
IMPACT OF ROBOTIZATION ON MERCHANDISE EXPORTS:
EMPIRICAL EVIDENCE FOR THE PERIOD 1995-2019

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Biographical Note

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Abstract

In the past few decades, the world has witnessed a remarkable transformation in industrial production, characterized by a significant upsurge in global trade and the widespread adoption of advanced technologies. Among these technologies, robots have emerged as a prominent force in shaping the manufacturing landscape. This study explores the influence of robot adoption on merchandise exports for a panel of 32 developed and developing nations, during the period between 1995 and 2019. The results obtained through a fixed effects model are in line with the existing literature, demonstrating that the adoption of robots exhibits a statistically significant and positive impact on exports. Moreover, the control variables foreign direct investment, production index, exchange rate, and unit labor costs also reveal a statistically significant and positive impact on merchandise exports.

This study's findings hold relevance in the current global landscape, providing valuable insights for policymakers, economists, and businesses.

Keywords: Robots; Robotization; Merchandise; Exports; Panel Data

Resumo

Nas últimas décadas, o mundo experienciou uma revolução na produção industrial, definida por um aumento dramático no comércio global e pela ampla adoção de novas tecnologias.

Entre essas tecnologias, os robôs surgiram como uma força proeminente na moldagem do cenário da indústria transformadora. Este estudo explora o impacto da adoção de robôs nas exportações de mercadorias para um painel de 32 países desenvolvidos e em desenvolvimento, entre os anos de 1995 e 2019. Os resultados obtidos através de um modelo de efeitos fixos estão em linha com a literatura existente, demonstrando que a adoção de robôs apresenta um impacto estatisticamente significativo e positivo nas exportações. Além disso, as variáveis de controle, como o investimento direto estrangeiro, o índice de produção, a taxa de câmbio e os custos unitários de mão de obra, também revelam um impacto estatisticamente significativo e positivo nas exportações de mercadorias.

As conclusões deste estudo são relevantes no panorama global atual, fornecendo informações valiosas para políticos, economistas e empresas.

Keywords: Robots; Robotização; Exportações; Dados em painel

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List of Acronyms, and Abbreviations

ER	Real Effective Exchange Rate
FDI	Foreign Direct Investment
IFR	International Federation of Robotics
OECD	Organisation for Economic Co-operation and Development
PI	Production Index
ULC	Unit Labor Costs
WDI	The World Bank's World Development Indicators

1. Introduction

In the last few decades, robots have become an essential part of the production processes particularly in the manufacturing industry (DeStefano & Timmis, 2021). According to the International Federation of Robotics (IFR), in 2020, there was a record of 2.7 million industrial robots operating in factories around the world, an increase of 12% compared to 2019. From 1995 to 2019, a growth of 332% was observed on the stock of robots in the world (IFR, 2022). Although the utilization of robots is rapidly increasing in the service industries, the majority of robots are still employed in manufacturing to provide handling and welding operations (IFR, 2022). Robots have the main purpose of achieving automatic production through computer programming. They also can integrate with other industries and are an essential mean of intelligent manufacturing, industrial transformation and upgrading (Lin et al., 2022). Additionally, robots can perform a relatively wide range of tasks, including welding, painting, and packaging with little human intervention (Brynjolfsson & McAfee, 2014). This technology has revolutionized the manufacturing process, allowing for greater efficiency, precision, and cost-effectiveness. By automating labor-intensive tasks, robots have enabled manufacturers to produce higher quality products in a shorter period (Alguacil et al., 2020).

The continuous expansion in the adoption of robots is present not only on firm level but also on a daily basis and in almost every sphere of our life. This surge of robotization is what Brynjolfsson and McAfee (2014) like to call the “Second Machine Age”. This increasing robotization of manufacturing activities is observable on developed and developing countries (Baur et al., 2022).

The increasing use of robots has also led to increasing research into their impact at different levels. The available literature has focused mainly on the impact of industrial robots’ applications on productivity (e.g. Ballestar et al., 2020; Alguacil et al., 2022), economic growth (e.g. Hidalgo et al., 2007), employment (e.g. Lankisch et al., 2017; Graetz & Michaels, 2018) and income distribution (e.g. Brynjolfsson & McAfee, 2014). There are also studies focusing on understanding the effect it has on the quality of exported products (e.g. Lin et al., 2022). Although all of these studies have shown that robotization has a positive impact on the variable studied, other studies concluded the opposite effect, that robotization has a negative effect on exports and local jobs (e.g. Faber (2020) for the US, Stemmler (2019) for Brazil and Kugler et al. (2020) for Colombia).

Literature on the impact of robotization on exports is scarce. There are studies showing that “robotization increases total exports, and this effect works both along the extensive (number of exported product varieties) and intensive margins (average value of exported product variety)” (Ndubuisi & Avenyo, 2018, p.4). Melitz and Ottaviano (2008) achieved the same result as the previous authors. Moreover, the few existing studies focus on single countries (e.g. Camiña et al., 2020). In this way, the present work aims to analyze the impact of the adoption of robots on merchandise exports for a set of developed and developing countries, along the intensive margin. With the increasing emergence of new technologies and the development of the economic globalization, it is extremely important to study the effects of these technologies in the international trade.

In order to answer to the question raised – Does Robotization affect merchandise exports? – it will be used a quantitative methodology, based on an econometric model with panel data. More specifically, it will be studied 32 developed and developing countries, between 1995 and 2019.

This study makes noteworthy contributions to the field. It provides additional evidence on the determinants of exports, such as those identified by Krugman (1985) and Ndubuisi & Avenyo (2018).

This document is divided into five chapters and presents the following structure. The initial section corresponds to the introduction to this paper. The second chapter encompasses a comprehensive theoretical framework, which is composed of the “Literature Review” of the essential concepts for the study: robotization and its evolution (section 2.1), followed by the analysis of the relationship between robotization and exports (section 2.2), and lastly an analysis of existing empirical studies about this relationship (2.3). Chapter 3 focuses on the “Methodology”, where it is defined the econometric model as well as the methodology adopted to answer to the research question. In this chapter it is also presented the variables of the model and their source. Subsequently it is presented chapter 4 “Robotization and Exports: Empirical Results” where it is showed the results obtained and its discussion. Lastly, in the “Conclusion”, it is presented the main conclusions, limitations, and suggestions for future studies.

2. Literature Review

This section presents a theoretical framework and a review of the underlying concepts related to this work. First, it is presented the concept of robotization as well as the evolution of robot adoption over time. Second, the impact of robotization on exports will be discussed. Lastly, it will be presented an analysis of empirical studies of the same issue.

2.1. Robotization and its evolution

Robotization is the process of perceiving and acting in the physical world with computer-controlled mechanical devices (Liu et al., 2022); in other words, it is the introduction of robots to carry out human tasks. Since the beginning of the introduction of robots in industrial processes, it was observed a relief of heavy workloads to humans and it has increased productivity (Liu et al., 2022). It has primarily occurred in manufacturing, but it has also occurred in other industries such as agriculture and services (Baur et al., 2022). These changes have had a distorting influence on local markets, prompting study into the economic implications of robotization (Baur et al., 2022).

Robotization has led to an increase in the number of routine jobs performed by machines and robots, making human labour less productive in tasks that can be performed by robots and reducing the relative need for less skilled workers (Autor et al., 2003). This shift has had a significant impact on the labour market, creating a new era of automation and efficiency. As robots become more sophisticated, they are able to take on more complex tasks, allowing businesses to streamline their operations and increase their productivity. In addition, the use of robots has enabled companies to reduce their labour costs, allowing them to remain competitive in a global economy (e.g. Autor et al., 2003; Acemoglu & Autor, 2011; Autor & Dorn, 2013; Lankisch et al., 2019).

Modern industrial robots are highly flexible, versatile, and autonomous machines. Their primary goal is to learn how to perform routine tasks through self-learning in order to achieve success, similar to the process of machine learning (Graetz et al., 2018).

According to the International Federation of Robotics (IFR), the adoption of robots in the world observed its maximum growth between 2016 and 2017 with 15,41% growth, followed by 2017-2018 and 2015-2016 (see Figure 1). Also, between 1995 and 2019 the countries that more adopted robots were Japan, USA, Germany, China and Korea, which

means that robots have been adopted by developed and developing countries. On Figure 1, it is possible to see the evolution of robots adoption along the years.

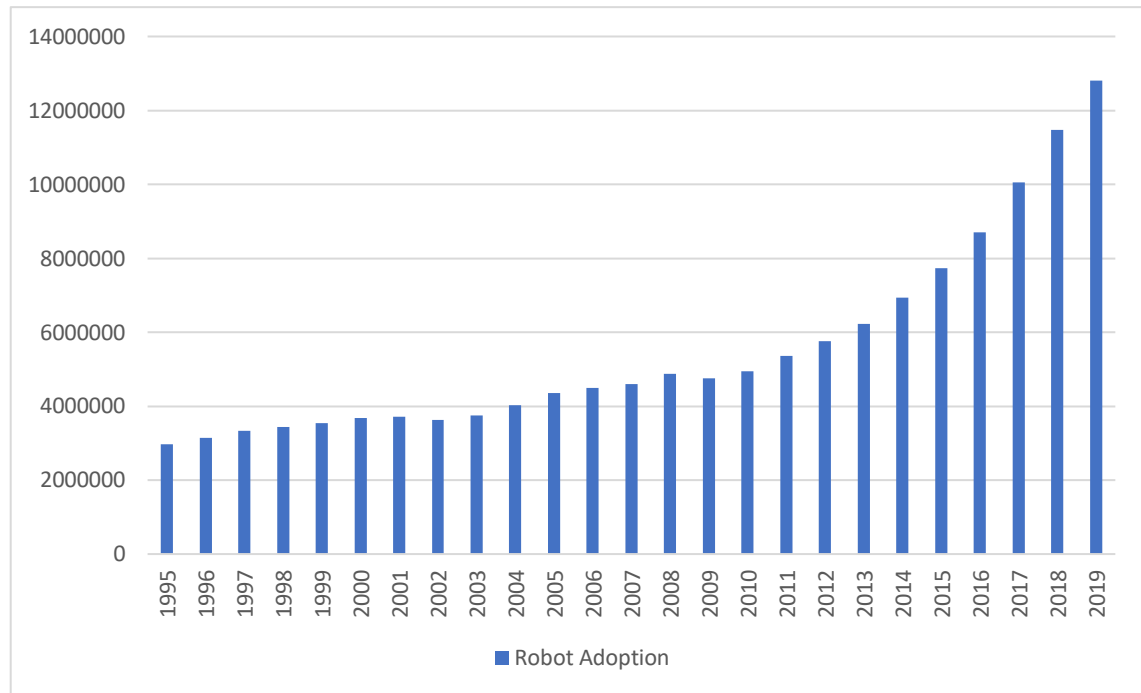


Figure 1 - Robot Adoption in the world between 1995 and 2019

Source: International Federation of Robotics

As can be observed in Figure 1, there has been an exponential growth in the adoption of robots since 2009. This exponential increase in robot adoption represents a significant milestone in technological advancement, with far-reaching effects on the economy, society, and organizations.

