EFFECTS OF TECHNOLOGICAL CHANGE ON EMPLOYMENT AND TRADE IN DEVELOPING ECONOMIES

Nurillaev Karamat

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Hokkaido University

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ABSTRACT

Technological change is a key driver of economic growth and is crucial for developing countries to close the gap with advanced economies. However, its implications for jobs remain a controversial issue (Graetz and Michaels, 2018; Frey and Osborne, 2017; Acemoglu and Restrepo, 2020). Employment challenges are especially pressing in developing countries. According to ILO (2022), global unemployment reached 205.2 million in 2022, with 176.5 million of the unemployed residing in non-high-income countries. At the same time, developing economies are rapidly adopting new technologies. For instance, the number of operational industrial robots worldwide grew from 1 million in 2010 to over 3 million in 2020, with a significant share of this expansion occurring in emerging and developing markets (IFR, 2021). These trends raise an important question: Do new technologies present an opportunity or pose a threat to developing economies? This thesis investigates this issue across three chapters and examines the effects of technological change on employment, export performance, and competitiveness in developing economies.

Chapter 2 investigates effects of product and process innovation on employment growth in developing countries, utilizing a dataset of 17,103 firms from 53 developing economies. Employing instrumental variable (IV) estimation to address potential endogeneity concerns, it finds that new products and services serve as a major source of employment growth, whereas the impact of process innovation is limited. Furthermore, the findings emphasize the significant role of market structure in this relationship. Specifically, within the manufacturing sector, product innovation has a stronger positive impact on employment growth in firms with fewer competitors than in those operating in highly competitive markets. A similar pattern is observed in the service sector, particularly in retail and wholesale trade. These findings suggest that the employment effects of innovation depend not only on firm-level factors but also on market conditions and the competitive landscape.

Chapter 3 examines the impact of industrial robot adoption on export performance in developed and developing economies from 2005 to 2020. In recent decades, global manufacturing industries have undergone rapid technological advancements and experienced significant growth in international trade. Using data from the International Federation of Robotics and OECD Input-Output tables, this chapter analyzes how industrial robots impact export dynamics. To address potential endogeneity concerns, global industry-specific robotization trends serve as an instrumental variable for domestic robot adoption. The

findings show that industrial robots significantly increase exports of intermediate goods across both developing and advanced economies. In developing countries, these results remain robust even when accounting for Chinese automation trends and the role of highly robotized industries. Furthermore, the findings indicate that robots contribute to an increase in the export of final goods in developed economies.

Chapter 4 builds on the previous chapter by exploring additional dimensions of technological change and their impact on export market share, a key measure of competitiveness. Specifically, it examines the effects of technological advancements, including industrial robots, R&D investments, and Information and Communication Technology (ICT) adoption, on export performance. Utilizing panel data for 17 industries across 60 developed and developing economies from 2005 to 2020, this study finds that domestic robot adoption enhances competitiveness, with stronger effects in developing economies compared with advanced ones. The results indicate that R&D investment consistently strengthens market share across various industries. Furthermore, the findings suggest that technology adoption by developing countries contributes more to expanding their market shares in other developing economies than in advanced economies.

Chapter 5 synthesizes key findings and discusses their policy implications. It also acknowledges the limitations and proposes avenues for future research.

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CHAPTER 1

INTRODUCTION

The impact of technological change on jobs remains a topic of debate. Most of the existing studies are based on advanced economies but do not provide a clear answer. Meanwhile, in developing economies, concerns about a job crisis frequently dominate headlines. For instance, Harvard Business Review (2023) highlights that in India, only less than half of the 950 million working-age population is actually employed. Similarly, IMF (2024) warns that by 2030, half of all new entrants into the global labor force will come from Sub-Saharan Africa, which requires the creation of up to 15 million new jobs annually. Such labor market challenges are not limited to a few countries but are widespread across developing economies. In 2023, all 20 countries with the highest unemployment rates were developing nations, as shown in Figure 1.1.

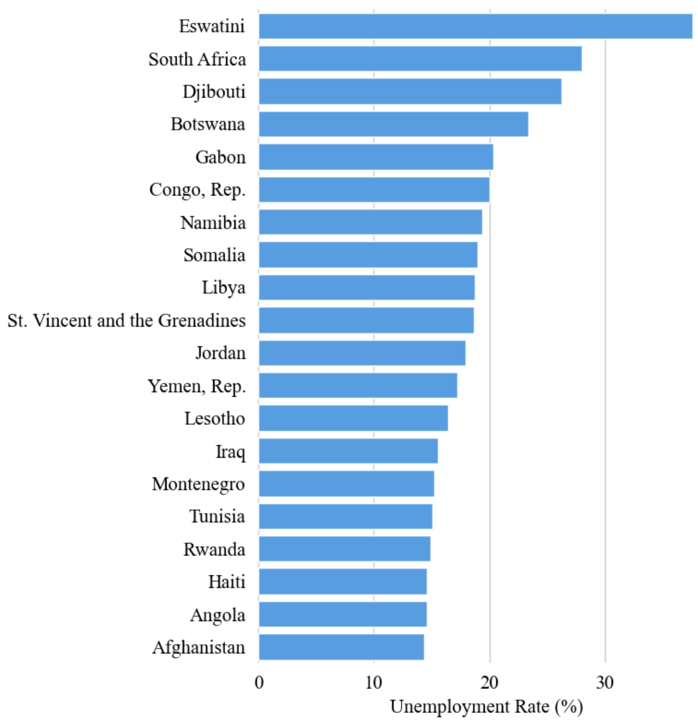

Figure 1.1: Top 20 Countries with the Highest Unemployment Rates.

Source: World Bank (2023).
Note: Unemployment refers to the share of the total labor force that is without work but available for and actively seeking employment.

At the same time, developing countries have been adopting technologies to narrow the gap with advanced economies. Firms in these economies report substantial innovation activities, particularly in industries such as manufacturing and professional services, where 50% to 60% of firms engage in either product or process innovations (Cirera and Maloney, 2017).[1] Moreover, developing countries have intensively adopted industrial robots over the past two decades, as shown in Figure 1.2. Despite lower labor costs in developing economies, much of the recent global robotization trend has been fueled by these countries' efforts to catch up and improve their global competitiveness. China stands out in this trend as the world's largest robot market, increasing its robot stock from 4,461 units in 2005 to 1,501,535 units in 2022. However, the rapid diffusion of robots is not limited to China. In 2022, several other developing economies—including Mexico (51,957 units), Thailand (39,406), India (37,995), Turkey (22,735), Vietnam (22,470), and Brazil (18,631)—were ranked among the world's top 20 countries by robot stock (International Federation of Robotics, 2023).[2]

These patterns of technological change in developing economies raise important questions about their economic implications. This thesis investigates these issues through three core research questions. First, it examines how firm-level innovations, measured through product and process innovations, influence employment growth. Second, it explores the impact of industrial robot adoption on trade outcomes, particularly export performance in developing economies. Third, it analyzes whether robotization contributes to increasing the export market shares of developing countries in international markets. Through these three main chapters, the thesis makes an attempt to provide a comprehensive understanding of how technological change shapes employment, trade, and competitiveness in developing economies.

Specifically, Chapter 2 examines the impact of product and process innovation on employment growth. Firms adopt sophisticated technologies to produce better goods and services. This study utilizes data from the 2013 World Bank Enterprise Survey, covering 17,103 firms across 53 developing countries. It investigates whether innovation leads to job

[1] Cirera et al. (2022) argues that many firms in developing countries remain significantly behind the technology frontier and may be unaware of the full extent of their lag.

[2] The trend in robotization coincides with growing concerns about the future of work in developing economies. World Bank (2016) states that "The share of occupations that could experience significant automation is actually higher in developing countries than in more advanced ones, where many of these jobs have already disappeared.

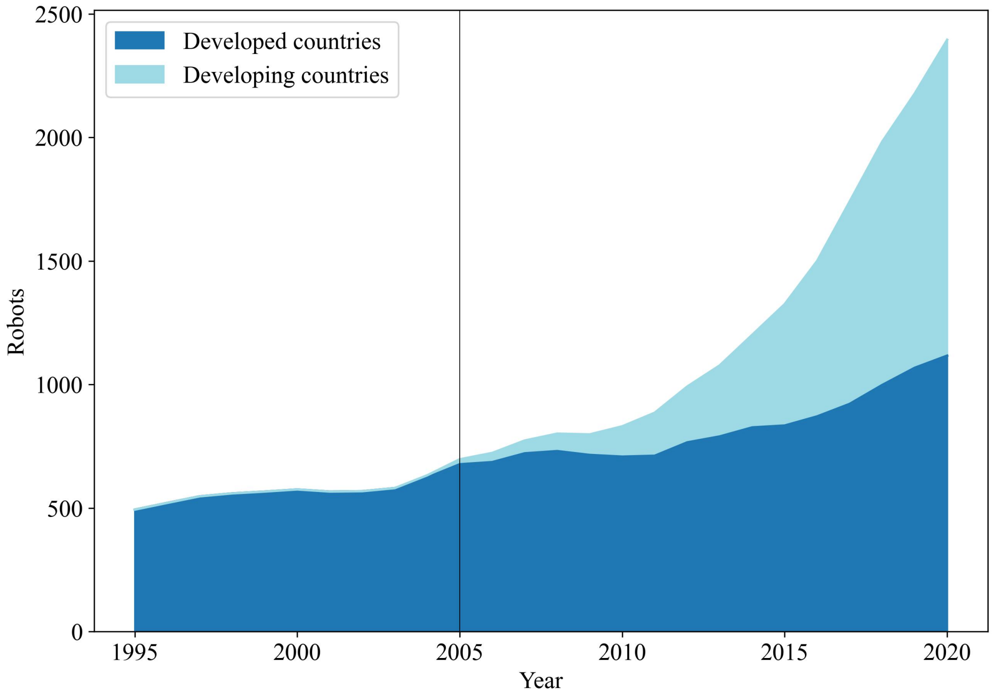

Figure 1.2: Robot Stocks by Country Groups *(in thousand units).*

Source: International Federation of Robotics.

creation or displacement, with a focus on the role of market competition in shaping this relationship. Understanding this relationship is crucial for developing economies, where job creation is essential for socio-economic development.

From Chapter 3, our focus shifts to industrial robots as a key measure of technological change. The chapter investigates whether industrial robots benefit export performance in 53 developed and developing economies from 2005 to 2020.[3] To identify the causal effect, this study utilizes global sector-specific robotization trends as an instrument. The study explores the impact of automation on international trade, particularly its role in export of intermediate and final goods, measured at current prices in U.S. dollars.

To complement the previous research, Chapter 4 focuses on export competitiveness. The chapter attempts to explain recent changes in global trade structure, the increasing dominance of the Global South, from the perspective of technological advancements in emerging and developing economies.[4] Specifically, using panel data on 17 industries

[3]Export-led industrial growth is a widely adopted policy approach in both developed and developing economies (Reed, 2024; Altenburg, 2011; Lederman et al., 2010)

[4]Some other studies relate the dominance of the Global South in trade structure to the decline of trade costs (Autor, 2015; Hummels, 2007), the expansion of global production networks (Cingolani et al., 2018; Costinot et al., 2013), and international specialization patterns (Hanson, 2012; Timmer et al., 2014) in emerging economies.

across 60 economies from 2005 to 2020, Chapter 4 examines the relationship between technological advancements—such as industrial robot adoption, R&D investments, and ICT diffusion—and export market shares, a key indicator of international competitiveness.

Briefly, the findings of this dissertation by chapter can be summarized in the following major points. Chapter 2 demonstrates that product innovation is the main source of employment growth in developing countries, especially in the service sector. In addition, the results show that process innovation does not lead to job losses. Moreover, across market structures, firms with market power translate their innovation efforts into higher employment growth compared with firms facing high competitive pressure.

Chapter 3 demonstrates the applicability of industrial robots in developing countries. The results indicate that industrial robots in developing economies foster the export of intermediate goods. Importantly, the positive effect of industrial robots on exports in developing economies remains robust after accounting for Chinese robotization trends and industry-specific robot adoption patterns. Furthermore, the findings show that in high-income countries, robot adoption provides additional benefits by increasing exports of final goods.

Chapter 4 further shows that home-country robot adoption increases competitiveness of industries, particularly in developing economies. R&D consistently emerges as a key determinant of export competitiveness, providing broad benefits in all industries. More importantly, the findings demonstrate that technology adoption has a greater impact on the South-South trade structure: developing countries that adopt advanced technologies increase their market shares in other developing economies. However, the results show that competitive pressure—measured by the average level of competitors—is also a significant factor that determines export market shares for developing and emerging economies.

CHAPTER 2

INNOVATION AND EMPLOYMENT GROWTH IN DEVELOPING COUNTRIES: THE ROLE OF MARKET STRUCTURE

Abstract

This study explores the relationship between product and process innovation and employment growth using a dataset of 17,103 firms in 53 developing countries. Employing instrumental variable (IV) estimation, we find that product innovation plays a significant role in driving employment growth in developing countries. Meanwhile, the impact of process innovation on employment appears to be limited. Moreover, we find that the employment effects of product innovation vary substantially depending on the market structure. In particular, within the manufacturing sector, product innovation has a more pronounced, positive effect on employment growth at firms with fewer competitors than at their counterparts operating in more competitive environments. Similar effects are observed within comparable service sector industries such as retail and wholesale trade. These findings emphasize that employment effects of innovation are not solely firm-determined but also depend on market conditions and competitors.

2.1 INTRODUCTION

Job creation is a policy priority in many developing countries where high levels of unemployment persist. In 2022, the International Labour Organization reported that 86% of 205.2 million job seekers were from developing countries. Although innovation is seen as a key driver of economic growth and competitiveness, the impact of innovation on employment is not clear-cut and might vary depending on market structure. Crucially, policymakers seeking to design effective job-creation strategies must understand how innovation and market structure affect employment in developing countries.

Research on developed countries indicates product innovation enlarges employment (Harrison et al., 2014; Dachs and Peters, 2014), whereas results for process innovation remain mixed (Lachenmaier and Rottmann, 2011; Evangelista and Vezzani, 2012). Recent studies on developing countries reveal similar patterns but with contextual differences related to the business environment (Okumu et al., 2019) and development level (Cirera and Sabetti, 2019). Another crucial factor that shapes this relationship is market structure. Previous studies emphasize the role of competition in labor-creative and labor-destroying mechanisms of innovation (Vivarelli, 2014; Garcia et al., 2004; Harrison et al., 2014). Furthermore, research has shown that firms across market structures differ in key dimensions such as innovation profitability (Piekkola and Rahko, 2020), price-setting behavior (Bils and Klenow, 2004; Fabiani et al., 2006) and competitive response to new product launches (Robinson, 1988; Kuestor et al., 1999). Nevertheless, we know little about how these attributes contribute to differences in employment effects of innovation across various market structures.

This paper examines the impact of different types of innovations on employment growth in developing countries. Furthermore, it investigates whether the employment effects of innovation differ across market structures. We employ the model proposed by Harrison et al. (2014) for Enterprise Survey conducted in 2012–2013, which includes 17,103 manufacturing and service firms in developing countries. As an indicator of market structure, we consider the number of competitors a firm faces in its respective product market.

The main findings show that product innovation is the primary driver of firm-level employment growth in developing countries. However, process innovation does not have a significant impact on employment growth. Moreover, the effect of product innovation on employment varies across market structures. Firms with a small number of competitors experience larger employment growth due to product innovation, especially in the manufacturing sector. We attribute this difference to variations in the competitive response to new products and the efficiency of new product production. In the services sector, where heterogeneity prevails, the market structure does not significantly influence the impact of innovation on employment, except in cases where the sample is limited to similar industries such as retail and wholesale trade.

This paper makes two significant contributions. First, our research provides a better understanding of the employment effects of innovation in a wide range of developing countries, adding to the growing body of evidence on this topic (Cirera and Sabetti, 2019; Crespi and Tacsir, 2019). Second, our study goes beyond the innovation and employment nexus by addressing market structure. We test the hypothesis that employment effects of innovation differ across market structures and provide a more granular understanding of how competition affects this relationship. Unlike previous studies, which have examined this question in only Korean and Turkish manufacturing firms (Dalgıç et al., 2023; Lim and Lee, 2019), we investigate this issue across 53 developing countries. Furthermore, we expand previous research by investigating the role of market structure in the service sector in detail.

The paper proceeds as follows. Section 2 presents the relevant literature and hypotheses development. Section 3 describes the data, descriptive statistics, and methodology. Section 4 discusses the results, and Section 5 concludes.

2.2 LITERATURE BACKGROUND AND HYPOTHESES

2.2.1 Employment effects of innovation

At the firm level, innovation is typically assessed through product and process innovation. According to OECD/Eurostat (2018), product innovation refers to the development of new or significantly improved goods or services. Process innovation, on the other hand, is new or improved production methods that increase efficiency and lower costs. However, not all firm operations qualify as innovation. For instance, expanding a product range in the retail, wholesale, or transport sectors is regarded as innovation only when it requires substantial modifications to business processes.

The impact of innovation on employment is multifaceted, and different types of innovation (i.e., product and process) can result in distinct outcomes in terms of employment growth (see Vivarelli, 2014; Calvino and Virgillito, 2017; Pianta, 2006; Van Reenen, 1997). Process innovation, for instance, can lead to a reduction in employment due to labor-saving effects. Through process innovation, firms can achieve equivalent output levels while employing fewer inputs, such as labor. However, labor displacement could be counterbalanced by lower product prices from cost savings that increase demand for products, thus increasing employment.

Product innovation, on the other hand, generates new demand through the introduction of new or improved products, which typically have a positive effect on employment. The positive effect is stronger, particularly for new products that are novel to the market. However, even with product innovation, conflicting mechanisms are at play. The positive impact can be significantly reduced or canceled out if new products replace existing products, are less labor-intensive, or more importantly, if competitors react to new products immediately by adapting or enhancing their own offerings.

Most empirical investigations of how innovation affects employment are based on developed countries and support positive impact of product innovation (Harrison et al., 2014; Hall et al., 2008; Giuliodori and Stucchi, 2012; Dachs and Peters, 2014; Van Reenen, 1997; Dachs et al., 2017; Hou et al., 2019).[1] However, the empirical evidence for the process innovation is controversial and ranges from negative (Evangelista and Vezzani, 2012) to positive (Greenan and Guellec, 2000; Lachenmaier and Rottmann, 2011; Zhu et al., 2021).

