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Technology Adoption and Productivity: Evidence from UK SMEs

By *José M. Liñares-Zegarra and John O.S. Wilson*

Abstract: This study examines the impact of digital technology adoption, both individually and in bundles, on the productivity of small and medium-sized enterprises (SMEs) in the UK. Drawing on data from the 2022 and 2023 waves of the Longitudinal Small Business Survey (LSBS), we investigate whether the adoption of production-enhancing technologies, such as artificial intelligence, robotics, and automation (AIRA), cloud computing, business intelligence (BI), computer-aided design (CAD), Virtual/Augmented reality (VR/AR) and the Internet of Things (IoT), yields superior productivity outcomes. An extensive econometric analysis of numerous estimable models, which control for firm-level heterogeneities, reveals that BI, cloud computing, and CAD are significantly associated with higher productivity. In contrast, AIRA shows smaller, only marginally significant effects, while IoT and VR/AR show no significant effects. We find limited evidence of positive complementarities among technology bundles, suggesting potential inefficiencies in their combined use. Firm size, age, prior profitability, and growth ambitions are positively associated with productivity. Ownership structure and leadership demographics moderate some of the technology's effects. Women-led, family-owned, and minority-ethnic group-led SMEs face barriers that constrain digital technology adoption and productivity gains. Overall, the results offer valuable insights for policymakers seeking to enhance SME productivity through digital transformation.

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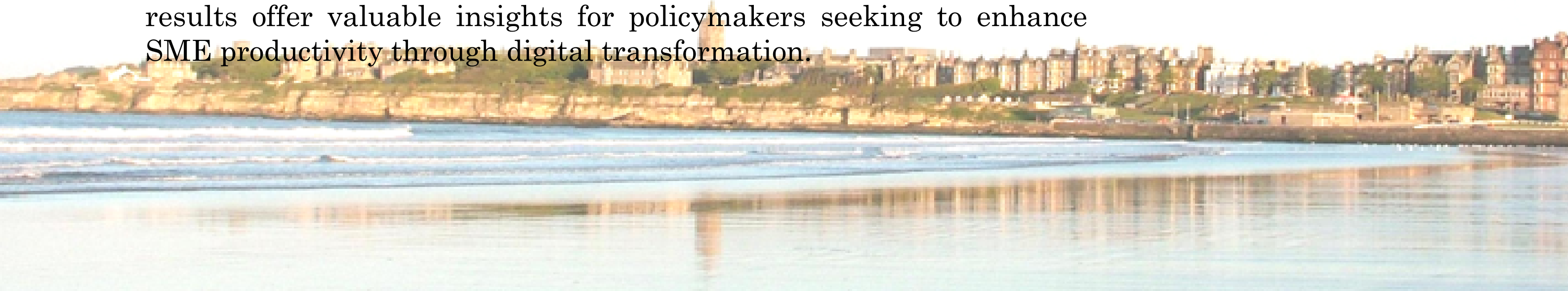

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Technology Adoption and Productivity: Evidence from UK SMEs

José M. Liñares-Zegarra
Essex Business School, University of Essex, Colchester Campus, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ
jmlina@essex.ac.uk

John O.S. Wilson
Centre for Responsible Banking & Finance, Business School, University of St Andrews, North Haugh, St Andrews, KY16 9RJ, Tel: +44 (0)1334 46 2803
jsw7@st-andrews.ac.uk

Abstract
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Keywords: SME Productivity; Product-enhanced Technologies; Technology Bundles; Complementarity; Substitutability; Technology Adoption

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Technology Adoption and Productivity: Evidence from UK SMEs

Non-technical Summary

Scope of Study

Small and medium-sized enterprises (SMEs) are the backbone of the UK economy, making up 99% of all businesses. Despite their importance, SMEs often struggle with low productivity compared to larger firms. One promising way to boost productivity is through the adoption of digital technologies. This study examines the impact of various digital technologies, used individually or in combination, on the productivity of UK SMEs.

This study fills a gap in our understanding of how digital technologies affect SME productivity. While previous research has typically examined the impact of individual technologies, such as artificial intelligence (AI), this study is among the first to investigate the effects of a broad range of production-enhancing technologies and to assess whether adopting multiple technologies together as a 'technology bundle' leads to greater productivity gains than using them individually.

The study uses the most recent data from the UK's Longitudinal Small Business Survey (LSBS), focusing on the years 2022 and 2023. This nationally representative survey collects detailed information on the performance, technology use, and business characteristics of SMEs. Six key advanced digital technologies are examined: artificial intelligence, robotics, and automation (AIRA), cloud computing, business intelligence (BI), computer-aided design (CAD), the Internet of Things (IoT), and virtual/augmented reality (VR/AR).

Key Findings

- *Not All Technologies Are Equally Important*. Some technologies are more effective than others in boosting productivity. Business intelligence and cloud computing stand out as the most impactful, followed by CAD and, to a lesser extent, AIRA. In contrast, IoT and VR/AR have shown little to no positive effects on productivity. This suggests that data-driven tools like BI and cloud services are particularly valuable for SMEs in terms of productivity.
- *Technology Bundles: More Isn't Always Better.* While it might seem logical that using more technologies together would lead to greater benefits, this is not always the case. Some combinations of technologies result in lower productivity. For example, pairing VR/AR with AIRA or CAD often leads to diminishing returns. This could be due to overlapping functions, integration challenges, or the complexity of managing multiple systems at once.

- *Firm Characteristics Matter.* The impact of technology adoption varies depending on SME characteristics. Larger, older, and profitable SMEs tend to benefit more from digital tools. However, women-led, family-owned, and minority-ethnic-led businesses often face barriers (including limited access to finance, weaker digital infrastructure, or fewer support networks) that limit their ability to adopt and benefit from these technologies.
- *Growth Ambitions Also Matter*. SMEs with stronger growth ambitions exhibit higher productivity, reinforcing the link between performance and strategic orientation.
- *Location and Industry Matter.* The adoption of digital technologies among UK SMEs is uneven, with England and business services firms leading the uptake, particularly in cloud computing, business intelligence, and CAD. By contrast, SMEs in Wales, Scotland, and Northern Ireland, as well as in sectors such as transport, retail, and accommodation, lag significantly behind, suggesting regional and sectoral divides.

Practical and Policy Implications

- Digital technologies offer great promises for improving SME productivity, but their benefits are not automatic. Rather than adopting more technologies, careful selection and implementation of the right tools are key to success. Firms should focus on technologies that align with business goals and capabilities.
- Policy support should focus on helping firms choose the right technologies for their production needs. Financial incentives, training, and advisory services could usefully be targeted at high-impact technologies such as BI and cloud computing. Policies should also target underserved groups of SMEs, including women-led and family-owned SMEs.

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1. Introduction

Small and medium-sized enterprises (SMEs) are central to the UK economy, representing 99% of all registered businesses, employing over 16 million individuals, and accounting for approximately 60% of private sector employment (Department for Science, Innovation and Technology, 2025). SMEs are prevalent across all sectors of the economy, especially in construction, professional services and retail (Federation of Small Businesses, 2024).

SMEs are crucial for economic vitality, sustainability and growth. Their dominance in the business population, combined with their importance for job creation and economic growth, is recognised by successive UK governments. For example, the SME Action Plan for the period 2022-2025 outlines various measures to reduce barriers to SME success (Department for Business, Energy & Industrial Strategy, 2023). More recently, the UK Government's SME Digital Adoption Taskforce highlights the potential of SMEs in driving productivity through digital innovation. The taskforce sets an aim for UK SMEs to become the most digitally capable of any leading industrialised country by 2035.[1]

Historically, SMEs have faced significant productivity challenges that hinder their growth and financial performance, with resultant consequences for the overall national economy (Royal Society of Edinburgh, 2024).[2] Barriers to productivity include a lack of adoption of digital technologies, poor management practices, and limited formal training schemes (Department for Business and Trade, 2024; ONS, 2025). SMEs often lack access to suitable export markets and innovative ecosystems. A ScaleUp Institute report suggests that enabling SMEs (through programmes and incentives to support internationalisation and innovation) to become regular exporters would add over £1

[1] Roland (2020) argues that targeted interventions for high-growth SMEs are more effective than broad support, especially in overcoming technology adoption barriers.

[2] Owalla *et al.* (2022) provide a detailed mapping and overview on SME productivity research.

billion annually in Gross Value Added (GVA) to the UK economy (ScaleUp Institute, 2024). A Department for Science (2025) report suggests that the adoption of emerging technologies and the resultant productivity enhancements will contribute approximately 8.4% to real GDP by 2035.

Despite their significant role in the economy, the productivity of SMEs consistently lags behind that of larger firms.[3] Oldemeyer *et al.* (2025) argue that SMEs face unique structural challenges in terms of resources, geographic location, financial constraints, and digital maturity. The adoption of production-enhancing technologies, such as artificial intelligence (AI), robotics, and other advanced technologies, has the potential to become a key factor affecting business model development (Nafizah *et al.*, 2024), and productivity growth among UK SMEs. However, despite SMEs constituting the bulk of the UK's business population and over half of private sector turnover (Hutton & Murray, 2024), significant disparities in the uptake of new technologies continue to persist (Calvino *et al.*, 2022).

Financial constraints, common among SMEs, limit their capacity to invest in innovative technologies. Credit rationing and borrowers' discouragement (arising from fear of rejection of loan applications) are prevalent across innovative SMEs (Lee *et al.*, 2015; Brown *et al.*, 2022). Consequently, this limits their ability to adopt new technologies necessary to drive productivity and competitiveness. Bettiol *et al.* (2024) suggest that the productivity returns from technology adoption are non-linear. The

[3] The Office for National Statistics notes that 70.9% of UK workers are employed in firms, many of which are SMEs, with productivity below the national mean. This reflects a substantive proportion of underperforming SMEs, which leads to a drag on the overall level of productivity growth (ONS, 2024).

authors argue that industrial policies should encourage the adoption of Industry 4.0 technologies, particularly among SMEs.[4] Furthermore, while incorporating emerging technologies such as AI, Big Data, and Robotics into the production process could lead to increased productivity (Hwang & Kim, 2022; British Chambers of Commerce, 2024), many SMEs remain reluctant to embrace these technologies, given the perceived risks and lack of familiarity with these investments. This leads to a conservative approach toward the adoption of innovative technologies. Geographic factors (urban agglomerations, urban areas or peripheral areas) could provide SMEs with better access to resources, networks and knowledge spillovers (Jespersen *et al.*, 2018; Mueller & Jungwirth, 2022; Schwaeke *et al.*, 2025), which can facilitate innovation and technology adoption.

Understanding drivers of technology adoption for SMEs is of obvious practical significance and an important policy-relevant question for addressing competitiveness in a rapidly evolving business environment. Indeed, public policy recognises the importance of digital technologies in enhancing SME productivity. The SME Digital Adoption Taskforce Final Report estimates that a 1% productivity uplift across SMEs could add £94 billion annually to the UK's GDP (Department for Business and Trade, 2025). The Taskforce emphasises that AI and other technologies can streamline operations, reduce administrative burdens, and enhance decision-making. However, barriers such as high

[4] Industry 4.0, also known as the Fourth Industrial Revolution, refers to the integration of advanced digital technologies into manufacturing and industrial processes

switching costs, lack of expertise, and fragmented support systems hinder adoption.[5] Hwang and Kim (2022) find that (in the context of Korean manufacturing) SMEs that adopt digital technologies (including AI and robotics) experience an average productivity increase of over 26% compared to non-adopters. This underscores the potential for analysing the UK SME sector, where the pressure to enhance productivity is pronounced. As SMEs continue to embrace digital transformation, their ability to leverage these technologies is critical for sustaining growth and enhancing productivity.

Despite growing interest in the impact of digital technologies, research remains limited by data availability. Any available evidence tends to report only the impacts of specific technologies on performance. However, many innovative technologies are adopted by firms as bundles. Technology bundles are digital innovations that can lead to improvements in firms' productivity, achieve operational efficiencies, and innovative capabilities by integrating complementary digital tools.

