors, such as employment or capital. This approach was followed by D’Ambrosio et al. [34] in their attempts to measure reshoring, by using Italian firm-level administrative data to construct a binary indicator of reshoring activities.

## Chapter 3

# Data, Variables and Descriptive Analysis

### 3.1 Data Description

The analysis developed in the following sections is based on the commercial activity of a subset of Italian firms operating in the manufacturing sector, observed over the period 2010–2023. The empirical analysis is based on the integration of two complementary data sources, COEWEB-ISTAT and AIDA-Moody's.

COEWEB-ISTAT records the universe of import and export transactions carried out by Italian firms between 2010 and 2023, providing information on transaction values, partner countries, transport modes, product codes at the 8-digit Combined Nomenclature level, and the related ATECO 2007 sector classification. These trade data are then combined with firm-level information from AIDA-Moody's, which reports balance sheet variables and each firm's main industry of activity.

The dataset is organized into two distinct layers: a transaction-level dataset and a firm-level dataset. The former records each import and export transaction carried out by each firm in each year of observation, whereas the latter aggregates the information at the firm-year level. The initial transaction-level dataset includes 15.467.002 observations referring to 56.415 firms. However, since the objective of the analysis is to trace firms' behaviour over time with respect to both offshoring and reshoring dynamics, the sample was restricted to firms observed throughout the entire time window considered.

To this end, a rectangularization procedure was implemented. First, the variable `num_anni_oss_perfirm` was created to count the number of years in which each firm appears in the firm-level dataset. Subsequently, using the condition `keep if num_anni_oss_perfirm == 14`, only firms observed in all fourteen years of the analysis period were retained. The identifiers of these firms were then used to select

the corresponding observations in the transaction-level dataset.

As a result of this procedure, the rectangularized transaction-level dataset includes 8.972.190 observations referring to 4.565 firms, while the rectangularized firm-level dataset contains 63.910 observations, corresponding to fourteen annual observations for each firm. In the remainder of the analysis, these two datasets are referred to as `transaction_level_rettangolare` and `firm_level_rettangolare`, respectively.

The analysis of imports and exports, summarized in Table 3.1, was conducted using the `transaction_level_rettangolare` dataset, where the variables `import` and `export` report the monetary value, expressed in euros, of each transaction. Aggregating these variables over the entire observation period and across all firms included in the sample shows that total imports amount to approximately EUR 522 billion, while total exports are slightly above EUR 619 billion. At the aggregate level, the firms included in the sample can therefore be classified as net exporters.

A particularly relevant feature emerging from the descriptive statistics is the large gap between the mean and the median transaction values, for both imports and exports. For imports, the average transaction value is EUR 158.831, whereas the median is only EUR 3.018. For exports, the corresponding figures are EUR 108.987 and EUR 4.181, respectively. This pattern suggests a highly skewed distribution, characterized by a limited number of very large transactions that substantially increase the mean. Consistently, half of import transactions have a value below EUR 3.018, despite the maximum recorded value reaching EUR 781 million for a single import transaction. The very high standard deviation, amounting to approximately EUR 3 million for imports and EUR 1.4 million for exports, further confirms the strong heterogeneity of transaction values and the presence of extreme observations.

| Variable | N       | Sum      | Mean     | p50  | SD      | Min | Max      |
|----------|---------|----------|----------|------|---------|-----|----------|
| import   | 3289509 | 5.22e+11 | 158831.4 | 3018 | 3069386 | 1   | 7.81e+08 |
| export   | 5682681 | 6.19e+11 | 108987   | 4181 | 1370221 | 1   | 6.77e+08 |
| total    | 8972190 | 1.14e+12 | 127261.7 | 3769 | 2154955 | 1   | 7.81e+08 |

**Table 3.1:** Descriptive statistics of total imports and exports

Moreover, Figure 3.1 reports the yearly evolution of total imports and total exports over the 2010–2023 period, with the aim of providing an initial overview of aggregate trade dynamics within the sample. Both imports and exports display an overall increasing trend throughout the observation window. Exports systematically exceed imports in each year, further confirming the net-exporter profile of the firms included in the sample.

A slight decline can be observed around 2019–2020, plausibly reflecting the disruptions associated with the COVID-19 pandemic and the related slowdown

in international trade flows. This contraction is followed by a marked recovery in the 2021–2023 period. The post-pandemic increase is particularly pronounced for exports, suggesting an acceleration of outward trade activity in the final years of the sample.

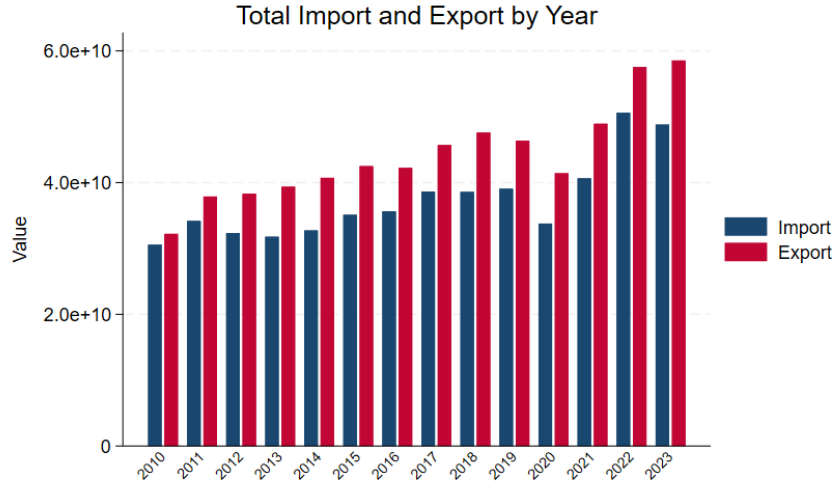


**Figure 3.1:** Total imports and exports from 2010 to 2023

Considering the dataset as a whole, export transactions account for 63.3% of total trade operations, while import transactions represent the remaining 36.7%. However, when the analysis is conducted in terms of monetary value rather than number of transactions, the distribution appears more balanced: imports account for 45.7% of total trade value, whereas exports represent 54.3%. This evidence suggests that, although export transactions are more frequent, import operations tend to display a higher average value per transaction.

## 3.2 Geographic Distribution of Firms Across Italian Territory

A further relevant dimension of the analysis concerns the geographical distribution of firms. Each firm is assigned to a single province of origin, interpreted as its primary operational location, based on the province most frequently observed across its transactions over the full observation period.

This classification is constructed starting from the variable *provinci*, a two-character province code available at the transaction level. In most cases, each firm is associated with only one province across all transactions, which directly identifies the corresponding value of the newly created variable *provincia*. When

multiple provinces are observed for the same firm, the modal province — that is, the province appearing most frequently across the firm’s transactions — is selected. This procedure allows each firm to be consistently assigned to one primary province over the entire period of analysis.

Starting from this province-level classification, Italian provinces are then aggregated into three macro-areas following the ISTAT classification: North, Centre, and South and Islands. The distribution of firms across macro-areas is reported in Table 3.2.

The geographical distribution of the sample is strongly concentrated in Northern Italy, reflecting the well-documented clustering of Italian manufacturing activities in the Po Valley and in the surrounding industrial districts. By contrast, Southern Italy and the Islands represent the least represented macro-area, in line with the persistent structural gap in manufacturing capacity between Northern and Southern Italy.

| macro_area | Freq. | Percent | Cum.   |
|------------|-------|---------|--------|
| Centro     | 653   | 14.30   | 14.30  |
| Nord       | 3,538 | 77.50   | 91.81  |
| Sud        | 374   | 8.19    | 100.00 |
| Total      | 4,565 | 100.00  |        |

**Table 3.2:** Number of firms by geographic area

In terms of trade volumes, the geographical concentration broadly mirrors the distribution of firms across macro-areas. As shown in Table 3.3, firms located in Northern Italy account for the largest share of both aggregate import and export values. This result confirms the central role of Northern regions not only in terms of the number of firms included in the sample, but also in terms of the overall intensity of international trade activity.

Average trade intensity at the firm-year level, measured through mean import and export values, is also highest among firms located in the North. This evidence suggests a positive association between firms’ location within Italy’s main industrial areas and their degree of engagement in international trade. By contrast, firms located in the Centre and, especially, in the South and Islands display lower aggregate trade volumes and lower average trade values, consistently with the more limited manufacturing base observed in these macro-areas.

Figures 3.2 and 3.3 report the evolution of total import and export values by macro-area over the observation period. The predominance of firms located in Northern Italy is evident and remains persistent throughout the entire time window. By contrast, the Centre and the South and Islands display substantially lower trade volumes and comparatively flatter trajectories.

| macro_area | import                                                                | export                                                              |
|------------|-----------------------------------------------------------------------|---------------------------------------------------------------------|
| Centro     | <b>1.04e+11</b><br><b>301354.4</b><br><b>3886</b><br><b>6043837</b>   | <b>6.55e+10</b><br><b>102445.8</b><br><b>4700</b><br><b>1539913</b> |
| Nord       | <b>3.93e+11</b><br><b>138804.1</b><br><b>2774</b><br><b>2493738</b>   | <b>5.21e+11</b><br><b>108920.5</b><br><b>4085</b><br><b>1337721</b> |
| Sud        | <b>2.57e+10</b><br><b>226594.2</b><br><b>9648.5</b><br><b>2662475</b> | <b>3.27e+10</b><br><b>126391.5</b><br><b>4685</b><br><b>1511270</b> |
| Total      | <b>5.22e+11</b><br><b>158831.4</b><br><b>3018</b><br><b>3069386</b>   | <b>6.19e+11</b><br><b>108987</b><br><b>4181</b><br><b>1370221</b>   |

**Table 3.3:** Descriptive statistics of imports and exports by geographic area

Export values for Northern firms show a broadly increasing trend over time, with a temporary contraction around 2019–2020. This decline is consistent with the disruption of international trade flows associated with the COVID-19 pandemic and is followed by a marked recovery in the subsequent years. The import series also increases over the period, with a more pronounced acceleration in the final years of the sample. This pattern may reflect the combined effect of post-pandemic supply chain disruptions, rising input costs, and the recovery of production activity.

The Centre and the South and Islands do not display similarly pronounced cyclical movements, remaining at considerably lower levels throughout the period. Overall, the evidence suggests that aggregate trade fluctuations are mainly driven by firms located in Northern Italy, reflecting their higher degree of international exposure and their central role within the Italian manufacturing system.

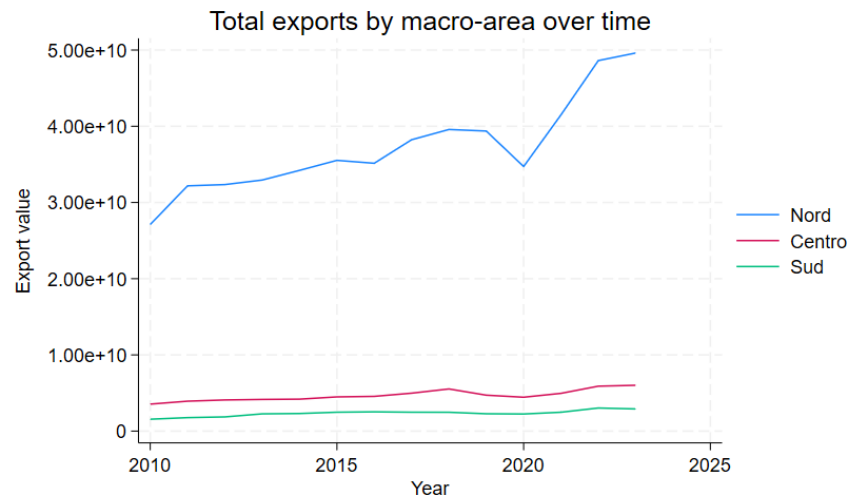


**Figure 3.2:** Total exports by macro-area over time

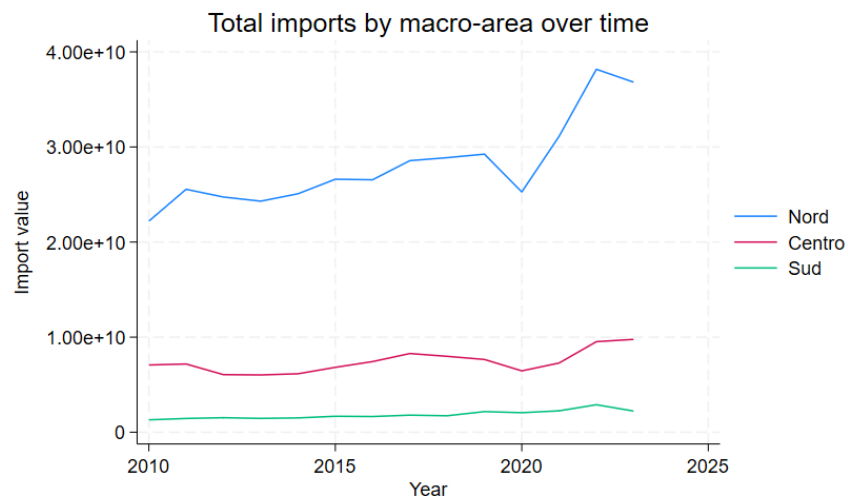


**Figure 3.3:** Total imports by macro-area over time

### 3.3 Geographic Distribution of Imports and Exports

Moving to a more detailed level of analysis, the geographical scope of firms' international trade can be examined by considering the partner countries appearing in the dataset as origins of imports or destinations of exports. These countries are identified through the three-letter variable *iso*.

Figure 3.4 maps the geographical footprint of the sample firms' trade activity over the full observation period. Overall, the dataset includes 222 distinct trading partner countries, covering all major world regions. Trade intensity, measured by the total number of transactions and represented by progressively darker shades of blue, is strongly concentrated in Western Europe. Germany, France, Spain, and the United Kingdom emerge as the most active trading partners, confirming the importance of geographically proximate and economically integrated European markets for Italian manufacturing firms.

Outside Europe, China stands out as the main non-European counterpart, consistently with its central role as a global sourcing hub for manufacturing inputs. The United States also records significant trade activity, particularly on the export side, together with selected economies in the Middle East and South-East Asia. By contrast, many countries in Sub-Saharan Africa, Central Asia, and the Pacific display relatively limited transaction volumes. This evidence suggests that, while the commercial presence of the firms in the sample is geographically broad, trade activity is highly concentrated in a restricted set of major partner economies.

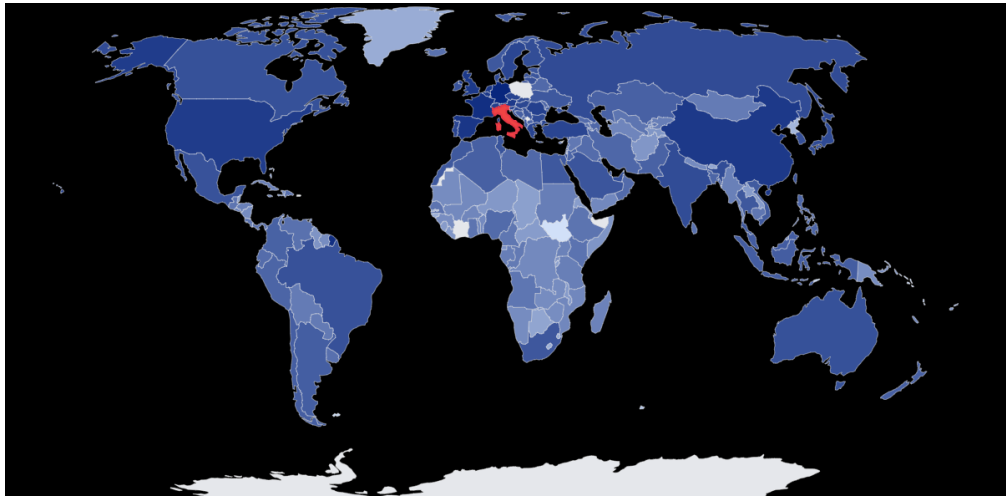


**Figure 3.4:** Geographic distribution of total transactions

Given the large number of countries involved in trade relationships with the

firms in the sample, a further descriptive step consists in identifying the main trading partners over the full observation period. Specifically, three rankings are constructed: the top ten countries by total number of transactions, the top ten countries by total import value, and the top ten countries by total export value, as shown in Table 3.4.

To build these rankings, trade flows are aggregated at the country level using the variable `iso`, which identifies each trading partner through a three-letter country code. The total number of transactions is computed using the variable `ntrans`, while import and export values are aggregated separately through the variables `imp` and `exp`, respectively.

Across all three rankings, Germany emerges as the dominant trading partner, ranking first in terms of total transaction volume, import value, and export value. This result reflects the strong integration between Italian and German manufacturing supply chains and is consistent with the broader pattern of intra-industry trade within the European single market. France ranks second in all three classifications, further confirming the central role of neighbouring EU economies in the international trade activity of Italian manufacturing firms.

Beyond the first two positions, the rankings show more differentiated patterns. China ranks third both in terms of total transactions and import value, highlighting its role as a key sourcing destination for Italian manufacturing firms. By contrast, the United States ranks third in terms of export value, while it does not appear among the leading import partners, suggesting a more asymmetric trade relationship in which Italian firms export significantly to the US market but source relatively less from it.

Switzerland, the Netherlands, Belgium, and Austria also appear consistently across the rankings. Their presence reflects, on the one hand, geographic proximity and strong European trade integration and, on the other hand, the importance of logistics and commercial hubs in shaping observed trade flows.

### **3.3.1 Classification of Countries Based on GNI**

To investigate the geographic dimension of offshoring and reshoring, a classification of trading partner countries is required. Identifying whether trade flows originate from or are directed towards high-cost or low-cost economies is essential to distinguish genuine reshoring episodes — defined as a structural reallocation of sourcing away from low-cost origins — from simple supply chain reshuffling among countries with similar cost profiles. All partner countries are identified in the dataset by their ISO 3166-1 alpha-3 code and classified into two mutually exclusive groups following the World Bank income classification (FY2026). In practical terms, a variable “`country_type`” was created and valorized as follows: for countries with a GNI per capita above USD 13,935 at the Atlas method, it took the value “premium”, while

| <b>iso</b> | <b>ntrans</b> | <b>iso</b> | <b>imp</b> | <b>iso</b> | <b>exp</b> |
|------------|---------------|------------|------------|------------|------------|
| DEU        | 1043795       | DEU        | 1.12e+11   | DEU        | 8.72e+10   |
| FRA        | 364374        | FRA        | 5.45e+10   | FRA        | 6.83e+10   |
| CHN        | 240224        | CHN        | 4.05e+10   | USA        | 5.30e+10   |
| NLD        | 207993        | ESP        | 3.66e+10   | GBR        | 3.23e+10   |
| BEL        | 161283        | NLD        | 3.26e+10   | ESP        | 2.79e+10   |
| GBR        | 159075        | BEL        | 2.67e+10   | CHE        | 2.56e+10   |
| ESP        | 155741        | GBR        | 2.13e+10   | CHN        | 1.87e+10   |
| AUT        | 131225        | CHE        | 2.06e+10   | POL        | 1.85e+10   |
| USA        | 85234         | AUT        | 1.34e+10   | BEL        | 1.48e+10   |
| CHE        | 56985         | USA        | 1.32e+10   | AUT        | 1.42e+10   |

**Table 3.4:** Ranking of countries by total transactions, total exports and total imports, from left to right

all remaining economies — upper-middle, lower-middle and low-income — are classified as low-cost. This threshold is directly interpretable in terms of relative factor costs and correctly assigns major sourcing destinations such as China, Vietnam and Bangladesh to the low-cost group, while placing Italy’s main European trading partners in the premium category. To provide with a segmentation of the dataset based on this newly created variable, there are 79 countries classified as premium and 143 countries as low-cost.

Despite being numerically fewer, premium countries account for the vast majority of transactions — 80.51% of all import and export flows — while low-cost countries represent less than one in five transactions (Table 3.5). This asymmetry reflects the structural orientation of Italian manufacturing trade towards neighbouring European economies, which are predominantly high-income.

In terms of trade values, the aggregate import and export flows are substantially larger towards premium countries in absolute terms (Table 3.6). However, the average value per individual transaction differs by direction of flow. On the import side, transactions from low-cost countries record a higher average value than those from premium countries, suggesting that when firms source from low-cost origins they tend to do so in larger individual shipments. On the export side, the pattern reverses: transactions directed towards premium countries have a higher average value than those towards low-cost countries.

| country_type | Freq.     | Percent | Cum.   |
|--------------|-----------|---------|--------|
| lowcost      | 1,748,272 | 19.49   | 19.49  |
| premium      | 7,223,918 | 80.51   | 100.00 |
| Total        | 8,972,190 | 100.00  |        |

**Table 3.5:** Transactions by country type

| country_type | Sum                  | Mean                 | p50           |
|--------------|----------------------|----------------------|---------------|
| lowcost      | 1.01e+11<br>1.21e+11 | 216497.7<br>94285.13 | 17037<br>8360 |
| premium      | 4.21e+11<br>4.99e+11 | 149272.4<br>113263.6 | 2085<br>3166  |
| Total        | 5.22e+11<br>6.19e+11 | 158831.4<br>108987   | 3018<br>4181  |

**Table 3.6:** Descriptive statistics of imports and exports by country type

Consistently with the analysis of total imports and total exports conducted above, it's interesting to check whether the decomposition of the trades based on the `country_type` confirms or not the trend showed in Figure 3.1. Looking at Figures 3.5 and 3.6, displaying the total import and export values by country type over the fourteen-year observation period, premium countries account for the vast majority of trade flows, with low-cost countries representing a structurally smaller share of both imports and exports. The two figures allow a comparison of the magnitude and dynamics of trade flows by country type across the full sample period.

On the import side, flows from premium countries follow a clear upward trend throughout the period, with a visible but temporary contraction in 2020 consistent with the global trade disruption induced by the COVID-19 pandemic, followed by a strong recovery that accelerates markedly from 2021 onwards. Imports from low-cost countries are considerably smaller in absolute terms but also display a positive trend, with a notable spike in 2022 — likely reflecting commodity price increases and supply chain pressures in the post-pandemic period — followed by a partial reversal in 2023.

