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AUTOMATION AND GROWTH IN THE EUROPEAN UNION: SECTORAL INSIGHTS FROM ROBOT DENSITY ANALYSIS

Nicoleta Mihaela DORAN[1], Gabriela BADAREU[1✉], Dorin Mădălin DOGARU[2], Cosmin Alexandru SPIRIDON[2], Elena JIANU[3], Axinte GHEORGHE[1]

[1]Faculty of Economics and Business Administration, University of Craiova, Craiova, Romania
[2]Faculty of Economics and Business Administration, West University of Timisoara, Timisoara, Romania
[3]University Politehnica of Bucharest, Bucharest, România

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Abstract. This study explores the impact of robot density on economic performance across three key sectors in selected EU countries. While prior research has discussed the benefits and drawbacks of automation, few have empirically assessed its sector-specific effects on gross value added. Using panel data from Eurostat, the International Federation of Robotics (2024), and World Robotics, the paper applies the Method of Moments Quantile Regression (MMQR) to capture heterogeneous impacts across performance levels. Core variables include gross value added, real economic growth, R&D expenditure, and the number of specialists in scientific and technological fields. Results indicate that increased robot density significantly enhances value added, particularly in higher-performing sectors. The influence of R&D and human capital varies across sectors, highlighting the need for targeted policy design. The paper's novelty lies in its differentiated, cross-sectoral approach, offering robust evidence on how and where robotics contributes to value creation. It advances the literature by integrating technological adoption with sectoral economic outcomes through advanced econometric techniques. Policymakers are encouraged to support automation through fiscal incentives, invest in reskilling programs, and develop innovation strategies tailored to specific sectors to foster inclusive and sustainable growth within the EU's evolving economic landscape.

Keywords: automation, sectoral performance, robot density, gross value added, industrial robotics, MMQR.

JEL Classification: O33, O32, O14, L16, C23, C14.

✉Corresponding author. E-mail: *gabriela.badareu@edu.ucv.ro*

1. Introduction

In recent years, robotics has emerged as a transformative force across numerous economic sectors, significantly impacting value creation in diverse fields (Bechar & Vigneault, 2016; Badareu et al., 2024; Doran et al., 2024; Gat et al., 2016; Kangru et al., 2019; Skibniewski & Golparvar-Fard, 2016; Zhang et al., 2018). Besides enhancing process efficiency, robots have played a role in raising output levels, reducing operational expenses, and improving safety standards. Furthermore, in specific contexts, robotics has facilitated greater sustainability (Galin & Meshcheryakov, 2019; Kangru et al., 2019; Lowenberg-DeBoer, 2018; Manta et al., 2024; Marinoudi et al., 2019; Oke et al., 2019; Xiao et al., 2022; Zheng et al., 2025). The use of robots is regarded as an innovative solution addressing critical challenges faced by these sectors, such as labor shortages, high complexity and risks in processes, and the need to meet market demands more rapidly and effectively (Choi, 2019; Damaševičius et al., 2024). Consequently, the integration of robotics across various industries not only optimizes internal processes but also plays a pivotal role in strengthening regional economies by maximizing resource utilization, enhancing production efficiency, and increasing global market competitiveness (Ganeshkumar et al., 2023). The implementation of advanced technologies, including autonomous industrial and agricultural robots, is part of a broader global trend of digitalization and automation driving economic performance worldwide, even amidst challenges related to labor shortages and increasingly stringent market demands (Kangru et al., 2019).

In agriculture, a sector vital to the economy robotics has become a promising solution to significant challenges such as process efficiency and persistent labor shortages (Shakoor et al., 2019). The use of robots in agriculture has evolved substantially over recent decades, encompassing applications such as planting, harvesting, crop monitoring, and irrigation (Pedersen et al., 2017; Zhang et al., 2018). For instance, harvesting robots, such as those employed in fruit and vegetable picking, perform tasks with far greater precision than human workers, thereby reducing losses and improving yields (Bogue, 2018a). Additionally, robots can monitor environmental conditions, such as soil moisture and temperature, providing critical data for optimizing agricultural processes (Fountas et al., 2020). These advancements enable farmers to manage resources more effectively and adopt more sustainable practices, thereby increasing the sector's value addition. Robotics also addresses one of contemporary agriculture's most significant challenges: the labor shortage. According to a report by the Organization for Economic Co-operation and Development (OECD, 2024), agricultural labor forces are declining in many regions, pressuring the sector to adopt automated solutions to compensate for the lack of workers. Thus, robotics not only supports productivity growth but also fosters more efficient resource management and enhanced economic sustainability.

Similarly, the construction sector faces considerable challenges, such as workplace safety concerns and less automation than in other industries (Skibniewski & Golparvar-Fard, 2016).). Interest in deploying robots in construction has risen significantly, given their potential to address critical issues related to worker safety and process efficiency. Robots have been utilized in areas such as material handling, structural component prefabrication, and quality inspections (Bock, 2015). For example, robots can undertake hazardous tasks, such as handling heavy materials or welding metal structures, thereby reducing workplace injury risks (Saidi et al., 2016). Furthermore, automating inspection and quality control processes through computer vision and sensor technologies improves precision and reduces errors that could compromise construction safety and quality (Xiao et al., 2022). A study by Oke et al. (2019) highlights that robotics in construction has led to significant improvements in precision and efficiency, directly contributing to enhanced value creation within the sector.

The industrial sector have similarly benefited from robotics, particularly in consumer goods production and the automotive industry. Industrial robots have been widely deployed in assembly, painting, welding, and quality inspection processes, where efficiency and precision are paramount (Feldmann, 2022). In the automotive sector, for instance, robots perform highly precise assembly of parts and components, enhancing product quality and reducing human errors (Bogue, 2018b). Robotics thus improves production efficiency, enhances product quality, and supports long-term innovation and competitiveness within these industries.

Robots also enable operational cost reductions by optimizing production processes. Tasks that previously required extensive manual labor can now be performed more rapidly by robots, leading to reduced production costs and increased profit margins (McAfee & Brynjolfsson, 2016). Additionally, robots facilitate production diversification and product customization, offering greater flexibility to meet market demands (Antón et al., 2022; Carleton et al., 2021). Consequently, the automation of industrial processes constitutes a key factor in strengthening competitiveness and enhancing the capacity for value creation in the industrial sector.

In addition to boosting efficiency and productivity, robotics contributes to cost reduction, improves quality and safety, and enables product diversification and customization. In this context, automation and robotics technologies play a critical role in overcoming traditional challenges faced by these sectors and in fostering long-term sustainable economic growth. The adoption of these advanced technologies represents an essential pathway for the future of these industries, which must embrace innovative solutions to remain competitive in an increasingly technologized global economy.

While numerous studies have explored the impact of robotics across various economic branches, they have generally focused on the advantages and challenges associated with robotic implementation in sectors such as agriculture, industry and construction, without directly examining the relationship between robot density (the number of robots per 10,000 employees) and the gross value added generated in these sectors. Existing approaches often adopt a generalized perspective, limiting a detailed understanding of how robotics specifically contributes to productivity, efficiency, or economic growth within these domains.

To address this gap in the literature, the study employs a quantitative approach to explore how robot density relates to value added in the aforementioned sectors. Applying the Method of Moments Quantile Regression (MMQR) over the 2016–2022 period, this study investigates the effect of robot density on gross value added across the agriculture, industry, and construction sectors in 12 European Union member states: Austria, Czech Republic, Denmark, Finland, France, Germany, Italy, the Netherlands, Slovakia, Slovenia, Spain and Sweden. The selected countries represent a diverse spectrum in terms of both automation levels and economic performance, thus providing a solid foundation for comparative analysis. With Germany representing a high-automation context and countries like Slovenia and Slovakia reflecting more moderate levels of technological adoption, the sample enables a comprehensive exploration of how robot density relates to value creation across different economic and regional settings.

This research is particularly relevant as it seeks to provide a nuanced understanding of how robot density acts as a catalyst for value creation in distinct economic sectors, contributing to a deeper comprehension of the factors driving economic competitiveness. Unlike existing literature, which often discusses the impact of robotics in general terms, this study examines the specific correlation between the number of robots and gross value added in each sector, offering detailed and quantifiable insights.

This approach allows not only the identification of general trends but also a differentiated evaluation of the effects of robot density in accordance with the particular characteristics of each economic sector and country. The results will provide a solid foundation for industrial policies and technology investment strategies, directing efforts toward areas where robotics has the greatest impact on sustainable economic growth.

The structure of the study is divided into five key sections. Section 2 outlines the theoretical background and surveys the existing literature relevant to the research topic. Section 3 details the analytical framework, including the econometric techniques employed and the data sources utilized. Section 4 presents and interprets the empirical findings, while Section 5 reflects on their broader implications, drawing conclusions and suggesting potential directions for policy development and future research, alongside a discussion of the study's limitations.