Furthermore, recent firm- and industrial-level empirical evidence indicates significant heterogeneity in the employment effects of innovation with respect to business cycles (Peters et al., 2022; Lucchese and Pianta, 2012; Ortiz and Fumás, 2020). These studies suggest that the employment effects of innovation can be less or more pronounced during expansions and contractions. Ortiz and Fumás (2020) relate these heterogeneities to differences in the intensity of competition across business cycles, highlighting the important role of market structure in this relationship.

2.2.2 Employment effects of innovation in developing countries

Product innovation plays a critical role in job creation within developing countries, despite distinct innovation features and labor market characteristics. Unlike in advanced countries, where innovation is related to patents (Argente et al., 2020), R&D (Mairesse and Mohnen, 2004), and established networks with academia and research institutes (Bellucci and Pennacchio, 2016), innovation in developing countries is often improvement of existing products and production methods through technology acquisition (Cirera and Maloney, 2017; Zanello et al., 2015). However, firms in developing countries can achieve success through imitation or incremental innovation that adapts to local specificities (Kim et al.,

[1]Besides product and process innovation, recent studies deal with the employment effects of AI (Acemoglu et al., 2022; Mutascu, 2021), industrial robots (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018), and automation technologies (Autor, 2015; Fort, 2017)

2013). Moreover, the absence of minimum wage laws and collective bargaining agreements may provide firms with greater flexibility to adjust their workforce or wages in response to changes in technology or market conditions (Haltiwanger et al., 2014).

While empirical evidence on the impact of innovation on employment in developing countries is limited, recent studies provide valuable insights. Research suggests that product innovation in developing countries increases labor demand (Cirera and Sabetti, 2019; Crespi and Tacsir, 2019). In addition, Avenyo et al. (2019) and Naidoo et al. (2023) emphasize importance of the characteristics of new products in the magnitude of product innovation. Furthermore, Cirera and Sabetti (2019) demonstrate that the positive impact of product innovation on labor demand is larger in low-income countries, despite the incremental character of innovations in these economies. The authors explain that in low-income countries, labor efficiency is lower, and new products use more labor compared with existing products.

On the other hand, studies show a limited impact of process innovation on employment growth in developing countries (Baffour et al., 2020; Cirera and Sabetti, 2019; Elejalde et al., 2015; Medase and Wyrwich, 2021). The literature posits several explanations for the modest impact of process innovation on labor in the case of developing countries. First, if process innovation displaces labor, the price reduction afterward compensates for labor reduction (Benavente and Lauterbach, 2008). Second, productivity growth from process innovation is ambiguous in developing countries (Hummels, 2007; Wadho and Chaudhry, 2018; Demmel et al., 2017). The absence of productivity increase due to the process might be a possible reason why it does not impact firm labor demand.

Based on the above, we posit the following hypothesis:

H1. In developing countries, employment growth is affected primarily by product innovation, not process innovation.

2.2.3 Innovation, employment growth, and market structure

Market structure plays a crucial role in shaping the employment effects of innovation (Dalgıç et al., 2023; Lim and Lee, 2019). Compensation and displacement effects may weaken or strengthen according to market structure (Vivarelli, 2014). Firms in various market structures differ in their market power, innovation capabilities, and the uncertainties of translating innovation efforts into successful outcomes.

Indeed, recent studies have demonstrated the importance of market structure in this relationship, particularly with respect to process innovation. Lim and Lee (2019) show that process innovation reduces employment only in monopolistic firms in Korean manufacturing and with similar finding reported by Dalgıç et al. (2023) for manufacturing firms in Turkey. The negative impact of process innovation on labor in monopolistic markets is explained by price-setting behavior. In concentrated markets, firms can have market power, the ability to influence the price at which they sell products or set prices above marginal cost without losing market revenues. Such firms tend not to incorporate cost reduction due to process innovation in their prices. In contrast, firms in competitive markets change prices more frequently (Bils and Klenow, 2004; Fabiani et al., 2006; Koga et al., 2020). In such markets, cost reductions are likely to be passed on to consumers in the form of lower prices, resulting in increased demand and, thus employment. This compensation mechanism of process innovation via price decrease is more effective in competitive markets (Vivarelli, 2014).

On the other hand, product innovation by firms in concentrated markets might result in higher employment growth rates for two reasons. First, firms in concentrated markets are better at appropriating gains from innovation. Studies have documented that economic value from innovation is higher for firms in industries with lower competitive pressure (Blundell et al., 1999; Greenhalgh and Rogers, 2006) . Piekkola and Rahko (2020) argue that the profitability of product and process innovation depends on firm market share. The paper shows that firms with high market share generate larger profits from innovation, as they have a higher capability of spreading high fixed costs of innovation over larger output scales. This can be particularly the case in manufacturing industries compared with service. In manufacturing, innovation is often linked to R&D investment or equipment purchases (Goedhuys and Veugelers, 2012; Medda, 2020) which require high fixed costs, while innovation in services focuses on more non-technological aspects such as collaboration with clients and suppliers, or workforce skill (Gallouj and Savona, 2009; Tether, 2005; Pires et al., 2008).

Second, firms with a small number of competitors might introduce new products more successfully. Innovation exposes firms to risks and uncertainties (Webster et al., 2010). New products might fail to gain sufficient demand or could be quickly replicated by competitors.

While innovation is a risky activity, the literature suggests that firms with few competitors face lower risks and uncertainties when introducing new products. Specifically, research on Chilean manufacturing firms shows that market risk for new products to be successful is lower when product innovation faces fewer competitors (Fernandes and Paunov, 2015). Also, uncertainties are better mitigated by firms in concentrated industries due to their internal resources and better access to external financing (Khan et al., 2020). Furthermore, empirical evidence from business studies shows that product innovators with high market shares experience less intensive competitive reactions from their rivals (Bowman and Gatignon, 1995; Robinson, 1988). The authors explain that incumbents in concentrated markets avoid aggressive competitive conduct. However, innovation uncertainties might still exist for service firms with significant market share, due to new entrants. Recent evidence by Nayyar et al. (2021) on developing countries, suggests that lower start-up costs are contributing to high entry-exit rates in the service sector. With minimal entry barriers, new competitors may attempt to compete on price to rapidly capture market share from established incumbents.

Overall, innovation is expected to have a positive impact on employment mainly through new products and services in developing countries. We use the number of competitors a firm faces in its product market as the main measure of market structure and posit the following hypothesis:

H1. In developing countries, positive impact of product innovation on employment growth is larger for firms with few competitors in their product market than firms with many competitors.

2.3 METHODOLOGY AND DATA

2.3.1 Model

We adopt the model by Harrison et al. (2014) to study the employment effects of innovation in developing countries. One of the key advantages of this model is that it enables us to disentangle some of the theoretical employment effects of innovation discussed earlier. Another advantage is its applicability in cross-sectional analysis. This framework has been used in several cross-country studies on developing countries (Cirera and Sabetti, 2019;

Crespi and Tacsir, 2019). Next, we briefly introduce the model and refer to Harrison et al. (2014).

The model uses a multiproduct framework where firms are observed in two periods, $t = 1$ and $t = 2$, and may engage in process or product innovation between the periods. In the second period ($t = 2$), firm can produce two types of products: old and new products, denoted by $j = 1$ and $j = 2$, respectively. To produce old and new products, a firm uses labor, capital, and intermediate goods as inputs. We assume that the production function follows the constant returns to scale (CRS) property, meaning that if all input factors are increased by the same proportion, output increases by the same proportion. Output of each product depends on Hicks-neutral technological productivity, indexed by θ_{jt}.

Based on the above conditions, Harrison et al. (2014) derives the following employment growth equation: $l_i - y_{1i} = a_0 + a_1 d_i + \beta y_{2i} + u_i$. In this equation, employment growth l is affected by four key sources: i) efficiency improvements in the production of existing products, denoted as a_0 ; ii) the output growth for existing products, represented by y_1; iii) efficiency increase in production of existing products due to process innovation, a_1; iv) the output growth for new products.

To estimate the labor demand equation above, Harrison et al. (2014) replaces real output growth of old and new products with sales growth rates, and derive the following reduced estimation framework:

$$l_i - g_{1i} = a_0 + a_1 d_i + \beta g_{2i} + u_i, \tag{2.1}$$

where l stands for the rate of employment growth over a period ($t = 1$ and $t = 2$), g_{1i} and g_{2i} are the corresponding nominal sales growth rates for old and new products, a_0 is average efficiency growth in production of the old product, binary variable d_i is process innovation related to old products, and u_i is the unobserved random disturbance. The parameter β captures sales growth from new products as a proxy for product innovation.

However, substitution of the output growth for both old and new products with a nominal sales growth rate introduces a potential identification issue in Equation (2.1). The error term may include the effect of price differences between old and new products, creating a correlation between the sales growth rate (g_2) and the error term. This measurement error issue can be addressed using an instrument that is correlated with new product sales but not with the error term. For instance, an instrument linked to the success of the new product but unrelated to price differences between old and new products serves this purpose.

As for the instrument, we follow existing literature, such as Harrison et al. (2014) and Cirera and Sabetti (2019), and use two instruments that determine if the product innovation is entirely new, and the firm is engaged in R&D activity. We verify the validity and strength of these instruments through tests for weak instruments (first-stage statistics), endogeneity, and overidentification.

2.3.2 Data

This paper uses data from the World Bank Enterprise Survey (WBES) conducted in 2012-2013. The WBES survey includes detailed questions on innovation activities in firms in developing countries. Additionally, this survey contains information on sales structure divided into new and old products of innovative firms which is the core variable that allows us to construct our main variables. Our final dataset comprises 17,103 manufacturing and services firms from 53 countries in Africa, Eastern Europe, Central Europe, Central Asia, the Middle East, and South Asia (see Table 2.A.2 and Table 2.A.1 in Appendix).

2.3.3 Main variables

Employment growth (l)

Employment growth of full-time permanent workers between 2013 and 2010 (or 2012 and 2009) is our dependent variable. To ensure consistency and comparability in employment measurement across firms and countries, the WBES provides to survey respondents a standardized definition of full-time permanent workers. According to WBES, full-time permanent workers include all paid employees who are contracted for a term of one or more fiscal years and/or have a guaranteed renewal of their employment contract, provided they work full-time.

Product innovation proxied by sales of new products g_2

The WBES asks firms whether they introduced new or significantly improved products or services (product innovation) between 2010 and 2013. Firms that report product innovations are asked to indicate the percentage of 2013 sales attributable to the new product. We use sales data for 2010 to calculate sales growth from old products (g_1) and new products (g_2). With this approach, we can use sales growth from new products as a proxy for product innovation.

Process innovation (d)

In addition, we include process-only innovation as one of the main variables. The WBES also asks whether an establishment has introduced new or significantly improved methods to produce or supply products or services (process innovations) from 2010 to 2013. Thus, the process-only variable is a dummy equaling one if a firm has introduced only a process innovation.

Market structure

As previously discussed, the impact of innovation on employment depends on market structure. We use two WBES questions to measure market structure. The first identifies a firm's primary market: local, national, or international. The second asks for the number of competitors for firms operating in local or national markets. Based on these answers, firms are classified as firms with few competitors (fewer than five) or many competitors (six or more competitors). By default, firms whose main market is international are classified as firms with many competitors. This assumption is justified by the expectation that the international market is generally considered competitive. However, we also present results separately for firms with many competitors, excluding international firms, to evaluate the potential influence of international firms on the findings.

Our indicator of market structure has several advantages over other traditional measures of competition, such as the concentration ratio and the Herfindahl–Hirschman index. First, the number of competitors is a straightforward and easily accessible measure of competition, making it valuable for cross-country analyses. Second, traditional concentration, or share-based indexes may not accurately reflect actual competition, particularly when firms operate in specific regional or international markets. These indexes tend to overlook the nuances of competition in such contexts. In contrast, our approach combines the numbers of competitors with information on specific geographic markets of firms, allowing for a more localized understanding of competition.

It is essential to acknowledge that the complexity of competition cannot be fully captured by a single measure. Therefore, we supplement our analysis with the price margin index, to enhance robustness, and gain a more comprehensive understanding of the role of competition in the employment effects of innovation. Several papers in the literature have used similar strategies to measure competition based on firm survey-based data, including Aghion et al. (2005), Stewart (1990), Nickell et al. (1994).

Other control variables

Firm size is included as an additional control variable. Firm size is included as a dichotomous variable for firms with 20-99 employees and another for firms with 100 employees or more. Furthermore, the estimation framework includes country, industry, and year dummies for all equations. Controlling these variables helps us mitigate any bias deriving from country-, industry-, and time-specific fixed effects, and their influence on the preciseness of our results.

Table 2.1 illustrates descriptive statistics for variables categorized by industry and market structure. The variables are grouped by innovation status (non-innovators, process-only innovators, and product innovators). Nearly half of firms have engaged in some form of innovation. The proportion of innovators in the service sector is lower than in the manufacturing sector; only about 37% of firms in the service sector engage in innovation. Despite the low innovation rate in the service sector, the employment growth rate in this sector is higher than that in the manufacturing sector. This pattern aligns with recent evidence in emerging markets, where the service sector has become the main source of employment (Nayyar et al., 2021).

Product innovators experience the highest employment growth in all subsamples, ranging between 12.6% to 17.9%, highlighting the role that new products and services in employment growth. Process-only innovators have the highest sales and productivity growth rates, indicating that process innovation may have strong labor displacement and compensation effects.

Descriptive statistics by market structure show that firms with many competitors have slightly higher innovation rates. This difference is driven by a higher rate of engagement in process innovation by firms in this market structure. Interestingly, the difference between employment growth for firms with few and many competitors is not substantial. However, firms with few competitors have higher productivity and sales growth rates than their counterparts. New product sales seem to cannibalize old product sales in all sample groups; however, the cannibalization rate is lower for firms with a small number of competitors than for firms with many competitors, supporting H2.

Table 2.1: Descriptive statistics for variables by type of industry and market structure

	Total	Industry		Market structure	
		Manufact.	Service	Few comps	Many comps
Total number of firms	17,103	9,139	7,964	13,408	3,695
Non-innovators (%)	51.7	42.0	62.9	50.7	55.5
Process only innovators (%)	14.0	16.4	11.3	15.1	10.3
Product innovators (%)	34.2	41.7	25.7	34.2	34.2
Employment growth (%)					
All firms	11.8	10.2	13.6	11.8	11.7
Non-innovators	9.8	7.2	11.8	9.8	10.0
Process only innovators	12.2	11.5	13.3	11.9	13.6
Product innovators	14.5	12.6	17.9	14.7	13.9
Sales growth (%)					
All firms	20.5	21.0	19.9	19.2	25.0
Non-innovators	18.0	16.0	19.5	16.0	24.3
Process only innovators	23.6	25.2	20.9	22.4	30.1
Product innovators	22.9	24.3	20.3	22.5	24.6
of which:					
Old products	-16.4	-16.6	-16.1	-17.7	-11.7
New products	39.3	40.9	36.4	40.2	36.3
Labor productivity growth (%)					
All firms	15.8	17.3	13.9	14.4	20.6
Non-innovators	16.2	17.3	15.4	14.4	22.1
Process only innovators	17.0	18.6	14.3	16.1	21.8
Product innovators	14.5	16.9	10.2	13.6	17.8

Source. Author's illustration based on World Bank Enterprise Survey 2013
Note. Firms with few competitors are establishments with fewer than five competitors in their main market. Firms with many competitors include establishments with more than six competitors and firms whose main market is international markets. All growth indicators are based on reported data for the last fiscal year and the two years prior.

2.4 RESULTS AND DISCUSSIONS

Our analysis consists of two steps. First, we estimate Equation (2.1) using ordinary least squares (OLS) and instrumental variable (IV) regressions for the entire sample and the manufacturing and services sectors to examine the impact of innovation on employment in developing countries regardless of market structure. In the second step, we relax our assumption that employment effects of innovation are uniform across firms, instead estimate our regression separately based on firms' specific market structures. We check the robustness of our results in Section 4.3.

2.4.1 Employment effects of product and process innovation

Table 2.2 illustrates the results of our basic specification by OLS and IV regressions using *completely new-to-market* and *R&D intensity* variables as instruments for sales growth due to new products. We estimate impact of innovation employment by sector and compare the results for the manufacturing and service sectors. In all regressions, we include industry, year, and country fixed effects.

Table 2.2: Employment effects of product and process innovation in developing countries

	OLS estimation			IV estimation		
	Total (1)	Manufact. (2)	Service (3)	Total (4)	Manufact. (5)	Service (6)
Sales growth due to new products	0.55*** (0.025)	0.59*** (0.028)	0.42*** (0.048)	0.97*** (0.061)	0.90*** (0.089)	1.06*** (0.085)
Process only innovation	-0.13*** (0.016)	-0.14*** (0.020)	-0.11*** (0.027)	-0.03 (0.022)	-0.05 (0.033)	-0.00 (0.031)
Firm size: *medium*	-0.08*** (0.011)	-0.08*** (0.016)	-0.08*** (0.017)	-0.08*** (0.012)	-0.08*** (0.016)	-0.08*** (0.017)
Firm size: *large*	-0.06*** (0.014)	-0.08*** (0.017)	-0.03 (0.026)	-0.06*** (0.014)	-0.08*** (0.017)	-0.04* (0.027)
Constant	-0.07** (0.029)	-0.04 (0.040)	-0.10 (0.137)	-0.12*** (0.030)	-0.09** (0.043)	-0.08 (0.100)
Observations	17103	9139	7964	17103	9139	7964
R-squared	0.148	0.159	0.148	0.122	0.140	0.113
First stage F stat.	-	-	-	260.46	109.12	167.93
Test for endogeneity	-	-	-	53.88	14.54	54.18
P-value	-	-	-	0.00	0.00	0.00
Test for overident.	-	-	-	0.85	1.12	0.94
P-value	-	-	-	0.65	0.56	0.62

Source. Author's calculations using World Bank Enterprise Survey 2012-2013.
Note. Robust standard errors are in parentheses. All regressions include industry, country and year dummies. Test for endogeneity and overidentification are based on Wooldridge's (1995) robust test score test. Instruments for sales growth due to new products are new to the firm (dummy equals 1 if a new product is completely new to the firm) and R&D activity (2: if the firm engages in both internal and external; 1: if it engages in internal or external; 0: if it engages in neither). *** p<.01, ** p<.05, * p<.1.

