

Article

Robot-based automation and new firm formation: the role of formal human capital development

Chrystalla Kapetanidou^{1,*} and Marios Samdanis²

¹University of Southampton Business School, University of Southampton, Southampton SO16 7QF, United Kingdom

²Brunel Business School, Brunel University of London, Uxbridge UB8 3PN, United Kingdom

*Corresponding author. University of Southampton Business School, University of Southampton, Southampton, SO16 7QF, United Kingdom. E-mail: c.kapetanidou@soton.ac.uk

Abstract

Industrial robots are reshaping manufacturing, yet their role in new firm formation remains underexplored. Robot-based automation reinforces incumbent advantages while reconfiguring tasks in ways that may create opportunities for entrepreneurial entry. Formal human capital development can renew knowledge and skills to recognize and pursue opportunities. Drawing on the task-based theory of technological change and the Varieties of Capitalism framework, we examine how the intensity of robot-based automation relates to new firm formation and the moderating role of formal human capital development in this relationship. Using 2006–16 panel data for seven industries across thirteen European countries, we find that robot density is associated with lower new firm formation, while formal adult education and training relate positively to entry, though its moderating role varies across institutional and industry contexts. Entrepreneurial adjustment to automation depends not only on technology, but also on institutional and industry characteristics conditioning the role of formal human capital development.

Key words: technological change; entrepreneurship; capitalism, varieties of; manufacturing.

JEL classification: O3; L26

1. Introduction

Entrepreneurship fosters innovation and industrial renewal as economies adapt to technological change (Schumpeter 1934). In manufacturing, however, robot-based automation often unfolds in industries dominated by established firms, as the substantial investment and complementary technical and organizational capabilities it requires favour incumbents with greater scale and resources (Koch, Manuylov, and Smolka 2021;

Stiebale, Suedekum, and Woessner 2024). At the same time, automation reallocates tasks between labour and capital (Acemoglu 2025), generating production needs that may create opportunities for entrepreneurial entry. New firms may therefore contribute to industrial adaptation and renewal, even though they face significant barriers to entry (Autor, Mindell, and Reynolds 2021).

Research on robot-based automation has focused primarily on productivity, employment, and task composition (Acemoglu and Restrepo 2019; Kapetanious and Pissarides 2025; Richiardi *et al.* 2025), leaving its implications for new firm formation underexplored. To address this gap, we draw on Acemoglu and Restrepo's (2019) task-based theory of technological change to explain how automation shapes entrepreneurial entry. In this view, automation does not merely replace labour with capital; it reorganizes production by reallocating tasks between them, raising productivity in some activities while creating new labour-complementary tasks. Applied to industrial robots, this task reconfiguration can generate technical and organizational requirements (Friel 2024).

Incumbents can meet many of these requirements internally, but others may be too specialized, uncertain, or peripheral to fit their established routines or strategic priorities (Cassiman and Ueda 2006; Bahoo-Torodi 2024). Requirements that are neither internalized by incumbent firms nor fully met by established suppliers can create opportunities for new firms, particularly in specialized or complementary activities such as integration, maintenance, and support (Jacobides and Winter 2005; Friel 2024). This explains why new entrants remain relevant even when capital intensity and incumbent advantages constrain entry into core production.

Such opportunities do not necessarily translate into new firm formation. Prospective entrepreneurs draw on human capital to interpret changing production needs (Bahoo-Torodi 2024; Gruber, Dencker, and Nikiforou 2024). Human capital comprises knowledge and skills accumulated through education, training, and experience (Becker 1964). Yet its relevance may diminish when automation alters technical, organizational, and commercial requirements (Unger *et al.* 2011). We thus focus on formal human capital development, understood as structured renewal and extension of knowledge and skills beyond initial education (Brown, Lauder, and Cheung 2020). Its entrepreneurial value, we argue, lies not simply in accumulating knowledge and skills, but in renewing them, broadening their range, and recombining them with prior expertise (Krieger *et al.* 2022). Such renewal, broadening, and recombination may strengthen entrepreneurial absorptive capacity, enabling prospective entrepreneurs to recognize opportunities and develop viable commercial responses as technological change reshapes manufacturing (Qian and Acs 2013).

Formal human capital development is embedded in national systems of skill formation (Desjardins 2017). We therefore draw on the Varieties of Capitalism (VoC) framework (Hall and Soskice 2001) to examine how the wider institutional environment shapes both formal human capital development and the extent to which renewed knowledge and skills can be mobilized for new firm formation. Yet the contribution of formal human capital development to new firm formation may also vary across industries within the same institutional context (Akkermans, Castaldi, and Los 2009). To capture this industry heterogeneity, we distinguish between high- and low-technology manufacturing industries, which entail different knowledge requirements for prospective entrants (Czarnitzki and Thorwarth 2012; Dilli 2021). Accordingly, we ask: how does the industry-level intensity of robot-based automation influence new firm formation, and how does formal human capital development shape this relationship across institutional and industry contexts?

We address these questions using panel data covering seven manufacturing industries across thirteen European countries from 2006 to 2016. We measure the intensity of robot-based automation using robot density (Guarascio, Piccirillo, and Reljic 2025) and capture formal human capital development through participation in formal adult education and training (AET) (Desjardins and Ioannidou 2020).

We find that higher robot density is associated with lower new firm formation, whereas participation in formal AET attenuates this negative relationship overall. However, this moderating effect varies across institutional and industry contexts.

This study makes three theoretical contributions. First, it extends research on automation (e.g., [Acemoglu and Restrepo 2019](#)) to entrepreneurship by showing that greater intensity of robot-based automation is associated with lower new firm formation. We explain this relationship through two countervailing mechanisms: the capital intensity of robot-based automation raises entry barriers ([Autor, Mindell, and Reynolds 2021](#)), whereas the reconfiguration of production tasks creates new opportunities for firm entry. Second, it advances research on entrepreneurship and human capital by focusing on formal human capital development as the ongoing renewal and recombination of knowledge and skills ([Unger et al. 2011](#); [Brown, Lauder, and Cheung 2020](#)). By showing that such development conditions the relationship between robot-based automation and new firm formation, this study highlights how continued knowledge and skill renewal may support entrepreneurial entry as production requirements evolve. Third, it contributes to institutional approaches to entrepreneurship ([Herrmann 2019](#); [Dilli 2021](#)) by establishing how national institutions and industry technological intensity jointly shape the entrepreneurial value of formal human capital development.

2. Theoretical background

2.1 Robot-based automation and new firm formation

Robot-based automation is a distinct form of automation centred on the use of industrial robots. The International Federation of Robotics ([IFR 2017: 2](#)) defines an industrial robot as an ‘automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which may be fixed in place or mobile for use in industrial automation applications’. As cyber-physical systems, industrial robots differ from purely software-based technologies because they perform physical tasks, while their re-programmability distinguishes them from conventional machinery designed for narrower or less adaptable operations ([Graetz and Michaels 2018](#)). These characteristics can enhance precision and occupational safety in manufacturing ([Caselli et al. 2025](#)), while their deployment can reshape resource requirements, technical needs, and the organization of production tasks ([Acemoglu 2025](#)).

Existing research has primarily examined how robot adoption affects firm outcomes, such as productivity and product innovation ([Koch, Manuylov, and Smolka 2021](#); [Antonioli et al. 2024](#)), and labour outcomes, such as employment and job quality ([Acemoglu 2025](#); [Nikolova, Lepinteur, and Cnossen 2025](#)). This study shifts attention to how the industry-level intensity of robot-based automation relates to new firm formation, as prospective entrants must navigate the technological and production conditions prevailing in their industries. Industry-level intensity refers to the extent to which robot-based automation is embedded in an industry’s production activities. It is commonly captured by robot density, measured as the number of industrial robots relative to industry labour input ([Graetz and Michaels 2018](#); [Guarascio, Piccirillo, and Reljic 2025](#)).

As robot-based automation intensifies, the capital requirements associated with it may raise entry barriers, while the resulting reconfiguration of production tasks may create opportunities for new firms. First, adopting industrial robots requires interdependent investments in robotic equipment, peripheral hardware, complementary software, systems integration, and workforce training ([Friel 2024](#); [Benmelech and Zator 2025](#)). Although industrial robots have become less expensive, their deployment remains costly because specialized expertise is required to integrate them into production systems, standardize inputs, and maintain precise process control ([Autor, Mindell, and Reynolds 2021](#)).

Moreover, investments tailored to particular production settings may be difficult to redeploy, leaving associated expenditures partly unrecoverable if entry fails and thereby creating sunk costs (Jacobides and Winter 2005). Incumbents are better positioned to absorb these risks by drawing on economies of scale, accumulated technological capabilities, and greater financial resources, whereas new ventures may have more limited access to external finance (Koch, Manuylov, and Smolka 2021). As a result, robot-based automation may tilt the competitive balance towards incumbents and away from new entrants.

Second, we argue that robot-based automation may create opportunities for entrepreneurial entry through task reconfiguration. Acemoglu and Restrepo's (2019) task-based framework explains how automation reshapes production and the allocation of tasks between labour and capital through three effects: a productivity effect, whereby automation lowers costs, expands output, and may sustain labour demand in non-automated tasks; a displacement effect, whereby capital assumes tasks previously performed by labour; and a reinstatement effect, whereby technological change creates new tasks in which labour has a comparative advantage. We describe the resulting changes in the allocation and composition of tasks, as well as the scale of production, as task reconfiguration. Such reconfiguration may generate new organizational and technical needs, creating demand for activities and inputs such as specialized components, systems integration, and production support (Autor, Mindell, and Reynolds 2021; Friel 2024).

Whether such needs create opportunities for entry depends on how incumbents and established suppliers respond. Incumbents may address some of them internally through intrapreneurial initiatives, especially if the required activities align with their strategic priorities (Lechevalier, Nishimura, and Storz 2014). By contrast, activities that are commercially uncertain, specialized, or peripheral to their core operations may remain outside their boundaries (Jacobides and Winter 2005; Cassiman and Ueda 2006). Established suppliers may meet some of the resulting demand, but requirements that remain weakly served can create openings for entrants with relevant operational or technical experience (Bahoo-Torodi 2024).

Although task reconfiguration may generate entrepreneurial opportunities in manufacturing, these may be more likely to arise in complementary niches within manufacturing than through direct competition in robot-intensive core production. The capital requirements of robot-based automation make entry into core production difficult, while incumbents are generally better positioned to internalize emerging production activities, adapt their operations, and capture the associated gains. Evidence from the United States and Europe is consistent with this reasoning, indicating that automation disproportionately benefits large and already highly productive manufacturers, thereby reinforcing industry concentration around "superstar" firms (Stiebale, Suedekum, and Woessner 2024; Firooz, Liu, and Wang 2025). Accordingly, we propose:

H1. Higher industry-level intensity of robot-based automation is associated with lower levels of new firm formation in manufacturing.

2.2 Human capital development and new firm formation

Beyond capital investment, prospective entrepreneurs must mobilize relevant knowledge and skills to turn perceived opportunities into new firms (Unger *et al.* 2011). This stock of knowledge and skills, accumulated through education, training, and experience, constitutes human capital (Becker 1964). Within manufacturing, prospective entrepreneurs draw on their human capital to interpret

technological change, assess its commercial potential, and develop new products, processes, or applications (Wozniak 1984; Qian and Acs 2013).