Prior studies identify a labour productivity premium associated with AI use by firms (Abrardi *et al.*, 2022; Czarnitzki *et al.*, 2023; Brown *et al.*, 2025), albeit they also reveal heterogeneities in productivity across various firm demographic dimensions. We examine this issue by exploring how the observed effects of technology adoption on performance differ based on growth ambitions (a growth-oriented SME may adopt and integrate technology more strategically, leading to greater productivity gains), firm leadership characteristics (such as whether the firm is women-led or minority ethnic-led,

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[5] The Productivity Institute's and Office for National Statistics national surveys reveal that cloud computing is the most widely adopted digital technology among UK firms, with up to 80% penetration across sectors (Massini *et al.*, 2025; ONS, 2025).

to test whether structural barriers like capital and networks impact the productivity benefits from technology adoption), as well as family ownership status (governance style, investment horizon, and risk preferences may influence the productivity returns from adopting certain technologies). This helps us identify which types of SMEs benefit from technology adoption and which SMEs risk being left behind.

In this study, we use data from the 2022 and 2023 waves of the UK Longitudinal Small Business Survey (LSBS) to investigate whether SMEs that adopt one or more production-enhancing technological tools achieve higher productivity levels. The LSBS is a nationally representative dataset commissioned by the Department for Business and Trade (DBT), and provides detailed information on SME performance, digital technology adoption, innovation, finance, and leadership characteristics. Our sample includes firms with fewer than 250 employees across all UK industry sectors and regions. Our primary outcome variable is labour productivity, measured as the natural logarithm of turnover per employee. Key independent variables include binary indicators for the adoption of six advanced production-enhancing technologies, comprising: artificial intelligence, robotics, and automation (AIRA), cloud computing, business intelligence (BI), computer-aided design (CAD), Virtual/Augmented reality (VR/AR) and the Internet of Things (IoT). We estimate log-linear regressions using OLS and multilevel mixed-effects models, accounting for firms nested within regions and postcode areas.

Lagged technology adoption variables are used to mitigate simultaneity bias. Interaction terms between technologies are included to test for complementarities or substitutability effects. Our control variables include firm size, age, profitability, innovation activity, leadership demographics (e.g., women-led, minority-ethnic-led), family ownership, industry sector, and legal status. This allows us to capture the productivity impacts of digital technology adoption, both individually and in bundles, while accounting for structural and contextual factors that shape SME performance.

By way of preview, the findings of our extensive econometric analysis suggest that the adoption of digital technologies by UK SMEs is positively associated with increased productivity, albeit the effects vary across technologies and firm characteristics. Business intelligence (BI) and cloud computing yield the highest productivity premiums, followed by computer-aided design (CAD) and artificial intelligence, robotics, and automation (AIRA). The Internet of Things (IoT) and virtual/augmented reality (VR/AR) have only limited or insignificant impacts on productivity. SMEs that adopt at least one production-enhancing technology report significantly higher labour productivity, with BI and cloud computing emerging as the most impactful tools.

Firm-level characteristics moderate the impact of technology adoption on productivity. Larger, older, and more profitable SMEs tend to benefit more from digital adoption, while women-led and family-owned firms exhibit lower productivity, possibly due to limited access to finance or networks. Minority-ethnic-led and women-led SMEs also face constraints that hinder their adoption of digital technology and productivity gains. Our results highlight the importance of strategic technology selection over indiscriminate bundling, particularly for resource-constrained firms. This suggests that policy interventions could usefully support targeted strategies by focusing on reducing barriers to adopting high-impact digital technologies faced by underserved SME groups.

The analysis of whether firm-level characteristics moderate the impact of technology adoption on productivity reveals that most technologies have consistent productivity effects across SME types, although some combinations show reduced gains. In particular, business intelligence/analytics, IoT, CAD, and VR/AR show negative interactions with certain ownership and leadership traits, particularly in family-owned, women-led, and MEG-led firms. Our results also suggest that bundling multiple technologies does not necessarily lead to substantive productivity gains. Interaction effects between technologies suggest that certain combinations, such as VR/AR with AIRA or CAD, and IoT with cloud computing, result in diminishing returns or substitutability. This could be linked to potential difficulties in technological use arising from complexity or overlapping functionalities.

Our study provides several significant extensions to the recent work of Brown et al. (2025) on the relationship between AI and productivity in UK SMEs, as well as to Massini et al. (2025) on the general adoption of advanced digital technologies by UK firms. Brown et al. (2025) focus exclusively on AI adoption using the 2018–2021 LSBS waves, whereas we draw on the detailed technology-use questions introduced only in the 2022 LSBS, which are not available in later waves, and complement these with the 2023 survey wave to capture subsequent productivity outcomes. This enables us to assess six production-enhanced technologies both individually and in bundles, thereby extending Brown et al. (2025)'s AI-specific analysis and complementing Massini et al. (2025)'s evidence on multi-technology analysis. We also examine firm-level moderators such as growth ambition, female and minority-ethnic leadership, and family ownership, complementing Brown et al.'s emphasis on sectoral variation and Massini et al.'s focus on size, sector, and region. Finally, our empirical strategy advances prior work by combining lagged adoption measures with multilevel mixed-effects models that account for firms nested within regions and postcode areas, delivering a more granular understanding of how digital technologies, both singly and in combination, shape productivity across UK SMEs. This study addresses a gap in understanding whether bundles provide synergetic productivity benefits based on digital complementarities. It provides new evidence that technology complementarities can be limited or even negative, warning against assuming that more technology automatically leads to higher productivity, especially for SMEs and emerging technologies.

The remainder of this study is structured as follows. Section 2 provides a background discussion and review of relevant literature. In Sections 3 and 4, we describe the empirical methodology and data used. Section 5 presents the main results of our empirical analysis. Section 6 provides a summary of the main findings.

2. Literature review

Small and medium-sized enterprises (SMEs) play a crucial role in driving economic growth (OECD, 2017a, b), improving living standards, and advancing societal well-being (Owalla *et al.*, 2022).[6] Despite the number and importance of SMEs, a productivity gap persists across different enterprise sizes, with larger firms routinely reporting higher levels of productivity relative to their smaller counterparts. While a general consensus has emerged that technology adoption enhances SME productivity, the productivity gap between small and large enterprises persists (Hwang & Kim, 2022). OECD (2018) emphasises that SME manufacturers have consistently lower productivity than large manufacturers. Andrews *et al.* (2016) argue that large firms are better positioned to make technology investments, relative to their smaller counterparts, which are constrained by

[6] In a seminal contribution, Romer shows that technological change is the result of intentional investment decisions made by firms. Moreover, that knowledge has spillover effects that benefit the economy (Romer, 1986). Corrado *et al.* (2022) show the importance of intangible assets for real economic outcomes.

a lack of financial and technical resources. In line with this, Oldemeyer *et al.* (2025) confirm that SMEs face unique structural challenges related to financial constraints and digital maturity, which differentiate them from larger counterparts.

Given the apparent productivity differences across the firm size distribution, active policy interventions are likely to be necessary to reduce barriers to productivity growth (OECD, 2017a). Bettiol *et al.* (2024) find that Italian SMEs' labour productivity increased by 7% following the adoption of Industry 4.0. Related evidence suggests that incorporating emerging technologies, such as AI, Big Data, and Robotics, into the production process could lead to increased productivity (Hwang & Kim, 2022; British Chambers of Commerce, 2024). SMEs' productivity is likely to increase following the adoption of advanced technologies. Artificial Intelligence (AI) and its subset technology, Machine Learning, provide various powerful cognitive and decision-making functions to enhance a firm's capabilities, performance, and competitiveness (Nafizah *et al.*, 2024). A significant and positive relationship exists between AI adoption and firm-level productivity, where AI is viewed as a partial capital asset that amplifies the capacity of firms to produce more output (Czarnitzki *et al.*, 2023). Brown *et al.* (2025) find that UK SMEs adopting AI technologies experience substantial productivity gains compared to non-adopters, with the strongest effects observed among service-sector firms and among those with lower productivity. Lu *et al.* (2022) explore AI-enabled opportunities and transformation challenges for SMEs in the post-pandemic era.[7] They find that the adoption of AI can support SME growth by improving organisational performance and

[7] Detailed mappings and overviews on the adoption, implementation and performance impacts of AI and digital technologies are provided by Oduro *et al.* (2023), Schwaeke *et al.* (2025) and Oldemeyer *et al.* (2025) in SME productivity research.

resilience. However, they also note that SMEs face significant barriers emanating from skill shortages, financial constraints, and ethical concerns in the adoption and implementation of AI.

The resource-based theory (RBV) suggests that firms gain a competitive advantage by leveraging unique, inimitable resources (Wernerfelt, 1984; Barney, 1991). In SMEs, digital orientation, defined as the strategic approach to digital transformation, is a critical intangible resource. Escoz Barragan and Becker (2025) demonstrate that a sustained commitment to digital technologies leads to long-term efficiency gains.

Dynamic capabilities refer to a firm's ability to integrate, build, and reconfigure internal and external competencies in response to rapidly changing environments (Teece *et al.*, 1997). Sagala and Őri (2025) identify dynamic capabilities, such as digital capability, leadership orientation, learning, and collaboration, as crucial to SMEs in building the necessary agility and resilience to adapt to technological disruptions.

Prior evidence suggests that several factors drive the adoption of AI among SMEs. These include compatibility, readiness, efficiency improvement, and time savings (Schwaeke *et al.*, 2025). AI can enhance customer experiences and satisfaction, while increasing loyalty and opening up new market opportunities (Rizomyliotis *et al.*, 2022). Eller *et al.* (2020) show that SME digitalisation is driven by information technology, employee skills, and digital strategy. Segarra-Blasco *et al.* (2025), using a large sample of European SMEs, show that digitalisation is determined by the extent of internationalisation, organisational size, and the prevailing quality of digital skills and infrastructure.

Technology adoption is an important driver of firm performance. Brown *et al.* (2025) show that UK SMEs exhibit significant productivity gains from technology adoption, although their analysis is limited to AI-specific measures. Blichfeldt and Faullant (2021) find that firms operating in low-tech industries utilise digital technologies to generate product and service innovations, which subsequently feed through to higher performance. In contrast, in high-tech industries, the adoption of digital technologies has a direct impact on firm performance. For Germany, Czarnitzki *et al.* (2023) find that the adoption of AI technologies has a positive and significant impact on firm productivity. Using a dataset of firms drawn from five European countries, Massini *et al.* (2025) find that SMEs using cloud platforms report improved efficiency and customer responsiveness. While technology adoption is generally linked to improved performance, some evidence suggests that its impacts can be complex and context-dependent (Hao *et al.*, 2025).

Many technologies can be adopted as bundles. Technology bundles, which include digital innovations such as cloud computing, AI and data analytics, work together to enhance productivity and financial performance. Technology bundles can lead to improvements in firms' productivity and innovation capabilities. By integrating complementary digital tools, firms can achieve operational efficiencies, strategic agility, and innovation capabilities. However, successful implementation necessitates overcoming resource constraints and investing in organisational capabilities.

The performance benefits of technology bundles stem from their ability to generate synergies across business functions. However, adopting and utilising technology bundles poses challenges. Barriers such as prohibitive costs, skill shortages and integration complexity can inhibit utilisation. SMEs may struggle to adopt comprehensive bundles due to limited resources (Capital Economics, 2022; Kallmuenzer *et al.*, 2025).

SMEs face significant structural barriers to technology adoption compared to large firms. Buer *et al.* (2021) examine 212 Norwegian manufacturing firms. Compared to large enterprises, SMEs show a significantly lower level of digitalisation of the shop floor and organisational IT capabilities. Pirola *et al.* (2020) note that despite SMEs demonstrating an intermediate level of readiness for Industry 4.0, their management teams remain in the early stages of exploring appropriate adoption strategies. Oldemeyer *et al.* (2025) find that SMEs are more exposed to these challenges than large enterprises, particularly in terms of data availability and readiness for AI integration.

Within the population of SMEs, disparities exist. These disparities are shaped by structural barriers, including financial constraints, inadequate infrastructure, weak digital networks, and limited awareness of business opportunities (Brown *et al.*, 2022). Adopting technologies within SMEs not only improves productivity but also risks exacerbating disparities between adopters and non-adopters. Consequently, these firms face the risk of missing productivity gains from the combined effects of various technologies, leading to a widening of the gap between digital leaders and laggards. Without targeted interventions, such as access to finance support and training programs, the digital divide may exacerbate economic disparities between large firms and SMEs.