2. Literature review

2.1. Robots enhancing sustainability and efficiency in agriculture

In recent decades, the agricultural industry has begun to adopt digital technologies aimed at increasing both yield and quality while reducing farming costs (Marinoudi et al., 2019; Bechar & Vigneault, 2016; Yerebakan & Hu, 2024; Calitz et al., 2017). This transformation has been a key driver of agricultural productivity growth, spurred by intensified processes, mechanization, and automation (Zhang et al., 2013). Automation is no longer confined to standardized processes; numerous agricultural activities can now be optimized through the use of robots, without completely eliminating human involvement. In many cases, robots collaborate with humans, combining technological efficiency with human expertise (Marinoudi et al., 2019).

The literature highlights multiple benefits associated with agricultural process automation, such as resource optimization and cost reduction. The use of multitasking robots and advanced sensors aids in minimizing the waste of water, chemical inputs, and energy (Acaccia et al., 2003; Gat et al., 2016). Additionally, fully autonomous agricultural robots increase labor efficiency and reduce labor costs (Cheng et al., 2023). Studies have demonstrated that automation significantly enhances the productivity of agricultural machinery through improved efficiency, reliability, and precision (Sivaraman et al., 2006). Pedersen et al. (2017) found that robotic equipment used for sowing and re-sowing increased sugar beet yields by approximately 7.7%, particularly under conditions where conventional machinery struggled to operate efficiently.

A substantial expansion in the use of autonomous robots has been observed in systems based on the Internet of Things (IoT), which integrate advanced sensors, software applications, and processing power for data exchange (Castellano & Glock, 2024; Emmi et al., 2023). These technologies have been utilized in tasks such as adaptive navigation (Zhang et al., 2021) and weed detection (Khan et al., 2020). Both terrestrial and aerial mobile robots have become essential for monitoring agricultural lands and optimizing parameters such as soil moisture and temperature (Acaccia et al., 2003; Pathan et al., 2020; Shamshiri et al., 2018).

According to Zimmer et al. (2021), robotic applications reduce reliance on human resources, enable significant cost savings in production, and increase production capacity. Similarly, Bogue (2025) argues that robots, through their capabilities and key benefits, address labor shortages, lower labor costs, and facilitate precision farming practices. Thus, agricultural automation directly contributes to reducing production costs and increasing the value added to agricultural products. Shockley et al. (2022) emphasize that small-scale autonomous equipment offers substantial economic benefits, particularly for small farms. Moreover, the implementation of IoT-based sustainable solutions reduces greenhouse gas emissions, enhancing the agricultural sector's reputation in the global market (Van Henten et al., 2002). Studies by Gonzalez-de-Soto et al. (2015, 2016) also show that agricultural robots reduce fuel consumption and atmospheric pollutant emissions. Systems such as vision-based autonomous navigation provide adaptability to variable environmental conditions, enhancing farmers' ability to respond quickly to changes and optimize production (Mohanraj et al., 2016). In addition, Wolfert et al. (2023) show IoT-enabled robots increase small farm profitability by 12% in the EU, but effects diminish in regions with low digital literacy (moderating effect).

Recent studies have also highlighted that robots enable agricultural processes to be tailored more closely to environmental needs. For instance, Jobe et al. (2025) demonstrated that robots are capable of analyzing microclimates within farms, optimizing irrigation, and minimizing water waste. Similarly, the work of Negrete (2025) showed that AI-driven robots can help in pest management, reducing the need for harmful pesticides and enhancing ecological balance.

Thus, we see that the integration of robots in agriculture not only increases efficiency and profitability, but also offers significant environmental benefits by promoting more sustainable agricultural practices. These advanced technologies allow for precise monitoring and control of agricultural processes, helping to reduce resource consumption, improve crop yields, and minimize environmental impact (Doran et al., 2024; Mihai et al., 2023). These findings align with the Factor-augmenting theoretical model, which explains how robots, as "precision capital," can lead to yield gains (Acemoglu & Restrepo, 2018). However, the substitution of tasks by robots is limited by crop variability, a factor highlighted by Lowenberg-DeBoer et al. (2020), who emphasize that not all types of crops can equally benefit from automation due to their specific characteristics.

Despite significant advancements in automation and the use of digital technologies in agriculture, there is a lack of research addressing their combined impact on economic and environmental sustainability, particularly in the context of the value added generated by the agricultural sector. The majority of current studies concentrate on the ecological benefits and operational efficiency gains brought about by robots and digital technologies in agriculture. However, there is a significant gap in research analyzing their direct impact on profitability, production costs, and the competitiveness of the agricultural sector across various regions. Furthermore, there is a shortage of generalized analyses exploring the economic benefits of agricultural robot adoption at the European Union level, considering the infrastructural and economic diversity among member states.

This research seeks to fill this gap in the literature through a quantitative assessment of the link between robot density and value added in agriculture in selected European Union countries. This approach contributes to a better understanding of the economic impact of advanced technologies in different contexts within the European Union by examining a diverse selection of countries, including both developed and developing nations. Drawing on this framework, the first hypothesis is proposed:

H1: *The density of robots in the agricultural sector of the selected European Union countries significantly drives an increase in the added economic value of agricultural activities.*

2.2. Enhancing productivity and innovation in construction with robotics

Automation in the construction sector began gaining traction as early as the 1970s, with Japan pioneering the implementation of robotic systems to boost quality and efficiency of modular housing prefabrication (Bock, 2007). These foundational initiatives marked the beginning of a gradual but steady evolution in construction robotics. In more recent years, the field has transformed into a multidisciplinary domain, incorporating cutting-edge technologies such as Advanced Technologies for Construction and Environmental Visualization (ATCEV), deep learning, and Building Information Modeling (BIM). These innovations are aimed at boosting productivity and streamlining construction processes (Xiao et al., 2022).

One of the prominent areas where robotics has made substantial inroads is in architectural design. Sophisticated software tools now enable the swift and accurate generation of 3D and 4D visual models, thereby enhancing the precision and efficiency of design planning (Castro-Lacouture, 2009). Similarly, the deployment of sensor-based and laser-guided automated inspection systems has proven effective in minimizing structural defects and reducing unnecessary expenditures (Balaguer & Abderrahim, 2008). Collectively, these technological advancements not only enhance quality control but also significantly improve operational efficiency and contribute to greater value generation within the construction industry.

A study conducted by Chang and Hasanzadeh (2024) highlights the critical role of robots in construction, emphasizing how trust-building between workers and robots can enhance safety and productivity. By developing a roadmap for trust in three phases – static, dynamic, and adaptive – the research provides a framework for effectively integrating robots into construction sites, ensuring both operational efficiency and worker safety. it can be observed that the successful implementation of robots in construction depends on fostering trust through clear and adaptive strategies, which will drive innovation and improve overall industry performance. This contribution is valuable as it addresses an essential aspect of technology adoption in high-risk environments.

Moreover, Ohueri et al. (2024) highlighted three significant innovations in Human-Robot Collaboration (HRC) applied to building deconstruction: virtual reality–based training for human-robot teams, AI-supported material sorting, and emotionally adaptive robots capable of adjusting their behavior in response to dynamic conditions. These advancements are expected to significantly enhance safety, efficiency, and adaptability in deconstruction tasks, while also paving the way for future research directions in Construction 5.0.

The adoption of robotic technologies is reshaping the construction industry by reducing reliance on manual labor, increasing workplace safety, and boosting operational efficiency. Automation in areas such as earthmoving and prefabrication, coupled with developments in autonomous assembly techniques, is contributing to greater precision and improved structural outcomes. With ongoing technological progress and a more technically skilled labor force, the sector is poised for continued innovation and productivity gains (Melenbrink et al., 2020).

Moreover, recent studies, such as that of Faheem et al. (2024), emphasizes notable advancements in the use of artificial intelligence and robotics for handling complex and hazardous construction operations, underscoring the expanding role of intelligent systems in enhancing performance under challenging conditions. These state-of-the-art tools, including machine learning and visual computing, are critical for developing systems focused on continuous safety monitoring, error detection, progress tracking, and maintenance assessments. Additionally, Bademosi and Issa (2021) finds that robot adoption in EU construction raises value added only when paired with modular design standards, a moderating institutional factor. Furthermore, Islam et al. (2025) highlight significant improvements in construction project outcomes, with firms employing robotics and automation technologies delivering results such as 30% faster task completion, 40% lower material consumption, and 50% fewer workplace incidents, resulting from the integration of AI-enabled protective solutions and automated machines. Also, Bogue (2025) emphasizes that a diverse range of robots are finding uses in the construction industry, automating and improving many traditional practices. These technologies bring significant benefits, including reduced labor requirements, improved safety, increased productivity, reduced environmental impact, and enhanced overall efficiency, thus addressing many of the challenges faced by the industry.

