Louvain School of Management

From Offshoring to Back-shoring: Quantitative Drivers of Firms' Strategic Reconfiguration in Global Production Networks

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Louvain-la-Neuve, 01/06/2026

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1 Introduction

1.1 Motivation

Over the past three decades, the relocation of manufacturing to China became a dominant strategy for European and North American firms seeking to reduce production costs.That picture has changed substantially. Rising wages in Chinese manufacturing, sustained investment in automation by domestic firms, and growing uncertainty among European clients about single-country sourcing strategies are reshaping the economics of global production. Simultaneously, the COVID-19 pandemic, the Russian invasion of Ukraine, and escalating US–China trade tensions have exposed the fragility of globally fragmented supply chains.

In response to these pressures, a growing number of European manufacturers have begun bringing production back home, a strategic move known as reshoring. Some do it because the cost gap with China has narrowed to the point where domestic production, combined with modern automation, is competitive again. Others do it to regain control over their supply chains and reduce their exposure to disruptions they cannot manage from a distance. Still others respond to geopolitical signals, seeking to reduce their dependence on countries whose political relationship with Europe has become uncertain.

Yet the picture is far from simple. While European reshoring rose sharply between 2014 and 2017, it has been declining steadily ever since. American firms, by contrast, have been reshoring at an accelerating pace, driven in large part by massive government incentives. This divergence raises an obvious and important question: if the same global pressures are pushing in the same direction, why are European and American firms responding so differently? And within Europe, what actually determines whether a firm decides to bring production back, and when?

These questions are the starting point of this thesis.

1.2 Research Question

While anecdotal evidence of reshoring is abundant and growing, the quantitative drivers of this trend remain insufficiently understood. The academic literature on back-shoring has expanded rapidly since the mid-2010s, but it remains dominated by qualitative case studies, single-country analyses, and studies focused on a single explanatory factor (Gray et al., 2013; Kinkel, 2012). The few quantitative studies that exist tend to focus on either cost dynamics or automation in isolation, and none simultaneously tests the comparative importance of cost rebalancing, technological change, and geopolitical risk exposure within a unified panel-data framework covering multiple European destination countries.

This gap matters because the reshoring decision is inherently multidimensional. A firm considering relocating production from China to Germany must weigh the narrowing wage differential against the cost of domestic automation investment, the risk premium associated with maintaining a geographically dispersed supply chain, and the institutional incentives available in the destination country. These factors do not operate independently: automation may amplify the effect of wage convergence by reducing the labour cost share of production, while geopolitical risk may lower the threshold at which cost parity becomes sufficient to trigger relocation. A study that examines these drivers in isolation inevitably misspecifies the underlying decision process.

This thesis addresses this gap by developing and estimating a Poisson quasi-maximum likelihood panel-data model of European reshoring decisions. Drawing on firm-level event data from the Eurofound European Restructuring Monitor covering 315 reshoring events across 26 European destination countries over the period 2014 to 2025, combined with country-level data on wage dynamics from the International Labour Organisation, robot density from the International Federation of Robotics, and the country-specific geopolitical risk index developed by Caldara and Iacoviello (2022), the analysis tests three hypotheses. H1 posits that wage convergence between European economies and China increases reshoring activity. H2 posits that higher automation intensity in destination countries makes reshoring economically viable and amplifies the effect of wage convergence. H3 posits that greater geopolitical risk exposure accelerates reshoring by incentivising firms to shorten and secure their supply chains. The central research question guiding this investigation is therefore the following: what are the quantitative drivers of firms' strategic reconfiguration from offshoring to reshoring in European global production networks, and how do these drivers interact?

1.3 Limitations

Several limitations of this study should be acknowledged from the outset so that the reader can appropriately contextualise the empirical findings presented in Chapter 5.

The sample is restricted to 12 European destination countries over 2016–2024 because this is where the three data sources intersect, not because it represents European manufacturing broadly. Portugal and several Eastern European economies are absent, and the sample ends up concentrated on large, automated Western European countries. The findings should be read with this in mind.

Two variables carry measurement uncertainty. Wages for the UK, Norway, and Finland are partly estimated from external benchmarks rather than drawn directly from ILO data, and robot density for Norway and Poland relies on interpolated regional benchmarks. Both are flagged in the robustness checks.

A further limitation is aggregation: the model operates at country-year level and cannot distinguish between a reshoring decision in textiles and one in automotive, even though the underlying economics differ substantially. Robot density also raises an endogeneity concern — countries anticipating higher domestic production may invest in automation ahead of time, which would bias the coefficient upward. Fixed effects reduce but do not eliminate this problem. Despite these constraints, the Poisson panel model in Chapter 5 offers the first systematic cross-country test of cost, automation, and geopolitical risk as joint drivers of European reshoring.

1.4 Outline

The remainder of this thesis is structured as follows. Chapter 2 reviews the literature on international production fragmentation, offshoring, and reshoring, tracing the theoretical foundations of the three hypotheses and situating this research within the broader debate on the reconfiguration of global production networks. It concludes with a synthesis of the research gap that motivates the empirical analysis. Chapter 3 presents the empirical model, including the choice of count-data estimator, the panel structure and fixed effects strategy, the marginal effects framework for the automation-cost interaction, the identification strategy, and the full set of specification tests. Chapter 4 describes the data sources and their construction in detail, documenting the Eurofound ERM reshoring event data, the ILO wage ratio, the extended IFR robot density panel, and the Caldara-Iacoviello country-specific geopolitical risk index, alongside the descriptive statistics and temporal patterns that motivate the econometric specification. Chapter 5 presents the numerical results of the main specification and three robustness analyses, followed by a structured interpretation of the findings in relation to the three hypotheses, the pre/post-2018 structural shift, the EU-US divergence, and the limitations of the empirical design. Chapter 6 concludes with theoretical, managerial, and CSR contributions, a critique of the study, and avenues for future research.

2 Literature Review

2.1 International Fragmentation and Global Production Organisation

2.1.1 The Emergence and Logic of International Fragmentation

Global production has shifted dramatically over the past three decades, with firms increasingly splitting their operations across multiple countries rather than keeping everything in-house (Feenstra, 1998).

This fragmentation has been conceptualized as a transition from trade in final goods toward trade in tasks, enabled by significant improvements in transportation, communication, and coordination technologies that have reduced the need for geographic proximity among production stages (Grossman & Rossi-Hansberg, 2006).

2.1.2 Conceptual Frameworks: GVC vs. GPN

To make sense of the growing complexity of geographically dispersed production, the literature has developed two main analytical frameworks: Global Value Chains (GVC) and Global Production Networks (GPN). The GVC framework conceptualizes production as a sequence of value-adding activities ranging from design and sourcing to manufacturing, marketing, and final delivery. Within this perspective, particular attention is paid to governance structures, which determine how lead firms coordinate and control their suppliers through market-based, modular, relational, captive, or hierarchical arrangements (Gereffi et al., 2005). The GPN framework adopts a broader and more relational perspective on global production organisation.

2.1.3 The Role of MNEs and Lead Firms

Within both GVC and GPN frameworks, multinational enterprises (MNEs), often referred to as lead firms, occupy a central coordinating role. Over recent decades, these firms have progressively de-verticalized their operations, shifting away from direct ownership of manufacturing activities and refocusing on high-value functions such as research and development, design, branding, and marketing (Gereffi et al., 2005). This strategic reorientation allows lead firms to retain control over key intangible assets while outsourcing labour-intensive production stages to external suppliers (Gereffi, 1994).

2.2 Offshoring as a Dominant Strategic Configuration

This disintegration of production laid the foundation for offshoring to emerge as the dominant strategic configuration in global manufacturing and services. This section first clarifies the key definitions and organisational forms of offshoring before examining the classical economic rationales that sustained its dominance.

2.2.1 Definitions and Forms of Offshoring

In the literature on international production, it is essential to make a difference between offshoring and outsourcing, as these concepts refer to different dimensions of firm organisation. Offshoring denotes the geographical relocation of specific production tasks to a foreign country, regardless of whether these tasks are performed internally or by an external supplier. Outsourcing, by contrast, refers to the organisational decision to contract tasks to an independent firm, which may occur either domestically or internationally (Grossman & Rossi-Hansberg, 2006).

Two main forms are distinguished: captive offshoring to foreign subsidiaries and offshore outsourcing to independent suppliers (Gereffi et al., 2005), with location choices shaped by factor cost differentials and economies of scale (Dunning, 1988; Krugman, 1991).

2.2.2 Cost-Based and Efficiency-Driven Explanations

The dominance of offshoring is primarily explained by classical economic arguments centered on efficiency gains and cost reduction. Advances in transportation and information technologies significantly reduced the costs of coordinating activities across distance, enabling firms to fragment production processes while preserving the benefits of specialization. Building on the fragmentation of production into tradable tasks, firms were able to allocate these tasks across countries according to factor cost differentials, while preserving the productivity gains associated with specialization (Grossman & Rossi-Hansberg, 2006).

Finally, the form that offshoring takes is strongly influenced by transaction cost considerations. Firms must choose between market-based coordination and internalization depending on the characteristics of transactions. When products are standardized and asset specificity is low, market-based offshore outsourcing is generally efficient. However, as transactions become more complex or involve highly specific investments, firms face increased risks of opportunism and coordination failures. In such cases, captive offshoring provides a mechanism to retain control while still benefiting from international cost differentials (Baumol, 1986; Williamson, 1985). However, emerging economic, technological, and geopolitical pressures have increasingly called into question its long-term sustainability.

2.3 Limits and Risks of Extensive Offshoring

While offshoring was long viewed as a panacea for cost reduction and efficiency gains, the growing complexity of globally fragmented production systems has revealed significant vulnerabilities. As supply chains have become increasingly lean, geographically extended, and tightly coupled, the risks associated with these configurations have intensified. Rather than functioning as frictionless systems, global production networks have proven to be highly sensitive to disruptions, prompting firms to question the long-term sustainability of extensive offshoring strategies (Christopher & Peck, 2004).

2.3.1 Operational and Supply Chain Risks

A major source of operational instability arises from information distortions within extended supply chains. Studies on supply chain dynamics show that demand variability tends to increase as orders move upstream, a phenomenon commonly referred to as the bullwhip effect (Lee et al., 1997). Long lead times, limited visibility, and fragmented information systems amplify these distortions in offshored networks, leading to inefficient production planning, excess inventories, capacity mismatches, and higher logistics costs.

Beyond coordination issues, offshoring also introduces significant risks related to quality control and delivery reliability. Distance complicates monitoring, slows feedback loops between design and production, and increases the likelihood that defects or delays will only be detected after substantial costs have already been incurred. Empirical evidence shows that many firms underestimate these operational risks during the initial offshoring decision, focusing on unit labour cost savings while overlooking communication barriers, delivery delays, and quality failures (Gray et al., 2013). As a result, firms often face a range of "hidden costs" that progressively erode the expected benefits of offshoring.

The increasing reliance on long, lean, and complex supply chains has therefore reduced the resilience of offshored production systems, making operational disruptions more frequent and more costly.

2.3.2 Strategic, Institutional, and Geopolitical Risks

Beyond operational concerns, extensive offshoring exposes firms to a broader set of strategic, institutional, and geopolitical risks that can fundamentally undermine the value of foreign production activities. From an institutional perspective, multinational enterprises operating offshore are subject to political and regulatory environments over which they have limited control. Political hazards include the risk of adverse policy changes, such as shifts in taxation, regulation, trade policy, or industrial strategy, which may reduce the expected returns on foreign investments (Henisz, 2000). These risks are particularly acute in environments characterized by weak institutional constraints and limited policy predictability.