Human capital takes general and specific forms. General human capital comprises knowledge and skills that are transferable across contexts and often acquired through formal education (Gruber, Dencker, and Nikiforou 2024). Specific human capital, by contrast, is less transferable because its value is more closely tied to particular occupations or industries. It may develop through vocational pathways, on-the-job learning, domain-relevant experience, or exposure to start-up activity (Krieger et al. 2022). Human capital can support entrepreneurial entry when the knowledge and skills of prospective entrepreneurs remain relevant to prevailing technologies, production requirements, and market needs (McMullen and Shepherd 2006). Maintaining this relevance may be challenging in the context of manufacturing, where technological change reshapes the complementarities between human skills and physical capital (Goldin and Katz 2008). As production conditions evolve, established expertise may become less applicable, increasing the importance of renewing and recombining knowledge and skills (Unger et al. 2011).

Entrepreneurial entry may therefore depend not only on accumulated human capital but also on individuals' ability to renew and recombine their existing expertise as production conditions change. Human capital development refers to this continued renewal and recombination of knowledge and skills (Brown, Lauder, and Cheung 2020; Woessmann 2025). AET provides an important institutional mechanism for such development by enabling individuals to update and extend their knowledge and skills beyond initial education (Desjardins 2017; Brown, Lauder, and Cheung 2020).

AET encompasses both formal and non-formal learning. Formal AET comprises structured learning within recognized education and qualification systems that leads to qualifications transferable across educational and occupational settings (Kosyakova and Bills 2021). As these formal systems operate within regulated frameworks and are subject to quality-assurance procedures, they provide a recognized baseline of competence. Furthermore, as adult learners bring prior experience and context-specific learning needs (Knowles et al. 1984), formal AET supports the active renewal and recombination of existing knowledge and skills, rather than simply adding to initial educational attainment. Non-formal AET refers to organized learning outside recognized education and qualification systems. However, it varies across countries, and it does not typically lead to nationally recognized qualifications. It therefore provides a less consistent baseline of knowledge and skill development across institutional contexts than formal AET (Desjardins and Ioannidou 2020). Accordingly, we focus on formal human capital development, operationalized through participation in formal AET.

Formal human capital development may help prospective entrepreneurs renew, broaden, and recombine their knowledge and skills. Entrepreneurial entry in manufacturing requires diverse technical, managerial, and interpersonal skills, yet individuals possess different combinations of these skills depending on their prior education and experience (Brown, Lauder, and Cheung 2020; Krieger et al. 2022). By helping individuals complement existing knowledge and address skill gaps, formal human capital development may strengthen entrepreneurial absorptive capacity, defined as the capacity to understand new knowledge, recognize its commercial value, and combine technical and business knowledge to bring it to market through new firm creation (Qian and Acs 2013). Integrating newly acquired knowledge with prior expertise (Zahra and George 2002) could enable prospective entrepreneurs to better interpret technological change and recognize and pursue entrepreneurial opportunities that were previously less visible to them (Kaplan and Tripsas 2008). At the industry level, higher formal AET participation reflects broader engagement in formal human capital development, potentially increasing the pool of prospective entrants able to pursue new opportunities. Accordingly, we propose:

H2. Higher levels of formal human capital development are positively associated with new firm formation in manufacturing.

While the capital requirements of robot-based automation may constrain entrepreneurial entry into manufacturing, task reconfiguration can create opportunities for new firm formation. For those displaced by automation or facing weaker employment prospects, formal human capital development may help update existing production knowledge and skills to address unmet operational needs (Gruber, Dencker, and Nikiforou 2024). By contrast, productivity gains and task reinstatement may generate demand for complementary activities, creating opportunities for prospective entrepreneurs to adapt prior expertise to emerging needs and develop new ventures (Autor, Mindell, and Reynolds 2021; Fossen and Sorgner 2021; Friel 2024). Although formal human capital development may not remove financing and other entry barriers, it may increase the likelihood that unmet production needs are identified and addressed through new firm formation, partially offsetting the entry-constraining effects of robot-based automation. On this basis, we propose:

H3. The negative association between industry-level intensity of robot-based automation and new firm formation in manufacturing is weaker at higher levels of formal human capital development.

2.3 VoC and new firm formation

The effects of robot-based automation on entrepreneurship depend not only on the technology itself but also on the national institutions that shape how economies adapt to it. Evidence shows that its employment effects vary across countries depending on their institutional arrangements (Reljić, Cirillo, and Guarascio 2023; Van Overbeke 2023; Kapetanidou and Pissarides 2025). Building on this insight, we expect the role of formal human capital development in new firm formation to vary across national institutional contexts. Central to this variation are national systems of skill formation, which shape how skills are developed, renewed, and mobilized in entrepreneurial activities (Desjardins 2017). Because formal human capital development is organized and supported differently across these systems (Brown, Lauder, and Cheung 2020), its capacity to moderate the relationship between robot-based automation and new firm formation may differ accordingly. To explain this heterogeneity, we draw on the VoC framework (Hall and Soskice 2001) and its extensions in entrepreneurship research (Herrmann 2019).

The VoC framework emphasizes institutional complementarities that generate distinctive comparative advantages. It distinguishes two ideal types: liberal market economies (LMEs), like the UK, where coordination is primarily market-based, and coordinated market economies (CMEs), such as Germany, which rely more heavily on non-market coordination through trade unions, employer associations, and the state (Hall and Soskice 2001). Although the VoC literature explains how these complementarities shape national patterns of innovation and comparative advantage (Jackson and Deeg 2008), it has largely focused on established firms, paying less attention to the role of new entrants in economic adaptation (Herrmann 2019). Recent research extending the VoC theory addresses this gap by examining how institutional configurations shape cross-national patterns of entrepreneurship (Dilli, Elert, and Herrmann 2018; Herrmann 2019; Dilli 2021). Building on this foundation, we argue that such configurations not only influence the extent of formal human capital development but also determine how it interacts with the broader institutional environment to either facilitate or constrain new firm formation.

LMEs are characterized by flexible labour markets, limited employment protection, developed venture capital systems, and market-driven training provision. This configuration may facilitate rapid resource reallocation, radical innovation, and new firm formation (Herrmann 2019). As robot-based automation intensifies, these advantages may be constrained in core production, where high capital and integration costs reinforce incumbent dominance (Fernandez-Macias et al. 2021). Skill formation in LMEs tends to emphasize general human capital, while labour-market flexibility can reduce employers' incentives to finance transferable retraining (Hall and Soskice 2001). Comparative evidence indicates relatively high participation in job-related, employer-sponsored formal AET in LMEs (Desjardins and Ioannidou 2020), while public support for formal retraining outside employment is relatively limited (Desjardins 2017). Because such provision is embedded in existing employment relationships and aligned with employers' immediate needs, its benefits are likely to accrue primarily within incumbent firms. Access outside employment may depend more heavily on individuals' prior human capital and financial resources, leaving prospective entrepreneurs to finance their own development and bear the associated costs and risks (Ioannidou and Parma 2022).

CMEs, by contrast, rely more heavily on non-market coordination among the state, employer associations, trade unions, and other social partners (Hall and Soskice 2001). Skill-formation systems in CMEs, as exemplified by Germany's dual apprenticeship system, combine broad vocational education with firm-based training (Busemeyer and Trampusch 2012), supporting long-term employment relationships and incremental innovation (Hall and Soskice 2001). CMEs are characterized by strong employer involvement in vocational curricula and greater reliance on initial VET than on continuous adult learning (Carstensen and Ibsen 2021; Ibsen and Thelen 2025). Although participation in employer-sponsored formal AET tends to be lower than in LMEs (Desjardins and Ioannidou 2020), coordinated training arrangements play an important role in how firms and workers adapt to automation (Friel 2024). Institutional arrangements tend to favour incumbents, but new firms may still enter specialized niches and supplier relationships that complement established production systems (Sorge and Streeck 2018). Formal human capital development may help prospective entrants renew knowledge and skills, strengthening their capacity to pursue such complementary opportunities.

Not all economies fit neatly within the LME–CME dichotomy. Hall and Soskice (2001) described those occupying this space as mixed market economies (MMEs), often characterized by weaker institutional complementarities and less favourable innovation outcomes (Malik 2017). Schneider and Paunescu (2012) subsequently differentiated this intermediate category into LME-like economies (LLMEs), hybrid economies (HEs), and state-dominated economies (SDEs). LLMEs combine relatively flexible labour markets with active labour-market policies and comparatively accessible adult-learning systems (Desjardins 2017). By supporting occupational mobility and the redeployment of updated knowledge and skills, this institutional configuration may strengthen the capacity of formal human capital development to mitigate the negative association between robot-based automation and new firm formation.

Finally, HEs and SDEs represent alternative configurations that lack the stable institutional complementarities associated with LMEs and CMEs. HEs comprise a heterogeneous group, whereas SDEs are characterized by extensive state intervention and more restrictive labour-market regulation (Schneider and Paunescu 2012). Despite these differences, both tend to exhibit comparatively fragmented skill-formation arrangements. At the firm level, training accompanying advanced manufacturing technologies may consist mainly of equipment-specific instruction addressing immediate operational needs, offering few opportunities to develop transferable skills (Da Roit and Iannuzzi 2023). Lower participation in formal human capital development further suggests weaker systemic support for skill renewal (Desjardins 2017). Incumbents may benefit from established networks and

familiarity with these institutional environments (Malik 2017; Dilli 2021), while prospective entrepreneurs receive less support for applying updated knowledge and skills to emerging production needs. The moderating role of formal human capital development may therefore be weaker and less systematic in these contexts.

Across these institutional configurations, significant variation exists in both the opportunities for formal human capital development and the extent to which renewed knowledge and skills can support new firm formation. Therefore, we propose:

H4. The moderating effect of formal human capital development on the negative association between industry-level robot-based automation and new firm formation in manufacturing varies across VoC configurations.

2.4 Industry technological intensity and new firm formation

Although the VoC framework highlights institutional complementarities, it pays less attention to within-country industry heterogeneity (Akkermans, Castaldi, and Los 2009). Empirical evidence shows that robot adoption is uneven across manufacturing, with robot use more concentrated in automotive, electrical equipment, and machinery, and far less in food, textiles, wood, and paper (Antonioli *et al.* 2024; Benmelech and Zator 2025). Yet the prevalence of robot use within an industry provides limited insight into the knowledge and skill renewal required as robot-based automation changes production tasks and generates new technical and organizational demands. As these requirements vary across industries (Crouch, Schröder, and Voelzkow 2009), the contribution of formal human capital development to new firm formation may also differ across industries. To account for this heterogeneity, we focus on industry technological intensity, distinguishing between high- and low-technology industries according to the relative importance of R&D in production and innovation activities (Audretsch and Acs 1991; Czarnitzki and Thorwarth 2012).