This can be framed within the theoretical model of Modular Design as a Moderating Factor in Construction Robotics, based on the findings of Bademosi and Issa (2021), who investigates the impact of robots on value-added in the EU construction sector. They emphasize that the benefits of robotics in construction are contingent upon high levels of design standardization. He argues that robots stimulate value-added only in contexts with a high degree of modular design, which is essential for maximizing their efficiency. This model supports the hypothesis that robotics in construction can drive value creation, but only under conditions where modularity and standardization are present.

Although significant progress has been made in advancing automation within the construction sector, its widespread adoption remains constrained. Feldmann (2022) points out that despite growing attention to robotics and automation technologies is on the rise, the substantial upfront investment often deters broader implementation, as anticipated long-term savings may not sufficiently offset initial costs. In a similar vein, research by Bademosi and Issa (2021) and Hu et al. (2021) highlights the pivotal influence of factors such as overall construction expenses, the scale of government involvement, and the degree of prefabrication. These elements are instrumental in determining the pace and scale at which robotic technologies are embraced across the construction industry.

While the potential of robotics in construction is substantial, the sector is currently experiencing only partial adoption. The widespread implementation of such technologies is contingent upon overcoming various economic and regulatory obstacles. This scenario mirrors gaps identified in agricultural research, where the association between robot utilization and value added remains under-investigated. Current research on automation and digitalization in the construction sector emphasizes overarching trends, often suggesting positive economic effects from increased efficiency and productivity. However, there is a lack of research directly studying the influence of robot deployment on economic value output, particularly within the context of diverse national settings.

Moreover, the existing literature does not offer a comprehensive analysis of this issue, especially in relation to an extensive set of countries, especially within the European Union. In this context, economic and infrastructural divergences among member states could have significant implications for the outcomes of such studies. Such gaps emphasize the necessity for in-depth research into the precise influence of robotic density on the construction sector's economic performance, taking into account the varied economic and infrastructural conditions across EU member states.

In light of this, the following represents the second hypothesis:

H2: *Increasing the deployment of robotics in construction may contribute to higher value generation in this field across all participating nations, independent of their economic maturity.*

2.3. The Impact of industrial robots on performance and industrial dynamics

Industrial robots have become a fundamental component of contemporary manufacturing, driving substantial changes in production systems and reshaping the structure of global industries (Bartoš et al., 2021; Papavasileiou et al., 2025; Pedersen et al., 2016; Singh & Banga, 2022; van Dam, et al., 2021). Progress in AI, integrated sensors, and visual recognition systems has substantially strengthened robotic capabilities, making it possible for them to handle intricate operations with remarkable accuracy and safety. Advancements in technology have brought about meaningful increases in productivity, cost-effectiveness, and production quality, establishing robotics as a critical asset for firms seeking to remain competitive in an increasingly volatile and fast-paced global market. Nevertheless, the deployment of robotics is not without its challenges, particularly with respect to labor market implications and the substantial capital investment required for implementation. A comprehensive understanding of these diverse impacts is essential for businesses, policymakers, and labor representatives as they adapt to this evolving technological landscape.

As reported in the 2024 edition of the World Robotics (2024) Report, operational robots in manufacturing facilities totaled 4,281,585 in 2023, marking a 10% rise compared to the previous year. This growth has been largely driven by rapid advancements in AI and sensor-based systems, which continue to enhance the efficiency and reliability of industrial robots, thereby further elevating productivity across a wide range of manufacturing processes (Galin & Meshcheryakov, 2019).

Asia continues to lead the global adoption of industrial robotics, accounting for roughly 70% of the newly installed units were deployed in Asia, followed by Europe with 17% and the Americas with 10% (International Federation of Robotics, 2024). Among the sectors driving this growth, the automotive industry is particularly prominent, with countries such as Spain, Slovakia, and Hungary registering significant increases in robot deployment – 31%, 48%, and 31%, respectively. These figures reflect the strategic role of robotics in improving operational efficiency and sustaining international competitiveness.

The broader implications of industrial robot adoption on labor markets and economic structures have sparked considerable academic interest. In an analysis of Japan, Dekle (2020) identified three key mechanisms through which robotics influences employment. First, the substitution effect occurs when robots replace humans in repetitive or hazardous roles, thereby decreasing the demand for manual labor. Second, the productivity effect emerges as automation reduces production costs, boosting demand and potentially increasing sectoral employment. Third, the general equilibrium effect suggests that automation-induced economic growth can generate broader employment gains across the entire economy.

Technological advances have also given rise to collaborative robots, or cobots, which are equipped with sophisticated AI, sensors, and vision systems, enabling them to operate safely alongside human workers (Zhao et al., 2022). This collaboration not only enhances safety but also contributes to higher productivity. Moreover, the adaptability of industrial robots allows them to be deployed across multiple industries and applications – from assembly lines to quality assurance – making them vital tools for optimizing production across diverse economic sectors (Goel & Gupta, 2020).

Robotic technologies have brought significant advancements to the aerospace sector, enabling manufacturers to streamline operations by cutting costs, minimizing labor requirements, improving output quality, and unlocking new possibilities in production processes (Bogue, 2018b). Despite reducing human labor in specific functions, the deployment of robots yields a positive economic impact by improving productivity and expanding demand in technology-dependent industries. When implemented effectively, robotization can stimulate economic growth and generate new job opportunities, counteracting fears of widespread job displacement (McAfee & Brynjolfsson, 2016).

A major advantage of industrial robots lies in their ability to improve product quality. Their precision and consistency in performing tasks enable the production of higher-quality goods, which are crucial for maintaining competitive advantage in global markets (Barosz et al., 2020).

However, the integration of robots into industry is not without its challenges. One of the most common concerns is the potential for job losses, especially in industries that rely heavily on manual labor. Nevertheless, recent studies suggest that the introduction of robots does not necessarily result in a significant reduction in employment, but rather a shift in the workforce towards more specialized skills (McAfee &Brynjolfsson, 2016).

The initial investment required for acquiring and installing industrial robots, along with ongoing maintenance costs, can be a barrier for many companies. "The high upfront costs associated with robot purchases can create financial challenges, especially for smaller businesses" (Jung & Lim, 2020). However, over time, the reduction in production costs and the increased operational efficiency brought about by robotic automation can offset these initial expenditures, making robot investments more feasible in the long term.

On the other hand, Urrea and Kern (2025) examine the evolution of industrial robotics, focusing on the role of AI, machine learning, and sensors in enhancing efficiency and human-robot collaboration. It highlights barriers like high costs, system incompatibilities, and ethical issues, particularly for SMEs, it proposes research avenues focused on affordable modular design, unified standards, and ethical guidelines to tackle issues related to scalability and long-term viability in robotics. Although robotics has reached a high level of maturity in numerous industrial fields, it continues to face considerable technical and societal obstacles (Dzedzickis et al., 2022). To overcome these challenges, researchers emphasize the need for firm-level innovation capabilities – a cornerstone of endogenous growth theory (Romer, 1990). Efforts to improve intelligent equipment and human-robot collaboration must be paired with adaptive management practices (e.g., decentralized decision-making, upskilling) to fully harness productivity gains. As Bachmann et al. (2024) demonstrate, robots increase value added by 5% in EU industrial firms – but only when complemented by such organizational innovation. This aligns with the broader endogenous growth paradigm, where technology diffusion depends on localized investments in human capital and Research and Development.

In conclusion, while industrial robots offer economic advantages (productivity, cost reduction, quality), maximizing their benefits requires addressing both technical barriers and firm-level adaptability. Robotization thus represents a dual challenge and opportunity: it demands workforce reskilling and managerial innovation to achieve sustainable growth, particularly in the EU's diverse industrial landscape.

While robotics has been widely studied, there remains a lack of empirical evidence quantifying its contribution to value creation, particularly across European countries with differing levels of technological advancement and innovation capacity. To bridge this gap, the present research puts forth the following final hypothesis:

H3: *The deployment of industrial robots across European nations positively influences the expansion of industrial value-added output.*

According to the literature, the use of robots in different sectors such as agriculture, industry and construction, has introduced both significant advantages and considerable challenges. One of the key benefits is increased productivity. Robots enhance the efficiency of production processes by reducing the time required for repetitive and labor-intensive tasks. This leads to substantial productivity growth in industries like automotive, as highlighted by Kangru et al. (2019) and Bachmann et al. (2024).