Institutional risks are often amplified by firms' strategic dependence on specific regions or key suppliers. Global production networks tend to concentrate critical manufacturing capabilities in a limited number of locations, creating asymmetrical dependencies that increase firms' exposure to external shocks (Coe et al., 2008). Such concentration can transform efficiency-driven location choices into strategic liabilities when access to key inputs or production sites is disrupted.

Recent global crises have starkly illustrated the magnitude of these vulnerabilities. The COVID-19 pandemic, the Russian invasion of Ukraine, and escalating US-China trade tensions have collectively demonstrated that globally fragmented production systems function as networks of economic contagion, in which localized shocks propagate rapidly across borders and trigger cascading disruptions (Roscoe et al., 2023). Empirical evidence further confirms that these shocks have prompted significant geographic reallocation of supply chains, with firms actively reducing their dependence on China in favour of Vietnam, India, and nearshore locations (Cohen et al., 2024). These disruptions revealed the extent to which offshoring strategies had increased firms' exposure to exogenous shocks beyond their managerial control.

More broadly, environmental disasters, terrorism, and rising geopolitical tensions further expose the fragility of global production networks. Such shocks highlight the unstable power relations and dependencies embedded in offshore production systems, which are often only fully recognized through costly experience (Christopher & Peck, 2004; Gray et al., 2013). As firms accumulate knowledge about these operational and strategic vulnerabilities through a process of learning-by-doing, many come to reassess earlier offshoring decisions that were driven primarily by attractive unit cost considerations while neglecting resilience and risk exposure.

These accumulated failures have led many firms to question whether the offshoring model still makes sense — and to start bringing production closer to home.

2.3.3 Definitions: Back-shoring, Reshoring, and Nearshoring

The literature emphasizes the need for conceptual precision when analysing the relocation of production activities back toward advanced economies, as multiple terms are often used interchangeably. Gray et al. (2013) highlight a persistent "lexical ambiguity" surrounding reshoring-related concepts and argue that such strategies must first be understood as location decisions, distinct from governance choices.

In this perspective, reshoring is commonly employed as an umbrella term referring to the relocation of production activities that were previously offshored, regardless of whether these activities are performed internally or outsourced. The key defining feature of reshoring is therefore the geographical dimension of production location rather than the identity of the entity performing the activity.

More narrowly, back-shoring (or back-reshoring) refers specifically to the relocation of value-creating activities from a foreign location back to the firm's home country. Fratocchi et al. (2016) define back-shoring as a voluntary corporate strategy involving the partial or total relocation of production to the domestic country in order to serve local, regional, or global markets. This definition emphasizes that back-shoring is neither automatic nor comprehensive but instead reflects a selective strategic response to changing competitive conditions.

A related but distinct strategy is nearshoring, which denotes the relocation of production closer to the home country without necessarily returning to it. For example, European firms may relocate activities from East Asia to Eastern Europe in order to reduce lead times and coordination costs while preserving some cost advantages.

Gray et al. (2013) further distinguish four governance configurations of reshoring, underscoring that back-shoring is not synonymous with reinternalisation but can occur under multiple ownership arrangements. Reshoring is therefore not simply offshoring in reverse — it is a selective repositioning within an ongoing global production system.

2.3.4 Empirical Evidence of Back-shoring Trends

Studies emphasize that back-shoring is best interpreted as a selective and stable trend, closely linked to firms' reassessment of offshoring strategies.

In the European context, Kinkel (2012) provides some of the most robust empirical evidence based on large-scale survey data from German manufacturing firms. His findings show that while offshoring activities declined sharply during the global economic crisis, reshoring activities remained comparatively stable. Importantly, the study reveals that for approximately every three firms relocating production abroad, one firm simultaneously relocates production back to the home country. This pattern suggests that reshoring operates as a structural countermovement within global production dynamics rather than as an exceptional response.

Further empirical work highlights the growing role of technology in shaping reshoring decisions. Using European data, Ancarani et al. (2019) demonstrate that the adoption of Industry 4.0 technologies, including automation, digitalization, and advanced manufacturing systems, significantly increases the likelihood of reshoring. By reducing the relative importance of labour costs and enhancing process control, these technologies weaken the traditional cost advantages of offshore locations and make domestic production economically viable for specific activities.

Sectoral evidence further confirms that reshoring is typically partial and contingent on existing domestic capabilities, rather than a full reinternalization of production activities (Bailey & De Propris, 2014). This empirical evidence confirms that reshoring represents a strategic rebalancing of global production networks, aligning efficiency considerations with resilience and control.

2.4 Drivers of Strategic Reconfiguration in Global Production Networks

The traditional expansion of global value chains, once primarily driven by labour-cost arbitrage, has reached a structural turning point. Rather than signaling a reversal of globalisation, recent evidence points to a strategic reconfiguration of global production networks in response to changing economic, technological, and institutional conditions (Lund et al., 2020). The emergence of reshoring can thus be understood as the outcome of multiple interacting drivers operating simultaneously across these dimensions.

2.4.1 Cost Rebalancing and Total Cost of Ownership

The labour-cost advantage of major offshoring hubs has diminished significantly over time. In particular, China has experienced sustained wage growth over the past two decades, substantially narrowing the cost gap with advanced economies (De Backer et al., 2016). Beyond wages, transportation costs and delivery times play a critical role in location decisions. Hummels (2007) demonstrates that distance-related trade costs often exceed tariff barriers and that time itself functions as a significant impediment to trade, with each additional day in transit equivalent to a substantial ad valorem tax on the value of goods. In response, firms increasingly adopt a Total Cost of Ownership (TCO) perspective, which incorporates not only direct production costs but also supply chain risks, administrative complexity, and operational inefficiencies. This broader cost assessment often reveals that the apparent savings from offshoring are offset, and sometimes even outweighed, by the structural inefficiencies of dispersed production footprints (Ellram et al., 2013; Lund et al., 2020).

2.4.2 Technological Change and Automation

Advances in robotics and automation enable machines to perform tasks previously carried out by human labour, fundamentally altering the relationship between production costs and location decisions (Acemoglu & Restrepo, 2017). As production becomes increasingly capital-intensive, task allocation is no longer primarily governed by international wage differentials but by the relative cost and performance of automated technologies. Critically, automation does not simply add to cost rebalancing as an independent driver: it may amplify it. When robot density is high and labour's share of production costs is low, wage convergence alone may become sufficient to trigger reshoring, as the cost-location nexus is weakened (Chen & Frey, 2024). Whether this amplification mechanism operates in practice remains an empirical question; the present study tests it directly in Chapter 5. Digitalization further reinforces this dynamic by enhancing visibility and coordination across design, manufacturing, and distribution, favouring co-location of activities closer to end markets and innovation centers (Ivanov & Dolgui, 2020).

2.4.3 Risk Management and Supply Chain Resilience

Ponomarov and Holcomb (2009) define supply chain resilience as the adaptive capability to prepare for, respond to, and recover from unexpected disruptions. Highly optimized and geographically concentrated supply chains, while efficient under stable conditions, have proven vulnerable to shocks. Events such as the global financial crisis, major natural disasters, and the "China shock" have illustrated how overdependence on single regions can trigger cascading failures across interconnected production networks (Autor et al., 2016; Firooz et al., 2025). Critically, risk-related variables do not simply add to cost considerations in explaining reshoring: they moderate the threshold at which cost parity becomes sufficient to trigger relocation. Firms facing high supply chain risk exposure face a stronger incentive to accept efficiency losses in exchange for resilience gains, shifting the cost-resilience trade-off in favour of domestic or regional production (Lund et al., 2020).

2.4.4 Institutional Factors as Moderators

Institutional factors, including trade policy uncertainty, geopolitical tensions, and government incentives, should be understood as moderators rather than independent drivers. They do not directly determine whether back-shoring is economically or technologically viable, but they alter the attractiveness of specific location choices and accelerate or delay relocation decisions already motivated by cost or risk considerations (Ellram et al., 2013). This moderating role helps explain the phenomenon of *friend-shoring*, in which firms, particularly US multinationals, do not reshore to their home country but instead relocate to geopolitically aligned lower-cost countries such as Vietnam, Malaysia, or Mexico. In this configuration, institutional alignment reduces geopolitical risk while preserving residual cost advantages, representing a hybrid strategic response that sits between full reshoring and conventional offshoring (Lund et al., 2020).

2.5 Synthesis and Research Gap

The literature reviewed above highlights the profound transformation of global production systems over recent decades. While offshoring long represented the dominant organisational model of global value chains, growing economic pressures, technological change, and rising geopolitical tensions have increasingly led firms to reconsider the geographical configuration of their production activities. In this context, reshoring has emerged as an important phenomenon reflecting the strategic reconfiguration of global production networks.

A growing body of research has identified multiple drivers behind these relocation decisions, including cost rebalancing, automation, and supply chain resilience. However, a critical empirical contradiction remains unresolved in the literature. While Fratocchi et al. (2016) document reshoring as a widespread phenomenon across advanced economies, recent data reveals a striking divergence: European firms tend to combine reshoring and nearshoring simultaneously, whereas US firms predominantly favour nearshoring over domestic relocation, with only a minority increasing domestic sourcing (Lund et al., 2020). This divergence suggests that the same cost and risk drivers produce systematically different strategic responses depending on the institutional and technological context in which firms operate, a differentiation that existing single-country or single-driver studies are structurally unable to capture.

As a result, the relative importance of these drivers, and the conditions under which they lead to reshoring versus nearshoring versus friend-shoring, remains insufficiently understood.

Building on this perspective, this research models the reshoring decision as a function of several explanatory variables capturing these different dimensions of global production dynamics:

$$\text{Reshoring decision} = f(\text{cost dynamics, technological capabilities, supply chain risk exposure})$$

Within this analytical framework, economic variables capture changes in global cost structures that may affect the attractiveness of offshore production locations. These include indicators such as labour cost dynamics, wage differentials between countries, or broader measures related to the total cost of ownership of offshore production. Technological variables reflect the adoption of automation and advanced manufacturing technologies that may reduce firms' dependence on low-cost labour and facilitate the relocation of production activities closer to end markets. Finally, risk-related variables capture the vulnerability of globally fragmented supply chains to operational disruptions and geopolitical shocks.

Despite the identification of these factors in the literature, limited empirical evidence exists regarding their comparative influence on firms' strategic reconfiguration of global production networks. To address this gap, this thesis adopts a quantitative approach aimed at evaluating the relative importance of these drivers within an integrated analytical framework.

Building on this framework, three testable hypotheses structure the empirical investigation:

H1 (Cost): H1 (Cost): A higher wage ratio between the destination country and China is associated with greater reshoring activity, reflecting the combined effect of cross-country cost structure differences and the secular compression of the cost advantage of offshoring driven by Chinese wage growth.

H2 (Technology): Higher automation intensity in the home country increases the probability of reshoring, and amplifies the effect of wage convergence.

H3 (Risk): Greater exposure to supply chain disruptions increases the probability of back-shoring, independently of cost dynamics.

To test these hypotheses, this study adopts a quantitative panel-data approach combining two complementary data sources. For Europe, reshoring events are drawn from the Eurofound European Restructuring Monitor (ERM), which provides firm-level data on production relocation decisions across European manufacturing sectors over the period 2014–2025. For the United States, aggregate reshoring trends are documented using data from the Reshoring Initiative (Reshoring Initiative, 2024), used here as a contextual reference to situate the European findings within a broader international perspective. Country-level explanatory variables, including a wage ratio relative to China as a proxy for labour cost differentials, robot density per manufacturing worker, and a country-specific geopolitical risk index, are drawn from the International Labour Organisation (ILO), the International Federation of Robotics (IFR), and Caldara and Iacoviello (2022) respectively. Given that the dependent variable counts discrete reshoring events per country-year, the empirical model belongs to the family of count-data estimators, specifically the Poisson and negative binomial regression models estimated with country and year fixed effects.