On the export side, the dominance of premium destinations is even more pronounced, with low-cost countries absorbing only a marginal fraction of total outflows across all years. Premium exports show a sustained and accelerating growth trajectory, particularly after 2021, confirming that Italian manufacturing

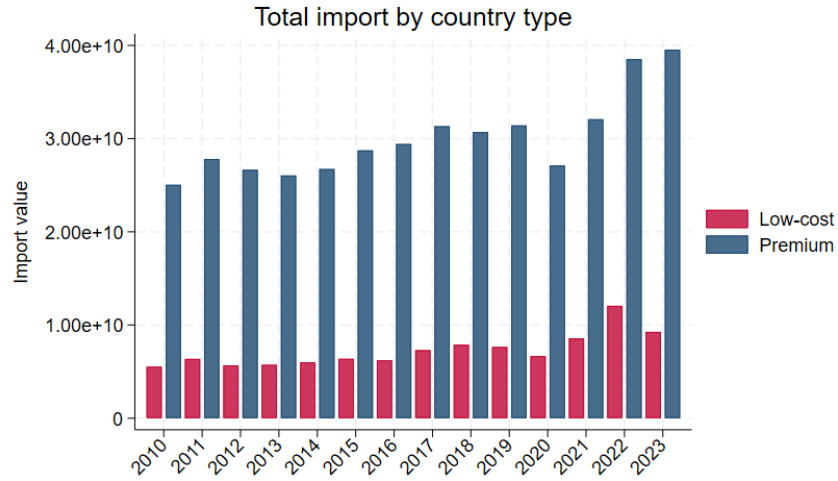


**Figure 3.5:** Total imports by country type

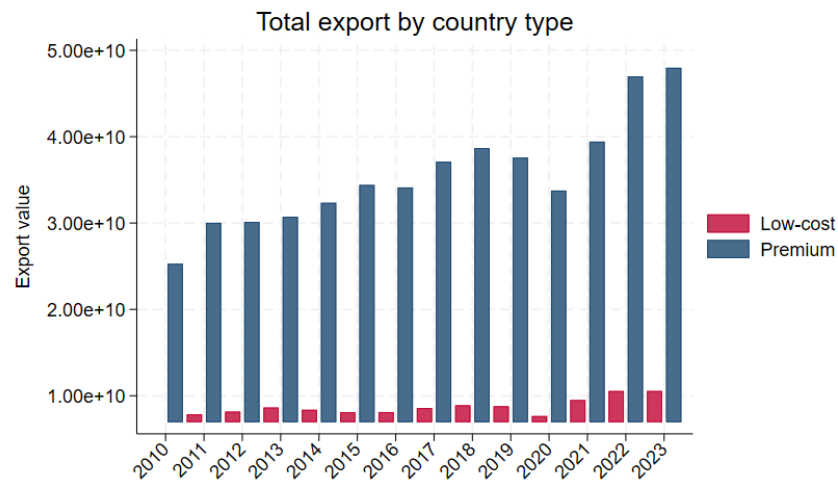


**Figure 3.6:** Total exports by country type

firms sell their output predominantly to high-income markets. Export flows towards low-cost countries remain flat and negligible throughout the period, indicating that the role of low-cost economies in the sample is almost exclusively that of input suppliers rather than end markets.

Following the same analytical approach adopted for the overall import and export rankings presented earlier in this chapter, Tables 3.7 and 3.8 report the top ten trading partner countries by total import and export value, presented separately for premium and low-cost economies. This disaggregation serves two purposes. First, it identifies the specific countries that drive trade flows within each group, moving beyond the aggregate premium/low-cost distinction to characterise the actual geographic composition of the sample's international activity. Second, it provides a preliminary mapping of the sourcing and market structure of Italian manufacturing firms: the top import partners reveal where firms procure their inputs, while the top export partners indicate the main destination markets for their output. Presenting the two groups separately allows a direct comparison of the geographic concentration and composition of trade across high-income and lower-income economies.

| <b>iso</b> | <b>tot_im~t</b> | <b>n_trans</b> | <b>iso</b> | <b>tot_im~t</b> | <b>n_trans</b> |
|------------|-----------------|----------------|------------|-----------------|----------------|
| <b>DEU</b> | <b>1.12e+11</b> | <b>1043795</b> | <b>CHN</b> | <b>4.05e+10</b> | <b>240224</b>  |
| <b>FRA</b> | <b>5.45e+10</b> | <b>364374</b>  | <b>TUR</b> | <b>1.03e+10</b> | <b>51310</b>   |
| <b>ESP</b> | <b>3.66e+10</b> | <b>155741</b>  | <b>IND</b> | <b>6.85e+09</b> | <b>33820</b>   |
| <b>NLD</b> | <b>3.26e+10</b> | <b>207993</b>  | <b>TUN</b> | <b>3.89e+09</b> | <b>10405</b>   |
| <b>BEL</b> | <b>2.67e+10</b> | <b>161283</b>  | <b>BRA</b> | <b>2.94e+09</b> | <b>7607</b>    |
| <b>GBR</b> | <b>2.13e+10</b> | <b>159075</b>  | <b>BGD</b> | <b>2.62e+09</b> | <b>8770</b>    |
| <b>CHE</b> | <b>2.06e+10</b> | <b>56985</b>   | <b>BGR</b> | <b>2.47e+09</b> | <b>12862</b>   |
| <b>AUT</b> | <b>1.34e+10</b> | <b>131225</b>  | <b>RUS</b> | <b>2.43e+09</b> | <b>5384</b>    |
| <b>USA</b> | <b>1.32e+10</b> | <b>85234</b>   | <b>UKR</b> | <b>2.37e+09</b> | <b>3248</b>    |
| <b>CZE</b> | <b>9.96e+09</b> | <b>37262</b>   | <b>THA</b> | <b>2.24e+09</b> | <b>8518</b>    |

**Table 3.7:** Ranking of top import partners by country type. Left: premium countries; right: low-cost countries

The top ten import partners in the premium segment are predominantly high-income European economies, with Germany leading by a substantial margin, followed by France, Spain, the Netherlands, Belgium and the United Kingdom. The presence of Switzerland and the United States indicates that premium sourcing extends beyond the immediate European neighbourhood to include other advanced

economies. Germany not only records the highest import value but also the largest number of transactions in the entire dataset, indicating a commercial relationship that is exceptionally dense and diversified rather than concentrated in a few large flows.

China dominates the low-cost import ranking with a value nearly four times that of the second-ranked country, Turkey. The number of transactions associated with China is also the highest in the low-cost segment, confirming its role as a broad-based and high-volume supplier. The remaining countries — including India, Tunisia, Brazil, Bulgaria, Russia, Ukraine and Thailand — record considerably lower values, with a relatively high per-transaction average consistent with sourcing of standardised inputs.

| <b>iso</b> | <b>tot_ex~t</b> | <b>n_trans</b> | <b>iso</b> | <b>tot_ex~t</b> | <b>n_trans</b> |
|------------|-----------------|----------------|------------|-----------------|----------------|
| <b>DEU</b> | <b>8.72e+10</b> | <b>1043795</b> | <b>CHN</b> | <b>1.87e+10</b> | <b>240224</b>  |
| <b>FRA</b> | <b>6.83e+10</b> | <b>364374</b>  | <b>TUR</b> | <b>1.36e+10</b> | <b>51310</b>   |
| <b>USA</b> | <b>5.30e+10</b> | <b>85234</b>   | <b>RUS</b> | <b>1.13e+10</b> | <b>5384</b>    |
| <b>GBR</b> | <b>3.23e+10</b> | <b>159075</b>  | <b>BRA</b> | <b>7.56e+09</b> | <b>7607</b>    |
| <b>ESP</b> | <b>2.79e+10</b> | <b>155741</b>  | <b>MEX</b> | <b>5.87e+09</b> | <b>7602</b>    |
| <b>CHE</b> | <b>2.56e+10</b> | <b>56985</b>   | <b>IND</b> | <b>5.28e+09</b> | <b>33820</b>   |
| <b>POL</b> | <b>1.85e+10</b> | <b>41439</b>   | <b>TUN</b> | <b>4.14e+09</b> | <b>10405</b>   |
| <b>BEL</b> | <b>1.48e+10</b> | <b>161283</b>  | <b>DZA</b> | <b>3.90e+09</b> | <b>604</b>     |
| <b>AUT</b> | <b>1.42e+10</b> | <b>131225</b>  | <b>ZAF</b> | <b>3.61e+09</b> | <b>3346</b>    |
| <b>NLD</b> | <b>1.36e+10</b> | <b>207993</b>  | <b>EGY</b> | <b>3.56e+09</b> | <b>4325</b>    |

**Table 3.8:** Ranking of top export partners by country type. Left: premium countries; right: low-cost countries

The export rankings for the premium segment closely mirror the import rankings, with Germany again leading, followed by France, the United States, the United Kingdom, Spain, Switzerland, Poland, Belgium, Austria and the Netherlands. This symmetry suggests that premium economies function simultaneously as suppliers and buyers within integrated bilateral trade relationships. The United States stands out as a major export destination despite its geographic distance, pointing to a significant transatlantic trade flow within the premium segment.

In the low-cost export ranking, China again leads, confirming its dual role as both primary import source and major export destination within the low-cost segment. Turkey and Russia rank second and third respectively, followed by Brazil, Mexico, India, Tunisia, Algeria, South Africa and Egypt. The presence of African

markets exclusively in the export ranking — and not among the main import origins — suggests an asymmetric pattern of integration, where these economies absorb goods from Italian manufacturing firms without contributing symmetrically on the sourcing side.

## **3.4 Commercial Analysis of Imports and Exports**

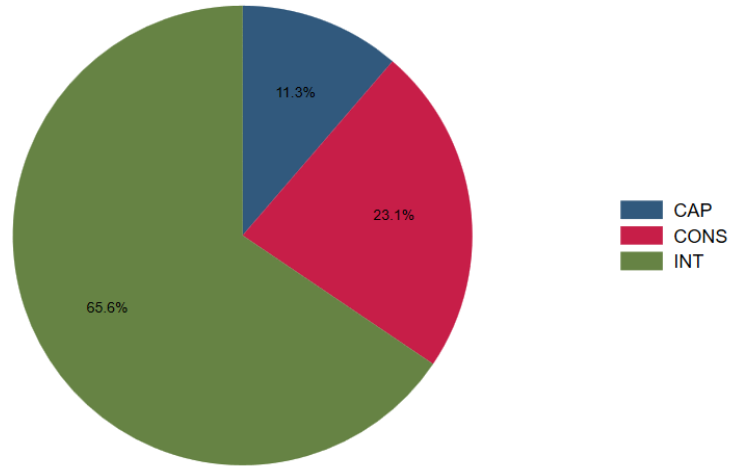
### **3.4.1 Product-Type Classification of Transactions**

A further dimension of the dataset is introduced by classifying each NC4 product code according to its end-use category, following the Classification by Broad Economic Categories, Revision 5 (BEC Rev.5), developed by the United Nations Statistics Division (2018). The BEC5 system provides a framework for converting trade data into three mutually exclusive end-use categories consistent with the System of National Accounts: intermediate goods (INT), defined as inputs used in the course of production; consumer goods (CONS), defined as final products destined for household use; and capital goods (CAP), defined as durable assets employed in production. The classification is implemented through a crosswalk from NC4 codes to BEC5 end-use categories. Since each NC4 code may map to multiple BEC5 categories, the modal category — defined as the most frequently occurring end-use designation within that NC4 code — is assigned as the definitive classification. Mixed categories (e.g. CAP/INT, CONS/INT) are recoded into their primary component before the modal assignment is applied. A lookup table mapping each NC4 to its end-use category is then derived and merged into both the transaction-level and firm-year datasets — using NC4 as the key for the former and the main export NC4 as the key for the latter. Out of 8,972,190 total transactions, 8,965,884 are successfully classified (99.93%), with 6,306 remaining unmatched due to incomplete coverage of the BEC5 crosswalk — a share sufficiently small to be considered negligible.

Starting by describing how many distinct NC4 belongs to each type of product, Figure 3.7 shows the distribution of the 1,228 classified NC4 codes across the three end-use categories. The majority of distinct product codes are classified as intermediate goods (65.55%), followed by consumer goods (23.13%) and capital goods (11.32%). This distribution reflects the breadth of intermediate product categories in the Harmonized System — a large variety of raw materials, components and semi-finished goods are traded under distinct NC4 codes — relative to the more concentrated classification of capital and consumer goods.

Moving to a proper transactions' analysis under the three-category standpoint, Table 3.9 reports that intermediate goods represent the largest share of both distinct NC4 codes (65.55%) and total transactions (49.94%), confirming their central role in international trade flows. Consumer goods account for a disproportionately high

Distribution of NC4 codes by product type

**Figure 3.7:** Percentage of distinct NC4 codes by product type

| nc4_type | Freq.     | Percent | Cum.   |
|----------|-----------|---------|--------|
| CAP      | 1,273,417 | 14.20   | 14.20  |
| CONS     | 3,214,946 | 35.86   | 50.06  |
| INT      | 4,477,521 | 49.94   | 100.00 |
| Total    | 8,965,884 | 100.00  |        |

**Table 3.9:** Distribution of transactions by product type

share of transactions (35.86%) relative to their share of distinct codes (23.13%), which may suggest that consumer good products tend to be exchanged repeatedly and at high frequency — consistent with the standardised and recurring nature of consumer goods trade. Capital goods show the reverse pattern, with their share of transactions (14.20%) slightly exceeding their share of distinct codes (11.32%).

Focusing now on imports and exports, the summary Table 3.10 reveals a clear hierarchy across product categories that holds consistently for both import and export flows. Intermediate goods dominate trade in both directions, followed by consumption goods, while capital goods represent the smallest share. This ranking aligns with the broader literature on international trade, where the fragmentation of global value chains tends to amplify cross-border flows of intermediate inputs relative to final goods, as it's been mentioned above when analyzing the offshoring phenomenon's characteristics

A second notable pattern is that exports systematically exceed imports across all three categories, pointing to a structural trade surplus that is not confined to a specific product type but appears as a general feature of the country's trade

position.

| nc4_type | Sum      | Mean     | p50  |
|----------|----------|----------|------|
| CAP      | 7.28e+10 | 140540.6 | 2916 |
|          | 9.57e+10 | 126614.8 | 5500 |
| CONS     | 1.62e+11 | 179700.2 | 3056 |
|          | 1.90e+11 | 82138.94 | 3335 |
| INT      | 2.88e+11 | 153994.2 | 3039 |
|          | 3.33e+11 | 127738.3 | 4758 |
| Total    | 5.22e+11 | 158923.8 | 3020 |
|          | 6.19e+11 | 109012.6 | 4185 |

**Table 3.10:** Descriptive statistics of imports and exports by product type

Lastly, as performed at the overall and at the country level, the same study of the trend in imports and exports across the fourteen year period has been carried out by considering the categories of product. By looking at Figures 3.8 and 3.9 and considering both export and import flows, intermediate goods consistently dominate throughout the entire period, followed by consumption goods and capital goods. All three categories display a broadly stable trajectory until 2020, when a temporary dip — attributable to the COVID-19 pandemic — is visible across the board. From 2021 onward, a sharp upward acceleration characterises all product types, particularly for intermediate and consumption goods, likely driven by the post-pandemic demand rebound and supply chain restructuring. The export and import dynamics are closely mirrored, suggesting a deep integration of the country into global value chains in both directions of trade.

### 3.4.2 Trade Flows by Product Type and Country Type

To complete the descriptive characterisation of the dataset, the country-level and product-level classifications are examined jointly. This combined analysis serves a specific purpose in the context of the subsequent offshoring and reshoring investigation: identifying which types of goods are predominantly sourced from low-cost economies provides the empirical foundation for the firm-level analysis, where the geographic orientation of sourcing is a key predictor of reshoring behaviour.

At the transaction level, the distribution between premium and low-cost partners is remarkably similar across the three product categories, with premium countries accounting for approximately 79-82% of transactions in all groups (Table 3.11 ).

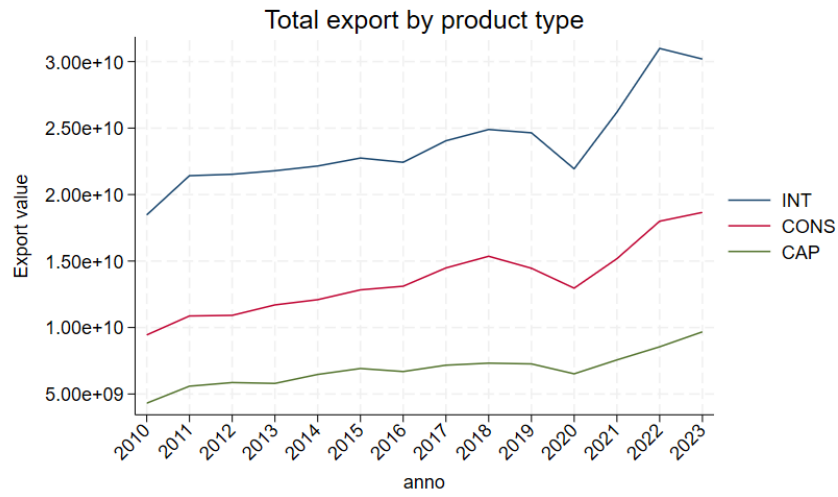


Figure 3.8: Total exports by product type

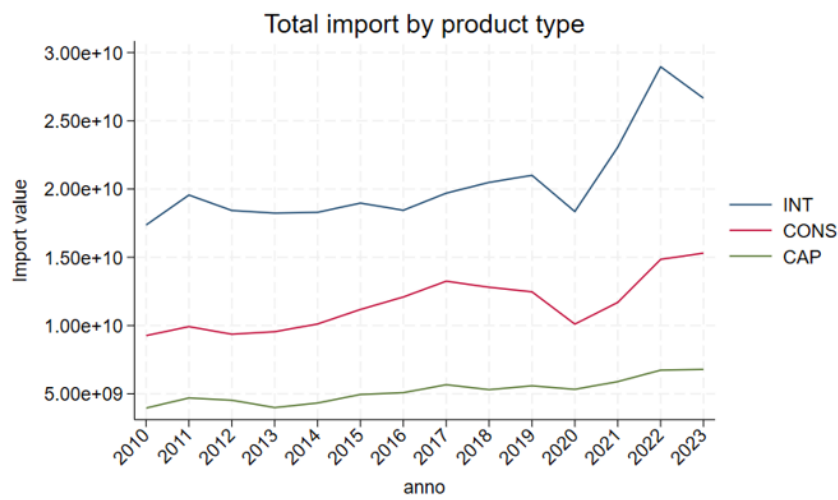


Figure 3.9: Total imports by product type

The type of good traded does not appear to substantially alter the geographic composition of trade flows when measured by transaction frequency alone.

| nc4_type | country_type       |                    | Total               |
|----------|--------------------|--------------------|---------------------|
|          | lowcost            | premium            |                     |
| CAP      | 271,058<br>21.29   | 1,002,359<br>78.71 | 1,273,417<br>100.00 |
| CONS     | 577,005<br>17.95   | 2,637,941<br>82.05 | 3,214,946<br>100.00 |
| INT      | 899,551<br>20.09   | 3,577,970<br>79.91 | 4,477,521<br>100.00 |
| Total    | 1,747,614<br>19.49 | 7,218,270<br>80.51 | 8,965,884<br>100.00 |

**Table 3.11:** Number and share of transactions by country type and product type

Delving into the analysis of imports and exports, the import value analysis reveals meaningful differences in the geographic sourcing patterns across product categories. For each category, the share of imports from low-cost countries is computed as the ratio of total import value from low-cost partners to total import value from all partners. Consumer goods record the highest low-cost import share (22.1%), followed by intermediate goods (19.2%) and capital goods (14.1%). This pattern suggests that firms source consumer products relatively more intensively from lower-income economies, while relying predominantly on premium partners for capital equipment — consistent with the expectation that machinery and durable investment goods are acquired from technologically advanced economies, regardless of cost considerations. On the export side, the pattern is partially reversed. By computing the same share of exports to low-cost countries, capital goods record the highest share directed towards low-cost destinations (23.9%), while consumer goods are sold predominantly to premium markets, as their share is equal to 13.2%. Intermediate goods display a broadly symmetric pattern, with similar low-cost shares on both the import and export side. Tables 3.12 and 3.13 below give us information about the monetary value of imports and exports over the period based on the products exchanged being capital good, intermediate good and consumer good.

The temporal evolution of low-cost import shares by product type is reported in Figure 3.10. Shares remain broadly stable or slightly increasing across all three categories over the observation period, with a common spike in 2022 likely reflecting post-pandemic commodity price pressures and supply chain disruptions.

| nc4_type | Sum      |
|----------|----------|
| CAP      | 7.28e+10 |
| CONS     | 1.62e+11 |
| INT      | 2.88e+11 |
| Total    | 5.22e+11 |

Table 3.12: Total imports by product type and country type

| nc4_type | Sum      |
|----------|----------|
| CAP      | 9.57e+10 |
| CONS     | 1.90e+11 |
| INT      | 3.33e+11 |
| Total    | 6.19e+11 |

Table 3.13: Total exports by product type and country type

The absence of a clear declining trend at the aggregate level — which would constitute a direct reshoring signal — motivates the firm-level analysis in the following sections, where individual heterogeneity in sourcing behaviour can be examined more precisely through the offshoring and reshoring measures constructed in the following sections.

### 3.4.3 Commercial Classification of Transactions: ATECO-Level and NC-Level

The transaction-level dataset includes two complementary classification systems that describe trade flows from different perspectives. The first is ATECO 2007, the Italian classification of economic activities, which represents the national adaptation of the European NACE Rev. 2 standard. In the dataset, ATECO codes are available at the 5-digit level through the variable `ateco2007_str`, which identifies the sector associated with each specific import or export transaction. A second ATECO-related variable, `ateco2007_impr_str`, instead identifies the firm's

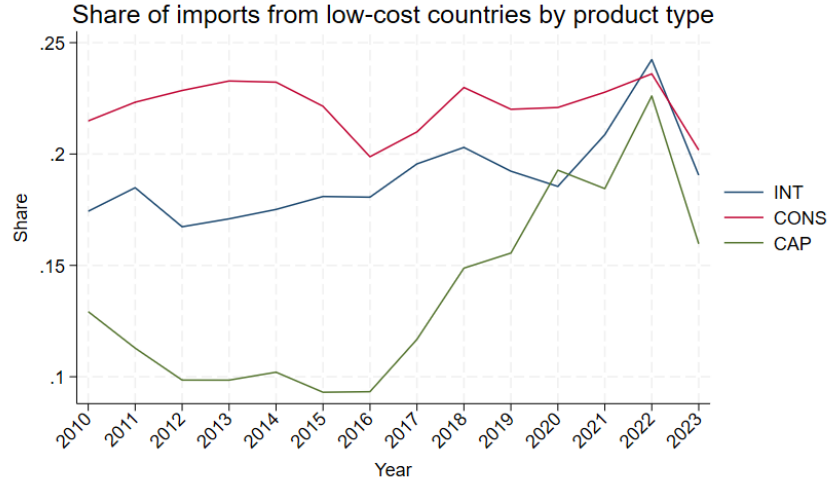


**Figure 3.10:** Share of imports from low-cost countries by product type

primary declared economic activity.

This distinction is relevant for the empirical approach adopted in the analysis. While `ateco2007_str` captures the sectoral nature of each trade transaction, `ateco2007_impr_str` refers to the firm's registered business activity. Since the objective is to measure offshoring as a trade-based phenomenon, the analysis focuses on the relationship between what firms import and what they export, rather than on the comparison between imports and firms' administrative sector classification. Overall, the dataset contains 352 distinct 5-digit ATECO codes, providing a detailed representation of the sectoral composition of trade flows.

The second classification system is the Combined Nomenclature (CN), the European Union's product classification used for international trade in goods and based on the Harmonized System. In the original dataset, each transaction is recorded at the highly granular 8-digit NC8 level. For the empirical analysis, these NC8 codes are aggregated to the 4-digit NC4 level by truncating the original NC8 string. This choice is consistent with the logic underlying narrow offshoring measures and reflects a trade-off between product-level detail and interpretability. While NC8 codes would provide a more granular description of traded products, their excessive level of detail would increase complexity and reduce the readability of the results. By contrast, NC4 codes preserve meaningful product-level information while allowing broader coverage and greater comparability across firms and years. After this aggregation, the dataset includes 1,239 distinct NC4 codes across all transactions.

In order to identify the most relevant sectors and products in the dataset, the top 10 ATECO 2007 sectors and the top 10 NC4 product categories are computed on

the basis of the total monetary value of all import and export transactions. These rankings provide an overview of the sectors and product groups that contribute most to overall trade flows, highlighting the main areas of economic and product-level concentration within the sample.

Table 3.14 reports the rankings based on the ATECO 2007 classification. The sectoral distribution is strongly influenced by the automotive industry, with the manufacture of motor vehicles (29100) and the manufacture of parts and accessories for motor vehicles (29320) ranking among the leading sectors in both exports and imports. This evidence reflects the deep integration of Italian automotive firms and suppliers within European and global value chains.