Prior evidence suggests that location plays a significant role in the adoption of technology. In rural areas, a lack of digital infrastructure (e.g. broadband networks) can inhibit the adoption of digital technologies for SMEs located in these areas. Holl and Rama (2024) find that rural SMEs and those located in small towns are less likely to adopt digital technologies. Dowell *et al.* (2024) find that the use of AI differs significantly between rural and urban SMEs, with rural SMEs being less likely to adopt such technologies. Mahmood *et al.* (2024) We find that the adoption of digital technologies is more prevalent in London and the South East compared to other parts of the UK.

Similar patterns are also observed when comparing minority-ethnic group (MEG)-led and non-MEG-led SMEs. MEG-led SMEs often struggle to secure funding from traditional financial services providers. This is attributed to perceptions of elevated risk, lack of collateral, or discriminatory lending practices (Fraser, 2009). This reduces their ability to invest in digital technologies. Korosteleva *et al.* (2025) find that the growth of MEG-led SMEs is constrained by underinvestment in digital tools. Ram *et al.* (2017) argue that MEG-led SMEs tend to distrust public institutions. This hinders their ability to participate in government initiatives, placing them at a greater risk of missing the productivity benefits associated with technology bundling.

Prior studies have investigated the impacts of individual technologies on productivity. However, this neglects the combined effects of technology bundles. Consequently, prior evidence for single technologies, specific sectors, or large enterprises offers limited insights. Consequently, the present study addresses this evidence gap by investigating which SMEs adopt digital technologies and how these combinations influence SME productivity in the UK. By doing so, we provide a detailed understanding of how complementarity drives firm performance, and which elements condition the successful adoption of digital technologies by SMEs.

3. Empirical methodology

We investigate the relationship between the adoption of digital technology, both individually and as a bundle, and SME productivity. Our primary objective is to determine whether adopting technologies, particularly as a bundle, yields greater productivity benefits than adopting individual tools. That is, whether firms that adopt multiple technologies simultaneously exhibit greater productivity than those adopting single tools or none at all.

The primary outcome variable is firm productivity. We measure productivity as the natural logarithm of turnover (revenue) per employee to normalise its distribution and facilitate interpretation of coefficient estimates as approximate percentage changes. Turnover refers to the total revenue generated by the business over the past 12 months across all UK production sites (variable P1). The total workforce comprises both employees on the payroll (excluding owners and partners, as captured in variable A2) and working owners or partners (A2A). Consequently, our productivity measure reflects the average output per worker, encompassing both paid staff and self-employed individuals who actively contribute to the business. Our key independent dummy variables measure the adoption of specific production-enhancing technologies, such as artificial intelligence, robotics, and automation (AIRA); cloud computing; CAD software; BI/analytics; IoT; and VR/AR. Table 1 presents detailed definitions of all variables used in this study.

As our baseline model, we estimate log-linear productivity regressions using OLS (Equation 1). To reduce simultaneity bias between productivity and technology adoption, we introduce lagged versions of key predictors, including technology use, so they temporally precede productivity performance.

$$Y_{it} = \beta_0 + \beta_1 X_{it-1} + \beta_2 Z_{it-1} + \varepsilon_{it} \quad (1)$$

Where Y_{it} is the natural logarithm of productivity (turnover per worker) for firm *i* at time *t=2023*, X_{it-1} represents lagged technology adoption indicators, Z_{it-1} is a vector of firm-level controls, and ε_{it} is the idiosyncratic error term.

We also estimate multilevel models (mixed models) to explicitly account for the hierarchical structure of the data, where firms are nested within Government Office Regions (GORs, including Scotland, Wales and Northern Ireland) and postal code areas.

$$Y_{it} = \beta_0 + \beta_1 X_{it-1} + \beta_2 Z_{it-1} + \beta_3 (Z_{it-1} \times X'_{it-1}) + u_r + u_p + \varepsilon_{it} \quad (2)$$

$$Y_{it} = \beta_0 + \beta_1 X_{it-1} + \beta_2 Z_{it-1} + \beta_3 (X_{it-1} \times X'_{it-1}) + u_r + u_p + \varepsilon_{it} \quad (3)$$

Where: Y_{it} is the natural logarithm of productivity (turnover per worker) for firm *i* at time *t=2023;* X_{it-1} represents lagged technology adoption indicators; Z_{it-1} is a vector of lagged firm-level controls; $Z_{it-1} \times X'_{it-1}$ test for interactions of technology and firm characteristics (Equation 2); $X_{it-1} \times X'_{it-1}$ test for technological bundling and complementarities (Equation 3); u_r and u_p are random intercepts for Government Office Regions and postcode areas; and ε_{it} is the idiosyncratic error term.

This allows us to isolate the firm-level productivity impacts of technology adoption, while also accounting for region- and location-specific factors (arising from differences in digital infrastructure and policy environments) that may influence both technology adoption and productivity. To assess whether productivity increases with the adoption of technology bundles, we estimate models that include interaction terms between pairs of technologies. We aim to assess whether adopting one baseline technology alongside another results in a productivity impact that varies when a technology is adopted individually. A positive and significant interaction term indicates that there is complementarity between certain technologies. A negative and significant interaction term indicates possible substitutability or redundancy among certain technologies.

All models include relevant firm-level covariates, including: firm size; firm age; profit status; use of bank finance; growth ambitions; innovatory activity; leadership characteristics (whether the SME is women-led or MEG-led); family ownership status, location (whether in an urban or rural area); region; industry; sector and legal form. Standard errors in all models are clustered at the Government Office Region level to account for within-region correlation in the error terms.

Overall, our empirical approach is designed to test whether the adoption of digital technology (especially in technology bundles) drives productivity among UK SMEs, while accounting for firm-level heterogeneities, temporal ordering, and regional location.

4. Data

We use the most recent data from the 2022 and 2023 waves of the UK Longitudinal Small Business Survey (LSBS), commissioned by the Department for Business and Trade (DBT). The LSBS is a nationally representative survey of UK SMEs, collecting detailed annual information on business performance, digital adoption, innovation, finance, and leadership demographics. Our sample comprises firms with fewer than 250 employees, spanning all major industry sectors and UK regions. For the purposes of this study, we restrict the dataset to the 2022 and 2023 waves, which include the most comprehensive and up-to-date measures of digital technology adoption and SME productivity.

Our primary outcome variable is productivity, measured by sales turnover per employee. Our main independent variables are derived from the LSBS technology adoption modules: a dummy variable equal to 1 if in 2022, the firm reported using one of six advanced technologies including: artificial intelligence, robotics, and automation (AIRA); business intelligence and analytics; CAD software; cloud computing; Internet of Things (IoT); and virtual/augmented reality.

We include a comprehensive set of firm-level controls, including size, industry sector, innovation activity, ownership, and leadership demographics (MEG-led and women-led SMEs). Although a two-year window limits the depth of our longitudinal analysis, we leverage the dataset's longitudinal nature to incorporate lagged adoption, enabling us to examine the temporal relationship between technology adoption and productivity.

Table 2 reports summary statistics. The dependent variable, ln(Productivity), is the natural logarithm of labour productivity, with a mean of 10.63 (SD = 1.17). By type of digital technology, cloud computing (41.4%) and business intelligence (9.9%) are more commonly used than artificial intelligence, robotics, and automation (5.9%) or VR/AR (2.9%). Approximately 57.2% of SMEs report adopting at least one technology. Figures 1 to 6 highlight regional and industry sector disparities in the adoption of digital technologies among UK SMEs. England consistently leads in adoption across all technologies, with the highest rates observed in cloud computing (42.0%, Figure 3) and business intelligence/analytics (10.2%, Figure 2). In contrast, SMEs in Wales, Scotland, and Northern Ireland exhibit a lower uptake in digital technologies. For example, the use of AI, robotics, and automation is just 2.7% in Wales, compared to 6.3% in England (Figure 1), while VR/AR adoption is lowest in Northern Ireland at just 1.4% of the SME population (Figure 6).

Variation is evident across industry sectors. SMEs in business services are the most active adopters across all technologies, with particularly high usage of cloud computing (53.5%, Figure 3), business intelligence (13.8%, Figure 2), and CAD (25.2%, Figure 4). In contrast, industry sectors such as transport, retail, food service/accommodation, and other services lag behind in the use of most technologies.

For instance, VR/AR adoption in the transport and accommodation industry sector is only 1.3% (Figure 6), and CAD adoption is 11.5% (Figure 4). The production and construction sector exhibits a strong uptake of CAD (23.4%, Figure 4) and IoT (26.6%, Figure 5), which reflects a general engagement and alignment of SMEs with design and operational technologies in this industry sector.

The majority of SMEs are non-employing firms (74%), and nearly half are over 20 years old (46.6%). Many firms are profitable (77.3%), family-owned (87.7%), and located in urban areas (67.6%). Around 56.4% of SMEs aim to grow, while 26.7% are classified as innovators. Firms led by women (19.0%) or ethnic minorities (5.5%) represent a smaller share of the sample. By geographic region, England represents 88.5% of the sample, followed by Scotland (5.7%), Wales (3.9%), and Northern Ireland (1.9%). SMEs are concentrated in business services (32.5%), manufacturing (24.1%), other services (23.4%), and transport/retail (20.1%). The most common legal forms are a company (46.8%) and a sole proprietorship (40.9%). The correlation matrix presented in Table 3 indicates low pairwise correlations among the variables used in the empirical analysis. Most coefficients have absolute values that fall well below 0.3. These low correlations support the inclusion of all variables in subsequent multivariate analyses without immediate concerns for multicollinearity.

5. Main results

5.1 The impact of technology on productivity

The results presented in Table 4 show that SMEs adopting at least one production-enhancing technology have significantly higher productivity, demonstrating a positive effect of adopting any technology on productivity (0.201 – 0.193). Table 5 provides additional evidence that the use of specific production-enhancing technologies can be associated with higher productivity. The key variable of interest, Technology, remains consistently positive across all model specifications, although its statistical significance varies depending on the specific technology. The productivity premium is largest for SMEs using business intelligence or analytics technologies (0.180 - 0169), followed by cloud-based computing (0.167 – 0.156), while only marginally statistically significant for the case of AI, robotics, or automation (0.079 – 0.078).

Table 6 examines the relationship between SME productivity and the use of three additional production-enhancing technologies: Computer-Aided Design (CAD); Internet of Things (IoT); and Virtual/Augmented Reality (VR/AR). The results are more mixed compared to those presented in Table 4A. Among these three aforementioned technologies, only CAD exhibits a statistically significant positive association with productivity (0.095–0.106), suggesting modest productivity gains similar to those from AI, robotics, or automation. In contrast, the coefficients for IoT and VR/AR are not statistically significant across models, indicating no evidence of productivity enhancement flowing from the adoption of these technologies. These results suggest that, after controlling for firm size, age, and other firm-level characteristics, the adoption of digital technologies is associated with increased productivity. However, benefits are not consistent across all technologies, with data-driven tools especially significant for increasing productivity.[8]

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[8] We also run a model with all technologies in a single regression, so each estimated coefficient indicates the effect of that technology while holding the others constant. Results reported in Figure 7 remain similar for Business intelligence/analytics, cloud computing, and CAD software. Artificial intelligence, robotics, and automation (AIRA) and VR/AR are no longer significant, suggesting that productivity gains are also influenced by the co-adoption of technologies.

The signs of the coefficients on the control variables in Tables 5 and 6 are as expected. Firm size and age are positively and significantly associated with productivity, reflecting the importance of operational scale and experience in driving productivity. Prior profitability and growth ambitions exhibit a strong and highly significant relationship with productivity across all models, suggesting a link between productivity and financial performance. The coefficient on Women-led firms is negative and significant, which may be related to structural barriers such as differential access to capital or networks (Carter *et al.*, 2015). Family-owned firms also exhibit a negative and significant association with productivity, which may reflect specific governance dynamics or growth ambitions for this type of firm (Barbera & Moores, 2013; Aguilera *et al.*, 2024).[9]

The inclusion of regional, industry sector and legal form control variables enhances the robustness of the coefficient estimates. Thus, supporting the inference that technology adoption, particularly in business intelligence/analytics, cloud-based computing, computer-aided design (CAD), and artificial intelligence, robotics, and automation (AIRA), plays a key role in enhancing SME productivity.