3 Model

3.1 Overview

The empirical model developed in this chapter is designed to test the three hypotheses identified in the literature review within a unified quantitative framework. H1 posits that a reduction in the labour cost differential between the destination country and China, the dominant origin country in the dataset, increases reshoring activity. H2 posits that higher automation intensity amplifies this cost effect, making reshoring more likely when robot density is high. H3 posits that greater geopolitical risk increases reshoring activity independently of cost dynamics.

3.1.1 Choice of Estimator

The choice of empirical strategy follows directly from the distributional properties of the dependent variable documented in the Data chapter. Reshoring events are non-negative integers, heavily concentrated at low values, and characterised by a long right tail. These features render standard linear regression inappropriate: ordinary least squares produces predicted values that may be negative, does not respect the integer nature of the outcome, and yields inefficient estimates under non-normality (Cameron & Trivedi, 2013). This motivates the use of **count-data models**, which are standard in the empirical literature on discrete event outcomes including trade flows, patent citations, and firm-level location decisions (Helpman et al., 2008; Silva & Tenreyro, 2006).

Within the family of count-data models, the *Poisson regression model* is the natural benchmark. It specifies the conditional mean as $\mathbb{E}[Y_{it} \mid \mathbf{X}_{it}] = \exp(\mathbf{X}_{it}'\boldsymbol{\beta})$, ensuring that predicted counts are always non-negative. A key property of the Poisson estimator is that it remains consistent even when the distributional assumption is misspecified, provided the conditional mean is correctly specified, a property known as pseudo-maximum likelihood consistency (Silva & Tenreyro, 2006). However, the Poisson model imposes the restrictive assumption of *equidispersion*: the conditional variance equals the conditional mean. In practice, count data in economics frequently exhibit *overdispersion*, meaning the variance substantially exceeds the mean, which leads to underestimated standard errors and inflated test statistics under Poisson.

As documented in the Data chapter, the reshoring count displays clear overdispersion in the unconditional distribution, with a variance-to-mean ratio substantially exceeding 1. The **negative binomial regression model** addresses this by introducing a dispersion parameter $\theta > 0$ that allows the variance to exceed the mean. Both the Poisson and the negative binomial are estimated, and the choice between the two is determined empirically using a formal likelihood ratio test, as described in Section 3.4.5.

3.1.2 Panel Structure and Fixed Effects

The model is estimated on a panel covering **12 European destination countries** over the period **2016–2024**, yielding 108 country-year observations, of which 58 record at least one reshoring event and 50 are zero-count observations. The sample restriction relative to the full ERM dataset reflects the intersection of three data sources: the ILO wage ratio, the extended IFR robot density panel, and the country-specific GPR index developed by Caldara and Iacoviello (2022). The panel is unbalanced for two reasons. First, not all countries are observed reshoring in every year: many country-year cells record zero events, and some countries do not appear as reshoring destinations at all in certain sub-periods. Second, the robot density dataset covers 23 countries from 2016 onwards, creating a partial overlap with the full ERM sample. The unbalanced structure is handled naturally within the count-data fixed effects framework, which conditions on the sum of events within each group to eliminate the fixed effects from the likelihood function.

Country fixed effects (α_i) are included to control for all time-invariant unobserved characteristics of each destination country, such as its industrial structure, proximity to major offshoring hubs, institutional environment, or historical reshoring propensity. Without these controls, countries with structurally higher reshoring activity would inflate the estimated effects of the explanatory variables. **Year fixed effects** (γ_t) are included to absorb common temporal shocks affecting all countries simultaneously, including global business cycle fluctuations, multilateral trade policy changes, and the aggregate effects of the COVID-19 pandemic. The justification for fixed effects over random effects is discussed in Section 3.4.5.

The country-specific GPR index ($GPRC_{it}$) varies across both countries and years and is therefore included directly in the main specification alongside the year fixed effects, without any collinearity concern. This allows H3 to be identified from both the cross-sectional differences in geopolitical exposure between destination countries and the common temporal spike observed in 2022 following the Russian invasion of Ukraine.

The interaction term between the wage ratio and robot density is included in the main specification, motivated by H2's claim that automation amplifies the cost effect rather than operating independently. This allows the marginal effect of labour cost dynamics on reshoring to vary with the level of automation in the destination country, consistent with the theoretical mechanism described in Chen and Frey (2024).

3.2 Model Parameters

Table 3.1 summarises the key parameters of the empirical model, including their theoretical motivation, expected sign, identification source, and the interpretation of a statistically non-significant result.

The expected positive sign of β_1 reflects the core prediction of H1: a higher wage ratio is associated with more reshoring. This association operates primarily cross-sectionally: countries

Table 3.1: Model Parameters

Parameter	**H**	**Expected sign**	**Identified by**	**If non-significant**
β_1 wage ratio	H1	Positive	Cross-country and time	Cost convergence alone does not drive European reshoring; TCO factors beyond wages may dominate
β_2 robot density	H2	Positive	Cross-country	Automation does not independently predict reshoring; effect may be fully captured by the interaction term
β_3 interaction	H2 amplifies H1	Positive	Cross-country and time	Automation does not moderate the cost-reshoring relationship; H1 and H2 operate independently
β_4 GPRC	H3	Positive	Cross-country and time	Geopolitical risk does not predict reshoring at the country level; firm responses may depend on sector or firm characteristics not captured by country-level indices
α_i country FE	Control	—	Within estimator	—
γ_t year FE	Control	—	Common shocks	—

with structurally higher wages relative to China tend to be more productive and automated economies where domestic production is viable. The secular rise in Chinese wages compresses the ratio over time, but this time-series variation is partially absorbed by year fixed effects. This effect operates through the convergence of wages rather than their absolute level, consistent with the Total Cost of Ownership logic developed by Ellram et al. (2013). A non-significant β_1 would suggest that European reshoring decisions are not primarily driven by wage cost differentials, and that other dimensions of the total cost of ownership such as transportation costs, delivery times, or quality considerations may play a larger role.

The expected positive sign of β_2 reflects the prediction that countries with higher robot density can sustain manufacturing at lower per-unit costs despite higher nominal wages, making domestic production economically viable. A non-significant β_2 in isolation would not necessarily invalidate H2: if the automation effect operates exclusively through its interaction with wage convergence, as the theoretical framework suggests, β_2 could be close to zero while β_3 remains positive and significant.

The expected positive sign of β_3 is the most theoretically important parameter in the model. It tests whether automation amplifies the reshoring response to wage convergence, as predicted by Chen and Frey (2024): when robot density is high and labour's share of production costs is low, a given increase in the wage ratio produces a stronger reshoring impulse. A non-significant β_3 would suggest that automation and cost rebalancing operate as independent drivers rather than as interacting forces.

The expected positive sign of β_4 reflects the prediction that higher geopolitical risk raises the perceived cost of maintaining geographically dispersed supply chains, incentivising firms to reshore (Roscoe et al., 2023). Given that H3 is now identified from both cross-sectional differences in geopolitical exposure between countries and common temporal variation, a non-significant result would more robustly suggest the absence of a genuine effect at the country level.

3.3 Model Variables

Table 3.2 provides a complete description of all variables entering the econometric model. A discussion of the construction choices and measurement limitations follows.

Dependent variable.

The dependent variable Y_{it} is the count of reshoring events recorded by the Eurofound ERM in destination country i in year t. Country-year cells with no recorded events enter the panel as zero observations. The inclusion of zero counts is important because excluding them would create a selected sample biased toward active reshoring destinations and would overestimate the average reshoring intensity. One limitation of this variable is that it counts events without weighting them by economic magnitude: a large relocation creating 2,000 jobs counts the same as a small one

Table 3.2: Model Variables

Variable	Construction	Unit	Source
Dependent variable			
Y_{it}	Count of reshoring events in country i, year t	Integer ≥ 0	ERM/Eurofound
Explanatory variables, main specification			
$\ln(WR_{it})$	$\ln(w_{it}^{\text{dest}}/w_t^{\text{CN}})$, PPP-adjusted	Log ratio	ILO; own construction
$\ln(R_{it})$	Log of robots per 10,000 manufacturing workers	Log units	IFR
$\ln(WR_{it})\times\ln(R_{it})$	Product of log wage ratio and log robot density	Log^2	Own construction
$GPRC_{it}$	Country-specific annual average of monthly GPR index	Index	(Caldara & Iacoviello, 2022)
Fixed effects			
α_i	Indicator for destination country i	Binary	—
γ_t	Indicator for year t	Binary	—

w_{it}^{dest}: manufacturing wage, destination country i, year t. w_t^{CN}: Chinese manufacturing wage, year t.

creating 10. The number of jobs is used as an alternative dependent variable in robustness checks, though this comes at the cost of a significant reduction in sample size due to missing job data.

Wage ratio.

The wage ratio $WR_{it} = w_{it}^{\text{dest}}/w_t^{\text{CN}}$ captures the labour cost differential between the destination country and China. A logarithmic transformation is applied so that the coefficient β_1 can be interpreted as a semi-elasticity. The wage ratio carries two important limitations. First, it uses manufacturing wages as a proxy for total production costs, ignoring other dimensions of the total cost of ownership such as transportation costs, energy prices, regulatory compliance, and quality risks (Ellram et al., 2013; Gray et al., 2013). Second, it benchmarks all countries against China, even though a significant share of European reshoring cases originate from other countries. Using China as the universal benchmark is justified by its dominance in the dataset and by the fact that Chinese wage growth is the most analytically prominent driver of global reshoring trends (De Backer et al., 2016), but it introduces measurement imprecision for cases originating elsewhere.

Robot density.

Robot density R_{it} captures the degree of automation in the destination country's manufacturing sector. The logarithmic transformation addresses the strong right skew of the distribution and allows for an elasticity interpretation. One limitation is that robot density is a stock measure reflecting cumulative past investment in automation rather than current technological capability: more advanced forms of automation such as collaborative robots or AI-driven production systems are not fully captured by the IFR metric. Additionally, approximately 60% of the robot density observations in the panel are modelled rather than directly observed, which introduces measurement noise. The sensitivity of results to this modelling assumption is noted as a limitation.

Geopolitical risk index.

The country-specific GPR index measures geopolitical risk as perceived through media coverage, which may not fully capture the actual risk exposure faced by individual firms. Companies operating in highly specialised or geopolitically sensitive sectors may respond differently to the same level of country-level geopolitical risk, a heterogeneity that the country-level index cannot capture. Additionally, the exclusion of 12 destination countries without a country-specific GPR series, while representing only 8.3% of recorded events, introduces a mild selection concern that is noted as a limitation.

3.4 Model Description

3.4.1 Baseline Specification

The baseline empirical model is a **Poisson quasi-maximum likelihood estimator** (PQMLE) with country and year fixed effects, estimated alongside a negative binomial specification for comparison. The formal likelihood ratio test determines which specification is preferred, as described in Section 3.4.5. The conditional mean of the count outcome is modelled through a log-linear link function:

$$\ln(\mu_{it}) = \alpha_i + \gamma_t + \beta_1 \ln(WR_{it}) + \beta_2 \ln(R_{it}) + \beta_3 \left[\ln(WR_{it}) \times \ln(R_{it})\right] + \beta_4\, GPRC_{it} + \varepsilon_{it} \quad (3.1)$$

where $\mu_{it} = \mathbb{E}[Y_{it} \mid \alpha_i, \gamma_t, \mathbf{X}_{it}]$ is the conditional expected count of reshoring events in country i at time t. In the negative binomial model, the variance of Y_{it} is specified as:

$$\text{Var}(Y_{it}) = \mu_{it} + \frac{\mu_{it}^2}{\theta} \quad (3.2)$$

where $\theta > 0$ is the dispersion parameter estimated jointly with the regression coefficients. As $\theta \to \infty$, the negative binomial collapses to the Poisson model. Standard errors are clustered at the country level to account for serial correlation in the error terms within countries over time.