The prominence of leather goods and luggage (15120), footwear (15201), and outerwear (14130) confirms the relevance of traditional Made in Italy sectors — particularly fashion, luxury, and accessories — among the most export-intensive activities in the sample. Chemical and plastics-related sectors, such as 20160 and 20140, also appear consistently across the rankings, suggesting their role both as producers of intermediate inputs and as importers of raw materials and semi-finished goods.

Pharmaceutical sectors, particularly 21200 and 21100, are more prominent on the import side than on the export side. This pattern may indicate a stronger reliance on internationally sourced pharmaceutical preparations, active ingredients, or related intermediate inputs. Finally, basic steel (24100) and industrial equipment (28250) further point to the importance of capital and intermediate goods within the manufacturing trade structure of the sample. Sector definitions follow the ATECO 2007 classification provided by ISTAT [35].

| ateco2~r | tot_ex~t | ateco2~r | tot_im~t | ateco2~r | tot_tr~e |
|----------|----------|----------|----------|----------|----------|
| 29100    | 3.98e+10 | 29100    | 6.67e+10 | 29100    | 1.07e+11 |
| 29320    | 3.27e+10 | 21200    | 3.31e+10 | 29320    | 5.00e+10 |
| 15120    | 1.76e+10 | 24100    | 2.54e+10 | 21200    | 4.19e+10 |
| 20160    | 1.45e+10 | 29320    | 1.73e+10 | 24100    | 3.25e+10 |
| 15201    | 1.42e+10 | 20160    | 1.64e+10 | 20160    | 3.09e+10 |
| 14130    | 1.41e+10 | 20140    | 1.50e+10 | 14130    | 2.33e+10 |
| 28250    | 1.26e+10 | 26302    | 1.05e+10 | 15120    | 2.26e+10 |
| 20594    | 1.24e+10 | 10110    | 1.03e+10 | 20140    | 2.02e+10 |
| 17120    | 1.23e+10 | 14130    | 9.14e+09 | 15201    | 1.91e+10 |
| 24201    | 9.82e+09 | 21100    | 8.55e+09 | 20594    | 1.89e+10 |

**Table 3.14:** Ranking of ATECO sectors by export value, import value and total transaction value, from left to right

Table 3.15, instead, reports the rankings based on the NC4 product classification.

Overall, the product-level evidence is broadly consistent with the sectoral patterns previously identified through the ATECO classification.

Automotive-related products dominate the rankings. Parts and accessories of motor vehicles (8708), passenger cars (8703), and goods vehicles (8704) account for a substantial share of export values and also appear among the leading import categories. This confirms the central role of the automotive sector in the trade activity of the firms included in the sample and further highlights its strong integration within international value chains.

On the export side, bags and luggage (4202) and footwear (6403) rank among the most relevant product categories, consistently with the importance of fashion, luxury, and leather goods within Italian manufacturing. Industrial products, such as valves and similar appliances (8481) and seamless steel tubes (7304), further point to the relevance of capital and intermediate goods exports. Wine (2204) is the only agri-food product included among the top export categories, reflecting Italy's well-established competitive position in this segment.

The import profile appears more differentiated. Alongside automotive products, the leading import categories include smartphones and telephones (8517), computers (8471), pharmaceutical products (3002), and flat-rolled stainless steel products (7219). This composition suggests that firms in the sample source high-technology components, pharmaceutical inputs, and advanced materials from abroad. Such evidence is consistent with a trade structure in which imported goods are often linked to specific stages of production rather than exclusively to the purchase of final goods.

Product classifications follow the Combined Nomenclature at the 4-digit level, as provided by the European Commission and Eurostat [36, 37].

## **3.5 Construction of the Main Variables**

### **3.5.1 Main Export Sector and Product**

After describing the original variables included in the dataset, the analysis proceeds by introducing a set of newly constructed variables. As discussed above, the transaction-level dataset contains a large number of ATECO and NC4 codes, both on the import and export side. For this reason, it was necessary to identify, for each firm and year, the most relevant export sector and product category in terms of monetary value.

Starting from the `transaction_level_rettangolare` dataset, export values were first aggregated at the firm-year-sector level using the 5-digit transaction-level ATECO code. For each firm-year observation, the main export sector was then identified as the ATECO code associated with the highest total export value in

| NC4  | tot_ex~t | NC4  | tot_im~t | NC4  | tot_tr~e |
|------|----------|------|----------|------|----------|
| 8708 | 3.23e+10 | 8703 | 5.31e+10 | 8703 | 7.14e+10 |
| 8704 | 1.88e+10 | 3004 | 1.97e+10 | 8708 | 4.94e+10 |
| 8703 | 1.83e+10 | 8708 | 1.72e+10 | 3004 | 2.57e+10 |
| 4202 | 1.71e+10 | 3002 | 1.22e+10 | 8704 | 2.46e+10 |
| 8481 | 1.13e+10 | 8517 | 1.03e+10 | 4202 | 2.16e+10 |
| 3811 | 1.01e+10 | 7219 | 8.86e+09 | 8481 | 1.55e+10 |
| 2204 | 9.98e+09 | 8701 | 6.62e+09 | 3811 | 1.32e+10 |
| 7304 | 9.82e+09 | 8471 | 6.56e+09 | 3002 | 1.26e+10 |
| 6403 | 9.68e+09 | 0203 | 6.37e+09 | 6403 | 1.21e+10 |
| 4810 | 8.78e+09 | 8704 | 5.73e+09 | 7304 | 1.20e+10 |

**Table 3.15:** Ranking of NC4 products by export value, import value and total transaction value, from left to right

that year. This variable, named `main_export_sector_do`, therefore captures the sector in which firm (i) records the largest export value in year (t).

Formally, for each firm (i) and year (t), the main export sector is defined as:

$$\text{main\_export\_sector\_do}_{i,t} = \arg \max_s \sum_j \text{export}_{i,t,j,s} \quad (3.1)$$

where  $s$  indexes ATECO sectors and  $j$  indexes individual transactions.

An analogous procedure was applied to the NC4 product classification. Export values were aggregated by firm, year, and NC4 product code, and the product category associated with the highest total export value was selected as the firm's main export product category for that year. The resulting variable, `main_export_NC4`, identifies the NC4 category in which each firm records its largest export value in a given year. Formally, for firm in year , let :

$$\text{main\_export\_NC4}_{i,t} = \arg \max_k \sum_j \text{export}_{i,t,j,k} \quad (3.2)$$

where  $j$  indexes individual transactions and  $k$  indexes NC4 product categories.

The rationale for anchoring these variables to export transactions is straightforward. By relying on export values rather than on import activity or on the firm's registered sector, the analysis identifies the area in which each firm's core productive specialization is most clearly revealed in each year. In this sense, each firm is treated as if it were primarily specialized in its dominant export category. Although

this represents a simplifying assumption, it makes the measurement of offshoring more tractable while preserving the most economically relevant dimension of the firm’s observed trade activity.

Both variables are defined at the firm-year level, allowing the firm’s main export sector and main export product category to vary over time as its export composition changes. These variables serve as the reference categories throughout the empirical analysis. In particular, the offshoring and reshoring measures discussed in the following sections are constructed by focusing on imports occurring within the firm’s main export sector or main export NC4 category.

Consistently with the descriptive analysis conducted on the original classification variables, the distribution of the newly constructed variables also shows substantial heterogeneity. Across the full sample, 298 distinct main export sectors and 712 distinct main export NC4 categories are observed, indicating a high degree of variation in the productive specialization of the firms included in the dataset.

Moreover, following the procedure adopted to identify the most relevant ATECO sectors and NC4 product categories in the overall transaction-level dataset, the same ranking exercise is replicated using the newly constructed main export variables. Specifically, the top 10 `main_export_sector_do` and top 10 `main_export_NC4` categories are computed based on their total export value across the full observation period.

In addition to reporting aggregate monetary values, table 16 also provides with information on the number of firms for which each ranked sector or product category represents the main export specialization in at least one firm-year observation. This additional information makes it possible to distinguish between categories that are relevant because they are highly concentrated among a limited number of large exporters and categories that are more widely represented across the sample.

The ranking of the top ten main export sectors by aggregate export value confirms the dominance of the automotive cluster. The manufacture of motor vehicles (29100) and the manufacture of parts and accessories for motor vehicles (29320) occupy the first two positions, involving a broadly comparable number of firms and generating similar export volumes. The third-ranked sector, leather goods and luggage (15120), stands out as the only traditional Made in Italy category approaching automotive-level export values, despite being associated with a relatively limited number of firms. This suggests the presence of a small group of highly export-intensive luxury producers. Footwear (15201) and outerwear (14130) also appear in the ranking, reinforcing the relevance of fashion-related activities within the sample. Overall, the ranking reflects two central pillars of Italian manufacturing: automotive and fashion. The remaining sectors — plastics (20160), rubber products (22111), paper and paperboard (17120), industrial cooling and ventilation equipment (28250), and specialty chemicals (20594) — highlight the breadth of Italy’s intermediate and capital goods manufacturing base.

| main_e~o | sector~p | n_firm~t | main_e~4 | sector~p | n_firm~t |
|----------|----------|----------|----------|----------|----------|
| 29100    | 3.36e+10 | 70       | 8708     | 3.01e+10 | 83       |
| 29320    | 3.02e+10 | 81       | 4202     | 2.96e+10 | 39       |
| 15120    | 2.97e+10 | 50       | 8704     | 2.96e+10 | 13       |
| 14130    | 1.81e+10 | 71       | 4011     | 1.62e+10 | 12       |
| 20160    | 1.66e+10 | 55       | 8481     | 1.12e+10 | 90       |
| 22111    | 1.62e+10 | 14       | 7304     | 1.05e+10 | 7        |
| 17120    | 1.26e+10 | 38       | 2204     | 1.04e+10 | 45       |
| 28250    | 1.23e+10 | 57       | 3811     | 1.01e+10 | 2        |
| 15201    | 1.14e+10 | 68       | 6203     | 9.61e+09 | 25       |
| 20594    | 1.06e+10 | 28       | 4810     | 9.35e+09 | 6        |

**Table 3.16:** Ranking of main export sectors and products by export value. Left: main ATECO sectors; right: main NC4 products

At the product level, the centrality of the automotive sector is further confirmed. Parts and accessories of motor vehicles (8708), goods vehicles (8704), and pneumatic tyres (4011) all rank among the leading NC4 categories. A notable result concerns goods vehicles (8704), which generate export volumes comparable to motor vehicle parts (8708) while involving a much smaller number of firms. This points to a high degree of concentration in truck and commercial vehicle exports, likely driven by a limited number of large operators. A similar concentration pattern is observed for prepared additives (3811) and seamless steel tubes (7304), which display high export values relative to the number of firms involved. Bags and luggage (4202) rank second overall, consistently with the relevance of leather goods identified at the ATECO level, while wine (2204) confirms its role as one of Italy's flagship export products. Valves and similar appliances (8481) represent the most widely diffused product category across firms, suggesting a more fragmented and competitive supply structure in this segment. Men's apparel (6203) and coated paper (4810) complete the ranking, further reflecting the industrial diversity of the sample.

The stability of firms' main export categories over time provides an additional indication of specialization patterns. Across the sample, 42.85% of firms maintain the same main export NC4 category throughout the entire observation period, while 57.15% change their primary product category at least once over the fourteen-year window. At the broader sectoral level, stability is slightly higher: 47.19% of firms retain the same main export ATECO sector over the full period, whereas 52.81% record at least one sectoral reorientation.

The higher instability observed at the product level is consistent with the greater granularity of the NC4 classification. A firm may adjust its main product category

while remaining within the same broader ATECO sector, since changes in the product mix are generally more frequent and less demanding than shifts across sectors. Overall, these figures point to substantial heterogeneity in the stability of firms' productive specialization. This evidence supports the decision to use firm-year-level main export variables, rather than time-invariant firm-level proxies, throughout the empirical analysis.

A further layer of analysis concerns the evolution over time of the most relevant `main_export_sector_do` categories in terms of monetary value. When aggregate trade flows are considered, the manufacture of motor vehicles (29100) consistently emerges as the dominant main export sector throughout the entire observation period, confirming the structural centrality of the automotive industry within the sample.

However, Figures 3.11 and 3.12 provide additional insights once trade flows are disaggregated by direction. In particular, the comparison between exports and imports reveals that the same main export sector may be associated with different trade profiles depending on whether outward sales or inward sourcing flows are considered. This distinction is relevant because it allows the analysis to identify not only the sectors driving firms' export specialization, but also the extent to which these sectors are connected to imported inputs or components.

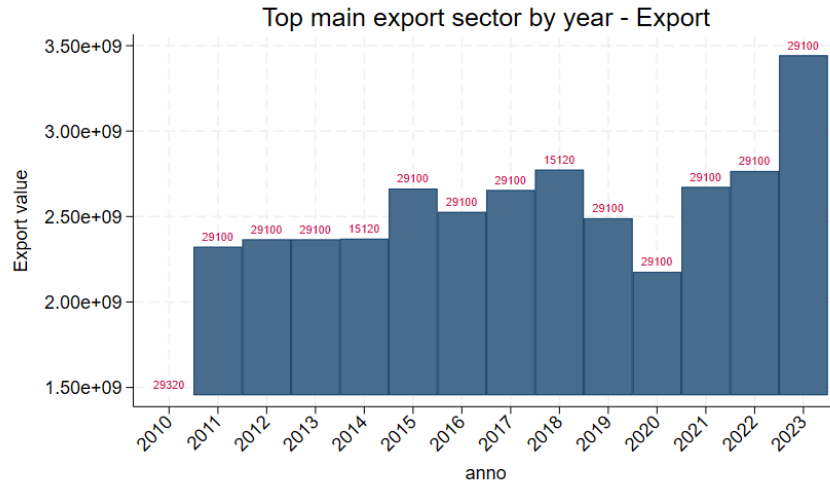


**Figure 3.11:** Top main export sector by exports over time

On the export side, sector 29100 dominates in most years, although not throughout the entire period. In 2010, the leading sector is the manufacture of parts and accessories for motor vehicles (29320), while in 2014 and 2018 leather goods and luggage (15120) record the highest export value among all main export sectors. Overall, export values display a broadly increasing trajectory over the observation

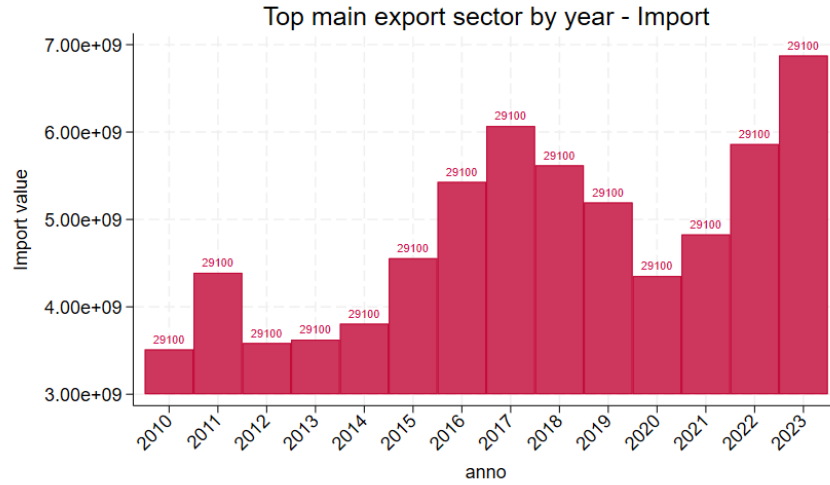


**Figure 3.12:** Top main export sectors by imports over time

window, with a temporary contraction around 2019–2020 and a sharp acceleration in the final years of the period.

On the import side, by contrast, sector 29100 dominates without exception across all fourteen years. Import values associated with the leading sector are also systematically higher than the corresponding export values of the top sector in each year. The import series follows a broadly upward trend as well, although it displays a decline around 2019–2021, followed by a marked increase in 2022–2023.

The same procedure is then replicated at the NC4 product level, as reported in Figures 3.13 and 3.14. This additional level of analysis makes it possible to verify whether the patterns observed at the sectoral level are also reflected in the product composition of trade flows, thereby providing a more granular view of firms' main export specialization and related import activity.

At the NC4 product level, the pattern is more heterogeneous than the one observed using the ATECO sector classification.

On the export side, three product categories alternate in the leading position throughout the observation period: parts and accessories of motor vehicles (8708), goods vehicles and trucks (8704), and bags and luggage (4202). The alternation between automotive-related products and luxury goods is particularly noteworthy. Bags and luggage (4202) rank first between 2013 and 2015 and again in 2018, years in which this category records some of the highest export values observed over the full period. By contrast, 8704 and 8708 dominate the ranking in the remaining years. Overall, export values follow an upward trajectory, with a temporary contraction around 2019–2020 and a sharp increase in 2023, mainly driven by goods vehicles and trucks (8704).

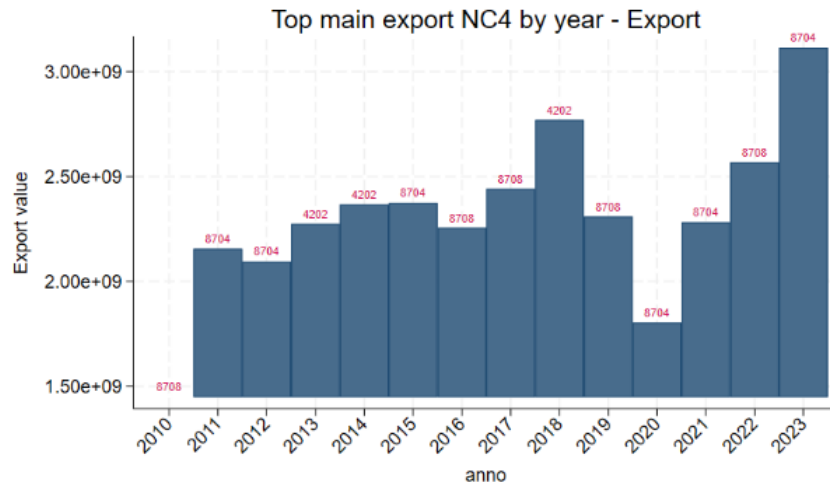


**Figure 3.13:** Top main export NC4 by exports over time

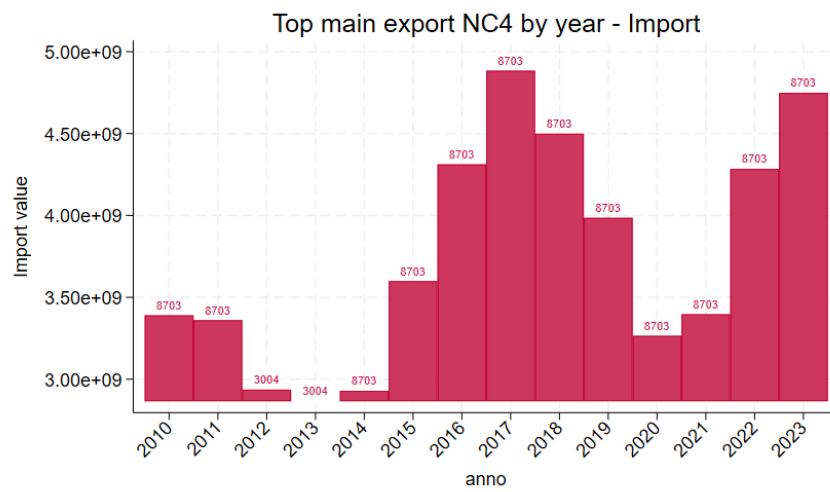


**Figure 3.14:** Top main export NC4 by imports over time

On the import side, passenger motor cars (8703) dominate almost continuously across the observation window, recording consistently high and increasing import values. The only exception occurs in 2012–2013, when medicaments (3004) briefly occupy the first position. This is the only non-automotive product category leading the import ranking over the entire period. From 2014 onwards, import values for 8703 display a strong upward trend, interrupted by a visible decline in 2020 and followed by a recovery culminating in a new peak in 2023.

Compared with the ATECO-level analysis, the NC4 disaggregation reveals greater variability on the export side, where luxury goods alternate with automotive products as leading categories. At the same time, it confirms the persistent dominance of automotive-related products on the import side, suggesting a strong and stable reliance on imported vehicles or automotive components within the trade structure of the sample.

Building on the previous ranking of the top 10 export sectors by total trade value, this section refines the analysis by restricting transactions to each firm’s main export sector and adding a geographic dimension. Rather than capturing all sectoral activity, this approach focuses exclusively on the sector in which each firm concentrates the largest share of its exports, thereby reflecting core productive specialization. For each of the resulting top 10 sectors, the primary import and export country is identified, along with its classification as premium or low-cost. This allows the sectoral ranking to be read not only in terms of trade volumes but also in terms of the geographic and economic profile of the main trading partners.

First, as it’s possible to capture from Table 3.17, nine out of ten sectors source primarily from premium countries, with Germany, France, the Netherlands (NLD), and Spain (ESP) among the most frequent primary import origins. The only exception is sector 14130 (manufacture of other wearing apparel), where the primary import origin is China (CHN), the sole low-cost country appearing among the top 10. This makes sector 14130 the only case in which the primary sourcing partner is a low-cost economy, a finding consistent with the well-documented role of China as a major supplier in the global apparel industry. (Gereffi & Memedovic (2003) — *The Global Apparel Value Chain: What Prospects for Upgrading by Developing Countries*, UNIDO).

Moving to Table 3.18, all ten sectors direct their exports primarily toward premium economies, with no low-cost country appearing as a primary destination in any case. Germany (DEU) is the most recurring destination, appearing in five out of ten sectors, followed by France (FRA) in two sectors, and Switzerland (CHE) and the United States (USA) each appearing once. This concentration toward a small set of Western European and North American markets suggests that firms specialised in their main export sector tend to sell predominantly to high-income economies, regardless of the specific sector considered.

The analysis is then replicated at the product level, shifting from export sectors

| main_evo | iso | countrye | tot_imvt | ateco_np |
|----------|-----|----------|----------|----------|
| 29100    | DEU | premium  | 2.14e+10 | 5.65e+10 |
| 21200    | FRA | premium  | 8.23e+09 | 2.49e+10 |
| 24100    | FRA | premium  | 2.76e+09 | 1.49e+10 |
| 29320    | DEU | premium  | 2.17e+09 | 7.47e+09 |
| 26302    | NLD | premium  | 2.40e+09 | 5.43e+09 |
| 26200    | NLD | premium  | 1.87e+09 | 4.95e+09 |
| 14130    | CHN | lowcost  | 9.23e+08 | 4.84e+09 |
| 20160    | FRA | premium  | 7.74e+08 | 4.61e+09 |
| 10110    | FRA | premium  | 1.28e+09 | 4.56e+09 |
| 10411    | ESP | premium  | 2.89e+09 | 4.47e+09 |

Table 3.17: Ranking of main export sectors by country type and imports

| main_evo | iso | countrye | tot_exvt | ateco_np |
|----------|-----|----------|----------|----------|
| 29100    | DEU | premium  | 4.89e+09 | 2.45e+10 |
| 29320    | DEU | premium  | 5.72e+09 | 2.41e+10 |
| 15120    | CHE | premium  | 4.88e+09 | 1.63e+10 |
| 20160    | DEU | premium  | 2.75e+09 | 1.30e+10 |
| 17120    | DEU | premium  | 1.96e+09 | 1.20e+10 |
| 20594    | FRA | premium  | 1.42e+09 | 1.04e+10 |
| 28250    | DEU | premium  | 1.86e+09 | 1.03e+10 |
| 24201    | USA | premium  | 1.47e+09 | 9.37e+09 |
| 14130    | CHE | premium  | 1.11e+09 | 9.25e+09 |
| 15201    | FRA | premium  | 3.69e+09 | 8.84e+09 |

Table 3.18: Ranking of main export sectors by country type and exports

to main export NC4 codes. For each firm, only transactions corresponding to its main export product are retained, and the primary import and export country is identified for each of the resulting top 10 NC4 products. Compared to the sector-level analysis, this breakdown adds the product type dimension through the BEC5 classification, which distinguishes between intermediate goods (INT), consumer goods (CONS), and capital goods (CAP), allowing the geographic pattern to be read alongside the nature of the goods traded.