Another major advantage is the reduction of production costs. Once implemented, robots can lower long-term costs by optimizing the use of human resources and minimizing human errors. This benefit is particularly evident in the manufacturing industry, where automation results in significant cost savings (Frey & Osborne, 2017).

Robots also improve quality and consistency in production. Their ability to perform tasks with high precision ensures a consistent level of product quality, which is critical in sectors such as automotive and electronics. This has been emphasized by Bogue (2018a), who notes that precision-driven automation contributes to superior product outcomes.

Furthermore, the deployment of robots creates new jobs and technological roles. Although some jobs may be replaced by automation, new opportunities emerge, including positions like robot programmers, maintenance technicians, and AI specialists. This shift is particularly pronounced in high-tech industries, as observed by Dauth et al. (2017).

Despite these advantages, challenges and disadvantages persist. Over time, these include concerns about workforce displacement and the need for significant financial investments in robotic technology. Figure 1 provides an overview of these challenges, emphasizing the necessity for ongoing adaptation and research to ensure that the benefits of robotization are maximized across various sectors.

As a result, a primary disadvantage of using robots in industries is job displacement. Robots take over roles involving repetitive and manual tasks, such as those in industry or large-scale agriculture. This can lead to job losses for unskilled or semi-skilled workers, particularly in regions where such activities are predominant. Studies by Acemoglu and Restrepo (2020) highlight that this phenomenon specifically affects regions where human labor is essential for operations.

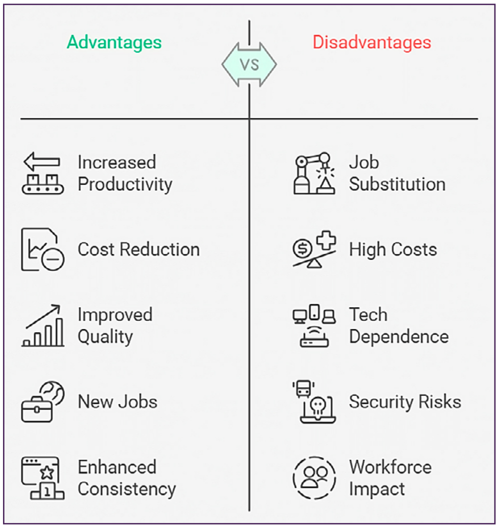

Figure 1. Advantages and disadvantages of robot utilization in key economic sectors (source: own processing)

Another drawback pertains to the high initial costs of implementing robots. Although long-term savings may offset these expenses, the upfront investments required for purchasing and integrating robots into production processes are substantial. This represents a significant barrier for small and medium-sized enterprises, particularly in sectors such as construction, where the initial capital needed to implement robotic technology can be difficult to secure (Bogue, 2018b).

Additionally, the increased reliance on technology brings security risks. The implementation of robots in industrial processes amplifies vulnerabilities to cyberattacks. Attacks on IT systems or technical failures can cause significant production disruptions, negatively affecting efficiency and performance. According to research by Brynjolfsson and McAfee (2014), these technological risks are more acute in industries with widespread use of robots, as reliance on technology deepens.

Finally, robotization may negatively impact workforce diversity. In certain sectors, robotization favors the concentration of jobs among specific groups of workers, such as those with advanced technical skills, while other groups, particularly those without technical training, may be excluded from the labor market. This phenomenon can exacerbate existing economic and social inequalities and lead to a polarization of the labor market (Brynjolfsson & McAfee, 2014).

To accurately assess the specific impact of robot density on sectoral economic performance, this study includes three essential control variables: real GDP growth (GDP), research and development expenditure (RD), and Human Resources in Science and Technology (HRST). These variables are consistently recognized in the literature as core drivers of productivity and value generation. The inclusion of GDP growth reflects broader macroeconomic conditions that influence sectoral output levels, aligning with the findings of Graetz and Michaels (2018), who emphasize the need to control for aggregate demand shocks. R&D expenditure is incorporated to capture the role of innovation as a complementary or competing driver of productivity, particularly in high-tech sectors, as documented by Bachmann et al. (2024) and Acemoglu and Restrepo (2018). Lastly, HRST is introduced as a proxy for the availability of skilled labor, which conditions the absorptive capacity for technological adoption (Grafström & Alm, 2025; Urrea & Kern, 2025). This variable reflects the critical role of human capital in ensuring that robotics are not only deployed but also effectively integrated into production processes. Together, these control variables allow the model to more precisely identify the unique contribution of robot density, while accounting for structural factors that may independently influence gross value added across sectors.

This study represents a methodological and empirical extension of the research conducted by Doran et al. (2024), which assessed the economic effects of robot deploymen in three critical areas: manufacturing, construction, and the broader industrial sector excluding construction. While their analysis provided important insights into how robotics affects various technology-intensive sectors differently, the present study advances this framework by integrating the agricultural sector into the investigation, with a substantial contribution to national Gross Domestic Product (GDP). This sector, despite being traditionally underrepresented in automation-related research, maintains a fundamental role in national economic output and employment, particularly in rural and semi-rural regions of the European Union.

In contrast to the recent study, we have not excluded manufacturing but incorporated it within the broader scope of the industrial sector, recognizing the growing convergence between manufacturing and other industrial domains. The inclusion of the agricultural sector is grounded in the increasing relevance of agri-tech innovations and precision farming technologies, which signal a gradual but notable transformation of agricultural production systems. As automation tools such as autonomous machinery, robotic harvesters, and AI-powered monitoring systems become more accessible, their potential to enhance productivity, reduce labor shortages, and promote sustainable practices becomes increasingly significant. By examining this sector alongside the others, the study not only captures a more holistic picture of automation's economic effects but also contributes to a growing body of literature that explores the intersection of digitalization and sustainable rural development. This broader analytical scope enables a better understanding of how robotics can support balanced economic growth across diverse sectoral environments.

In light of the findings in existing literature, our research aims to deepen the understanding of the economic impact of robotization through a comprehensive analysis of its effects on various economic sectors. This study will contribute to the expansion of knowledge in the field of automation technologies, providing a more nuanced perspective on how robotization influences productivity, efficiency, and value-added across fundamental sectors of the economy. Specifically, the study focuses on assessing the impact of these technologies not only in the developed regions of the European Union, where advanced technologies are already being implemented on a large scale, but also in the developing regions, where the process of adopting automation is still in its early stages. This comparative approach will offer a more detailed understanding of how robotization can support balanced economic growth, reducing disparities between more advanced and less developed regions, and will contribute to the formulation of more effective public policies aimed at promoting sustainable and inclusive development within the European Union.

3. Data and methodology

This paper explores how robot density influences industrial performance within a panel of 12 EU member states chosen for in-depth analysis, aiming to explore the economic impact of automation. Covering the period from 2016 to 2022, the study draws on data from Eurostat (2006), the International Federation of Robotics [IFR, 2024], and the World Robotics (2024) database. The countries analyzed include Austria, Czechia, Denmark, Finland, France, Germany, Italy, the Netherlands, Slovakia, Slovenia, Spain, and Sweden. The selection of the twelve EU countries was guided by three primary criteria: data availability and consistency for the 2016–2022 period across all variables included in the study; diversity in levels of robot adoption, from high (Germany, Sweden) to moderate or emerging (Slovakia, Slovenia); and regional and economic heterogeneity across the European Union, allowing for the assessment of how automation impacts economies with varying industrial structures, labor markets, and innovation capacities. This selection ensures both robustness and representativeness in analyzing the relationship between robot density and economic performance. The analysis focuses on key sectors of the economy, as reflected by the Gross Value Added (GVA) metric in agriculture, forestry, and fishing (AGRI); construction (CONS); industry excluding construction (IND). While GVA is used as the main indicator of sectoral economic performance, we acknowledge the benefit of further disaggregating it into its core components: compensation of employees, consumption of fixed capital, and gross operating surplus/mixed income. However, such a breakdown was not feasible across all countries and sectors due to inconsistencies in data reporting over the analyzed period. The primary variable under investigation – robot density (ROBOTS) – is defined as the number of industrial robots deployed per 10,000 workers, serving as an indicator of automation intensity within the studied economies. The analysis also integrates several other factors related to macroeconomic conditions and innovation, such as the rate of real GDP growth (GDP), investment in Research and Development (RD), and the percentage of the workforce employed in science and technology fields (HRST). The control variable HRST was operationalized based on Eurostat's definition, which includes individuals aged 25–64 who have completed tertiary education (ISCED levels 5–8) and/or are employed in scientific and technical occupations (ISCO groups 2 and 3). This variable serves as a proxy for a country's capacity to support and implement advanced technological systems, such as robotics, by indicating the proportion of the workforce with the requisite skills in science and technology.