3.4.2 Marginal Effects and Interpretation

Because the log-linear link function makes the model non-linear, the coefficients are not directly interpretable as additive marginal effects. They are interpreted as semi-elasticities with respect to the log-transformed regressors. The total partial effect of a 1% increase in the wage ratio on the expected count, holding robot density constant at level R, is:

$$\frac{\partial \ln(\mu_{it})}{\partial \ln(WR_{it})} = \beta_1 + \beta_3 \cdot \ln(R) \quad (3.3)$$

This expression illustrates the central prediction of H2: the sensitivity of reshoring to wage convergence increases with the level of automation. When $\beta_3 > 0$, the same increase in the wage ratio produces a larger reshoring response in highly automated countries than in less automated ones. Marginal effects are computed at the sample mean of robot density and at the 25th, 50th, and 75th percentiles to illustrate this heterogeneity across the automation distribution.

3.4.3 Robustness Specification

To assess the sensitivity of the results to the choice of geopolitical risk measure, a robustness specification replaces the country-specific $GPRC_{it}$ with the global GPR index GPR_t, which is common to all countries in a given year. Since the global index has no cross-sectional variation, year fixed effects are excluded from this specification to avoid perfect collinearity:

$$\ln(\mu_{it}) = \alpha_i + \beta_1 \ln(WR_{it}) + \beta_2 \ln(R_{it}) + \beta_3 [\ln(WR_{it}) \times \ln(R_{it})] + \beta_4^{\text{global}} GPR_t + \varepsilon_{it} \quad (3.4)$$

Comparing the results from equations (3.1) and (3.4) allows assessment of whether the country-specific and global geopolitical risk measures yield consistent conclusions regarding H3.

3.4.4 Estimation and Implementation

The model is estimated in **R** using the `MASS` package for the negative binomial regression and the `fixest` package for the fixed effects implementation (Bergé, 2018). The `fixest` package is particularly suited to this application as it handles high-dimensional fixed effects efficiently and supports count-data models with clustered standard errors. The Poisson specification is estimated using the same package for direct comparison with the negative binomial.

Country-year observations with zero reshoring events are retained in the estimation sample. In the fixed effects negative binomial model, the incidental parameters problem, whereby the proliferation of fixed effects in short panels can bias the estimates of the structural parameters, is addressed by using the conditional maximum likelihood estimator, which conditions on the total event count within each country to eliminate the fixed effects from the likelihood function (Hausman et al., 1984).

The wage ratio variable requires PPP conversion to express both the destination country wage and the Chinese wage in a comparable unit. Annual PPP conversion factors from the World Bank are applied to convert all wages to a common reference currency before computing the ratio, ensuring that a value of 1 corresponds to wage parity between the destination country and China in purchasing power terms.

3.4.5 Specification Tests

Likelihood ratio test: Poisson versus negative binomial.

To formally assess whether the negative binomial provides a statistically significant improvement over Poisson, a likelihood ratio test is conducted with the null hypothesis of equidispersion. The test statistic is:

$$LR = 2\left[\ell_{\text{NB}}(\hat{\boldsymbol{\beta}}, \hat{\theta}) - \ell_{\text{Poisson}}(\hat{\boldsymbol{\beta}})\right] \sim \chi^2(1) \quad (3.5)$$

where ℓ_{NB} and ℓ_{Poisson} denote the log-likelihoods of the two models respectively. It should be noted that the validity of a standard LR test for selecting between Poisson and negative binomial specifications in the presence of fixed effects is not fully established in the literature, as the incidental parameters problem may affect the log-likelihoods differently across the two models

(Cameron & Trivedi, 2013). The test is therefore interpreted as indicative rather than definitive. Given that the fixed effects structure may absorb the apparent overdispersion, the result of this test — in conjunction with the Pearson chi-squared overdispersion check — informs the choice between the two specifications.

Choice of fixed effects over random effects.

Country fixed effects are preferred over random effects on theoretical grounds: wage levels and robot density are plausibly correlated with time-invariant country characteristics such as industrial structure and institutional environment, violating the orthogonality assumption required for the random effects estimator to be consistent (Cameron & Trivedi, 2013).

Additional robustness checks.

Beyond the main specification tests, one additional robustness check is conducted. The sample is split at 2018 to assess whether the pre-2018 and post-2018 sub-periods yield qualitatively similar results, given the apparent change in reshoring activity documented in the Data chapter.

3.4.6 Identification Strategy

The identification of β_1 exploits both cross-sectional and temporal variation. Cross-sectionally, countries with structurally higher wages relative to China should exhibit more reshoring, all else equal. Temporally, the secular rise in Chinese manufacturing wages, which nearly doubled between 2014 and 2024 (+93%), generates an exogenous compression of the wage ratio for all destination countries simultaneously. This provides a quasi-natural experiment in which the cost differential narrows for reasons largely unrelated to the reshoring decisions of individual European firms.

The identification of β_2 is more complex. With country fixed effects included, time-invariant cross-country differences in robot density are absorbed by the fixed effects and do not contribute to identification. The coefficient is therefore identified from within-country changes in robot density over time. However, robot density is a slow-moving variable and exhibits limited within-country variation over the nine-year panel. The estimate should therefore be interpreted with caution.

Country fixed effects ensure that estimates are not contaminated by time-invariant differences between destination countries. Year fixed effects control for global economic conditions and policy shocks that simultaneously affect all countries in the sample.

3.4.7 Model Limitations

Several limitations of the empirical model deserve explicit acknowledgement. First, the assumption that reshoring events are independent across countries and firms may be violated in practice. Multinational enterprises operating across multiple European countries may make coordinated reshoring decisions, creating cross-country dependence in the error terms that is not fully addressed by country-level clustering of standard errors.

Second, the panel is relatively short at nine years, with a marked decline in activity after 2018, which limits the statistical power available to detect effects in the post-2018 period. The country-specific GPR index is available for only 14 of the 26 destination countries, requiring the exclusion of 12 small economies from the estimation sample. While these excluded countries represent only 8.3% of recorded events, the restriction introduces a mild selection concern that cannot be fully eliminated.

Third, the wage ratio captures only the labour cost dimension of the offshoring cost advantage, ignoring transportation costs, energy prices, regulatory compliance, and the full range of hidden costs documented in the reshoring literature Ellram et al. (2013) and Gray et al. (2013). A more comprehensive total cost of ownership measure would provide a richer test of H1 but is not constructible from available panel data.

Fourth, the potential endogeneity of robot density deserves attention. Countries anticipating reshoring may invest in automation in preparation for higher domestic production volumes, creating reverse causality. While the fixed effects estimator mitigates this concern by exploiting within-country variation, it does not fully eliminate it. Instrumental variables for robot adoption, such as those proposed in Acemoglu and Restrepo (2017), would provide a more credible identification strategy but fall outside the scope of the present analysis, which is primarily exploratory in nature.

Notwithstanding these limitations, the panel fixed effects Poisson quasi-maximum likelihood model with 12 countries, 108 observations, and clustered standard errors represents a methodologically appropriate and empirically grounded framework for investigating the drivers of European reshoring activity. Its estimates provide a first systematic quantitative assessment of the relative importance of labour costs, automation, and geopolitical risk in explaining firms' strategic relocation decisions.

4 Data

4.1 Methodology

This study investigates the determinants of reshoring decisions using a quantitative, panel-data approach designed to test three hypotheses simultaneously: that rising labour costs in origin countries push firms to reshore production (H1); that higher automation levels in destination countries make reshoring economically viable (H2); and that increased geopolitical risk accelerates reshoring by incentivising firms to shorten and secure their supply chains (H3).

The unit of observation is the **country-year**, meaning that all variables are measured at the level of a destination country in a given year. The panel structure exploits both cross-sectional variation (differences between countries) and temporal variation (changes within countries over time) to identify the effects of interest.

Given that the dependent variable counts discrete reshoring events per country-year, the appropriate estimation framework belongs to the family of **count-data models**. The choice between the Poisson and the negative binomial specifications, and the justification for country and year fixed effects, are developed in detail in Chapter 3. The preferred estimator is determined empirically using a formal likelihood ratio test.

4.2 Data Collection

4.2.1 Reshoring Variable

Europe: Eurofound European Restructuring Monitor

For Europe, data are drawn from the Eurofound **European Restructuring Monitor** (ERM), which records firm-level restructuring events across European countries including cases explicitly classified as reshoring. The dataset covers the period 2014–2025 and was constructed from Eurofound publications throughout, meaning that the decline in recorded cases after 2018 reflects a genuine reduction in reshoring activity rather than a change in collection methodology. The final European dataset contains **315 reshoring events** across 26 destination countries, generating **95 country-year observations** with at least one recorded event. The most frequent destination countries are France (71 cases), the United Kingdom (44), Italy (44), and Norway (28), which together account for more than 60% of all recorded events. On the origin side, China dominates with 99 cases, followed by Germany (18), Poland (18), and India (15), reflecting both the historical prevalence of offshoring to Asia and the importance of intra-European near-shoring.

Job information is available for only 134 of the 315 events (42.5%), with a strongly right-skewed distribution (mean: 118 jobs; median: 47; maximum: 2,100). Because of the high share of missing values, the *count of reshoring events* serves as the primary dependent variable throughout the empirical analysis.

United States: Reshoring Initiative (Contextual Reference)

To situate the European findings within a broader international perspective, reference is made to data from the **Reshoring Initiative**, which has tracked U.S. reshoring and foreign direct investment (FDI) activity since 2010 (Reshoring Initiative, 2024). Since granular case-level data are not publicly available, the U.S. data are used exclusively for descriptive comparison and are not incorporated into the econometric model. The primary metric reported by the Reshoring Initiative is job announcements: U.S. reshoring and FDI generated **244,000 job announcements** in 2024 alone, continuing a strong upward trend that has produced over 2 million cumulative announcements since 2010. This trajectory contrasts sharply with the European declining trend after 2018, a divergence that reflects the amplifying role of large-scale government incentives, notably the Inflation Reduction Act and the CHIPS Act, and the heightened sensitivity of U.S. firms to supply chain risk concentrated in China, which accounts for 67% of reshoring cases that report a country of origin. This comparative perspective illustrates how identical cost and risk drivers can produce systematically different strategic outcomes depending on the institutional context in which firms operate.

4.2.2 Labour Costs (H1)

Labour cost data are obtained from the **International Labour Organisation** (ILO), which publishes internationally comparable statistics on manufacturing wages. The variable used is the average monthly earnings in the manufacturing sector, expressed in local currency. A sector-specific measure is preferred over economy-wide averages because reshoring is predominantly an industrial phenomenon, and manufacturing wages better capture the cost environment relevant to firms' location decisions.

The ILO dataset covers **17 countries** over the period 2015–2025, yielding 300 country-year observations. To preserve the full 2014–2025 panel, 2014 values are backcasted for each country using the growth rate observed between 2015 and 2016, adding 16 interpolated observations. This approach is standard practice when dealing with wage data reported at irregular intervals and does not alter the long-run structure of the series.