The increasing robotization of industrial production has raised concerns that many workers, especially those with fewer skills, could experience lower income and job losses. This situation could contribute to job polarization (Bloom et al., 2018). These concerns are based in part on the experience of countries from the Organisation for Economic Co-operation and Development (OECD), where robot adoption has increased productivity (Graetz & Michaels, 2018; Acemoglu & Restrepo, 2020).

The effects of robotization are not limited to the domestic market of the countries that adopt robots; it may also spread worldwide via supply chains and harm enterprises in less developed nations via many processes (Baur et al., 2022). Robotization has an effect on businesses' decisions about international sourcing in the era of global value chains (GVCs),

which may have an influence on the economy of trade partners overseas (Baur et al., 2022), and also on international trade. In the next section, it will be presented a literature review made on papers that studied the relationship between robotization and exports.

2.2. Robotization and exports

Robots are a critical tool for industrial transformation and business innovation, making them a powerful mean for countries to bolster their competitiveness. By leveraging the latest advancements in robotics technology, countries can gain a competitive edge in the global marketplace (Cao et al., 2021). According to Rodrik (2018), robotization may bring production closer to consumers in high-income countries, undermining hopes for industrialization and export-led growth in less developed countries.

Robots have a positive impact on firms' exports mostly through increasing firms' productivity (Cao et al., 2021) as productivity improvements within a company might encourage exports. Indeed, literature has shown that a firm's productivity level is the key determinant of its survival and growth (e.g. Melitz, 2003). Only high-productivity companies will be able to export because they can afford to offset the fixed costs associated with building export markets (Bernard & Schott, 2007). Furthermore, there are more studies finding that robotization boosts productivity (e.g. Graetz & Michaels, 2015; Kroll et al., 2018; Özcan, 2018). According to Ballestar et al. (2020), there is a relationship between the growth of exports and productivity: a self-selection pattern in more efficient organizations has been shown to explain both presence and progress in export markets, which feeds back into productivity via innovative practices.

According to Alguacil et al. (2022), the positive impact of robot adoption on exports is driven by its positive effect on firm total factor productivity, product innovation and importing. Importing new and more advanced inputs reduces certain restrictions on the manufacturing processes, resulting in a positive impact on firm productivity. As a result, firms with higher productivity may face the sunk costs of exporting (for which they are better prepared to support than firms with low productivity) and/or adapt or produce new goods to meet the needs of foreign customers. Additionally, there may be a direct correlation between imports and exports, as imports can facilitate cost savings and technological advancements of intermediate inputs (Alguacil et al., 2022).

Kroll et al. (2018), similarly to Alguacil et al. (2022), also found that robot adoption increases innovation. In any event, it is expected that the country's export performance is

affected as a result. This approach is compatible with international trade heterogeneous firm models, which indicate a positive relationship between productivity and export performance (Melitz, 2003). It also aligns with international trade literature, which indicates a positive relationship between innovation and export performance (Grossman & Helpman, 1989; 1991a; Chen, 2013). Moreover, robotization of industrial processes can lead to increased production flexibility by lowering the costs of creating many goods at the same time and, as a result, increasing the variety of exported products. The foregoing, whilst suggestive of export effects of robotization also indicates different ways it can affect export. On the one hand, increased productivity from robotization will improve export along the intense margin by raising the average value of tradable commodities. On the other hand, flexible production, caused by robotization, will primarily promote export along the extensive margin by increasing the range of marketable items (Ndubuisi & Avenyo, 2018).

As robotization reduces the role of labour costs as a driver of international competitiveness, low-income nations may lack the skills and infrastructure required for effective participation in new global value chains (GVCs) (Rodrik, 2018). Artuc et al (2023) discovered evidence suggesting that robot deployment in high-wage advanced economies facilitated trade between developed and less developed nations. The authors emphasize that such adoption will help workers in developing nations in the long run, notably through lower pricing and greater demand for intermediate commodities.

Because exporting manufactured goods is sometimes simpler than trading services, the manufacturing sector is considered to be crucial for exporting (Coad & Vezzani, 2019). According to Baur et al (2022), robotization has the potential to impact trade flows in two ways. The first channel refers to the change in relative manufacturing costs. Robotization may lower manufacturing costs in high-income nations to the point that low-income, labour-abundant countries may lose their relative cost advantage in producing formerly labor-intensive commodities. This might result in the relocation of manufacturing facilities, previously relocated to low-income countries, back to the origin country. The second channel acts by increasing the efficiency of robot-adopting enterprises, causing these firms to expand their production, contributing to increase exports for the country of origin (Rodrik, 2018). Artuc et al. (2020) found similar evidence: automation has the potential to significantly improve trade between the developed and developing countries, with export growth outpacing import growth; and, as robots become more affordable, developed nations may find it more economical to bring production back home to their own economies from

developing nations, as already mentioned. In addition, with the growing demand for personalized products, firms must rely more on their ability to efficiently provide customized, high-quality goods than on the scale of production in order to remain competitive (Zeng, 2017). Therefore, robotization can play a pivotal role in boosting firms' exports and involvement in GVCs (Zeng, 2017).

Also, Ndubuisi & Avenyo (2018) found strong evidence that robotization boosts overall exports, and this impact operates both along the extensive (number of exported product types) and intensive (average value of exported product variety) margins. The “results obtained using the volume and price of exports suggest that the positive effect of robotization on the intensive margin is driven by increases in both the quantity and unit prices of exports. Redefining the margins as the number of market destinations and the number of product by market destination, our results also show a positive effect of robotization.” (Ndubuisi & Avenyo, 2018, p.4).

Even though there are several studies associating the high rates of robot adoption to developed countries, this phenomenon also occurs in developing countries. And the cause for this wave of robotization is the increased rivalry that enterprises face both worldwide and locally in parallel with the sophisticated customer demands of recent times (Ndubuisi & Avenyo, 2018). As a result, sophisticated technology adoption and applications become a panacea that producers, if not exporters, employ to solve these issues and maintain their market share and competitiveness, either locally or worldwide (Ndubuisi & Avenyo, 2018). This reasoning is also compatible with several trade theories that highlight the critical role of technology in defining a country's export flows and performance (Posner, 1961; Krugman, 1985; Dosi et al., 1990; cited by Ndubuisi & Avenyo, 2018). Along these lines, it is reasonable to suggest that the rapid development in the adoption and deployment of robots at various stages of industrial processes may affect a country's export flows and performance.

Moreover, according to Lin et al (2022), the use of industrial robots greatly boosts the quality of Chinese manufacturing export goods. This boost is attributable to increased worker productivity and human capital levels in businesses.

Artuc et al. (2022) advocate for a significant efficiency channel of automation and claim that, in the long run, developing countries will benefit from robot adoption in the Global North through increased global demand for intermediate and final commodities. Baur et al. (2022) also concluded that robot adoption in developed countries does not always constitute a danger to export-led growth in developing nations.

To sum up, Figure 2 summarizes the channels through which robotization can impact exports. Firms adopting robotization can observe increases in their productivity, innovation, flexibility and relocation of activities back to the country of origin, all leading to an increase of exports.

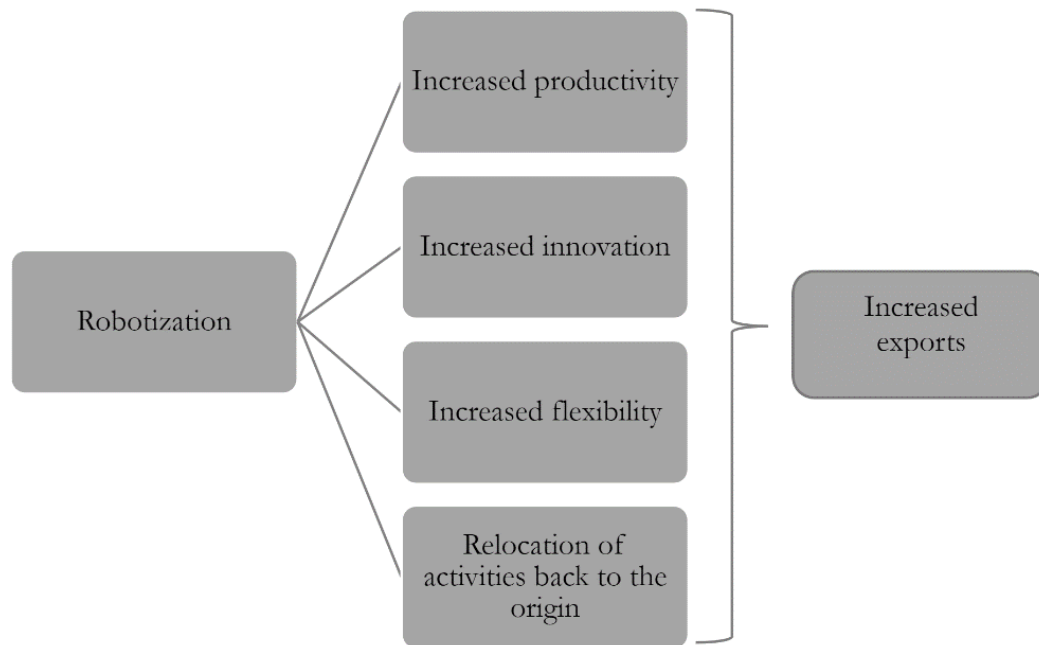


Figure 2 - Channels to increase exports through Robotization

2.3. Empirical Studies on the Relationship between Robotization and Exports

The use of robots has generated massive discussions over how it will affect the economy. Robotization may have a significant impact on labour markets and economic growth and, as highlighted in the previous section, exports.

Although robot technology has attracted extensive attention in recent years, current research on robot application and international trade has been mostly concerned with the macro level. For example, Berg et al. (2016) found that the use of robots eroded developing countries' labor cost advantage, affected the international division of labor, promoted the return of production and manufacturing to the country of origin, reduced employment opportunities, ultimately intensifying the inequality between developed and developing countries. The long-term economic effects of robotics outweigh their short-term drawbacks.