High-technology industries are characterized by high R&D intensity, frequent product and process innovation, and strong reliance on scientific and technological knowledge (Dilli, Elert, and Herrmann 2018). Rapid technological change heightens the need to develop, absorb, and apply new knowledge (Qian and Acs 2013). As robot-based automation advances rapidly in these industries, it can reconfigure production and create new labour-complementary tasks (Fossen and Sorgner 2021) that require renewed knowledge and skills. Process improvements aimed at increasing efficiency and productivity are also common in high-technology manufacturing, increasing the need for specialized capabilities to operate, maintain, adapt, and integrate robotic systems (Antonioli *et al.* 2024). Incumbents are better positioned to meet these requirements because they combine greater R&D resources, stronger absorptive capacity, and sustained investment in employee skill development (Czarnitzki and Thorwarth 2012). This can create significant knowledge-based barriers for prospective entrepreneurs. Formal human capital development may help address some of these barriers by supporting the acquisition and renewal of knowledge and its application to emerging production needs. Its contribution may be particularly important where national skill-formation systems support scientific and tertiary education and nurture a scientifically trained workforce (Dilli, Elert, and Herrmann 2018).

By contrast, low-technology industries exhibit lower R&D intensity and rely more heavily on incremental innovation, technologies embodied in machinery, and knowledge accumulated through production experience (Dilli, Elert, and Herrmann 2018). Although they deploy advanced machinery, such equipment is typically used to improve established processes rather than generate frontier

innovation (Crouch, Schröder, and Voelzkow 2009). Where robot-based automation creates opportunities to improve established production processes, prospective entrants often need to combine advanced technologies with industry-specific experience and tacit production know-how (Czarnitzki and Thorwarth 2012). Technologically lagging incumbents may also leave scope for productivity improvements through new entry (Fritsch and Changoluisa 2017). Even where entry barriers are lower than in high-technology manufacturing, prospective entrepreneurs still require experiential and industry-specific knowledge to identify and pursue these possibilities. Formal human capital development may support entry by updating occupationally grounded knowledge and skills, helping prospective entrepreneurs pursue process-oriented and niche opportunities. Its contribution may be greater where skill-formation systems prioritize vocational education and provide opportunities for continued skill renewal (Dilli 2021).

National institutions and industry technological intensity jointly shape entrepreneurial entry. VoC configurations differ in how they support human capital development and mobilize renewed skills, making some more favourable to high-technology entrepreneurship and others to low-technology entrepreneurship (Dilli 2021). High-technology entry depends more on scientific and technological knowledge, while low-technology entry relies more on vocational, tacit, and production-based skills. The contribution of formal human capital development to new firm formation may thus depend on how institutional arrangements support knowledge renewal and on the relevance of renewed capabilities to industry knowledge demands. Its role may consequently differ between high- and low-technology industries within the same VoC configuration. We thus propose:

H5. The moderating role of formal human capital development in the relationship between the intensity of robot-based automation and new firm formation in manufacturing varies jointly by VoC configuration and industry technological intensity.

3. Data and methods

3.1 Data

To test our hypotheses, we constructed a panel dataset covering seven manufacturing industries across thirteen European countries over the period 2006–16. The analysis draws on data from the IFR, EU KLEMS, Eurostat's Business Demography database, the European Labour Force Survey (LFS), and various additional international sources. Data on industrial robots are drawn from the IFR, which reports the annual operational stock of industrial robots by industry, country, and year. The IFR (2017) defines operational stock as the number of industrial robots currently in use and compiles these data primarily from robot suppliers worldwide. We focus exclusively on manufacturing industries, which account for approximately 90 per cent of global robot deliveries.

We combine the IFR (2017) data with EU KLEMS (Stehrer et al. 2019), which provides harmonized industry-country-year data derived primarily from national statistical offices and aligned with national accounts. EU KLEMS reports data on employment, wages, capital formation, and intermediate inputs. Because the IFR uses the International Standard Industrial Classification, Revision 4 (ISIC Rev. 4), whereas EU KLEMS uses NACE Revision 2, IFR manufacturing industries were matched with their corresponding EU KLEMS industries. The final sample comprises seven industries: food, beverages, and tobacco; textiles, apparel and leather; wood, paper and printing; chemicals, plastics and non-metallic mineral products; basic and fabricated metals; electrical and optical equipment; and

transport equipment. These industries are referred to using abbreviated labels in the empirical analysis (e.g., food & beverages, textiles, metals).

New firm formation is measured using Eurostat's Business Demography data (Eurostat 2022), which provide annual information on business population dynamics across EU member states based on national business registers. We use industry-country-year data on firm births covering the period 2006 to 2016. Formal human capital development is measured using the LFS (Eurostat 2023), an annual harmonized household survey across European countries. The LFS collects data on individuals' participation in education and training, labour market status, and demographic characteristics. Additional control variables are constructed using data from several sources, including the International Labour Organization (ILO 2022) and the World Bank (2024). The analytical sample includes Austria, Belgium, the Czech Republic, Denmark, Finland, France, Germany, Italy, the Netherlands, Slovakia, Spain, Sweden, and the United Kingdom. Consistent data across all relevant datasets are available for these countries over the period 2006–16. Denmark is retained in the sample, although data on new firm formation are unavailable across all industries for the years 2006–08.

3.2 Variables

The dependent variable is new firm formation, measured as the number of enterprise births by industry, country, and year. An enterprise birth occurs when a firm starts from scratch and creates a new combination of production factors without links to a pre-existing enterprise (Eurostat and OECD 2007). The measure therefore excludes reactivations, mergers, spin-offs, restructurings of incumbent firms, and entries arising solely from changes in legal form or activity classification. Because the distribution of enterprise births is positively skewed, the variable is transformed using the natural logarithm (Bonaccorsi *et al.* 2013; Colombelli and Quatraro 2018).

The main explanatory variable is robot density, used as an empirical indicator of the industry-level intensity of robot-based automation. Robot density is defined as the stock of operational industrial robots per 1,000 workers, disaggregated by industry, country, and year, and has been used in recent empirical research (Reljić, Cirillo, and Guarascio 2023; Guarascio, Piccirillo, and Reljić 2025). The variable is log-transformed, while observations reporting zero robot use or extreme values, particularly during the early years of the sample, are treated as missing.

Formal human capital development is measured by the AET participation rate, consistent with prior research on adult learning and skill formation (Desjardins 2017). This measure represents the share of individuals aged 25–64 who report participating in formal education or training during the four weeks preceding the survey, aggregated at the country-year level. By reflecting recent participation in formally recognized education and training rather than accumulated educational attainment, the measure provides an indicator of workforce knowledge and skill renewal, making it relevant for examining how human capital development shapes responses to robot-based automation (Brown, Lauder, and Cheung 2020). Formal AET spans managerial and technical domains, with participation concentrated in business, administration, and law, followed by technical disciplines (Eurostat 2023). This may help prospective entrepreneurs address skill gaps relevant to new firm formation.

To account for cross-national variation in institutional arrangements that influence new firm formation, this study adopts the VoC framework (Hall and Soskice 2001). Specifically, we draw on the revised typology developed by Schneider and Paunescu (2012), also employed by Malik (2017). Countries in our sample are categorized into LMEs, represented by the UK and Denmark; CMEs, comprising Austria, Belgium, France, and Germany; LLMEs, including Finland, Sweden, the Netherlands, and Spain; and HEs, covering the Czech Republic, Slovakia, and Italy. Although Schneider and Paunescu (2012) also identify SDEs, such as Portugal or Greece, these economies are

not included in our analysis due to data availability. Denmark represents a borderline case, as it combines relatively flexible labour-market arrangements with coordinated systems of skill formation and social protection. In this study, Denmark is classified as an LME based on its position in the 2005 observation window reported by [Schneider and Paunescu \(2012\)](#) and its classification in [Malik \(2017\)](#).

Industry heterogeneity is captured through technological intensity, based on established classifications of manufacturing industries according to R&D intensity ([Audretsch and Acs 1991](#); [Czarnitzki and Thorwarth 2012](#); [Dilli, Elert, and Herrmann 2018](#)). High- and medium-high-technology industries are combined into the high-technology category, while medium-low- and low-technology industries form the low-technology category. The classification applies an R&D intensity threshold of 3 per cent, measured as R&D expenditure relative to industry output ([Czarnitzki and Thorwarth 2012](#); [Hirsch-Kreinsen 2008](#)). Plastics and chemicals, electronics, and transport equipment are classified as high-technology industries. Food and beverages, metals, textiles, wood products, and paper are classified as low-technology industries.

We included a comprehensive set of control variables capturing broader education and skills, innovation and industry characteristics, and institutional and labour market conditions that may influence new firm formation. These include tertiary education, vocational enrolment, high-skill occupations, industry employment, wages, employment protection legislation, welfare state size, job tenure, population density, higher education R&D expenditure, industry R&D expenditure, capital intensity, industry concentration, digital intensity, domestic credit to the private sector, and venture-capital availability. The definitions and sources of the main variables used in this study are reported in [Table 1](#).

[Table 2](#) reports country-level averages for the period 2006–16 for three logged variables in manufacturing industries: new firms, robot density, and participation in formal AET. Considerable cross-country variation is evident. Denmark and Finland record the lowest levels of new firm formation, while Italy exhibits the highest rate, followed closely by the UK and France. Robot density is highest in Denmark, Finland, Germany, and Sweden, whereas the Czech Republic and Slovakia display the lowest levels of robot adoption. Participation in formal AET is strongest in Finland, the Netherlands, and Sweden, while France, Slovakia, and the Czech Republic show comparatively weaker engagement in formal AET. Differences also emerge across institutional contexts. LMEs exhibit relatively high participation in formal AET alongside heterogeneous levels of robot-based automation and new firm formation, whereas CMEs combine high levels of robot-based automation with more limited participation in formal AET. This descriptive evidence suggests that greater intensity of robot-based automation does not necessarily coincide with higher participation in formal AET across countries.

[Table 3](#) presents industry-level averages for new firm formation and robot density, revealing substantial variation across manufacturing industries. Transport equipment is the most robot-intensive industry, yet records the lowest rate of new firm formation. High robot density in this industry also reflects broader national industrial patterns, as countries with sizeable automotive sectors, including Germany, Italy, and France, exhibit some of the highest levels of robot adoption. Textiles display comparatively high levels of new firm formation despite low robot density. New firm formation is, on average, higher in low-technology than in high-technology industries, whereas robot density tends to be higher in high-technology industries despite considerable variation within both groups.

[Table 4](#) presents summary statistics for the variables used in the analysis. On average, the logarithm of new firms per industry, country, and year is approximately 6.00. Robot density has a mean value of 1.48. As shown in [Tables 2](#) and [3](#), robot density varies substantially across both countries and industries.

Table 1. Definitions and sources of main variables.