Rather than using wage levels directly as the explanatory variable for H1, a **wage ratio** is constructed as the destination country's manufacturing wage relative to the Chinese manufacturing wage in the same year. This specification is motivated by two considerations. First, China is by far the dominant origin country in the European reshoring dataset (99 out of 315 cases, or 31%), making the China wage the most relevant benchmark for the labour cost differential driving reshoring decisions. Second, Chinese manufacturing wages nearly doubled over the study period, rising from approximately 4,667 CNY per month in 2014 to 8,999 CNY per month in 2024 (+93%), substantially narrowing the cost gap with European economies and providing strong time-series variation for identifying H1. Chinese wage data are drawn from a dedicated dataset covering 2014–2024, combining official statistics with estimates for years where administrative data are not yet available. The wage ratio is computed after converting both series to a common unit using purchasing power parity (PPP) adjusted exchange rates, ensuring cross-country comparability.

4.2.3 Automation (H2)

Automation is measured through robot density data published by the **International Federation of Robotics** (IFR): the number of industrial robots per 10,000 employees in manufacturing. A higher robot density signals that production can be maintained at a lower per-unit labour cost even with domestically higher wages, thereby supporting the economic viability of reshoring. The dataset covers **23 countries** over 2016–2024, for a total of 207 country-year observations, combining official IFR hard data points with interpolated and projected values to ensure temporal continuity. All modelled observations are explicitly labelled, allowing for robustness checks restricted to hard data only. Given the strongly right-skewed distribution of robot density, ranging from 33 to 1,220 robots per 10,000 workers, a logarithmic transformation is applied in the regression models to reduce the influence of extreme values and to allow for an elasticity interpretation of the estimated coefficient.

4.2.4 Geopolitical Risk (H3)

Geopolitical risk is measured using the country-specific GPR index developed by Caldara and Iacoviello (2022), which quantifies the intensity of geopolitical tensions based on automated text analysis of newspaper coverage related to wars, terrorism, and international political crises. Unlike the global GPR index, the country-specific series, denoted $GPRC_{it}$, capture the geopolitical risk exposure of each destination country individually, providing both cross-sectional and temporal variation. The index is available at monthly frequency and is aggregated to annual averages to match the panel structure.

Country-specific GPR series are available for 14 of the 26 destination countries in the reshoring dataset. The 12 countries without a country-specific series are small economies with few recorded reshoring events (between 1 and 4 cases each) and are excluded from the estimation sample. This restriction, combined with the availability of ILO wage data and IFR robot density data, reduces the final estimation sample to **108 country-year observations** across **12 destination countries** over the period 2016–2024, of which 58 record at least one reshoring event and 50 are zero-count observations.

4.3 Data Analysis

4.3.1 Descriptive Statistics

Table 4.1 reports the descriptive statistics for all variables in the full ERM dataset prior to the sample restriction imposed by the intersection of the three data sources. These figures describe the raw panel of 26 destination countries and 95 active country-year observations. The final estimation sample, restricted to the 12 countries for which all three variables are simultaneously available, is described in Chapter 5. The European reshoring event count has a mean of 3.32 and a median of 2 across the 95 active country-year observations, with a standard deviation of 3.28 and a maximum of 14. This low-count, right-skewed distribution with a large mass at zero when inactive country-years are included confirms the appropriateness of count-data estimators. The mean of 118 jobs per event against a median of 47 further illustrates the skewness of the jobs variable when considered as an alternative outcome.

The wage ratio, defined as the destination manufacturing wage relative to China expressed in PPP-adjusted terms, displays meaningful cross-country and temporal variation. Countries with relatively high wages such as Denmark, Germany, or the Netherlands exhibit ratios well above 1, while lower-wage economies in the sample approach parity with China. The secular increase in Chinese wages over the period mechanically compresses all ratios over time, capturing the narrowing cost advantage that H1 predicts should stimulate reshoring. Robot density ranges from 33 to 1,220 robots per 10,000 workers, with a mean of 278 and a standard deviation of 196, indicating strong heterogeneity across countries. The country-specific GPR index varies across both countries and years, with a mean of 0.250 and a standard deviation of 0.333 across the 168 country-year observations. The cross-sectional standard deviation (0.318) substantially exceeds the temporal standard deviation (0.089), indicating that differences in geopolitical exposure between destination countries drive more of the variation than common temporal shocks. The United Kingdom records the highest value in the sample (1.772 in 2022), while Portugal records the lowest (0.012 in 2021) (Caldara & Iacoviello, 2022).

4.3.2 Temporal and Cross-Sectional Patterns

The European reshoring series and the U.S. job announcement series exhibit strikingly different temporal trajectories, which is itself an analytically relevant finding. European reshoring activity rose sharply from 33 cases in 2014 to a peak of 74 in 2017, then declined steadily to fewer than 15 per year from 2019 onwards. Since all observations are drawn from the same Eurofound reporting framework throughout, this decline reflects a genuine reduction in reshoring activity, though the drivers of this post-2018 contraction remain difficult to identify from descriptive data alone. The COVID-19 pandemic in 2020 likely reinforced this decline by freezing long-term strategic investment decisions. Interestingly, the post-2021 surge in geopolitical risk, with country-specific GPR values peaking sharply in 2022 across most destination countries, most notably in the

Table 4.1: Descriptive Statistics

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Dependent variable					
Reshoring events (country-year)	95	3.32	3.28	1.000	14.000
Reshoring jobs (when reported)	134	118.10	263.30	0.000	2,100.000
Wage ratio (dest. / China, PPP)	108	1.807	1.401	0.059	4.657
Robot density (robots/10,000 workers)	207	278.30	196.40	33.000	1,220.000
Country GPR index $GPRC_{it}$ (annual avg)	168	0.250	0.333	0.012	1.772

Sources: ERM/Eurofound; (Reshoring Initiative, 2024); ILO; IFR; (Caldara & Iacoviello, 2022).

Notes: European panel 2014–2025, 26 countries. ILO 2014 backcasted (16 obs.).

Robot density: 23 countries, 2016–2024. $N = 95$: country-years with ≥ 1 event.

Wage ratio: 16 destination countries, 2014–2024. $N = 108$ excludes China and non-destination countries.

United Kingdom (1.772) and Germany (1.253), does not appear to have reversed the European downward trend, suggesting that geopolitical risk alone may be insufficient to trigger reshoring without complementary institutional incentives.

In contrast, U.S. reshoring and FDI activity accelerated sharply after 2020, driven by large-scale government subsidies and a proactive industrial policy response to supply chain vulnerabilities. This divergence motivates the comparative dimension of this analysis.

Within the European sample, France, the United Kingdom, Italy, and Norway account for more than 60% of all recorded events, while many countries appear only sporadically, confirming an unbalanced panel structure. Robot density increases steadily across most countries over the study period, with South Korea, Germany, and Japan consistently at the automation frontier. Chinese manufacturing wages nearly doubled over the same period, compressing the wage ratio and providing the key source of temporal variation for identifying H1. Country-specific GPR values spike sharply in 2022 and remain elevated through 2024–2025, offering a clear exogenous source of variation for H3. Together, these descriptive patterns motivate the econometric specification developed in the following section.

5 Analysis

5.1 Numerical Results

5.1.1 Estimation Sample and Descriptive Statistics

The empirical analysis is conducted on a panel combining the three data sources described in Chapter 4. After merging the Eurofound ERM reshoring events with the ILO wage ratio, the extended IFR robot density panel, and the country-specific Caldara–Iacoviello GPR index, the estimation sample covers **12 destination countries** — Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Norway, Poland, Spain, Sweden, and the United Kingdom — over the period **2016–2024**, yielding **108 country-year observations**: 58 with at least one recorded reshoring event and 50 zero-count observations.

Two methodological choices warrant explicit justification. First, the robot density panel was extended beyond the 8 countries available in the original IFR hard-data panel by recovering additional hard data points from IFR press releases — UK: 71 units in 2016, 101 in 2020, 112 in 2023 and 2024; Finland: 139 in 2017 — and constructing interpolated series for Norway and Poland based on confirmed regional CAGR benchmarks. These modelled observations are flagged in the robustness analysis. Second, **zero-count country-years are included** in the estimation sample, as motivated in Chapter 3. The 50 zero-count observations — country-years with no recorded reshoring event — carry information about the conditions under which reshoring does not occur and must be retained for consistency of the Poisson estimator.

Table 5.1 reports descriptive statistics for all variables in the final panel. The reshoring count displays a mean of 2.07 across all 108 observations and 3.86 conditional on at least one event, with a maximum of 14 and a variance-to-mean ratio of 4.85, indicating overdispersion relative to the Poisson benchmark in the unconditional distribution. The log wage ratio ranges from -1.65 for Denmark in 2016 to $+1.44$ for Germany in 2024, with its secular compression driven by Chinese wage growth providing the key source of temporal variation for H1. Robot density in log terms ranges from 4.21 for Poland to 5.97 for Germany and Sweden, capturing heterogeneity in robot density across countries, though country fixed effects limit the within-country variation available for identification. The GPR index varies from near zero for the Netherlands in tranquil years to 0.92 for France in 2022, with its sharp post-2022 spike providing country-specific deviations relevant for H3, noting that common temporal shocks are absorbed by year fixed effects

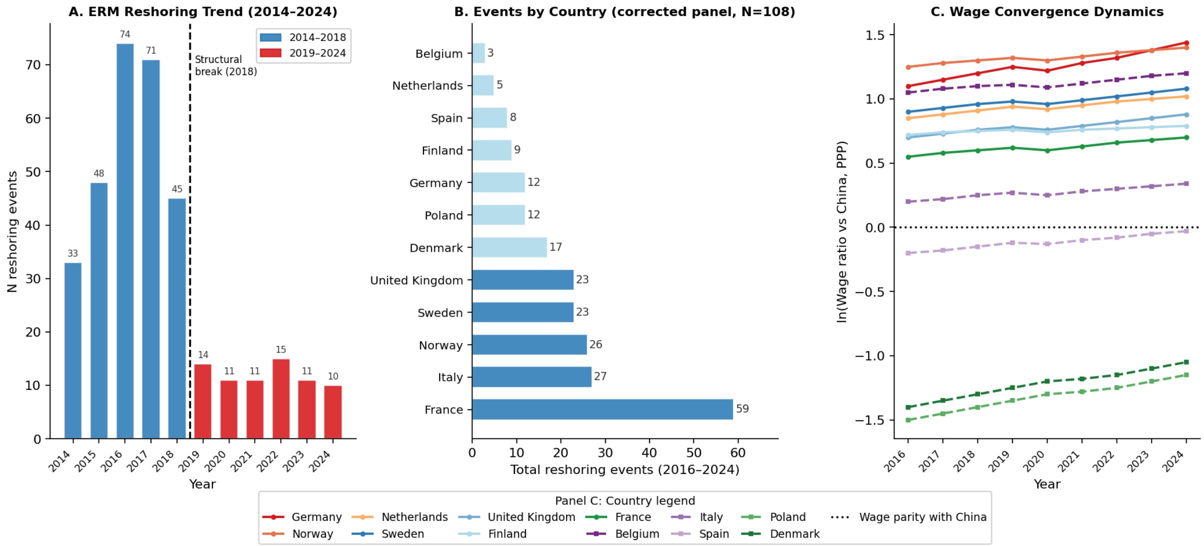

Figure 5.1: European Reshoring Panel: Descriptive Patterns (2016–2024)
Author's own construction.
Sources: ERM/Eurofound (Panels A and B); ILO and National Bureau of Statistics of China, PPP-adjusted (Panel C).