According to Artuc et al. (2018), Stapleton and Webb (2020), Obashi and Kimura (2021), and Cali and Presidente (2021), the use of robots boosted technical efficiency and value-added, expanded trade scale, and improved regional trade complementarity and competitiveness.

Concerning the adoption of robots on exports, we conducted a search across academic databases such as Google Scholar, ScienceDirect, and JSTOR using key words such as "exports" and "robotization.", in order to obtain empirical studies on the subject. Our search yielded a total of nine relevant studies, which are summarized in Table 1. This table presents a chronological organization of the research, offering a consolidated overview of the studies conducted on the relationship between robot adoption and its implications for exports.

Among the nine studies analysed, five are conducted at the macro level, while the remaining four are conducted at the micro level.

At the macroeconomic level, we found that all papers concluded that robotization leads to an increase in exports (e.g. Artuc et al., 2020; Ndubuisi & Avenyo, 2018; César et al., 2022; Wang & Li, 2022, Altomonte et al., 2020). The data used by these authors range from 1995 to 2019, for 1 to 71 countries. Specifically, Cesar et al. (2022) examined data from 2010 to 2015 for United States. Wang & Li (2022) focused on data from China between 2006 and 2019. Altomonte et al. (2020) conducted their study using data from 2006 to 2018 for 17 European countries. Artuc et al. (2020) analyzed data from 24 countries between 1995 and 2015. Lastly, Ndubuisi & Avenyo (2018) utilized data ranging from 1995 to 2013 for 71 countries. Moreover, all of them consider the stock of industrial robots as the main independent variable. These studies suggests that the increased use of robots in industrial settings has had a positive impact on exports, indicating that robotization can be a powerful tool for economic growth. These papers primarily adopt a bilateral analysis, examining both the exporter and importer sides of the relationship. To accurately assess their findings, the authors employed an econometric model comprising of Ordinary Least Squares regressions (OLS) (César et al., 2022), Benchmark regressions (Wang & Li, 2022), OLS and Instrumental Variables (IV) Regressions (Artuc et al., 2020), Fixed Effects Model (FEM), OLS Regressions (Ndubuisi & Avenyo, 2018), and Levin-Lin-Chu test (LLC) (Altomonte et al., 2020).

Regarding micro-level analysis, the authors reached to the same conclusion as those above: robotization has a positive impact on export activities (e.g. Alguacil et al., 2022; Baur et al., 2022; Caminã et al., 2020; Cao et al., 2021). Two of these papers focus on Spanish

manufacturing firms, one from 1990 to 2014 (Alguacil et al., 2022) and the other between 1991 and 2016 (Caminã et al., 2020). Baur et al. (2022) analyzed data from four Latin American countries, while Cao et al. (2021) studied 15 manufacturing industries in China. The research made by Cao et al. (2021) indicates that robotization has a positive effect on export activities across a variety of countries and industries. Firm labour, firm productivity, size, and age are some common control variables among these authors. Concerning the econometric methods used, Alguacil et al. (2022) employed a combination of Propensity Score Matching (PSM) and Difference in Differences (DID) techniques; Baur et al. (2022) employed long-term differences between 2001 and 2007 to account for lagged effects in the adoption of robots; Cao et al. (2021) utilized an Instrumental Variables-Two Stage Least Squares (IV-2SLS) regression; and Caminã et al. (2020) employed an Ordinary Least Squares (OLS) regression to obtain their results.

Table 1 – Summary of Empirical Studies

Author (Year)	Period (Country)	Disaggregation level	Method	Dependent Variable	Main Independent Variables	Control Variables	Main Findings
Alguacil et al. (2022)	1990-2014 Spanish manufacturing firms	Micro level (impact on firm level trade)	Combination of the PSM and DID techniques	Availability to export; export value declared by firms; ratio of exports over the firm output ^a	% of firms in each industry using robots. Use of dummy for industry.	Size (measured by employment and turnover); Labour productivity; Shares of exports and imports to and from OECD economies; Share of R&D expenditures in total purchases; Time- varying changes in industrial structure.	Positive, significant, and sizeable effect of the use of robots on export activities.
Baur et al. (2022)	2001-2007 Mexico, Brazil, Peru, and Uruguay	Micro level (firm level)	Long differences between 2001 and 2007 to account for lagged effects in the adoption of robots	Firm-level exports to OECD	Stock of industrial robots	HS 6-digit product; imports from the rest of the world.	Exports in the same industry decrease, but exports increase for products along the value chain

Author (Year)	Period (Country)	Disaggregation level	Method	Dependent Variable	Main Independent Variables	Control Variables	Main Findings
César et al. (2022)	2010-2015 United States	Macro level	OLS regressions	Exports per worker; Logarithm of exports per worker	Stock of industrial robots	(LFP rate, women's LFP rate, local employment shares in agriculture, manufacturing, services and finance; demographic variables and economic conditions	Increased exports to high- income and upper-middle- income economies.
Wang & Li. (2022)	2006–2019 434 prefecture- level cities from China	Macro level	Benchmark regression	Share of processing trade exports in total exports; share of general trade exports in total exports; ratio of general trade exports to processing trade exports.	Stock of industrial robots	GDP per capita; Urbanization rate; Investment level in fixed assets; Financial level; Environment pressure; Human capital attainment; level of openness.	Decrease on the export share of processing trade, increased the share of general trade exports, and promoted the transformation and upgrading of the firms' export model.
Cao et al. (2021)	2011-2013 15 manufacturing industries in China	Micro level (firms' exports)	IV-2SLS regression	Firm exports	Stock of industrial robots	Firm productivity, scale, age, capital intensity, asset liquidity and ownership category; fixed effects	Robots significantly promote firms' exports, mainly owing to an improvement in

Author (Year)	Period (Country)	Disaggregation level	Method	Dependent Variable	Main Independent Variables	Control Variables	Main Findings
						at the industry and year level	firms' productivity.
Altomonte et al. (2020)	2006-2018 17 European Countries	Macro level	LLC Test	Exports	Stock of industrial robots	Competitiveness, GDP, Employment.	Exports are positively affected by the use of industrial robots.
Artuc et al. (2020)	1995-2015 24 developed countries 16 sectors	Macro level (effects on trade patterns, wages and welfare).	OLS and IV Regressions	Imports and exports	Stock of industrial robots	Fluctuations in income; population; exchange rates; distance; common language	Increase in exports to less developed countries.
Caminã et al. (2020)	1991-2016 2000-2016 5511 Spanish industrial firms	Micro level	OLS Regression	Labour productivity and employment in manufacturing firms	Stock of industrial robots	Firm labour, firm capital, firm human capital, computer-aided design and manufacturing, data- driven control, flexible production systems	Firms that used robots presented sales levels five times higher than that of firms that did not use robots, as well as an added value and exports clearly higher on average.

Author (Year)	Period (Country)	Disaggregation level	Method	Dependent Variable	Main Independent Variables	Control Variables	Main Findings
Ndubuisi & Avenyo (2018)	1995-2013 71 countries	Macro level (country level)	FEM and OLS Regressions	Total export value	Stock of industrial robots	GDP; population sizes; distance; adjacency; Colony; official common language; membership in a similar trade agreement.	Increasing of total exports, and this effect works both along the extensive (number of exported product varieties) and intensive margins (average value of exported product variety).

^a the authors also studied other variables such as firm total factor productivity; log of firm employment; possible introduction of a new product; availability to import; import value declared by firms; ratio of imports over the firm output.

Legend: PSM – Propensity score matching; DID – Differences in differences; LFP - Labour force participation; LLC - Levin, Lin, and Chu; OLS – Ordinary Least Square; IV-2SLS - Instrumental Variable Two-Stage Least Squares; FEM – Fixed Effects Model.

3. Analyzing the Impact of Robotization on Export Performance: Methodology and Data

This chapter is devoted to introducing the econometric model that will be used to get to the results, as well as the variables that are involved in the model. The model is designed to provide an analytical framework for the empirical investigation of the research question; “Does robotization affect merchandise exports?”.

Furthermore, in this chapter, the method and source of data collection will be elaborated upon. The data plays a critical role in the empirical analysis, as it serves as the foundation upon which the model is built. Therefore, it is essential to provide a detailed explanation of how the data was collected, as well as its source. Also, it will be made an analysis on the evolution of the variables over time as well as the calculation of the descriptive statistics.

3.1. Econometric model and its variables

As previously discussed, the primary goal of this paper is to assess the impact of robotization on exports. Specifically, this paper will focus on the effect of robot adoption on the intensive margin of exports. The intensive margin of exports refers to the degree to which an exporting country amplifies the value of its existing exports by selling more units or broadening the market share of its existing products (Ndubuisi & Avenyo, 2018). It is a measure of a country's export competitiveness and captures the responsiveness of exports to changes in relative prices, which can be an important determinant of a country's trade performance (Ndubuisi & Avenyo, 2018). This can be measured in various ways, including changes in export volume (i.e., the number of units sold), export unit price, or export market share. Measuring the intensive margin of exports can provide valuable insights into the competitiveness and efficiency of a country's export sector, as well as the extent to which it is able to capitalize on existing export opportunities (Ndubuisi & Avenyo, 2018). This concept is of great importance in international trade and is frequently used in empirical studies to analyze the factors influencing a country's export performance.

In the current literature, there are different approaches or methodologies for analyzing data, which can be broadly categorized into two main types: quantitative and qualitative data analysis methods (Antwi & Hamza, 2015; Slevitch, 2011). For the present study, a quantitative approach based on an econometric model is deemed the most suitable

to answer the research questions, given its ability to provide a more comprehensive and objective analysis.

The econometric model to be estimated is given by the following equation:

$$\ln X_{ijt} = \alpha_0 + \beta_1 \ln Robots_{it} + \beta_2 \ln PI_{it} + \beta_3 \ln ER_{it} + \beta_4 \ln FDI_{it-1} + \beta_5 \ln ULC_{it} + u_{it} \quad (1)$$

where t stands for year; i stands for country; X_{it} represents the Exports, which is the dependent variable of interest; $Robots_{it}$ represents the Stock of Industrial Robots, which is the main explanatory variable; PI_{it} is the Production Index (2015=100); ER_{it} stands for the index level of the real effective exchange rate expressed in year 2010 constant price; FDI_{it-1} is the Foreign Direct Investment stocks in the year $t-1$; ULC_{it} denotes Unit Labour Costs expressed in year 2010 constant price; u_{it} is the error term. The selection of the control variables (GDP, ER, FDI and ULC) is based on the fact that this paper solely focuses on the supply-channel aspect of trade, as highlighted in Bayar (2018). Moreover, these variables are also the most frequently used in the studies synthetized in table 1. All variables are expressed in natural logarithmic form. This means that the values of these variables have been transformed using the natural logarithm function, which allows for easier analysis and interpretation of their relationships. By taking the logarithm of these variables, we can better understand the magnitude and direction of their effects on the outcome of interest (Hill et al., 2018). Hill et al. (2018) claim that this method is frequently used in statistical modelling and econometric analysis to increase the accuracy and reliability of results since it enables to interpret coefficients as elasticities.