Variables	Description	Source
Dependent variable		
New firms	Log of new enterprise births by country, industry and year	Eurostat
Main independent variables		
Robot density	Log of industrial robots per 1,000 workers by country, industry and year	IFR; KLEMS
Formal AET	Log of the share of adults aged 25–64 participating in formal learning activities by country and year	Eurostat
Education and skill controls		
Tertiary education	Log of tertiary-educated population (aged 25–34) per 1,000 by country and year	Eurostat
High-skill occupations	Log of the share of manufacturing employees in high-skill occupations (managers, professionals, technicians/associate professionals) by country and year	International Labour Organisation
Vocational enrolment	Log of the share of secondary students in vocational/technical programmes (ISCED 2–3) by country and year	United Nations Educational, Scientific and Cultural Organization Institute for Statistics (UIS)
Innovation and industry characteristics		
Technology intensity	Categorical variable indicating whether a manufacturing industry belongs to a high-technology or low-technology sector	Organisation for Economic Co-operation and Development (OECD)
Industry R&D	Log of R&D expenditure by country, industry and year	KLEMS
GERD higher education sector	Log of R&D expenditure by higher-education sector as a share of GDP by country and year	OECD
Market concentration	Log of the Herfindahl–Hirschman Index of firm-size distribution	World Bank
Digital intensity	Dummy variable equal to 1 for digital-intensive manufacturing industries (transport equipment, electronics, wood/paper) and 0 otherwise	OECD
Capital intensity	Log of gross fixed capital per 1,000 workers by country, industry, and year	KLEMS
Institutional and labour-market conditions		
VoC	Categorical variable indicating institutional regime type: LME, LLME, CME, HE	Schneider and Paunescu (2012) ; Malik (2017)

continued

Table 1. Continued

Variables	Description	Source
Wages	Log of total employee compensation (in millions of 2010 US dollars) to employment (in thousands), by country, industry, and year	KLEMS
Employment	Log of total employment in millions by country, industry and year	KLEMS
Employment protection	Log of OECD index for individual and collective dismissal regulations (regular contracts) by country and year	OECD
Welfare state	Log of total social expenditure as a share of gross domestic product (GDP) by country and year	Eurostat
Job tenure	Log of the share of employees aged 25 and over with more than 10 years of continuous tenure by country and year	Eurostat
Population density	Log of population per land use area in square kilometre by country and year	World Bank
Venture capital	Venture capital availability, 1–7 (best) by country and year	World Economic Forum
Domestic credit to the private sector	Log of domestic credit to private sector as a share of GDP by country and year	World Bank

3.3 Methodology

This section outlines the empirical model used to examine the relationship between the industry-level intensity of robot-based automation and new firm formation. We begin by estimating the direct effect of robot density on new firm formation using the following ordinary least squares specification:

$$\ln B_{ict} = \beta_0 + \beta_1 \ln(R_{ict}/E_{ict}) + \beta_2 \ln F_{ct} + \beta_3 \ln Z_{ict} + \beta_4 \ln C_{ct} + a_c + \gamma_t + \varepsilon_{ict} \tag{1}$$

where the left-hand side variable B_{ict} denotes the logarithm (annual) birth of firms in industry i in country c in year t . The main regressor R_{ict}/E_{ict} is robot density in industry i in country c in year t . The vector F_{ct} includes the independent variable formal AET, the vector Z_{ict} comprises industry-country-year controls, C_{ct} includes other country-year variables; and ε_{ict} is the error term.

The central hypothesis of this study is that the relationship between the industry-level intensity of robot-based automation and new firm formation is conditional on a country’s level of formal human capital development. To test this, the following equation is estimated:

$$\ln B_{ict} = \beta_0 + \beta_1 \ln(R_{ict}/E_{ict}) + \beta_2 \ln F_{ct} + \beta_3 \ln(R_{ict}/E_{ict}) * \ln F_{ct} + \beta_4 \ln Z_{ict} + \beta_5 \ln C_{ct} + a_c + \gamma_t + \varepsilon_{ict} \tag{2}$$

To examine heterogeneity in this moderated relationship, we extend the analysis by interacting robot density and formal AET with indicators for VoC and technological intensity. We further assess the robustness of the results using alternative specifications, including lagged models and instrumental variable approaches.

Table 2. Means and standard deviations of key variables across countries.

Country	New firms		Robot density		Formal AET	
	Mean	SD	Mean	SD	Mean	SD
CMEs						
Austria	4.794	0.686	1.010	1.901	1.361	0.124
Belgium	4.818	0.887	1.160	1.734	0.896	0.081
France	6.983	1.029	1.683	1.503	-0.052	0.469
Germany	6.894	0.639	2.268	1.243	1.160	0.077
LMEs						
Denmark	4.443	0.601	2.949	0.438	1.839	0.120
UK	6.985	0.465	0.663	1.687	1.780	0.139
LLMEs						
Finland	4.742	0.689	2.281	0.955	2.145	0.053
Netherlands	5.769	0.615	1.484	1.302	1.970	0.044
Spain	6.735	1.032	1.735	1.474	1.136	0.160
Sweden	5.356	0.613	2.030	1.610	1.942	0.091
HEs						
Czech Republic	6.678	1.204	-0.063	2.016	0.803	0.116
Italy	7.392	0.902	1.983	1.517	1.010	0.788
Slovakia	6.055	1.485	0.060	1.922	0.454	0.203

Note: New firms report the average of the log-transformed counts of newly registered enterprises across the sampled manufacturing industries. Robot density denotes the average of the log-transformed annual ratio of industrial robot stock to employment (per thousand workers) for those same sectors. Formal AET captures the average of the log-transformed share of adults aged 25–64 who participated in formal education or training in the 4 weeks preceding the survey. All calculations include observations with a positive number of robots.

Table 3. Means and standard deviations of key variables across industries.

Industry	New firms		Robot density	
	Mean	SD	Mean	SD
High-tech manufacturing industries				
Electronics	5.430	1.006	1.346	1.168
Plastics and chemicals	5.940	1.025	2.151	0.763
Transport equipment	4.587	1.028	3.600	0.831
Low-tech manufacturing industries				
Food and beverages	6.322	1.125	1.130	1.394
Textiles	6.352	1.331	-0.772	1.520
Metal	6.887	1.113	2.179	1.132
Wood products and paper	6.591	1.103	0.304	1.346

Note: New firms report the average of the log-transformed counts of newly registered enterprises across the sampled manufacturing industries. Robot density denotes the average of the log-transformed annual ratio of industrial robot stock to employment (per thousand workers) for those same sectors. All calculations include observations with a positive number of robots.

Table 4. Summary statistics for all variables across industries and countries.

Variables	Mean	SD
Dependent variable		
New firms	6.004	1.323
Main independent variables		
Robot density	1.481	1.743
Formal AET	1.262	0.652
Education and skill controls		
Tertiary education	3.524	0.298
High-skill occupations	3.464	0.211
Vocational enrolment	3.378	0.401
Innovation and industry characteristics		
Industry R&D	7.152	2.139
GERD higher education sector	−0.723	0.412
Market concentration	−2.787	0.363
Capital intensity	5.047	0.540
Institutional and labour-market conditions		
Wages	3.800	0.441
Employment	4.776	1.148
Employment protection	0.940	0.200
Welfare state	3.189	0.192
Job tenure	3.734	0.123
Population density	4.832	0.934
Venture capital	3.474	0.797
Domestic credit to the private sector	4.541	0.413

Note: Wages are measured in millions of 2010 US dollars. Price values were converted from national currencies using PPPs. All calculations include observations with a positive number of robots.

4. Findings

4.1 Main findings

Table 5 presents the ordinary least squares regression results for Equations (1) and (2). Column (1) presents the baseline specification including control variables only. Column (2) introduces robot density, which is negatively and statistically significantly associated with new firm formation. The coefficient indicates that a 1 per cent increase in robot density is associated with an approximately 0.18 per cent decrease in new firm formation, holding other factors constant. This result is consistent with Hypothesis 1, which states that higher industry-level intensity of robot-based automation is associated with lower rates of new firm formation.

Column (3) adds formal AET. Formal AET is positively and statistically significantly associated with new firm formation, while the coefficient on robot density remains negative. This result is consistent with Hypothesis 2, suggesting that formal human capital development has a positive effect on new firm formation in manufacturing industries. Column (4) includes an interaction term between robot density and formal AET. The interaction coefficient is positive and statistically significant, indicating that the negative association between robot density and new firm formation varies with the

Table 5. Regression results: Robot density, formal AET, and VOC.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot density		-0.179*** (0.017)	-0.178*** (0.017)	-0.233*** (0.031)	-0.225*** (0.032)	-0.021 (0.168)	0.060*** (0.019)	0.741*** (0.183)
Formal AET			0.300*** (0.117)	0.240*** (0.119)	0.218* (0.116)	0.287*** (0.115)	-0.332 (0.328)	0.323 (0.364)
Robot density*formal AET				0.050*** (0.019)	0.044** (0.020)			-0.385*** (0.106)
Robot density*LLME							-0.331*** (0.024)	-1.221*** (0.195)
Robot density*CME							-0.215*** (0.025)	-0.985*** (0.184)
Robot density*HE							-0.258*** (0.033)	-0.955*** (0.207)
Formal AET*LLME							0.930* (0.508)	-0.047 (0.545)
Formal AET*CME							0.564* (0.341)	-0.267 (0.374)
Formal AET*HE							1.056* (0.582)	0.430 (0.591)
Robot density*formal AET*LLME								0.508*** (0.112)
Robot density*formal AET*CME								0.489*** (0.107)
Robot density*formal AET*HE								0.408*** (0.148)
Tertiary education	0.002 (0.217)	0.136 (0.212)	0.213 (0.219)	0.223 (0.220)	0.232 (0.210)	0.209 (0.218)	0.213 (0.207)	0.139 (0.208)

continued

Table 5. Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot density*tertiary education						-0.046 (0.047)		
High-skill occupations	0.324 (0.447)	0.189 (0.416)	-0.166 (0.438)	-0.232 (0.439)	0.057 (0.451)	-0.127 (0.441)	-0.173 (0.447)	-0.235 (0.442)
Vocational enrolment	0.193 (0.125)	0.139 (0.123)	0.150 (0.123)	0.156 (0.119)	0.068 (0.124)	0.141 (0.125)	0.014 (0.109)	0.048 (0.108)
Industry R&D	-0.313*** (0.017)	-0.241*** (0.018)	-0.242*** (0.018)	-0.241*** (0.018)	-0.210*** (0.021)	-0.242*** (0.018)	-0.253*** (0.018)	-0.251*** (0.018)
GERD higher education sector	0.260 (0.259)	0.360 (0.249)	0.340 (0.249)	0.338 (0.251)	0.295 (0.251)	0.325 (0.251)	0.431* (0.248)	0.454* (0.249)
Market concentration	-0.578 (0.564)	-0.446 (0.523)	-0.224 (0.534)	-0.266 (0.530)	-0.419 (0.551)	-0.259 (0.540)	0.019 (0.524)	-0.100 (0.517)
Digital intensity	-0.338*** (0.042)	-0.298*** (0.039)	-0.298*** (0.039)	-0.301*** (0.039)	-0.275*** (0.039)	-0.294*** (0.039)	-0.296*** (0.038)	-0.295*** (0.038)
Wages	-0.527*** (0.109)	-0.334*** (0.110)	-0.336*** (0.110)	-0.331*** (0.111)	-0.297*** (0.111)	-0.338*** (0.109)	-0.341*** (0.108)	-0.342*** (0.112)
Employment	0.811*** (0.033)	0.892*** (0.030)	0.892*** (0.030)	0.877*** (0.031)	0.895*** (0.032)	0.899*** (0.029)	0.917*** (0.029)	0.901*** (0.028)
Employment protection	0.162 (0.815)	0.509 (0.765)	0.328 (0.772)	0.297 (0.775)	-0.150 (0.762)	0.384 (0.776)	0.451 (0.846)	0.255 (0.843)
Welfare state	-0.913 (0.616)	-0.905 (0.561)	-1.065 (0.565)	-1.029 (0.566)	-0.876 (0.610)	-1.078 (0.567)	-0.906* (0.546)	-1.024* (0.552)
Job tenure	1.035* (0.600)	1.477*** (0.574)	1.612*** (0.575)	1.510*** (0.570)	1.810*** (0.575)	1.599*** (0.579)	2.023*** (0.600)	2.015*** (0.592)
Population density	4.122*** (1.666)	5.026*** (1.541)	5.593*** (1.577)	5.478*** (1.572)	7.152*** (1.690)	5.600*** (1.579)	5.330*** (1.497)	6.196*** (1.518)

continued

Table 5. Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Capital intensity					-0.187*** (0.060)			
Venture capital					0.247*** (0.092)			
Domestic credit to the private sector					0.176 (0.295)			
VoC dummies							✓	✓
Country dummies	✓	✓	✓	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓	✓	✓	✓
N	947	947	947	947	947	947	947	947
R-squared	0.828	0.850	0.851	0.852	0.856	0.851	0.862	0.866