This research applies a methodical combination of statistical and econometric tools to strengthen the reliability and richness of its conclusions. It begins with descriptive statistics, which provide an overview of the data by examining measures of central tendency, variability, and distribution. This initial step is essential for spotting patterns or irregularities that might influence further analysis. The next phase involves assessing cross-sectional dependence, based on the methodologies of Pesaran (2015) and Fan et al. (2016), to identify interconnections among the panel data units – an important step to prevent biased or inaccurate results. Following this, to assess slope heterogeneity, the study applies the Pesaran and Yamagata (2008) procedure, which tests whether the relationships between variables differ across cross-sectional units, thus questioning the commonly assumed homogeneity of coefficients in panel data models.The methodology then assesses the stationarity of the data through unit root analysis, based on Im's et al. (2003) approach. Identifying whether the variables are stationary or non-stationary informs the choice of econometric techniques and helps prevent spurious regression results. Subsequently, cointegration analysis is performed using Westerlund's (2005) and Pedroni's (2004), methods employed to test for a persistent long-term association among variables. Evidence of cointegration supports the notion that, despite short-term divergences, the variables tend to evolve together over time. We acknowledge the limitations associated with unit root testing in short panels. The panel used in this study has a temporal dimension of T = 7 (2016–2022), which may compromise the power and reliability of conventional unit root tests. Despite this constraint, we employed the Im et al. (2003) test, which is widely accepted in small-T panel settings and allows for heterogeneity across cross-sections. Nonetheless, we interpret the results with caution and primarily use stationarity analysis as a robustness check rather than as a conclusive diagnostic.

The analysis adopts the Method of Moments Quantile Regression (MMQR), proposed by Machado and Santos Silva (2019), to address heterogeneity and distributional characteristics across the data. This advanced technique allows for the assessment of how explanatory variables influence different points (quantiles) of the dependent variable's distribution, making it particularly suitable for models that include individual-specific effects and potentially endogenous regressors.

The Method of Moments Quantile Regression (MMQR), developed by Machado and Santos Silva (2019), estimates the conditional quantiles of the dependent variable by modeling them as a function of observed covariates and unobserved heterogeneity. The general form of the model is expressed as:

$$Q_\tau\left(Y_{it} \mid Z_{it}\right) = \mu_\tau + Z_{it}\psi_\tau, \tag{1}$$

where $Q_\tau\left(Y_{it} \mid Z_{it}\right)$ is the conditional quantile of the dependent variable, Y_{it} (i.e., GVA in agriculture, construction, or industry) at quantile τ, Z_{it} is a vector of explanatory variables: robot density (ROBOTS), real GDP growth rate (GDP), research and development expenditure (RD), and human resources in science and technology (HRST), μ_τ captures the individual-specific effects at quantile τ, ψ_τ is the vector of quantile-specific slope coefficients.

This model allows for heterogeneity across quantiles and cross-sectional units, providing robust estimates even in the presence of non-normality or outliers. The MMQR is particularly suitable for analyzing the distributional effects of covariates when the relationship between variables varies at different levels of the outcome distribution.

Building on Machado and Santos Silva (2019), Eq. (1) is adapted to suit our models and is expressed as follows:

$$\mathrm{AGRI}_{it}\left(\tau_k \mid \alpha_i, x_{it}\right) = \alpha_i + \psi_1\tau\mathrm{ROBOTS}_{it} + \psi_2\tau\mathrm{GDP}_{it} + \psi_3\tau\mathrm{RD}_{it} + \psi_4\tau\mathrm{HRST}_{it}; \tag{2}$$

$$\mathrm{CONS}_{it}\left(\tau_k \mid \alpha_i, x_{it}\right) = \alpha_i + \psi_1\tau\mathrm{ROBOTS}_{it} + \psi_2\tau\mathrm{GDP}_{it} + \psi_3\tau\mathrm{RD}_{it} + \psi_4\tau\mathrm{HRST}_{it}; \tag{3}$$

$$\mathrm{IND}_{it}\left(\tau_k \mid \alpha_i, x_{it}\right) = \alpha_i + \psi_1\tau\mathrm{ROBOTS}_{it} + \psi_2\tau\mathrm{GDP}_{it} + \psi_3\tau\mathrm{RD}_{it} + \psi_4\tau\mathrm{HRST}_{it}. \tag{4}$$

The choice of the Method of Moments Quantile Regression (MMQR), developed by Machado and Santos Silva (2019), is particularly justified in the context of this study due to several methodological advantages over traditional panel regression approaches. Unlike standard fixed effects or random effects models that estimate mean effects, MMQR enables the analysis of the entire conditional distribution of the dependent variable (e.g., Gross Value Added) across different quantiles. This is crucial when the impact of key explanatory variables, such as robot density, is not uniform across all performance levels of a sector.

Furthermore, MMQR accounts for individual heterogeneity in both location (central tendency) and scale (dispersion), making it robust to unobserved effects and heteroskedasticity. In contrast, traditional estimators such as Pooled OLS or GMM may produce biased results under non-normal error structures or when effects vary across distributional quantiles. This feature is especially relevant in this study, where substantial cross-country variability and sectoral asymmetries exist. The MMQR thus provides richer and more reliable insights into how robot density affects sectoral performance across varying economic contexts.

4. Results and discussion

Table 1 provides a detailed descriptive analysis of the variables under study, offering insights into their central tendencies, dispersion, and distributional characteristics. Robot density (ROBOTS) has a mean of 203.96, ranging from 101 to 415, with a standard deviation of 65.31, indicating moderate variability. Its positive skewness (1.28) and kurtosis (4.27) reveal a right-skewed distribution with heavier tails, and the significant Jarque-Bera statistic (28.49, $p < 0.01$) confirms non-normality.

The gross value added in agriculture (AGRI) averages 14,219.02, with a wide range from 721.70 to 46,817.90 and a substantial standard deviation of 13,655.69, reflecting considerable variation among the countries. The data distribution is moderately right-skewed (0.68) with a flatter peak (kurtosis = 1.81). The Jarque-Bera statistic (11.40, $p < 0.01$) suggests a significant deviation from normality. Similarly, the gross value added in construction (CONS) exhibits a high mean of 45,293.38, ranging between 1,759.90 and 173,919, with substantial variability (SD = 45,693.40). The positive skewness (1.19) and kurtosis (3.25) indicate a right-skewed and slightly peaked distribution, further confirmed by the significant Jarque-Bera statistic (20.01, $p < 0.01$). The gross value added in industry (IND) has the highest mean (214,853.6), spanning from 14,543 to 985.742, with a large standard deviation (212,329.5), indicating extreme variability. This variable's high skewness (2.45) and kurtosis (5.36) point to a highly asymmetric and leptokurtic distribution. The significant Jarque-Bera statistic (108.31, $p < 0.01$) strongly supports its non-normality.

Table 1. Descriptive analysis

Variables	ROBOTS	AGRI	CONS	IND	GDP	RD	HRST
Maximum	415.00	46817.90	173919.00	985742.00	8.90	3.50	64.10
Minimum	101.00	721.70	1759.90	14543.00	–10.90	0.79	34.20
Mean	203.96	14219.02	45293.38	214853.60	1.92	2.27	50.28
Std. Dev.	65.30	13655.69	45693.40	212329.50	3.48	0.79	8.28
Skewness	1.27	0.67	1.18	2.45	–1.30	–0.21	–0.30
Kurtosis	4.27	1.81	3.24	5.36	5.66	1.84	1.94
Jarque-Bera	28.48	11.39	20.01	108.31	48.45	5.26	5.10
Probability	0.0000	0.0033	0.0000	0.0000	0.0000	0.0719	0.0779

For real GDP growth rate (GDP), the mean is 1.93, with extreme values ranging from –10.9 to 8.9 and a standard deviation of 3.49, reflecting considerable variation. The negative skewness (–1.30) suggests a left-skewed distribution, while the kurtosis (5.67) indicates a sharper peak. The Jarque-Bera test (48.46, $p < 0.01$) confirms significant non-normality. In contrast, research and development expenditure (RD) demonstrates lower variability, with a mean of 2.27 and a standard deviation of 0.79, spanning from 0.79 to 3.50. Its distribution is nearly symmetric (skewness = –0.21) and platykurtic (kurtosis = 1.85), and the Jarque-Bera test (5.26, $p > 0.05$) suggests no significant departure from normality.

Finally, the average value of human resources in science and technology (HRST) is 50.29, ranging from 34.20 to 64.10, with a standard deviation of 8.29. Its distribution is slightly left-skewed (–0.30) and relatively flat (kurtosis = 1.95). The Jarque-Bera test (5.10, $p > 0.05$) indicates approximate normality. Overall, the analysis reveals significant variability and pronounced non-normality in several variables, such as ROBOTS and IND, while variables like RD and HRST display characteristics closer to normal distributions. These results underscore the necessity of employing econometric methods that account for the observed heterogeneity and non-normality.