Columns 1–3 in Table 2.2 show OLS results for Equation 2.1 for the entire sample, the manufacturing and service sectors. Process-only innovation reduces firm-level labor, suggesting labor displacement effects outweigh labor compensation effects. These results hold for both the manufacturing and the service sectors. On the other hand, sales growth due to new products is positive and statistically significant for all sample groups. However, the coefficient is significantly less than one. This finding suggests that labor is used more efficiently in producing new products than old ones, implying potential reductions in labor due to product innovation. However, as discussed earlier, endogeneity issues related to the absence of price growth information may cause downward bias in the results of OLS estimation.

Columns 4–6 of Table 2.2 present IV model results using the proposed instruments. Process innovation is no longer significant. On the other hand, estimates for sales growth due to a new product have increased in magnitude. Estimates close to unity show no evidence that new products are produced with significantly less labor than old ones. Coefficient for sales attributed to new products is slightly larger in services than in manufacturing, though the difference is not statistically significant. This finding aligns with descriptive statistics, wherein service sector product innovators demonstrate the highest employment growth. Notably, Wooldridge's (1995) robustness test scores suggest the presence of endogeneity, indicating potential bias in the OLS estimates. Additionally, tests on overidentification restriction, and first-stage F statistics confirm instrument validity and strength for all sample groups.

Overall, the results suggest that new or improved products are the primary driver of employment growth at the firm level in developing countries. This finding supports H1 and is consistent with recent studies (Cirera and Sabetti, 2019; Crespi and Tacsir, 2019; Avenyo et al., 2019).

Moreover, the results indicate that the impact of process innovation on employment is limited. A similar finding has been demonstrated by previous literature on selected developing countries (Baffour et al., 2020; Elejalde et al., 2015; Medase and Wyrwich, 2021). One possible explanation is that initial labor displacement by process innovation is overcompensated by demand enlargement induced by lower prices. However, using a single dummy variable for all types of process innovations in regression might overlook the heterogeneous nature of process innovation. Process innovation varies from simple software installation to advanced automation technologies, all of which have different levels of impact on employment.

To examine the above issue, we conduct two additional exercises. First, instead of using a single dichotomous variable (0/1) for process innovation, we manually categorized the process innovation using text descriptions provided by each firm. Process innovation has been aggregated into four main categories: (1) new software installation, (2) new equipment and machinery installation, (3) installation of automation technologies, and (4) miscellaneous and included in regression (Table 2.A.3). Second, the Enterprise Survey asks about the novelty of process innovation: whether it is new to the firm, local, national, or international markets. While the novelty of process innovations is difficult to compare with what is already used by competitors due to the secrecy of business practices, we still utilized this question to confirm the robustness of our results further (Table 2.A.4). In both regressions, the impact of different types of process innovation was insignificant.

2.4.2 Employment effects of innovation across market structures

To test our hypotheses on different employment effects by market structure, we divide our sample into firms with few competitors and firms with many competitors. Table 2.3 shows the employment effects of innovation by firms according to market structure for all firms regardless of industry. In addition, we present results for firms with many competitors, both with, and without firms that operate predominantly in international markets, to confirm the inclusion of the latter within the competitive conditions group and assess any potential influence on the observed outcomes.

Table 2.3 shows notable differences in the employment effects of innovation across market structures. First, process innovation affects employment significantly only in competitive market structures, resulting in labor displacement (at a 10% significance level). In contrast, the estimate for firms with few competitors shows a positive effect that is not statistically significant. Second, product innovation is positively correlated with employment growth in both market structures, but the effect is more pronounced in firms with few competitors compared with ones facing higher competition (1.19 to 0.91). The difference is statistically significant. Importantly, the exclusion of firms operating mainly in international markets from the competitive market structure in column 3 of Table 2.3 does not substantially affect the results, providing support for considering these firms as

Table 2.3: IV estimation: Employment effects of innovation by market structures

	Firms with few competitors	Firms with many competitors	
	(1)	(2)	(3)
Sales growth due to new products	1.196***	0.906***	0.964***
	(0.117)	(0.072)	(0.081)
Process only innovation	0.010	−0.048*	−0.036
	(0.045)	(0.026)	(0.029)
Firm size: Medium	−0.048*	−0.083***	−0.086***
	(0.026)	(0.013)	(0.014)
Firm size: Large	−0.022	−0.079***	−0.081***
	(0.035)	(0.015)	(0.017)
Constant	−0.144**	−0.118***	−0.147***
	(0.064)	(0.035)	(0.037)
Observations	3695	13408	11888
R-squared	0.095	0.136	0.124
First stage F statistics	89.69	179.53	171.57
Test for endogeneity	27.86	29.56	35.55
P-value	0.00	0.00	0.00
Test for overidentification	1.70	0.55	1.19
P-value	0.42	0.75	0.54

Source. Author's calculations using World Bank Enterprise Survey 2012-2013.
Note. Robust standard errors are in parentheses. All regressions include industry, country and year dummies. Tests for endogeneity and overidentification are based on Wooldridge's (1995) robust test score test. Instruments for sales growth due to new products are *new to the firm* (dummy equals 1 if a new product is completely new to the firm) and *R&D activity* (2: if the firm engages in both internal and external; 1: if it engages in internal or external; 0: if it engages in neither). Column 3 excludes firms whose main market is international to assess their presence on the results observed in Column 2.
*** p<.01, ** p<.05, * p<.1.

competitive.

Our estimation results enrich the current literature on the role of market structure in the employment effects of innovation. First, in contrast to Lim and Lee (2019), who focused on the Korean manufacturing sector, our findings show that process innovation by firms with few competitors in developing countries does not lead to labor reductions. Second, Dalgıç et al. (2023) find that product innovation leads to employment growth only in concentrated industries in the Turkish manufacturing sector. Our analysis, conducted across a wide range of developing countries, shows that product innovation by firms within competitive markets and those within concentrated markets leads to employment growth, with the latter experiencing a more pronounced effect.

There are several plausible explanations for the larger impact of product innovation in concentrated markets. One possibility is a delay in response by competitors, which allows firms in such markets to enjoy a longer period of market advantage (Kuestor et al., 1999). Another possibility could be the ability of firms with few competitors to engage in price discrimination across products. By strategically manipulating prices for both old and new products, these firms generate more profit than those in competitive markets (Chen and Schwartz, 2013). Moreover, summary statistics reveal that firms with fewer competitors experience lower sales cannibalization of old products than firms in competitive markets. Finally, the relative labor efficiency in the production of the old and new products may differ across market structures. Competitive pressures drive firms to effectively utilize labor to produce new products.

Table 2.4 presents estimation results for the manufacturing and service sectors separately. According to Table 2.4, in the manufacturing sector, the magnitude of the employment effects of innovation varies depending on the market structure. The coefficient for process innovation is negative in more competitive market structures but only at a 10% significance level. Interestingly, in manufacturing, product innovation by firms with few competitors has a significantly larger effect on employment than it does for firms in a competitive environment.

In contrast to the manufacturing sector, we find no significant differences in the employment impact of innovation across market structures in the aggregate service sector. Several possible explanations can be put forward for these results. First, simple generalizations about the service sector may not hold due to its diverse range of industries. Second, our imperfect measure of competition may pose a challenge in the service sector, where identifying competitors is usually not straightforward (Rodie and Martin, 2001). Service-sector firms often face competition from related industries, other service sectors, and government enterprises, making accurate categorization more difficult. Finally, the rate of innovation in the service sector is lower than in manufacturing.

However, the hypothesis regarding the differential impact of product innovation across market structures is supported in certain service industries with similar characteristics. Specifically, the retail and wholesale trade, which represent 54.3% of the total service firms, are analyzed in the last two columns of Table 2.4. These industries share similarities in their core operations. Notably, our results indicate that firms in retail and wholesale trade with fewer competitors experience a larger employment growth due to product innovation.

Table 2.4: IV estimation: Employment effects of innovation by market structure across sectors

	Manufacturing firms		Service firms		Service firms: only retail and wholesale	
	Few comp.	Many comp	Few comp.	Many comp.	Few comp.	Many comp.
	(1)	(2)	(3)	(4)	(5)	(6)
Sales growth due to new products	1.273***	0.832***	1.104***	1.037***	1.332***	1.015***
	(0.170)	(0.107)	(0.168)	(0.099)	(0.200)	(0.162)
Process only innovation	0.031	−0.074*	−0.002	−0.014	0.037	0.005
	(0.068)	(0.039)	(0.060)	(0.037)	(0.063)	(0.050)
Firm size: Medium	−0.004	−0.098***	−0.094***	−0.069***	−0.094**	−0.066**
	(0.038)	(0.017)	(0.035)	(0.020)	(0.043)	(0.026)
Firm size: Large	0.023	−0.109***	−0.104	−0.030	−0.096	0.007
	(0.042)	(0.019)	(0.068)	(0.028)	(0.107)	(0.048)
Constant	−0.152*	−0.097**	0.068	−0.100	−0.099	−0.089**
	(0.091)	(0.049)	(0.140)	(0.117)	(0.062)	(0.044)
Observations	2012	7127	1683	6281	1005	3340
R-squared	0.073	0.163	0.125	0.115	0.161	0.092
First stage F statistics	35.45	74.68	66.71	113.56	43.04	62.22
Test for endogeneity	22.30	4.89	4.72	45.55	10.37	29.31
P-value	0.00	0.02	0.02	0.00	0.00	0.00
Overidentification test	2.04	2.22	0.71	0.57	0.25	0.92
P-value	0.36	0.32	0.69	0.75	0.87	0.62

Source. Author's calculations using World Bank Enterprise Survey 2012-2013.
Note. Robust standard errors are in parentheses. All regressions include industry, country and year dummies. Test for endogeneity and overidentification are based on Wooldridge's (1995) robust test score test. Instruments for sales growth due to new products are new to the firm (dummy equals 1 if a new product is completely new to the firm) and R&D activity (2: if the firm engages in both internal and external; 1: if it engages in internal or external; 0: if it engages in neither). *** p<.01, ** p<.05, * p<.1.

2.4.3 Robustness check

In this section, we examine the robustness of our results. We employ profit margin, as a measure of competition instead of the number of competitors. In a competitive market, firms do not make profits higher than the level sufficient to put capital to work (normal level of profit). Therefore, profit levels that are persistently higher than those of most firms in the market may indicate issues with the competitive structure (OECD, 2021). The profit margin we use is calculated as the difference between revenue and total costs divided by revenue:

$$\text{Profit margin} = \frac{\text{Revenue} - \text{Total cost}}{\text{Revenue}}. \tag{2.2}$$

Given the limited data availability for the service sector, our robustness analyses focus on the manufacturing sector. The WBES provides detailed information on the cost structure of firms exclusively within the manufacturing sector via income statements. To evaluate the robustness of our findings, we calculate the profit margin for all manufacturing firms in our sample, categorized by sector, and country. This analysis lets us identify firms within the highest profit margin quartile, corresponding to the top 25% of firms. A firm with a profit level surpassing 75% of the firms within the same industry and country may suggest weak competition. Table 2.5 presents the results for Equation (2.1) for the highest 25% and the lowest 75% of firms by profit margin within the manufacturing sector.

In the highest 25% quartile of firms, we observe significantly larger estimates for product innovation than in firms with lower profit margins. Additionally, process innovation has a negative effect on employment in firms with lower profit margins (significant at 5%). These results are consistent with the estimation results when the market structure is proxied by the number of competitors (columns 1 and 2 of Table 2.4). Therefore, the results for product, and process innovation in the manufacturing sector appear to be robust to alternative measures of market structure.

Table 2.A.5 provides a robustness test for country sample bias. In our firm samples, approximately 41% of the data comes from firms in only four countries (India, Egypt, Russia, and Bangladesh). To check whether the results are biased by the subsample formed by these four countries, we conduct separate regressions for firms in these specific countries and, separately, for other countries. This is done to establish whether the hypothesis on

Table 2.5: Robustness checks. IV estimation: price margin as a measure of competition

	High price margin (1)	High price margin (2)
Sales growth due to new products	1.248***	0.828***
	(0.258)	(0.094)
Process only innovation	0.111	−0.088**
	(0.093)	(0.036)
Firm size: Medium	−0.076**	−0.078***
	(0.038)	(0.018)
Firm size: Large	−0.062	−0.088***
	(0.042)	(0.019)
Constant	−0.110	−0.097**
	(0.103)	(0.048)
Observations	1979	7160
R-squared	0.061	0.165
First stage F statistics	16.88	93.25
Test for endogeneity	9.52	6.07
P-value	0.00	0.01
Test for overidentification	0.45	1.91
P-value	0.79	0.38

Source. Author's calculations using World Bank Enterprise Survey 2012-2013
Note. Robust standard errors are in parentheses. All regressions include industry, country, and year dummies. Tests for endogeneity and overidentification are based on Wooldridge's (1995) robust test score test. *** p<.01, ** p<.05, * p<.1

differences in employment effects across market structures still holds in both sub-samples. Despite higher estimates for product innovation in India, Egypt, Russia, and Bangladesh, Table 2.A.5 shows that in both country groups, firms with few competitors experience higher employment growth than their counterparts.

2.5 DISCUSSION AND CONCLUSIONS

Understanding the impact of innovation on employment and how it generates job opportunities in different market structures is a critical issue, especially for developing countries, where employment growth is a key driver for economic growth and poverty reduction. To investigate these questions, we adopted the model of Harrison et al. (2014) and applied it to World Bank Enterprise Survey for 17,103 firms in 52 developing countries conducted between 2012-2013.

Our findings show a strong positive impact of innovation on firm labor demand in developing countries. In particular, new products and services are the main source of employment growth. The finding is consistent with insights presented by Cirera and Sabetti (2019), Crespi and Tacsir (2019), and Avenyo et al. (2019) in developing countries. This line of research similarly emphasizes the role of product innovation in fostering firm employment. Furthermore, our results show, at the sectoral level, that product innovation in services increases employment more than it does in manufacturing. This finding provides a possible explanation for the prevailing trend identified by Nayyar et al. (2021), which underscores the significant role of service industries in job creation within these economies. Regarding process innovation, we have not found any impact on employment in developing countries. Instead, the results highlight a balance between labor displacement and compensation effects, both operating with comparable intensities.

Furthermore, our research extends the literature by providing new evidence on the role of market structure in the employment effects of innovation within developing economies. Prior studies by Dalgıç et al. (2023) and Lim and Lee (2019) have suggested that process innovation reduces employment in highly concentrated manufacturing industries in Korea and Turkey, respectively, with inconsistent results for product innovation. We show that process innovation does not impact employment, regardless of market structures. In contrast, our results demonstrate that market structure plays an important role in employment gains from product innovation. Firms with few competitors in their product markets experience higher employment growth from product innovation. This finding is observed in manufacturing and comparable service industries such as retail and wholesale trade. The findings remain robust with other measures of market structure. These results emphasize that innovation capabilities, return from innovation, and competitive reactions vary across market structures. Furthermore, our results are consistent with literature in a broader context. The studies illustrate that innovation profitability (Piekkola and Rahko, 2020) and the value of innovation (Blundell et al., 1999; Greenhalgh and Rogers, 2006) are larger for firms with market power.

In terms of policy implications, programs that focus on demand-side activities, such as the formation of new markets for innovative products through public procurement schemes or the establishment of new product and service quality requirements, could serve as effective instruments for innovation-led employment growth. In addition, differences in how firms with a small and high number of competitors translate innovation into employment growth highlight underlying mechanisms in developing countries. Firstly, differences in employment effects of innovation might signal issues with external financing for small innovative firms. Programs aimed at improving access to finance for small innovative firms can assist in achieving higher innovative growth. Secondly, lower employment growth rates from product innovation for firms facing high competition can reflect challenges with appropriation mechanisms, especially in developing countries. Therefore, implementing a robust intellectual property rights (IPR) system may facilitate faster growth for young and small innovative firms.

Despite our study's contributions, it has some limitations. First, it adopts a short-term approach to estimate the employment effects of innovation, which may not capture the full picture of how effects evolve over time, especially in monopolistic markets where the response to new product launches can take some time to materialize. Second, since our analysis is based on a short-term perspective, we assume that the introduction of innovation by firms does not immediately affect the number of competitors they face. However, in the long run, innovative activities may influence other firms' survival and market structure, which introduces potential endogeneity concerns in our estimates. Finally, we treat the process innovation as exogenous, expressed with single dummy variable. While it simplifies the analysis, often it might not be plausible assumption. Firm process innovation ranges from simple software to high-end automation technologies, with different level of productivity level. Also, exogeneity of process innovation could be easily violated by various factors, from demand changes to unobserved characteristics of firms. These are only a few lines of the many possible extensions.