Note: Robust standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
LMEs serve as the reference category in Columns (7) and (8).

level of formal AET. Across the observed range, robot density remains negatively associated with entry, but this association is weaker at higher levels of formal AET. These results are consistent with Hypothesis 3 and suggest that formal human capital development conditions the relationship between robot density and new firm formation by partially offsetting its adverse effects.

Column (5) accounts for broader capital and financial entry conditions by adding controls for capital intensity, domestic credit to the private sector, and venture capital availability. The results remain substantively consistent with the main specification in Column (4), providing further support for Hypothesis 3. Both capital intensity and robot density are statistically significant. The significance of capital intensity indicates that broader capital requirements are independently associated with new firm formation. Moreover, venture capital availability plays an important role in shaping the environment for new firm formation. Robot density and its interaction with formal AET retain their statistical significance. This is consistent with our argument that robot-based automation also entails changes in production tasks and requirements. Formal AET weakens the negative association between robot density and new firm formation by supporting the knowledge and skills needed to recognize and pursue entrepreneurial opportunities around robot-based automation.

Column (6) introduces an interaction term between robot density and higher educational attainment. The interaction term is not statistically significant, providing no evidence that higher educational attainment moderates the relationship between the industry-level intensity of robot-based automation and new firm formation. Considered alongside the significant interaction with formal AET, this result suggests that participation in formal human capital development, rather than tertiary educational attainment per se, is more relevant to how the relationship between robot-based automation and new firm formation varies across countries.

Columns (7) and (8) examine heterogeneity across VoC, with LMEs as the reference category. In Column (7), the interaction terms between robot density and institutional contexts are negative and statistically significant for LMEs, CMEs, and HEs, indicating that the association between robot density and new firm formation differs across institutional environments relative to LMEs.

Column (8) introduces the interaction terms between robot density, formal AET, and VoC. The interaction coefficients are positive and statistically significant for LMEs, CMEs, and HEs relative to LMEs. These estimates indicate that the conditional association between robot density and new firm formation varies jointly with the level of formal AET and the VoC categories. Overall, the results indicate that both the association between robot density and new firm formation and its moderation by formal AET differ across institutional contexts, consistent with Hypothesis 4. Among the control variables, employment levels, population density, and job tenure exhibit positive and statistically significant effects across all model specifications, indicating that greater employment opportunities, agglomeration, and workforce stability foster new firm formation. In contrast, industry R&D expenditure, wages, and digital sector intensity are consistently negatively associated with firm births.

Figure 1 presents the marginal effect of robot density on new firm formation across levels of formal AET, based on the interaction specification reported in Column (4). The marginal effect is negative across the observed range of formal AET, indicating that higher robot density is generally associated with lower rates of entrepreneurial entry. However, the magnitude of this negative relationship declines as participation in formal AET increases. This pattern indicates that formal AET weakens the negative relationship between the intensity of robot-based automation and new firm formation.

Figure 2 displays the marginal effect of robot density on new firm formation across logged levels of formal AET, estimated from the full interaction model reported in Column (8) of Table 5 and shown separately for each VoC. In LMEs, the marginal effect of robot density declines as formal

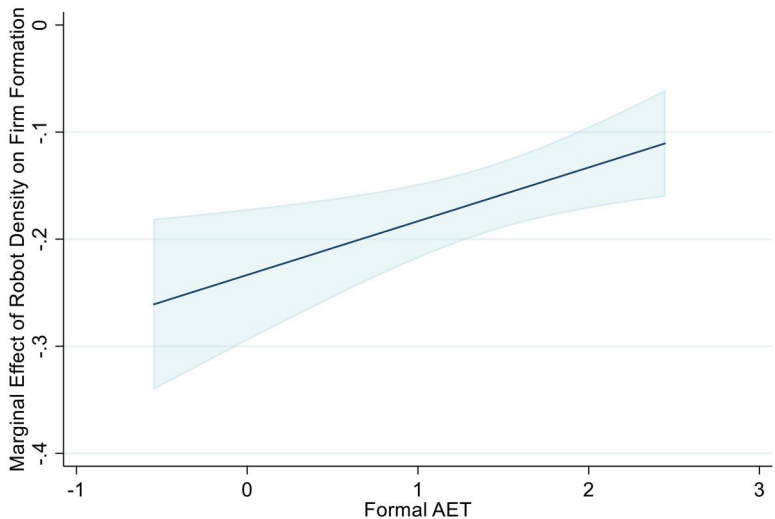


Figure 1. Marginal effect of robot density on new firm formation across levels of formal AET.
Note: The shaded area represents 95 per cent confidence intervals around the estimated marginal effects of robot density.

AET increases, shifting from weakly positive at lower levels of AET to negative at higher levels. By contrast, in LLMes and CMEs, the marginal effects are negative throughout but become progressively less negative as formal AET rises. In HEs, the marginal effect remains negative, with no statistically significant moderating effect of formal AET. The figure indicates that the association between robot density and entrepreneurial entry varies systematically across institutional contexts and is differentially conditioned by formal AET.

To further examine the institutional heterogeneity underlying the pooled results, Table 6 reports regression estimates disaggregated by VoC category. Robot density is negatively and statistically significantly associated with new firm formation in LLMes, CMEs, and HEs. The strongest negative relationship is found in LLMes. The interaction between robot density and formal AET varies systematically across VoC. The interaction term is positive and statistically significant in LLMes and CMEs, indicating that higher participation in formal AET is associated with a weaker negative relationship between robot density and new firm formation in these contexts. By contrast, the interaction term is negative and statistically significant in LMEs, indicating that higher participation in formal AET is associated with a stronger negative relationship between robot-based automation and new firm formation. These results show that the relationship between the intensity of robot-based automation and new firm formation is institutionally contingent and that the moderating role of formal AET differs across VoC.

Table 7 reports regression results examining the relationship between robot density and new firm formation across high- and low-technology industries, with high-technology industries serving as the baseline category. Columns (1) and (2) present the estimates for the full sample. In Column (1), robot density is more strongly associated with reduced entry in high-technology industries, whereas the corresponding association in low-technology industries is weaker. Formal AET supports entry primarily in high-technology sectors. Column (2) introduces interactions between robot density and formal

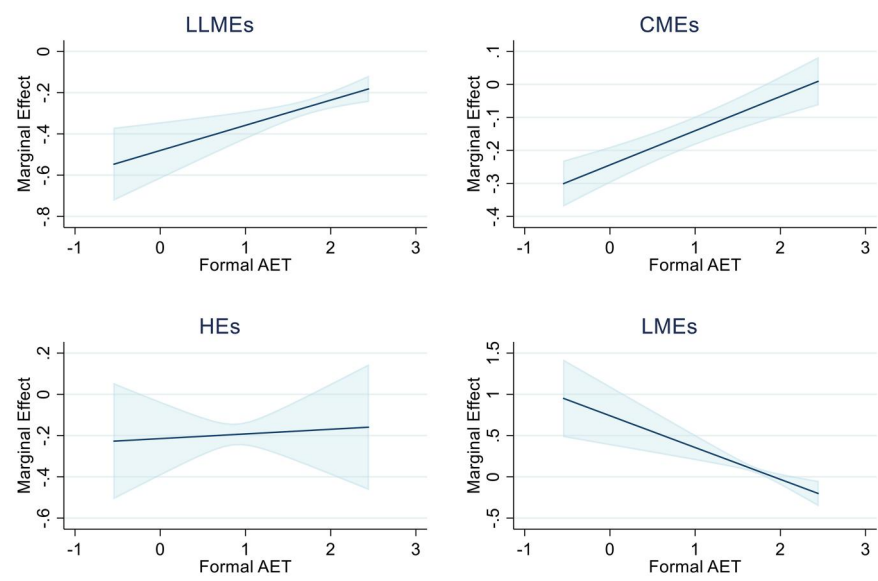


Figure 2. Marginal effect of robot density on new firm formation across levels of formal AET, by VoC.
Note: The shaded area represents 95 per cent confidence intervals around the estimated marginal effects of robot density.

AET. The interaction between robot density and formal AET is negative and statistically significant in high-technology industries, indicating that higher participation in formal AET is associated with a more negative relationship between robot density and entry in these industries. However, this moderating effect differs in low-technology industries, where it is weaker.

Columns (3)–(6) disaggregate these relationships across VoC contexts. In LLMEs, robot density is negatively and statistically significantly associated with new firm formation in high-technology industries. The positive and significant interaction between robot density and formal AET indicates that higher participation in formal AET attenuates this negative relationship. However, the corresponding moderating association in low-technology industries differs. The interaction is negative, suggesting that higher formal AET is associated with a more negative relationship between robot density and new firm formation in these industries.

In CMEs, robot density is also negatively and significantly associated with new firm formation in high-technology industries. The interaction between robot density and formal AET is weakly negative in these industries. By contrast, the estimates for low-technology industries indicate that higher participation in formal AET weakens the negative relationship between the intensity of robot-based automation and new firm formation. In HEs, robot density is strongly and negatively associated with new firm formation in high-technology industries. Formal AET attenuates this relationship in high-technology industries. In low-technology industries, however, the moderating role of formal AET differs, such that higher formal AET is associated with a more negative relationship between robot density and new firm formation.

In LMEs, robot density is positively and statistically significantly associated with new firm formation in high-technology industries. However, higher participation in formal AET is associated with a

Table 6. Regression results by VoC.