For the dependent variable, and following most papers in this area (e.g. Márquez-Ramos & Martínez-Zarzoso, 2010; Artuc et al., 2020; Ndubuisi & Avenyo, 2018), it is used the value of goods exports in current US\$.

Similarly to Graetz et al. (2018), the main explanatory variable, Robots, will be measured by the stock of robots of the countries. Including the stock of robots as an independent variable allows to explore the role of robotization in shaping export performance and can help identifying potential policy implications for countries looking to improve their export competitiveness (Graetz et al., 2018). The value of the coefficient on $\ln Robots_{it}$ is of particular interest for this study, as this coefficient indicates the percent

change in exports associated with a one percent change in robot adoption on the same year. It is expected that the coefficient β_1 is positive.

Concerning the control variables, the purpose of incorporating the Production Index (PI_{it}) is to measure the output or productive capacity of the economy. It reflects changes in production capacity levels. Aksoy & Ülengin (2017) included PI as a control variable in their study in order to assess the impact of it on firms' performance. Aksoy and Ülengin (2017), it is expected that this variable has a positive impact on the export performance of the country, thus it is expected for coefficient β_2 to be positive.

According to Bayar (2017), the real exchange rate is a crucial variable to consider when conducting analysis on exports in order to account for possible impacts of exchange rate fluctuations. In this study, it is also used this variable, as Artuc et al. (2020) did, as it represents the competitive factor of export goods and exhibits the price effect on trade. The real exchange rate can affect a country's export competitiveness by influencing the relative price of its goods compared to those of its trading partners. By controlling for the real exchange rate, it is possible to isolate the effects of robotization on exports from the effects of changes in the relative price of goods (Helpman et al., 2008). Also, the impact of robotization may differ across countries with different exchange rate regimes and different sectors of the economy depending on the extent to which they rely on imported inputs or export-oriented production (Helpman, 2018; Acemoglu & Restrepo, 2019). Our model uses ER_{it} , which is an index of the real effective exchange rate (year 2010 = 100), based on the consumer price index. An increase in ER_{it} indicates real currency depreciation. According to the export-demand theory, the depreciation of a country's currency can stimulate further export expansion. The depreciation or appreciation of a currency makes that country's export goods more or less competitive, inducing to an increased or decreased demand in the global market (Bayar, 2018). Therefore, we anticipate the coefficient β_3 to be positive.

Delaying the inclusion of explanatory variables such as foreign direct investment by one year is a justifiable approach because, as per Leichenko and Erickson's (1997) findings, the impact of investments on export performance, such as modernizing production plants, adjusting production structures, and disseminating new technology, takes time to influence production. It is extremely relevant to include this variable in this study for two main reasons. First, FDI can affect a country's production and export capacity (for example, if a foreign company invests in a domestic company that produces goods for export, this could increase

the country's overall export capacity). Second, FDI can affect a country's access to foreign markets (by investing in a country, foreign companies may be able to facilitate exports to their home countries or other markets where they have a presence) (Rahmaddi & Ichihashi, 2013). According to Rahmaddi & Ichihashi (2013), this variable is expected to impact positively exports “since increases in domestic capital formation will augment productive capacity, thus enabling producers to expand their output” (p. 340). Therefore, it is expected for β_4 to be positive.

Similar to Graetz and Michaels (2018) and Acemoglu and Restrepo (2017), it will also be used the unit labour costs as a control variable. Unit labour costs are considered an interesting variable for this study for two reasons. Firstly, unit labour costs can provide insights into the cost competitiveness of countries, which is crucial when assessing the effects of robotization (Acemoglu & Restrepo, 2017). By considering unit labour costs, it is taken into consideration the differences in labour market conditions and wage levels, which may influence the relationship between robots and various economic outcomes. Secondly, unit labour costs can act as a proxy for the relative cost of human labour compared to automation (Acemoglu & Restrepo, 2017). It helps to understand the substitution effect between labour and robots (Graetz & Michaels, 2018). Generally, lower unit labour costs lead to lower prices which lead to increased quantities of exports. However, higher unit labour costs are usually associated to high skilled labour, innovation, and higher value-added production, which can result in higher priced exports (Aiginger et al., 2013). Despite the difference in quantity versus value, both lower prices and higher value-added production contribute to increased export levels. Therefore, coefficient β_6 is expected to be positive.

The variables, their proxies and impact on exports are summarized in table 2. Table 2 also includes the source of data.

Table 2 - Variables description

Variable	Measure	Source	Expected Effect
Exports	Goods exports in current US\$	WDI	/
Robots	Stock of industrial Robots	IFR	+
Production Index (PI)	Production Index (2015=100)	OECD	+
Real Exchange Rate (ER)	Real effective exchange rate index (2010 = 100)	WDI	+
Foreign Direct Investment (FDI)	Foreign direct investment, stocks (million US\$)	UNCTAD	+
Unit Labour Costs (ULC)	Individuals actively workig, 2015=100	OECD	+

Legend: WDI - World Development Indicators; IFR - International Federation of Robotics; OECD - Organisation for Economic Co-operation and Development; UNCTAD - United Nations Conference on Trade and Development

The data regarding exports was collected from the World Development Indicators (WDI) database.

Our data on the stock of robots is sourced from the International Federation of Robotics (IFR). These data are derived from annual surveys conducted by robot suppliers and encompass approximately 90 percent of the global industrial robots market (Jurkat et al., 2022). The IFR employs the definitions established by the International Organization for Standardization (ISO) to measure both deliveries and stocks of "multipurpose manipulating industrial robots." According to the ISO's criteria, a machine qualifies as an industrial robot if it is an "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications." The data provided by the IFR are widely regarded as the most reliable and comprehensive source of information on industrial robots (Graetz & Michaels, 2018; Acemoglu & Restrepo, 2017). Nevertheless, it is important to acknowledge that these data possess certain limitations. The primary limitation is that the coverage of IFR

data is incomplete for several countries, resulting in an unbalanced panel for our analysis. Despite this drawback, the IFR data remain invaluable for examining the relationship between industrial robots and export performance. As the focus of the analysis is on merchandise exports, robots were calculated for Agriculture, Forestry, and fishing; Mining and quarrying; and finally manufacturing (IFR classifications, which is based on International Standard Industrial Classification of All Economic Activities (ISIC) revision 4 (Jurkat et al., 2022)).

The data for Production Index used in this study was obtained from the Organisation for Economic Co-operation and Development (OECD). The OECD is a database containing various economic indicators, including Production Index, which was extracted directly from there.

The index level of the real effective exchange rate (2010=100) was sourced from The World Bank's World Development Indicators (WDI) database through direct extraction. The WDI provides a wide collection of economic indicators, including the real effective exchange rate, allowing for a standardized measure of a country's currency value relative to a basket of other currencies. The data on foreign direct investment (FDI) was obtained from the United Nations Conference on Trade and Development (UNCTAD). Finally, the data on the Unit Labour Costs was obtained from the Organisation for Economic Co-operation and Development (OECD).

3.2. Characterization of the sample and descriptive analysis

This econometric research covers a sample of 32 developed and developing countries over the period of 25 years: between 1995 and 2019. This analysis will encompass all countries listed on Table A1. In this study, it is compiled data from 32 countries by carefully matching the information with the countries for which data on the stock of robots was available. The available data on robot stock was directly extracted from the International Federation of Robotics (IFR) and an analysis was conducted specifically on the countries for which data was available. To ensure a reliable dataset, countries without available information were removed from the database. The remaining variables were then matched for further analysis. Due to the limited availability of data for years prior to 1995, the analysis focused exclusively on data from that year onwards. This meticulous approach allowed to ensure the integrity and completeness of the dataset. Additionally, our total panel data is unbalanced

because of the data availability. By undertaking this rigorous data collection and cleansing process, the goal was to maximize the quality and reliability of the dataset, enabling more robust and accurate analysis in addressing the research objectives.

In order to obtain a better understanding of the variables of the model, it is essential to examine their descriptive statistics. Table 3 presents the descriptive statistics for all variables of the model. It is important to note that these statistics are calculated across all countries and for the entire 25-year period of this study. The table includes measures such as the mean, median, maximum, minimum, and standard deviation. These statistics provide valuable insights into the central tendencies, variability, and overall distribution of the variables. By analysing these descriptive statistics, we can obtain a clearer picture of the behaviour and characteristics of the variables, facilitating a deeper understanding of their dynamics and implications.

Table 3 - Descriptive Statistics

	X (in millions of US\$)	Robots (number)	PI (index)	ER (index)	FDI (in millions of US\$)	ULC (index)
Mean	221300,91	35129	90,47	96,94	323657,95	88,57
Median	110280,88	3728	96,55	98,47	104879,10	91,16
Maximum	1676914	507708	143	164,43	7806330	167,29
Minimum	1220,86	0	19,52	49	321	29,62
Standard Deviation	291680,23	88361	23,20	13,32	716272	17,12
No Obs.	796	800	790	797	797	783

As shown in table 3, the mean export value is 221 billion US dollars. Among the countries examined in this study, Germany, Japan, and the United States exhibit the highest average exports over the studied years. Conversely, Estonia, Lithuania and Latvia demonstrate the lowest export levels among the countries analysed (Table A2). These findings suggest notable disparities in export performance among the studied countries, with

Germany, Japan, and the United States emerging as leading exporters and Estonia, Lithuania and Latvia representing countries with comparatively lower export volumes. These disparities explain the high value for standard deviation.

Regarding the stock of robots, it presents an average of 35129 robots spread across the examined countries and years. Interestingly, the countries with both the highest and the lowest values for the stock of robots are the same as those observed for exports. This observation suggests a potential correlation between the stock of robots and exports.

In relation to PI, the mean value is approximately 90,47. Additionally, the standard deviation of 23,20 suggests a moderate degree of variability or dispersion in the Production Index values. The maximum value for this variable is 143 for Greece in 2000, while the minimum is 19,5 for Ireland in 1995.