Starting from the import side, Table 3.19, all ten products also show a premium country as the primary sourcing origin, with France (FRA) appearing in three cases, the Netherlands (NLD) in two, and Germany (DEU), Spain (ESP), Switzerland (CHE) each appearing once. Intermediate goods (INT) remain the most represented type, appearing in four out of ten products, alongside four consumer goods (CONS)

| main_e~4 | nc4_type | iso | countr~e | tot_im~t | nc4_to~p |
|----------|----------|-----|----------|----------|----------|
| 8703     | CONS     | DEU | premium  | 1.83e+10 | 4.38e+10 |
| 3004     | INT      | FRA | premium  | 7.30e+09 | 1.37e+10 |
| 8708     | INT      | DEU | premium  | 2.17e+09 | 7.45e+09 |
| 8517     | CAP      | NLD | premium  | 2.40e+09 | 5.35e+09 |
| 7219     | INT      | FRA | premium  | 2.58e+09 | 5.34e+09 |
| 1509     | CONS     | ESP | premium  | 2.80e+09 | 4.30e+09 |
| 8471     | CAP      | NLD | premium  | 1.24e+09 | 3.78e+09 |
| 1701     | CONS     | DEU | premium  | 2.05e+09 | 3.56e+09 |
| 4202     | CONS     | CHE | premium  | 6.91e+08 | 3.54e+09 |
| 3811     | INT      | FRA | premium  | 2.04e+09 | 2.98e+09 |

Table 3.19: Ranking of main export NC4 products by country type and imports

| main_e~4 | nc4_type | iso | countr~e | tot_ex~t | nc4_to~p |
|----------|----------|-----|----------|----------|----------|
| 8708     | INT      | DEU | premium  | 5.70e+09 | 2.37e+10 |
| 8704     | CAP      | DEU | premium  | 3.54e+09 | 1.86e+10 |
| 4202     | CONS     | CHE | premium  | 4.87e+09 | 1.62e+10 |
| 3811     | INT      | FRA | premium  | 1.40e+09 | 1.00e+10 |
| 2204     | CONS     | USA | premium  | 1.75e+09 | 9.80e+09 |
| 7304     | INT      | USA | premium  | 1.47e+09 | 9.37e+09 |
| 8481     | INT      | DEU | premium  | 1.22e+09 | 9.06e+09 |
| 4810     | INT      | DEU | premium  | 1.56e+09 | 8.73e+09 |
| 8483     | INT      | USA | premium  | 9.57e+08 | 5.77e+09 |
| 7113     | CONS     | USA | premium  | 8.88e+08 | 5.77e+09 |

Table 3.20: Ranking of main export NC4 products by country type and exports

and two capital goods (CAP). Notably, no low-cost country appears as a primary import origin for any of the top 10 NC4 products, which contrasts with the sector-level analysis where China emerged as the primary import origin for the apparel sector.

Moving to Table 3.20, it reports, for each of the top 10 main export NC4 products, the primary destination country along with its premium/low-cost classification, the export value toward that country, and the total export value across all destinations. Intermediate goods (INT) are the most represented product type, appearing in six out of ten products, followed by consumer goods (CONS) in three cases and capital goods (CAP) in one. All ten products show a premium country as the primary export destination, with the United States (USA) appearing in four cases, Germany (DEU) in three, Switzerland (CHE) and France (FRA) in one each. No low-cost country appears as a primary export destination for any of the top 10 NC4 products, confirming the pattern already observed at the sector level.

## Chapter 4

# Measuring Offshoring

### 4.1 From the Literature Gap to a Transaction-Based Measure

A limitation emerging from the existing literature concerns the empirical identification of offshoring and reshoring at the firm level. Previous contributions have often relied on survey-based evidence, aggregate trade indicators, input-output tables, or measures based on imported intermediates within the firm's industry [15, 38, 22, 25]. While these approaches have provided important insights into the international fragmentation of production and the reversal of previous relocation decisions, they do not always allow the researcher to observe whether a firm is simultaneously importing and exporting within the same product or sectoral domain. This is a relevant limitation, because offshoring is not only a matter of importing from abroad, but rather of organising production across countries in a way that connects foreign sourcing with the firm's own export activity.

Against this background, the present thesis contributes to the empirical discussion by developing a binary transaction-based measure of offshoring built directly from firm-level import and export flows. Instead of identifying offshoring only from the presence of imports, the measure requires the simultaneous occurrence of positive imports and positive exports within the firm's main export domain. This logic is implemented both at the NC4 product level and at the ATECO sectoral level, allowing the analysis to capture whether the firm imports goods that are coherent with the product or sector in which it mainly competes internationally. The same transaction-based framework then provides the foundation for the reshoring indicator, which is defined as a subsequent reduction in imports within the relevant main export category, conditional on prior offshoring and net of pure country-switching episodes. In this way, the empirical strategy explicitly links the measurement of offshoring and reshoring to observable commercial transactions,

reducing the distance between the theoretical concept of international production fragmentation and its operational implementation in the dataset.

The construction of both measures is described in detail in the following sections, which also presents the persistence measures and trajectory classifications that form the basis of the empirical analysis.

## 4.2 Offshoring Measurement and Variables

Before turning to the analysis of reshoring, a necessary step consists in defining a firm-level measure of offshoring. This is not simply a preliminary exercise, but a conceptual prerequisite for the analysis of reshoring itself. Indeed, the reversal or reconfiguration of international sourcing activities can only be meaningfully studied among firms that have previously engaged in some form of offshoring.

The identification of offshoring is therefore essential to determine whether, and to what extent, a firm participates in international production fragmentation. Moreover, the characteristics of a firm's offshoring trajectory — including its intensity, duration, and stability over time — are likely to influence the nature and timing of any subsequent reallocation of sourcing activity. In this sense, reshoring should be interpreted not as an isolated event, but as a potential evolution of a prior offshoring pattern.

The approach adopted in this thesis identifies offshoring through the simultaneous presence of import and export activity within the same sector or product category. This follows the logic of narrow offshoring measures developed in the literature, according to which imported inputs are considered more closely related to the firm's production activity when they belong to the same sector or product category as the firm's output.

The construction of the offshoring measure follows a multi-step procedure. The analysis first identifies each firm's main area of export specialization at the firm-year level and then evaluates whether imports occur within that same reference category. This procedure is implemented separately using both the ATECO-based sectoral classification and the NC4 product classification. The resulting measures are then used to classify firms' offshoring behaviour over the full observation period, with particular attention to the persistence and stability of their offshoring trajectories.

**Step 1 – Identification of the main export sector and product.** As discussed in the previous section, for each firm-year observation the main export sector is defined as the ATECO 2007 code associated with the highest total export value in that year. An analogous procedure is applied at the product level to identify the main export NC4 category, namely the 4-digit product code generating the largest export value for the firm in a given year. Both variables are computed

directly from the transaction-level dataset and subsequently merged into the firm-year panel.

**Step 2 – Construction of binary offshoring indicators.** Once the main export sector and main export product category have been identified, binary offshoring indicators are constructed at the firm-year level. This procedure is implemented separately using the ATECO sector classification and the NC4 product classification.

The main offshoring indicator, `offshoring_1`, takes the value of one when a firm records both strictly positive imports and strictly positive exports within its main export sector or main export NC4 category in a given year. Conversely, it takes the value of zero when this condition is not satisfied. The simultaneous presence of import and export activity within the same reference category is interpreted as evidence of vertical production fragmentation. In this framework, a firm that both sources from abroad and exports within the same sector or product category is considered to be engaged in an international division of labour related to its core area of activity.

As an additional sensitivity check, a broader specification is also constructed. This alternative indicator, `offshoring_2`, is based only on the presence of strictly positive imports within the firm's main export sector or main export NC4 category, regardless of whether exports in the same category are simultaneously observed. This second measure captures a less restrictive notion of offshoring and is used to assess the robustness of the results to alternative definitions of international sourcing activity.

Formally, `offshoring_1` is defined as follows:

$$\text{offshoring\_1\_ateco}_{i,t} = \mathbf{1} \left[ \begin{array}{l} \text{tot\_export\_v\_mainexpsec}_{i,t} > 0 \\ \cap \text{tot\_import\_v\_mainexpsec}_{i,t} > 0 \end{array} \right], \quad (4.1)$$

$$\text{offshoring\_1\_NC4}_{i,t} = \mathbf{1} \left[ \begin{array}{l} \text{tot\_export\_v\_mainexpNC4}_{i,t} > 0 \\ \cap \text{tot\_import\_v\_mainexpNC4}_{i,t} > 0 \end{array} \right]. \quad (4.2)$$

where  $i$  identifies the firm and  $t$  identifies the year.

**Step 3 – Offshoring intensity.** Beyond the binary classification, a continuous measure of offshoring intensity is constructed to capture the relative magnitude of foreign sourcing within the firm's main area of activity. For each firm-year observation, offshoring intensity is defined as the ratio between total imports and total exports in the relevant main category, conditional on both values being strictly positive.

This measure is computed separately at the ATECO and NC4 levels. Formally, for firm (i) in year (t), offshoring intensity is defined as:

$$\text{offshoring\_intensity\_NC4}_{i,t} = \frac{\text{tot\_import\_v\_mainexpNC4}_{i,t}}{\text{tot\_export\_v\_mainexpNC4}_{i,t}}, \quad (4.3)$$

$$\text{if offshoring\_1\_NC4}_{i,t} = 1, \quad (4.4)$$

$$\text{offshoring\_intensity\_ateco}_{i,t} = \frac{\text{tot\_import\_v\_mainexpsec}_{i,t}}{\text{tot\_export\_v\_mainexpsec}_{i,t}}, \quad (4.5)$$

$$\text{if offshoring\_1\_ateco}_{i,t} = 1. \quad (4.6)$$

This variable captures the depth of international sourcing relative to the firm's core export activity. An offshoring intensity value greater than one indicates that the firm imports more than it exports within its main product category or main export sector, suggesting a predominantly sourcing-oriented position in that category. By contrast, values below one indicate that exports exceed imports, pointing to a more export-driven trade profile. Values close to one suggest a relatively balanced relationship between foreign sourcing and export activity within the firm's main area of specialization.

**Step 4 – Persistence measures.** In addition to identifying whether a firm is engaged in offshoring in a given year, it is necessary to examine how this behaviour evolves over the full fourteen-year observation period. A year-by-year binary indicator provides useful information on the presence of offshoring at a specific point in time, but it does not capture the persistence, continuity, or volatility of the firm's international sourcing strategy.

To characterize the temporal pattern of offshoring beyond single-year observations, three persistence measures are computed for each firm over the full observation window. The first variable is the total number of offshoring years, which counts the number of years in which the binary offshoring indicator is equal to one. This measure captures the overall frequency with which a firm is classified as an offshorer during the period.

The second variable is the maximum offshoring spell, defined as the length of the longest consecutive sequence of years in which the offshoring indicator remains continuously equal to one. A longer maximum spell indicates a more sustained and uninterrupted engagement in international production fragmentation.

The third variable is the number of switches between offshoring and non-offshoring status. This measure captures how frequently a firm enters and exits offshoring over time, thereby providing an indication of the stability or volatility of its international sourcing behaviour.

All three measures are constructed separately for both the ATECO-based and NC4-based specifications. In particular, the following variables are generated:

- total offshoring years: `tot_anni_offshoring_1_NC4`  
`tot_anni_offshoring_1_ateco`;
- maximum offshoring spell: `max_offshoring_spell_1_NC4`  
`max_offshoring_spell_1_ateco`;
- number of switches: `n_switch_offshoring_1_NC4`  
`n_switch_offshoring_1_ateco`.

**Step 5 – Firm classification.** On the basis of the persistence measures described above, firms are ultimately assigned to five offshoring trajectory categories. This classification is based on the combination of the total number of offshoring years, captured by the variable `tot_anni_offshoring`, and two additional composite indices constructed from the previously defined persistence variables.

The first composite index is the share of offshoring years, which measures the proportion of observed years in which a firm is classified as an offshorer. This variable, denoted as `share_off_years`, is defined as follows:

$$\text{share\_off\_years}_i = \frac{\text{tot\_anni\_offshoring}_i}{\text{num\_anni\_oss\_perfirm}_i} \quad (4.7)$$

The index is computed separately for the ATECO-based and NC4-based offshoring measures, in order to capture persistence both at the sectoral and product levels. The higher the value of `share_off_years`, the more persistent and structurally embedded the firm's offshoring activity is over the observation period. Conversely, lower values indicate a more occasional or sporadic engagement in international production fragmentation.

Alongside the share of offshoring years, a stability index is constructed to capture the continuity of a firm's offshoring behaviour over time. While `share_off_years` measures how frequently a firm engages in offshoring during the observation period, the stability index provides additional information on whether this activity is concentrated in uninterrupted spells or characterized by frequent entry and exit.

The index is defined as a composite measure combining two dimensions: the length of the longest offshoring spell and the number of switches between offshoring and non-offshoring status. Formally, the stability index is defined as:

$$\text{stability}_i = \left[ \frac{1}{1 + \text{n\_switches}_i} \right] \times \left[ \frac{\text{max\_spell}_i}{\text{tot\_years\_offshoring}_i} \right] \quad (4.8)$$

The stability index is constructed to capture two conceptually distinct but complementary dimensions of offshoring continuity, each normalised to the unit interval, whose product defines the overall degree of structural engagement in international production fragmentation. Generally speaking, this index is high when transitions are infrequent and spells are long, and low otherwise. In other words, the closer to 1 it is, the more stable is the firm commitment and presence in offshoring activities. Let's analyse both of them separately, explaining what they are and how they affect the overall product.

**First term:**  $1/(1 + n\_switches)$ . The first component addresses the frequency of regime transitions — the number of times a firm switches between offshoring and non-offshoring status over the observation window. The functional form  $1/(1 + n\_switch)$  is chosen to satisfy four desiderata simultaneously. First, it attains its maximum value of one when  $n\_switch = 0$ , that is, when the firm never changes its offshoring status — the case of perfect regime continuity. Second, it decreases monotonically as the number of transitions increases, reflecting the intuition that each additional switch reduces the degree of structural commitment to international sourcing. Third, it remains strictly positive for any finite number of transitions, acknowledging that even a frequently switching firm retains some residual degree of stability. Fourth, the addition of one to the denominator ensures normalisation at the optimum and avoids division by zero. This form is the simplest strictly decreasing, bounded, and always-positive function of  $n\_switch$  that achieves a maximum of exactly one.

**Second term:**  $max\_spell/tot\_years\_offshoring$ . The second component captures the concentration of offshoring years within a single sustained episode. The ratio of the maximum consecutive offshoring spell to the total number of offshoring years measures what proportion of a firm's entire offshoring history is explained by its longest uninterrupted period of activity. The term attains its maximum value of one when all offshoring years form a single consecutive block — the case in which the firm engages in offshoring continuously without interruption for the entirety of its active period. As offshoring becomes fragmented across multiple shorter spells, the maximum spell shrinks relative to the total, driving the ratio toward zero. The term is bounded between zero and one by construction, since the maximum spell cannot exceed the total number of offshoring years.

**The multiplicative structure.** The two components are combined multiplicatively. The product imposes a joint requirement: both dimensions must simultaneously be high for the index to be high. A weakness in either dimension directly and proportionally penalises the overall index, regardless of the strength of the other. This reflects the underlying economic logic that structural offshoring requires both

continuity across time and the absence of frequent interruptions — satisfying only one condition is insufficient to characterise a firm as a stable international producer.

These reasonings were aimed at determining the conditions that have been used to categorize the firms in our dataset into five groups, which depict the firms' behaviour towards offshoring in a spectrum going from never been involved in these activities to deeply and regularly belonging to an international supply chain.

The five trajectory types are defined as follows.

| Category                       | Total years | Share | Stability  |
|--------------------------------|-------------|-------|------------|
| Never offshorers               | 0           | –     | –          |
| Spot offshorers                | 1           | –     | –          |
| Persistent stable offshorers   | –           | > 50% | > 0.5      |
| Persistent unstable offshorers | –           | > 50% | $\leq 0.5$ |
| Occasional offshorers          | > 1         | < 50% | –          |

**Table 4.1:** Definition of offshoring trajectory categories

To clarify, it is important to underline that this classification has been carried out both at ateco and NC4 level.

To comprehend the different classes a firm can fall into better, it is possible to affirm that:

Never offshorers (type 0) are firms with zero offshoring years throughout the entire observation window. These firms never simultaneously record positive imports and exports in their main product category in any year, and therefore exhibit no evidence of vertical production fragmentation at any point.

Spot offshorers (type 1) satisfy the offshoring condition in exactly one year. By construction, their stability index is undefined or degenerate — a single year cannot produce a meaningful spell or transition pattern — and their share of offshoring years is  $1/14$ , well below any reasonable threshold. These firms are best interpreted as having engaged in a one-off, transitory sourcing episode rather than in a structural reorganisation of production, and are treated separately from both never-offshorers and recurrent offshorers.

Persistent stable offshorers (type 2) satisfy both  $\text{share\_off\_years} \geq 0.50$  and  $\text{stability} \geq 0.50$ . The first condition ensures that the firm offshores in at least half of the observed years, capturing a high overall intensity of engagement. The second condition — requiring a stability index above 0.50 — implies that the firm's offshoring activity is characterised by few regime transitions and a high concentration of active years within a single prolonged spell. Together, these conditions identify firms for which offshoring represents a genuine structural feature of their production model rather than a cyclical or opportunistic response.

Persistent unstable offshorers (type 3) also satisfy  $\text{share\_off\_years} \geq 0.50$  but

fail to meet the stability threshold (stability  $< 0.50$ ). These firms offshore frequently — in terms of the share of years — but their activity is characterised by repeated entries and exits, short maximum spells relative to total offshoring years, or both. The combination of high intensity and low stability points to a pattern of recurrent but structurally fragile international sourcing, possibly reflecting sensitivity to external shocks, volatile input costs, or unstable supply relationships.

Occasional offshorers (type 4) record more than one offshoring year but a share of offshoring years below 0.50. These firms have engaged in offshoring on multiple occasions but for less than half of the observation period, suggesting a sporadic rather than structural orientation. Unlike spot offshorers, they have sufficient activity for the stability index to be meaningful, but their overall intensity is too low for them to be classified as persistent.

Once the categories have been determined, there are some descriptive statistics that can be carried out in order to understand whether some relevant considerations can be deduced by them.

First, Tables 4.2 and 4.3 report the distribution of firms across the five offshoring trajectory categories, computed separately at the NC4 product level and at the ATECO sector level.

| <code>firm_off_type_NC4_new</code> | Freq. | Percent | Cum.   |
|------------------------------------|-------|---------|--------|
| Never offshorer NC4                | 596   | 13.06   | 13.06  |
| Spot offshorer NC4                 | 388   | 8.50    | 21.56  |
| Persistent stable offshorer NC4    | 1,354 | 29.66   | 51.22  |
| Persistent unstable offshorer NC4  | 1,165 | 25.52   | 76.74  |
| Occasional offshorer NC4           | 1,062 | 23.26   | 100.00 |
| Total                              | 4,565 | 100.00  |        |

**Table 4.2:** Offshoring categories by main export NC4

| <code>firm_off_type_ateco_new</code> | Freq. | Percent | Cum.   |
|--------------------------------------|-------|---------|--------|
| Never offshorer ateco                | 556   | 12.18   | 12.18  |
| Spot offshorer ateco                 | 329   | 7.21    | 19.39  |
| Persistent stable offshorer ateco    | 1,526 | 33.43   | 52.81  |
| Persistent unstable offshorer ateco  | 1,179 | 25.83   | 78.64  |
| Occasional offshorer ateco           | 975   | 21.36   | 100.00 |
| Total                                | 4,565 | 100.00  |        |

**Table 4.3:** Offshoring trajectories by main export ATECO

The first notable finding is that offshoring is a widespread phenomenon in the

sample: the vast majority of Italian manufacturing firms engage in some form of international production fragmentation at least once over the observation period, with never-offshorers representing only around 13% of the sample under both specifications. Among firms that do offshore, persistent engagement — whether stable or unstable — is the modal pattern, accounting for over half the sample at both aggregation levels, suggesting that offshoring for most firms reflects a structural rather than opportunistic sourcing orientation. The occasional offshoring group — roughly one in five firms — points to a more selective relationship with international sourcing, while spot offshorers represent a small residual of firms with a single, isolated episode. Notably, the relative size of the five categories follows an identical ranking across both aggregation levels: persistent stable, persistent unstable, occasional, never and spot, in the same order, indicating that the aggregate structure of offshoring behaviour in the sample is robust to the choice of measurement level.

Moving to another field of analysis, given that we classified the firms both at ateco and NC4 level, it has been interesting to check whether the two classifications provided different results, meaning that a firm falling into a certain category for ateco differed to what it fell into for NC4. Therefore, Table 4.4 presents the cross-tabulation of the two classifications, allowing an assessment of their degree of concordance.

| firm_off_type_NC4_new | firm_off_type_ateco_new |              |                |                |              | Total           |
|-----------------------|-------------------------|--------------|----------------|----------------|--------------|-----------------|
|                       | Never off               | Spot offs    | Persisten      | Persisten      | Occasiona    |                 |
| Never offshorer NC4   | 516<br>86.58            | 39<br>6.54   | 7<br>1.17      | 8<br>1.34      | 26<br>4.36   | 596<br>100.00   |
| Spot offshorer NC4    | 23<br>5.93              | 258<br>66.49 | 10<br>2.58     | 11<br>2.84     | 86<br>22.16  | 388<br>100.00   |
| Persistent stable off | 6<br>0.44               | 4<br>0.30    | 1,266<br>93.50 | 62<br>4.58     | 16<br>1.18   | 1,354<br>100.00 |
| Persistent unstable o | 2<br>0.17               | 3<br>0.26    | 191<br>16.39   | 927<br>79.57   | 42<br>3.61   | 1,165<br>100.00 |
| Occasional offshorer  | 9<br>0.85               | 25<br>2.35   | 52<br>4.90     | 171<br>16.10   | 805<br>75.80 | 1,062<br>100.00 |
| Total                 | 556<br>12.18            | 329<br>7.21  | 1,526<br>33.43 | 1,179<br>25.83 | 975<br>21.36 | 4,565<br>100.00 |

**Table 4.4:** Offshoring trajectories by main NC4 and main ATECO

What stands out from this table is that the two classifications show strong concordance at the individual firm level, with the diagonal dominating in every row. The main source of divergence concerns firms at the margins of offshoring activity, particularly spot offshorers at NC4 level, a portion of whom are reclassified as occasional at the broader ATECO level — consistent with the expectation that

a firm active in only one product-year may still record multi-year activity at the sector level. Overall, this invariance in both the individual classification and the aggregate distribution provides strong evidence that the taxonomy captures a genuine underlying structure in firms' offshoring behaviour. The NC4 measure is retained as the baseline throughout the analysis given its greater granularity, with the ATECO classification serving as a robustness check.