Table 2 provides a detailed examination of cross-sectional dependency and slope heterogeneity within the dataset, providing valuable insights into the underlying structural relationships among the variables and models examined.

The analysis of cross-sectional dependence indicates strong interdependencies among all variables, as confirmed by the results of both Pesaran's CD test and Fan's CD test. For AGRI, the Pesaran's CD statistic is 8.02 ($p < 0.01$), and Fan's CD statistic is 83.83 ($p < 0.01$), strongly indicating the presence of cross-sectional dependence. Similar patterns are observed for other variables: CONS (Pesaran = 18.24, Fan = 148.41) and IND (Pesaran = 18.78, Fan = 153.13). The variable ROBOTS also shows substantial cross-sectional dependency (Pesaran = 17.41, Fan = 135.66), suggesting that robot density has a shared influence across countries. Further, macroeconomic indicators such as GDP (Pesaran = 18.99, Fan = 155.16) and innovation-related variables like RD (Pesaran = 9.04, Fan = 95.76) and HRST (Pesaran = 17.43, Fan = 134.58) exhibit strong cross-sectional dependencies. These results imply that externalities or common shocks, such as technological advancements or economic cycles, significantly affect all countries in the panel.

The slope heterogeneity analysis evaluates whether the relationships between variables differ across cross-sectional units. For Model-1 (AGRI, ROBOTS, GDP, RD, HRST), the first test statistic (0.910, $p = 0.363$) indicates no significant slope heterogeneity, while the second statistic (2.408, $p = 0.016$) suggests significant heterogeneity. This mixed outcome implies that the relationship between agricultural performance and the independent variables may vary across countries in certain aspects. For Model-2 (CONS, ROBOTS, GDP, RD, HRST), neither test statistic (0.339, $p = 0.734$; 0.898, $p = 0.369$) indicates significant slope heterogeneity, suggesting that the relationships in the construction sector are largely homogenous across countries. Similarly, for Model-3 (IND, ROBOTS, GDP, RD, HRST) both statistics (0.375, $p = 0.421$; 0.765, $p = 0.402$) are insignificant, indicating consistent relationships across countries in the industrial sector.

Table 2. Assessment of cross-sectional dependence and parameter slope variability

Detection of cross-sectional dependence across variables							
	AGRI	CONS	IND	ROBOTS	GDP	RD	HRST
Test CD Pesaran	8.02	18.24	18.78	17.41	18.99	9.04	17.43
p-val. Pesaran	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Test CD Fan	83.83	148.41	153.13	135.66	155.16	95.76	134.58
p-val. Fan	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Assessment of slope coefficient heterogeneity							
		Model-1		Model-2		Model-3	
		AGRI		CONS		IND	
Stat		0.91	2.408	0.339	0.898	0.375	0.621
p-value		0.363	0.016	0.734	0.369	0.421	0.402

Table 3 presents the results of cointegration tests, providing evidence of long-run equilibrium relationships among the core variables across the three sector-specific models –agriculture, construction, and industry. The Pedroni test statistics, which include the Modified Phillips-Perron t, Phillips-Perron t, and Augmented Dickey-Fuller t statistics, uniformly indicate strong statistical significance at the 1% level across all three models. This robust statistical evidence confirms the presence of cointegration, suggesting that the variables under examination – robot density, GDP growth, R&D expenditure, and HRST – exhibit stable long-term relationships with gross value added (GVA) within each sector. The consistency of cointegration across models supports the theoretical assumption that sectoral performance and technological variables co-move over time despite short-term fluctuations. Notably, the inclusion of innovation- and labor-related covariates (RD and HRST) strengthens the structural interpretation of these long-run relationships, underscoring the relevance of innovation ecosystems in shaping economic performance.

The findings from the Pedroni test are further substantiated by the Westerlund variance ratio test, albeit with slightly more nuanced results. While the test confirms significant cointegration in the construction and industrial models (p = 0.0367 and p = 0.0213, respectively), the agricultural model yields a non-significant result (p = 0.2414). This discrepancy may reflect sector-specific dynamics such as the structural rigidity of agriculture or the delayed manifestation of technological impacts in this sector. It also suggests that while long-run relationships exist, they may not be uniformly robust across all performance contexts –particularly

Table 3. Panel cointegration test results: Pedroni and Westerlund approaches

Test statistic	Model 1 – Stat	p-value	Model 2 – Stat	p-value	Model 3 – Stat	p-value
Pedroni test						
Modified Phillips-Perron t	4.09	0.0000	4.44	0.0000	4.28	0.0000
Phillips-Perron t	–12.10	0.0000	–8.19	0.0000	–9.45	0.0000
Augmented Dickey-Fuller t	–17.46	0.0000	–7.33	0.0000	–8.35	0.0000
Westerlund variance ratio test	0.70	0.2414	1.79	0.0367	1.89	0.0213

in sectors where technological diffusion is less mature. Taken together, the cointegration analysis validates the econometric foundation of the MMQR estimations presented later in the study. The presence of cointegration implies that any short-run deviations between variables are likely to converge toward equilibrium over time, thereby enhancing the reliability of inferences drawn from subsequent quantile regression results. These findings lend empirical support to the broader hypothesis that robotization, innovation inputs, and human capital are structurally interlinked with sectoral economic performance across the selected EU countries.

The results of the MMQR estimations, as shown in Table 4, the results indicate that robot density has a consistently positive and statistically significant impact on Gross Value Added (GVA) across the examined sectors: agriculture, construction, and industry. However, the magnitude and distributional pattern of this effect vary notably by sector, underscoring the importance of sector-specific dynamics in the adoption and productivity outcomes of robotics.

Table 4. MMQR estimation results for sectoral impact of robot density on GVA

		location	scale	Q25	Q50	Q75	Q90
ROBOTS							
AGRI	Coefficient	1.0929	0.3900	0.7499	1.0326	1.4662	1.5481
	Probability	(0.008)	(0.075)	(0.104)	(0.015)	(0.001)	(0.002)
CONS	Coefficient	1.5649	0.1908	1.4287	1.5510	1.7408	1.8092
	Probability	(0.000)	(0.416)	(0.000)	(0.000)	(0.000)	(0.001)
IND	Coefficient	1.8158	0.3576	1.6355	1.7792	2.2617	2.4448
	Probability	(0.000)	(0.052)	(0.000)	(0.000)	(0.000)	(0.000)
GDP							
AGRI	Coefficient	–0.0151	0.0075	–0.021	–0.0162	–0.0078	–0.0063
	Probability	(0.375)	(0.402)	(0.251)	(0.344)	(0.676)	(0.752)
CONS	Coefficient	–0.0129	0.0088	–0.0192	–0.0135	–0.0047	–0.0015
	Probability	(0.380)	(0.318)	(0.212)	(0.358)	(0.787)	(0.937)
IND	Coefficient	–0.0076	0.0083	–0.0160	–0.0085	–0.0022	0.0035
	Probability	(0.381)	(0.377)	(0.232)	(0.467)	(0.785)	(0.838)
RD							
AGRI	Coefficient	–0.1247	–1.3633	1.0741	0.0860	–1.4291	–1.7155
	Probability	(0.851)	(0.000)	(0.153)	(0.906)	(0.041)	(0.043)
CONS	Coefficient	0.2516	–0.9686	0.9428	0.3222	–0.6408	–0.9876
	Probability	(0.663)	(0.005)	(0.122)	(0.590)	(0.341)	(0.234)
IND	Coefficient	0.7556	–0.8422	1.6979	0.8933	0.0165	–0.5123
	Probability	(0.126)	(0.002)	(0.004)	(0.056)	(0.890)	(0.467)
HRST							
AGRI	Coefficient	–0.5895	1.2106	–1.6542	–0.7767	0.5687	0.8230
	Probability	(0.636)	(0.066)	(0.234)	(0.543)	(0.678)	(0.578)
CONS	Coefficient	–0.8260	1.0446	–1.5714	–0.9021	0.1364	0.5104
	Probability	(0.460)	(0.122)	(0.181)	(0.424)	(0.918)	(0.738)
IND	Coefficient	–1.9312	0.7021	–2.2991	–3.2342	–1.9925	–1.7837
	Probability	(0.043)	(0.098)	(0.012)	(0.004)	(0.039)	(0.063)