5.2 The moderating role of SME characteristics

The interaction analysis between individual technologies and firm characteristics is reported in Table 7, revealing several heterogeneous effects on productivity. For artificial intelligence, robotics, and automation (AIRA), none of the interactions, such as those aimed at growth, being women-led, MEG-led, or Family-owned SMEs, are statistically significant, suggesting that productivity effects are not sensitive across these groups. For

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[9] Bloom and Van Reenen (2007) find that family firms (particularly those with inherited leadership) underperform due to poor management practices.

Business intelligence/analytics interactions, Aim to grow (−0.288, $p = 0.060$) and Family-owned (−0.248, $p < 0.001$) SMEs exhibit negative and statistically significant, or borderline significant, results, indicating reduced productivity benefits for these SMEs. Cloud computing shows no significant interaction effects with any of the traits. Computer-aided design (CAD) exhibits a negative borderline-significant interaction with MEG-led firms (−0.245, $p = 0.066$), suggesting potential barriers to productivity gains in this group. For the Internet of Things (IoT), interactions with Women-led (−0.121, $p = 0.043$) and MEG-led (−0.359, $p = 0.008$) firms are negative and significant, pointing to lower productivity effects among these SMEs. Virtual/Augmented Reality (VR/AR) exhibits a significant negative interaction with Family-owned firms (−0.372, $p = 0.036$), indicating reduced returns from adoption in this group. Overall, the findings suggest that while many technologies yield broadly similar productivity effects across different firm types, ownership structure, and leadership demographics moderate the benefits of adoption.

5.3 Technological complementarities and productivity

Our results presented thus far suggest that the use of Business intelligence/analytics, Cloud computing, and Computer-aided design (CAD) by SMEs has a positive impact on productivity, even after accounting for the use of other technologies (as shown in Figure 7). This suggests that those technologies work well on their own, and they do not just benefit from being used together as a bundle with other technologies.

To provide further policy insights into the potential complementarities (co-adoption) of technologies, we use interaction terms to examine whether the combination of two different technologies has an additional impact on productivity. A positive and significant interaction term suggests complementarity, while a negative and significant interaction term indicates potential substitutability or redundancy. Adopting multiple technologies at once can bring benefits, but it might also cause inefficiencies, complexity, or higher costs that could outweigh the productivity gains from using new technology.

We employ the same full mixed-effects models as those presented in Tables 5 and 6, which include both a complete set of technology indicators and interaction terms between two technologies. The analysis of interaction terms between pairs of digital technologies (Table 8) extends the results presented in Tables 5 and 6, as well as Figure 7, by explicitly testing whether the joint adoption of technologies produces productivity gains. Although earlier findings suggest that Business intelligence/analytics, Cloud computing, and CAD are each important drivers of SME productivity, there is no evidence of statistically significant positive effects when combined with other technologies. In fact, several combinations exhibit significant negative interaction effects, suggesting substitutability or diminishing returns when adopted together. The strongest negative associations are observed for VR/AR with AI, robotics, and automation (−0.326, $p = 0.0002$), VR/AR with CAD (−0.318, $p = 0.0119$), IoT with Cloud computing (−0.220, $p = 0.0019$), and Business intelligence/analytics with Cloud computing (−0.173, $p = 0.0302$). These patterns probably indicate the complexity of integration, overlapping functionalities, or higher implementation costs that diminish the expected advantages of adopting multiple systems at the same time. We find marginally significant negative effects for Cloud computing with artificial intelligence, robotics, and automation (AIRA), IoT with artificial intelligence, robotics, and automation (AIRA), and Business intelligence/analytics with CAD, indicating possible substitutability effects (BEIS, 2020).

Taken together, these results reinforce the conclusion that the productivity benefits of Business intelligence/analytics, Cloud computing, and CAD derive from their individual use rather than from being bundled with other advanced technologies.

Furthermore, the lack of positive complementarities and the existence of several negative interactions indicate that indiscriminate bundling of multiple complex technologies may impede rather than improve productivity. For SMEs, particularly those with limited resources, digital transformation strategies may therefore be more effective when centred on carefully chosen, high-impact tools rather than broad, simultaneous adoption of multiple advanced production-enhancing technologies.

6. Conclusions

Small and medium-sized enterprises (SMEs) form the backbone of the UK economy, but consistently lag behind larger firms in terms of productivity. This persistent productivity gap has significant implications for regional and national economic growth, innovation, and competitiveness. Despite the growing availability of advanced digital technologies, many SMEs find it challenging to adopt and integrate these tools effectively. Structural barriers, including financial constraints, limited digital skills, and geographic disparities, further inhibit their capacity to benefit from technological advancements. While existing research has explored the impact of individual technologies on firm productivity, there remains a paucity of evidence regarding how combinations of technologies (technology bundles) impact productivity outcomes. In this study, we address this lack of evidence by providing empirical insights into whether adopting (combinations of) technologies results in greater productivity benefits than using them separately. We also seek to identify which types of SMEs are most likely to benefit from digital transformation and which may be left behind. By examining the effects of technology adoption and bundling, we aim to inform more targeted and effective policy interventions that support the growth and digital capabilities of SMEs in a rapidly evolving competitive environment.

Following an extensive descriptive and regression-based analysis, our results suggest that business intelligence and cloud computing yield the largest productivity enhancements. CAD provides modest but significant gains, while AIRA has smaller, only marginally significant effects. IoT and VR/AR have no statistically significant impacts. Contrary to expectations, bundling technology does not yield additional productivity benefits. Instead, several combinations are associated with negative interaction effects, suggesting potential substitutability, complexity, or inefficiencies. Firm size, age, profitability, and growth ambitions are strongly associated with higher productivity. Family-owned and women-led firms exhibit significantly lower productivity, possibly due to governance or structural disadvantages, whereas MEG-led firms face barriers to capturing productivity benefits from certain technologies.

The findings presented in this study might be of interest to the Department for Business and Trade (DBT), the industry-led SME Digital Adoption Taskforce, and other important organisations such as the British Business Bank, to guide potential digital adoption strategies that aim to boost productivity and competitiveness. To encourage the adoption of digital product-enhanced technologies, policy should also emphasise the selective adoption of digital technology tools, avoiding over-bundling that can reduce returns. Advice for SMEs on optimal bundling strategies also appears merited in order to avoid over-complexity and optimise productivity gains. Our results also suggest that a targeted approach is necessary to further promote the adoption of digital technologies and encourage investments in digital infrastructure among MEG-led and women-led SMEs.

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Table 1: Variable definitions

This table provides the names and definitions of explanatory variables. All variables are collected from the Longitudinal Small Business Survey.

Variable	Definition	LSBS code
Labour Productivity	It is measured by the ratio of P1: "approximate turnover of your business in the past 12 months across all your UK sites" over A2: "how many employees are currently on your payroll in the UK, excluding owners and partners, across all sites." + A2A: Including yourself, how many working owners and partners are there? Please include yourself if you are a working owner or partner. This variable has been winsorized at the 1% level to limit the influence of extreme values.	P1/(A2+A2A)
Production-enhanced technologies		
	Equals 1 if the business uses Artificial Intelligence (AI), robotics, and automation: AI refers to any human-like behaviour displayed by a machine or system. Robotic process automation is a form of business process automation technology based on software robots or on AI/digital workers.	F11BA
	Equals 1 if the business uses Business intelligence/analytics: Business analytics refers to skills, technologies, and practices for exploration and investigation of past business performance to gain insight and drive business planning.	F11BB
	Equals 1 if the business uses cloud-based computing: The on-demand availability of computer system resources, especially data storage and computing power, without direct active management by the user.	F11BC
	Equals 1 if the business uses Computer-aided design (CAD): The use of computers to aid in the creation, modification, analysis, or optimisation of a design.	F11BD
	Equals 1 if the business uses Internet of Things (IoT): Physical objects with sensors, processing ability, software, and other technologies that connect and exchange data with other devices and systems over the Internet or other communications networks.	F11BE

	Equals 1 if the business uses Virtual/augmented reality (VR/AR): VR is a simulated experience that gives the user an immersive feel of a virtual world. AR is an interactive experience that combines the real world and computer-generated content.	F11BF
Technology adoption	Equals 1 if the business uses at least one of the six listed advanced technologies in 2022.	
Technology bundles	The total number of advanced technologies adopted by a business in 2022, based on responses to six specific technologies.	
Size	Employees on payroll (excluding owners and partners) at the time of the interview. Micro (base category): 1-9 employees; Small: 10-49 employees; Medium: 50-249 employees.	A2SPSS1
Age	Age of the firm: 0 – 5 years (base category), 6 – 10 years, 11 – 20 years, 20+ years	A6SUM
Profit	Firm generates a profit or surplus after considering all sources of income in the last fiscal year.	P12
Bank finance	The business is currently using loans from formal financial institutions	H3H
Aim to Grow	Equals 1 if business aim to grow sales	R1
SME Innovator	SME has introduced new or significantly improved goods or services in the last 3 years	J1SUM
Women-led	Women-led businesses are defined as those majority-led by women, which is controlled by a single woman or having a management team of which a majority are women. 'Majority' here means over 50 percent.	WLED
Minority ethnic-led	A business where at least half of the leadership team comes from minority ethnic groups (as this is a UK survey, minority ethnic groups are those that are not White British, where White British includes White English, White Scottish etc). The leadership team comprises the directors and working owners. We can include members of several ethnic groups and can include people who describe themselves as mixed ethnicity where White British is one of those ethnicities.	MLED
Family Owned	The business is a family-owned business, which is one which is majority owned by members of the same family	A12
Urban	Broad urban/rural categorisation from postcode. Equals to 1 if firm is located in an urban area	URBRUR2

Region	Region where the firm has its headquarters. England (base category), Scotland, Wales, Northern Ireland.	NATION
Sector	Industry Sector: Production and construction (Manufacturing - base category; SIC 2007: ABCDEF).Transport, retail, and food service / accommodation (SIC 2007: GHI). Business services (SIC 2007: JKLMN). Other services (SIC 2007: PQRS).	SECTOR
Legal status	Other (e.g., base category -Limited Liability Partnership, Limited Liability Company, etc.), Sole Proprietorship, Company, Partnership	LEGAL

Table 2: Summary Statistics

This table presents the summary statistics based on data from the Longitudinal Small Business Survey 2022-2023. Cross-sectional survey weights were applied to represent the population of SMEs in the UK. Respondents who answered "I do not know" or refused to answer are excluded from the sample. Variable definitions are reported in Table 1.