Additionally, the following tables characterise the internal structure of each offshoring trajectory category by reporting the distribution of the five persistence measures — total offshoring years, maximum offshoring spell, number of transitions, share of offshoring years, and stability index — across the five groups identified in the classification. For a better visualization of the data, the descriptives have been splitted. The analysis is conducted separately at the NC4 product level and at the ATECO sector level. Since the categories are defined on the basis of these same variables, the descriptive statistics reported here do not serve to validate the classification itself but rather to quantify the degree of within-group heterogeneity and to characterise the typical profile of each trajectory type in terms of the underlying dimensions of offshoring continuity.

Starting with NC4-level descriptive, Tables 4.5 and 4.6 below help us highlighting that the internal distributions confirm that the five categories capture genuinely distinct behavioural profiles rather than arbitrary partitions of a continuous spectrum.

Table 4.5 reports the distribution of three absolute persistence measures within each offshoring trajectory category: the total number of years of offshoring, the maximum consecutive offshoring spell, and the number of transitions between offshoring and non-offshoring status.

Never-offshorers record zero values across all three measures by construction. Spot offshorers are equally uniform in the first two variables — exactly one offshoring year and one maximum spell of length one by definition — with the only variation arising in the number of transitions, which ranges between one and two depending on whether the single episode falls at the boundary or interior of the observation window. Persistent stable offshorers stand out for the near-coincidence of total offshoring years and maximum spell length: the median firm offshores in all fourteen years without interruption, and the number of transitions is close to zero for most firms in this group. Persistent unstable offshorers record a comparable number of total offshoring years but a substantially shorter maximum spell and a much higher number of transitions — averaging nearly four — indicating repeated and fragmented engagement with international sourcing. Occasional offshorers record few active years overall, yet their number of transitions is similar in absolute magnitude to that of persistent unstable offshorers, suggesting that even their limited offshoring activity is discontinuous rather than concentrated in a single coherent episode.

| firm_off_type_NC4_new | Mean     | p50 | Min | Max | N     |
|-----------------------|----------|-----|-----|-----|-------|
| Never offshorer NC4   | 0        | 0   | 0   | 0   | 8344  |
|                       | 0        | 0   | 0   | 0   | 8344  |
|                       | 0        | 0   | 0   | 0   | 8344  |
| Spot offshorer NC4    | 1        | 1   | 1   | 1   | 5432  |
|                       | 1        | 1   | 1   | 1   | 5432  |
|                       | 1.824742 | 2   | 1   | 2   | 5432  |
| Persistent stable off | 13.23191 | 14  | 7   | 14  | 18956 |
|                       | 13.23191 | 14  | 7   | 14  | 18956 |
|                       | .2245199 | 0   | 0   | 1   | 18956 |
| Persistent unstable o | 10.08498 | 10  | 7   | 13  | 16310 |
|                       | 7.008584 | 7   | 2   | 12  | 16310 |
|                       | 3.832618 | 3   | 2   | 10  | 16310 |
| Occasional offshorer  | 3.781544 | 4   | 2   | 6   | 14868 |
|                       | 2.385122 | 2   | 1   | 6   | 14868 |
|                       | 3.943503 | 4   | 1   | 9   | 14868 |
| Total                 | 7.463089 | 8   | 0   | 14  | 63910 |
|                       | 6.353122 | 5   | 0   | 14  | 63910 |
|                       | 2.117196 | 2   | 0   | 10  | 63910 |

**Table 4.5:** Descriptive statistics of offshoring trajectories by main NC4

Table 4.6 reports the two normalised persistence measures: the share of offshoring years over the full observation window (`share_off_years_NC4`) and the stability index (`stability_NC4`). While table 24 described the absolute dimensions of offshoring activity, these indices capture its relative intensity and structural consistency. The stability index is undefined for never-offshorers, who record a missing value in the second row of that category.

The share of offshoring years is mechanically fixed at one fourteenth for spot offshorers, reflecting their single active year. Persistent stable offshorers record the highest values of both indices: the median share equals one — meaning the typical firm in this group offshores in every observed year — and the stability index clusters tightly near one, confirming that this category identifies firms for which offshoring is a permanent and uninterrupted feature of their production model. Persistent unstable offshorers present the sharpest contrast: despite a high share of offshoring years — well above the 0.50 threshold — their stability index is consistently low, tightly distributed below 0.35, reflecting the chronic fragmentation of their activity despite its overall frequency. Occasional offshorers record both a low share and a low stability index, similar in magnitude to persistent unstable offshorers on the latter dimension but with a fundamentally different profile: their limited engagement is spread across few years that are themselves discontinuous, pointing to a sporadic and structurally weak relationship with international sourcing.

| firm_off_type_NC4_new | Mean                 | p50                  | Min                  | Max                  | N              |
|-----------------------|----------------------|----------------------|----------------------|----------------------|----------------|
| Never offshorer NC4   | 0<br>.               | 0<br>.               | 0<br>.               | 0<br>.               | 8344<br>0      |
| Spot offshorer NC4    | .0714286<br>.362543  | .0714286<br>.3333333 | .0714286<br>.3333333 | .0714286<br>.5       | 5432<br>5432   |
| Persistent stable off | .9451361<br>.88774   | 1<br>1               | .5<br>.5             | 1<br>1               | 18956<br>18956 |
| Persistent unstable o | .7203556<br>.1684374 | .7142857<br>.16      | .5<br>.0227273       | .9285714<br>.3333333 | 16310<br>16310 |
| Occasional offshorer  | .2701103<br>.1669796 | .2857143<br>.125     | .1428571<br>.02      | .4285714<br>.5       | 14868<br>14868 |
| Total                 | .5330778<br>.4324083 | .5714286<br>.3333333 | 0<br>.02             | 1<br>1               | 63910<br>55566 |

**Table 4.6:** Descriptive statistics of persistence measures by main NC4

Moving to ATECO-level standpoint, The ATECO-level results mirror the NC4 patterns with remarkable precision across all categories. Persistent stable offshorers record an equally high share of offshoring years and a stability index clustered near one, persistent unstable offshorers maintain the same combination of high share and low stability, and occasional offshorers show similarly low values on both dimensions. The numerical differences between the two specifications are minimal throughout — typically within one or two percentage points — and the qualitative interpretation of each category remains unchanged. This close alignment further confirms that the taxonomy is robust to the choice of aggregation level and that the behavioural profiles identified at the product level are not artefacts of the NC4 granularity but genuine structural features of the firms in the sample.

Table 4.7 reports the median offshoring intensity — defined as the ratio of imports to exports in the main NC4 in years of active offshoring — across the four categories for which the measure is defined.<sup>1</sup>

The results reveal a clear and monotonic relationship between the structural depth of offshoring and its intensity. Persistent stable offshorers record the highest median intensity, indicating that firms which offshore continuously and consistently also source internationally in proportionally larger volumes relative to their export activity. Persistent unstable offshorers show a substantially lower median intensity despite a comparable number of active years, suggesting that the fragmented nature

<sup>1</sup>The mean is heavily influenced by extreme values arising when export volumes in the main NC4 are close to zero, producing very large ratios. The variable is winsorized at the 99th percentile and the median is used as the preferred measure of central tendency throughout.

of their engagement reflects not only temporal discontinuity but also a shallower sourcing orientation. Occasional and spot offshorers record the lowest intensity values, consistent with the interpretation that their limited offshoring episodes involve relatively modest import volumes and do not represent a deep restructuring of the production process. Taken together, these findings suggest that the temporal and quantitative dimensions of offshoring are positively correlated — firms that offshore more persistently also tend to offshore more intensively — reinforcing the economic relevance of the trajectory classification constructed in Section 4.2.

| firm_off_type_NC4_new | Mean     | p50      | SD       | N     |
|-----------------------|----------|----------|----------|-------|
| Never offshorer NC4   | .        | .        | .        | 0     |
| Spot offshorer NC4    | 24.38789 | .0355746 | 89.98877 | 388   |
| Persistent stable off | 7.520229 | .3123337 | 39.88551 | 17916 |
| Persistent unstable o | 20.25621 | .1242237 | 75.32087 | 11749 |
| Occasional offshorer  | 23.04924 | .0607493 | 83.82929 | 4016  |
| Total                 | 13.93498 | .2161239 | 61.31526 | 34069 |

**Table 4.7:** Offshoring intensity across offshoring categories by main NC4

Having characterised the offshoring trajectory categories in terms of their temporal persistence and internal structure, it is natural to ask which productive sectors and products lie under each pattern of international sourcing. The trajectory classification identifies how firms offshore — continuously, intermittently, sporadically or not at all — but does not reveal the industrial context in which this behaviour occurs. Connecting the trajectory analysis to the sectoral dimension is important because it allows an assessment of whether the patterns documented earlier in this chapter — where the automotive industry and the fashion and luxury goods cluster emerged as the dominant sectors by trade value — are uniformly distributed across offshoring profiles or rather concentrated in specific trajectory types. The following Tables 4.8 and 4.9 report the top five sectors and products by import value within each trajectory category, providing a value-weighted characterisation of the productive specialisation of each offshoring profile. Import value has been used as the ranking criterion rather than total trade volume because offshoring is fundamentally a sourcing phenomenon.

Among persistent stable offshorers, motor vehicle manufacturing (29100) ranks first by a large margin, confirming the automotive sector as the primary locus of structural international sourcing in the sample. Basic steel (24100) and pharmaceuticals (21200) follow, pointing to industries characterised by deep dependence on imported inputs, alongside motor vehicle parts (29320) and plastics (20160). Persistent unstable offshorers show a similar top-two structure — automotive and pharmaceuticals — but at considerably lower import values, with telecom equipment (26302) and outerwear (14130) completing a more heterogeneous group.

| <b>firm_off_type_ateco_new</b>      | <b>main_e~o</b> | <b>imp_val</b> |
|-------------------------------------|-----------------|----------------|
| Never offshorer ateco               | 19201           | 2.05e+09       |
| Never offshorer ateco               | 21200           | 1.03e+09       |
| Never offshorer ateco               | 01111           | 4.85e+08       |
| Never offshorer ateco               | 10110           | 3.07e+08       |
| Never offshorer ateco               | 10130           | 2.32e+08       |
| Spot offshorer ateco                | 10110           | 2.42e+08       |
| Spot offshorer ateco                | 24100           | 1.58e+08       |
| Spot offshorer ateco                | 11050           | 8.32e+07       |
| Spot offshorer ateco                | 01111           | 7.42e+07       |
| Spot offshorer ateco                | 21200           | 6.00e+07       |
| Persistent stable offshorer ateco   | 29100           | 3.60e+10       |
| Persistent stable offshorer ateco   | 24100           | 1.25e+10       |
| Persistent stable offshorer ateco   | 21200           | 1.25e+10       |
| Persistent stable offshorer ateco   | 29320           | 6.69e+09       |
| Persistent stable offshorer ateco   | 20160           | 4.69e+09       |
| Persistent unstable offshorer ateco | 29100           | 1.35e+10       |
| Persistent unstable offshorer ateco | 21200           | 7.74e+09       |
| Persistent unstable offshorer ateco | 24100           | 2.42e+09       |
| Persistent unstable offshorer ateco | 26302           | 2.10e+09       |
| Persistent unstable offshorer ateco | 14130           | 1.73e+09       |
| Occasional offshorer ateco          | 21200           | 2.03e+09       |
| Occasional offshorer ateco          | 10512           | 8.07e+08       |
| Occasional offshorer ateco          | 10412           | 4.20e+08       |
| Occasional offshorer ateco          | 22111           | 3.47e+08       |
| Occasional offshorer ateco          | 24100           | 3.14e+08       |

**Table 4.8:** Top five main export sectors by total imports across offshoring categories

Never-offshorers and spot offshorers are dominated by petroleum products (19201), pharmaceuticals, agri-food processing and grain farming — sectors that import raw materials or finished goods but without the structural international sourcing relationship that characterises persistent offshoring. Pharmaceuticals (21200) is the only sector appearing across all five categories, reflecting its cross-cutting role in the sample regardless of offshoring trajectory.

At the product level, passenger cars (8703) lead persistent stable offshorers by import value, followed by pharmaceuticals (3004), motor vehicle parts (8708), stainless steel (7219) and olive oil (1509) — a combination of automotive, chemical and agri-food inputs that reflects the breadth of structural sourcing activity in this group. Persistent unstable offshorers also place passenger cars at the top, but at roughly one seventh of the import value recorded for persistent stable firms; smartphones and telecom equipment (8517), railway vehicle components (8607) and pharmaceuticals complete the group, suggesting a more technology-intensive but structurally weaker sourcing orientation. Never-offshorers and spot offshorers are

| <b>firm_off_type_NC4_new</b>      | <b>main_e~4</b> | <b>imp_val</b> |
|-----------------------------------|-----------------|----------------|
| Never offshorer NC4               | 2711            | 1.99e+09       |
| Never offshorer NC4               | 3004            | 9.76e+08       |
| Never offshorer NC4               | 7210            | 1.56e+08       |
| Never offshorer NC4               | 0201            | 9.38e+07       |
| Never offshorer NC4               | 0210            | 9.09e+07       |
| Spot offshorer NC4                | 3004            | 1.62e+09       |
| Spot offshorer NC4                | 0201            | 7.72e+07       |
| Spot offshorer NC4                | 7606            | 7.19e+07       |
| Spot offshorer NC4                | 0305            | 6.44e+07       |
| Spot offshorer NC4                | 0102            | 6.32e+07       |
| Persistent stable offshorer NC4   | 8703            | 1.71e+10       |
| Persistent stable offshorer NC4   | 3004            | 1.03e+10       |
| Persistent stable offshorer NC4   | 8708            | 6.96e+09       |
| Persistent stable offshorer NC4   | 7219            | 5.07e+09       |
| Persistent stable offshorer NC4   | 1509            | 4.37e+09       |
| Persistent unstable offshorer NC4 | 8703            | 1.49e+10       |
| Persistent unstable offshorer NC4 | 8517            | 2.06e+09       |
| Persistent unstable offshorer NC4 | 8607            | 1.81e+09       |
| Persistent unstable offshorer NC4 | 8901            | 1.44e+09       |
| Persistent unstable offshorer NC4 | 3004            | 1.43e+09       |
| Occasional offshorer NC4          | 0405            | 7.69e+08       |
| Occasional offshorer NC4          | 3004            | 6.91e+08       |
| Occasional offshorer NC4          | 8542            | 4.43e+08       |
| Occasional offshorer NC4          | 4011            | 4.23e+08       |
| Occasional offshorer NC4          | 9503            | 3.84e+08       |

**Table 4.9:** Top five main export NC4 products by total imports across offshoring categories

characterised by petroleum gases (2711), pharmaceuticals, beef (0201), fish (0305) and dairy (0405) — agri-food and raw material imports with no connection to the international production fragmentation that defines offshoring. As at the ATECO level, pharmaceuticals (3004) is the only product appearing in every category, confirming its structural independence from any single offshoring trajectory type.

Having characterised the overall distribution of offshoring trajectory categories in the sample, this section examines the relationship between offshoring behaviour and the end-use classification of the firm's main export product. The product type — whether a firm's core export activity involves intermediate, consumer or capital goods — may be systematically associated with different offshoring patterns, as the economic incentives and constraints underlying international production fragmentation differ substantially across these categories. Intermediate goods, being inputs into further production processes, are generally the most amenable to cross-border fragmentation; capital goods involve longer-term asset commitments

and higher switching costs; while consumer goods, particularly in the Italian manufacturing context, may derive part of their commercial value from domestic production. Table 4.10 reports the distribution of firm-year observations across offshoring trajectory categories, disaggregated by product type.

| main_export_NC4_type | firm_off_type_NC4_new |                    |                                 |                                   |                          | Total  |
|----------------------|-----------------------|--------------------|---------------------------------|-----------------------------------|--------------------------|--------|
|                      | Never offshorer NC4   | Spot offshorer NC4 | Persistent stable offshorer NC4 | Persistent unstable offshorer NC4 | Occasional offshorer NC4 |        |
| CAP                  | 1,179                 | 870                | 3,142                           | 3,295                             | 2,703                    | 11,189 |
| CONS                 | 3,231                 | 1,696              | 5,554                           | 4,226                             | 4,268                    | 18,975 |
| INT                  | 3,925                 | 2,865              | 10,256                          | 8,780                             | 7,892                    | 33,718 |
| Total                | 8,335                 | 5,431              | 18,952                          | 16,301                            | 14,863                   | 63,882 |

**Table 4.10:** Offshoring propensity across product types

The cross-tabulation reveals meaningful differences in offshoring propensity across product types. Intermediate goods dominate the sample in terms of total firm-year observations (33,718) and display the highest share of persistent stable offshorers: 10,256 out of 33,718 observations (30.4%) fall into this category, suggesting that firms whose core export product is an intermediate good tend to develop more continuous and stable international sourcing relationships. Consumer goods stand out for the opposite reason: 3,231 out of 18,975 observations (17.0%) are classified as never-offshorers — the highest share among the three product types — indicating that firms primarily exporting consumer goods are less likely to engage in international production fragmentation, a pattern consistent with the value that Italian manufacturing firms in this segment derive from domestic production. Capital goods record 3,142 out of 11,189 observations (28.1%) as persistent stable and 3,295 (29.4%) as persistent unstable, the only category where persistent unstable exceeds persistent stable — pointing to a more volatile engagement with international sourcing that may reflect the longer-term and less reversible nature of capital good procurement decisions.

## Chapter 5

# Measuring Reshoring

### 5.1 Definition of the Reshoring Indicator

The construction of the reshoring measure follows directly from the offshoring framework developed in the previous chapter and is implemented within the firm-year rectangular panel. The underlying logic is that a firm can only be classified as a reshoring firm if it has previously been involved in offshoring. For this reason, the reshoring indicator is anchored to the lagged offshoring status of each firm. This approach makes it possible to distinguish genuine reductions in international sourcing from two alternative situations: a general contraction in firm activity, affecting both imports and exports, and a geographical reallocation of sourcing across foreign partner countries without any actual reduction in the firm's reliance on foreign procurement.

The starting point is the NC4-based offshoring measure. For each firm-year observation, the dataset contains the total value of imports and exports in the firm's main export NC4 category. In the dataset, these correspond to the main NC4 import variable and the main NC4 export variable constructed in the previous chapter. These variables allow reshoring to be measured within the same product dimension used to identify offshoring, ensuring consistency between the two measures.

For readability, the formulas below use simplified mathematical notation. Let  $\text{ImportMainNC4}_{i,t}$  denote the value of main NC4 imports for firm  $i$  in year  $t$ , and let  $\text{ExportMainNC4}_{i,t}$  denote the value of main NC4 exports for the same firm-year observation. From these variables, two annual percentage changes are computed. The first one,  $\Delta \text{imp}_{i,t}$ , measures the proportional change in main NC4 imports relative to the previous year:

$$\Delta imp_{i,t} = \frac{\text{ImportMainNC4}_{i,t} - \text{ImportMainNC4}_{i,t-1}}{\text{ImportMainNC4}_{i,t-1}}, \quad (5.1)$$

if  $\text{ImportMainNC4}_{i,t-1} > 0$ .

The second one,  $\Delta exp_{i,t}$ , measures the analogous proportional change in exports:

$$\Delta exp_{i,t} = \frac{\text{ExportMainNC4}_{i,t} - \text{ExportMainNC4}_{i,t-1}}{\text{ExportMainNC4}_{i,t-1}}, \quad (5.2)$$

if  $\text{ExportMainNC4}_{i,t-1} > 0$ .

Both variables are defined as missing when the lagged denominator is equal to zero or missing. This avoids computing percentage changes for firm-year observations without prior trade activity in the relevant NC4 category. The use of lagged values is consistent with the panel structure of the dataset, where each firm is observed across years and the reshoring event is identified as a change relative to the previous year.

With these ingredients in place, the annual reshoring indicator is defined as a binary variable equal to one when four conditions are simultaneously satisfied. First, the firm must have been classified as an offshorer in the previous year. Second, imports in the main export NC4 category must decline by at least a given threshold  $\theta$ . Third, the proportional decline in imports must be stronger than the proportional decline in exports, so that the reduction is not simply interpreted as a general contraction in the firm's overall activity. Fourth, the firm-year observation must not be classified as a country-switching episode, since a reallocation of sourcing from one foreign country to another would not represent a genuine reduction in international procurement.

Formally, the reshoring indicator is defined as follows:

$$\text{Reshoring}_{i,t} = 1 \quad \text{if} \quad \begin{cases} \text{OffshoringNC4}_{i,t-1} = 1, \\ \Delta imp_{i,t} \leq -\theta, \\ \Delta imp_{i,t} < \Delta exp_{i,t}, \\ \text{CountrySwitch}_{i,t} \neq 1. \end{cases} \quad (5.3)$$

In this notation,  $\text{OffshoringNC4}_{i,t-1}$  corresponds to the lagged NC4 offshoring indicator, while  $\text{CountrySwitch}_{i,t}$  corresponds to the country-switching filter. The first condition ensures that reshoring is only evaluated for firms with prior evidence of offshoring. The second condition captures a reduction in foreign sourcing within the relevant NC4 category. The third condition introduces a control for firm-level contraction: if exports fall more than imports, the observed import decline may simply reflect a decrease in production or sales rather than a reshoring strategy.

Finally, the fourth condition excludes cases in which the firm is not reducing foreign sourcing but is instead changing the country from which it imports.

Three versions of the reshoring indicator are constructed by varying the import-reduction threshold  $\theta$ . The first specification applies no minimum threshold and captures any decline in main NC4 imports. The second specification requires a minimum import decline of 10 percent, while the third requires a decline of at least 20 percent. The most inclusive specification is used as the baseline measure, whereas the stricter thresholds are retained as robustness checks.

## 5.2 Country Switching Variable

The country-switching variable is introduced to separate reshoring from changes in the geographical composition of foreign sourcing. A firm may reduce imports from one country while increasing imports from another country within the same product category. In this case, the firm is not necessarily reducing its reliance on foreign production; rather, it is reallocating its sourcing strategy across foreign suppliers. For this reason, country-switching episodes are excluded from the reshoring definition.

The construction of this variable starts from the transaction-level dataset. Import transactions are first restricted to the firm's main export NC4 category and then aggregated at the firm-year-country level. This produces a measure of imports by firm, year, and partner country within the relevant NC4 product category. Let  $\text{ImportCountryNC4}_{i,t,c}$  denote imports of firm  $i$  from country  $c$  in year  $t$  within the firm's main export NC4 category. Country-level imports are computed as follows:

$$\text{ImportCountryNC4}_{i,t,c} = \sum_{j \in \mathcal{J}_{i,t,c}} \text{import}_{i,t,j}. \quad (5.4)$$

where  $\mathcal{J}_{i,t,c}$  denotes the set of import transactions associated with firm  $i$ , year  $t$ , partner country  $c$ , and the firm's main export NC4 category. This variable therefore captures the value of imports sourced by firm  $i$  from country  $c$  in year  $t$  within the product category used to define the firm's main export activity.

For each firm-country-year observation, the percentage change in imports relative to the previous year is then computed as:

$$\Delta \text{ImportCountryNC4}_{i,t,c} = \frac{\text{ImportCountryNC4}_{i,t,c} - \text{ImportCountryNC4}_{i,t-1,c}}{\text{ImportCountryNC4}_{i,t-1,c}}, \quad \text{if } \text{ImportCountryNC4}_{i,t-1,c} > 0. \quad (5.5)$$

Two binary indicators are created at the firm-country-year level. The first one equals one when imports from country  $c$  decline by at least 10 percent, while the

second one equals one when imports from country  $c$  increase by at least 10 percent. These two indicators are then aggregated at the firm-year level. A country-switching event is identified when, in the same firm-year observation, at least one partner country records a significant decline and at least one other partner country records a significant increase.