2.A APPENDIX

Table 2.A.1: Sample description by industry

Manufacturing			
Sector names	Obs	in %	ISIC codes
Food/beverages/tobacco	1508	16.50	15-16
Textile/leather/apparel	1763	19.29	17-19
Wood, paper	924	10.11	20-22
Chemicals	670	7.33	23-24
Rubber/plastics	589	6.44	25
Non-metallic mineral	746	8.16	26
Basic metals	1079	11.81	27-28
Machinery/equipment	550	6.02	29
Electrical appliances	496	5.43	30-33
Vehicles/trailers	286	3.13	34-35
Furniture products	528	5.78	36
Total	**9139**	**100.0**	–
Service			
Wholesale/Retail	4345	54.56	51-52
Construction	955	11.99	45
Transport/storage	709	8.90	60-63
Communication	104	1.31	64
Vehicles repair	605	7.60	50
Hotels and restaurants	940	11.80	55
Other service	306	3.84	37, 72, 93, 74
Total	**7964**	**100.0**	–

Table 2.A.2: Sample description by country

Country name	Freq.	Percent (%)	Cum. (%)
Albania	109	0.64	0.64
Armenia	174	1.02	1.65
Azerbaijan	122	0.71	2.37
Bangladesh	862	5.04	7.41
Belarus	152	0.89	8.30
Bosnia and Herzegovina	215	1.26	9.55
Bulgaria	205	1.20	10.75
Croatia	255	1.49	12.24
Czech Republic	120	0.70	12.95
DRC	214	1.25	14.20
Egypt, Arab. Rep.	1731	10.12	24.32
Estonia	151	0.88	25.20
Georgia	130	0.76	25.96
Ghana	279	1.63	27.59
Hungary	83	0.49	28.08
India	2817	16.47	44.55
Israel	367	2.15	46.69
Jordan	387	2.26	48.96
Kazakhstan	240	1.40	50.36
Kenya	384	2.25	52.60
Kosovo	131	0.77	53.37
Kyrgyz Republic	157	0.92	54.29
Latvia	137	0.80	55.09
Lebanon	343	2.01	57.10
Lithuania	124	0.73	57.82
Macedonia, FYR	293	1.71	59.53
Malawi	116	0.68	60.21
Moldova	198	1.16	61.37
Mongolia	240	1.40	62.77
Montenegro	68	0.40	63.17
Morocco	228	1.33	64.50
Namibia	99	0.58	65.08
Nepal	412	2.41	67.49
Nigeria	254	1.49	68.98
Pakistan	69	0.40	69.38
Poland	106	0.62	70.00
Romania	318	1.86	71.86
Russian Federation	1572	9.19	81.05
Serbia	217	1.27	82.32
Slovak Republic	71	0.42	82.73
Slovenia	165	0.96	83.70
South Sudan	239	1.40	85.10
Sudan	54	0.32	85.41
Tajikistan	131	0.77	86.18
Tanzania	123	0.72	86.90
Tunisia	480	2.81	89.70
Turkey	464	2.71	92.42
Uganda	146	0.85	93.27
Ukraine	296	1.73	95.00
Uzbekistan	183	1.07	96.07
West Bank and Gaza	175	1.02	97.09
Zambia	313	1.83	98.92
Yemen	184	1.08	100.00
Total	**17103**	**100.00**	–

Table 2.A.3: IV estimation: Employment effects of innovation in developing countries (process innovation categories)

	Total sample	Manufacturing	Service
	(1)	(2)	(3)
Sales growth due to	0.970***	0.909***	1.06***
new products	(0.062)	(0.09)	(0.085)
Process only innovation:	−0.031	−0.055	−0.006
Software	(0.025)	(0.037)	(0.035)
Process only innovation:	−0.034	−0.056	−0.006
Equipment installation	(0.041)	(0.066)	(0.054)
Process only innovation:	−0.025	−0.050	0.029
Automation technologies	(0.032)	(0.040)	(0.071)
Process only innovation:	−0.053	−0.058	−0.153
Others	(0.054)	(0.061)	(0.127)
Firm size:	−0.076***	−0.076***	−0.079***
Medium	(0.012)	(0.016)	(0.017)
Firm size:	−0.069***	−0.081***	−0.047*
Large	(0.014)	(0.017)	(0.027)
Constant	−0.126***	−0.096**	−0.079
	(0.030)	(0.043)	(0.100)
Observations	17 103	9139	7964
R-squared	0.122	0.14	0.113
First stage F statistics	256.9	108.39	167.25
Test for endogeneity	53.56	14.51	54.16
P-value	0.00	0.00	0.00
Test for overidentification	0.83	1.12	0.94
P-value	0.65	0.57	0.62

Source. Author's calculations using World Bank Enterprise Survey 2012-2013.
Note. Robust standard errors are in parentheses. All regressions include industry, country and year dummies. Tests for endogeneity and overidentification are based on Wooldridge's (1995) robust test score test. Instruments for sales growth due to new products are *new to the firm* (dummy equals 1 if a new product is completely new to the firm) and *R&D activity*. *** p<.01, ** p<.05, * p<.1.

Table 2.A.4: IV estimation: Employment effects of innovation in developing countries (process innovation by novelty degree)

	Total (1)	Manufacturing (2)	Service (3)
Sales growth due to new products	1.007*** (0.052)	0.975*** (0.071)	1.071*** (0.078)
Process only innovation: new to firm	−0.028* (0.016)	−0.036* (0.019)	−0.02 (0.027)
Process only innovation: *new to local market*	0.014 (0.019)	0.012 (0.023)	0.012 (0.032)
Process only innovation: *new to national market*	0.008 (0.027)	0.015 (0.034)	−0.001 (0.044)
Process only innovation: *new to international market*	−0.02 (0.037)	−0.056 (0.043)	0.066 (0.073)
Firm size: *Medium*	−0.076*** (0.012)	−0.075*** (0.016)	−0.079*** (0.017)
Firm size: *Large*	−0.07 *** (0.014)	−0.081*** (0.017)	−0.048* (0.027)
Constant	−0.13 *** (0.03)	−0.107** (0.042)	−0.076 (0.1)
Observations	17 103	9139	7964
R-squared	0.118	0.131	0.112
First stage F statistics	348.00	170.48	191.30
Test for endogeneity	72.93	25.47	62.21
P-value	0.00	0.00	0.00
Test for overidentification	1.01	1.12	1.05
P-value	0.60	0.56	0.58

Source. Author's calculations using World Bank Enterprise Survey 2012-2013.
Note. Robust standard errors are in parentheses. All regressions include industry, country, and year dummies. Tests for endogeneity and overidentification are based on Wooldridge's (1995) robust test score test. Instruments for sales growth due to new products are *new to the firm* (dummy equals 1 if a new product is completely new to the firm) and *R&D activity (2: if the firm engages in both internal and external; 1: if it engages in internal or external; 0: if it engages in neither)*. *** p<.01, ** p<.05, * p<.1.

Table 2.A.5: IV estimation: Robustness test for country sample bias

	Firms in India, Egypt, Russia and Bangladesh		Firms in other countries	
	(1)	(2)	(3)	(4)
Sales growth due to new products	1.400***	0.992***	1.070***	0.905***
	(0.209)	(0.124)	(0.148)	(0.099)
Process only innovation	0.128	−0.003	−0.064	−0.069**
	(0.078)	(0.050)	(0.061)	(0.033)
Firm size: *Medium*	−0.044	−0.061***	−0.040	−0.090***
	(0.049)	(0.018)	(0.031)	(0.019)
Firm size: *Large*	0.032	−0.068***	−0.056	−0.085***
	(0.060)	(0.020)	(0.044)	(0.024)
Constant	−0.252**	−0.117***	0.894***	0.694***
	(0.126)	(0.043)	(0.064)	(0.074)
Observations	1246	5736	2381	7565
R-squared	0.028	0.136	0.132	0.132
First stage F statistics	23.54	10.52	67.56	122.63
Test for endogeneity	19.38	10.52	11.91	22.04
P-value	0.00	0.00	0.00	0.00
Test for overidentification	1.28	2.13	1.57	0.11
P-value	0.52	0.34	0.45	0.99

Source. Author's calculations using World Bank Enterprise Survey 2012-2013.
Note. Robust standard errors are in parentheses. All regressions include industry, country, and year dummies. Tests for endogeneity and overidentification are based on Wooldridge's (1995) robust test score test. Instruments for sales growth due to new products are *new to the firm* (dummy equals 1 if a new product is completely new to the firm) and *R&D activity (2: if the firm engages in both internal and external; 1: if it engages in internal or external; 0: if it engages in neither).*
*** p<.01, ** p<.05, * p<.1.

CHAPTER 3

INDUSTRIAL ROBOTS AND EXPORT PERFORMANCE: CROSS COUNTRY INDUSTRIAL ANALYSIS FROM DEVELOPING AND DEVELOPED ECONOMIES

Abstract

Over the past decades, global manufacturing industries have witnessed rapid technological advancements and growth in international trade. Using data from the International Federation of Robotics, OECD Input-Output tables, this paper investigates the impact of industrial robot adoption on export performance across 53 developed and developing economies between 2005 and 2020. To address endogeneity issues, we instrument domestic robot adoption with global industry-specific robotization trends. Our findings show that industrial robots increase exports of intermediate goods in developing economies. The results remain robust to Chinese automation trends and the role of highly-robotized industries, which indicates the broader relevance of robots in export growth across sectors and countries. Industrial robots in advanced economies contribute to increases in both intermediate and final goods exports.

3.1 INTRODUCTION

Robots have become a key element of global manufacturing. Defined as "automatically controlled, reprogrammable multipurpose manipulators, programmable in three or more axes" (ISO 8373:2021), robots are extensively applied in repetitive manufacturing tasks that require precision, speed, and consistency. While robots have long been part of the production processes in advanced economies, most new robot adoptions over the last decade have occurred in developing economies (see **??**). So far, most literature has emphasized the implications of automation technologies on labor (Acemoglu and Restrepo, 2020; Adachi et al., 2024), productivity (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2022; Moll et al., 2022), and inequality (César et al., 2022), with a particular focus on high-income countries. Some recent studies have examined how automation processes in high-income countries impact developing economies through reshoring (De Backer and DeStefano, 2021; Stapleton and Webb, 2020) and trade channels (Artuc et al., 2023; Faber, 2020).

This paper examines how industrial robot adoption affects manufacturing export performance in developed and developing countries. To study this question, we match three sources of data: (i) industrial robot data obtained from the International Federation of Robotics (IFR), which provides the annual number of industrial robots shipped to each industry in different countries, covering about 90 percent of the global robotics market; (ii) data on exports of intermediate and final goods from the input-output tables of the OECD, which illustrate the flow of these goods by industry and country to various market destinations; and (iii) data on industrial capital, employment, and value-added at the 2-digit level derived from UNIDO statistical databases. To address potential endogeneity issues, we instrument domestic industry robot adoption by using industry-specific robotization trends in other regions of the world. Our identification strategy closely follows the approaches of Acemoglu and Restrepo (2020) and Dauth et al. (2021).

Our findings show that robots in developing economies increase intermediate goods exports. Specifically, the Poisson Pseudo Maximum Likelihood with Instrumental Variable (PPML-IV) estimates show that a 1 percentage increase in robots per million employees leads to a 0.136–0.140 percentage rise in intermediate exports. These results are robust to country- and industry-specific robotization trends and alternative measures of robotization. Furthermore, we find that robots benefit more advanced economies. In high-income countries, an increase in robot stocks increases the export of both intermediate and final goods. A 1 percentage increase in robots per million workers results in a 0.170–0.190 percentage increase in exports of intermediate and final goods.

Our paper builds on recent research that examines how automation technologies affect trade outcomes (Artuc et al., 2023; Baur et al., 2022; Zhou et al., 2024; Li et al., 2024). Closest to our work, Artuc et al. (2023) demonstrates that industrial robots in high-income countries increase exports and imports from the Global South. Furthermore, Baur et al. (2022) shows that robotization in Northern countries is associated with a decrease in imports within the same industry but an increase in imports from other industries. In this paper, we emphasize recent trends in robot adoption in developing countries and demonstrate that automation benefits developing economies too. In contrast to Zhou et al. (2024) and Li et al. (2024) which specifically focus on China—a country that has experienced significant robotization recently—we show that the positive impact of robots on exports is applicable across a broader range of developing economies.

Second, this paper contributes to a growing literature on how automation technologies affect developing countries. Most previous research focuses on the labor market implications of robot adoption (García et al., 2024; Maloney and Molina, 2019; Timmer et al., 2014; Brambilla et al., 2023). Another strand of research examines how robots in advanced economies affects developing countries through reshoring (Krenz et al., 2021; Carbonero et al., 2020) and trade channels (Faber, 2020; Stemmler, 2023; Kugler et al., 2020). We contribute to this literature by providing evidence on the economic outcomes of domestic automation in developing economies, particularly in terms of export growth.

Finally, our paper adds to the broader literature on trade and technology adoption. Much of the existing research emphasizes how "opening for trade" induces technological diffusion (Lileeva and Trefler, 2010; Bloom et al., 2016; Melitz and Redding, 2021). Recent studies have examined the ways in which different technologies such as the Internet (Fernandes et al., 2019; Kneller and Timmis, 2016) and other communication technologies (Fort, 2017) – influence foreign trade activity. However, industrial robots differ from communication technologies in their potential impact on trade. While ICT primarily facilitates global integration and coordination, boosting exports, robotics technology can affect trade in two ways, by reducing reliance on foreign sourcing, which may decrease trade, and by enhancing product quality, which can drive export growth.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature and outlines the potential mechanisms through which robots impact export performance. In Section 3, we describe our methodology and identification strategy. Section 4 presents our data sources and descriptive statistics, while Section 5 discusses our results, including a series of robustness checks. Finally, Section 6 concludes with a summary of our main findings and the discussion of the research limitations.

3.2 LITERATURE BACKGROUND

3.2.1 Industrial robots, trade and globalization

Modern robotics has advanced to perform complex repetitive tasks. Evidence shows that automation technologies have socio-economic implications in labor markets (Acemoglu and Restrepo, 2020; Adachi et al., 2024; Dottori, 2021). In advanced economies such as the United States, Germany, Japan and several European countries, studies find industrial robots reduce employment (Frey and Osborne, 2017; Dauth et al., 2021; Ni and Obashi, 2021; Chiacchio et al., 2018). However, other papers suggest that robot adoption creates job opportunities, especially for skilled workers (Humlum, 2019).

Although evidence on employment outcomes is mixed, the impact of robots on productivity appears more straightforward. Research indicates industrial robots increase labor productivity and total factor productivity (Graetz and Michaels, 2018; Dekle, 2020). Similarly, firms that adopt automation technologies experience higher efficiency and cost savings (Koch et al., 2021; Duan et al., 2023).

A recent strand of research examines how industrial robot adoption shapes trade patterns and global sourcing decisions. As robot prices decline, firms in developed countries increasingly find it profitable to relocate production back home. Several studies find that robots induce reshoring (Krenz et al., 2021; Carbonero et al., 2020; Bonfiglioli et al., 2022). Furthermore, a growing body of research shows how robotization in advanced economies affects labor markets in emerging countries, including Mexico (Faber, 2020), Brazil (Stemmler, 2023), Colombia (Kugler et al., 2020), and other developing regions (Gravina and Pappalardo, 2022). These studies suggest robots by advanced economies reduce demand for export goods from emerging economies: as advanced economies increasingly adopt robots, they replace imported inputs with automated domestic production.

In contrast to this reshoring narrative, other research questions the extent to which robots explain reshoring (Stapleton and Webb, 2020; Cilekoglu et al., 2024). At the micro-level, Cilekoglu et al. (2024) find that robot adoption increases global sourcing and promotes trade in inputs. Similarly, for Spanish manufacturing firms, Alguacil et al. (2020) show that automation increases firm export probabilities, export sales, and the share of exports in total output. Moreover, Antràs (2020) argues that reshoring is not a systematic trend, nor is technological change a significant factor behind any such shift. Artuc et al. (2023) support this perspective by showing that robot adoption in developed countries increases both imports from and exports to the Global South.

Despite these insights, most research focuses on advanced economies. Existing studies on emerging economies primarily focus on the impact of robots in advanced economies through reshoring and cross-border activity. However, industrial robots are also increasing rapidly in emerging economies (IFR, 2020). Robots are predominantly used in high-value, export-oriented industries such as electronics, computers, and automobile production, which typically require high precision and quality production methods. In contrast, labor-intensive sectors such as agriculture and mining remain the least automated. This context raises an important question: to what extent does domestic robot adoption in emerging economies impact trade outcomes, especially exports? Additionally, does industrial robot adoption in emerging economies influence trade flows from the Global South and their structure?

3.2.2 Robotics and export mechanisms

Studies highlight several potential mechanisms through which industrial robots impact export performance. First, industrial robots increase total factor productivity and reduce costs (Graetz and Michaels, 2018; Koch et al., 2021). By performing repetitive tasks quickly and accurately, robots significantly improve production efficiency. Aghion et al. (2020) find that when firms adopt automation technology, they experience higher sales and exports, which result from reductions in both domestic and export prices. A second potential channel through which robots improve export performance involves the production of higher-quality goods. The advanced engineering capabilities of robots allow them to perform high-precision tasks with minimal errors, such as welding, material handling, and painting (Esmaeilian et al., 2016). Indeed, several studies find that robots contribute to improvements in export quality (DeStefano and Timmis, 2024; Hong et al., 2022; Lin et al., 2022).

Third, robots might improve export performance through standardization of production processes. Robots facilitate product standardization and ensure consistent product quality. Traditional trade literature emphasizes the importance of product standards (Chen et al.,

2008) and consistent product quality for export success (Álvarez and Fuentes, 2011; Brooks, 2006). Standardized products are more readily accepted in global markets, making them appealing to foreign buyers, which, in turn, leads to higher export volumes.

Evidence from U.S. industries shows that robot adoption increases exports to wealthier market destinations, such as high-income and upper-middle-income countries, which leads to higher profits (Brambilla et al., 2023). This effect is likely to be significant in emerging economies, where robotization can generate larger quality improvements. DeStefano and Timmis (2024) demonstrate that product quality stemming from automation technologies is higher in developing economies than in advanced ones. In this paper, we analyze the relationship between industrial robot adoption and export performance by examining total exports and exports of final and intermediate goods across various destinations.

3.3 METHODOLOGY

We estimate the impact of industrial robot adoption on export performance using two Poisson Pseudo Maximum Likelihood (PPML) approaches: the standard PPML method and the PPML method with instrumental variables (PPML-IV). PPML is particularly suitable for this context as it handles zero trade flows and heteroskedastic errors more effectively than log-transformation-based approaches (Silva and Tenreyro, 2006, 2011). In implementing the PPML-IV approach, we follow Lin and Wooldridge (2019), Wooldridge (2015) and incorporate a control function in the second-stage Poisson Pseudo Maximum Likelihood (PPML) regression. The second-stage regression is conducted with the predicted residuals from the first stage included as an additional explanatory variable. A statistically significant coefficient on the residual term, ($\hat{v_2}$), indicates the rejection of exogenity, suggesting the presence of endogeneity in the model. The econometric model is specified as follows:

$$Export_{sijt}^{final/interm} = exp(a_0 + \beta Robot_{sit} + X_{sit} + \gamma_t + \delta_{st} + \mu_{ijt}) \cdot \varepsilon_{sijt}, \tag{3.1}$$

where $Export_{sijt}$ represents the value of export, measured at current prices in U.S. dollars, either for final or intermediate goods, from industry s of country i to country j in year t. $Robot_{sit}$ denotes the robot adoption, measured as the logarithm of the number of robots per million workers, in industry s of country i in year t. The control variables, X_{sit}, include the logarithm of capital and labor productivity at industry s of country i in year

t. In addition, our estimation framework accounts for several fixed effects to control for unobserved heterogeneities: γ_t represents year fixed effects, controlling for time-specific factors common across all countries and industries. The term δ_{st} captures industry-year fixed effects, accounting for shocks or trends specific to each industry across different years. Finally, μ_{ijt} represents exporter-importer-year fixed effects to address factors specific to the trade relationship between the exporting country i and the importing country j in each year. Robust standard errors are clustered at the country level.

To assess the robustness of our results, we implement several tests. First, robotics adoption is unevenly distributed across industries, with the automobile, computer, electronics, and electrical equipment sectors being the most robot-intensive in both emerging and advanced economies. To investigate whether these highly robotized industries affect our overall results, we re-estimate the models excluding these three sectors.

Similarly, within emerging economies, China has experienced rapid automation of its manufacturing sector, and Chinese manufacturing industries could significantly influence the results for developing countries. To address this concern, we exclude China from the sample of developing economies and re-examine the results for a robustness check.