	Mean	**Std.**	**N**
Ln (Productivity)	10.626	1.167	15,874
Artificial intelligence, robotics or automation (AIRA)	0.059	0.236	9,498
Business intelligence/business analytics	0.099	0.299	9,498
Cloud-based computing	0.414	0.493	9,498
Computer-aided design (CAD) software	0.190	0.393	9,498
Internet of Things (IoT)	0.260	0.439	9,498
Virtual reality (VR) and augmented reality (AR)	0.029	0.169	9,498
Technology adoption	0.572	0.495	9,498
Size: Zero employees (base category)	0.740	0.439	19,158
Size: Micro (1-9)	0.214	0.410	19,158
Size: Small (10-49)	0.040	0.196	19,158
Size: Medium (50-249)	0.007	0.081	19,158
Age: 0 – 5 years (base category)	0.106	0.308	19,111
Age: 6 – 10 years	0.148	0.355	19,111
Age: 11 – 20 years	0.280	0.449	19,111
Age: 20+ years	0.466	0.499	19,111
Profit	0.773	0.419	18,502
Bank Finance	0.076	0.265	19,158
Aim to grow	0.564	0.496	19,158
SME Innovator	0.267	0.442	19,158
Women-led	0.190	0.392	18,077
Minority ethnic-led	0.055	0.227	18,456
Family owned	0.877	0.329	19,117
Urban	0.676	0.468	19,121
Region: England (base category)	0.885	0.319	19,158
Region: Scotland	0.057	0.232	19,158
Region: Wales	0.039	0.193	19,158
Region: Northern Ireland	0.019	0.138	19,158
Sector: Manufacturing sector (base category)	0.241	0.427	19,158
Sector: Transportation and retail services	0.201	0.401	19,158
Sector: Business services	0.325	0.468	19,158
Sector: Other services	0.234	0.423	19,158
Legal status: Other (base category, e.g., LLP, LLC, etc.)	0.046	0.209	19,158
Legal status: Sole Proprietorship	0.409	0.492	19,158
Legal status: Company	0.468	0.499	19,158
Legal status: Partnership	0.077	0.266	19,158

Table 3: Correlation matrix

This table reports the pair-wise correlation matrix between all variables used in this study. * shows significance at *p*<.01.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Tech. adoption	1.000										
(2) Firm size	0.230*	1.000									
(3) Firm Age	0.005	0.135*	1.000								
(4) Profit	0.041*	0.065*	0.061*	1.000							
(5) Bank Finance	0.075*	0.147*	0.020*	-0.003	1.000						
(6) Aim to grow sales	0.168*	0.253*	-0.103*	0.022*	0.083*	1.000					
(7) Innovator	0.198*	0.090*	-0.064*	-0.004	0.035*	0.179*	1.000				
(8) Women-led	-0.050*	-0.007	-0.027*	-0.051*	-0.035*	-0.031*	-0.018	1.000			
(9) MEG-led	0.004	0.021*	-0.122*	-0.050*	0.011	0.043*	0.029*	-0.020*	1.000		
(10) Family business	-0.083*	-0.254*	-0.123*	0.070*	0.028*	-0.060*	-0.052*	0.001	0.031*	1.000	
(11) Urban	0.039*	0.085*	-0.021*	-0.028*	-0.050*	0.050*	0.023*	-0.001	0.108*	-0.115*	1.000

Table 4: The impact of the use of production-enhanced technologies on SME's productivity

This table presents OLS regressions of the effect of technology use on productivity. The base categories for categorical variables are: zero employees on the payroll (size), 0-5 years (business age). Z-statistics adjusted for clustering at regional level are reported in parentheses. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

Dependent Variable: Ln(productivity)	Use at least one production-enhanced technology	
	OLS	Mixed
Technology adopter $_{t-1}$	0.201***	0.193***
	(3.52)	(3.48)
Size: Micro 1 – 9 $_{t-1}$	0.147***	0.157***
	(3.17)	(3.43)
Size: Small 10 – 49 $_{t-1}$	0.306***	0.320***
	(6.05)	(6.12)
Size: Medium 50 – 249 $_{t-1}$	0.279***	0.283***
	(4.35)	(4.45)
Business age: 6 – 10 $_{t-1}$	0.249**	0.245***
	(2.99)	(2.89)
Business age:11 – 20 $_{t-1}$	0.258***	0.257***
	(3.35)	(3.31)
Business age: 20+ $_{t-1}$	0.378***	0.376***
	(5.58)	(5.40)
Profit $_{t-1}$	0.471***	0.474***
	(13.29)	(13.48)
Bank Finance $_{t-1}$	0.031	0.045*
	(1.02)	(1.86)
Aim to grow $_{t-1}$	0.147***	0.134***
	(4.00)	(3.51)
Innovator $_{t-1}$	-0.010	-0.012
	(-0.33)	(-0.44)
Women-lead $_{t-1}$	-0.230***	-0.231***
	(-6.23)	(-6.38)
MEG-led $_{t-1}$	0.009	-0.043
	(0.15)	(-0.79)
Family-owned $_{t-1}$	-0.189***	-0.180***
	(-3.86)	(-3.98)
Urban $_{t-1}$	0.015	-0.029
	(0.31)	(-0.94)
Regional / Sector Controls	YES	YES
Legal Status	YES	YES
Observations	3,775	3,775
Log likelihood	-5151.673	-5126.219

Table 5: The impact of the use of production-enhanced technologies on SME's productivity

This table presents OLS regressions of the effect of technology use on productivity. The base categories for categorical variables are: zero employees on the payroll (size), 0-5 years (business age). Z-statistics adjusted for clustering at regional level are reported in parentheses. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

Dependent Variable: Ln(productivity)	AI, robotics or automation		Business intelligence/business analytics		Cloud-based computing	
	OLS	Mixed	OLS	Mixed	OLS	Mixed
Technology $_{t-1}$	0.079*	0.078*	0.180***	0.169***	0.167***	0.156***
	(1.98)	(1.86)	(4.10)	(3.94)	(3.41)	(3.29)
Size: Micro 1 – 9 $_{t-1}$	0.165***	0.176***	0.163***	0.173***	0.151***	0.162***
	(3.54)	(3.80)	(3.49)	(3.75)	(3.40)	(3.68)
Size: Small 10 – 49	0.337***	0.350***	0.323***	0.337***	0.310***	0.325***
	(6.55)	(6.54)	(6.22)	(6.27)	(6.30)	(6.31)
Size: Medium 50 –	0.309***	0.312***	0.286***	0.291***	0.280***	0.285***
	(4.79)	(4.88)	(4.25)	(4.38)	(4.43)	(4.54)
Business age: 6 –	0.259***	0.254***	0.251**	0.246***	0.250**	0.246***
	(3.14)	(3.03)	(3.00)	(2.90)	(3.01)	(2.91)
Business age:11 –	0.267***	0.266***	0.265***	0.264***	0.261***	0.261***
	(3.47)	(3.42)	(3.49)	(3.43)	(3.43)	(3.38)
Business age: 20+	0.382***	0.380***	0.385***	0.383***	0.381***	0.379***
	(5.52)	(5.35)	(5.55)	(5.34)	(5.65)	(5.46)
Profit $_{t-1}$	0.474***	0.476***	0.479***	0.480***	0.472***	0.474***
	(12.63)	(12.85)	(12.59)	(12.73)	(12.96)	(13.19)
Bank Finance $_{t-1}$	0.041	0.055**	0.041	0.055**	0.032	0.047*
	(1.39)	(2.28)	(1.39)	(2.20)	(1.05)	(1.88)
Aim to grow $_{t-1}$	0.159***	0.145***	0.145***	0.133***	0.149***	0.136***
	(3.95)	(3.52)	(3.70)	(3.30)	(4.09)	(3.62)
Innovator $_{t-1}$	0.006	0.002	-0.012	-0.014	-0.008	-0.010
	(0.23)	(0.08)	(-0.45)	(-0.55)	(-0.27)	(-0.36)
Women-lead $_{t-1}$	-0.231***	-0.232***	-0.229***	-0.230***	-0.231***	-0.232***
	(-6.24)	(-6.34)	(-6.11)	(-6.20)	(-6.19)	(-6.31)
MEG-led $_{t-1}$	-0.001	-0.054	-0.003	-0.054	0.005	-0.046
	(-0.02)	(-0.97)	(-0.05)	(-1.02)	(0.08)	(-0.83)
Family-owned $_{t-1}$	-0.196***	-0.187***	-0.195***	-0.187***	-0.189***	-0.181***
	(-3.98)	(-4.12)	(-3.99)	(-4.08)	(-3.78)	(-3.88)
Urban $_{t-1}$	0.014	-0.031	0.013	-0.031	0.012	-0.032
	(0.28)	(-0.96)	(0.25)	(-0.94)	(0.24)	(-0.98)
Regional / Sector	YES	YES	YES	YES	YES	YES
Legal Status	YES	YES	YES	YES	YES	YES
Observations	3,775	3,775	3,775	3,775	3,775	3,775
Log likelihood	-5163.659	-5137.406	-5154.490	-5129.257	-5152.529	-5127.581

Table 6: The impact of the use of production-enhanced technologies on SME's productivity

This table presents OLS regressions of the effect of technology use on productivity. The base categories for categorical variables are: zero employees on the payroll (size), 0-5 years (business age). Z-statistics adjusted for clustering at regional level are reported in parentheses. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

Dependent Variable: Ln(productivity)	**Computer-aided design (CAD) software**		**Internet of things (IoT)**		**Virtual reality (VR) and augmented reality (AR)**	
	OLS	**Mixed**	**OLS**	**Mixed**	**OLS**	**Mixed**
Technology $_{t-1}$	0.095*	0.106**	0.023	0.029	0.126	0.132*
	(2.09)	(2.42)	(0.70)	(0.95)	(1.57)	(1.66)
Size: Micro 1 – 9 $_{t-1}$	0.167***	0.177***	0.164***	0.174***	0.167***	0.177***
	(3.51)	(3.75)	(3.49)	(3.72)	(3.63)	(3.89)
Size: Small 10 – 49	0.334***	0.346***	0.335***	0.347***	0.338***	0.351***
	(6.58)	(6.56)	(6.14)	(6.17)	(6.65)	(6.63)
Size: Medium 50 –	0.313***	0.315***	0.312***	0.314***	0.314***	0.317***
	(4.89)	(4.96)	(4.66)	(4.74)	(4.96)	(5.05)
Business age: 6 –	0.255**	0.251***	0.255**	0.250***	0.255**	0.250***
	(3.10)	(3.00)	(3.07)	(2.96)	(3.05)	(2.94)
Business age:11 –	0.262***	0.260***	0.264***	0.263***	0.265***	0.264***
	(3.43)	(3.39)	(3.41)	(3.37)	(3.44)	(3.40)
Business age: 20+	0.376***	0.373***	0.379***	0.377***	0.380***	0.378***
	(5.44)	(5.25)	(5.48)	(5.31)	(5.49)	(5.33)
Profit $_{t-1}$	0.471***	0.474***	0.472***	0.474***	0.473***	0.475***
	(12.95)	(13.19)	(12.60)	(12.81)	(12.68)	(12.88)
Bank Finance $_{t-1}$	0.041	0.055**	0.041	0.055**	0.043	0.057**
	(1.36)	(2.26)	(1.42)	(2.32)	(1.46)	(2.40)
Aim to grow $_{t-1}$	0.158***	0.143***	0.161***	0.147***	0.160***	0.146***
	(4.16)	(3.69)	(4.18)	(3.72)	(4.05)	(3.61)
Innovator $_{t-1}$	0.002	-0.004	0.012	0.007	0.009	0.005
	(0.06)	(-0.13)	(0.43)	(0.26)	(0.34)	(0.17)
Women-lead $_{t-1}$	-0.227***	-0.228***	-0.231***	-0.232***	-0.229***	-0.230***
	(-5.92)	(-6.03)	(-6.14)	(-6.25)	(-6.15)	(-6.25)
MEG-led $_{t-1}$	0.000	-0.053	-0.003	-0.056	-0.002	-0.055
	(0.00)	(-0.94)	(-0.04)	(-0.97)	(-0.04)	(-0.97)
Family-owned $_{t-1}$	-0.197***	-0.189***	-0.196***	-0.187***	-0.196***	-0.188***
	(-4.08)	(-4.27)	(-4.01)	(-4.16)	(-3.96)	(-4.10)
Urban $_{t-1}$	0.015	-0.032	0.015	-0.030	0.014	-0.031
	(0.29)	(-1.00)	(0.30)	(-0.94)	(0.29)	(-0.96)
Regional / Sector	YES	YES	YES	YES	YES	YES
Legal Status	YES	YES	YES	YES	YES	YES
Observations	3,775	3,775	3,775	3,775	3,775	3,775
Log likelihood	-5161.332	-5134.161	-5164.399	-5137.989	-5163.512	-5137.110

Table 7: Interaction effects between digital technologies and SME characteristics

This table reports the estimated interaction effects from a mixed model examining the relationship between individual digital technologies and selected firm characteristics (Aim to grow, Women-led, MEG-led, Family-owned) on SME productivity. Coefficients represent the additional effect of technology adoption on productivity for firms with the specified characteristic, relative to other firms, holding other factors constant.