In relation to the Real Exchange Rate, the mean value of 96,94 indicates the average level of the exchange rate across the examined countries and years. Additionally, the standard deviation of 13,32 suggests a moderate degree of variability or dispersion in the Real Exchange Rate values. The maximum value for Real Exchange Rate is 164,43 for Korea in 1997 while the minimum is 49 for Slovakia in 1995.

Regarding Foreign Direct Investment (FDI), the mean value is approximately 323658 US\$. The presence of a significant difference between the minimum (321 million US\$ for Lithuania in 1995) and maximum (7806330 million US\$ for USA in 2018) values suggests a considerable variation in the amount of FDI for the different countries in analysis and this is why the standard deviation is higher than the mean value.

Concerning Unit Labour Costs, the mean value of 88,57 indicates the average level of labour costs across the examined countries and years. The moderate standard deviation of 17,12 implies that while there is some variation in Unit Labour Costs, the values do not differ significantly from the mean. This indicates a degree of stability or consistency in labour cost levels across the analysed countries. For this variable, the maximum value is 167,29 for Turkey in 2019 and the minimum value is 29,62 for Hungary in 1995.

3.3. Evolution Over Time

This section will undertake an analysis of the main variables of interest, exports and robots.

Over time, there have been substantial changes in the evolution of exports of products, as measured in Balance of Payments (BOP) current US dollars, which indicate the expansion and transformation of international trade. Data from the World Development Indicators (WDI) database show that the value of exports of goods has generally increased over time. For instance, by 2019, the value of global goods exports had increased to almost \$320 billion from about \$111 billion in 1995 (see Figure 4). This significant growth emphasizes the growing importance of international trade to the world economy. The year of 2009 witnessed significant decreases in goods exports measured in Balance of Payments (BOP) current US dollars. Due to events like the East Asian financial crisis and the Mexican peso crisis, there was a slowdown in global economic development in 1995 (Reinhart & Rogoff, 2009). Similar to this, the subprime mortgage crisis in the United States in 2007 brought on the beginning of the global financial crisis, which had a significant impact on international commerce and economic activity, also reflected on the year of 2009 (IMF, 2009). On contrary to this, and following the 2008–2009 global financial crisis, numerous economies began to recover and reestablish stability in the years that followed (Switzer, Tu, & Wang, 2018). A phase of the world economy's recovery occurred between 2009 and 2011, when consumer and company confidence strengthened (Switzer et al., 2018). This resulted in a pickup in global trade and increased demand for exports of goods, which represented the highest growth on the last years (WDI, 2023).

It is evident that a breakdown in exports occurred between 2014 and 2015. This decline in export levels can be attributed to various factors, including the Eurozone debt crisis and a significant drop in commodity prices. The Eurozone debt crisis, characterized by economic instability and financial challenges within the Eurozone countries, had a dampening effect on trade activities (Reinhart et al., 2014). Additionally, the decline in commodity prices, such as oil and metals, negatively impacted export revenues for countries heavily reliant on commodity exports (Arezki & Ramey, 2016). The combined impact of these events resulted in a noticeable decrease in exports during the specified period. However, it is important to note that subsequent years, particularly from 2016 to 2017, witnessed a recovery and an increase in export volumes, suggesting a gradual stabilization and potential resilience in the export sector.

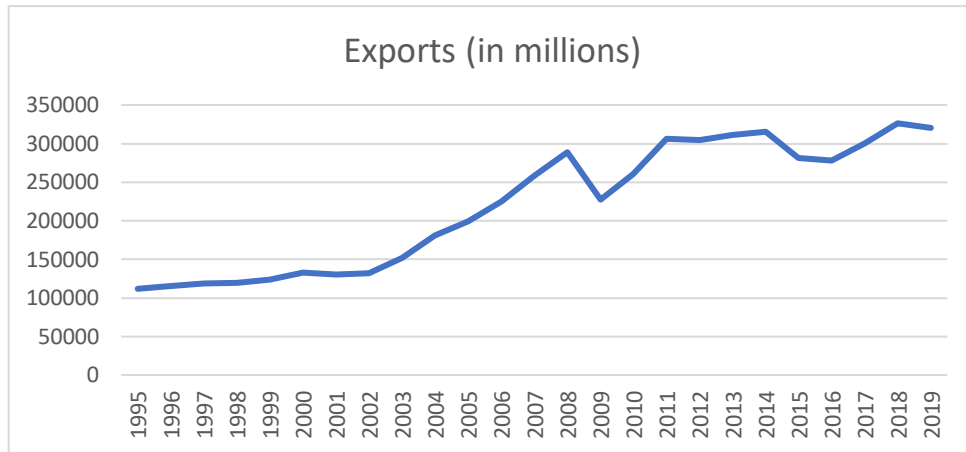


Figure 3 - Evolution of Exports

Over the last few years, robot adoption has experienced an important transformation as a result of technological advancements and increasing integration across industries (Artuc et al., 2020). The International Federation of Robotics (IFR) reports that the sale of industrial robots worldwide showed a steady growth in the last years, especially between 2010 and 2019. Global sales of industrial robots reached a peak in 2008 at about 1 billion units sold, but by 2019, it had soared to almost 2 billion units, representing a significant growth of 65% in just eleven years (IFR, 2020). As a result, in 2019, the adoption of industrial robots reached a significant milestone with the highest value ever. There are several explanations in this rising trend in robot usage. Robots are becoming smarter and more capable because to technological improvements, which also increases their efficiency, adaptability, and cost-effectiveness. Automation is a desirable alternative for many businesses looking to increase productivity and lower production costs due to the falling costs of robots and the rising labour costs in some places. The increased demand for personalization and the requirement for better quality control have also contributed to the deployment of robots across a variety of industries (IFR, 2020; Artuc et al., 2020). This growth in the robot adoption along the years can be seen in Figure 4.

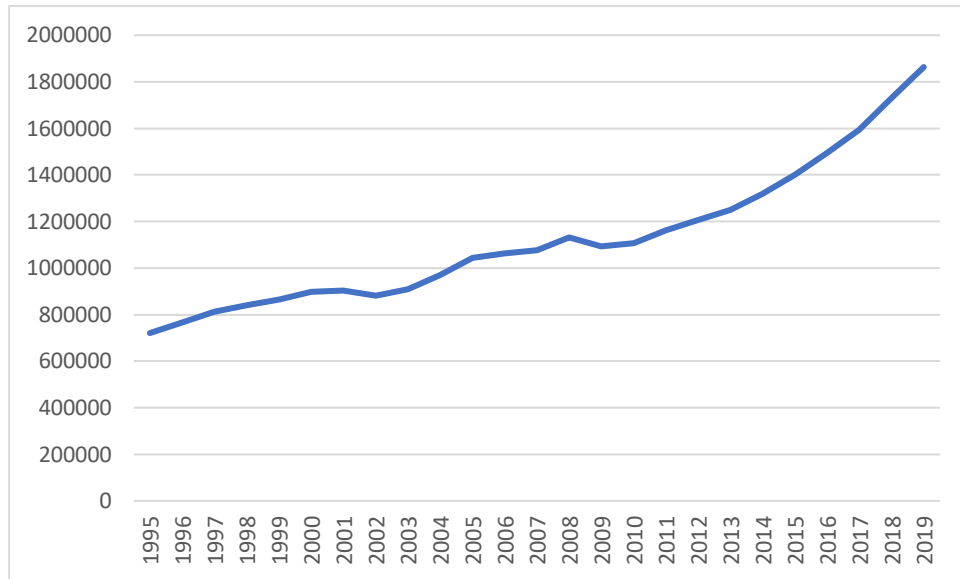


Figure 4 - Stock of Robots between 1995 and 2019 for the countries in analysis

4. Robotization and Exports: Empirical Results

In this new chapter, we focus on the analysis of the data and empirical results. The chapter is divided into two main sections. The first section examines the correlation between the variables under investigation, shedding light on their interrelationships and potential associations. By exploring the strength and direction of these correlations, we gain valuable insights into the connections between the variables. The second section delves into a detailed discussion of the empirical results. Here, we critically analyse the findings, interpret their implications, and explore any patterns or trends that emerge from the data.

4.1. Correlations

To assess the suitability of using the variables together for this study, we computed their correlation and presented the results in table 4.

Table 4 - Correlation between variables

	X	Robots	PI	ER	FDI	ULC
X	1					
Robots	0,7889	1				
PI	0,3759	0,3724	1			
ER	0,3948	0,3890	0,3513	1		
FDI	0,9084	0,3724	0,4509	0,3513	1	
ULC	0,5222	0,6509	0,4322	0,3761	0,4509	1

Correlation is a statistical measure that quantifies the strength and direction of the linear relationship between two variables (Moore et al., 2018). It provides insights into how changes in one variable are associated with changes in another variable. A correlation coefficient

ranges between -1 and 1, where values closer to -1 indicate a strong negative correlation, values closer to 1 indicate a strong positive correlation, and a value of 0 suggests no linear correlation (Moore et al., 2018).

All of the explanatory variables exhibit strong correlations with the dependent variable, with particular emphasis on the variables of Robots and FDI. These two variables display notably robust and significant correlations with the dependent variable. The presence of Robots demonstrates a substantial positive correlation, indicating that an increase in the level of robotic stock is associated with higher values of the dependent variable. Similarly, FDI exhibits a significant positive correlation, suggesting that higher levels of foreign direct investment lead to increased values of the dependent variable.

Analysing the above table, it is possible to conclude that none of the variables show a negative correlation between each other, indicating that none of them grow in opposite directions.

All variables have a good correlation with the dependent variable, which is of extreme importance when conducting this kind of studies. Also, all the control variables have a correlation between each other below 0,8, which means that they are all suitable for this analysis (Hill et al., 2018).

In the upcoming section, we will explore how these variables help us answer the research question we are focusing on.

4.2. Estimation Results and discussion

In order to answer to the research question "Does Robotization affect the Exports", a commonly used method that would be suitable is panel data regression. Panel data regression allows for the analysis of the relationship between the independent variable (robotization) and the dependent variable (exports) across multiple observations of the same individuals (in this case, countries) over time. This is particularly useful in this case because it allows for the control of time-invariant characteristics of each country, as well as capturing the dynamic relationship between robotization and exports over time (Reyna, 2007). Additionally, panel data regression allows for the inclusion of control variables and it allows for the use of various methods in estimations, such as the ordinary-least-squares (OLS) method, fixed effects, and random effects (Reyna, 2007). However, the pooled OLS method has limitations as it assumes homogeneity across all countries and does not account for

country-based heterogeneity. In contrast, the fixed-effects method explicitly models each country's effect, making it suitable for capturing the country-based effect of robotization on exports. The random-effects method acknowledges heterogeneity in the cross-section but assumes that the effects are random, independent, and identically distributed over the error term (Reyna, 2007).