Finally, we employ alternative measures of robot adoption to further validate our conclusions on the relationship between robotics and export performance. Our primary measure relies on reported robot stock values from the International Federation of Robotics (IFR), which follows an accounting method where robots are assumed to become obsolete after eight years of operation. For robustness, we use an alternative measure that incorporates a 10% annual depreciation rate, using initial robot stock and annual new installations information by country and industry. This method, originally developed by Graetz and Michaels (2018), has been widely adopted in recent studies exploring the economic impact of robotics (DeStefano and Timmis, 2024; Artuc et al., 2023).

3.3.1 Instrumental variable construction

Industrial robot adoption rates are subject to endogeneity concerns for two main reasons. First, trade might induce robot adoption which raises the concern of possible reverse causality. The issue arises if industries more engaged in trade are also more likely to adopt advanced technologies, including robots. In such cases, the observed relationship between robot adoption and trade might reflect trade-induced technological change rather than the causal effect of robots on trade. Indeed, trade literature suggests that trade induces technology adoption (Lileeva and Trefler, 2010; Bustos, 2011; Bloom et al., 2016). Second, unobserved factors —such as a country's broader technological capacity or government policies—could simultaneously influence robot adoption and export performance, leading to omitted variable bias.

To address these issues, we adopt an instrumental variable approach that relies on sector-specific robotization trends in countries with similar income levels. This method follows recent work by Acemoglu and Restrepo (2020), Dauth et al. (2021) and Artuc et al. (2023). The assumption is that external automation patterns are largely shaped by global technological developments and policy shifts outside the domestic economy, which makes them relatively exogenous to local trade conditions and unobserved determinants of export performance. Using these global sector-specific automation trends as instruments for local robot adoption, we isolate the component of robot adoption that is exogenous to domestic trade and other confounding influences. This approach helps identify the causal effect of robotics on export outcomes, addressing concerns of reverse causality and omitted variable bias.

3.4 DATA AND DESCRIPTIVE STATISTICS

This paper combines several data sources from 2005 to 2020 for 53 developed and developing countries. Table 3.A.1 in the Appendix details the various data sources and explains how they were harmonized for the analysis. Data on industrial robots across countries, industries, and years are sourced from the International Federation of Robotics (IFR). The IFR defines an industrial robot based on the International Organization for Standardization's criteria: an "automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or attached to a mobile platform for use in automation applications within an industrial environment." The robot data are available at the 2-digit level for non-manufacturing sectors and at the approximately 3-digit level for manufacturing sectors. A key strength of the IFR data is its coverage of roughly 90% of global robot sales, providing a robust foundation for cross-country and panel data analysis.

One limitation of the robotics data is that industrial robot sales and stocks are reported in units rather than asset values, which makes cross-country comparisons challenging. To address this issue, we define robot density by combining industrial robot data with industry-level employment, measuring it as the number of industrial robots per million employees. Another concern is that the IFR estimates robot stock based on the assumption of a fixed operational lifespan of 12 years without accounting for depreciation, potentially leading to an inaccurate reflection of their economic value over time. In our robustness checks, we adopt the approach of Graetz and Michaels (2018) to construct an alternative measure of robot stock at the country-industry level. This method assumes an annual depreciation rate of 10% and incorporates both the initial robot stock and annual new deliveries.

We obtain industrial export data from the OECD Input-Output Tables, which report flows of final and intermediate goods and services at current prices in U.S. dollars. The dataset covers 76 countries, plus the rest of the world, spanning the period from 1995 to 2020. To complement our regressions, we construct capital per million employees and labor productivity using data from the UNIDO Industrial Statistics Database. Capital and value-added, used to compute labor productivity, are measured at current prices in U.S. dollars at the 2-digit industry level. For country classifications, we follow the World Bank's 2005 income-level classification, categorizing all non-high-income countries as developing economies.

3.4.1 Descriptive statistics

Industrial robot adoption has been increasing for the last three decades (see Figure 1.2). According International Federation of Robotics (2023), the top five countries with the largest number of industrial robot stocks are China (1,501,535 units of industrial robots), Japan (414,281), the Republic of Korea (374,737), the United States (365,002), and Germany (259,636). However, robot adoption is not limited to advanced economies. Among the ten countries with the highest robot stocks, developing countries such as Mexico (51,957) and Thailand (39,406) rank 8th and 10th, respectively. The adoption of industrial robots in developing countries has accelerated significantly since 2005. By 2020, the total number of robots in developing economies had surpassed that of their advanced counterparts.

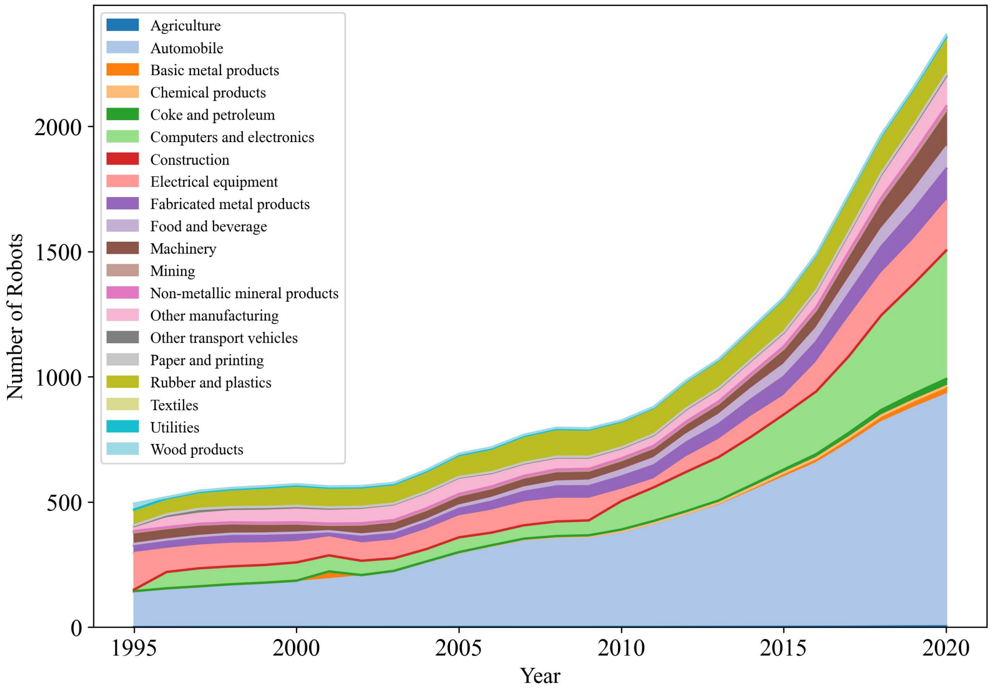

Figure 3.1: Global Robot Stocks by Industries *(in thousand units)*.

Source: International Federation of Robotics

Figure 3.1 presents the distribution of global industrial robot adoption across industries from 1995 to 2020. The top 3 industries with a high number of industrial robots are automobile, computers and electronics, electrical equipment, and machinery. Similarly, in developing economies, the automotive sector shows the highest concentration of robots, accounting for 34.1% of total installations, followed by computers and electronics at 26.5% and electrical equipment at 12.7% (Figure 3.1). These industries typically demand high levels of precision, speed, and consistent quality, particularly for repetitive and detail-oriented tasks. The high concentration of robotics in these sectors reflects a strategic response to global production standards and market demand, rather than serving as a direct mechanism for labor replacement. By contrast, labor-intensive sectors such as textiles, agriculture, and mining demonstrate the lowest levels of robotization in developing economies.

Table 3.1 provides summary statistics for the sample of developed and developing countries for the period 2005–2020. Each unit of observation represents the export of a home country (exporter) in a specific industry to a destination country (importer) in a given year. The number of observations is larger for developed countries, which shows extensive trade networks. The mean export values for both final and intermediate goods are higher in developed economies. The number of robots per employee is nearly double in advanced economies compared with developing ones, likely due to more advanced industrial structures and integration into global value chains.

Table 3.1: Summary statistics, estimation sample, 2005-2020

	Developed countries			Developing countries		
	mean	SD	N	mean	SD	N
Final goods	42.41	352.20	805650	38.29	583.47	602775
Intermediate goods	59.76	461.35	805650	51.97	537.62	602775
Robots per million employees	3.57	3.15	805650	2.14	2.37	602775
Labor productivity	21.57	4.15	805650	22.54	6.42	602775
Capital per million employees	16.52	7.70	805650	13.93	11.03	602775

Notes: Table reports means and standard deviations of estimation sample for developed and developing countries for the period of 2005-2020. Robots per million employees are measured as log (1+robot stock/employment), with employment in millions. Capital per million employees is measured as log (1+capital/employment) with capital at current prices in U.S. dollars and employment in millions. Final and intermediate goods exports are at current prices in U.S. dollars.

3.5 RESULTS AND DISCUSSIONS

3.5.1 Baseline results

Table 3.2 presents our main estimates on the effects of industrial robots on export performance in developing economies. All specifications account for year, industry-year, and exporter-importer-year effects, with robust standard errors clustered at the country level. The Poisson Pseudo Maximum Likelihood (PPML) estimates indicate that a 1 percentage point increase in the number of robot stocks per million workers leads to a 0.163 percentage point increase in export of total goods, 0.100 percentage point – final goods and 0.177 percentage point – intermediate goods in developing countries. The PPML results demonstrate a positive association between robotics and industry exports.

As discussed earlier, robot adoption may be subject to endogeneity concerns, such as reverse causality and omitted-variable bias. To address these issues, columns 4–6 of Table 3.2 instrument domestic industry-level robot adoption using industry-specific robotization trends in other regions of the world. The PPML-IV results, which account for potential endogeneity in robot density through instrumentation, provide slightly moderated yet robust findings. The impact of robot density remains positive and significant for total

Table 3.2: Impact of robot adoption on export structure in developing countries.

	PPML			PPML-IV		
	Total	Final goods	Interm goods	Total	Final goods	Interm goods
	(1)	(2)	(3)	(4)	(5)	(6)
Robot density	0.163***	0.100**	0.177***	0.136***	0.071	0.140***
	(0.029)	(0.038)	(0.033)	(0.032)	(0.046)	(0.035)
Capital per employee	0.004**	0.004***	0.004*	0.003*	0.003***	0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Labor productivity	0.057	0.305*	0.035	0.057	0.309*	0.036
	(0.056)	(0.149)	(0.041)	(0.056)	(0.150)	(0.040)
Constant	4.845***	-2.011	4.794***	4.922***	-2.018	4.886***
	(1.414)	(3.876)	(1.012)	(1.424)	(3.884)	(1.027)
$\hat{v_2}$				0.041	0.044	0.054
				(0.044)	(0.038)	(0.057)
Observations	602775	602775	602775	602475	602475	602475
KP F-stat				252.36	252.36	252.36
Year FE	YES	YES	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES	YES	YES
Exp-importer-year FE	YES	YES	YES	YES	YES	YES

Robust standard errors clustered at country-level in parentheses.
*** p<.01, ** p<.05, * p<.1.

exports and intermediate goods, though the coefficient for final goods loses statistical significance. Specifically, the PPML-IV results indicate that a 1 percentage point increase in robots per million employees leads to a 0.136–0.140 percentage point increase in exports of total and intermediate goods. These findings suggest that robot adoption facilitates the integration of developing economies into the global value chains and international production networks. The statistical insignificance of the control function,$\hat{v_2}$ indicates that endogeneity is not a severe issue in these specifications. Furthermore, the high Kleibergen-Paap F-statistic (252.36) confirms the strength and validity of the instrumental variables used.

Table 3.3 examines the impact of robot adoption on the export structure of developed countries using PPML and PPML-IV models. The results consistently show a significant positive relationship between robot adoption and exports across total, final goods, and intermediate goods categories. In the PPML-IV model, the coefficients for robot density are larger, with a 1 percentage increase in robot density leading to a 0.172 percentage increase in total exports, 0.158 percentage increase in final goods, and 0.184 percentage in intermediate goods. The control function term, $\hat{v_2}$, is significant at the 5% level,

Table 3.3: Impact of robot adoption on export structure in developed countries

	PPML			PPML-IV		
	Total	Final goods	Interm goods	Total	Final goods	Interm goods
	(1)	(2)	(3)	(4)	(5)	(6)
Robot density	0.122***	0.119***	0.124***	0.172***	0.158***	0.184***
	(0.010)	(0.016)	(0.010)	(0.029)	(0.031)	(0.029)
Capital per employee	0.003	0.004	0.003	0.002	0.003	0.001
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Labor productivity	0.113	0.092	0.132	0.110	0.090	0.128
	(0.145)	(0.099)	(0.187)	(0.138)	(0.095)	(0.179)
Constant	3.268	3.074	2.353	3.104	2.922	2.184
	(3.441)	(2.334)	(4.459)	(3.228)	(2.200)	(4.185)
$\hat{v}_2$				-0.070*	-0.057*	-0.082*
				(0.029)	(0.027)	(0.032)
Number of observations	805650	805650	805650	805200	805200	805200
KP F-stat				67.67	67.67	67.67
Year FE	YES	YES	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES	YES	YES
Exp-importer-year FE	YES	YES	YES	YES	YES	YES

Robust standard errors clustered at country-level in parentheses.
*** p<.01, ** p<.05, * p<.1.

and indicates the presence of unobserved factors contributing to endogeneity, which are accounted for in the model with instrumentation. The results suggest that developed countries benefit more broadly from robot adoption in their export structures, which reflects their higher technological capacity, more advanced production systems, and established roles in the global value chain.

In summary, we have demonstrated a positive impact of industrial robots on export performance in both developing and developed economies. In developing countries, industrial robots increase the export of intermediate goods only, while in developed economies, robots positively impact total, final, and intermediate goods.

3.5.2 Robustness analysis

Our baseline results show that robot adoption positively affects industrial exports of intermediate goods in developing economies. However, several factors could potentially influence these results. To ensure the reliability of our findings, we implement a series of robustness checks. One key concern is China's significant share in robot adoption within developing economies. Over the past decade, robot density in China has increased dramatically, from 15 to 246 industrial robots per 10,000 employees (IFR, 2021). Given China's large share of robot adoption among developing countries, its presence could bias the results. To address this, we exclude China from the sample of developing economies and re-estimate Equation (3.1). As shown in Table 3.4, excluding China does not affect the results for the remaining developing economies. The findings remain consistent with those reported in Table 3.2 and confirm the robustness of our baseline estimates against trends in Chinese manufacturing automation.

Table 3.4: Robot adoption and export structure in developing countries (China excluded)

	PPML			PPML-IV		
	Total	Final goods	Interm goods	Total	Final goods	Interm goods
	(1)	(2)	(3)	(4)	(5)	(6)
Robot density	0.141***	0.076	0.152***	0.126**	0.053	0.129**
	(0.033)	(0.048)	(0.034)	(0.040)	(0.057)	(0.046)
Capital per employee	0.002	0.005	0.001	0.002	0.004	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Labor productivity	0.036	0.309	0.012	0.037	0.312	0.013
	(0.062)	(0.191)	(0.045)	(0.062)	(0.192)	(0.044)
Constant	4.774**	-3.050	5.055***	4.799**	-3.045	5.082***
	(1.541)	(4.940)	(1.061)	(1.539)	(4.947)	(1.061)
$\hat{v}_2$				0.023	0.034	0.031
				(0.037)	(0.039)	(0.040)
Number of observations	582300	582300	582300	582000	582000	582000
KP F-stat				257.26	257.26	257.26
Year FE	YES	YES	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES	YES	YES
Exp-importer-year FE	YES	YES	YES	YES	YES	YES

Robust standard errors clustered at country-level in parentheses.
*** p<.01, ** p<.05, * p<.1.

A second potential concern is the concentration of robots in a few industries. The automobile, computers and electronics, and electrical equipment sectors account for nearly 70% of industrial robots and have higher automation levels compared with other industries. To assess whether the positive impact of robotics on export performance is driven by these sectors, we re-estimate the regression in Table 3.5, excluding these top three industries. The results in Table 3.5 show that the positive impact of robots on export performance persists even in less robotized industries. Specifically, a 1% increase in robot stock per million employees in these industries results in a 0.152 percentage increase in intermediate exports. This robustness check confirms the broader applicability of our findings across

Table 3.5: Robustness check (Top 3 robotized industries are excluded)

	PPML			PPML-IV		
	Total	Final goods	Interm goods	Total	Final goods	Interm goods
	(1)	(2)	(3)	(4)	(5)	(6)
Robot density	0.126***	0.063	0.141**	0.152***	0.098	0.151***
	(0.038)	(0.056)	(0.046)	(0.033)	(0.091)	(0.035)
Capital per employee	0.002	0.002	0.001	0.002	0.003	0.001
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Labor productivity	0.035	0.330	0.019	0.033	0.318	0.018
	(0.040)	(0.331)	(0.032)	(0.039)	(0.342)	(0.031)
Constant	5.266***	-2.977	5.159***	5.235***	-2.740	5.143***
	(1.034)	(8.839)	(0.816)	(1.039)	(9.037)	(0.838)
$\hat{v}_2$				-0.044	-0.056	-0.018
				(0.052)	(0.068)	(0.068)
Number of observations	494325	494325	494325	494025	494025	494025
KP F-stat				213.58	213.58	213.58
Year FE	YES	YES	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES	YES	YES
Exp-importer-year FE	YES	YES	YES	YES	YES	YES

Robust standard errors clustered at country-level in parentheses.
*** p<.01, ** p<.05, * p<.1.

various industries.

Table 3.A.2 in the Appendix demonstrates the sensitivity of the results by employing an alternative measure of robot adoption. Instead of relying on IFR robot stock data, we construct robot stock estimates using initial stock values, new annual installations, and a 10% annual depreciation rate. The findings confirm that industrial robots have a positive impact on exports of both final and intermediate goods in developing countries.

Table 3.6 incorporates the exchange rate as an additional control, a standard practice in gravity models, to assess the robustness of the baseline estimates. The inclusion of exchange rate changes accounts for aggregate shocks at the country level that may influence bilateral exports. The exchange rate data, sourced from the IMF, is reported in local currency units (LCU) per U.S. dollar. We compute the annual percentage change in the exchange rate to capture macroeconomic fluctuations affecting trade. This variable complements exporter-importer-year fixed effects, which already control for exchange rate variations at the bilateral level.