The country-switching indicator is therefore defined as follows:

$$\text{CountrySwitch}_{i,t} = 1 \quad \text{if} \quad \text{AnyDown}_{i,t} = 1 \cap \text{AnyUp}_{i,t} = 1. \quad (5.6)$$

This filter is important because it prevents the reshoring indicator from classifying as reshoring those cases in which the firm remains internationally sourced but changes the foreign country of origin. In other words, the filter helps isolate cases where the reduction in imports reflects a genuine contraction of foreign sourcing rather than a substitution between foreign suppliers.

### 5.3 Threshold Scenarios and Robustness

The choice of the import-reduction threshold is inherently arbitrary. Different thresholds capture different degrees of sourcing contraction, ranging from marginal reductions to more substantial structural changes. For this reason, three reshoring indicators are constructed.

The first scenario applies no minimum threshold and only requires main NC4 imports to decline relative to the previous year. This is the most inclusive specification and captures any reduction in international sourcing, even if small. The second scenario requires a minimum decline of 10 percent, balancing the need to filter out minor fluctuations with the objective of preserving meaningful reshoring episodes. The third scenario requires a decline of at least 20 percent and represents the most conservative definition.

In all three cases, the remaining conditions are held constant: the firm must have offshored in the previous year, the decline in imports must exceed the decline in exports, and no simultaneous country-switching episode must be detected. This structure allows the robustness of the reshoring measure to be assessed without altering its conceptual definition.

### 5.4 Reshoring Trajectory Classification

Having constructed the annual reshoring indicator, the next step consists in developing a firm-level classification of reshoring trajectories. Following the logic adopted for offshoring, the first approach relies on persistence measures computed over the full observation period. However, reshoring differs substantially from offshoring because it is less stable and more episodic by nature.

### 5.4.1 Persistence Measures

Several persistence measures are constructed for each firm. The first is the total number of reshoring years, which counts the number of years in which the firm satisfies the reshoring condition. The second is the maximum reshoring spell, defined as the longest consecutive sequence of years in which the reshoring indicator is equal to one. The third is the number of transitions, which captures how frequently a firm switches between reshoring and non-reshoring status.

The share of reshoring years is computed as the ratio between the total number of reshoring years and the number of observed years. A stability index is also constructed analogously to the offshoring stability index, combining the number of transitions and the length of the longest reshoring spell.

Table 5.1 reports descriptive statistics for the main reshoring persistence measures.

| Variable                  | Mean            | p50             | p25             | p75             | Min             | Max             |
|---------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| <code>tot_anni_r~A</code> | <b>3.787567</b> | <b>4</b>        | <b>2</b>        | <b>5</b>        | <b>2</b>        | <b>10</b>       |
| <code>max_reshor~A</code> | <b>1.725782</b> | <b>2</b>        | <b>1</b>        | <b>2</b>        | <b>1</b>        | <b>8</b>        |
| <code>n_switch_r~A</code> | <b>5.529367</b> | <b>6</b>        | <b>4</b>        | <b>7</b>        | <b>1</b>        | <b>12</b>       |
| <code>share_resh~A</code> | <b>.2705405</b> | <b>.2857143</b> | <b>.1428571</b> | <b>.3571429</b> | <b>.1428571</b> | <b>.7142857</b> |
| <code>stability_~A</code> | <b>.0903601</b> | <b>.0714286</b> | <b>.047619</b>  | <b>.1</b>       | <b>.0128205</b> | <b>.5</b>       |

**Table 5.1:** Descriptive statistics of reshoring persistence measures

### 5.4.2 First-Pass Classification

As a first step, firms are classified using the same trajectory categories adopted for offshoring. Firms with no reshoring years are classified as never reshorers; firms with exactly one reshoring year are classified as spot reshorers; firms with a high share of reshoring years and a high stability index are classified as persistent stable reshorers; firms with a high share but low stability are classified as persistent unstable reshorers; and firms with more than one reshoring year but a low share are classified as occasional reshorers.

The distribution of firms across this first-pass classification is reported in Table 5.2.

The results reveal a degenerate distribution. The persistent stable category is empty, while persistent unstable reshorers account for only a small share of firms. Most reshoring firms fall into the occasional category, while the remaining observations are split between never and spot reshorers. This outcome suggests that the taxonomy developed for offshoring does not translate mechanically to the reshoring context.

| <b>firm_resshore_type_A</b> | <b>Freq.</b> | <b>Percent</b> | <b>Cum.</b>   |
|-----------------------------|--------------|----------------|---------------|
| <b>Never</b>                | <b>1,183</b> | <b>25.91</b>   | <b>25.91</b>  |
| <b>Spot</b>                 | <b>760</b>   | <b>16.65</b>   | <b>42.56</b>  |
| <b>Persistent unstable</b>  | <b>133</b>   | <b>2.91</b>    | <b>45.48</b>  |
| <b>Occasional</b>           | <b>2,489</b> | <b>54.52</b>   | <b>100.00</b> |
| <b>Total</b>                | <b>4,565</b> | <b>100.00</b>  |               |

**Table 5.2:** Distribution of firms across reshoring categories using the first classification

### 5.4.3 The Episodic Nature of Reshoring

The failure of the stability-based taxonomy to produce meaningful reshoring categories reflects a fundamental difference between offshoring and reshoring. Offshoring tends to be a persistent and self-reinforcing activity, because once firms establish foreign sourcing relationships they may develop organisational routines, supplier-specific knowledge, and sunk investments. Reshoring, by contrast, appears to be more episodic and reactive.

The descriptive evidence supports this interpretation. Firms that reshore more than once often do so in non-consecutive years, and the stability index remains low even among firms with multiple reshoring episodes. This indicates that reshoring is rarely observed as a continuous and stable trajectory. Instead, it is more plausibly interpreted as a sequence of discrete adjustments to shocks, cost changes, supply disruptions, or strategic reorientations.

For this reason, the stability-based classification is not retained as the preferred taxonomy for reshoring. However, the persistence measures remain useful for documenting the heterogeneity of reshoring behaviour across firms.

### 5.4.4 Revised Frequency-Based Taxonomy

In light of the evidence described above, a revised firm-level reshoring taxonomy is constructed using only the frequency dimension, measured by the total number of reshoring years. Four categories are defined.

Never reshorers are firms with no reshoring years. Spot reshorers are firms with exactly one reshoring year. Occasional reshorers are firms with between two and four reshoring years. Recurrent reshorers are firms with at least five reshoring years, corresponding to reshoring activity in at least roughly one third of the observation period.

The distribution of firms across the revised categories is reported in Table 5.3.

| <code>firm_reshore_type_s</code><br><code>imp</code> | Freq.        | Percent       | Cum.          |
|------------------------------------------------------|--------------|---------------|---------------|
| Never reshorer                                       | <b>1,183</b> | <b>25.91</b>  | <b>25.91</b>  |
| Spot reshorer                                        | <b>760</b>   | <b>16.65</b>  | <b>42.56</b>  |
| Occasional reshorer                                  | <b>1,801</b> | <b>39.45</b>  | <b>82.02</b>  |
| Recurrent reshorer                                   | <b>821</b>   | <b>17.98</b>  | <b>100.00</b> |
| <b>Total</b>                                         | <b>4,565</b> | <b>100.00</b> |               |

**Table 5.3:** Distribution of firms across reshoring categories using the revised classification

The revised classification produces a more informative distribution of firms across categories. Never reshорers represent firms with no evidence of sourcing reduction over the observation period, while spot reshорers capture isolated episodes. Occasional reshорers identify firms that reshore repeatedly but not systematically, whereas recurrent reshорers represent the group most frequently involved in reshoring episodes. This revised taxonomy is therefore retained as the main firm-level reshoring classification for the subsequent empirical analysis.

## Chapter 6

# Research Questions

The previous chapters developed the empirical framework used to identify offshoring and reshoring at the firm level. After describing the dataset, the structure of trade flows, the classification of countries and products, and the construction of transaction-based measures of offshoring and reshoring, the thesis can now formulate the main research questions guiding the empirical analysis.

The purpose of this chapter is to translate the methodological framework into a clear research agenda. The questions are deliberately introduced after the measurement chapters, since they rely on the operational definitions of offshoring trajectories, offshoring intensity, product type, country switching, low-cost sourcing, and reshoring episodes developed above. At this stage, the objective is not yet to present the econometric models or the variables used in each specification, but rather to clarify the main dimensions through which the thesis investigates reshoring among Italian manufacturing firms.

The research questions focus on five complementary aspects of the offshoring-reshoring relationship. The analysis first examines whether different offshoring trajectories are associated with different reshoring propensities. It then investigates whether the intensity of prior foreign sourcing affects the probability of reshoring and whether this relationship varies across product types. The chapter also considers whether the COVID-19 pandemic accelerated reshoring, especially among firms more exposed to lockdown-related disruptions. Finally, it explores whether rising Chinese labour costs are associated with firms' propensity to reshore from China.

### 6.1 Offshoring Trajectories and Reshoring Propensity

International sourcing relationships may generate sunk costs, supplier-specific investments, organisational learning, and path dependence. The literature on

global value chains emphasises that the fragmentation of production across borders is not costless to establish and may become difficult to reverse once firms have developed stable foreign sourcing relationships [14]. This implies that the probability of reshoring may depend not only on whether a firm has previously offshored, but also on the type of offshoring trajectory it has followed over time.

This issue is particularly relevant because reshoring is generally described as a selective and heterogeneous phenomenon rather than as a mechanical reversal of previous offshoring decisions [22, 20]. Firms with persistent and stable offshoring patterns may be more deeply embedded in foreign sourcing networks, while firms with unstable or occasional offshoring behaviour may be more flexible in adjusting their sourcing strategy.

**RQ1:** *Do firms with different offshoring trajectories – persistent stable, persistent unstable, occasional, and spot – differ in their propensity to reshore?*

## 6.2 Offshoring Intensity and Reshoring Propensity

Beyond the persistence of offshoring, firms may also differ in the intensity of their reliance on foreign sourcing. Cost-based theories of offshoring suggest that firms relocate or source production stages abroad to exploit cross-country differences in factor costs, especially through the import of intermediate inputs [17]. A stronger dependence on imported inputs or products within the firm’s main export domain may therefore reflect a deeper exposure to international sourcing.

At the same time, the expected cost advantages of offshoring may be partially offset by hidden costs, including coordination difficulties, quality problems, transport costs, and reduced flexibility [23]. Firms with higher offshoring intensity may therefore be more exposed to these hidden costs and may have stronger incentives to reconsider their sourcing strategy.

**RQ2:** *Does a higher intensity of offshore sourcing, measured as the share of imports relative to exports in the firm’s main product category, predict a greater probability of reshoring?*

## 6.3 Product Type and the Offshoring-Reshoring Relationship

The reversibility of offshoring may vary depending on the type of product involved. The task-based view of offshoring conceptualises international production fragmentation as the relocation of specific tasks rather than entire industries, implying that different production stages may differ in terms of tradability, complexity, and organisational requirements [16]. As a result, the relationship between offshoring and reshoring may not be homogeneous across product categories.

Intermediate, consumer, and capital goods differ in terms of supplier substitutability, relationship-specific investments, and coordination needs. The literature on global sourcing and incomplete contracts suggests that contractual frictions and relationship-specific investments are particularly relevant when production is complex or difficult to codify [18]. The product type of the firm's main export activity may therefore moderate its propensity to reduce foreign sourcing.

**RQ3:** *Does the type of good a firm primarily trades – intermediate, consumer, or capital – moderate its propensity to reshore?*

## 6.4 COVID-19 and the Acceleration of Reshoring

The COVID-19 pandemic represents a major external shock to global supply chains. The literature on reshoring and global value chains emphasises that disruptions, uncertainty, and vulnerability to external shocks can alter firms' evaluation of geographically fragmented production networks [22, 14]. By disrupting international logistics and exposing the fragility of lean global sourcing models, the pandemic may have changed the perceived costs and benefits of offshoring.

This effect may have been stronger for firms operating in non-essential sectors, which were more directly affected by lockdown restrictions and temporary production closures. If the pandemic increased the perceived cost of relying on complex international sourcing networks, these firms may have faced stronger incentives to reduce foreign sourcing and reorganise production closer to the domestic market.

**RQ4:** *Did the COVID-19 pandemic and the associated supply chain disruptions lead to a differential acceleration of reshoring among firms in non-essential sectors relative to firms in essential sectors?*

## 6.5 Low-Cost Country Sourcing and Reshoring

A central motivation for offshoring is the possibility of exploiting international cost differentials, and among the low-cost economies represented in the dataset China

stands out on two grounds. First, it is by a wide margin the most important low-cost sourcing origin for the firms observed, anchoring the procurement strategies of entire labour-intensive industries. Second, it is the country whose labour cost has risen the most over the observation period: Chinese manufacturing wages increased almost continuously and nearly tripled across the years studied, eroding precisely the advantage that had made it attractive. For both reasons, China is the most informative case in which to test the cost-convergence mechanism.

In cost-based models of production fragmentation, low factor costs — above all labour costs — are what draw firms abroad in the first place [17], while the reshoring literature identifies the erosion of an expected cost advantage as one of the possible drivers of the relocation of production back to the home country [22]. If this mechanism is relevant, its clearest empirical trace should lie not in low-cost sourcing in general, but in the specific relationship between a firm's dependence on China and the rising cost of Chinese labour: as that cost increases, firms that had sourced their main product from China should become more likely to scale back that dependence.

**RQ5:** *Do firms that sourced their main product from China become more likely to reshore from China as Chinese labour costs rise?*

The following chapter will develop the empirical strategy used to test each question, presenting the corresponding model specifications, variables, results, and interpretation.

## Chapter 7

# Empirical Model and Results

### 7.1 Empirical Strategy

This chapter specifies the empirical models used to address the five research questions formulated in Chapter 6 and discusses the corresponding results. All specifications share a common econometric framework, described once here and then adapted to each question.

The dependent variable throughout is the annual reshoring indicator constructed in Chapter 5, which identifies reshoring from observed trade behaviour rather than from firms' own declarations, in the spirit of the administrative-data approach of [34]. The baseline is `reshoring_B`, the version built at the NC4 product level with a minimum import-decline threshold of 10%; the no-threshold version (`reshoring_A`) and the 20% version (`reshoring_C`) are retained as robustness checks. The whole set of measures is replicated at the sector level, taking the firm's main export ATECO sector (5-digit) rather than its main export NC4 category as the reference domain (`reshoring_A_sec`, `reshoring_B_sec`, `reshoring_C_sec`); these sector-level measures provide a further robustness check on the level of aggregation and are reported for the trajectory, intensity and Chinese-wage questions. Because the outcome is binary, all models are estimated by logistic regression (`logit`), with standard errors clustered at the firm level to account for the panel structure of the data and for serial correlation within firms over the fourteen-year window. Year fixed effects (`i.anno`) are included in every specification as controls for aggregate shocks common to all firms in a given year — most notably the COVID-19 disruption — and are not themselves objects of interest; the only exception is the low-cost-sourcing model of Section 7.6, where the key regressor is defined at the year level and year fixed effects cannot be included.

Since the three import-decline thresholds are the natural axis along which the robustness of every result is assessed, each research question is estimated on all

three reshoring measures, and the three estimates are reported side by side (no threshold / 10% / 20%). The 10% measure is commented as the main specification, while the no-threshold and 20% measures are read as robustness: as a rule the sign of the effect is preserved and its statistical significance tends to strengthen as the threshold becomes more demanding. Using this threshold for commenting the results is aimed at both avoiding to take into account very slight reduction of imports and not being significantly stringent in considering the same reduction.

A second fundamental convention concerns the quantity reported. For most questions the effect is discussed, tabulated and plotted on the probability scale, through predictive margins or average marginal effects, because probabilities are more directly interpretable than the multiplicative odds ratios of a logit model; the full odds-ratio tables are reported in the Appendix. The one exception is the difference-in-differences design used for the pandemic (Section 7.5): there the interaction term of interest is not estimable on the probability scale once year fixed effects are included, so the odds ratio is used consistently in the text, in the in-text table and in the figure. In each case the in-text table, the figure and the surrounding discussion refer to the same quantity.

A final convention concerns the coding of the offshoring trajectory. For estimation, the trajectory variable is recoded so that its categories run in increasing order of engagement — never, spot, occasional, persistent unstable, persistent stable — and so that *persistent stable offshorer* occupies the last position and is set as the omitted reference category. Every trajectory comparison is therefore read against the most deeply and continuously embedded offshorers, which answers the substantive question of how each trajectory’s reshoring propensity compares with that of firms firmly locked into foreign sourcing, rather than the comparatively uninformative comparison against firms that, by construction, can never reshore. The *never offshorer* category is in fact dropped from estimation altogether: having no prior offshoring, these firms predict the absence of reshoring perfectly, and are excluded by the estimator together with the first year of the panel. The estimated models therefore compare offshorers with one another. Beyond year fixed effects, the reported specifications include no further controls; sector fixed effects are introduced separately, as a robustness check discussed in Section 7.2, at the 2-digit (division) level rather than at the 5-digit level, since the fine-grained sectors leave too few firm-year observations per cell and induce perfect separation.

## 7.2 Offshoring Trajectories and Reshoring Propensity

The first question is whether the way a firm has offshored over time — its trajectory, rather than the mere fact of having offshored — shapes its subsequent propensity

to reshore. The premise, drawn from the literature on the stickiness of global value chains, is that international sourcing relationships generate sunk costs, supplier-specific investments and path dependence, so that the reversibility of offshoring need not be uniform across firms with different sourcing histories [14]. The model estimates the predicted probability of reshoring for each trajectory type, anchored to persistent stable offshorers; Figure 7.1 plots these predicted probabilities across the three reshoring thresholds.

## Model

The reshoring indicator is regressed on the firm's offshoring trajectory, entered as a set of categorical dummies with the persistent-stable trajectory as the reference, and on year fixed effects, with standard errors clustered at the firm level:

$$\Pr(R_{i,t} = 1) = F\left(\beta_0 + \sum_k \beta_k \text{Traj}_i^k + \sum_t \gamma_t \text{Year}_t\right),$$

where  $F(\cdot)$  is the logistic function and  $\text{Traj}_i^k$  are the trajectory categories (spot, occasional, persistent unstable), each read against the persistent-stable baseline. The coefficients of interest are the  $\beta_k$ , which measure how each trajectory's reshoring propensity compares with that of the most deeply embedded offshorers.

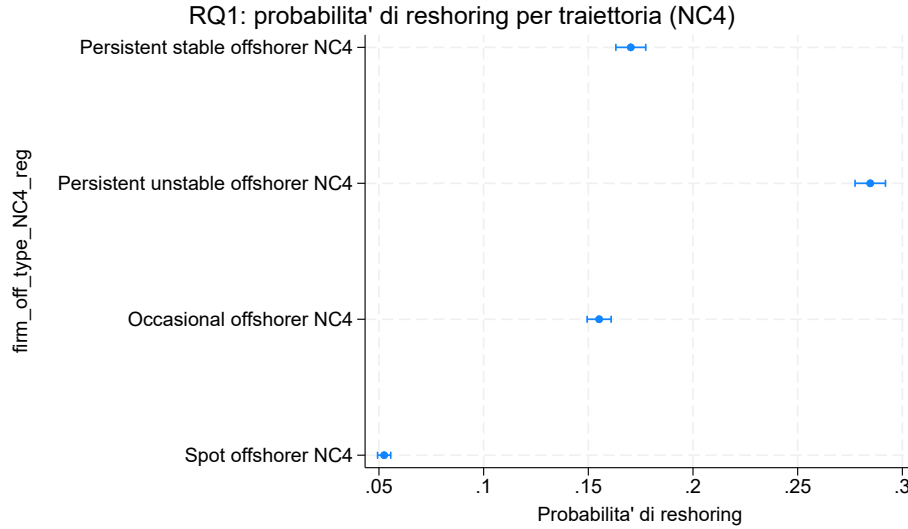


**Figure 7.1:** Predicted probability of reshoring by offshoring trajectory (NC4 level), across the three reshoring thresholds. Reference category: persistent stable offshorer.

At the baseline 10% threshold the predicted probabilities line up in a clear but non-monotonic order. Persistent unstable offshorers are the most reshoring-prone group, with a predicted probability of about 30.7%, well above the persistent stable reference (18.3%); occasional offshorers sit slightly below the reference (16.7%), while spot offshorers are by far the least likely to reshore (5.7%). In probability terms, moving from a persistent stable to a persistent unstable trajectory raises the reshoring probability by roughly twelve percentage points, whereas a single, isolated offshoring episode (spot) lowers it by about thirteen. The formal significance of these contrasts, reported as odds ratios in Table 8.1 in the Appendix, confirms that the spot and persistent unstable gaps relative to the persistent stable baseline are highly significant, while the occasional gap is small.

The ordering is preserved across the two robustness thresholds, and the pattern expected of a genuine effect emerges: as the threshold becomes more demanding the persistent unstable advantage widens (its predicted probability moves from 31.9% with no threshold to 29.1% at 20%, against a persistent stable baseline that falls from 20.7% to 15.9%), while the position of occasional offshorers relative to the reference shifts from significantly below it under the loosest measure to statistically indistinguishable from it under the strictest one (odds ratio moving from 0.785 to 1.038). The ATECO-level replication tells the same story (Figure 7.2): the predicted probabilities reproduce the spot–occasional–persistent–unstable ordering, with occasional offshorers essentially indistinguishable from persistent stable ones at the sector level, consistent with the coarser granularity of the ATECO classification relative to NC4 (the sector-level estimates are reported in Table 8.1).

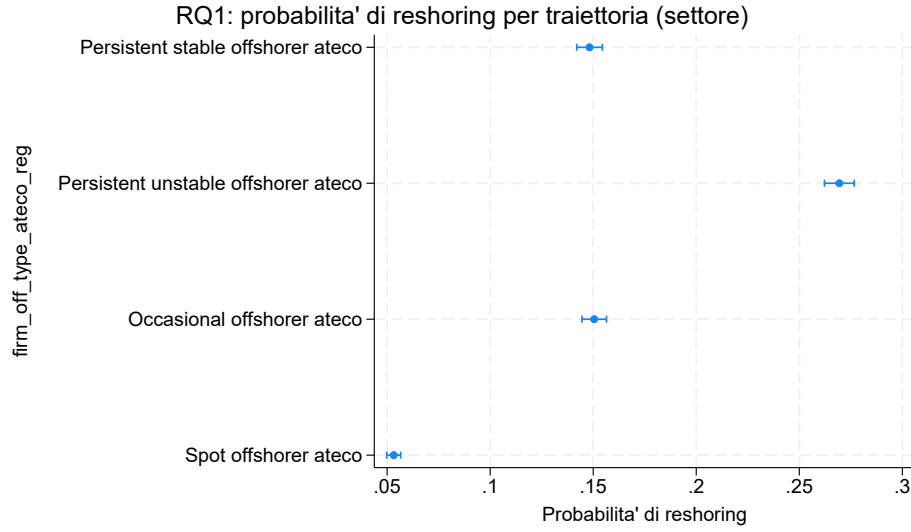


**Figure 7.2:** Predicted probability of reshoring by offshoring trajectory (ATECO level), across the three reshoring thresholds — robustness to the level of aggregation. Reference category: persistent stable offshorer.