	(1) LLMes	(2) CMEs	(3) HEs	(4) LMEs
Robot density	−0.487*** (0.068)	−0.320*** (0.030)	−0.325*** (0.102)	0.415*** (0.153)
Formal AET	0.110 (0.743)	0.078 (0.254)	1.246 (1.289)	0.567 (0.583)
Robot density*formal AET	0.136*** (0.036)	0.106*** (0.018)	0.103 (0.109)	−0.238*** (0.087)
Tertiary education	−1.992 (2.242)	−0.058 (0.234)	0.111 (2.090)	−0.384 (3.499)
High-skill occupations	0.811 (1.063)	−1.657 (1.027)	−0.962 (1.878)	3.808 (3.193)
Vocational enrolment	−0.225 (0.371)	0.477 (0.843)	5.118 (5.054)	−0.161 (0.443)
Industry R&D	−0.219*** (0.022)	−0.413*** (0.030)	−0.268*** (0.037)	−0.130*** (0.031)
GERD higher education sector	0.693 (1.439)	0.101 (1.300)	0.061 (0.604)	0.625 (1.689)
Market concentration	−0.643 (0.641)	−0.880 (1.158)	4.945* (2.660)	2.527 (1.765)
Digital intensity	−0.383*** (0.057)	−0.171*** (0.043)	−0.376*** (0.119)	−0.003*** (0.047)
Wages	−0.329*** (0.143)	0.910*** (0.196)	−0.488*** (0.151)	−0.623*** (0.235)
Employment	0.743*** (0.037)	1.014*** (0.039)	1.721*** (0.192)	0.716*** (0.054)
Employment protection	1.415 (2.118)	1.282 (1.606)	2.627 (2.677)	−3.786 (6.410)
Welfare state	−1.910 (1.241)	−1.858 (3.799)	−1.545 (5.004)	0.312 (3.772)
Job tenure	1.098 (1.223)	1.485 (2.638)	−2.124 (7.926)	3.889 (6.734)
Population density	−1.988 (7.946)	17.324** (6.939)	11.132 (24.629)	−0.519 (6.399)
Country dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
N	298	307	209	133
R-squared	0.882	0.934	0.765	0.957

Note: Robust standard errors are reported in parentheses.

* $P < 0.10$, ** $P < 0.05$, *** $P < 0.01$.

weakening of this positive relationship. The corresponding relationship in low-technology industries follows the same direction but is less pronounced. The results in Columns (3)–(7) reveal systematic heterogeneity in how formal AET moderates the relationship between the intensity of robot-based automation and new firm formation across VoC contexts and industry technological intensity, consistent with Hypothesis 5.

Table 7. Regression results by VoC and technological intensity.

	(1) Full sample	(2) Full sample	(3) LLMes	(4) CMEs	(5) HEs	(6) LMEs
Robot density	−0.264*** (0.019)	−0.209*** (0.032)	−0.579*** (0.075)	−0.312*** (0.026)	−0.676*** (0.114)	0.996*** (0.351)
Formal AET	0.506*** (0.115)	0.633*** (0.132)	0.075 (0.599)	0.506** (0.249)	0.896 (0.995)	1.727*** (0.609)
Robot density*formal AET		−0.055** (0.024)	0.144** (0.056)	−0.045* (0.027)	0.483*** (0.137)	−0.667*** (0.198)
Robot density*low-tech	0.201*** (0.025)	0.173*** (0.053)	0.708*** (0.012)	0.060 (0.055)	1.034*** (0.139)	−0.372 (0.348)
Formal AET*low-tech	−0.439*** (0.049)	−0.558*** (0.078)	−0.010 (0.199)	−0.516*** (0.107)	−1.095*** (0.323)	−1.065** (0.457)
Robot density*formal AET*low-tech		0.034 (0.034)	−0.255*** (0.073)	0.191*** (0.043)	−1.081*** (0.156)	0.351* (0.195)
Tertiary education	0.219 (0.203)	0.214 (0.202)	−0.951 (1.683)	−0.019 (0.211)	0.780 (1.704)	−0.627 (2.939)
High-skill occupations	−0.294 (0.395)	−0.234 (0.395)	0.810 (0.789)	−1.634* (0.891)	−0.744 (1.519)	4.746* (2.789)
Vocational Enrolment	0.160 (0.100)	0.156 (0.101)	−0.228 (0.309)	0.580 (0.715)	2.849 (3.991)	−0.193 (0.354)
Industry R&D	−0.096*** (0.030)	−0.103*** (0.031)	0.010 (0.035)	−0.355*** (0.049)	0.026 (0.060)	−0.113** (0.055)
GERD higher education sector	0.435** (0.216)	0.432** (0.215)	0.190 (1.131)	0.073 (1.190)	−0.068 (0.456)	0.645 (1.465)
Market concentration	0.120 (0.484)	0.155 (0.485)	−0.276 (0.490)	−0.735 (1.034)	5.416** (2.174)	2.803* (1.432)
Digital intensity	−0.221*** (0.036)	−0.220*** (0.036)	−0.253*** (0.044)	−0.127*** (0.044)	−0.144 (0.128)	0.011 (0.047)
Wages	−0.313*** (0.099)	−0.327*** (0.097)	−0.521*** (0.124)	0.782*** (0.174)	−0.738*** (0.126)	−1.275*** (0.284)
Employment	0.586*** (0.045)	0.598*** (0.045)	0.271*** (0.059)	0.857*** (0.047)	1.337*** (0.182)	0.722*** (0.088)
Employment protection	0.167 (0.690)	0.230 (0.689)	1.168 (1.554)	1.215 (1.371)	2.562 (2.102)	−3.862 (5.569)
Welfare state	−1.316** (0.520)	−1.349*** (0.519)	−2.134** (0.957)	−1.674 (3.269)	−0.699 (3.942)	0.532 (3.304)
Job tenure	1.528*** (0.510)	1.646*** (0.518)	0.078 (0.988)	1.603 (2.320)	−5.979 (6.229)	4.376 (5.692)
Population density	5.370*** (1.486)	5.426*** (1.485)	−5.873 (6.480)	16.410*** (5.987)	4.325 (19.360)	0.084 (5.223)
Country dummies	✓	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓	✓
Technology intensity dummies	✓	✓	✓	✓	✓	✓
N	947	947	298	307	209	133
R-squared	0.875	0.876	0.925	0.944	0.844	0.968

Note: Robust standard errors are reported in parentheses.
* $P < 0.10$, ** $P < 0.05$, *** $P < 0.01$.
High-tech is used as the reference group in Columns (1)–(6). Columns (1)–(2) report full-sample estimates. Columns (3)–(6) report estimates by VoC.

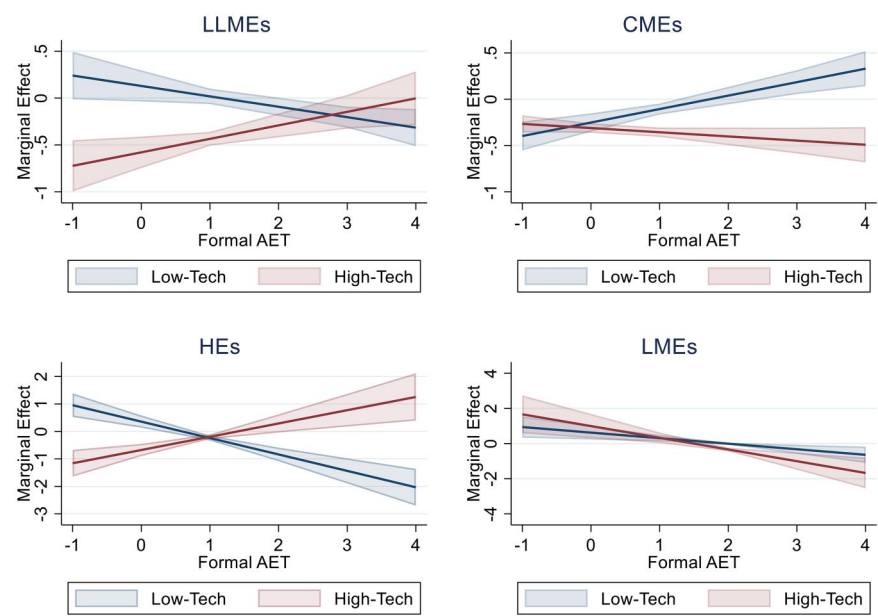


Figure 3. Marginal effect of robot density on new firm formation across levels of formal AET, by technological intensity and VoC.

Note: The shaded area represents 95 per cent confidence intervals around the estimated marginal effects of robot density.

Figure 3, which builds directly on the estimates reported in Table 7, plots the marginal effect of robot density on new firm formation across levels of formal AET for each VoC, revealing heterogeneity across institutional and industry contexts. In LLMes, the marginal effect of robot density in high-technology industries increases with formal AET, moving from clearly negative at lower levels of AET towards zero at higher levels. In low-technology industries, the marginal effect declines slightly as formal AET increases and remains close to zero, indicating a weaker moderating role for formal AET. In CMEs, the marginal effect of robot density in high-technology industries is negative and becomes modestly more negative as formal AET increases. By contrast, in low-technology industries, the marginal effect increases with formal AET, shifting from negative values at lower levels of AET towards positive values at higher levels. This finding suggests that in CMEs, formal AET is more likely to support new firm formation in low-technology than in high-technology industries.

In HEs, the marginal effect of robot density in high-technology industries increases sharply with formal AET, shifting from strongly negative at low levels of formal AET to positive at higher levels. By contrast, in low-technology industries, the marginal effect of robot density on new firm formation becomes increasingly negative as formal AET rises. In LMEs, the marginal effect declines with formal AET in both industries, with the decline more pronounced in high-tech industries than in low-tech industries. Figure 3 shows that the marginal effect of robot density varies not only by institutional configuration but also by industry technological intensity, with opposing slopes across high- and low-technology industries in LLMes, CMEs, and HEs, and declining effects with formal AET in both industries in LMEs.

4.2 Robustness checks

To assess the robustness of the results, we conduct additional analyses using alternative model specifications. The specifications reported in Columns (3), (4), and (8) of Table 5 are re-estimated using 1-year lags of robot density and formal AET, addressing potential concerns about reverse causality (Table 8, Columns 1–3). The results remain robust. To further address potential endogeneity of robot density, a two-stage least squares estimation was implemented using annual robot stock in Germany between 1995 and 2005 as an instrument (Table 8, Columns 4–6). Germany, which has one of the highest levels of robot density in manufacturing in the sample, provides consistent data dating back to 1995. This approach leverages exogenous variation in technological trends within an advanced economy to better isolate the causal effect of robot adoption, mitigating concerns related to reverse causality and unobserved industry-level shocks. The IV results are similar to the baseline regressions, confirming the robustness of the main findings. The first-stage F-statistics are well above the conventional threshold of ten, indicating a strong instrument (Staiger and Stock 1997).

Table 9 reports a series of robustness checks examining the relationship between the intensity of robot-based automation, formal AET, and new firm formation across VoC contexts and industry technological intensity. Columns (1)–(4) re-estimate the corresponding specifications reported in Table 7 using 1-year lags of robot density and formal AET, for each institutional environment, while Columns (5)–(7) report alternative specifications based on a reclassification of Denmark. Given that Denmark represents a borderline case within the VoC framework, these robustness checks reassign Denmark to the CME and LLME categories to assess whether the main results are sensitive to this institutional classification. Columns (5) and (6) estimate the models for LLMEs and CMEs under the updated classification. Column (7) reports the results for LMEs, which comprise only the UK in this specification and are therefore based on fewer observations. The main findings remain robust to the use of lagged ordinary least squares specifications and alternative institutional classifications.