In the agricultural sector, as shown also in Figure 2, the coefficient estimates for ROBOTS suggest a modest but positive effect at the lower and middle quantiles (Q25 and Q50), with the effect becoming statistically significant and considerably stronger at higher quantiles (Q75 and Q90). Specifically, the coefficient reaches 1.4662 at Q75 and 1.5481 at Q90, both significant at the 1% level. These findings suggest that the contribution of robot density to agricultural value added is more pronounced in high-performing agricultural systems. This distributional pattern may reflect structural constraints in lower-performing contexts, such as limited capital investment, lower digital infrastructure, or labor market rigidities, which inhibit the effective integration of robotics. Conversely, in technologically advanced and capital-intensive agricultural environments, robotic technologies are more likely to yield measurable productivity gains, thereby enhancing value creation. The agricultural sector presents a somewhat more selective pattern of influence. Although the study confirms a positive and significant relationship between robot density and value added at higher quantiles, the results are less robust at lower quantiles. This is consistent with the findings of Bechar and Vigneault (2016) and Shockley et al. (2022), who argue that agricultural robotics is most beneficial in large-scale, technologically advanced operations. Additionally, Lowenberg-DeBoer et al. (2020) emphasize the limitations posed by crop variability and infrastructure constraints, which may partly explain the muted effect of robot density in lower-performing agricultural contexts. The present findings also reinforce Wolfert et al. (2023), who found that the benefits of agricultural automation are moderated by digital literacy and regional infrastructure, both of which may be lacking in countries or areas with low agricultural GVA.

In the construction sector, robot density also shows a positive and statistically significant effect on GVA, though with a more uniform distribution across quantiles. The coefficients are consistently significant from Q25 to Q90, ranging from 1.4287 to 1.8092, indicating that the benefits of robotization in construction are not confined to the upper end of the performance distribution. This finding suggests that even moderately performing construction contexts can leverage robotics – particularly in domains such as prefabrication, material handling, and automated inspection – to enhance productivity and safety. Unlike agriculture, the broader impact observed in construction may be attributed to the increasing modularization and standardization of construction processes, which facilitate the integration of automation technologies across various project types and scales. The findings for the construction sector contribute to a more nuanced and cautiously optimistic view compared to previous research. While existing literature, including Bademosi and Issa (2021) and Feldmann (2022), points to substantial potential for robotics in construction, it also highlights significant barriers to widespread adoption, such as high upfront costs, lack of modular design, and limited standardization. Our results confirm that robot density has a strong and statistically significant impact on construction value added at higher quantiles, suggesting that automation is more successful in large-scale or highly organized projects (Figure 3). However, the lack of significance at the scale level and mixed effects at lower quantiles are consistent with the literature's concerns about fragmented implementation and uneven institutional readiness.

The industrial sector exhibits one of the most robust and consistently positive relationships between robot density and value added (Figure 4). Across all quantiles, the coefficients for ROBOTS are statistically significant, with p-values at or below the 5% level – and most notably at the 1% level from Q25 through Q90. The effect of robot density increases steadily across the distribution, from 1.6355 at Q25 to 2.4448 at Q90, highlighting a monotonic and intensifying impact. These results reinforce the transformative role of robotics in industry, where automation technologies are widely adopted and deeply integrated into core production systems. The consistent and growing influence of robot density suggests that robotics is a key driver of industrial productivity, especially in high-output and technologically advanced contexts. These findings align with the broader literature, including studies by Dauth et al. (2017) and Goel and Gupta (2020), which emphasize the critical role of robotics in enhancing operational efficiency, minimizing variability, and supporting scalable production models. The strong coefficients in the upper quantiles echo the endogenous growth theory proposed by Romer (1990) and extended by Aghion et al. (2020), indicating that firm-level innovation capabilities – such as adaptive management and investment in advanced technologies – amplify the productivity effects of robotics.

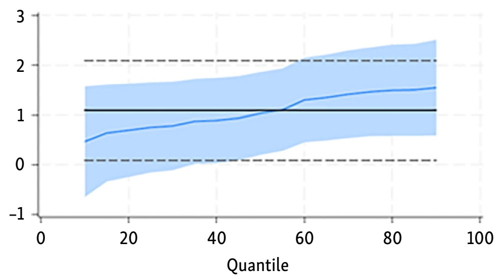

Figure 2. Quantile effects of robot density on gross value added in the agricultural sector

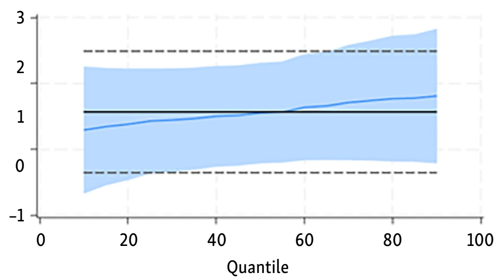

Figure 3. Quantile regression analysis of robot density effects on construction sector GVA

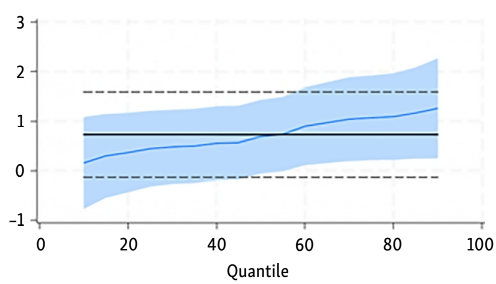

Figure 4. Quantile effects of robot density on gross value added in the industrial sector

Taken together, the findings illustrate that robot density is a significant and positive contributor to economic performance across all sectors, with its influence varying in intensity and distribution. While the agricultural sector exhibits a more conditional benefit – stronger in high-performing systems, the industrial sector demonstrates broad-based and intensifying returns to robot adoption. The construction sector falls between these two extremes, reflecting growing but uneven integration of automation technologies. These patterns emphasize the need for sector-specific policies that not only promote robot adoption but also address structural barriers to technology diffusion, particularly in lower-performing regions or sectors.

The results of this study substantiate and, in several cases, extend existing findings on the economic effects of robot density, particularly in the industrial sector. In line with Graetz and Michaels (2018) and Acemoglu and Restrepo (2020), this study confirms that robotics adoption significantly enhances sectoral productivity. However, by applying the Method of Moments Quantile Regression (MMQR), our findings go further by revealing how these benefits vary across the conditional distribution of gross value added, rather than being confined to average effects. This distributional nuance adds important depth to the literature, highlighting that the positive impact of robot density is especially pronounced at the upper quantiles of performance, where technological readiness and absorptive capacity are generally higher.

Moreover, the positive but differentiated sectoral effects observed in this study resonate with the broader theoretical framework proposed by Acemoglu and Restrepo (2018). Their factor-augmenting model views robots as "precision capital" that substitutes for labor in specific tasks while augmenting overall productivity. The empirical findings here provide strong support for this theoretical proposition in industry sector, partial support in construction, and more conditional support in agriculture.

In the agricultural sector, the control variables exhibit mixed and mostly insignificant effects across quantiles. GDP exhibits no statistically significant relationship with AGRI across any quantile (all p-values > 0.25), indicating that overall economic growth has no direct or robust impact on agricultural value added in the selected EU countries. R&D expenditure (RD) shows a statistically significant negative effect at Q75 and Q90 (p = 0.041 and 0.043, respectively), suggesting that higher R&D spending may either reflect inefficiencies in agricultural innovation or a reallocation of resources toward more research-intensive, non-agricultural sectors. Interestingly, RD displays a strongly negative and significant effect on the scale parameter, indicating greater heterogeneity in outcomes where R&D intensity is higher. HRST (human resources in science and technology) has no statistically significant relationship with AGRI across any quantile, reinforcing the view that the absorptive capacity of skilled labor in agriculture remains limited or unevenly distributed across the performance spectrum.

In the construction sector, the control variables continue to exhibit generally weak or non-significant effects. GDP is insignificant across all quantiles (p > 0.21), implying that macroeconomic growth does not translate directly into construction value added. R&D expenditure (RD) shows a significant negative effect on the scale parameter (p = 0.005), suggesting greater dispersion in construction outcomes under varying levels of R&D, which may reflect misalignment between research activities and practical applications in construction. Across quantiles, RD is positive but not statistically significant, indicating that its potential benefits may not be consistently realized in the construction sector. Similarly, HRST remains insignificant across all quantiles, implying that the level of scientific and technical human capital may not yet be a strong determinant of construction productivity under current conditions.