Table 3.6 shows that across both PPML (columns 1–3) and PPML-IV (columns 4–6), the coefficients on robot density remain positive and statistically significant for total and intermediate goods, with magnitudes comparable to the baseline specification in Table 3.2. Although the exchange rate variable is negative and significant for only final goods exports, its inclusion does not substantially change the estimated coefficients for robot adoption or other covariates. These findings confirm that the positive effect of robot adoption on export performance is robust to the inclusion of exchange rate fluctuations, which can influence trade flows through changes in price competitiveness.

Table 3.6: Robustness Check: Exchange Rate Inclusion

	PPML			PPML-IV		
	Total	Final goods	Interm goods	Total	Final goods	Interm goods
	(1)	(2)	(3)	(4)	(5)	(6)
Robot density	0.161***	0.102**	0.174***	0.138***	0.077	0.141***
	(0.029)	(0.038)	(0.031)	(0.034)	(0.046)	(0.036)
Capital per employee	0.004***	0.004***	0.004*	0.004**	0.004***	0.003
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Labor productivity	0.070	0.318*	0.044	0.070	0.321*	0.045
	(0.067)	(0.145)	(0.046)	(0.066)	(0.146)	(0.046)
Exchange rate	-0.284	-0.599***	-0.204	-0.286	-0.555***	-0.193
	(0.145)	(0.139)	(0.152)	(0.164)	(0.128)	(0.185)
Constant	4.501**	-2.371	4.551***	4.574**	-2.366	4.638***
	(1.703)	(3.783)	(1.156)	(1.710)	(3.790)	(1.169)
$\hat{v_2}$				0.035	0.039	0.047
				(0.043)	(0.038)	(0.054)
Number of observations	600825	600825	600825	600525	600525	600525
KP F-stat				252.36	252.36	252.36
Year FE	YES	YES	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES	YES	YES
Exp-importer-year FE	YES	YES	YES	YES	YES	YES

Robust standard errors clustered at country-level in parentheses.
*** p<.01, ** p<.05, * p<.1.

3.6 CONCLUSION

Globally, manufacturing sectors are increasingly adopting automation in production processes. Over the past decade, many developing countries have integrated robots into their manufacturing systems. This paper examines the impact of robot adoption on export performance in developed and developing countries from 2005 to 2020, using industry-level data from 53 countries. To address endogeneity concerns related to industrial robot adoption, we use industry-specific robotization levels in other regions as an instrumental variable.

Our findings show that robot density across industries increases export performance for both developed and developing countries. Robots in developing economies contribute to an increase in intermediate goods export. The results remain robust after accounting for China's dominant role in robotization among developing economies and excluding the most automated industries. This indicates that robots have a broad application across sectors and countries in promoting export growth. Furthermore, the benefits of robot adoption appear greater for developed economies compared with their developing counterparts.

These findings have several policy implications. First, while automation technologies have raised concerns about labor displacement and inequality, our results suggest that robotics can serve as an instrument for exports and economic growth through improved production quality and efficiency, particularly in developing countries. Second, the findings highlight the importance of policies that support trade openness and technology adoption. Increased openness to trade allows developing countries to access advanced production practices and cutting-edge technologies. Trade openness enables access to advanced technologies, while technologies such as robotics enhance productivity, linking developing economies more effectively to global value chains and driving sustainable growth.

APPENDIX

3.A APPENDIX

Table 3.A.1: Data Matching Across Sources

No	Sector name	International Federation of Robotics	OECD Input-Output Tables	UNIDO
1	Food products, beverages, and tobacco products	10-12	D10T12	15
2	Textiles, wearing apparel, leather and related products	13-15	D13T15	17, 18, 19
3	Wood and furniture	16	D16	20
4	Paper and printing	17-18	D17T18	21, 22
5	Coke and refined petroleum products	19	D19	23
6	Chemicals, pharmaceuticals, medicinal chemicals	20-21	D20, D21	24
7	Rubber and plastics products	22	D22	25
8	Other non-metallic mineral products	23	D23	26
9	Basic metals	24	D24	27
10	Fabricated metal products, except machinery	25	D25	28
11	Computer, electronic and optical products	260, 261, 262 , 263, 265	D26	30
12	Electrical equipment	271, 275, 279	D27	31
13	Motor vehicles, trailers and semi-trailers	29	D29	34
14	Other transport equipment	30	D30	35

Notes: Table reports the industry classification used in the analysis, as well as the corresponding codes in the IFR, OECD Input-Output Tables and UNIDO data sets.

Table 3.A.2: Robustness check (Alternative measure of robot adoption)

	PPML			PPML-IV		
	Total	Final goods	Interm goods	Total	Final goods	Interm goods
	(1)	(2)	(3)	(4)	(5)	(6)
Robot density	0.177***	0.111**	0.194***	0.149**	0.063	0.157**
	(0.032)	(0.037)	(0.038)	(0.046)	(0.064)	(0.054)
Capital per employee	0.004**	0.004***	0.004*	0.004**	0.003**	0.003
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Labor productivity	0.057	0.301*	0.035	0.057	0.306*	0.036
	(0.056)	(0.146)	(0.041)	(0.055)	(0.148)	(0.040)
Constant	4.835***	-1.921	4.778***	4.913***	-1.911	4.866***
	(1.400)	(3.806)	(0.988)	(1.408)	(3.819)	(1.007)
$\hat{v}_2$				0.034	0.061	0.045
				(0.061)	(0.057)	(0.078)
Number of observations	602775	602775	602775	602475	602475	602475
KP F-stat				74.42	74.42	74.42
Year FE	YES	YES	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES	YES	YES
Exp-importer-year FE	YES	YES	YES	YES	YES	YES

Robust standard errors clustered at country-level in parentheses.
*** p<.01, ** p<.05, * p<.1.

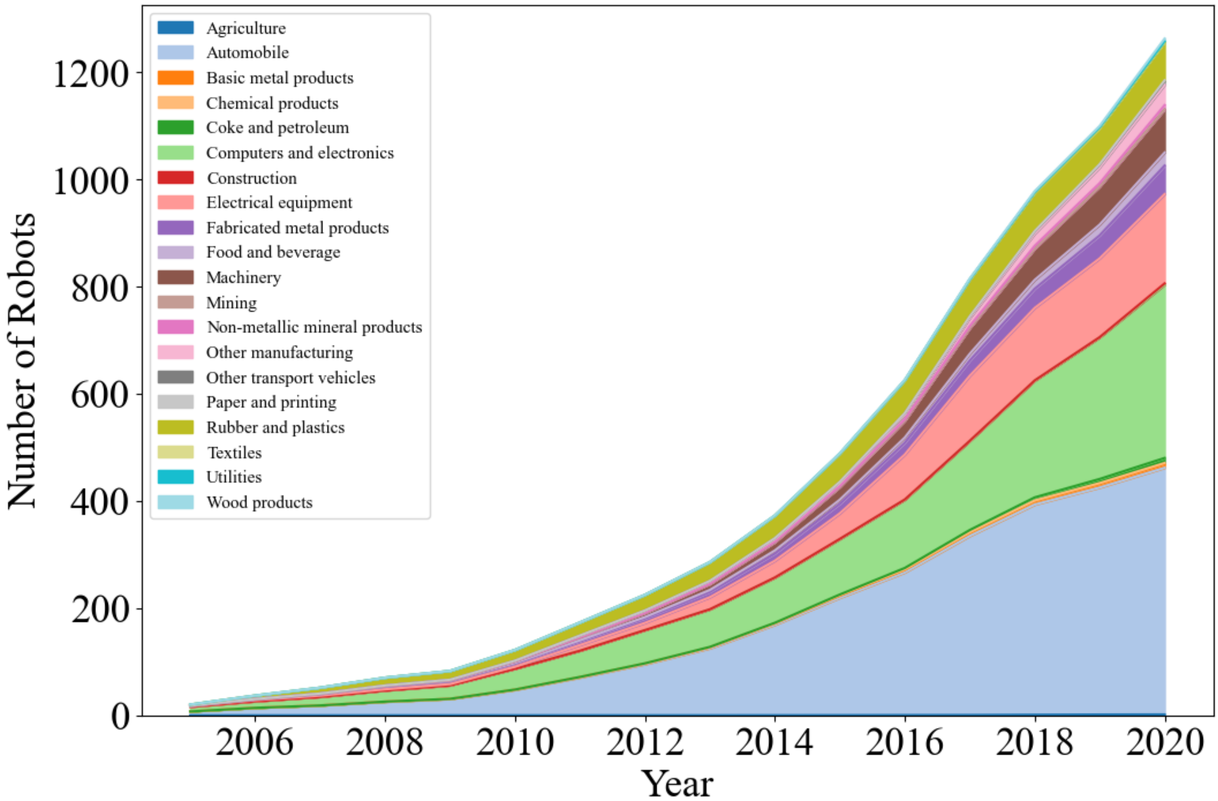

Figure 3.1: Robot Stocks by Industries in Developing Economies*(in thousand units)*

Source: International Federation of Robotics

CHAPTER 4

TECHNOLOGICAL ADVANCEMENTS AND EXPORT MARKET SHARES

Abstract

This paper examines how recent technological advancements—particularly industrial robotics, R&D, and ICT—affect export market shares in both developing and developed countries. We employ panel data model techniques and match industrial robot data for 17 industries across 60 economies with trade flows from the OECD Inter-Country Input-Output tables for 2005-2020. Our findings show that domestic industry robot adoption significantly increases export market shares, with a stronger effect in developing economies compared with advanced ones. R&D investment consistently enhances export competitiveness, underscoring the importance of innovation across all industries. Notably, the benefits of technology adoption for export market shares are more pronounced within South-South trade patterns. Sector-level results demonstrate that robot adoption is especially effective in high-tech and capital-intensive industries, while R&D increases competitiveness across a broader range of sectors.

4.1 INTRODUCTION

Over the past three decades, the global economy has undergone significant structural changes. The share of trade between advanced economies has declined by 15% since 1995, while trade within the Global South has increased by 14.1%, as illustrated in Figure 4.1. Existing studies debate the possible factors, including falling trade costs in emerging economies (Autor, 2015; Hummels, 2007), the expansion of multistage global production networks (Cingolani et al., 2018; Costinot et al., 2013), international specialization patterns (Hanson, 2012; Timmer et al., 2014), and Chinese export growth (Di Giovanni et al., 2014). To contribute to this discussion, we examine the role of technology adoption by developing countries in shaping these structural patterns.

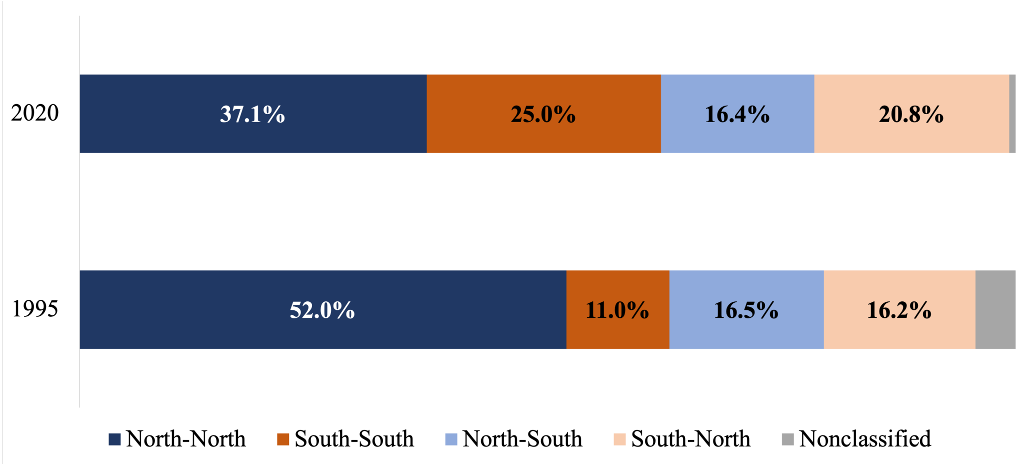

Figure 4.1: Global trade by developed and developing countries, percent of total, 1995-2020.

Source: UNCTAD Trade and Development Report 2022

In this paper, we investigate the effect of recent technological advancements—specifically industrial robots, R&D, and ICT—on export market shares across destinations in both developing and developed countries. The study combines industry-level data from the International Federation of Robotics (IFR) with the OECD Inter-Country Input-Output Tables and UNIDO's Industrial Statistics Database, covering 17 industries across 60 countries from 2005 to 2020. We rely on a fixed-effects (FE) estimation as the primary method, which accounts for unobserved time-invariant heterogeneity at the country-industry-destination level. To ensure the robustness of the findings, we complement the FE analysis with nonlinear fractional response models, including fractional probit and correlated random effects estimators.

The findings demonstrate several important patterns that partially explain the structural changes observed in global trade. First, domestic industry robot adoption has a positive and significant effect on export market shares, particularly in developing countries. A 10 percent increase in robot density corresponds to a 0.020 percentage point gain in market share for developing economies, compared with a 0.007 percentage point gain for developed economies. R&D investment consistently increases market shares across industries and income levels. In contrast, ICT adoption shows limited significance.

Second, more importantly, technology adoption by industries in developing countries significantly increases their market share in other developing countries, particularly in low-income destinations. This indicates that technological advancements not only facilitate trade but also drive structural change within the Global South. In contrast, developed countries predominantly target middle- and high-income destinations, reflecting distinct trade dynamics. However, for developing countries, technology adoption by competitors and destination countries creates substantial competitive pressures. Specifically, the significant negative effects of competitors' technology adoption on the market share of domestic industries underscore the challenges to maintain competitiveness in increasingly automated markets.

Third, the effect of technology adoption on export market shares shows clear sectoral differences. Automation technologies, such as robotics, are particularly effective in high-tech and capital-intensive sectors, including electrical equipment and automobiles, where efficiency and precision are critical for competitiveness. On the other hand, R&D shows broader applicability across a wider range of industries. Regarding competitors' technology adoption, we find a unique pattern: resource-based industries, such as mining and petroleum, maintain competitive advantages despite high levels of robot adoption by rivals. These findings emphasize the role of natural resource endowments and economies of scale in sustaining competitiveness in specific industries.

This paper is structured as follows: Section 2 reviews the literature on robotics, technology, and trade. Section 3 outlines the methodological framework and econometric model. Section 4 details the data and descriptive statistics. Section 5 presents regression results on the impact of technology adoption on export market shares. Section 6 concludes with policy implications and future research directions.

4.2 LITERATURE BACKGROUND

4.2.1 Technology, trade and market shares

This paper builds on extensive research on the interaction between trade and technology. While early studies focused on how trade openness facilitates technology diffusion (Perla et al., 2021; Lileeva and Trefler, 2010; Eaton and Kortum, 1997), recent research emphasizes the impact of technological advancements on trade patterns. For instance, broadband expansion in France (Malgouyres et al., 2021) and the UK (Kneller and Timmis, 2016), Internet penetration in China (Fernandes et al., 2019) and ICT adoption in East Africa (Xing, 2018). Studies demonstrate that innovation facilitates entry into new international markets and export diversification (Cassiman and Golovko, 2011; Becker and Egger, 2013; Cirera et al., 2015). Recent studies demonstrate that automation and robotics increase export quality, especially in developing economies (DeStefano and Timmis, 2024; Hong et al., 2022).

Despite the well-documented research on aspects of technology and trade, how technology adoption enhances competitiveness remains a critical area of inquiry. International competitiveness is defined as the ability of a country or industry to outperform foreign counterparts (Castellacci, 2008). It is often measured through export market share. This metric, relative to global exports within the same industry, serves as a proxy for both comparative and competitive advantage (Fagerberg, 1988; Balassa, 1965; Levchenko and Zhang, 2016; French, 2017). Existing literature emphasizes technological factors as one of the key determinants of competitiveness (Amendola et al., 1993; Amable and Verspagen, 1995; Carlin et al., 2001; Montobbio, 2003; Jongwanich, 2010; Dosi et al., 2015). Among specific technological factors, R&D activities and patenting are frequently identified as significant determinants of export competitiveness (Fagerberg, 1988; Soete, 1987; Amendola et al., 1993).

However, studies on competitiveness often fail to account for destination markets and the relative technological capacity of competitors. Trade literature emphasizes the importance of destination markets for export pricing (Kilinc, 2019; Manova and Zhang, 2012) and quality decisions (Brambilla and Porto, 2016; Bastos and Silva, 2010). Destination market factors can make certain technologies more relevant for gaining market share in specific markets. For instance, R&D might be more critical for high-income markets where demand for sophisticated goods is higher, whereas cost-reducing innovations might provide a competitive advantage in low-income markets.

Moreover, competitiveness is determined not only by the absolute technological capacity of domestic industries but also by its relative performance compared with competitors. Studies emphasize the role of competitive pressure in export performance (Landesmann and Pfaffermayr, 1997; Benkovskis et al., 2020). Similar technology adoption by competing industries or host countries can erode a domestic industry's competitive advantage in specific markets. For example, recent research has associated robotization trends with structural changes, such as reshoring (Stapleton and Webb, 2020; Cilekoglu et al., 2024). Advanced economies use robots to relocate production domestically, reducing demand for imports from emerging economies.

This study advances the literature on export competitiveness by examining the role of emerging technologies, such as industrial robotics and ICT. In contrast to Mao and Zhang (2015), which focuses on Chinese industrial exports, this research broadens the scope to assess the impact of these technologies on export market shares across both developed and developing countries.

4.3 METHODOLOGY

This study examines the relationship between technology adoptions and export market share using an Ordinary Least Squares (OLS) fixed effects framework, the econometric model is specified as follows:

$$\begin{aligned} Market\_share_{sijt} = a + \beta_1 Robot_{sit} + \beta_2 Robot\_dest_{sjt} + \beta_3 Robot\_comp_{jst} \\ + \gamma R\&D_{sit} + \delta ICT_{sit} + X_{sit} + \lambda_t + \mu_{st} + \varepsilon_{sijt}, \end{aligned} \quad (4.1)$$

where $Market\_share_{sijt}$ represents the market share of industry s of country i within the destination country j in year t. The variable $Robot_{sit}$ captures robot adoption in industry s of the home country i in year t, reflecting technological progress within the domestic exporting industry. Similarly, $Robot\_dest_{sjt}$ measures the robotics intensity in destination country j for industry s in year t. This metric captures the technological advancement of the destination country industry and its potential competition or complementarities with the exports from home country.