**Table 7.1:** Predicted probability of reshoring by offshoring trajectory (NC4 level), by reshoring threshold. Predictive margins from the logit model; reference category persistent stable offshorer; year fixed effects included. Significance of the contrasts against the reference is reported in Table 8.1.

| Trajectory                    | No threshold | 10%   | 20%   |
|-------------------------------|--------------|-------|-------|
| Spot offshorer                | 0.057        | 0.057 | 0.057 |
| Occasional offshorer          | 0.170        | 0.167 | 0.164 |
| Persistent unstable offshorer | 0.319        | 0.307 | 0.291 |
| Persistent stable (ref.)      | 0.207        | 0.183 | 0.159 |

A final concern is that the trajectory effect might be an artefact of the sectoral composition of the sample: offshoring trajectories are not evenly distributed across industries, so a sector that both hosts persistent offshorers and reshores unusually often could generate the observed pattern spuriously. To address this, the baseline model is re-estimated with sector fixed effects, introduced at the 2-digit (division) level in each domain — NC4 chapters for the product-level model, ATECO divisions for the sector-level model. Table 7.2 compares the two specifications at the 10% threshold. The odds ratios move by between one and four per cent, and no sign, ordering or significance verdict changes: in particular, occasional offshorers remain

statistically indistinguishable from the persistent stable reference at the sector level ( $p = 0.96$  with fixed effects,  $p = 0.60$  without). The 2-digit aggregation also preserves the estimation sample in full (4,009 firm clusters in both specifications), which is precisely why the division level is preferred to the 5-digit one. The relationship between offshoring trajectory and reshoring propensity is therefore not confounded by the sectoral composition of the sample.

**Table 7.2:** Offshoring trajectory and reshoring propensity: robustness to sector fixed effects (10% threshold). Logit, odds ratios; reference category persistent stable offshorer; year fixed effects included; standard errors clustered by firm. Sector fixed effects are 2-digit NC4 chapters (product-level model) and 2-digit ATECO divisions (sector-level model); their coefficients are not reported.

| Trajectory (ref. pers. stable) | NC4      |           | ATECO    |           |
|--------------------------------|----------|-----------|----------|-----------|
|                                | No FE    | Sector FE | No FE    | Sector FE |
| Spot offshorer                 | 0.265*** | 0.255***  | 0.319*** | 0.308***  |
| Occasional offshorer           | 0.893*** | 0.864***  | 1.018    | 0.998     |
| Persistent unstable            | 1.977*** | 1.932***  | 2.163*** | 2.135***  |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Taken together, these results give a clear answer: offshoring trajectories are not equivalent in their association with reshoring, and the relationship is non-monotonic in the degree of persistence. Compared with the most deeply embedded offshorers, firms with only sporadic experience (spot, and to a lesser extent occasional) are markedly less likely to reshore, while firms whose offshoring has been frequent but chronically unstable are markedly more likely to do so. This is consistent with the sunk-cost and path-dependence account of value-chain participation [14], but with an important qualification: it is not raw persistence that predicts a high reshoring propensity, but persistence combined with instability. A plausible reading is that persistent stable offshorers have invested the most in durable, relationship-specific foreign sourcing arrangements and therefore face the highest switching costs, which anchors them at a comparatively low reshoring propensity; persistent unstable offshorers have accumulated a similar degree of temporal exposure without the same relationship-specific depth, leaving them both more frequently engaged with foreign sourcing and more exposed to the recurring frictions that the reshoring literature identifies as drivers of a return [19].

## 7.3 Offshoring Intensity and Reshoring Propensity

The second question moves from the temporal structure of offshoring to its *volume*: whether the intensity of a firm’s reliance on foreign sourcing, rather than its history, predicts reshoring. Cost-based theories of offshoring hold that firms source stages abroad to exploit cross-country differences in factor costs, above all through the import of intermediate inputs [17]; at the same time, the reshoring literature stresses that these expected advantages are partly offset by hidden coordination, quality and logistics costs, which grow with the depth of the sourcing relationship [19]. Intensity is measured, as in Chapter 4, by the (log) ratio of imports to exports within the firm’s main NC4 category, lagged by one year to avoid simultaneity; the effect is summarised by the average marginal effect of this regressor on the probability of reshoring, plotted in Figure 7.3. The variable is also log-transformed, since offshoring intensity is heavily right-skewed.

### Model

The reshoring indicator is regressed on the firm’s lagged offshoring intensity — the one-year-lagged log ratio of imports to exports in the main product — controlling for the offshoring trajectory and for year fixed effects, with firm-clustered standard errors:

$$\Pr(R_{i,t} = 1) = F\left(\beta_0 + \beta_1 \text{Int}_{i,t-1} + \sum_k \delta_k \text{Traj}_i^k + \sum_t \gamma_t \text{Year}_t\right),$$

where  $\text{Int}_{i,t-1}$  is lagged intensity. The coefficient of interest is  $\beta_1$ ; because it is a logit coefficient, the effect is discussed as the corresponding average marginal effect on the probability of reshoring.

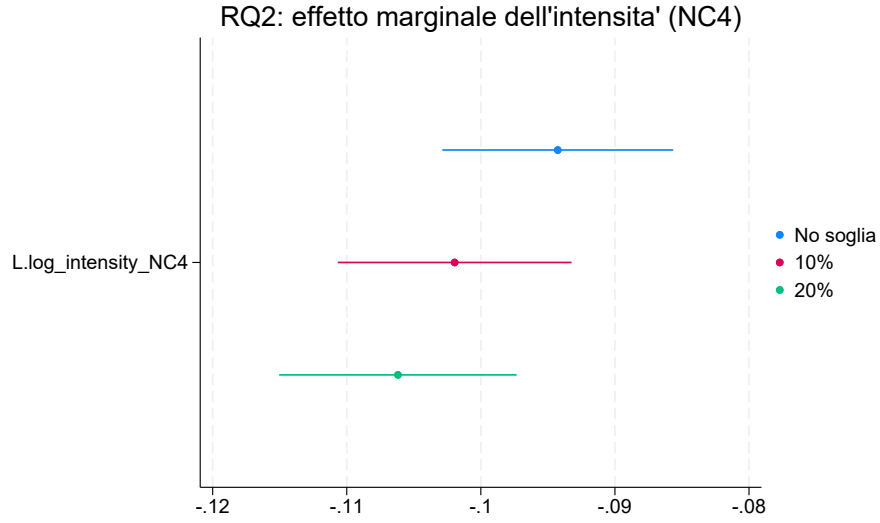


**Figure 7.3:** Average marginal effect of lagged offshoring intensity on the probability of reshoring (NC4 level), across the three reshoring thresholds.

Before interpreting the estimate it is worth being clear about what it measures. The reshoring indicator is, by construction, a statement about a *change* — a fall in main-NC4 imports conditional on prior offshoring — whereas the regressor is a *level*: the import-to-export ratio observed the year before the outcome is measured. The question is therefore not whether a falling ratio coincides with reshoring, which would be close to definitional, but whether the level of foreign- sourcing dependence observed in one year predicts a subsequent reduction of it.

At the baseline 10% threshold the average marginal effect is negative and highly significant: a one-log-point increase in the lagged import-to-export ratio is associated with a reduction of about 1.9 percentage points in the probability of reshoring the following year, holding the offshoring trajectory fixed. The effect is stable across the two robustness thresholds (about  $-1.9$  percentage points under both the no-threshold and the 20% measures) and is reproduced almost exactly at the ATECO level ( $-1.9$  percentage points, Figure 7.4), as reported in Table 7.3 and, in odds-ratio form, in Table 8.2.

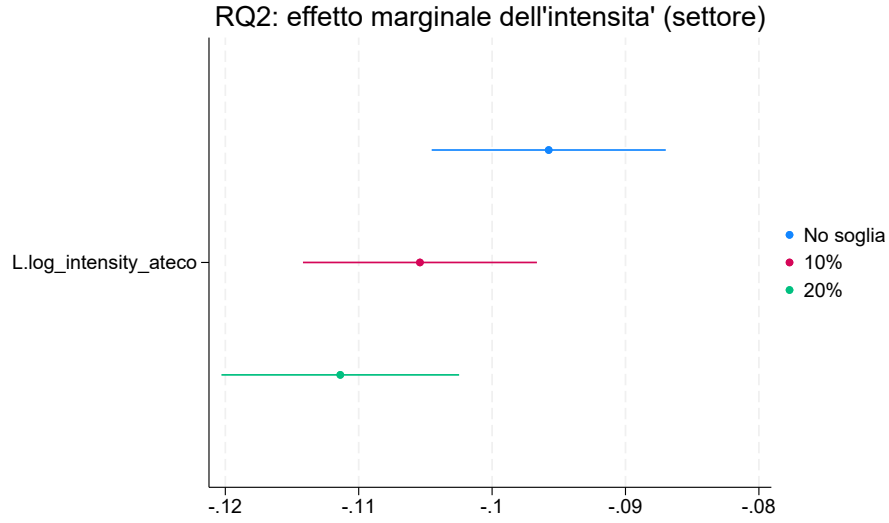


**Figure 7.4:** Average marginal effect of lagged offshoring intensity on the probability of reshoring (ATECO level), across the three reshoring thresholds — robustness to the level of aggregation.

**Table 7.3:** Average marginal effect of lagged offshoring intensity on the probability of reshoring, by reshoring threshold. Average marginal effects from the logit model; trajectory controls and year fixed effects included. Standard errors in parentheses.

|                          | No threshold           | 10%                    | 20%                    |
|--------------------------|------------------------|------------------------|------------------------|
| Lagged intensity (NC4)   | -0.0186***<br>(0.0008) | -0.0193***<br>(0.0008) | -0.0190***<br>(0.0008) |
| Lagged intensity (ATECO) | -0.0177***<br>(0.0008) | -0.0185***<br>(0.0007) | -0.0185***<br>(0.0007) |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

It is worth pausing on the trajectory dummies that enter this specification as controls. Estimated on the sub-sample of firms with strictly positive lagged intensity, and read as odds ratios against the persistent-stable baseline, they do not merely reproduce the pattern of Section 7.2: they sharpen and, in one respect, reverse it. Conditional on lagged intensity, spot offshorers show by far the highest odds of reshoring (odds ratio 16.3 at the 10% threshold), followed by occasional (6.5) and persistent unstable offshorers (3.0), all far above the persistent-stable reference (Table 8.2). The ordering is the mirror image of the depth ranking: the firms with the most marginal foreign-sourcing relationship — spot offshorers, who

source abroad in a single year — are, once that relationship’s intensity is held fixed, the readiest to discontinue it, whereas the deeply embedded persistent-stable offshorers remain the most anchored. This is the same lock-in logic seen from the trajectory side, and it reinforces the reading of the intensity effect above.

The negative sign runs against a naive cost-arbitrage prior, under which the firms most exposed to foreign sourcing might be expected to have the most to gain from reversing it. It is, however, consistent with the sunk-cost and lock-in logic of Antràs [14]: a high import-to-export ratio identifies a firm whose main product category has become structurally oriented towards foreign sourcing, built on supplier relationships that are costly to unwind, and therefore less — not more — likely to be reversed. Read alongside the trajectory result of Section 7.2, the two findings reinforce rather than duplicate one another: the temporal dimension (how continuously a firm has offshored) and the volume dimension (how heavily it sources relative to its exports) are conceptually distinct, yet both point the same way — greater depth of the sourcing relationship is associated with a lower propensity to reshore — which strengthens the case for a lock-in reading of the offshoring–reshoring relationship over a purely cost-based one.

## 7.4 Product Type and Reshoring Propensity

The third question asks whether the end-use type of a firm’s main product — intermediate (INT), consumer (CONS) or capital (CAP) goods, following the BEC5 classification of Chapter 3 — moderates its propensity to reshore. The task-based view conceptualises offshoring as the relocation of specific tasks rather than whole industries, so that production stages differ in tradability, complexity and the depth of relationship-specific investment they require [16, 18]. A plausible working hypothesis, built on that general logic, is that intermediate goods — typically the most standardised and substitutable inputs — are also the easiest to reshore, and thus the most reshoring-prone category. This is a working conjecture of our own, built on the general reasoning of that literature rather than an explicit prediction drawn from it. Intermediate goods are set as the reference category, and the specification interacts product type with the offshoring trajectory; the resulting predicted probabilities by product type are plotted in Figure 7.5.

### Model

The main specification is additive: the reshoring indicator is regressed on the product-type of the firm’s main product, with intermediate goods as the reference, on the offshoring trajectory and on year fixed effects, with firm-clustered standard

errors:

$$\Pr(R_{i,t} = 1) = F\left(\beta_0 + \sum_g \beta_g \text{Type}_i^g + \sum_k \delta_k \text{Traj}_i^k + \sum_t \gamma_t \text{Year}_t\right),$$

where  $\text{Type}_i^g$  are the product-type categories (capital, consumer), each read against intermediate goods. The coefficients of interest are the  $\beta_g$ , which capture whether product type moves the reshoring propensity. A second specification, used as a robustness check, adds the full interaction between product type and trajectory, allowing the product-type effect to vary across trajectories.

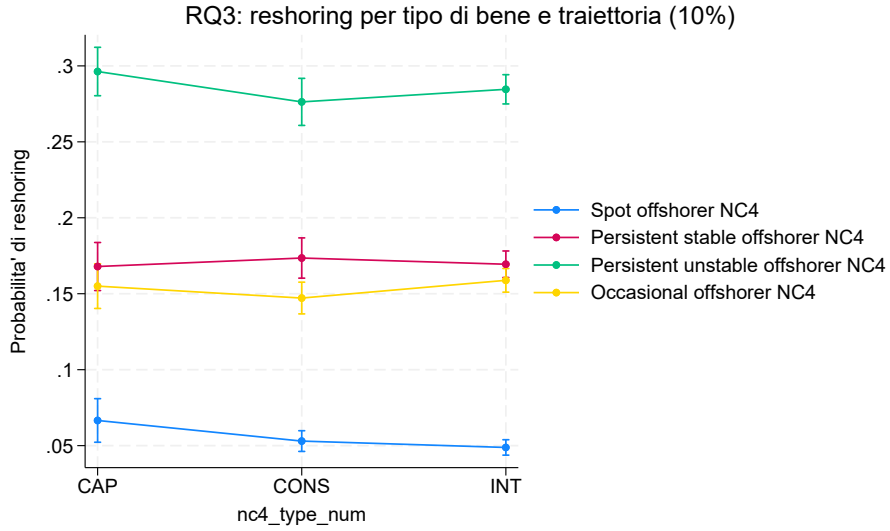


**Figure 7.5:** Predicted probability of reshoring by product type and offshoring trajectory (10% threshold).

The question is answered most directly by the additive specification, in which the effect of product type is assumed common across trajectories and is read as a single comparison against intermediate goods; the interacted specification, which lets that effect vary by trajectory, is used below as a robustness check. In the additive model the product-type main effects are small and statistically insignificant at every threshold: relative to intermediate goods, capital goods carry an odds ratio of 1.02 ( $p = 0.47$  at the 10% threshold) and consumer goods of 0.97 ( $p = 0.35$ ), and neither approaches significance under the no-threshold or 20% measures either (Table 8.3). Read on the probability scale, the same message is even clearer: the predicted probability of reshoring is essentially flat across product types, at about 20.7% for capital goods, 20.3% for intermediate goods and 19.9% for consumer goods at the 10% threshold — a spread of well under one percentage point — and the ordering is stable across all three thresholds (Table 7.4).

The interacted specification, which allows the product-type effect to differ across trajectories, does not overturn this conclusion. When the predicted probabilities are broken down by trajectory (Figure 7.5), the near-flat product-type ordering reappears inside each trajectory, and the interaction terms are almost all statistically indistinguishable from one: the only individually significant term is that between a spot trajectory and capital goods, with no systematic pattern elsewhere. The product-type gap therefore remains negligible whether it is estimated on average or allowed to vary by trajectory.

**Table 7.4:** Predicted probability of reshoring by product type (NC4 level), by reshoring threshold. Predictive margins from the additive logit model; reference category intermediate goods (INT); trajectory controls and year fixed effects included. The statistical significance of the differences across product types is reported, as odds ratios, in Table 8.3, where none of the product-type coefficients is significant at conventional levels.

| Product type             | No threshold | 10%   | 20%   |
|--------------------------|--------------|-------|-------|
| Capital (CAP)            | 0.218        | 0.207 | 0.194 |
| Consumer (CONS)          | 0.213        | 0.199 | 0.185 |
| Intermediate (INT, ref.) | 0.216        | 0.203 | 0.189 |

The data do not bear out this hypothesis. The predicted probabilities are essentially flat across product types, and none of the differences is statistically significant, so the type of good a firm trades does not move its propensity to reshore. One particularity is nonetheless worth noting, if only as an observation: contrary to the initial intuition, the point estimates place capital goods slightly above the others. Although this difference is not significant and no weight should be placed on it, a tentative reading — offered here as my own interpretation rather than as an established finding — is that capital goods, being more complex, more dependent on specialised skills and on proximity between production and engineering, and less easily replaced by an alternative foreign supplier, might be the goods for which bringing production home is the more natural response when an offshore arrangement is reconsidered. In any case, the product-type effect is dwarfed by that of the offshoring trajectory: what a firm reshores depends on how it offshored far more than on what it makes.

## 7.5 COVID-19 and the Acceleration of Reshoring

The fourth question asks whether the COVID-19 pandemic produced a differential acceleration of reshoring among firms in non-essential sectors — which were subject

to mandatory production closure during the March 2020 lockdown — relative to firms in essential sectors, which were authorised to keep operating. The question is posed openly, without a prior as to the direction of the effect: the identification strategy is a difference-in-differences (DiD) design comparing the change in reshoring propensity before and after 2020 across the two groups.

## Construction of the treatment variable

The essential/non-essential classification is built from the Italian government’s *Decreto* MISE of 25 March 2020, Allegato 1 [39], which lists the ATECO activities authorised to remain open during the lockdown. Because the decree specifies activities at varying levels of ATECO granularity — sometimes an entire 2-digit division, sometimes only specific 5- or 6-digit sub-classes — the matching proceeds hierarchically: where the decree opens or closes an entire division, the match is made at the 2-digit level (the first two digits of the firm’s main export sector); where only specific sub-classes are affected, the match is made at the firm’s full 5-digit main export sector code. A small number of residual cases, in which the decree is more granular than the available 5-digit code, are resolved by prevalence — assigning the code to whichever status characterises the majority of the corresponding activities — and documented individually in the do-file (for example, code 22290 is assigned essential status, falling within the plastics division that the decree leaves open, while codes 23199, 28291, 28293 and 28299 are assigned non-essential status). The resulting split allocates approximately 32.7% of firm-year observations to essential sectors and 67.3% to non-essential sectors.

## Model

The reshoring indicator is regressed on a full interaction between the non-essential dummy and a post-2020 dummy, with year fixed effects and firm-clustered standard errors:

$$\Pr(R_{i,t} = 1) = F\left(\beta_0 + \beta_1 \text{NonEss}_i + \beta_2 \text{Post2020}_t + \beta_3 (\text{NonEss}_i \times \text{Post2020}_t) + \sum_t \gamma_t \text{Year}_t\right),$$

where  $F(\cdot)$  is the logistic function. The coefficient of interest is  $\beta_3$ , on the interaction term: it captures the differential change in reshoring odds for non-essential-sector firms after 2020, relative to essential-sector firms, net of the level difference between the two groups and of the common year effects. Sector fixed effects are not included, because the non-essential dummy is itself defined at the sector level and would be collinear with them. Because this interaction is not estimable on the probability scale once year fixed effects are included, the effect is reported throughout — text, table and figure — as an odds ratio (Figure 7.6).

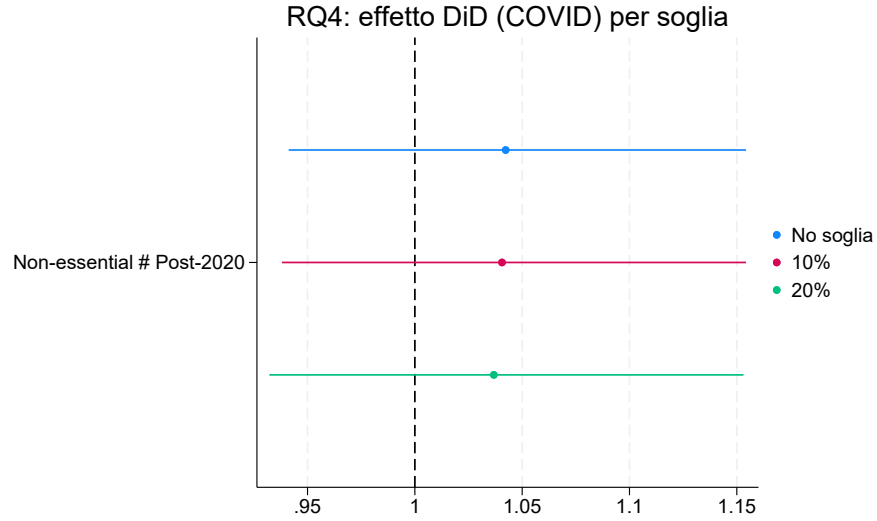


**Figure 7.6:** Difference-in-differences estimate of the pandemic effect on reshoring: odds ratio of the non-essential $\times$ post-2020 interaction, across the three reshoring thresholds. The vertical line marks an odds ratio of one.

## Parallel trends

The DiD design rests on the assumption that, absent the pandemic, the two groups would have followed parallel trends in reshoring propensity. Figure 7.7 plots the annual share of firms classified as reshorers, separately for essential and non-essential sectors, over 2010–2023. Throughout the pre-2020 period non-essential sectors display a systematically higher level of reshoring — a gap of roughly two to five percentage points, fairly stable from 2011 onward — but the two series move together, rising and falling in tandem (including a joint peak in 2018) without any visible divergence in slope as 2020 approaches. This is consistent with the parallel-trends assumption: the pre-existing level gap is absorbed by the non-essential main effect, and the interaction term isolates any differential change in slope around 2020.

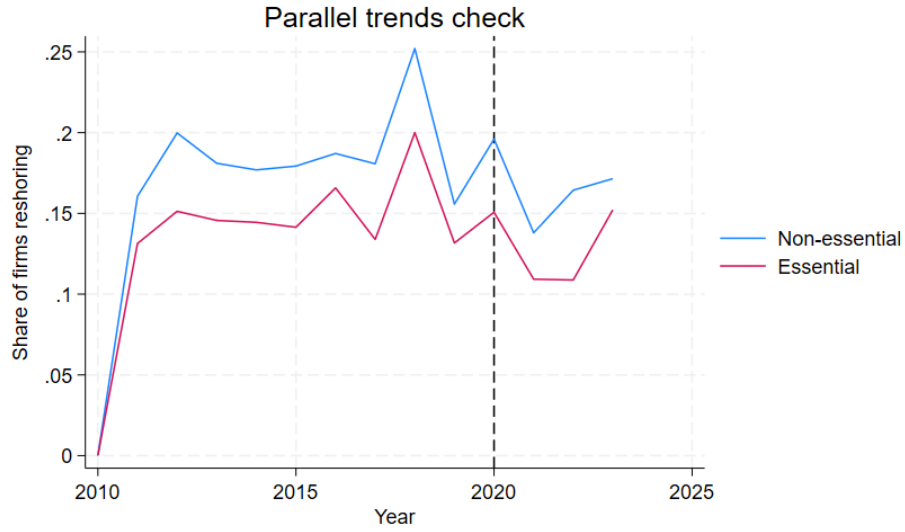


**Figure 7.7:** Parallel-trends check: annual share of firms reshoring, essential vs. non-essential sectors, 2010–2023. The vertical line marks 2020.