To determine the most appropriate method, it will be used the Hausman test. The Hausman test is a crucial statistical tool in econometrics that enables the comparison of the reliability of two distinct models used to estimate the same parameters. This test is particularly useful in determining whether to use a fixed effects model or a random effects model in panel data analysis. By comparing the estimates of the two models, the test can identify whether the differences between them are statistically significant. If the differences are significant, then the fixed effects model is preferred, while if the differences are not significant, then the random effects model is preferred (Baltagi, 2014).

Using an unbalanced panel data set, we start by estimating a pooled regression model by OLS and then fixed effects in cross section. In Table 6, it is displayed the results for these two estimations. To account for heteroscedasticity/autocorrelation, robust estimators of the standard deviation are employed to validate the statistical inference. This approach helps address the potential biases caused by these issues and enhances the reliability of the analysis (Hill et al., 2018). The use of pooled OLS method can present issues as it assumes homogeneity across all countries. However, despite this limitation, it is still valuable in assessing the robustness and stability of estimation signs across different methods and that is why we have estimated it in this study (Hill et al., 2018). Subsequently, we rely on the most suitable method for our interpretations, as indicated by the Hausman test. The coefficient estimates provided here represent the elasticity coefficients of exports, indicating the responsiveness of exports to a 1% change in the explanatory variables.

First, it is estimated the equation (1) by using the full sample of countries (32) for which we have relevant data to investigate whether growth in merchandise exports can be attributed to robotization.

As previously mentioned, the Hausman test evaluates the null hypothesis that the random effects estimator is consistent and efficient, while the fixed effects estimator is only consistent. If the p-value of the Hausman test is less than the chosen significance level (e.g., 0,05), the null hypothesis can be rejected and conclude that the fixed effects model is more appropriate (Hill et al., 2018). In this particular study, for the full sample and for both

equations, the results of the Hausman test (Table 5) indicate that the fixed-effect model is the most appropriate estimation model.

Table 5 - Results for Hausman Test for equation 1

	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section Random	85,5758	5	0,0000

Table 6 - Estimation Results for equation 1 (Dependent Variable: Exports)

Variables	Pooled OLS	Cross fixed effects
Constant	3,1860*** (4,8855)	0,4064 (0,9083)
Robots	0,1518*** (22,4330)	0,025*** (4,9817)
PI	-0,3497*** (-5,3093)	0,3497*** (7,0235)
ER	0,3906** (2,8811)	0,5807*** (8,7095)
FDI	0,5966*** (42,8888)	0,3747*** (14,8665)
ULC	0,0215 (0,2144)	0,5369*** (7,1439)
F-Statistic	1270,232***	1122,769***
R ²	0,8933	0,9823
N. Observations	765	765

Notes: (1) *** p < 0.01; ** p < 0.05; * p < 0.1, (2) t- statistics presented in brackets was calculated using cross-section estimation of standard errors and covariance using the Seemingly Unrelated Regression (SUR) method with Panel-Corrected Standard Errors (PCSE), correcting heteroscedasticity; these estimations were made using EViews software.

Table 6 shows the results for equation (1). For the Pooled OLS, the signs of the coefficient estimates does not align entirely with our expectations. For PI, we anticipated the coefficient to be positive but it is showing as negative. However, as explained in previous paragraphs, this may be due to the fact that pooled OLS model neglects the presence of heterogeneity among individuals by assuming a uniform coefficient for all of them. In this way, we focus the analysis on the results of the Fixed effects model.

The R^2 indicates the proportion of the variation in the dependent variable that is explained by the independent variables in a regression model (Hill et al., 2018). A higher R-squared value generally indicates a better fit of the regression model to the data, as it suggests that a larger proportion of the variation in the dependent variable is explained by the independent variables. So, for this particular study, an R-squared value of 0,9823 means that approximately 98% of the variability in the dependent variable can be explained by the independent variables included in the model. In other words, the model is able to account for a significant portion of the variation in the data.

The analysis of the fixed-effect model reveals compelling evidence supporting the significance of all variables, which confirms the findings expected from the existing literature. Moreover, it is noteworthy that all variables exhibit a positive influence on exports. In other words, *ceteris paribus*, an increase in any of the variables will induce an increase in exports. These results underscore the alignment between the empirical findings and the theoretical expectations established in the literature.

Generally, the coefficients presented indicate the percentage change in exports associated with a 1% change in the corresponding variable, and this change occurs in the same direction. The results displayed in table 6 provide insights into the relationship between the variables and their impact on exports. Concerning the main explanatory variable, Robots, results indicate that, *ceteris paribus*, a 1% increase (decrease) in the level of robotic stock leads to a 0,025% increase (decrease) in exports.

These results suggests that countries with a greater presence of robotic technology in their production processes tend to experience increased export values. This result is in line with the existing literature (e.g. Ndubuisi & Avenyo, 2018; Altomonte et al, 2020; Artuc et al., 2020; César et al., 2022).

Concerning the control variables, results are also in line with expectations. Starting with the Production index, countries with a more robust and productive manufacturing

sector tend to have higher export values. Similar to Aksoy & Ülengin (2017), we also concluded that higher PI leads to higher exports.

Regarding exchange rate, a higher exchange rate appears to be associated with higher export values, potentially making exports more competitive in international markets. These findings align with the conclusions drawn by Artuc et al. (2020).

In regards to FDI (Foreign Direct Investment), countries attracting greater levels of foreign investment tend to experience increased export values, indicating that foreign capital inflows contribute to higher exports. Rahmaddi & Ichihashi (2013) also got to the same result.

Concerning ULC (Unit Labor Cost), countries with higher unit labor costs, which can be an indicator of labor productivity or wages, tend to have higher export values, suggesting that factors affecting labor costs play a role in export competitiveness. This result is in line with the perspective of Graetz & Michaels (2018).

Since the period under analysis was impacted by a financial crisis, and in order to test the robustness of the estimators, it is possible to expand our model by adding a dummy variable to account for the crisis years. The dummy variable takes the value of 1 for the year of 2009 (which was the most affected by the crisis), and 0 for all other years. This allows us to capture and analyse any potential effects or differences in the data during those specific crisis years. The modified equation is presented below:

$$\ln X_{ijt} = \alpha_0 + \beta_1 \ln Robots_{it} + \beta_2 \ln PI_{it} + \beta_3 \ln ER_{it} + \beta_4 \ln FDI_{it-1} + \beta_5 \ln ULC_{it} + \sum_{n=2}^x \alpha_n D_n + u_{it} \quad (2)$$

where D_1 is a period dummy that takes number 1 for years 2008 and 2009, and 0 for the others.

As previously made for equation 1, it was also performed the Hausman test for equation 2 in order to evaluate which model is more suitable for this analysis (fixed effect or random effect). The results of the Hausman test (Table 7) indicate that the fixed-effect model is the most appropriate estimation model.

Table 7 - Results for Hausman Test for equation 2

	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section Random	82,4622	6	0,0000

The results for the inclusion of the dummy (equation (2)) are showed in Table 8.

Table 8 - Estimation Results for equation 2 (Dependent Variable: Exports)

Variables	Cross fixed effects
Constant	0,3651 (0,6494)
Robots	0,0244*** (4,1049)
PI	0,3343*** (8,2639)
ER	0,5914*** (9,9494)
FDI	0,3783*** (13,6385)
ULC	0,5425*** (7,4439)
D1	-0,0676*** (-3,0878)
F-Statistic	1096,284***
R ²	0,9824
N. Observations	765

Notes: (1) *** p < 0.01; ** p < 0.05; *p < 0.1, (2) t- statistics presented in brackets was calculated using White cross-section estimation of standard errors and covariance using period cluster, correcting heteroscedasticity; these estimations were made using EViews software.

The coefficient of the dummy variable in the second estimation is -0,0676, with a corresponding p-value of 0,0050. These results indicate that the dummy variable for the year of 2009 have a statistically significant impact on the dependent variable (merchandise exports) at the conventional significance level of 0,05. Since the coefficient is negative, it indicates that the year 2009 has a negative effect on the dependent variable. In simpler terms, *ceteris paribus*, the results suggest that exports in 2009 are, on average, 0,0676% lower compared to other years. This implies that the year 2009 had a negative impact on export levels when considering the other factors controlled for in the model.

This suggests that the global financial crisis that occurred during those years may have had a significant effect on the relationship between the variables being analysed. The significant coefficient implies that, on average, there is a significant difference in merchandise exports between the crisis year of 2009 and other years.

For the rest of the variables, all of them remain statistically significant and all of them continue having a positive coefficient, affecting positively the exports.

5. Conclusions

Exports play a crucial role in the growth and development of a country. They serve as an engine for economic expansion, creating employment opportunities, and promoting technological advancements (Rodriguez & Rodrik, 2001). Furthermore, the recent growth on robot adoption has created debate among experts regarding their impact on exports. The integration of robots in production processes has improved efficiency, productivity, and quality, therefore bolstering a country's export competitiveness (Acemoglu & Autor, 2011; Graetz & Michaels, 2018).

This study examined a diverse sample of 32 developed and developing countries over a period of 25 years, aiming to investigate the relationship between robotization and exports. The findings of this research are aligned with the existing literature, highlighting the positive and statistically significant impact of the explanatory variables on exports. The main explanatory variable, Robots, has shown to have a positive and significant impact on the export performance. Notably, control variables such as foreign direct investment, production index, exchange rate, and unit labor costs all exhibited significant positive effects on export values.

The results highlight the importance of embracing robotization and attracting foreign investment as key drivers of export growth. The integration of robots in production processes enhances efficiency and productivity, leading to higher export volumes. Moreover, foreign direct investment plays a crucial role in expanding export-oriented industries and improving competitiveness (Keller, 2004).

The production index, which reflects overall economic activity, also exhibited a positive influence on exports. A higher production index indicates a more vibrant economy with increased demand for goods, translating into higher export levels.

Additionally, the exchange rate and unit labor costs were found to be significant determinants of export performance. Maintaining a competitive exchange rate is vital for export competitiveness, as it affects the relative price of goods in international markets (Bahmani-Oskooee & Rhee, 2007). Moreover, controlling unit labor costs is crucial, as higher labor costs can hinder export growth.