5. Discussion and conclusion

Robot-based automation is reshaping manufacturing, with important implications not only for production but also for entrepreneurial entry. Our findings show that greater intensity of robot-based automation is associated with lower new firm formation, while formal human capital development generally weakens this negative relationship. However, this moderating role is not uniform. Its strength and direction vary across VoC configurations and between high- and low-technology industries, indicating that the entrepreneurial value of renewed knowledge and skills depends both on the institutional conditions under which they are mobilized and on their relevance to industry-specific demands. The following sections examine these differences and consider their broader implications for entrepreneurial entry in manufacturing.

5.1 Institutional heterogeneity

Viewed through the VoC framework, our findings reveal substantial institutional variation in both the relationship between robot-based automation and new firm formation and the moderating role of formal human capital development. This suggests that the entrepreneurial consequences of robot-based automation are shaped by national institutional configurations, including how skill-formation systems support the renewal of knowledge and skills relevant to new firm formation.

In LMEs, robot-based automation is positively associated with new firm formation at lower levels of formal human capital development, but this association weakens and becomes negative as formal AET rises. Prior evidence suggests that formal AET has tended to be concentrated in job-related and

Table 8. Robustness checks by VoC.

	(1) Lagged OLS	(2) Lagged OLS	(3) Lagged OLS	(4) IV	(5) IV	(6) IV
Robot density	−0.180*** (0.017)	−0.237*** (0.033)	1.220*** (0.402)	−0.306*** (0.020)	−0.412*** (0.030)	0.766*** (0.340)
Formal AET	0.255** (0.127)	0.191 (0.130)	0.163 (0.746)	0.265** (0.119)	0.158 (0.120)	0.370 (0.574)
Robot density*formal AET		0.052*** (0.020)	−0.641*** (0.224)		0.089*** (0.021)	−0.457** (0.231)
Robot density*LLME			−1.752*** (0.408)			−1.455*** (0.409)
Robot density*CME			−1.473*** (0.403)			−1.110*** (0.410)
Robot density*HE			−1.381*** (0.420)			−1.183** (0.407)
Formal AET*LLME			0.107 (0.899)			−0.326 (0.753)
Formal AET*CME			−0.187 (0.754)			−0.266 (0.589)
Formal AET*HE			0.597 (0.874)			0.447 (0.759)
Robot density*formal AET*LLME			0.789*** (0.227)			0.650*** (0.236)
Robot density*formal AET*CME			0.747*** (0.225)			0.519** (0.233)
Robot density*formal AET*HE			0.604** (0.253)			0.512** (0.246)
Tertiary education	0.186 (0.233)	0.191 (0.234)	0.095 (0.224)	0.315 (0.232)	0.337 (0.237)	0.280 (0.224)
High-skill occupations	−0.194 (0.460)	−0.241 (0.462)	−0.361 (0.469)	−0.221 (0.452)	−0.340 (0.465)	−0.448 (0.479)
Vocational enrolment	0.141 (0.123)	0.149 (0.118)	0.024 (0.116)	0.110 (0.131)	0.119 (0.124)	−0.004 (0.113)
Industry R&D	−0.244*** (0.019)	−0.242*** (0.019)	−0.254*** (0.019)	−0.191*** (0.600)	−0.186*** (0.020)	−0.197*** (0.020)
GERD higher education sector	0.301 (0.263)	0.310 (0.265)	0.330 (0.271)	0.414 (0.254)	0.414 (0.262)	0.530** (0.265)
Market concentration	−0.461 (0.516)	−0.516 (0.513)	−0.411 (0.499)	−0.155 (0.548)	−0.226 (0.547)	−0.061 (0.538)
Digital intensity	−0.314*** (0.040)	−0.316*** (0.041)	−0.311*** (0.039)	−0.269*** (0.041)	−0.272*** (0.042)	−0.271*** (0.041)
Wages	−0.309*** (0.114)	−0.306*** (0.116)	−0.298*** (0.117)	−0.197*** (0.118)	−0.182*** (0.122)	−0.191*** (0.121)
Employment	0.886*** (0.031)	0.871*** (0.031)	0.897*** (0.029)	0.950*** (0.034)	0.927*** (0.034)	0.942*** (0.031)
Employment protection	0.463 (0.804)	0.435 (0.805)	0.477 (0.884)	0.598 (0.793)	0.558 (0.806)	0.309 (0.900)

continued

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Table 8. Continued

	(1) Lagged OLS	(2) Lagged OLS	(3) Lagged OLS	(4) IV	(5) IV	(6) IV
Welfare state	−0.947 (0.625)	−0.934 (0.626)	−0.873 (0.620)	−1.041* (0.571)	−0.975* (0.570)	−0.989* (0.562)
Job tenure	1.573*** (0.595)	1.466** (0.595)	1.877*** (0.596)	1.913*** (0.601)	1.749*** (0.594)	2.165*** (0.613)
Population density	4.356*** (1.570)	4.199*** (1.564)	5.533*** (1.557)	6.174*** (1.643)	6.003*** (1.633)	6.878*** (1.587)
VoC dummies			✓		✓	✓
Country dummies	✓	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓	✓
N	863	863	863	947	947	947
R-squared	0.856	0.857	0.871	0.840	0.839	0.850
First-stage F-statistic				692.91	321.29	34.866

Note: Robust standard errors are reported in parentheses.
* $P < 0.10$, ** $P < 0.05$, *** $P < 0.01$.
LMEs is used as the reference category in Columns (3) and (6).

employer-sponsored provision, while publicly supported retraining remains relatively limited and unevenly accessible (Desjardins and Ioannidou 2020). Incumbents may thus be better positioned to integrate renewed knowledge and skills with their existing capital-intensive production infrastructure. Decentralized wage-setting may further enable incumbents to respond to emerging skill demands through wage premiums, increasing the opportunity cost of entrepreneurial entry for workers with newly developed capabilities (Dilli, Elert, and Herrmann 2018). At the same time, weak labour-market protections and limited welfare provision place greater adjustment risks on individuals, while evidence suggests that workers displaced by automation may be less likely to undertake retraining (Ioannidou and Parma 2022). As formal AET expands, renewed capabilities may be increasingly absorbed into incumbent adjustment rather than translate into new firm formation.

In CMEs, robot-based automation is associated with lower new firm formation at lower levels of formal human capital development, but this negative association weakens as formal human capital development expands, becoming positive at higher levels. This is consistent with complementarities between collective skill-formation institutions and coordinated production systems (Busemeyer and Trampusch 2012). Although job-related formal AET tends to be less prevalent than in LMEs (Desjardins and Ioannidou 2020), its integration with occupational, sectoral, and inter-firm networks may allow renewed knowledge and skills to circulate beyond individual firms and be translated more readily into entrepreneurial entry. Rather than challenging incumbents directly, entrants may pursue specialized niches and supplier relationships that connect them to and complement established production systems (Sorge and Streeck 2018). Such relationships may lessen the need for prospective entrepreneurs to develop an equivalent capital-intensive asset base independently, thereby easing some of the entry barriers surrounding robot-based automation.

A related pattern is observed in LLMEs, where the negative association between robot-based automation and new firm formation weakens as formal human capital development increases, becoming less negative at higher levels. This may reflect the combination of labour-market flexibility, stronger

Table 9. Robustness checks by VoC and technological intensity.

	(1) Lagged OLS LLMEs	(2) Lagged OLS CMEs	(3) Lagged OLS HEs	(4) Lagged OLS LMEs	(5) OLS LMEs'	(6) OLS CMEs	(7) OLS LMEs
Robot density	-0.577*** (0.086)	-0.297*** (0.026)	-0.696*** (0.127)	1.608*** (0.505)	-0.582*** (0.088)	-0.301*** (0.027)	1.364*** (0.258)
Formal AET	-0.630 (0.597)	0.591*** (0.181)	1.748 (1.553)	4.772* (2.483)	-0.143 (0.505)	0.747*** (0.191)	3.093*** (1.238)
Robot density*formal AET	0.147*** (0.058)	-0.055*** (0.026)	0.498*** (0.148)	-0.989*** (0.283)	0.140*** (0.058)	-0.059*** (0.028)	-0.633*** (0.117)
Robot density*low-tech	0.685*** (0.125)	0.038 (0.056)	1.170*** (0.147)	0.062 (0.575)	0.664*** (0.126)	0.083 (0.054)	-0.921*** (0.410)
Formal AET*low-tech	-0.208 (0.204)	-0.547*** (0.107)	-1.229*** (0.365)	-0.683 (0.759)	0.004 (0.199)	-0.656*** (0.111)	-0.641 (0.402)
Robot Density*formal AET*low-tech	-0.251*** (0.075)	0.204*** (0.043)	-1.212*** (0.167)	0.100 (0.321)	-0.247*** (0.075)	0.156*** (0.042)	0.889*** (0.270)
Tertiary education	-1.973 (1.970)	-0.048 (0.210)	-0.061 (1.821)	-6.742 (4.490)	-0.142 (1.366)	0.057 (0.172)	-7.394*** (3.215)
High-skill occupations	0.706 (0.846)	-0.827 (0.982)	-0.773 (1.204)	9.559* (5.485)	0.565 (0.643)	-2.054*** (0.824)	7.396 (4.605)
Vocational enrolment	-0.176 (0.348)	0.150 (0.599)	1.831 (6.460)	-0.242 (0.521)	-0.083 (0.244)	0.034 (0.553)	0.201 (0.308)
Industry R&D	0.018 (0.035)	-0.367*** (0.052)	0.012 (0.064)	-0.086 (0.056)	0.010 (0.034)	-0.290*** (0.039)	-1.298*** (0.272)
GERD higher education sector	-0.148 (1.135)	-0.171 (1.196)	-0.389 (0.454)	-1.558 (1.602)	0.202 (0.960)	-1.023 (0.803)	-0.030 (5.370)
Market concentration	-0.329 (0.510)	-0.608 (0.939)	4.305* (2.420)	2.063 (1.514)	0.079 (0.494)	-1.811*** (0.773)	-0.120 (1.527)

continued

Table 9. Continued

	(1) Lagged OLS LLMEs	(2) Lagged OLS CMEs	(3) Lagged OLS HEs	(4) Lagged OLS LMEs	(5) OLS LMEs'	(6) OLS CMEs	(7) OLS LMEs
Digital intensity	-0.277*** (0.045)	-0.147*** (0.045)	-0.200*** (0.127)	0.016 (0.048)	-0.236 (0.042)	-0.120*** (0.043)	-0.432 (0.118)
Wages	-0.483*** (0.128)	0.816*** (0.179)	-0.708*** (0.134)	-1.321*** (0.264)	-0.510*** (0.124)	0.670*** (0.169)	-0.598*** (0.284)
Employment	0.266*** (0.061)	0.851*** (0.047)	1.313*** (0.176)	0.700*** (0.088)	0.342*** (0.054)	0.796*** (0.045)	0.906*** (0.099)
Employment protection	0.431 (1.365)	2.568* (1.468)	3.722 (2.701)	-7.259 (5.591)	-0.081 (1.270)	0.450 (1.352)	1.169 (9.182)
Welfare state	-2.938*** (1.171)	-2.031 (3.404)	-4.977 (4.404)	5.106 (3.867)	-2.109*** (0.918)	3.872*** (1.428)	-1.288 (5.442)
Job tenure	-0.266 (1.167)	1.677 (1.684)	-14.016* (7.176)	9.569 (11.107)	0.649 (0.799)	-1.133 (1.270)	-5.357 (9.230)
Population density	-4.706 (7.985)	16.233 (6.028)	10.867 (26.198)	-0.040 (3.360)	-0.984 (2.627)	3.809* (1.961)	36.767*** (1.290)
Country dummies	✓	✓	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓	✓	✓
Technology intensity dummies	✓	✓	✓	✓	✓	✓	✓
N	270	279	188	126	354	363	77
R-squared	0.931	0.945	0.854	0.971	0.922	0.943	0.833