Base technology	Interacted with	Estimated coefficient	Standard Error (SE)	p-value	N	Log pseudolik elihood
Artificial Intelligence, robotics, automation (AIRA)	Aim to grow	0.2047	0.1883	0.2768	3775	-5116.9
	Women-lead	0.1151	0.0908	0.2051	3775	-5117.17
	MEG-led	0.0457	0.1781	0.7977	3775	-5117.45
	Family-owned	0.0087	0.1481	0.9533	3775	-5117.47
Business intelligence / analytics	Aim to grow	-0.2877	0.1531	0.0602	3775	-5114.72
	Women-lead	-0.0143	0.0743	0.8471	3775	-5117.46
	MEG-led	-0.2088	0.1822	0.2517	3775	-5116.66
	Family-owned	-0.2483	0.0552	0.0000	3775	-5113.44
Cloud computing	Aim to grow	-0.1139	0.0871	0.1909	3775	-5116.3
	Women-lead	-0.0838	0.0939	0.3721	3775	-5116.95
	MEG-led	-0.0233	0.1716	0.8918	3775	-5117.46
	Family-owned	0.041	0.0855	0.6321	3775	-5117.35

Computer-aided design (CAD)	Aim to grow	-0.094	0.1176	0.4241	3775	-5116.91
	Women-lead	-0.1166	0.0797	0.1434	3775	-5116.78
	MEG-led	-0.2452	0.1335	0.0663	3775	-5116.39
	Family-owned	0.0314	0.0706	0.6567	3775	-5117.4
Internet of Things (IoT)	Aim to grow	-0.112	0.0935	0.231	3775	-5116.49
	Women-lead	-0.1214	0.0599	0.0427	3775	-5116.4
	MEG-led	-0.3593	0.1354	0.008	3775	-5114.4
	Family-owned	-0.0485	0.0424	0.2521	3775	-5117.27
Virtual/augmented reality (VR/AR)	Aim to grow	-0.0606	0.3537	0.864	3775	-5117.44
	Women-lead	0.2226	0.1948	0.253	3775	-5117.07
	MEG-led	0.2451	0.1887	0.1939	3775	-5117.2
	Family-owned	-0.3721	0.1771	0.0357	3775	-5115.57

Table 8: Interaction effects between pairs of digital technologies

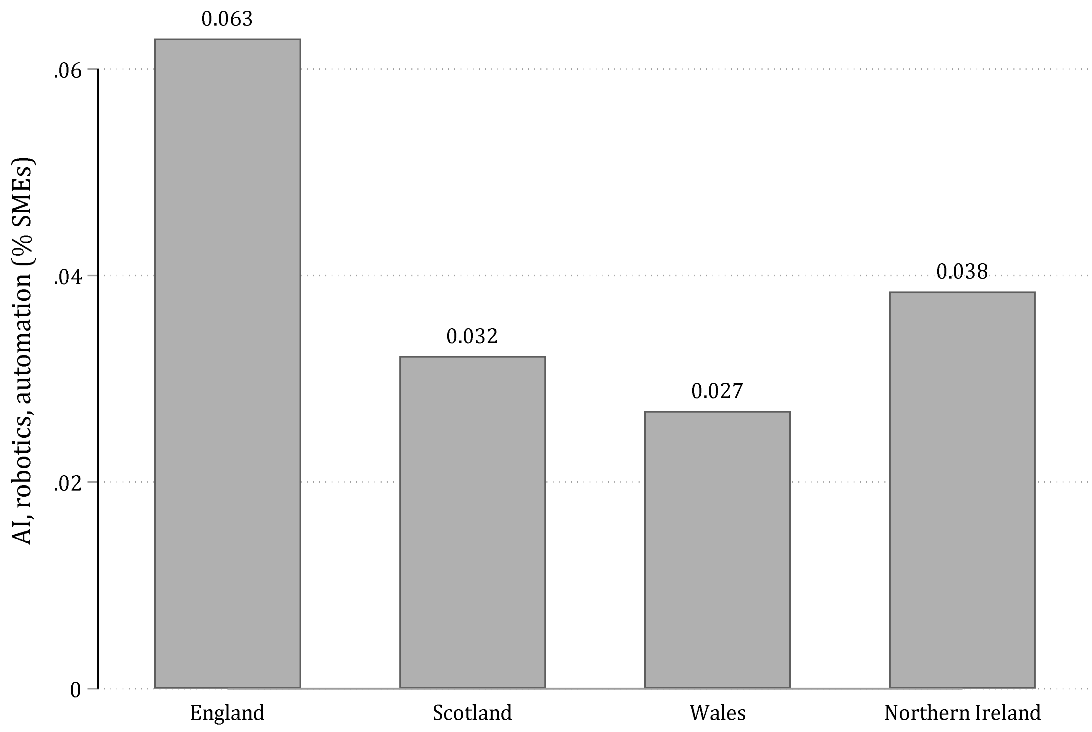
This table reports the estimated interaction effects from a mixed model between pairs of individual digital technologies. Coefficients represent the effect of technology bundles on productivity.

Base technology	Interacted with	Estimated coefficient	Standard Error (SE)	p-value	N	Log pseudolik elihood
Artificial Intelligence, robotics, automation (AIRA)	Business intelligence / analytics	0.082	0.0913	0.3688	3775	-5117.21
	Cloud computing	-0.2578	0.1391	0.0638	3775	-5115.93
	Computer-aided design (CAD)	-0.0439	0.08	0.5831	3775	-5117.39
	Internet of Things (IoT)	-0.1703	0.089	0.0556	3775	-5116.26
	Virtual/augmented reality (VR/AR)	-0.3257	0.0866	0.0002	3775	-5115.78
Business intelligence / analytics	Artificial Intelligence, robotics, automation (AIRA)	0.082	0.0913	0.3688	3775	-5117.21
	Cloud computing	-0.1732	0.0799	0.0302	3775	-5116.02
	Computer-aided design (CAD)	-0.1323	0.0706	0.0611	3775	-5116.19
	Internet of Things (IoT)	-0.0949	0.0786	0.2272	3775	-5116.71
	Virtual/augmented reality (VR/AR)	-0.1377	0.1332	0.3012	3775	-5117.13
Cloud computing	Artificial Intelligence, robotics, automation (AIRA)	-0.2578	0.1391	0.0638	3775	-5115.93
	Business intelligence / analytics	-0.1732	0.0799	0.0302	3775	-5116.02
	Computer-aided design (CAD)	0.0612	0.0907	0.5001	3775	-5117.15
	Internet of Things (IoT)	-0.2196	0.0706	0.0019	3775	-5112.84

	Virtual/augmented reality (VR/AR)	-0.22	0.197	0.2641	3775	-5116.96
Computer-aided design (CAD)	Artificial Intelligence, robotics, automation (AIRA)	-0.0439	0.08	0.5831	3775	-5117.39
	Business intelligence / analytics	-0.1323	0.0706	0.0611	3775	-5116.19
	Cloud computing	0.0612	0.0907	0.5001	3775	-5117.15
	Internet of Things (IoT)	0.0696	0.0873	0.4254	3775	-5117
	Virtual/augmented reality (VR/AR)	-0.3175	0.1263	0.0119	3775	-5115.8
Internet of Things (IoT)	Artificial Intelligence, robotics, automation (AIRA)	-0.1703	0.089	0.0556	3775	-5116.26
	Business intelligence / analytics	-0.0949	0.0786	0.2272	3775	-5116.71
	Cloud computing	-0.2196	0.0706	0.0019	3775	-5112.84
	Computer-aided design (CAD)	0.0696	0.0873	0.4254	3775	-5117
	Virtual/augmented reality (VR/AR)	-0.002	0.1435	0.9891	3775	-5117.47
Virtual/augmented reality (VR/AR)	Artificial Intelligence, robotics, automation (AIRA)	-0.3257	0.0866	0.0002	3775	-5115.78
	Business intelligence / analytics	-0.1377	0.1332	0.3012	3775	-5117.13
	Cloud computing	-0.22	0.197	0.2641	3775	-5116.96
	Computer-aided design (CAD)	-0.3175	0.1263	0.0119	3775	-5115.8
	Internet of Things (IoT)	-0.002	0.1435	0.9891	3775	-5117.47

Figure 1: Use of Artificial Intelligence, robotics, and automation (AIRA)

This figure presents the proportion of small and medium-sized enterprises (SMEs) using artificial intelligence (AI), robotics, and automation, disaggregated by region and industry sector.



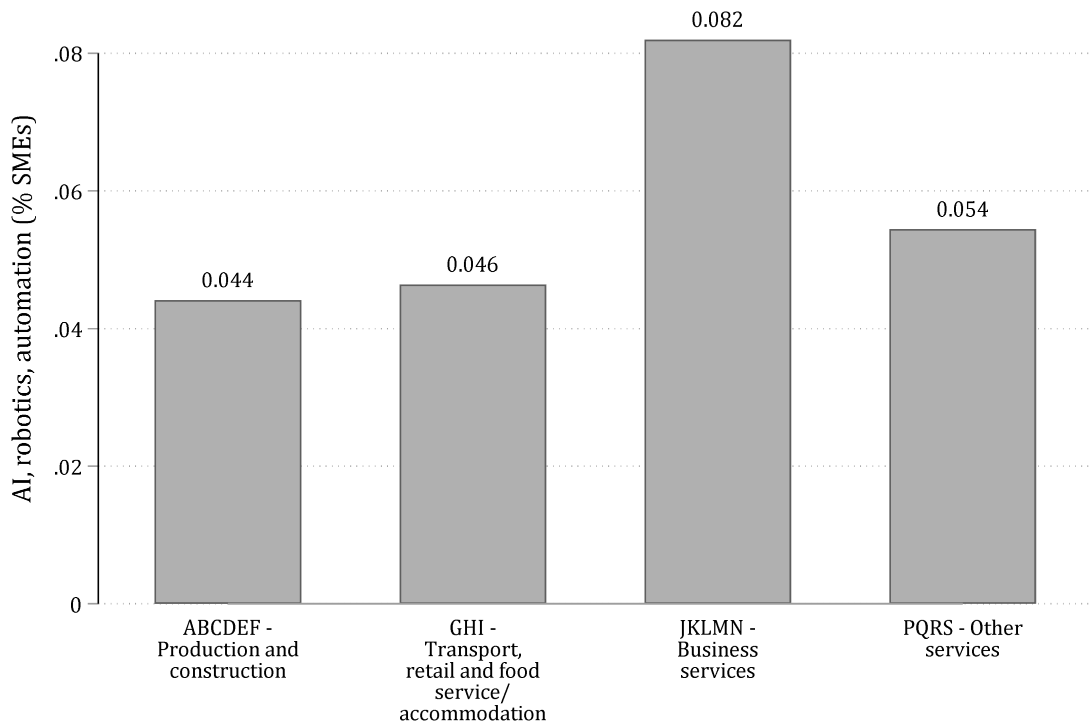
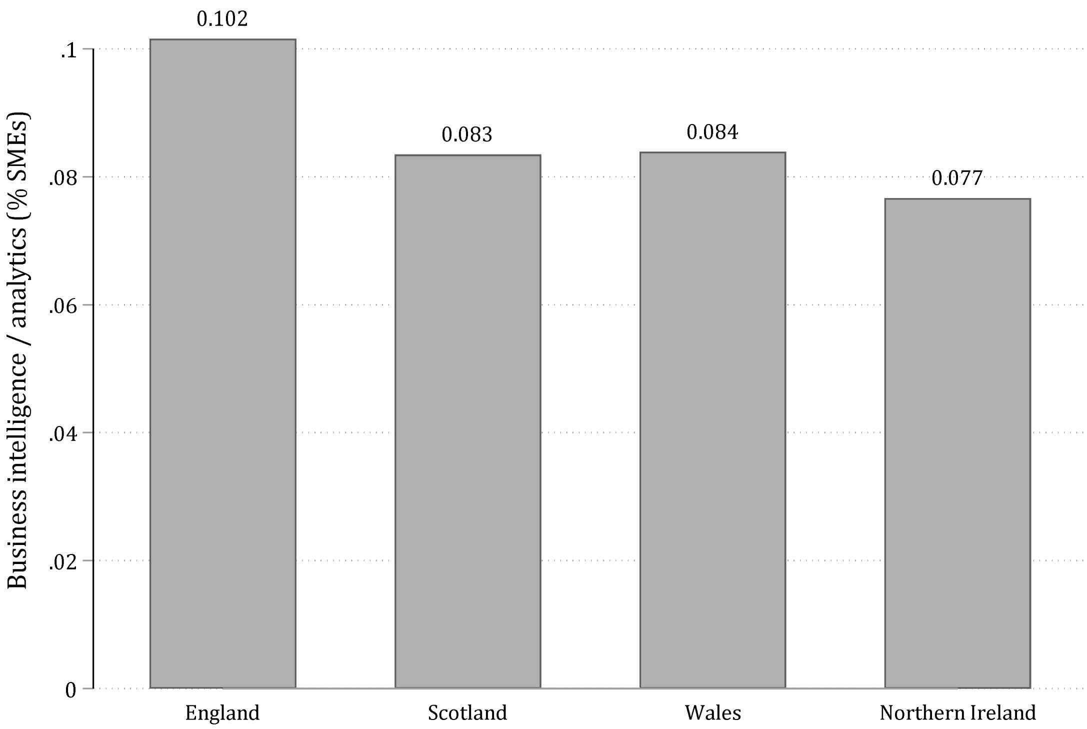


Figure 2: Use of Business intelligence/analytics

This figure presents the proportion of small and medium-sized enterprises (SMEs) using business intelligence/analytics, disaggregated by region and industry sector.