The variable $Robot\_comp_{jst}$ denotes the robotics intensity in competing country industries that export to the same destination market j in industry s in year t. The variable is calculated as a weighted average of the robotics adoption in competitor industries, where the weights are based on their initial market shares in the destination market. The variable is constructed as follows:

$$Robot\_comp_{jst} = \sum_{k \neq i} \left(Initial\ market\ share_{kjs,t=2000} \cdot Robot_{kst} \right), \quad (4.2)$$

where $Initial\ market\ share_{kjs,t=2000}$ represents the initial market share of competitor country k (other than home country i) in the destination market j, in the same industry s, and in the year 2000. $Robot_{kst}$ denotes industrial robot adoption level in industry s of competitor country k in year t. This variable captures the competitive pressure in the destination market arising from the robotics intensity of other exporters in the same industry.

To capture the role of other technological factors, the model includes $R\&D_{sit}$, which represents research and development expenditures in industry s of the home country i in year t and ICT_{sit}, which measures the intensity of information and communication technology usage in the same industry and country over time. These variables capture innovation and digital technology adoption, respectively, both of which are expected to impact the competitiveness of the domestic industry's exports. Also, our control variable, X_{sit}, reflects labor productivity at industry s of country i in year t.

Furthermore, the model incorporates several fixed effects. Specifically, λ_t represents year fixed effects, which control for time-specific global trends and shocks. The term μ_{st} captures industry-year fixed effects, which accounts for dynamics specific to each industry across years. Finally, ε_{sijt} represents the error term, assumed to be independently and identically distributed.

We employ the fixed effects estimation method to control for omitted variable bias due to time-invariant unobserved heterogeneity. Accounting for unobserved heterogeneity allows us to isolate the effects of explanatory variables and obtain more accurate estimates.

To ensure consistency of our findings across estimation methods, we extend the analysis using nonlinear models, converting the dependent variable for export market shares into a fractional form bounded between 0 and 1. The fractional probit model, employing a probit link function, captures the bounded nature of the dependent variable, addressing potential biases in linear specifications. To begin, we present the pooled fractional response (PFR) model, which does not account for unobserved heterogeneity but serves as an initial reference point. Next, we employ the correlated random effects (CRE) model, which includes time-averaged covariates to account for correlations between unobserved heterogeneity and explanatory variables, utilizing both within- and between-group variation. Finally, following Wooldridge (2019) and Bates et al. (2024), the CRE model is extended to account for unbalanced panels (CREU) to ensure robust estimation even when data on export shares for some home country industries are missing over certain periods. Together, these models demonstrate the reliability and robustness of our results across different econometric specifications.

4.4 DATA AND DESCRIPTIVE STATISTICS

Our main source of data comes from the International Federation of Robotics (IFR). The IFR provides detailed information on the number of robots delivered to each country, industry, and year. One of the key advantages of the IFR dataset is its broad coverage: it captures approximately 90% of global robot supplies. However, there are several limitations in the dataset regarding robot adoption. First, the IFR reports data in terms of the number of robots installed per country and industry, rather than in asset values. This creates challenges for making comparisons across industries and countries, as the technological features and capabilities of robots vary significantly. To address this issue, we supplement the number of robots with employment data from the United Nations Industrial Development Organization (UNIDO). This allows us to express robot adoption on a per-employee basis. This approach helps normalize the data and makes it more comparable across countries and industries. Second, robot adoption in North America is provided as a whole rather than with a country-specific breakdown up until 2011. This aggregate level measurement introduces noise in the robotization variable for countries in North America. To mitigate this issue, we exclude observations for North America prior to 2011 from our sample.

The second main data source used in this paper is the OECD Inter-Country Input-Output (ICIO) tables. The ICIO tables provide harmonized data on inter-industry flows of final and intermediate goods and services, including both domestically produced and imported products, which are measured at current prices in U.S. dollars, for 38 OECD member countries and 38 non-OECD countries from 1995 to 2020. We use this data source to construct our export market share variable for home country industries in different destinations. The ICIO tables are provided at the ISIC Rev.4 division level and cover 45 industries. In contrast, the IFR dataset on robot adoption provides data for 17 industries at a more aggregated level. To ensure consistency across datasets, we aggregate the data from ICIO tables and match them with the IFR industry classification. Table 4.A.1 in the appendix details the methodology and mapping used for this paper.

In addition to IFR and ICIO datasets, we complement our regressions with employment and value-added data from UNIDO's Industrial Statistics database, which reports at the 2-digit industrial activity level. Furthermore, we use World Bank's 2005 income classification data to categorize countries by income level.

While the original ICIO dataset includes 76 countries, our final dataset consists of 60 countries due to data availability constraints. The IFR dataset does not provide industrial robot adoption data for 15 countries present in the ICIO dataset: Bangladesh, Brunei, Chile, Côte d'Ivoire, Cameroon, Costa Rica, Cyprus, Jordan, Kazakhstan, Cambodia, Laos, Luxembourg, Myanmar, Nigeria, and Senegal. In addition, although Argentina appears in both the ICIO and IFR datasets, it is excluded from our final dataset due to missing industry-level employment data in the UNIDO dataset. Table 4.A.2 in the appendix presents a detailed description of our final sample by country.

4.4.1 Descriptive statistics

Table 4.1 illustrates key differences in descriptive statistics of export market shares and technology adoption across all countries, as well as between developing and developed economies. On average, export market shares are higher for developed countries (mean: 2.08) compared with developing countries (mean: 1.33), reflecting the stronger competitive positioning of advanced economies in global trade. However, both groups exhibit significant variability, as indicated by the wide standard deviations and high maximum values, suggesting that some industries or countries dominate in their respective export markets.

Technological disparities are seen in the adoption of robotics and R&D intensity. Developed countries show a significantly higher mean for robot adoption (2.89) and R&D intensity (4.26) compared with developing countries (1.08 and 2.62, respectively), underscoring their technological edge. Interestingly, labor productivity is slightly higher in developing countries (12.22) than in developed ones (11.8), possibly due to sectoral differences or the presence of resource-driven economies with high output per worker. Host and competitor robotics levels are similar across country groups, with slightly higher averages for competitors, suggesting comparable competitive pressures in destination mar-

Table 4.1: Descriptive statistics by country groups

	Observations	Mean	SD	Min	Max
All countries					
Export market share	797832	1.67	4.89	0	99.28
Robot home	797832	1.89	2.00	0	10.18
Robot host	797832	1.89	2.00	0	10.18
Robot competitors	797832	2.59	1.58	0	7.11
R&D adoption	797832	3.36	1.48	0.02	11.73
Labor productivity	797027	12.03	3.27	0	23
Developing countries					
Export market share	357951	1.33	4.61	0	99.28
Robot home	357951	1.08	1.49	0	8.45
Robot host	357951	1.91	2.01	0	10.18
Robot competitors	357951	2.62	1.59	0	7.11
R&D adoption	357951	2.62	1.30	0.02	9.95
Labor productivity	357383	12.22	3.93	0	23
Developed countries					
Export market share	439881	2.08	5.18	0	90.4
Robot home	439881	2.89	2.08	0	10.18
Robot host	439881	1.86	1.99	0	10.18
Robot competitors	439881	2.54	1.57	0	7.11
R&D adoption	439881	4.26	1.14	0.19	11.73
Labor productivity	439644	11.80	2.17	0	19.84

kets. These differences provide valuable context for understanding the role of technology in shaping export market shares across economic contexts.

Table 4.A.3 in the appendix presents summary statistics for country groups based on their export destinations. Developed economies have a stronger presence in high-income markets, where they are likely to export high-value goods, while developing countries have a relatively better presence in low-income markets. On average, domestic robot adoption in developing countries exceeds host-country robot adoption when exporting to low- and lower-middle-income countries. In contrast, developed countries consistently demonstrate higher domestic robot adoption than host-country adoption across all income groups, with values ranging from 2.88 to 2.9.

Table 4.2 illustrates the mean values of variables across industries. The automobile industry stands out with the largest levels of robot adoption at home (3.96) and among competitors (5.91), reflecting its reliance on advanced automation. Similarly, rubber and plastics show high robot adoption by competitors (4.44), highlighting the automation intensity in this sector. In contrast, chemical products and mining exhibit the lowest levels of domestic industry robotization (0.26 and 0.43, respectively), likely due to their dependence on resource extraction rather than advanced manufacturing technologies.

Table 4.2: Descriptive statistics by industries total sample

Industries	**N**	**Market share**	**Robot home**	**Robot compet.**	**R&D adoption**	**Labor productivity**
Mining	5108	1.48	0.43	0.12	4.09	10.39
Food and beverage	52452	1.48	1.78	1.99	3.53	12.17
Textiles	52674	1.59	0.63	0.77	2.56	11.56
Wood products	50628	1.63	1.41	1.69	2.60	11.72
Paper and printing	52220	1.67	0.82	1.52	3.14	12.14
Coke and petroleum	37014	1.67	2.37	2.08	4.70	12.97
Chemical products	49124	1.60	0.26	0.36	4.20	12.76
Rubber and plastics	49966	1.70	3.67	4.44	3.01	12.04
Non-metallic mineral prod.	51536	1.65	1.40	2.33	3.16	12.24
Basic metal products	51200	1.61	1.86	2.33	3.31	12.50
Fabricated metal prod.	49974	1.70	2.51	3.49	2.86	11.88
Computers and electronics	43214	1.87	2.56	4.07	4.30	11.84
Electrical equipment	48744	1.73	2.12	3.15	3.39	11.76
Machinery	50864	1.73	1.88	3.33	3.01	11.90
Automobile	49520	1.72	3.96	5.91	3.42	11.90
Other transport vehicles	44332	1.79	1.71	2.06	3.39	11.98
Other manufacturing	50864	1.64	2.06	2.71	3.33	11.77

R&D adoption is highest in coke and petroleum (4.7) and computers and electronics (4.3), underscoring their focus on innovation to maintain competitiveness. On the other hand, textiles and wood products show the lowest R&D adoption levels (2.56 and 2.6, respectively), aligning with their lower technological intensity. For labor productivity, coke and petroleum (12.97) and chemical products (12.76) lead, reflecting the capital-intensive nature of these industries, while mining reports the lowest labor productivity (10.39), which is consistent with its resource-dependent processes. These disparities illustrate the diverse technological and productivity dynamics across industries.

4.5 RESULTS AND DISCUSSIONS

4.5.1 Baseline results

Table 4.3 reports the effect of technology adoption on export market shares across all, developed, and developing countries using fixed-effect estimation. The results demonstrate the significant role of domestic robot adoption, R&D intensity, and robot adoption by competitor industries in export market shares in all country groups.

Table 4.3: Technology adoption and export market shares by country group

	All countries (1)	Developed countries (2)	Developing countries (3)
Robot home	0.135***	0.074***	0.201***
	(0.007)	(0.008)	(0.012)
Robot host	-0.015*	0.001	-0.033***
	(0.006)	(0.008)	(0.009)
Robot competitors	-0.054***	0.047*	-0.133***
	(0.016)	(0.018)	(0.024)
R&D adoption	0.134***	0.084***	0.163***
	(0.008)	(0.010)	(0.011)
Labor productivity	0.007***	-0.006*	-0.007***
	(0.001)	(0.003)	(0.001)
Constant	1.054***	1.459***	1.192***
	(0.049)	(0.066)	(0.068)
Number of obs.	796607	357237	439370
Year FE	YES	YES	YES
Ind-Year FE	YES	YES	YES

Note. Market share reflects the export share of a home country (exporter) in a specific industry to a destination country (importer) in a given year. Each observation corresponds to a non-singleton unique combination of exporter, importer, industry, and year. Robust standard errors clustered at the exporter-industry level are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Domestic robot adoption and R&D consistently show positive and significant effects on export market shares across all country groups, with a stronger magnitude in developing countries. A 10% increase in the number of robots per ten thousand employees raises market shares by 0.021 percentage points in developing countries, compared with 0.007 percentage points in developed ones. Similarly, a 10% increase in R&D expenditures per ten thousand employees increases market shares by 0.016 percentage points in developing countries, compared with 0.008 percentage points in developed counterparts. These findings highlight the technological catch-up effect observed in developing countries, where automation and R&D yield relatively higher marginal gains. In contrast, the effects in developed countries are incremental, reflecting their already mature technological infrastructure.

The effect of robot adoption by host countries and competing industries on export market shares shows meaningful differences in the competitive strategies of developed and developing economies. In developed countries, host country robot adoption does not have a statistically significant effect on domestic export shares, while increased robotization in competing industries has a positive but weak effect, with a marginal significance at $p < 0.10$.

In contrast, in developing economies, both factors indicate a negative and significant effect. Specifically, a 10% increase in robot density by competing industries corresponds to a 0.013 percentage point reduction in market shares for developing countries' industries. Similarly, an equivalent increase in robot density by host countries leads to a 0.003 percentage point decline in domestic export market shares.

These findings stress the important implications of global automation trends for developed and developing economies. The negative effect of host-country robot adoption observed in developing economies suggests that automation in destination markets reduces demand for imported intermediate goods. This likely reflects a shift toward greater reliance on domestic sourcing by host countries. Findings indicate that developing countries' exports are vulnerable when robots are adopted in competing industries, which often rely on cost competitiveness. High levels of robot adoption in competing industries erode this advantage, intensifying the competitive pressures for developing economies in maintaining their market shares. These dynamics reveal the dual challenge posed by automation: diminished demand from key trading partners and increased competition from technologically advanced rivals.

Table 4.A.4 in the Appendix provides estimates of both linear and nonlinear models for all countries using each methodology mentioned in Section 4.3 (comparable to column 1 of Table 4.3). To implement fractional probit models and ensure comparability with linear models, the market share dependent variable was transformed from percentages to fractions within the [0, 1] range. Moving from left to right across the table, the first two columns report estimates from pooled ordinary least squares (POLS) and fixed effect (FE) linear regressions, which is the main estimation method used in our analysis. The third through eighth columns show estimates from pooled fractional response (PFR), correlated random effects (CRE) and correlated random effects accounting for unbalanced panel data (CREU). The magnitudes of the coefficients for nonlinear models are not directly comparable to the estimates from the linear models. To facilitate comparison, the average partial effects (APEs) of each nonlinear model are reported in the corresponding columns.

Both linear and non-linear models in Table 4.A.4 tell a consistent story. Domestic robot adoption and R&D spending positively affect market shares in export destinations, while the robotization level of competitors in the same market has a significant negative effect on the home industry's market share. However, the estimators that account for unobserved heterogeneity perform comparably well in mitigating bias. Despite the bounded nature of the dependent variable, nonlinear approaches do not demonstrate greater efficiency compared with linear specifications. Accounting for panel imbalance in column 7 does little change to the CRE estimates, which suggests panel imbalance is not an issue. In fact, FE estimates provide a close approximation to the Average Partial Effects (APEs) of more complex nonlinear models such as CRE and CREU. This suggests that the nonlinearity in the data is negligible, or that the assumption of constant marginal effects is reasonable. Similar patterns of change across methods are observed for other variables as well.

4.5.2 Technology Adoption and Export Market Across Market Destinations

Table 4.4 presents the effects of technology adoption on export market shares in low and lower-middle-income, middle-income, and high-income country destination markets (L-LMIC, MIC, and HIC, respectively). The results demonstrate distinct patterns in the role of technology across these markets.

For developed countries, the adoption of industrial robots increases export market share in high-income and middle-income destinations, with estimated coefficients of 0.10 and 0.08, respectively. However, no significant impact is found for low-income or low-middle-income countries. This pattern suggests that developed economies target higher-income and middle-income markets with advanced technologies, likely due to higher purchasing power, more sophisticated infrastructure, and greater demand for capital-intensive goods. For developed countries, R&D appears to be important in gaining market shares in low-income or low-middle-income countries.

In contrast, for developing countries, industrial robot adoption shows a significant positive impact on export market shares across all destination income groups. More importantly, the estimates for low-income and low-middle-income markets are the largest across market destinations (0.362). Specifically, a 10 percentage increase in the number of robots per employee in a developing country corresponds to a 0.03 percentage point increase in export market share to low-income and low-middle-income destinations, with smaller but still positive effects in middle-income and high-income markets. These findings suggest that developing countries may leverage automation as a strategic tool to penetrate low-income markets, which might provide greater opportunities for expansion.

Table 4.4: Technologies and export market shares by destination income groups (developed vs. developing economies)

Home country	Developed countries			Developing countries		
Destination	L-LMIC	MIC	HIC	L-LMIC	MIC	HIC
	(1)	(2)	(3)	(4)	(5)	(6)
Robot home	0.041*	0.098***	0.081***	0.328***	0.168***	0.152***
	(0.017)	(0.017)	(0.011)	(0.033)	(0.023)	(0.013)
Robot host	-0.011	-0.009	0.004	-0.065**	-0.044*	-0.016
	(0.018)	(0.018)	(0.012)	(0.023)	(0.022)	(0.010)
Robot competitors	0.013	0.122**	0.044	-0.201***	-0.158**	-0.108***
	(0.030)	(0.045)	(0.027)	(0.060)	(0.057)	(0.027)
R&D adoption	0.120***	0.074***	0.067***	0.238***	0.125***	0.139***
	(0.023)	(0.018)	(0.012)	(0.030)	(0.019)	(0.012)
Labor productivity	0.001	-0.003	-0.012**	-0.006	-0.011**	-0.005***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)
Constant	0.981***	1.138***	1.865***	1.253***	1.534***	0.998***
	(0.114)	(0.144)	(0.098)	(0.148)	(0.159)	(0.080)
Number of obs.	97054	90351	169832	116161	107567	215642
Year FE	YES	YES	YES	YES	YES	YES
Ind-Year FE	YES	YES	YES	YES	YES	YES

Note: Market share reflects the export share of a home country (exporter) in a specific industry to a destination country (importer) in a given year. Each observation corresponds to a non-singleton unique combination of exporter, importer, industry, and year. Robust standard errors clustered at the exporter-industry level are reported in parentheses.
*** p<.01, ** p<.05, * p<.1

However, challenges arise as robot adoption in host and competing industries negatively impacts developing countries' export shares across all destination markets. For example, a 10% increase in robot density in competing industries results in a significant 0.0201 percentage point reduction in market shares in L-LMICs. These findings suggest that while technology adoption facilitates trade among developing countries, it also exposes them to competitive pressures from automation in rival and host industries. R&D, meanwhile, has consistently positive effects across all destinations, underscoring its importance in enabling developing countries to improve product quality and capture larger shares in both low- and high-income markets.

4.5.3 Technology Adoption and Export Market Across Industries

Table 4.5 examines the relationship between technology adoption and market shares across industries. The results demonstrate a clear pattern that the type of technology matters for specific needs and dynamics of each sector. Advanced automation technologies significantly increase export market shares in high-tech and capital-intensive industries such as electrical equipment (0.45), fabricated materials (0.37), machinery (0.21), and automobile industries (0.21). These industries benefit from the precision, efficiency, and scalability provided by robotics, which are critical for a competitive advantage in global markets.