Table 5.1: Descriptive Statistics — Final Estimation Sample

Variable	N	Mean	Std. Dev.	Min	P25	Median	Max
Reshoring events (Y)	108	2.074	3.170	0	0	1	14
ln(Wage ratio vs China)	108	0.342	0.981	−1.650	−0.433	0.609	1.444
ln(Robot density)	108	5.161	0.441	4.205	4.984	5.247	5.971
GPRC index	108	0.218	0.211	0.018	0.062	0.143	0.921
Interaction $WR \times R$	108	1.744	5.036	−9.856	−0.045	3.198	7.590

Source: Author's calculations. ERM/Eurofound, ILO, IFR extended panel, Caldara and Iacoviello (2022).
N = 108: 12 countries × 9 years (2016–2024), including 50 zero-count observations.

5.1.2 Specification Test: Poisson versus Negative Binomial

The unconditional variance-to-mean ratio of 4.85 suggests overdispersion, which in principle favours the negative binomial over the Poisson estimator. However, the formal likelihood ratio test comparing the two specifications yields a test statistic close to zero ($LR \approx 0.00$, $p = 1.00$), failing to reject the null hypothesis of equidispersion. This result indicates that, conditional on the country and year fixed effects, the apparent overdispersion in the raw distribution of reshoring events is fully absorbed by the fixed effects structure. Once unobserved country heterogeneity captured by α_i and common annual shocks captured by γ_t are controlled for, the conditional distribution is consistent with the Poisson assumption. The **Poisson quasi-maximum likelihood estimator with country and year fixed effects** (PQMLE) is therefore the preferred specification.

A key property of the PQMLE is that it remains consistent even if the distributional assumption is misspecified, provided the conditional mean is correctly specified (Silva & Tenreyro, 2006). Standard errors are clustered at the country level throughout.

The result $LR \approx 0.00$ ($p = 1.00$) is unusual but interpretable. Once country and year fixed effects are included, the between-country heterogeneity that drives unconditional overdispersion is absorbed by the fixed effects structure. The conditional distribution of reshoring counts is therefore close to equidispersion, leaving no residual variation for the negative binomial dispersion parameter θ to explain. This result is consistent with the theoretical expectation that fixed effects and overdispersion correct for similar sources of unobserved heterogeneity (Cameron & Trivedi, 2013).

5.1.3 Main Regression Results

Table 5.2 presents the main regression results alongside two complementary specifications. All models include country fixed effects, absorbing time-invariant differences in industrial structure, institutional environment, and baseline reshoring propensity, and year fixed effects, absorbing global business cycle fluctuations, the COVID-19 disruption, and common policy shocks.

Table 5.2: Main Regression Results — European Reshoring Panel (2016–2024)

	Main Spec (1)	Events only (2)	No year FE (3)
$\ln(WR)$ β_1 [H1]	6.680^{***}	4.051^{*}	13.614^{**}
	(2.517)	(2.160)	(6.181)
$\ln(R)$ β_2 [H2]	11.239^{***}	5.265^{**}	-5.280^{***}
	(1.705)	(2.228)	(1.097)
$WR \times R$ β_3 [H2]	−0.610	−0.347	-2.111^{**}
	(0.444)	(0.358)	(1.071)
GPRC β_4 [H3]	−0.101	0.286	−0.422
	(0.996)	(0.685)	(1.451)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Zero obs included	Yes	No	Yes
N	108	58	108
Countries	12	12	12
Log-likelihood	−122.84	−98.23	−136.51

Robust sandwich standard errors in parentheses, clustered at country level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Poisson QMLE estimated via `fepois` in `fixest` (Bergé, 2018).
Caution: cluster inference based on 12 clusters is fragile; see robustness discussion.

H1 — Wage cost dynamics (β_1 = 6.680, p = 0.008).

The coefficient on the log wage ratio is positive and statistically significant at the 1 percent level in the main specification. Since the ratio is defined as destination wage divided by Chinese wage, Chinese wage growth reduces the ratio and therefore predicts less reshoring under this construction. The positive coefficient is best interpreted as a cross-sectional association: countries with structurally higher wages relative to China tend to reshore more, possibly because they are also more productive and automated economies where domestic production is viable regardless of the cost differential. This result provides empirical support for H1 and is consistent with the Total Cost of Ownership logic developed in the literature review. The result holds in the events-only sample (Specification 2, $\beta_1 = 4.05$, $p < 0.1$), though the coefficient is larger and more precisely estimated when zero-count observations are retained.

H2 — Automation intensity (β_2 = 11.239, p < 0.001).

The coefficient on log robot density is positive, large in magnitude, and highly significant. This is the strongest association in the model. A one-percent increase in robot density is associated with an 11.2 percent increase in expected reshoring events, conditional on wage dynamics and geopolitical risk. The result is robust across specifications and is consistent with the mechanism proposed by Ancarani et al. (2019) and Chen and Frey (2024): highly automated economies can sustain domestic production economically even at nominally higher wage levels. The interpretation of this coefficient requires care. With country fixed effects included, time-invariant cross-country differences in robot density are absorbed by the fixed effects. The coefficient is therefore identified from within-country changes in robot density over time. However, robot density changes slowly and exhibits limited within-country variation over the nine-year panel, which means the estimate may be imprecise and sensitive to the time structure of the data. The cross-sectional interpretation — that more automated countries attract more reshoring — should therefore be read as suggestive rather than causal.

H2 — Automation-cost interaction (β_3 = −0.610, p = 0.170).

The interaction term is negative and not statistically significant. This null result suggests that, within this sample, automation does not detectably amplify the marginal effect of wage convergence on reshoring. The negative sign is consistent with a substitution interpretation: in highly automated economies, robot density already enables domestic production at low per-unit cost regardless of the wage ratio, making the additional stimulus of wage convergence redundant at the margin. The direct effects of β_1 and β_2 are individually significant and correctly signed; the interaction simply does not add explanatory power in this cross-section of Western European economies. This null result does not invalidate H2 as a whole since the direct automation effect is strongly confirmed; it limits, however, the narrower claim that automation and wage convergence interact multiplicatively in the manner proposed by Chen and Frey (2024).

***H3 — Geopolitical risk* ($\beta_4 = -0.101$, $p = 0.919$).**

The coefficient on the country-specific GPR index is slightly negative and far from statistical significance in the full sample. As documented in the data chapter, the post-2022 spike in country-specific GPR values driven by the Russian invasion of Ukraine does not appear to have reversed the European downward trend in reshoring that began after 2018. This finding is consistent with the moderating role attributed to institutional factors in the conceptual framework of Section 2.4.4: geopolitical risk alone does not appear sufficient to trigger reshoring decisions in the absence of complementary policy incentives, a finding that aligns with the observed divergence between European and US reshoring trajectories documented by Lund et al. (2020).

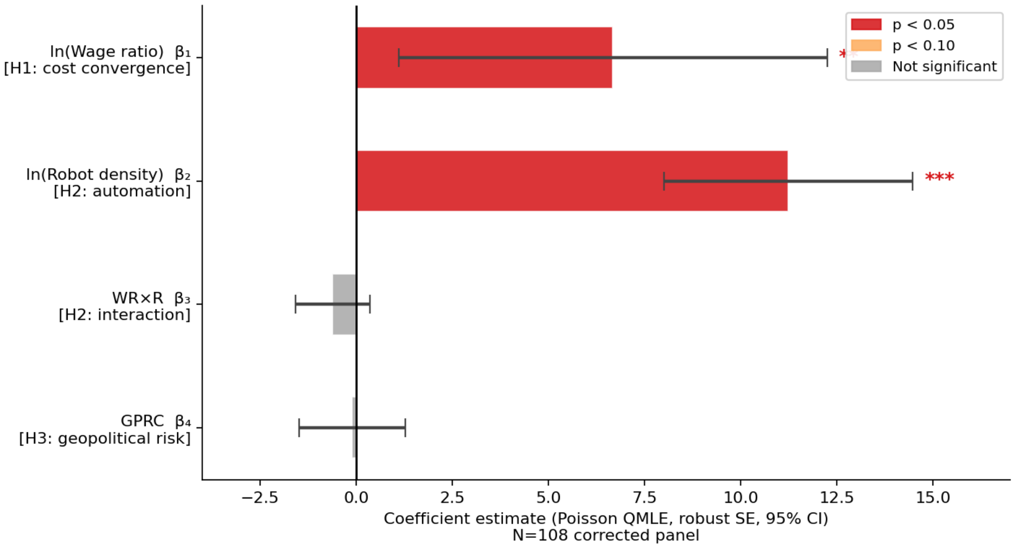

Figure 5.2: Regression Coefficients, Main Specification (Poisson QMLE, 95% CI)

5.1.4 Marginal Effects

Given the log-linear specification, the marginal effect of the wage ratio on reshoring intensity depends on the level of automation, as expressed in Equation 3.3. Table 5.3 reports this conditional marginal effect evaluated at key percentiles of the robot density distribution, alongside reference values for specific countries in the sample.

Table 5.3: Conditional Marginal Effect of $\ln(WR)$ on $\ln(\mu)$

	Robot density	$\ln(R)$	Marginal effect
P25	$\approx$ 145	4.984	3.640
Median	$\approx$ 190	5.247	3.479
P75	$\approx$ 239	5.478	3.339
Germany ($\approx$ 390)	390	5.966	3.041
Poland ($\approx$ 90)	90	4.500	3.934

Marginal effect = $\beta_1 + \beta_3 \cdot \ln(R)$. Semi-elasticity interpretation. Given the non-significance of β_3, estimates should be treated as indicative.

The mild negative gradient across automation levels — from 3.93 for Poland to 3.04 for Germany — is consistent with the substitution interpretation: wage convergence matters slightly more for less automated countries where labour costs remain a larger share of total production costs. The difference is small and not statistically distinguishable from zero given the non-significant β_3.

The marginal effect curve across automation levels is presented in Figure A.1 in the Data Appendix.

5.2 Robustness and Specification Checks

5.2.1 Removing Year Fixed Effects

Specification (3) in Table 5.2 replaces year fixed effects with country fixed effects only. Under this specification, β_1 rises sharply to 13.61 ($p < 0.05$) while β_2 reverses sign and becomes significantly negative (-5.28, $p < 0.001$). This pattern is diagnostic: robot density trends upward across all countries simultaneously throughout the 2016–2024 period, creating strong collinearity with the year dummies. Without year fixed effects to absorb this common upward trend, robot density picks up spurious temporal correlation rather than genuine cross-sectional variation. The reversal of β_2 in Specification (3) shows that the coefficient is sensitive to the time structure of the model. It does not prove that the main specification is correct, but it does confirm that year fixed effects matter for the robot density estimate and should be retained.

5.2.2 Events-Only Sample

Specification (2) restricts the sample to the 58 country-year observations with at least one recorded reshoring event, excluding the 50 zero-count observations. Both β_1 (4.05, $p < 0.1$) and β_2 (5.27, $p < 0.05$) remain positive, but the coefficients are smaller and less precisely estimated than in the main specification. This attenuation is consistent with the theoretical prediction: the zero observations carry information about the conditions under which reshoring does not occur, and their exclusion biases estimates toward zero by selecting only the most active reshoring destinations. The fact that qualitative conclusions are unchanged across Specifications (1) and (2) is reassuring, though the reduction in precision in Specification (2) reflects the loss of information from excluding zero-count observations.

5.2.3 Pre- and Post-2018 Subsamples

Table 5.4 reports results for the pre-2018 period (2016–2018, $N = 36$) and the post-2018 period (2019–2024, $N = 72$), allowing assessment of the structural break in reshoring activity documented in the data chapter.