In the industrial sector, the control variables present more differentiated patterns. GDP remains insignificant throughout the distribution (p-values > 0.23), again indicating a limited direct impact of economic growth on industrial GVA. R&D expenditure (RD) is positively and significantly associated with value added at Q25 and Q50 ($p = 0.004$ and 0.056), which suggests that R&D investments are particularly effective in boosting industrial output in less productive or mid-performing contexts. However, the scale parameter for RD is significantly negative ($p = 0.002$), implying that higher R&D intensity contributes to greater performance variability, likely due to differences in R&D efficiency or innovation absorption across countries. HRST, meanwhile, exerts a statistically significant negative effect at lower quantiles (Q25 and Q50, $p = 0.012$ and 0.004), indicating that in less advanced industrial contexts, the presence of scientific and technical human capital does not always translate into productivity gains – possibly due to sectoral misalignment, underutilization of skills, or lagging innovation ecosystems.

This study offers an in-depth analysis of how robot density influences gross value added across four key sectors – agriculture, construction, and industry – using the MMQR approach. The results support the proposed hypotheses and provide nuanced insights.

The results offer partial support for Hypothesis H1, which posits that higher robot density positively influences gross value added in agriculture. While the positive and significant impact of robot density is evident at higher quantiles (Q75 and Q90), lower quantiles exhibit weaker or insignificant effects. This suggests that advanced agricultural systems, which are better equipped to integrate robotics, reap greater productivity benefits. These findings align with Bechar and Vigneault (2016) and Duckett et al. (2018), who emphasize that the adoption of precision farming technologies is most effective in large-scale, resource-intensive agricultural operations.

The results confirm H2, demonstrating that robot density enhances gross value added in the construction sector, particularly at higher quantiles. The intensified effects at higher quantiles (Q75 and Q90) point to the advantages of robotic technologies in large-scale construction contexts, where critical demands for safety, efficiency, and precision exist. This evidence supports the conclusions of Bock and Linner (2015) and Balaguer and Abderrahim (2008), who highlight that robotics plays a pivotal role in automating repetitive and hazardous tasks. However, the non-significant results at the location scale suggest challenges in achieving widespread integration of robotics across construction projects, especially smaller or less complex ones.

In the case of the industrial sector, Hypothesis H3 – that robot density significantly enhances gross value added – is strongly supported by the empirical evidence. The results reveal a consistently positive and statistically significant relationship across all quantiles, with the most pronounced effects observed at Q75 and Q90. These findings are consistent with prior studies by Graetz and Michaels (2018) and Dauth et al. (2017), which highlight the role of robotics in driving productivity gains through process automation and the reduction of operational inefficiencies. Overall, the results emphasize the transformative impact of robotics in strengthening industrial competitiveness and enabling large-scale production.

The findings of this study are largely in line with existing research on robotics and industrial performance. Across all analyzed sectors, the results confirm previous evidence underscoring the positive effects of robot adoption on productivity and operational efficiency.

However, the quantile-based analysis offers a more refined perspective by uncovering how the impact of robotics varies across different output levels. Notably, while studies such as Acemoglu and Restrepo (2020) and Graetz and Michaels (2018) emphasize overall productivity improvements, this research demonstrates that the benefits of robotics are particularly pronounced in high-performing environments, such as large-scale industrial operations.

The study also diverges from some findings in the literature, particularly regarding the construction sector. While the results confirm the benefits of robotics, the lack of significance at certain quantiles echoes the challenges noted by Bogue (2018a) and Florez et al. (2013), who identify barriers to adoption in smaller or resource-constrained projects. Additionally, the mixed effects of R&D and human resources across sectors point to sector-specific dynamics, suggesting that the alignment of innovation and workforce capabilities with industrial needs is crucial for maximizing the benefits of robotics.

The results obtained through the MMQR model offer a valuable complement to existing empirical studies on automation and economic performance. Seminal works such as those by Graetz and Michaels (2018) and Acemoglu and Restrepo (2020) have demonstrated that the adoption of industrial robots is generally associated with increased labor productivity and value added. However, these studies primarily rely on mean-based estimation methods (e.g., OLS, fixed effects), which do not capture the heterogeneity of effects across the conditional distribution of economic outcomes.

This study advances the existing literature in several important ways. First, by applying the MMQR, we are able to estimate the effects of robot density not just on average, but across different performance levels of each sector. This allows us to identify where automation has the greatest impact – for instance, in the upper quantiles of industrial GVA – while also revealing contexts where the effect is weaker or more variable. Such insights are particularly relevant for policymaking, as they allow for more targeted interventions.

Second, our sector-specific focus provides a level of granularity often missing in previous research. Rather than analyzing only aggregate industrial output, we examine agriculture, construction and industry separately, thus uncovering distinct patterns of robotization and its relationship to value creation. This sectoral disaggregation reveals, for example, that construction shows weaker responsiveness to robot density at lower quantiles, while industry exhibits consistent and increasing effects across all levels of performance.

Third, we incorporate innovation-related controls such as expenditures on R&D and the presence of scientific and technological human resources – factors that have infrequently been explored in conjunction with robot density in empirical panel research. This allows us to explore the interplay between automation and a country's absorptive capacity for technological change.

Lastly, by using updated panel data from twelve EU countries for the period 2016–2022, our study reflects current dynamics within a region characterized by both advanced and emerging automation economies. The European context also adds relevance, given the region's emphasis on digital cohesion and technological convergence.

Taken together, these contributions position the present study as a more nuanced and flexible approach to understanding the economic impact of robot density. Rather than providing a single average effect, we highlight the distributional consequences of automation, and how these effects differ by sector and national context – offering new perspectives for both academic research and policy formulation.

Despite these contributions, the model has limitations. First, the measure of robotization (robots per 10,000 employees) does not capture differences in robot type, function, or intensity of use, which may vary significantly across sectors. Second, due to data constraints, the analysis is limited to twelve countries and four sectors, excluding services or emerging industries where robotics is growing. Additionally, the MMQR method does not account for dynamic effects or feedback loops over time.

Future research may address these limitations by incorporating longitudinal dynamics, differentiating between types of robotics technologies, and expanding the sample to include non-EU or non-industrial economies. Machine learning methods and sector-specific case studies could also complement panel quantile approaches to offer deeper insight.

5. Conclusions

The research examines how robot density affects the economic outcomes across four major sectors – agriculture, construction and industry across twelve European Union countries over the 2016–2022 period. By applying the Method of Moments Quantile Regression (MMQR), the analysis moves beyond average effects and provides a distributional perspective that reveals how automation impacts different levels of performance within each sector.

The findings provide robust evidence of a positive relationship between robot density and Gross Value Added (GVA), but with important sectoral distinctions. In agriculture, robot density shows a stronger effect in the upper quantiles, suggesting that high-performing agricultural systems are better positioned to benefit from automation. In construction, the relationship is significant primarily at higher quantiles, but less consistent overall – highlighting the sector's relatively slower adoption and higher entry barriers for robotic integration. In industry, robot density contributes positively and significantly at every quantile, with its strongest impact evident in high-output environments. These results reflect the greater maturity of automation in these sectors and their higher absorptive capacity for technological advancement.

The analysis also reveals that while robot density is a key driver of performance, its interaction with other innovation-related factors such as R&D expenditure and human capital in science and technology (HRST) is more complex. These control variables exhibit mixed effects across sectors and quantiles, suggesting that the benefits of automation are closely linked to the broader innovation and skills environment.

By accounting for heterogeneity across countries and performance levels, the study provides a nuanced view of automation's role in sectoral development. This contributes to the literature by highlighting not only the positive impact of robot density, but also the distributional differences in its effectiveness, which can inform differentiated policy strategies.

To fully leverage the potential of robotics, policymakers should adopt sector-specific approaches that account for varying levels of technological readiness and economic structure. Investments in workforce training, targeted support for R&D, and incentives for technology adoption are essential – particularly in agriculture and construction, where benefits are more uneven. Ensuring access to robotics and innovation for both high- and low-performing regions is crucial to promote inclusive and sustainable growth.

While the study provides valuable insights into the impact of robot density on industrial performance, it is not without limitations. The analysis focuses on twelve European Union countries, which may not fully capture global variations in the adoption and effects of robotics, especially in economies with distinct levels of technological sophistication and industrial organization. Additionally, the study examines only four key sectors, excluding other industries such as services or logistics, where robotics also plays a critical role. Another limitation lies in the use of robot density as a proxy for automation; this measure does not differentiate between the types of robots or their specific applications, which may lead to oversimplified interpretations of their impact.

Future research can build on this study by expanding its geographical scope to include countries outside the European Union, providing a more comprehensive understanding of robotics' global economic impact. Further investigations could also explore the role of robotics in additional sectors, such as healthcare, logistics, and the service industry, to understand its broader implications. Disaggregating robot density by type (e.g., collaborative robots versus industrial robots) and function could yield more nuanced insights into how different technologies contribute to productivity. Longitudinal studies examining the long-term economic, social, and environmental consequences of robotic adoption would also be valuable, offering a deeper perspective on the sustainability and inclusivity of automation in various industries.

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