In contrast, R&D investment emerges as effective for gaining market shares in nearly all industries, with particularly high magnitudes in innovation-intensive sectors such as "Rubber and plastics", "Fabricated metal products, "nonmetallic mineral products" and "Machinery". This indicates that R&D capabilities play an important role in export performance wide range of industries.

Interestingly, for industries such as wood, paper, coke, petroleum, and chemical products, high levels of robotization in competing countries within the same markets are associated with higher market shares for home countries. At first glance, these findings appear counterintuitive. However, several factors can explain these results. First, these industries rely on natural resources and raw materials, where production capacity and access to high-quality resources are often more critical than advanced automation. This dependence on resource endowments is also reflected in the estimates for the impact of robot adoption in home countries, which tend to be less pronounced or stable. Even with increased robot adoption, competing countries might struggle to offset the comparative advantage of resource-rich home countries. Second, resource-intensive industries frequently operate with economies of scale and cost advantages associated with resource extraction or processing. While competitors may adopt robots to enhance production efficiency, they may still face higher costs relative to resource-abundant exporters. This dynamic allows resource-rich countries to retain a competitive edge in shared destination markets.

Table 4.5: Technology adoption and export market shares across industries

	Industries	Robot		Robot host		Robot competitor		R&D adoption		Labor productivity		Obs.
		Coef	Std. err	Coef	Std. err	Coef	Std. err	Coef	Std. err	Coef	Std. err	
1	Mining	0.041	(0.12)	0.007	(0.04)	0.600	(0.51)	-0.032	(0.12)	-0.006	(0.02)	4768
2	Food and beverage	0.038***	(0.01)	-0.009	(0.01)	0.061*	(0.03)	-0.034**	(0.01)	0.001	(0.00)	52452
3	Textiles	0.004	(0.01)	-0.012	(0.02)	-0.129	(0.09)	0.257***	(0.02)	0.033***	(0.00)	52674
4	Wood products	0.023*	(0.01)	-0.008	(0.01)	0.168***	(0.04)	0.177***	(0.01)	0.011***	(0.00)	50628
5	Paper and printing	0.122***	(0.01)	-0.003	(0.01)	0.262***	(0.05)	0.271***	(0.02)	-0.011***	(0.00)	52220
6	Coke and petroleum	-0.051***	(0.01)	-0.012	(0.01)	0.103***	(0.03)	0.072***	(0.02)	0.000	(0.00)	36431
7	Chemical products	0.002	(0.01)	-0.025	(0.01)	0.349***	(0.07)	0.122***	(0.01)	-0.001	(0.00)	49068
8	Rubber and plastics	0.180***	(0.01)	0.001	(0.01)	-0.032	(0.02)	0.536***	(0.02)	-0.003*	(0.00)	49966
9	Non-metallic mineral prod.	0.244***	(0.02)	0.012	(0.01)	-0.168***	(0.04)	0.409***	(0.02)	0.001	(0.00)	51536
10	Basic metal products	0.090***	(0.01)	-0.007	(0.01)	0.054*	(0.03)	0.127***	(0.01)	0.012**	(0.00)	51200
11	Fabricated metal products	0.371***	(0.02)	0.001	(0.01)	-0.231***	(0.04)	0.302***	(0.02)	0.002	(0.00)	49968
12	Computers and electronics	0.110***	(0.01)	0.009	(0.01)	-0.146***	(0.03)	0.143***	(0.01)	-0.001	(0.00)	43208
13	Electrical equipment	0.451***	(0.02)	-0.013	(0.01)	-0.207***	(0.02)	0.111***	(0.02)	0.004*	(0.00)	48742
14	Machinery	0.211***	(0.01)	0.006	(0.01)	0.086***	(0.02)	0.212***	(0.01)	0.013***	(0.00)	50864
15	Automobile	0.212***	(0.01)	0.001	(0.01)	-0.035	(0.02)	0.112***	(0.01)	0.001*	(0.00)	49520
16	Other transport vehicles	0.067***	(0.02)	-0.008	(0.02)	0.041	(0.05)	0.058**	(0.02)	0.006	(0.00)	44216
17	Other manufacturing	0.169***	(0.01)	-0.008	(0.01)	-0.041	(0.04)	0.326***	(0.02)	0.008***	(0.00)	50860

Note: Market share reflects the export share of a home country (exporter) in a specific industry to a destination country (importer) in a given year. Each observation corresponds to a non-singleton unique combination of exporter, importer, industry, and year. Robust standard errors clustered at the exporter-industry level are reported in parentheses.

*** p<.01, ** p<.05, * p<.1

4.6 CONCLUSION

This study investigates the relationship between technology adoption and export market shares, with a particular focus on robotics, R&D, and ICT adoption. The findings show the important role of home-country robot adoption in export market shares, particularly for developing economies. The results demonstrate that home-country robot adoption corresponds to a significant gain in market share, with a stronger impact observed in developing countries compared with developed ones. This indicates that automation serves as a strategic tool for productivity improvements and cost reductions, allowing developing countries to compete effectively in both low-income and high-income markets.

Furthermore, the results show R&D serves as an important driver of export market shares across all industries. This finding highlights the importance of innovation efforts in bridging technological gaps, enhancing product quality, and fostering export diversification. ICT adoption, on the other hand, showed limited significance in this study, suggesting that its benefits may depend on complementary factors, such as infrastructure and market integration.

The sectoral analysis further demonstrates that the effect of technology adoption varies across industries. Advanced automation technologies significantly increase export market shares in high-tech and capital-intensive industries, while R&D investments play a crucial role in driving competitiveness across a broader range of sectors, including resource-intensive, as well as innovation-driven industries. Interestingly, resource-rich industries continue to retain competitive advantages despite high levels of automation in rival industries, likely due to their dependence on economies of scale and access to raw materials.

However, the research also emphasizes potential challenges arising from technological advancements in partner countries and competing industries. While robot adoption by destination countries and rival industries was found to be statistically insignificant in most cases, the negative coefficient for competitor robot adoption in developing economies suggests that high levels of automation in rival industries could pose competitive pressures. This dynamic underscores the importance of not only fostering technology adoption domestically but also strategically managing competition in global markets.

These findings contribute to the growing body of literature on the interplay between technology and trade by emphasizing export market shares. Policymakers and firms should consider targeted investments in robotics and R&D to sustain competitiveness, particularly in industries where these technologies yield the greatest returns.

4.A APPENDIX

Table 4.A.1: Data Matching Across Sources

No	Sector name	International Federation of Robotics	OECD Input-Output Tables	UNIDO
1	Food products, beverages, and tobacco products	10-12	D10T12	15
2	Textiles, wearing apparel, leather and related products	13-15	D13T15	17, 18, 19
3	Wood and furniture	16	D16	20
4	Paper and printing	17-18	D17T18	21, 22
5	Coke and refined petroleum products	19	D19	23
6	Chemicals, pharmaceuticals, medicinal chemicals	20-21	D20, D21	24
7	Rubber and plastics products	22	D22	25
8	Other non-metallic mineral products	23	D23	26
9	Basic metals	24	D24	27
10	Fabricated metal products, except machinery	25	D25	28
11	Computer, electronic and optical products	260, 261, 262 , 263, 265	D26	30
12	Electrical equipment	271, 275, 279	D27	31
13	Motor vehicles, trailers and semi-trailers	29	D29	34
14	Other transport equipment	30	D30	35

Notes: Table reports the industry classification used in the analysis, as well as the corresponding codes in the IFR, OECD Input-Output Tables and UNIDO data sets.

Table 4.A.2: Sample description by country

Country name	Freq.	Percent (%)	Cum. (%)
Australia	13022	1.63	1.63
Austria	14050	1.76	3.39
Belgium	14204	1.78	5.17
Bulgaria	14341	1.80	6.97
Belarus	12093	1.52	8.49
Brazil	14272	1.79	10.28
Canada	13203	1.65	11.93
Switzerland	14006	1.76	13.69
China	14390	1.80	15.49
Colombia	13459	1.69	17.18
Czechia (Czech Republic)	13860	1.74	18.91
Germany	14341	1.80	20.71
Denmark	13369	1.68	22.39
Egypt	14246	1.79	24.17
Spain	14205	1.78	25.95
Estonia	14293	1.79	27.74
Finland	13515	1.69	29.44
France	13662	1.71	31.15
United Kingdom	2904	0.36	31.51
Greece	14136	1.77	33.29
Hong Kong	7636	0.96	34.24
Croatia	14225	1.78	36.03
Hungary	14341	1.80	37.82
Indonesia	14215	1.78	39.61
India	14201	1.78	41.39
Ireland	11338	1.42	42.81
Iceland	6914	0.87	43.67
Israel	12933	1.62	45.29
Italy	14341	1.80	47.09
Japan	13520	1.69	48.79
South Korea	14193	1.78	50.57
Lithuania	13950	1.75	52.31
Latvia	14162	1.78	54.09
Morocco	11984	1.50	55.59
Mexico	14026	1.76	57.35
Malta	10699	1.34	58.69
Malaysia	14280	1.79	60.48
Netherlands	14293	1.79	62.27
Norway	14192	1.78	64.05
New Zealand	14341	1.80	65.85
Pakistan	11075	1.39	67.24
Peru	13410	1.68	68.92
Philippines	14223	1.78	70.70
Poland	14130	1.77	72.47
Portugal	13925	1.75	74.22
Romania	14341	1.80	76.01
Russia	14406	1.81	77.82
Saudi Arabia	13843	1.74	79.55
Singapore	14026	1.76	81.31
Slovakia	13580	1.70	83.01
Slovenia	13098	1.64	84.66
Sweden	13814	1.73	86.39
Thailand	12510	1.57	87.96
Tunisia	10618	1.33	89.29
Turkey	14341	1.80	91.08
Taiwan	14238	1.78	92.87
Ukraine	14385	1.80	94.67
United States	14026	1.76	96.43
Vietnam	14234	1.78	98.21
South Africa	14254	1.79	100.00
Total	**797832**	**100.00**	–

Table 4.A.3: Descriptive statistics by export destinations for developed and developing economies.

	Developed countries				Developing countries			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
L-LMIC								
Export market share	1.64	4.24	0	87	1.66	5.76	0	99.28
Robot home	2.9	2.09	0	10.18	1.09	1.5	0	8.45
Robot host	0.64	1.14	0	6.35	0.65	1.14	0	6.35
Robot competitors	2.27	1.57	0	7.03	2.32	1.6	0	7.03
R&D adoption	4.27	1.15	0.19	11.73	2.65	1.31	0.02	9.95
Labor productivity	11.8	2.19	0	19.84	12.22	3.93	0	23
MIC								
Export market share	2.01	5.1	0	90.4	1.42	4.32	0	89.56
Robot home	2.89	2.09	0	10.18	1.07	1.49	0	8.45
Robot host	1.41	1.53	0	7.17	1.42	1.54	0	7.17
Robot competitors	2.63	1.54	0	6.81	2.7	1.57	0	6.81
R&D adoption	4.27	1.15	0.19	11.73	2.61	1.31	0.02	9.95
Labor productivity	11.8	2.18	0	19.84	12.24	3.98	0	23
HIC								
Export market share	2.37	5.67	0	82.15	1.12	4.01	0	90.65
Robot home	2.88	2.08	0	10.18	1.07	1.49	0	8.45
Robot host	2.8	2.11	0	10.18	2.83	2.12	0	10.18
Robot competitors	2.65	1.55	0	7.11	2.74	1.58	0	7.11
R&D adoption	4.25	1.14	0.19	11.73	2.6	1.29	0.02	9.7
Labor productivity	11.8	2.15	0	19.84	12.22	3.91	0	23

Notes. Destination income groups are categorized as follows: L-LMIC refers to low and lower-middle-income countries, MIC represents middle-income countries, and HIC denotes high-income countries.

Table 4.A.4: Technology adoption and export market shares by country group

	POLS	FE	FRE		CRE		CREU	
	Coef	Coef	Coef	APE	Coef	APE	Coef	APE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot home	0.0055***	0.0013***	0.1269***	0.0051***	0.0308***	0.0012***	0.0312***	0.0012***
	(0.0001)	(0.0001)	(0.0027)	(0.0001)	(0.0017)	(0.0001)	(0.0017)	(0.0001)
Robot host	0.0011***	-0.0001*	0.0263***	0.0011***	-0.0027	-0.0001	-0.0027	-0.0001
	(0.0001)	(0.0001)	(0.0027)	(0.0001)	(0.0015)	(0.0001)	(0.0015)	(0.0001)
Robot competitors	-0.0056***	-0.0005***	-0.1529***	-0.0061***	-0.0152***	-0.0006***	-0.0157***	-0.0006***
	(0.0002)	(0.0002)	(0.0043)	(0.0002)	(0.0040)	(0.0002)	(0.0040)	(0.0002)
R&D adoption	0.0005***	0.0013***	0.0103**	0.0004**	0.0347***	0.0014***	0.0359***	0.0014***
	(0.0001)	(0.0001)	(0.0034)	(0.0001)	(0.0020)	(0.0001)	(0.0021)	(0.0001)
Labor productivity	0.0004***	0.0001***	0.0141***	0.0006***	0.0017**	0.0001**	0.0017**	0.0001**
	(0.0000)	(0.0000)	(0.0011)	(0.0000)	(0.0005)	(0.0000)	(0.0006)	(0.0000)

Notes. Market share represents the export share of a home country (exporter) in a specific industry to a destination country (importer) in a given year. Each observation corresponds to a unique exporter-importer-industry-year combination. CRE estimation includes time averages of covariates. CREU estimation additionally accounts for observation-specific selection effects based on the frequency of appearances in the dataset. All regressions include year fixed effects. Robust standard errors clustered at the exporter-industry level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4.A.5: Technology adoption and export market shares (sequential inclusion of variables)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot home	0.158***	0.158***	0.158***	0.159***	0.144***	0.157***	0.152***
	(0.038)	(0.038)	(0.039)	(0.039)	(0.037)	(0.040)	(0.039)
Robot host		-0.005	-0.003	-0.003	-0.005	-0.003	-0.004
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Robot comp			-0.052	-0.052	-0.053	-0.052	-0.052
			(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Labor prod.				0.010**	0.006	0.010**	0.004
				(0.004)	(0.004)	(0.004)	(0.004)
R&D adoption					0.143***		0.242***
					(0.032)		(0.060)
ICT adoption						0.015	-0.161**
						(0.024)	(0.056)
Constant	1.370***	1.379***	1.510***	1.392***	0.994***	1.360***	1.052***
	(0.073)	(0.069)	(0.073)	(0.098)	(0.123)	(0.117)	(0.117)
Number of obs.	797416	797416	797416	796607	796607	796607	796607
Year FE	YES	YES	YES	YES	YES	YES	YES
Ind-Year FE	YES	YES	YES	YES	YES	YES	YES

Notes. Market share represents the export share of a home country (exporter) in a specific industry to a destination country (importer) in a given year. Each observation corresponds to a unique exporter-importer-industry-year combination. CRE estimation includes time averages of covariates. CREU estimation additionally accounts for observation-specific selection effects based on the frequency of appearances in the dataset. All regressions include year fixed effects. Robust standard errors clustered at the exporter-industry level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

CHAPTER 5

CONCLUDING REMARKS

This dissertation has investigated the effect of technological change on employment and trade outcomes. The research contributes to a deeper understanding of how these factors influence employment growth, trade, and competitiveness in both developed and developing economies.

In Chapter 2, the research shows that product innovation serves as a significant driver of employment growth in developing economies, particularly in service sectors. The finding that product innovation in service industries has a greater impact on employment compared with manufacturing underscores the critical role of service sectors in developing economies. The study also highlights the moderating role of market structure, showing that firms with fewer competitors achieve higher employment gains from product innovation. This dynamic suggests that market conditions and firm capabilities significantly shape the employment outcomes of innovation. These findings emphasize the importance of policies that promote innovation activities in developing economies, such as providing financial incentives for R&D investments, strengthening intellectual property rights (IPR) frameworks, and access to funding for small and medium-sized enterprises (SMEs).

Chapter 3 extends the discussion to automation by examining the impact of robot adoption on export performance. The results show that industrial robots enhance exports in both developed and developing economies. In developing economies, robots contribute to an increase in intermediate goods exports. This finding demonstrates the role of robotic technologies in improving the position of developing countries within global supply chains. These insights underscore the need for policies that foster both trade openness and technology adoption. By facilitating access to advanced production technologies, developing countries can integrate into global value chains.

Chapter 4 focuses on several technological change metrics such as robotics, R&D, and ICT adoption and their effect on export market shares. The findings show that home-country robot adoption significantly increases export market shares, particularly in developing economies, where automation serves as a critical tool for improving productivity and reducing costs. R&D emerges as a consistent driver of export performance across all industries. The sectoral analysis demonstrates that advanced automation technologies are more effective in high-tech and capital-intensive industries, while R&D investments yield competitiveness gains across a broader range of sectors. Interestingly, ICT adoption shows limited significance, suggesting that its effectiveness depends on complementary factors such as infrastructure and market integration. The challenges posed by technological advancements in competitor countries further emphasize the need for strategic domestic policies that balance the benefits of technology adoption with the pressures of global competition.

The findings of this dissertation carry important implications for policymakers. First, fostering innovation through targeted support for product innovation, particularly in service sectors, can significantly drive employment growth in developing economies. Programs that improve access to finance and strengthen IPR protections can further amplify these benefits. Second, promoting automation technologies like robotics can enhance export performance, but it must be complemented by policies that address labor market disruptions and ensure equitable economic outcomes. Trade openness and international collaboration in technology transfers are crucial for developing economies to access and leverage advanced production technologies.

Third, investments in R&D should be prioritized as they yield benefits across industries, driving both competitiveness and diversification in export markets. Policymakers should encourage public-private partnerships in R&D and ensure that innovation ecosystems are inclusive and effectively integrated into global value chains.

This dissertation is subject to several limitations. Chapter 2 examines the short-term effects of innovation on employment over a three-year interval, potentially overlooking the long-term impacts of innovations that take time to mature. In Chapter 4, the use of fixed-effects models addresses unobserved heterogeneity but does not fully resolve endogeneity issues such as reverse causality or omitted variable bias. Advanced methods, such as instrumental variable approaches or the generalized method of moments, could better establish causality. Aggregate-level analysis used in Chapters 3 and 4 of the dissertation might hide important differences between firms or regions. Future research should take a closer, more detailed look at these variations to gain better insights.

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