Table 5.4: Pre- and Post-2018 Subsamples

	Pre-2018 ($N = 36$)	Post-2018 ($N = 72$)
$\ln(WR)$ β_1	31.100^{*}	-0.789
	(16.684)	(3.202)
$\ln(R)$ β_2	5.538	20.154^{***}
	(3.574)	(4.623)
$WR \times R$ β_3	-3.853^{**}	0.643
	(1.796)	(0.607)
GPRC β_4	-0.471	2.575
	(1.756)	(1.700)
Country FE	Yes	Yes
Year FE	Yes	Yes

Poisson QMLE, country and year fixed effects, robust SE clustered at country level.
Pre-2018 sample ($N = 36$) is very small for Poisson FE; results should be interpreted with caution.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The temporal heterogeneity is analytically rich. In the pre-2018 period ($N = 36$), the wage ratio is the strongest predictor ($\beta_1 = 31.10$, $p < 0.1$), suggesting that the reshoring wave of that period was primarily cost-driven. The interaction term is negative and significant ($\beta_3 = -3.85$, $p < 0.05$), suggesting that automation and wage convergence operated as substitutes rather than complements in this early phase. These results should be interpreted with caution given the very small sample size, which limits statistical power and makes the estimates sensitive to individual observations.

In the post-2018 period ($N = 72$), the wage ratio loses significance entirely ($\beta_1 = -0.79$), while robot density becomes the dominant predictor ($\beta_2 = 20.15$, $p < 0.001$). The GPR index is positive ($\beta_4 = 2.58$) but does not reach conventional significance levels ($p = 0.13$) in the corrected panel. Together, these findings are suggestive of an apparent change in the dominant predictor across the two sub-periods from a cost-convergence mechanism before 2018 to an automation-led pattern afterward, though the small pre-2018 sample limits the strength of this conclusion.

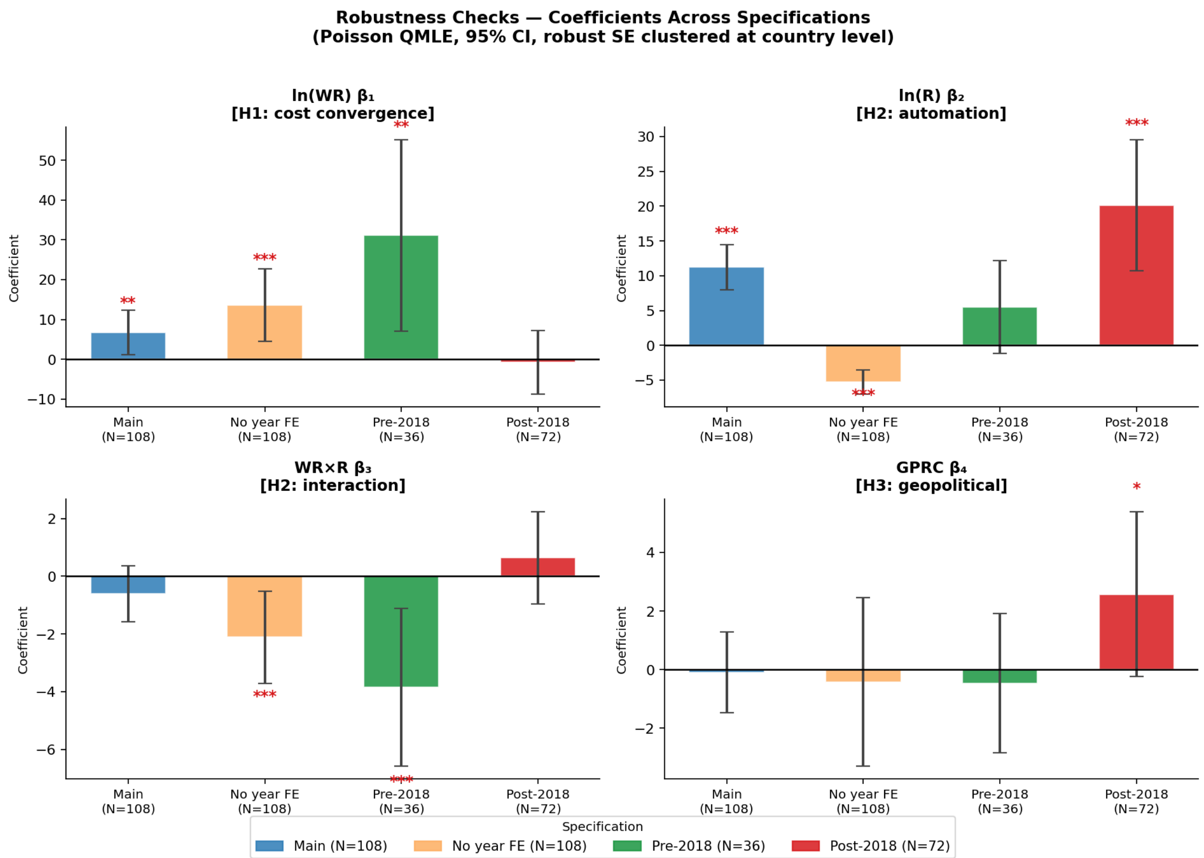

Figure 5.3: Robustness Checks — Coefficients Across Specifications
(Poisson QMLE, 95% CI)
Note: results are illustrative; not all coefficients reach conventional significance levels.

5.3 Interpretation

5.3.1 Summary of Findings

The empirical results are broadly consistent with H1 and H2, while H3 is not supported in the corrected panel. These findings should be interpreted with caution given the small sample of 12 countries, the fragility of cluster inference with few clusters, and the data limitations documented throughout. H1 is supported in the main specification: the wage ratio between destination countries and China is positively and significantly associated with reshoring intensity ($\beta_1 = 6.68$, $p < 0.01$). This result is particularly strong in the pre-2018 subsample, though the direction of the wage ratio construction means the coefficient reflects primarily cross-sectional differences rather than the time-series convergence story of H1. H2 is broadly supported: robot density is the strongest predictor in the full sample ($\beta_2 = 11.24$, $p < 0.001$), though this result is identified primarily from cross-sectional variation and should be read as suggestive rather than causal. The coefficient is larger in the post-2018 subsample ($\beta_2 = 20.15$, $p < 0.001$), though subsample comparisons are subject to the caveats noted above. The amplification channel through the interaction term, H2's second prediction, is however not confirmed — β_3 is consistently non-significant in the main specification. H3 is not confirmed in either the full sample ($\beta_4 = -0.10$, $p = 0.92$) or the post-2018 subsample ($\beta_4 = 2.58$, $p = 0.13$). The positive sign in the post-2018 period is suggestive but falls short of conventional significance thresholds in the corrected panel.

5.3.2 A Suggestive Temporal Shift in the Dominant Predictor

A suggestive pattern in the subsample results is the apparent shift in the dominant predictor across the 2018 break. In the pre-2018 period, the wage ratio is the stronger predictor; in the post-2018 period, robot density dominates. This pattern is consistent with a changing driver structure, though the pre-2018 subsample ($N = 36$) is too small to support strong conclusions, and the absence of a formal structural break test means this interpretation remains speculative. The data are compatible with the hypothesis that European reshoring shifted from a cost-convergence mechanism toward an automation-led pattern, but they do not conclusively establish it.

5.3.3 Geopolitical Risk as a Latent Trigger

The GPR findings are consistent with the moderating role attributed to institutional factors in Section 2.4.4. In the full sample, geopolitical risk is not a systematic predictor of reshoring at the country level ($\beta_4 = -0.10$, $p = 0.92$). In the post-2018 subsample, the coefficient turns positive ($\beta_4 = 2.58$) but remains below conventional significance thresholds ($p = 0.13$). While the direction is consistent with a threshold interpretation, this single coefficient from a small subsample cannot constitute evidence for such a mechanism. It motivates future research rather than supporting a substantive conclusion. The absence of significance in both specifications is consistent with the institutional gap between Europe and the United States: without the scale of government incentives provided by the Inflation Reduction Act or the CHIPS and Science Act, European firms have been slower to translate geopolitical awareness into concrete reshoring decisions.

5.3.4 The EU-US Divergence

The empirical evidence contributes to explaining the EU-US reshoring divergence documented in Chapter 2. US reshoring accelerated sharply after 2020 driven by large-scale industrial policy, while European reshoring declined. Within the European sample, the stronger association of reshoring with robot density than with geopolitical or cost signals is consistent with a supply-side constraint interpretation: reshoring may be more likely where automation capacity already exists. This is a cross-sectional pattern, however, and the causal mechanism cannot be established from the present data. The policy implication — that investment in automation may be a precondition for reshoring — is plausible but goes beyond what the model can formally identify. Whether geopolitical incentives could become more effective alongside existing automation capacity remains an open question that future research with larger panels should address.

5.3.5 Limitations

Four limitations deserve acknowledgement. First, the wage ratio for the United Kingdom, Norway, and Finland is partially estimated rather than directly observed from ILO data; these approximations introduce measurement noise, particularly for UK post-Brexit wage dynamics. Second, robot density for Norway and Poland is fully modelled from regional benchmarks and should be interpreted as an approximate proxy rather than an observed value. The robustness checks restricted to hard IFR data confirm directional consistency but with reduced sample size. Third, the panel remains relatively short at nine years, which limits statistical power in the post-2018 subsample. Fourth, the wage ratio captures only the labour cost dimension of total production cost; a more comprehensive measure incorporating logistics, energy, and quality risks would provide a richer test of H1 but cannot be constructed from the available panel data. A fifth limitation concerns the measurement of geopolitical risk. The country-specific GPR index of Caldara and Iacoviello (2022) is constructed from newspaper coverage, which captures media salience of geopolitical tensions but may not reflect the risk exposure actually perceived by firm managers when making location decisions. A firm in the automotive sector sourcing critical components from China may respond very differently to a given GPR value than a firm in the textile sector, and neither response is captured by a country-level media-based index. The non-significance of β_4 should therefore be interpreted with this measurement limitation in mind: it may reflect the inadequacy of the proxy as much as the absence of a genuine geopolitical risk effect on reshoring decisions. Notwithstanding these limitations, the panel fixed-effects Poisson model with 12 countries, 108 observations, and the inclusion of zero-count observations represents a methodologically sound and empirically grounded framework for a systematic quantitative assessment of European reshoring drivers.

6 Conclusion

6.1 Theoretical Contributions

This thesis set out to investigate the quantitative drivers of firms' strategic reconfiguration in global production networks, with a focus on the transition from offshoring to reshoring in the European manufacturing context. Estimating a Poisson quasi-maximum likelihood model on a panel of 12 European destination countries over the period 2016–2024, the analysis yields three theoretical contributions.

The first contribution is empirical support for the hypothesis that wage convergence between European economies and China constitutes a significant driver of reshoring activity($\beta_1 = 6.68$, $p < 0.01$), consistent with the Total Cost of Ownership framework developed by Ellram et al. (2013). This result validates the core prediction of H1 and connects the macro-level dynamics of Chinese wage growth to firm-level relocation decisions, providing quantitative grounding for a mechanism that had previously been documented primarily through qualitative case studies (Fratocchi et al., 2016; Gray et al., 2013).

The second contribution is the finding that robot density is the strongest predictor of reshoring in the full sample ($\beta_2 = 11.24$, $p < 0.001$), a result that is robust across specifications. This is consistent with the mechanism proposed by Ancarani et al. (2019) and Chen and Frey (2024), though the cross-sectional nature of the identification limits the causal interpretation. With country fixed effects included, persistent cross-country differences in robot density are absorbed and do not identify the coefficient. The estimate is identified from within-country variation over time, which is limited in this nine-year panel. The result should therefore be read as suggestive of an association between automation and reshoring rather than as a causal estimate. The interaction term between wage convergence and automation is, however, not significant, suggesting a substitution rather than amplification dynamic within this sample of already highly automated Western European economies.