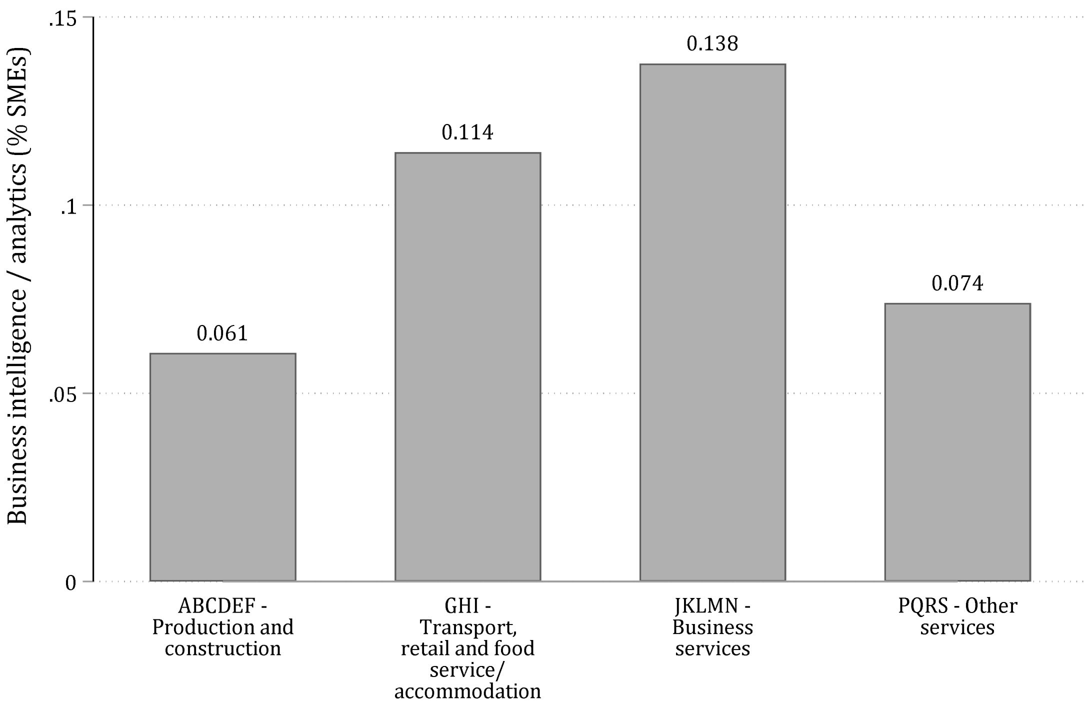
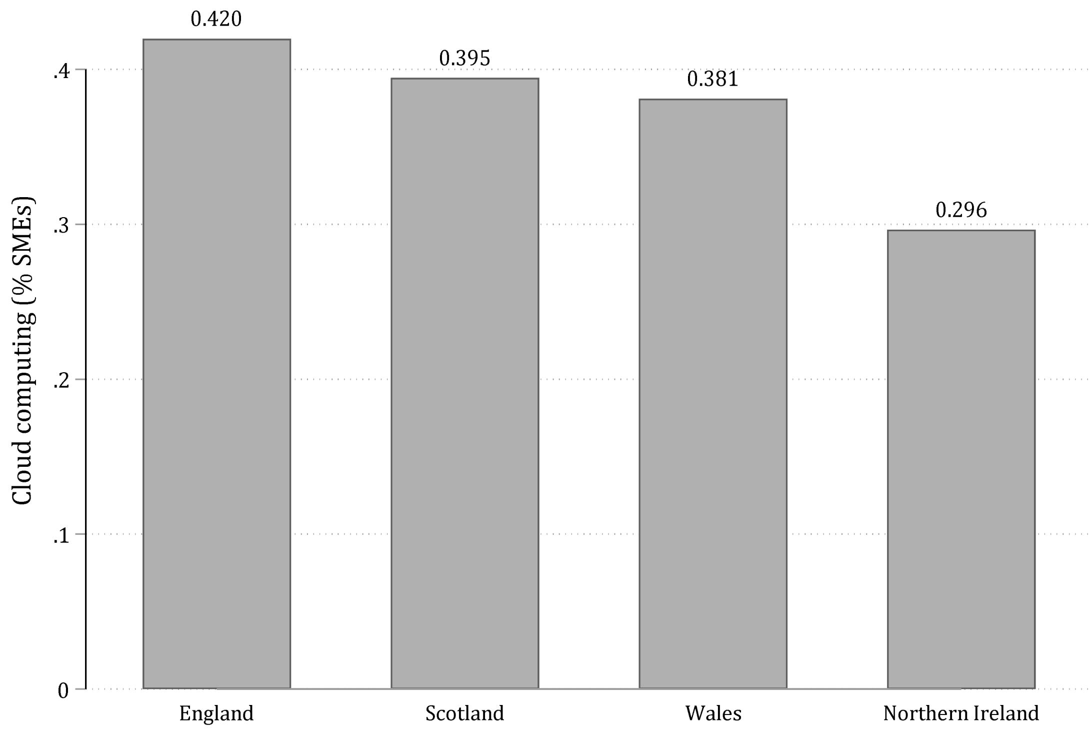


Figure 3: Use of Cloud computing

This figure presents the proportion of small and medium-sized enterprises (SMEs) using cloud computing, disaggregated by region and industry sector.



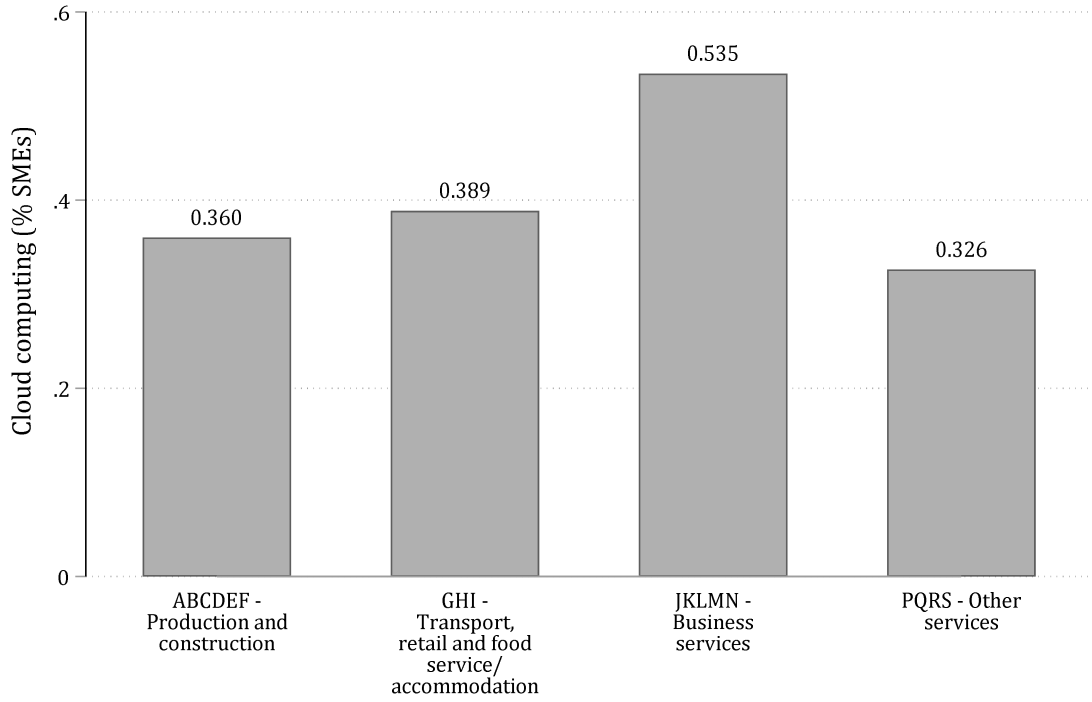
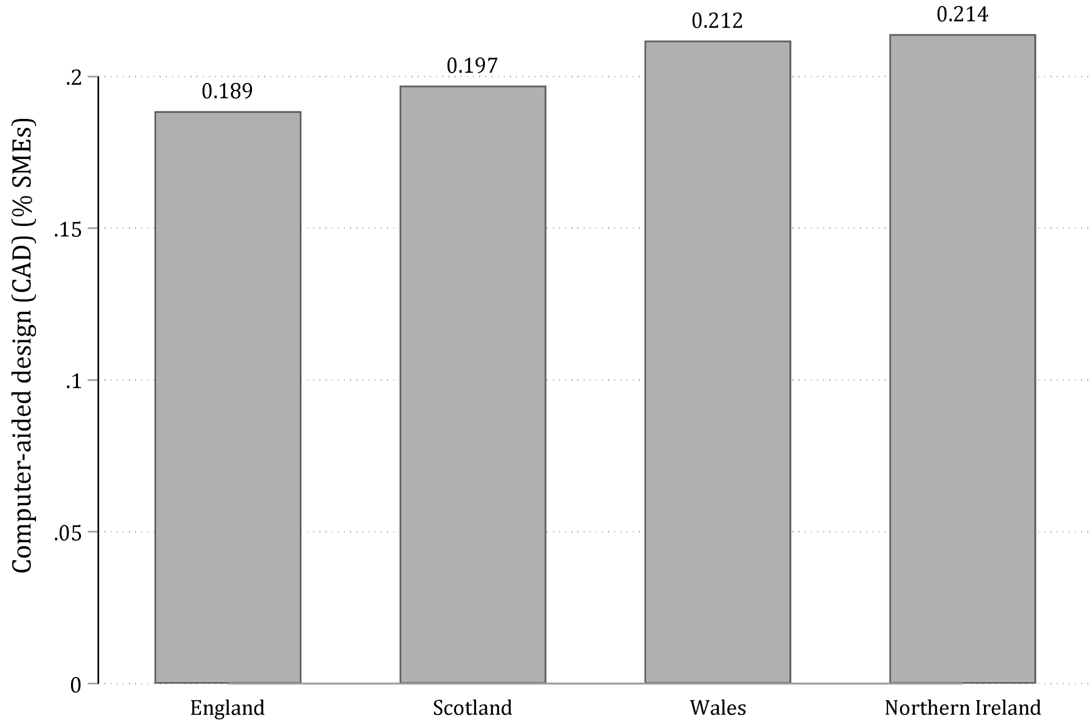


Figure 4: Use of Computer-aided design (CAD)

This figure presents the proportion of small and medium-sized enterprises (SMEs) using CAD software, disaggregated by region and industry sector.