## Results

The difference-in-differences interaction is small, imprecisely estimated and statistically indistinguishable from one at the baseline 10% threshold (odds ratio 1.041,  $p = 0.45$ ; the 95% confidence interval comfortably contains one), and the same holds under the two robustness thresholds (odds ratios 1.042 and 1.037). There is therefore no statistical evidence that firms in sectors forced to close during the March 2020 lockdown subsequently accelerated their reshoring relative to firms in sectors that remained open. The non-essential main effect is positive and significant (odds ratio 1.256), confirming the pre-existing level gap visible in Figure 7.7; the post-2020 main effect is not significant (odds ratio 1.094,  $p = 0.17$ ); and — the object of the question — neither is the interaction (Table 7.5, with the full model in Table 8.4).

**Table 7.5:** COVID-19 difference-in-differences (NC4 level), by reshoring threshold. Odds ratios from the logit model; reference categories essential sector and pre-2020; year fixed effects included. Standard errors in parentheses.

|                                  | No threshold        | 10%                 | 20%                 |
|----------------------------------|---------------------|---------------------|---------------------|
| Non-essential (ref. essential)   | 1.261***<br>(0.046) | 1.256***<br>(0.046) | 1.282***<br>(0.048) |
| Post-2020 (ref. pre-2020)        | 1.064<br>(0.068)    | 1.094<br>(0.072)    | 1.123*<br>(0.076)   |
| Non-essential $\times$ Post-2020 | 1.042<br>(0.054)    | 1.041<br>(0.055)    | 1.037<br>(0.056)    |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

The result is not sensitive to how the post-period is defined. Re-estimating the model with the post-period starting in 2021 rather than 2020 — so that 2020, a year of transition and severe disruption, is excluded from the treated period — leaves the interaction even smaller and still far from significance (odds ratio 1.014,  $p = 0.81$ ; Table 7.6).

**Table 7.6:** COVID-19 difference-in-differences: robustness with a 2021 post-period threshold (10% measure, NC4 level). Odds ratios from the logit model; year fixed effects included; standard errors in parentheses.

|                                  | Odds ratio          |
|----------------------------------|---------------------|
| Non-essential (ref. essential)   | 1.267***<br>(0.045) |
| Post-2021 (ref. pre-2021)        | 0.889*<br>(0.058)   |
| Non-essential $\times$ Post-2021 | 1.014<br>(0.059)    |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

To illustrate the null result in probability terms, Figure 7.8 plots the predicted probability of reshoring for the four sector-by-period cells. This figure is produced from a reduced model estimated *without* year fixed effects, purely so that the cell probabilities can be drawn: with year fixed effects included, the non-essential $\times$ post-2020 combination is not estimable on the probability scale, which is why the statistical result must be read from the regression odds ratio rather than from this figure. The illustrative probabilities move very little around 2020 — from about

14.5% to 13.7% in essential sectors and from about 17.5% to 17.2% in non-essential ones — with no visible differential acceleration.

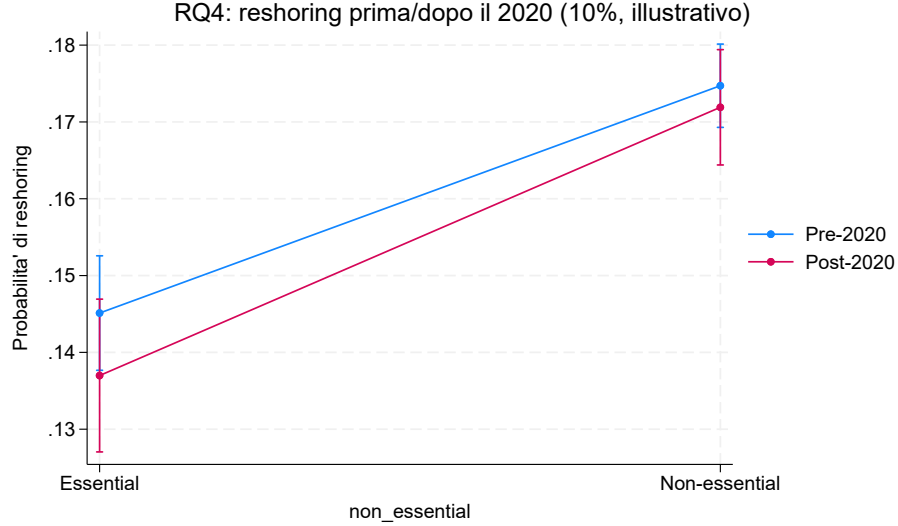


**Figure 7.8:** Illustrative predicted probability of reshoring, essential vs. non-essential sectors, before and after 2020 (10% threshold). Estimated without year fixed effects for illustration only; the statistical test is the interaction odds ratio in Table 7.5.

The evidence thus points to a null result: over this window and with this measure, the pandemic did not accelerate reshoring differentially in the sectors most exposed to the lockdown. Two readings, both consistent with the more cautious strand of the literature, help make sense of it. The observation window may be too short relative to the time a structural sourcing decision takes to materialise and to be picked up by a transaction- based measure; reshoring, as characterised in Chapter 5, is an episodic and often delayed adjustment rather than an immediate reaction. And the acute uncertainty of the pandemic may itself have discouraged rather than encouraged active reorganisation in the short run, with firms postponing complex structural decisions even as their longer-run assessment of offshore risk shifted in ways a four-year post-period cannot capture. Both are in line with the characterisation of reshoring as a slow and selective adjustment [22].

## 7.6 Chinese Labour Costs and Reshoring from China

The final question turns to the cost mechanism that motivates offshoring in the first place. Among the low-cost economies in the sample, China is both the single most important sourcing origin and the country whose labour cost rose most over the period, with manufacturing wages nearly tripling; it is therefore the most informative case in which to test whether the erosion of a cost advantage traces through to reshoring at the firm level. Cost-based models hold that low labour costs are what draw firms abroad [17], while the reshoring literature identifies the erosion of that advantage — the convergence of sourcing costs — as a structural driver of a return [22]. The outcome is here constructed on the firm’s flows *with China only*, and the key regressor is the Chinese manufacturing wage (`china_wage_k`, in thousands of CNY); the model is estimated on the subsample of firms that sourced their main product from China. The effect is summarised by the average marginal effect of the Chinese wage on the probability of reshoring, reported in Table 7.7. Following the strand of the literature that reads the erosion of the offshore labour-cost advantage as a driver of reshoring [22], it is plausible to expect reshoring from China to become more likely as Chinese wages rise over the period; the estimates below are broadly consistent with this expectation.

### Construction of the data

Two purpose-built variables underlie this analysis. The first is the Chinese manufacturing wage. Annual average wages in Chinese manufacturing were obtained from the National Bureau of Statistics of China [40]; over the period Chinese manufacturing pay rose from about 36,700 to about 108,000 CNY — a cumulative increase of roughly 195%, or nearly a threefold rise. The level was rescaled into thousands of CNY (`china_wage_k`) and assigned to each firm-year according to its calendar year, so that the regressor is the national manufacturing wage prevailing in that year. Being a national, year-level series common to all firms, this variable is collinear with calendar time, which is why year fixed effects cannot be included in the model.

The second variable is a China-specific reshoring indicator, built by applying the behavioural definition used throughout the thesis to the firm’s trade flows with China alone. Starting from the transaction data, imports from and exports to China within the firm’s main product (NC4) are isolated and aggregated to the firm-year level. A firm is treated as offshoring to China when, in a given year, it records both positive imports from and positive exports to China in its main product; and it is coded as reshoring from China when, conditional on having offshored to China in the previous year, its imports from China in the main product

fall — by at least the relevant threshold (10% in the baseline, with the no-threshold and 20% versions as robustness) — and fall by more than its exports to China, this last condition preventing mere country-switching from counting as reshoring, exactly as in the main measure. The model is then estimated on the subsample of firms that were offshoring to China in the previous year, so that the wage effect is identified only on the firms actually exposed to Chinese sourcing. The sector-level counterpart is constructed identically, replacing the main NC4 product with the main ATECO sector.

At the baseline 10% threshold the Chinese wage has a positive and significant average marginal effect at the product level: each additional thousand CNY of Chinese manufacturing pay is associated with an increase of about 0.0009 in the probability that a China-sourcing firm reshores from China. The effect strengthens as the threshold becomes more demanding — from 0.0008 ( $p < 0.05$ ) with no threshold to 0.0012 ( $p < 0.01$ ) at 20% — exactly the pattern expected of a genuine relationship. At the coarser ATECO level the same effect is present in sign but weaker and, at the baseline, not statistically significant, becoming marginal only under the strictest threshold; the contrast between the two levels is itself informative, in that the product-level measure isolates the China dependence more precisely than the sector aggregate.

## Model

The China-specific reshoring indicator is regressed on the Chinese manufacturing wage and on the offshoring trajectory, estimated on the subsample of firms that offshored to China in the previous year, with firm-clustered standard errors:

$$\Pr(R_{i,t}^{\text{CHN}} = 1) = F\left(\beta_0 + \beta_1 \text{Wage}_t^{\text{CHN}} + \sum_k \delta_k \text{Traj}_i^k\right), \quad \text{for } \text{Off}_{i,t-1}^{\text{CHN}} = 1.$$

Year fixed effects cannot be included, because the Chinese wage  $\text{Wage}_t^{\text{CHN}}$  is a national year-level series and is therefore collinear with calendar time. The coefficient of interest is  $\beta_1$ , discussed as the corresponding average marginal effect.

**Table 7.7:** Average marginal effect of the Chinese manufacturing wage (per thousand CNY) on the probability of reshoring from China, by reshoring threshold. Average marginal effects from the logit model estimated on the China-sourcing subsample; trajectory controls included; year fixed effects not included (see text). Standard errors in parentheses.

|                      | No threshold           | 10%                     | 20%                     |
|----------------------|------------------------|-------------------------|-------------------------|
| Chinese wage (NC4)   | 0.00079**<br>(0.00035) | 0.00094***<br>(0.00035) | 0.00116***<br>(0.00034) |
| Chinese wage (ATECO) | 0.00033<br>(0.00033)   | 0.00036<br>(0.00033)    | 0.00063*<br>(0.00032)   |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Because the effect is expressed per thousand CNY, its economic size is best appreciated over the full rise in Chinese wages rather than per unit. On the odds scale, the product-level estimate corresponds to an odds ratio of about 1.004 per thousand CNY (Table 8.5); compounded over the near-tripling of Chinese manufacturing pay observed across the period — an increase of roughly seventy thousand CNY — this implies a cumulative rise of the order of 35% in the odds of reshoring at the 10% threshold, rising to roughly 47% under the 20% threshold. These cumulative figures are offered as an illustration of magnitude, not as a directly estimated coefficient.

Two cautions must accompany the interpretation of this result. First, the model is estimated on the China-sourcing subsample and, because the Chinese wage is a year-level variable, it cannot include year fixed effects: the wage therefore coincides with calendar time and necessarily absorbs other contemporaneous shocks of the same period — the pandemic, the tariff escalation, and the broader geopolitical tensions of the early 2020s. The estimate should accordingly be read as an *association* compatible with the cost-convergence mechanism [22], not as an isolated causal effect of Chinese labour costs. Second, and for the same reason, no figure is reported for this question: a marginsplot of the wage effect would conflate the wage with the passage of time and would be more misleading than informative, so the result is presented through the regression estimates alone. With these qualifications, the evidence is consistent with the cost-convergence mechanism: at the product level, firms tied to China become measurably more likely to retreat from it as Chinese wages rise, and the association strengthens precisely as the reshoring measure becomes more demanding — the pattern one would expect if the erosion of the cost advantage were indeed at work, even though the design cannot isolate it from the other shocks of the same years.

## Chapter 8

# Conclusion and Future Developments

This thesis set out to establish whether reshoring is a real and measurable phenomenon among Italian manufacturing firms, and, if so, what drives it. The starting point was an observation and a gap. Public and policy debate has increasingly framed the return of production to advanced economies as a structural turn, yet the empirical evidence underpinning that narrative remains thin, largely because reshoring is difficult to observe: it is rarely declared, and studies have often relied on surveys or on isolated, publicised cases. The question that motivated the analysis was therefore both empirical and methodological, not only *whether* Italian manufacturing firms reshore and *what shapes* their decision to do so, but also *how* such behaviour can be identified from objective data in the first place.

To address it, the work followed two complementary approaches. The first was the construction, from firm-level trade data, of behavioural measures of offshoring and reshoring: rather than asking firms what they did, reshoring was inferred from observing a sustained contraction of imports in a firm's main product, conditional on a prior history of offshoring, and net of simple country-switching. This produced a firm-year panel in which offshoring trajectories and reshoring episodes could be tracked over fourteen years. The second approach was econometric: a series of logit models, estimated on those measures and reported throughout across three reshoring thresholds and two levels of aggregation, testing which firm-level and external factors are associated with a higher propensity to reshore. The two approaches are not separable: the measures make the regressions possible, and the regressions give the measures their economic meaning.

The central finding is that reshoring, where it occurs, is strongly conditioned by a firm's own offshoring history. The way a firm has sourced abroad, therefore the temporal structure of its offshoring and the intensity of its foreign sourcing, is

by a wide margin the most robust predictor of its propensity to reshore. Firms whose offshoring has been frequent but chronically unstable are markedly the most likely to reshore, while firms with only sporadic foreign-sourcing experience are the least; and, going against a naive cost-arbitrage intuition, firms most intensively reliant on foreign sourcing reshore *less*, not more. Both results point the same way: the deeper and more embedded the offshoring relationship, the less reversible it is. This pattern is consistent with the sunk-cost and lock-in view of global value chains [14], and its emergence in a large panel of Italian manufacturing firms is, in itself, one of the contributions of this work.

Alongside the offshoring history, one external cost factor left a measurable trace. On the subsample of firms sourcing from China, turned out to be the sample's single most important low-cost origin, the rise in Chinese labour costs is positively and significantly associated with reshoring at the product level, and the association strengthens as the reshoring measure becomes more stringent. This is consistent with the cost-convergence mechanism emphasised in the reshoring literature [22]; however, because the design cannot separate the wage from the other shocks of the same years, it is best read as an association rather than an isolated causal effect.

Two of the questions returned null results, and they are reported as such rather than explained away. The type of good a firm primarily trades (intermediate, consumer or capital) does not significantly move its propensity to reshore: the three categories are statistically indistinguishable across every specification. And the COVID-19 shock produced no differential acceleration of reshoring in the sectors most exposed to the 2020 lockdown; the difference-in-differences interaction is not significant under any definition of the post-period. These non-findings are informative rather than empty: they indicate that reshoring, in this sample, is driven by firm-level history far more than by the nature of the product or by an aggregate external shock. The COVID result in particular is best read in light of the short post-pandemic window available here: reshoring is a slow, episodic adjustment, and four post-2020 years may simply be too few for a structural response to surface in a trade-based measure.

## Limitations

After having presented the results, it is important to acknowledge that the followed approach brings with it some limitations. The first one concerns the unit of observation: the entire analysis only considers each firm's *main* export sector and product, its principal ATECO and NC4 category. This choice keeps the measures easier to compute and focuses them on a firm's core activity, but it necessarily does not take into account the possibility that reshoring events may involve secondary product lines. A firm may bring back a group of auxiliary processes or products while its principal process or product remains offshored, and such episodes are

invisible to a main-product measure; the volume of reshoring captured here should therefore be read as a lower bound on the underlying phenomenon.

A second limitation is temporal. The observation window ends in 2023, leaving only a short post-pandemic period, which is likely too short to assess the medium-run consequences of COVID-19 for reshoring, given that structural sourcing decisions take time to materialise and to surface in a trade-based measure. Having clarified this, it is more accurate to interpret the null result on the pandemic as the absence of a *short-run* differential acceleration rather than the absence of any effect over a longer horizon.

Finally, the estimates should be read as associations rather than causal effects: the analysis identifies which firms reshore and how this covaries with their offshoring history and with external cost conditions, but the design does not exploit exogenous variation and therefore cannot isolate the causal impact of any single factor.

## Directions for Future Researches

These limitations point directly to two natural extensions. The first is to broaden the unit of analysis from the single main product to a substantially larger set of each firm's products. Considering a broader set of products and processes for each firm could reveal a considerably larger volume of reshoring activity than the main view suggests.

The second extension follows from the China result. Having found that rising Chinese labour costs are associated with reshoring from China, a natural question is whether the same mechanism operates for low-cost origins more generally. Extending the analysis to the full set of low-cost countries whose labour costs rose over the period would help in understanding whether the cost-convergence pattern is specific to China or a general feature of other lower-labour-cost countries.

## Appendix: Extended Estimation Tables

**Table 8.1:** Offshoring trajectory and reshoring propensity — odds ratios by reshoring threshold. Logit, odds ratios; reference category persistent stable offshorer; year fixed effects included; standard errors clustered by firm in parentheses. Never offshorers are excluded (they cannot satisfy the lagged- offshoring precondition). Panel A: NC4 level. Panel B: ATECO level.

| Trajectory (ref. persistent stable) | No threshold        | 10%                 | 20%                 |
|-------------------------------------|---------------------|---------------------|---------------------|
| <i>Panel A — NC4 level</i>          |                     |                     |                     |
| Spot offshorer                      | 0.228***<br>(0.009) | 0.265***<br>(0.011) | 0.316***<br>(0.013) |
| Occasional offshorer                | 0.785***<br>(0.027) | 0.893***<br>(0.031) | 1.038<br>(0.037)    |
| Persistent unstable offshorer       | 1.805***<br>(0.057) | 1.977***<br>(0.064) | 2.183***<br>(0.074) |
| <i>N</i>                            | 51,597              | 51,597              | 51,597              |
| <i>Panel B — ATECO level</i>        |                     |                     |                     |
| Spot offshorer                      | 0.278***<br>(0.012) | 0.319***<br>(0.014) | 0.375***<br>(0.016) |
| Occasional offshorer                | 0.906***<br>(0.031) | 1.018<br>(0.036)    | 1.171***<br>(0.042) |
| Persistent unstable offshorer       | 2.021***<br>(0.063) | 2.163***<br>(0.069) | 2.374***<br>(0.079) |
| <i>N</i>                            | 52,117              | 52,117              | 52,117              |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table 8.2:** Offshoring intensity and reshoring propensity — odds ratios by reshoring threshold. Logit, odds ratios; trajectory controls (reference category persistent stable offshorer) and year fixed effects included; standard errors clustered by firm in parentheses. The intensity rows are the object of interest; the trajectory rows are controls, reported here for completeness. (The average marginal effects of intensity are reported in Table 7.3.)

|                                         | No threshold        | 10%                 | 20%                 |
|-----------------------------------------|---------------------|---------------------|---------------------|
| <i>Panel A — NC4 level</i>              |                     |                     |                     |
| Lagged intensity                        | 0.910***<br>(0.004) | 0.903***<br>(0.004) | 0.899***<br>(0.004) |
| Spot offshorer (control)                | 13.94***<br>(1.77)  | 16.33***<br>(2.07)  | 19.57***<br>(2.49)  |
| Occasional offshorer (control)          | 5.80***<br>(0.26)   | 6.46***<br>(0.29)   | 7.35***<br>(0.34)   |
| Persistent unstable offshorer (control) | 2.79***<br>(0.09)   | 3.02***<br>(0.10)   | 3.28***<br>(0.11)   |
| <i>N</i>                                | 31,823              | 31,823              | 31,823              |
| <i>Panel B — ATECO level</i>            |                     |                     |                     |
| Lagged intensity                        | 0.909***<br>(0.004) | 0.900***<br>(0.004) | 0.895***<br>(0.004) |
| Spot offshorer (control)                | 16.91***<br>(2.31)  | 19.56***<br>(2.66)  | 23.15***<br>(3.15)  |
| Occasional offshorer (control)          | 6.35***<br>(0.29)   | 7.03***<br>(0.32)   | 7.93***<br>(0.36)   |
| Persistent unstable offshorer (control) | 3.08***<br>(0.10)   | 3.26***<br>(0.11)   | 3.52***<br>(0.12)   |
| <i>N</i>                                | 33,901              | 33,901              | 33,901              |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table 8.3:** Product type and reshoring propensity — odds ratios from the additive model, by reshoring threshold (NC4 level). Logit, odds ratios; reference categories persistent stable offshorer and intermediate goods (INT); year fixed effects included; standard errors clustered by firm in parentheses. This is the specification that answers the research question directly; the interacted model is discussed as a robustness check in the text. None of the product-type coefficients (CAP, CONS) is statistically significant at conventional levels, at any threshold.

|                                                                    | No threshold        | 10%                 | 20%                 |
|--------------------------------------------------------------------|---------------------|---------------------|---------------------|
| <i>Product-type main effects (ref. INT) — object of interest</i>   |                     |                     |                     |
| Capital (CAP)                                                      | 1.016<br>(0.032)    | 1.024<br>(0.033)    | 1.032<br>(0.034)    |
| Consumer (CONS)                                                    | 0.982<br>(0.028)    | 0.973<br>(0.028)    | 0.967<br>(0.029)    |
| <i>Trajectory main effects (ref. persistent stable) — controls</i> |                     |                     |                     |
| Spot offshorer                                                     | 0.229***<br>(0.009) | 0.266***<br>(0.011) | 0.317***<br>(0.014) |
| Occasional offshorer                                               | 0.785***<br>(0.027) | 0.894***<br>(0.031) | 1.039<br>(0.037)    |
| Persistent unstable offshorer                                      | 1.806***<br>(0.057) | 1.977***<br>(0.064) | 2.182***<br>(0.074) |
| <i>N</i>                                                           | 51,556              | 51,556              | 51,556              |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table 8.4:** COVID-19 and reshoring — difference-in-differences, odds ratios by reshoring threshold (NC4 level). Logit, odds ratios; reference categories essential sector and pre-2020; year fixed effects included (year dummies omitted from the table); standard errors clustered by firm in parentheses.

|                                  | No threshold        | 10%                 | 20%                 |
|----------------------------------|---------------------|---------------------|---------------------|
| Non-essential (ref. essential)   | 1.261***<br>(0.046) | 1.256***<br>(0.046) | 1.282***<br>(0.048) |
| Post-2020 (ref. pre-2020)        | 1.064<br>(0.068)    | 1.094<br>(0.072)    | 1.123*<br>(0.076)   |
| Non-essential $\times$ Post-2020 | 1.042<br>(0.054)    | 1.041<br>(0.055)    | 1.037<br>(0.056)    |
| <i>N</i>                         | 59,345              | 59,345              | 59,345              |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table 8.5:** Chinese labour costs and reshoring from China — odds ratios and average marginal effects of the Chinese manufacturing wage (per thousand CNY), by reshoring threshold. Logit estimated on the China-sourcing subsample; trajectory controls included; year fixed effects not included (the regressor is defined at the year level; see Section 7.6); standard errors clustered by firm in parentheses.

|                                          | No threshold           | 10%                     | 20%                     |
|------------------------------------------|------------------------|-------------------------|-------------------------|
| <i>Panel A — NC4 level (N = 3,943)</i>   |                        |                         |                         |
| Chinese wage — odds ratio                | 1.0034**<br>(0.0015)   | 1.0042***<br>(0.0016)   | 1.0054***<br>(0.0016)   |
| Chinese wage — avg. marginal effect      | 0.00079**<br>(0.00035) | 0.00094***<br>(0.00035) | 0.00116***<br>(0.00034) |
| <i>Panel B — ATECO level (N = 4,647)</i> |                        |                         |                         |
| Chinese wage — odds ratio                | 1.0014<br>(0.0014)     | 1.0016<br>(0.0015)      | 1.0029*<br>(0.0015)     |
| Chinese wage — avg. marginal effect      | 0.00033<br>(0.00033)   | 0.00036<br>(0.00033)    | 0.00063*<br>(0.00032)   |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

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