In conducting this study, several limitations were encountered that required careful consideration and appropriate methodological approaches. Cross-country differences posed a challenge, as variations in institutional frameworks, policies, and economic conditions could

have influenced the results. To address this, a fixed effect model was employed to account for country-specific heterogeneity and mitigate potential biases as well as the addition of the period dummy. Additionally, data limitations were observed specifically related to the availability and quality of data on robots. This limited the depth of analysis and interpretation of the results regarding the role of robotization. Furthermore, endogeneity emerged as a concern, as the relationship between certain variables and exports may be influenced by unobserved factors. To mitigate this issue, it was used cross-section estimation of standard errors and covariance using the Seemingly Unrelated Regression (SUR) method with Panel-Corrected Standard Errors (PCSE). These limitations highlight the importance of acknowledging and addressing methodological challenges to ensure the validity and reliability of the findings.

This study holds considerable relevance in the current global landscape. As countries strive to enhance their export potential and to become more competitive, understanding the factors that drive export growth becomes essential. By shedding light on the significant role of various variables in fostering exports, this research contributes valuable insights to policymakers, businesses, and economists. It underscores the importance of embracing robotization and attracting foreign investment while emphasizing the need to improve production capacity, maintain competitive exchange rates, and manage labor costs effectively.

By leveraging these insights, countries can position themselves competitively in the global market and strengthen their export capabilities. This research contributes to the broader understanding of the factors driving export growth and underscores the importance of a comprehensive approach to bolstering export performance and achieving long-term economic prosperity.

In future studies, it would be relevant to incorporate an additional equation introducing a dummy variable to account for the impact of the Covid years and/or the Russian War. By including this variable, it would be possible to examine how exports were influenced by these significant events, allowing for an understanding of their effects on export dynamics. It would also be interesting to do the same kind of analysis by sector and to use more advanced estimation models in order to account for endogeneity.

References

- Acemoglu, D., & D. Autor (2011). Skills, tasks and technologies: implications for employment and earnings.” In *Handbook of Labor Economics* 4,1043-1171. Amsterdam: North-Holland.
- Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares and employment. *The American Economic Review*, 108(6), 1488–1542.
- Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labour. *Journal of Economic Perspectives*, 33(2), 3-30. doi: 10.1257/jep.33.2.3
- Acemoglu, D., & Restrepo, P. (2017). Robots and jobs: Evidence from US labour markets. *Journal of Political Economy*, 127(5), 2417-2463.
- Aiginger, K., Vogel, J., & Bärenthaler-Sieber, S. (2013). Competitiveness under New Perspectives. Retrieved from <https://www.oecd.org/economy/Competitiveness-under-New-Perspectives.pdf>
- Aksoy, A., & Ülengin, F. (2017). The Impacts of Robotization on Firm Performances: A Study on Turkish Manufacturing Industries. *Procedia Computer Science*
- Alguacil, M., Lo Turco, A., & Martínez-Zarzoso, I. (2022). Robot adoption and export performance: Firm-level evidence from Spain. *Economic Modelling*, 114, 105912. <https://doi.org/10.1016/j.econmod.2022.105912>
- Altomonte, C., Aquilante, T., & Ottaviano, G. (2020). *The Impact of Industrial Robots on Export Competitiveness*. Cambridge University Press.
- Antras, P. (2015). *Global production: Firms, contracts, and trade structure*. Princeton University Press. Retrieved from <https://press.princeton.edu/books/hardcover/9780691168272/global-production>
- Antwi, S., & Hamza, K. (2015). Qualitative and Quantitative Research Paradigms in Business Research: A Philosophical Reflection. *European Journal of Business and Management*, 7(3), 217–226.
- Arezki, R., & Ramey, V. A. (2016). Breaking the oil spell: The Gulf Falcons' path to diversification. *Brookings Papers on Economic Activity*, 47(1), 365-440.
- Artuc, E., P. Bastos and B. Rijkers (2020), “Robots, Tasks and Trade”, CEPR Discussion Paper 14487.

- Artuc, E., Bastos, P., Copestake, A., & Rijkers, B. (2023). Robots and Trade: Implications for Developing Countries. In 2178234629 1498305059 L. Y. Ing & 2178234630 1498305059 G. M. Grossman (Authors), *Robots and ai: A new economic era*. Abingdon, Oxon: Routledge.
- Autor, D.H., and D. Dorn (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US LaborMarket. *American Economic Review* 103(5), 1553-1597.
- Autor, D.H., Levy, F., and Murnane, R.J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4), 1279-1333.
- Aw, B. Y., Roberts, M. J., & Xu, D. Y. (2008). R&D Investments, Exporting, and the Evolution of Firm Productivity. *American Economic Review*, 98(2), 451–456. <https://doi.org/10.1257/aer.98.2.451>
- Bahmani-Oskooee, M., & Rhee, H. J. (2007). Exchange Rate Volatility and Trade Flows: A Review Article. *Journal of Economic Studies*, 34(3), 211-255.
- Ballestar, M. T., Díaz-Chao, N., Sainz, J., & Torrent-Sellens, J. (2020). Knowledge, robots and productivity in SMEs: Explaining the second digital wave. *Journal of Business Research*, 108, 119–131. <https://doi.org/10.1016/j.jbusres.2019.11.017>
- Baltagi, B. (2014). Panel data and difference-in-differences estimation. *Encyclopedia of Health Economics*, 425-433. doi:10.1016/b978-0-12-375678-7.00720-3
- Bayar, G. (2018). Estimating export equations: a survey of the literature. *Empirical Economics*, 54(2), 629–672. <https://doi.org/10.1007/s00181-016-1220-3>
- Bayar, G., & Tokpunar, S. (2014). Determinants of Turkish Manufacturing Industry Production in Sub-Sectors: A Panel Data Analysis. *Business and Economics Research Journal*, 5(1), 67-85. <https://www.berjournal.com/determinants-of-turkish-manufacturing-industry-production-in-sub-sectors-a-panel-data-analysis>
- Baur, A., Flach, L., & Gourevich, I. (2022). The Effect of Robotization in OECD Countries on Latin American Exports. *Policy debate of the hour*, 23(5), 33-36
- Berg, A., Buffie, E. F., & Zanna, L. F. (2016). Robots, growth, and inequality. *Finance & Development*, 53(3), 10-13.
- Bernard, A. B., Jensen, J. B., Redding, S. J., & Schott, P. K. (2007). Firms in international trade. *Journal of Economic perspectives*, 21(3), 105-130.
- Bernard, A. B., Redding, S. J., & Schott, P. K. (2007). Comparative advantage and heterogeneous firms. *The Review of Economic Studies*, 74(1), 31-66.

- Bloom, D., McKenna, M., & Prettnner, K. (2018). Demography, unemployment, automation, and digitalization: Implications for the creation of (decent) jobs, 2010–2030. National Bureau of Economic Research. DOI 10.3386/w24835
- Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W. W. Norton & Company.
- Cali, M., & Presidente, G. (2021). Automation and manufacturing performance in a developing country. Policy Research Working Papers. doi:10.1596/1813-9450-9653
- Camiña, E., Díaz-Chao, Á. and Torrent-Sellens, J. (2020) “Automation technologies: Long-term effects for Spanish industrial firms,” *Technological Forecasting and Social Change*, 151, p. 119828. Available at: <https://doi.org/10.1016/j.techfore.2019.119828>.
- Cao, Y., Chen, Shaojian & Tang, H. (2021) “Robots, productivity, and firm exports,” SSRN Electronic Journal [Preprint]. Available at: <https://doi.org/10.2139/ssrn.3980375>.
- César, A. M., Falcone, G., & Garriga, P. (2022). Robots, exports and top income inequality: evidence for the US. Documentos de Trabajo del CEDLAS.
- Chandra, P., & Long, C. (2013). VAT rebates and export performance in China: Firm-level evidence. *Journal of Public Economics*, 102, 13-22.
- Chen, W. (2013). The extensive and intensive margins of exports: The role of Innovation. *The World Economy*, 36(5), 607-635. doi:10.1111/twec.12032
- Ciccone, A., & Hall, R. E. (1993). Productivity and the density of economic activity.
- Coad, A., & Vezzani, A. (2019). Three cheers for industry: Is manufacturing linked to R&D, exports, and productivity growth?. *Structural Change and Economic Dynamics*, 50, 14-25.
- DeStefano, T. & Timmis, J. (2021) “Robots and export quality,” Policy Research Working Papers [Preprint]. Available at: <https://doi.org/10.1596/1813-9450-9678>.
- Dosi, G. Pavitt, K. & Soete, L. (1990). *The economics of technological change and international trade*. Harvester Wheatsheaf Publishers, Brighton.
- Faber, M. (2020). Robots and reshoring: Evidence from Mexican labour markets. *Journal of International Economics*, 127, 103384. <https://doi.org/10.1016/j.jinteco.2020.103384>
- Farinas, J. C. & A. Martin-Marcos (2007), ‘Exporting and Economic Performance: Firm-level Evidence for Spanish Manufacturing’, *World Economy*, 30(4), 618–646
- Graetz, G., & Michaels, G. (2018). *Robots at Work*. The Review of Economics and

- Statistics, 100(5), 753–768. https://doi.org/10.1162/rest_a_00754
- Graetz, G., & Michaels, G. (2018). The impact of robots on employment, wages, and output: A meta-analysis. *Labour Economics*, 50, 59-68. doi: 10.1016/j.labeco.2017.12.005
- Grossman, G. M., & Helpman, E. (1991). Quality Ladders and Product Cycles. *The Quarterly Journal of Economics*, 106(2), 557.
- Guner, B., Lee, J., and Lucius, H. (2010), “The impact of industry characteristics on export performance: a three country study”, *International Journal of Business and Economics Perspectives*, Vol. 5 (2), pp. 126-141.
- Helpman, E. (2018). Globalization and wage inequality. *Econometrica*, 86(6), 1979-2013.
- Helpman, E., Melitz, M. J., & Rubinstein, Y. (2008). Estimating trade flows: Trading partners and trading volumes. *The Quarterly Journal of Economics*, 123(2), 441-487.
- Hémous, D., & M.Olsen (2014). The rise of the machines: Automation, horizontal innovation and income inequality. CEPR Discussion Papers 10244, Center for Economy Policy Research.
- Hidalgo, C. A., Winger, B., Barabási, A. L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, 317(5837), 482–487.
- Hill, R. C., Griffiths, W. E., & Lim, G. C. (2018). *Principles of econometrics* (4th ed.). John Wiley & Sons.
- Hirschman, A. (1958). *The strategy of economic development*. Yale University Press.
- IFR International Federation of Robotics. (2022). International Federation of Robotics. <https://ifr.org/>
- International Monetary Fund. (2009). *Global Financial Stability Report: Navigating the Financial Challenges Ahead*.
- Jurkat, A., Klump, R., & Schneider, F. (2022). Tracking the rise of robots: The IFR database. *Jahrbücher Für Nationalökonomie Und Statistik*, 242(5–6), 669–689. doi:10.1515/jbnst-2021-0059
- Keller, Wolfgang. 2004. "International Technology Diffusion." *Journal of Economic Literature*, 42 (3): 752-782.
- Koch, M., Manuylov, I., & Smolka, M. (2021). Robots and firms. *The Economic Journal*, 131(638), 2553-2584
- Kroll, H. Horvat, D. & Jäger, A. (2018) Effects of automatisisation and digitalisation on