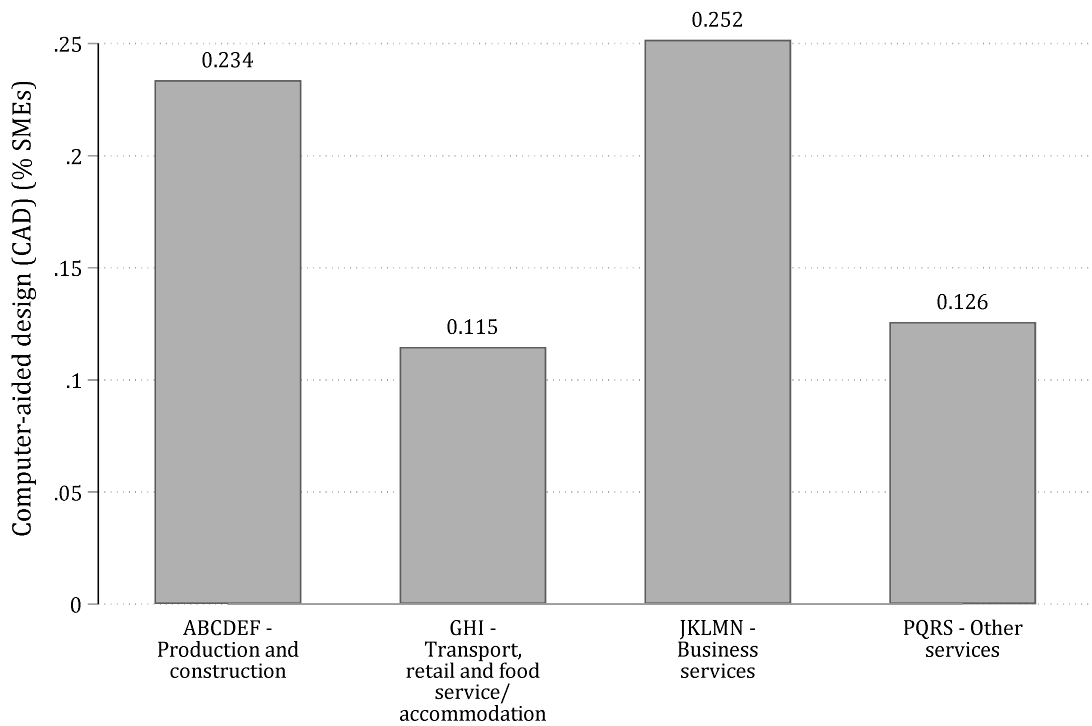


Figure 5: Use of Internet of Things (IoT)

This figure presents the proportion of small and medium-sized enterprises (SMEs) using IoT, disaggregated by region and industry sector.

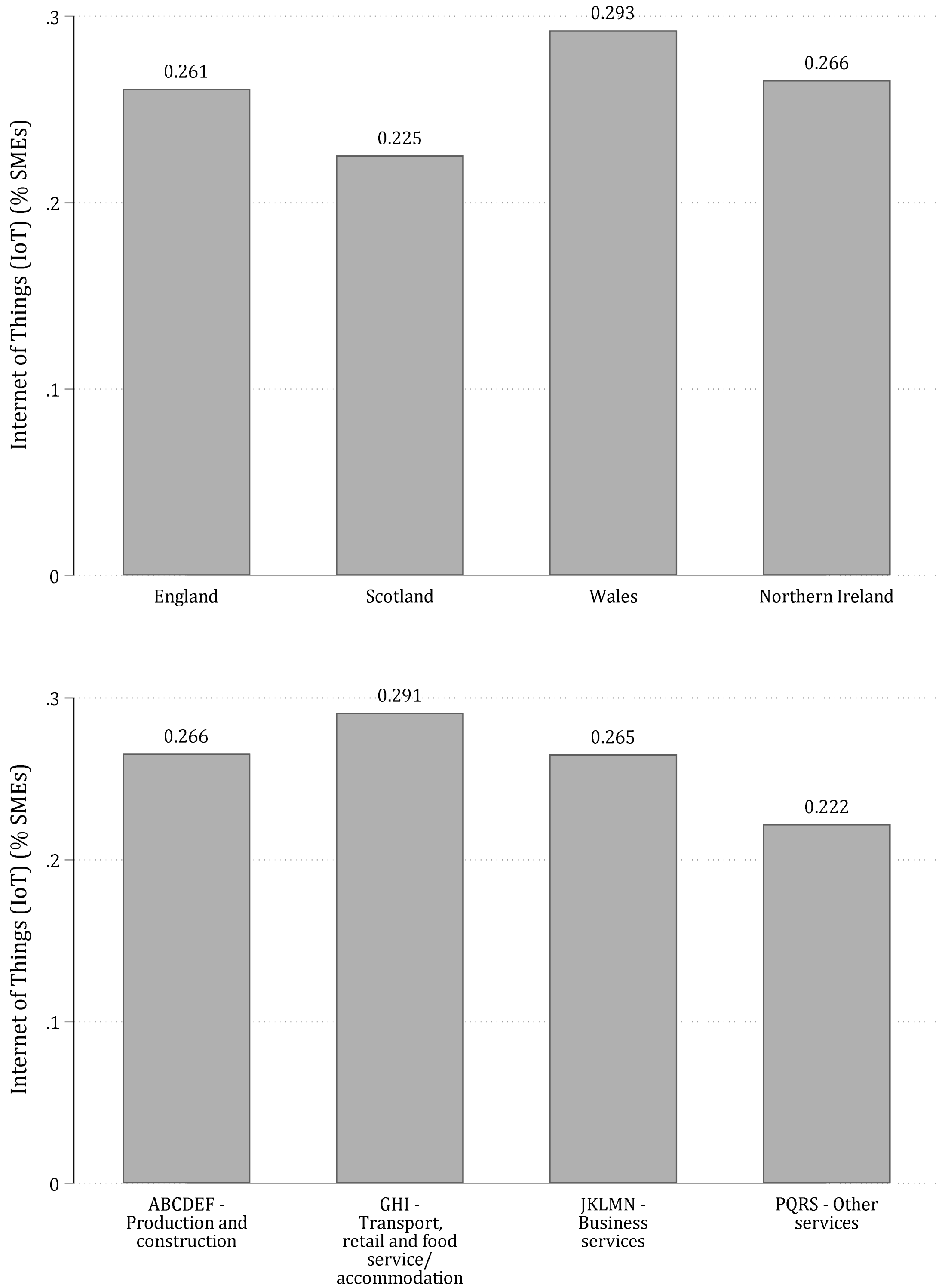


Figure 6: Use of Virtual/augmented reality (VR/AR)

This figure presents the proportion of small and medium-sized enterprises (SMEs) VR/AR, disaggregated by region and industry sector.

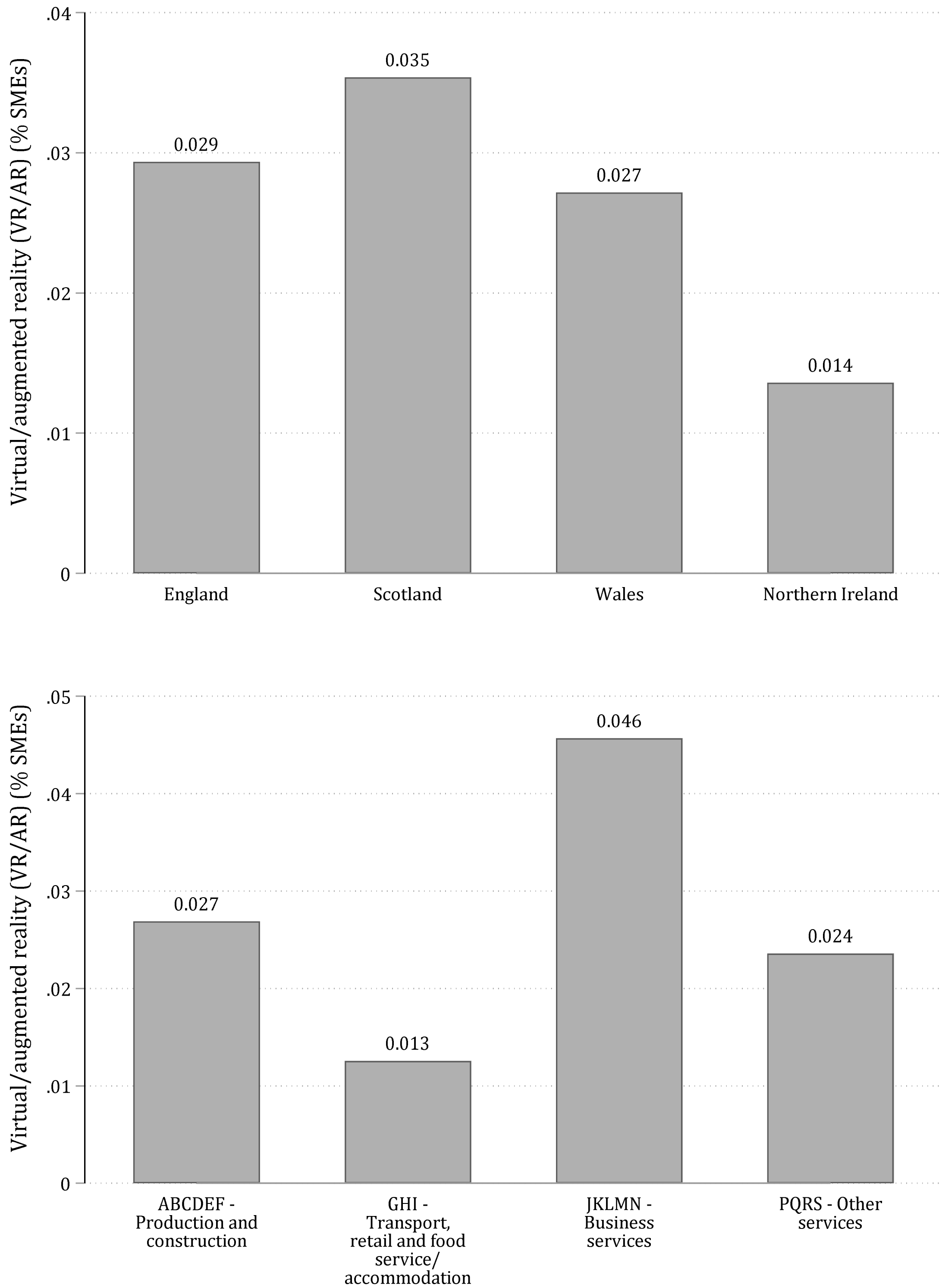
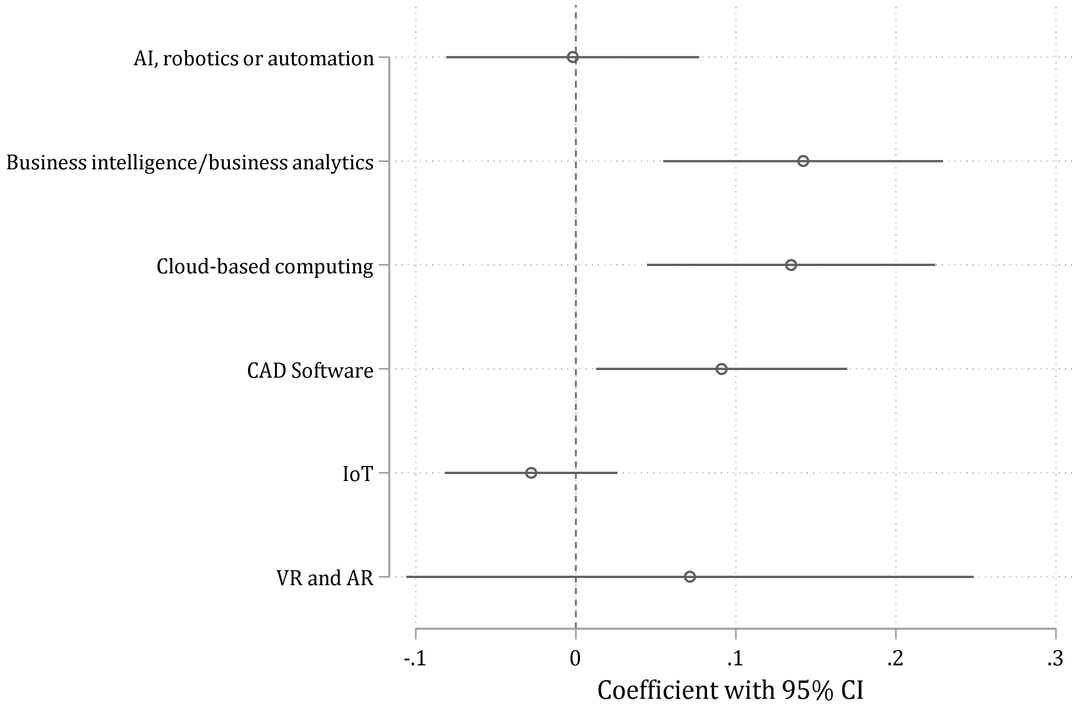


Figure 7: The effect of technology on productivity (joint estimation based on a mixed model)

The figure plots estimated coefficients from a mixed-effects model. Each specification includes the full set of control variables used in Tables 5 and 6, and all technologies are entered simultaneously.



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