Note: Robust standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
High-tech is used as the reference category in Columns (1)–(4). Columns (5)–(7) report OLS estimates based on alternative classifications of Denmark.

welfare protection than in LMEs, and production coordination that, while present, is less integrated than in CMEs (Schneider and Paunescu 2012). Although formal AET tends to be similarly concentrated in job-related provision as in LMEs (Desjardins and Ioannidou 2020), active labour-market policies, welfare protection, and publicly supported retraining may reduce the risks of occupational transition and enable renewed knowledge and skills to be redeployed beyond incumbent firms (Desjardins 2017; Brown, Lauder, and Cheung 2020). Greater labour-market flexibility and less extensive production coordination than in CMEs may nevertheless limit the extent of such skill redeployment. Formal human capital development weakens the negative association between robot-based automation and new firm formation.

In HEs, greater intensity of robot-based automation is associated with lower new firm formation, while formal human capital development does not significantly moderate this relationship. Fragmented institutional arrangements and weak coordination among education, labour-market, and production systems may constrain the translation of renewed knowledge and skills into entrepreneurial entry (Malik 2017; Dilli 2021).

Collectively, these findings reveal that both the relationship between robot-based automation and new firm formation and the moderating role of formal human capital development vary across VoC contexts. However, institutional and industry heterogeneity need to be considered jointly, as aggregate institutional comparisons may obscure how the entry barriers and opportunities associated with robot-based automation vary with industry technological intensity (Akkermans, Castaldi, and Los 2009).

5.2 Industry heterogeneity across institutional contexts

When industries are grouped by technological intensity, robot-based automation is associated with lower new firm formation in high-technology industries, while this association is less negative in low-technology industries. Formal human capital development moderates this relationship differently across the two groups, strengthening the negative association in high-technology industries while weakening it in low-technology ones. Considering institutional and industry heterogeneity jointly shows that the entry barriers and entrepreneurial opportunities associated with robot-based automation vary across national institutional contexts and between high- and low-technology industries.

In LMEs, the relationship observed in the VoC-level analysis persists across both high- and low-technology industries. Formal human capital development shifts the association between robot-based automation and new firm formation in a more negative direction in both industry groups, suggesting that incumbents' advantage in utilizing renewed knowledge and skills extends across different technological contexts. Consequently, industry technological intensity appears to affect the magnitude, rather than the direction, of the broader LME pattern.

In CMEs, the aggregate institutional relationship is concentrated primarily in low-technology manufacturing, where the estimated association between robot-based automation and new firm formation becomes less negative as formal human capital development increases and turns positive at higher levels. One explanation lies in the close correspondence between coordinated skill-formation and production systems and the knowledge demands of low-technology industries. These industries rely less on scientific knowledge and more on vocational expertise, production experience, and incremental problem-solving capabilities (Crouch, Schröder, and Voelzkow 2009). Strong initial VET systems and dense supplier networks may provide the occupational foundations and inter-firm connections through which formal AET can update and redeploy such knowledge in new ventures. The alignment between CME skill-formation systems and the vocational, experience-based knowledge demands of low-technology manufacturing (Dilli 2021) may explain why the favourable moderating role of formal human capital development is concentrated in these industries.

In LLMs, however, the overall pattern differs markedly between high- and low-technology industries. Formal human capital development shifts the association between robot-based automation and new firm formation in a positive direction in high-technology industries, but in a negative direction in low-technology industries. In high-technology industries, accessible adult-learning systems and welfare protection may support transition to entrepreneurship, while the general human-capital orientation of LLMs may provide a broad analytical and transferable foundation on which formal AET can build to meet the scientific, technical, and commercial demands of robot-based production (Desjardins 2017; Brown, Lauder, and Cheung 2020). In low-technology industries, entrepreneurial entry may rely more heavily on process-specific knowledge and occupational expertise developed through workplace experience and specialized training (Crouch, Schröder, and Voelzkow 2009). Compared with CMEs, less extensive production coordination in LLMs may provide fewer inter-firm channels through which renewed knowledge can support collaboration between incumbents and prospective entrants, limiting the extent to which formal AET contributes to new firm formation.

HEs are more heterogeneous than LMEs and CMEs (Schneider and Paunescu 2012), and their fragmented coordination may shape variation in the role of formal human capital development across industries. In high-technology industries, the negative association between robot-based automation and new firm formation weakens as formal AET increases and becomes positive at higher levels. Despite institutional incoherence (Kenworthy 2006), technological capabilities can become selectively concentrated in advanced sectors (Malik 2017). As technological change creates specialized requirements and niches that incumbents may not fully exploit, formal human capital development may enable prospective entrants to apply renewed capabilities to these opportunities. In low-technology industries, weaker coordination than in CMEs may provide fewer inter-firm channels for renewed capabilities to support entry. This may be reinforced where production is oriented toward cost efficiency and technology-related training focuses on immediate operational needs rather than the development of transferable skills that could support new firm formation (Da Roit and Iannuzzi 2023).

The implications of robot-based automation for new firm formation, and the role of formal human capital development in shaping them, are not uniform but depend on how national institutional arrangements intersect with industry technological intensity. While this study centres on entrepreneurial entry, we do not assume that greater new firm formation necessarily leads to positive outcomes such as job creation or economic growth (Eberhart, Lounsbury, and Aldrich 2022). As Shane (2008) points out, most new ventures remain small and few scale sufficiently to generate substantial employment. Instead, the significance of these new firms lies in their potential to limit the disproportionate concentration of market power among incumbents (Firooz, Liu, and Wang 2025), thereby helping to preserve organizational diversity and industry renewal.

This study demonstrates that expanding formal human capital development does not translate into greater entrepreneurial entry across all institutional and industry contexts. Depending on the institutional environment and industry knowledge demands, renewed knowledge and skills may enable prospective entrants to identify and pursue emerging opportunities or strengthen incumbent adaptation. Formal human capital development should be viewed as a context-dependent policy instrument, the consequences of which depend on who can access and mobilize renewed capabilities and how they are applied by prospective entrants or established incumbents in high- or low-technology industries. Skills, industrial, and automation policies should jointly account for institutional arrangements and industry technological characteristics.

5.3 Theoretical contributions and future research

This study makes three theoretical contributions. First, it extends research on automation beyond its consequences for employment and productivity (Acemoglu and Restrepo 2019; Richiardi *et al.*, 2025) to its implications for entrepreneurial entry in manufacturing. We find that greater industry-level intensity of robot-based automation is associated with lower rates of new firm formation. We theorize this relationship as reflecting two countervailing mechanisms. The capital-intensive character of robot-based automation reinforces incumbent advantages in investment capacity, scale, and accumulated organizational capabilities (Autor, Mindell, and Reynolds 2021; Koch, Manuylov, and Smolka 2021). Yet the reconfiguration of production tasks may create new requirements that provide openings for new firms, particularly, though not exclusively, through demand for complementary products and services that incumbents do not produce internally. Incumbent advantages may outweigh the new opportunities created by task reconfiguration, while still leaving some scope for new firm formation.

Second, this research advances research on human capital and entrepreneurship by examining how human capital development conditions the relationship between robot-based automation and new firm formation. We bring the continued renewal of knowledge and skills through formal AET into explanations of entrepreneurial entry (Brown, Lauder, and Cheung 2020). Whereas entrepreneurship research has largely treated human capital as an accumulated stock (Unger *et al.* 2011), we emphasize its ongoing renewal as technological change generates new technical, organizational, and market needs. In manufacturing, formal human capital development matters not as a source of particular technical or managerial knowledge, but as a means of renewing and recombining existing knowledge and skills. Viewed through the lens of entrepreneurial absorptive capacity (Qian and Acs 2013), the positive association between formal human capital development and new firm formation does not imply that education creates more opportunities for entry. Rather, continued knowledge and skill renewal can broaden the ways prospective entrepreneurs interpret and respond to changing production requirements (Kaplan and Tripsas 2008), helping them connect prior expertise to emerging needs associated with automated production and develop viable commercial responses.

Third, we contribute to institutional approaches to entrepreneurship (Herrmann 2019; Dilli 2021) by showing how national institutional arrangements and industry technological intensity jointly affect new firm formation (Crouch, Schröder, and Voelzkow 2009; Dilli 2021). Responding to calls to examine institutional effects across different industrial contexts (Akkermans, Castaldi, and Los 2009; Herrmann 2019), our findings indicate that the entrepreneurial value of formal human capital development depends not only on how national institutions support the development and mobilization of renewed capabilities, but also on their relevance to industry-specific knowledge demands. Whereas entrepreneurship research has focused predominantly on high-technology manufacturing (Hirsch-Kreinsen 2008; Dilli, Elert, and Herrmann 2018; Dilli 2021), considering both high- and low-technology industries allows us to examine this relationship across distinct knowledge and skill contexts. By contrasting these industry types, we show that the moderating role of formal human capital development under automation varies with the intersection of national institutional arrangements and industry technological intensity.

This study points to three avenues for future research. First, the individual-level mechanisms linking formal AET to new firm formation remain open to investigation. Longitudinal studies could examine whether knowledge and skill renewal develop cognitive flexibility, defined as the capacity to adjust mental models to changing conditions (Martin and Rubin 1995), and enable prospective entrepreneurs to interpret technological change (Kaplan and Tripsas 2008). Second, our industry-level measure of new firm formation provides limited insight into how entrants position themselves relative

to established producers. Firm- or product-level data could distinguish entrants that compete directly with incumbents from those that complement incumbent production (Sorge and Streeck 2018), helping clarify the structure and competitive dynamics of manufacturing production ecosystems (Kapetaniou et al. 2018). Third, formal human capital development may help prospective entrepreneurs respond to automation-related opportunities but does not resolve financing barriers to capital-intensive manufacturing. Future research could examine whether renewed capabilities improve access to finance by strengthening entrant credibility, legitimacy, and venture preparedness (Colombo, Meoli, and Vismara 2019).

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