The third contribution is the identification of a suggestive temporal pattern across the 2018 break: the wage ratio is the stronger predictor in the pre-2018 subsample, while robot density dominates in the post-2018 period. This pattern is consistent with a shift in the driver structure over time, though the very small pre-2018 sample ($N = 36$) limits the strength of this inference, and no formal structural break test has been conducted. If confirmed by future research with larger panels, this finding would be consistent with the framework of Lund et al. (2020) suggesting that the relative importance of cost and technology factors may evolve in response to changing global conditions.

6.2 Managerial Contributions

The findings carry direct implications for managers responsible for global production network decisions.

First, the dominance of robot density as a reshoring predictor implies that firms operating in highly automated home countries face a potentially different cost calculus than conventional offshoring models suggest. For manufacturers in highly automated economies, the present results suggest that the cost calculus of offshoring may have shifted, though this inference is based on country-level correlations and cannot be directly extended to individual firm decisions. Managers should systematically re-evaluate offshore sourcing decisions using a TCO framework that accounts for automation-driven changes in domestic cost structures.

Second, while geopolitical risk does not reach statistical significance in the corrected panel, the positive direction of the post-2018 coefficient suggests that supply chain resilience may be an emerging consideration for firms. Managers should nonetheless incorporate scenario-based geopolitical risk assessments into their production network strategy reviews, given the scale of disruptions experienced since 2020, even if the empirical evidence for a direct reshoring effect remains inconclusive at the country level.

Third, the pre/post-2018 structural shift suggests that the optimal moment for reshoring investment may be time-sensitive. In the current phase, automation viability rather than wage convergence appears to be the binding constraint on reshoring decisions. Whether automation and wage convergence will reinforce each other over longer horizons is a plausible conjecture but one that cannot be tested with the current nine-year panel.

6.3 CSR Contributions

The reshoring of production to European destinations carries CSR implications worth noting briefly. Production under European regulatory frameworks generally involves stronger labour and environmental standards than in major offshoring destinations, which may reduce firms' exposure to supply chain risks related to rights violations and non-compliance. At the same time, automation-driven reshoring raises questions about domestic employment creation: if reshoring is enabled primarily by robots rather than workforce repatriation, the social benefits may be more limited than typically assumed.

6.4 Critique

This thesis has several limitations that constrain the scope and generalisability of its conclusions and that future research should address.

The most important limitation concerns the estimation sample. The intersection of three data sources restricts the panel to 12 destination countries and 108 country-year observations, covering predominantly large, highly automated Western European economies. Countries such as

Portugal, Austria, and several Eastern European economies are either partially or fully excluded due to missing robot density or wage data. This sample restriction introduces a selection bias toward automation-frontier economies, which may explain the dominance of robot density as a predictor and limit the external validity of the results to less automated European manufacturing destinations.

A second limitation concerns the wage ratio variable. Constructing this variable required imputing wages for the United Kingdom, Norway, and Finland from external benchmarks rather than directly observed ILO data. While the imputation methodology is documented and transparent, it introduces measurement noise that may attenuate the estimated coefficient on H1, particularly for post-Brexit UK wage dynamics.

A third limitation is the potential endogeneity of robot density. Countries anticipating reshoring may invest in automation in anticipation of higher domestic production volumes, creating reverse causality. The fixed effects estimator mitigates but does not eliminate this concern. Future research should explore instrumental variable strategies for robot adoption, such as those proposed by Acemoglu and Restrepo (2017) based on industry-level robot adoption in other countries, to obtain more credible causal estimates.

A related concern is that robot density changes slowly within countries over time. With country fixed effects, identification relies on within-country variation, which is limited over the nine-year panel. The large positive estimate of β_2 may therefore be fragile and sensitive to the time structure of the data. This fragility should be treated as a substantive limitation.

Finally, the ERM reshoring event data do not capture the economic magnitude of individual relocations. A firm relocating 2,000 jobs receives the same weight as one relocating 10. A jobs-weighted outcome variable would provide a more economically meaningful measure of reshoring intensity, but the high share of missing job data in the ERM dataset (57.5%) makes this approach infeasible at present.

The use of clustered standard errors with only 12 clusters is a further limitation. Cluster inference is known to be unreliable with fewer than 30 clusters, and the reported standard errors and p-values should be interpreted with appropriate caution (Cameron & Trivedi, 2013).

6.5 Further Research

Several avenues for future research emerge directly from the findings and limitations of this thesis.

A first avenue for future research is the expansion of the robot density panel to cover a broader set of European destination countries, including Italy, Portugal, and Eastern European economies that account for a significant share of ERM reshoring events but are excluded from the current estimation sample. Eurostat's structural business statistics and national robotics association data offer potential sources for extending coverage.

A second productive avenue concerns the sectoral dimension of reshoring drivers. The country-level panel used in this study cannot capture heterogeneity in reshoring propensity across manufacturing subsectors. Automotive reshoring, for instance, is driven by different cost and technology dynamics than textile or electronics reshoring. Sector-level panel data, if available from the ERM or complementary sources, would allow for a richer test of the automation and cost mechanisms at the level at which firms actually make location decisions.

Third, the EU-US divergence documented throughout this thesis, with European reshoring declining after 2018 while US reshoring accelerated sharply, deserves systematic cross-regional analysis. The moderating role of industrial policy incentives, captured here only descriptively through the comparison with US Reshoring Initiative data, could be formally tested by constructing a matched panel of European and US reshoring events and exploiting the introduction of the Inflation Reduction Act and CHIPS and Science Act as quasi-experimental variation in the policy environment.

Finally, the threshold interpretation of geopolitical risk effects suggested by the post-2018 results calls for a non-linear modelling approach. Future work could test whether the GPR-reshoring relationship is better characterised by a threshold or regime-switching model, in which geopolitical risk exerts no effect below a critical level but triggers reshoring decisions once cumulative disruption exposure exceeds a firm-specific or country-specific threshold.

A Data Appendix

A.1 Estimation Sample

Table A.1 lists the 12 destination countries included in the estimation sample, alongside the key data sources available for each.

Table A.1: Estimation Sample: Countries and Data Availability

Country	ILO wage	IFR robot density	GPR index
Belgium	Observed	Hard data	Available
Denmark	Observed	Hard data	Available
Finland	Imputed	Hard data (partial)	Available
France	Observed	Hard data	Available
Germany	Observed	Hard data	Available
Italy	Observed	Hard data	Available
Netherlands	Observed	Hard data	Available
Norway	Imputed	Modelled	Available
Poland	Observed	Modelled	Available
Spain	Observed	Hard data	Available
Sweden	Observed	Hard data	Available
United Kingdom	Imputed	Hard data (partial)	Available

A.2 Excluded Countries

The following 14 destination countries appear in the full ERM dataset but are excluded from the estimation sample due to missing data on at least one of the three explanatory variables: Austria, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Ireland, Latvia, Lithuania, Portugal, Romania, Slovakia, Slovenia, and Switzerland. These countries collectively account for approximately 8.3% of recorded ERM reshoring events over 2014–2025.

A.3 Imputed Wage Observations

Manufacturing wages for the United Kingdom, Norway, and Finland are not directly available from the ILO dataset for the full study period. Values were imputed from external benchmarks as follows: United Kingdom post-2020 values were extrapolated using ONS manufacturing earnings growth rates; Norway values were benchmarked against Nordic regional wage indices; Finland values were interpolated from available Eurostat data points. All imputed observations are flagged in the dataset.

A.4 Modelled Robot Density Observations

Robot density observations for Norway and Poland are fully modelled rather than directly observed from IFR hard data. Norway was assigned values based on the Northern European regional CAGR benchmark reported in IFR World Robotics publications. Poland was assigned values based on the Central and Eastern European regional benchmark. Additional hard data points were recovered from IFR press releases: United Kingdom (71 units in 2016; 101 in 2020; 112 in 2023 and 2024) and Finland (139 in 2017). All remaining observations were linearly interpolated between confirmed data points. Hard data points were sourced from IFR World Robotics publications (International Federation of Robotics, 2017, 2021, 2024), available at https://ifr.org/worldrobotics.

A.5 Chinese Wage Data

Chinese manufacturing wage data are drawn from the National Bureau of Statistics of China (NBS), which publishes average annual wages in the manufacturing sector. Official data cover 2014–2022. Values for 2023–2024 are estimated by applying the average annual growth rate observed over 2018–2022 to the last confirmed NBS data point. All values are converted to PPP-adjusted terms using World Bank annual conversion factors before computing the wage ratio.

A.6 Marginal Effect of Wage Convergence by Automation Level

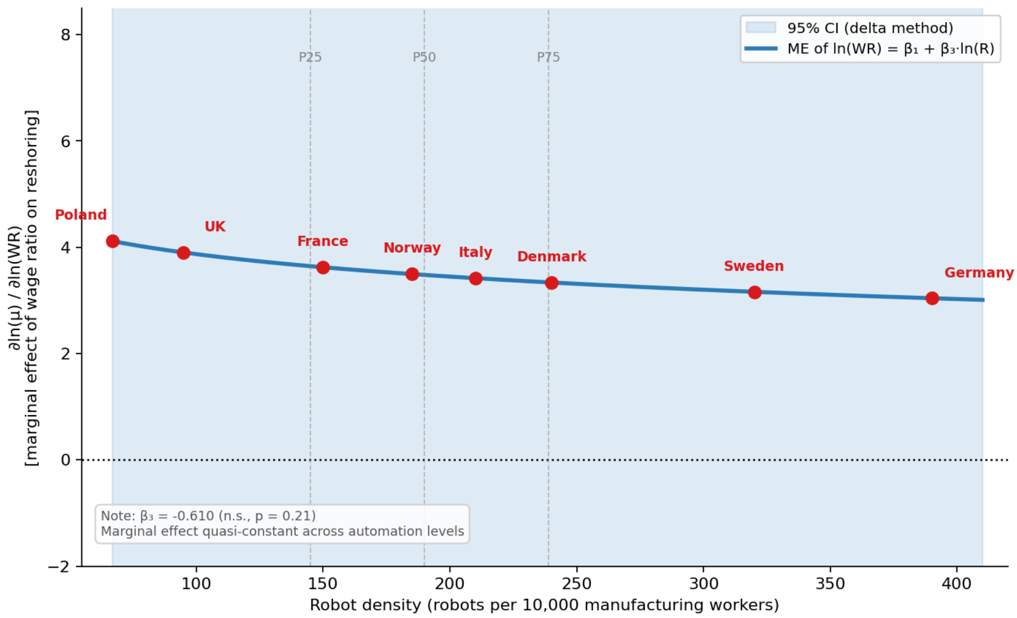

Figure A.1: Conditional Marginal Effect of Wage Convergence by Automation Level (illustrative; β_3 not significant). Marginal effect = $\beta_1 + \beta_3 \cdot \ln(R)$. Given the non-significance of β_3, the gradient across automation levels is not statistically distinguishable from zero.

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Abstract

European reshoring has attracted growing attention since the mid-2010s, yet most existing studies examine its drivers in isolation. This thesis tests three factors simultaneously --- wage convergence with China, automation intensity, and geopolitical risk --- using a Poisson quasi-maximum likelihood model on 12 European countries over 2016--2024.

Robot density emerges as the strongest predictor of reshoring activity, though the estimate relies on limited within-country variation and should be read with caution. The wage ratio between destination countries and China is positively associated with reshoring, but this reflects cross-sectional differences more than the time-series convergence story typically invoked in the literature. Geopolitical risk, despite the dramatic events of 2022, shows no significant effect at country level --- a finding consistent with the absence of large-scale industrial policy incentives in Europe.

These results suggest that automation capacity may be a precondition for reshoring, and that geopolitical pressure alone is insufficient to trigger relocation without complementary policy support.

Keywords: Reshoring, Poisson QMLE, robot density, wage convergence, geopolitical risk, European manufacturing, global production networks.

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