- Manufacturing companies' production efficiency and innovation performance. Fraunhofer ISI Discussion Papers Innovation Systems and Policy Analysis, No. 58
- Krugman, P. (1985). A 'technology gap' model of international trade. In: Jungenfelt, K., Hague, D. (Eds.), *Structural adjustment in Advanced Economies*. Macmillan, London.
- Kugler, A., M. Kugler, L. Ripani and R. Rodrigo (2020), "U.S. Robots and Their Impacts in the Tropics: Evidence from Colombian Labour Markets", NBER Working Paper 28034.
- Lankisch, C., K. Prettner, & A. Prskawetz (2019). How can robots affect wage inequality? *Economic Modelling*, 81, 161-169.
- Leichenko, R. M., & Erickson, R. A. (1997). Foreign direct investment and state export performance. *Journal of regional science*, 37(2), 307-329.
- Lin, C., Xiao, S., & Yin, Z. (2022). How do industrial robots applications affect the quality upgrade of Chinese export trade? *Telecommunications Policy*, 46(10), 102425. <https://doi.org/10.1016/j.telpol.2022.102425>
- Liu, Z. et al. (2022) "Robot learning towards smart robotic manufacturing: A Review," *Robotics and Computer-Integrated Manufacturing*, 77, p. 102360. Available at: <https://doi.org/10.1016/j.rcim.2022.102360>.
- Márquez-Ramos, L., & Martínez-Zarzoso, I. (2010). The effect of technological innovation on International Trade. *Economics*, 4(1). doi:10.5018/economics-ejournal.ja.2010-11
- Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, 71(6), 1695–1725. <https://doi.org/10.1111/1468-0262.00467>
- Melitz, M. J., & Ottaviano, G. I. (2008). Market Size, Trade, and Productivity. *The Review of Economic Studies*, 75(1), 295–316. <https://doi.org/10.1111/j.1467-937x.2007.00463.x>
- Moore, D. S., McCabe, G. P., & Craig, B. A. (2018). *Introduction to the Practice of Statistics* (9th ed.). W. H. Freeman.
- Movahedi, M., & Gaussens, O. (2011). Innovation, productivity, and export: Evidence from SMEs in Lower Normandy, France. *RePEc: Research Papers in Economics*. <https://mpira.ub.uni-muenchen.de/40443/>
- Ndubuisi, G., & Avenyo, E. (2018, December). Estimating the effects of robotization on

- exports. Working Paper Series, Maastricht University
- Obashi, A., & Kimura, F. (2021). New developments in international production networks: Impact of digital technologies*. *Asian Economic Journal*, 35(2), 115-141. doi:10.1111/asej.12240
- OECD (2023), Investment (GFCF) (indicator). doi: 10.1787/b6793677-en (Accessed on 13 March 2023)
- Özcan, R. (2018). How will robotization affect relative macroeconomic positions of the IDB member countries?
- Posner, M. (1961). International trade and technical change. *Oxford Economic Papers* 13, 323–341.
- Rahmaddi, R., & Ichihashi, M. (2013). The role of foreign direct investment in Indonesia's manufacturing exports. *Bulletin of Indonesian Economic Studies*, 49(3), 329–354. <https://doi.org/10.1080/00074918.2013.850632>
- Reinhart, C. M., & Rogoff, K. S. (2009). *This Time Is Different: Eight Centuries of Financial Folly*. Princeton University Press.
- Reinhart, C. M., & Rogoff, K. S. (2014). Recovery from financial crises: Evidence from 100 episodes. *American Economic Review*, 104(5), 50-55.
- Rodriguez, F., & Rodrik, D. (2001). Trade policy and economic growth: A skeptic's guide to the cross-national evidence. *NBER Macroeconomics Annual*, 15, 261-325.
- Rodrik, D. (2018). New technologies, global value chains, and developing economies. National Bureau of Economic Research. <https://doi.org/10.3386/w25164>
- Samuelson, P. A. (1997). *Economics: An introductory analysis*. New York: McGraw-Hill.
- Siggel, E. (2006). International competitiveness and comparative advantage: A survey and a proposal for measurement. *Journal of Industry, Competition and Trade*, 6, 137-159.
- Slevitch, L. (2011). Qualitative and quantitative methodologies compared: Ontological and epistemological perspectives. *Journal of Quality Assurance in Hospitality and Tourism*, 12(1), 73–81.
- Stemmler, H. (2019), “Automated Deindustrialization: How Global Robotization affects Emerging Economies - Evidence from Brazil”, CEGE Discussion Paper 382.
- Stapleton, K., & Webb, M. (2020). Automation, Trade and Multinational Activity: Micro Evidence from Spain. SSRN Electronic Journal. <https://doi.org/10.2139/ssrn.3681143>

- Switzer, L. N., Tu, Q., & Wang, J. (2018). Corporate governance and default risk in financial firms over the post-financial crisis period: International evidence. *Journal of International Financial Markets, Institutions and Money*, 52, 196-210.
- The World Bank, World Development Indicators (2023). Retrieved from <https://data.worldbank.org/indicator/BX.GSR.GNFS.CD>
- The World Bank, World Development Indicators (2023). Retrieved from <https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?end=2019&locations=PT-GB&start=2000>
- Torres-Reyna, O. (2007). Panel Data Analysis Fixed and Random Effects using Stata. Retrieved from Torres-Reyna, O. (2007). Panel Data Analysis Fixed and Random Effects using Stata. Retrieved from <https://www.princeton.edu/~otorres/Panel101.pdf>
- University of Groningen, & Penn World Table. (n.d.). Penn World Table version 10.01 [Data file]. Retrieved from <https://www.rug.nl/ggdc/productivity/pwt/>
- Wang, D., & Li, G. (2022). Will the use of industrial robots promote transformation of export trade modes? Empirical evidence from China. *PloS one*, 17(6), e0267135.
- World Customs Organization. (n.d.). What is the Harmonized System? Retrieved April 18, 2023, from <https://www.wcoomd.org/en/topics/nomenclature/overview/what-is-the-harmonized-system.aspx>
- Zeng, D. Z. (2017). Measuring the effectiveness of the Chinese innovation system: A global value chain approach. *International Journal of Innovation Studies*, 1(1), 57-71.

Annexes

Annex 1: Sample countries

Table A 1 - Sample Countries

Country Code	Country name
DEU	Germany
USA	United States
AUT	Austria
AUS	Australia
BEL	Belgium
CAN	Canada
CHE	Switzerland
CZE	Czech Republic
DNK	Denmark
ESP	Spain
FIN	Finland
FRA	France
GBR	United Kingdom
GRC	Greece
IRL	Ireland
ISR	Israel
ITA	Italy
JPN	Japan
NLD	Netherlands
NOR	Norway
POL	Poland
PRT	Portugal
SWE	Sweden
SVN	Slovenia
SVK	Slovakia
TUR	Turkey
KR	Rep. of Korea
EST	Estonia
HUN	Hungary
LTU	Lithuania
NZL	New Zealand
LVA	Latvia

Annex 2: Variables mean by country

Table A 2 - Variables mean by country

Country	X (million)	Robots	PI	ER	FDI_STOCK	ULC
DEU	1012713,932	169507,900	88,911	102,847	692111,318	90,665

USA	1117600,720	179052,900	95,143	109,441	3436745,760	89,159
AUT	120095,478	6166,400	84,588	101,964	101799,605	88,167
AUS	149598,562	5305,520	100,945	86,729	348468,048	83,808
BEL	257059,453	6968,840	84,480	99,736	396538,760	89,905
CAN	355789,997	6207,680	101,721	86,359	598251,927	85,381
CHE	216168,556	4977,200	89,049	99,946	475250,196	95,729
CZE	85239,784	6927,480	77,859	84,457	77734,277	88,375
DNK	86197,534	3433,000	97,685	97,991	78119,510	87,327
ESP	218918,671	29201,640	114,057	96,418	415049,760	92,652
FIN	64253,006	3810,840	101,152	102,635	56861,277	85,203
FRA	450515,440	35701,800	103,868	100,596	506197,256	88,916
GBR	376975,765	19082,320	90,428	113,844	909990,331	86,066
GRC	20648,274	194,440	121,159	93,655	25098,276	89,309
IRL	125860,873	363,360	58,817	95,627	311814,662	109,945
ISR	44206,232	586,520	81,821	101,962	49684,117	87,758
ITA	385014,787	61065,720	115,276	98,628	250038,491	87,328
JPN	578165,474	424699,200	103,763	96,982	122354,725	111,519
NLD	384459,468	6051,080	93,941	99,872	617490,609	91,433
NOR	99275,794	928,720	91,634	94,050	101641,942	75,878
POL	123674,400	4651,200	69,323	92,935	114647,220	93,847
PRT	43748,370	2711,760	115,491	98,788	87336,579	95,406
SWE	138388,019	10381,160	104,499	105,380	215595,940	88,059
SVN	20564,084	1409,400	91,335	97,856	8187,625	84,574
SVK	47296,115	2696,280	65,011	81,076	31581,355	86,867
TUR	100648,040	4083,480	67,378	79,361	91192,916	92,340
KR	344075,608	124904,300	73,148	121,947	105345,092	94,406
EST	7880,617	54,240	71,896	92,211	11447,967	72,268
HUN	64216,379	2552,960	73,857	87,917	62317,298	80,266
LTU	15072,031	55,400	80,282	90,726	9896,441	83,674
NZL	25960,992	384,640	97,695	98,125	49081,892	87,510
LVA	7068,065	12,480	87,612	92,305	7928,856	73,382