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Artificial intelligence and firm-level productivity

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ABSTRACT

Artificial Intelligence (AI) is often regarded as the next general-purpose technology with a rapid, penetrating, and far-reaching use over a broad number of industrial sectors. The main feature of new general-purpose technology is to enable new ways of production that may increase productivity. However, to date, only a few studies have investigated the likely productivity effects of AI at the firm-level, presumably due to limited data availability. We exploit unique survey data on firms' adoption of AI technology and estimate its productivity effects with a sample of German firms. We employ both a cross-sectional dataset and a panel database. To address the potential endogeneity of AI adoption, we also implement IV estimators. We find positive and significant associations between the use of AI and firm productivity. This finding holds for different measures of AI usage, i.e., an indicator variable of AI adoption, and the intensity with which firms use AI methods in their business processes.

1. Introduction

Artificial Intelligence (AI) is often regarded as a new general-purpose technology, with a rapid, penetrating, and far-reaching use over a broad number of industrial sectors (Brynjolfsson et al., 2017; Agrawal et al., 2019a; Nolan 2020). The main feature of general-purpose technology is to enable new and complementary production methods that may increase productivity over time (Bresnahan and Trajtenberg 1995; Bresnahan et al., 2002; Brynjolfsson and Hitt 2003; Cardona et al., 2013). As such, it could be expected that the adoption of AI technologies – especially its machine learning component – by firms enacts new business opportunities and boosts productivity (Brynjolfsson and McAfee 2014).

In the literature, there are two views on how AI may positively contribute to productivity. On the one hand, AI can be regarded as an intangible capital asset that firms may invest in and use to generate output through a production function. For instance, several AI applications such as autonomous vehicles, voice-recognition, speech/text generating systems, predictive maintenance, or trained neural networks to optimize business energy consumption, would depict AI's potential to increase firm productivity (Brynjolfsson et al., 2017). On the other hand, authors have speculated about how AI-based techniques increase a firm's innovative capabilities and enhance firm productivity through their impact on R&D, innovation,

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and the generation of new ideas (Aghion et al., 2019; Cockburn et al., 2019). In this paper, we adopt the view of AI being a capital asset that enlarges the capacity of a firm to produce more, or more valuable output. Since AI is mainly an intangible asset, usually based on new software algorithms and big data analytics, analyzing the productivity impact of AI is closely connected to the literature on intangibles and productivity (Corrado et al., 2005, 2021; Haskel and Westland 2017).

Whether AI is actually a new driver for productivity growth is controversially discussed in the literature, and several scholars are rather skeptical about AI's potentials. Gordon (2014; 2018) claimed that U.S. productivity growth in the coming decades could be much slower and that IT, and innovative progress in general, will not have any propeller role in the observed productivity slowdown. Gordon argues that, for the period 2004 to 2014, no concluding evidence on the link between fundamental inventions (e.g., smartphones) and U.S. productivity performance has been presented so far. More recently, the hypothesis that human labor could be automated by super-intelligent computers, leading to a rapid acceleration of technology-driven growth and productivity increase has been rather rejected. Testing that hypothesis within the context of economic growth, Nordhaus (2021) suggests that AI would have to encompass all human tasks to reach such "economic singularity". Other authors argue that in an early stage of diffusion of a general-purpose technology, productivity effects may be underestimated.

Besides this clash of predictions on the role of AI adoption, the debate lacks conclusive and rigorous empirical evidence mainly due to the restricted availability of data on AI adoption in the business sector. Recent studies focused on analyzing the impact of AI using patent applications and scientific papers related to AI as the main measure of interest (Cockburn et al., 2019; Van Roy et al., 2020; Damioli et al., 2021). However, patent data might provide an incomplete and biased picture of AI's potential effect on productivity since not all AI methods are being patented, and many firms may adopt AI technologies invented by third parties. To analyze the effect of AI on innovative activities and productivity, other studies used data on specific components of AI technologies such as AI-based robots (Graetz and Michaels 2018; Acemoglu and Restrepo 2020) or the use of big data and data-driven managerial decisions (Brynjolfsson et al., 2011; Niebel et al., 2019; Ghasemaghaei and Calic 2019). While both robotization and big data analytics represent relevant elements of AI, they are neither entirely based on AI technology nor do they account for the entire scope of AI that is used in firms. As stressed by Raj and Seamans (2018), more comprehensive data on the use of AI – especially at the firm level – would be required to truly understand the contribution of AI to productivity.

To the best of our knowledge, this is one of the few papers that address this issue in detail by studying the relationship between AI and firm productivity, using data from a representative, large-scale survey that contains rich information on firms' AI adoption. We analyze cross-section as well as panel data from the German part of the European Commission's Community Innovation Survey (CIS). Differently to the standard CIS, the German innovation survey for the reference year 2018 included specific questions on the adoption of AI which covered all types of AI methods that can be used in a firm as well as all kinds of business areas where AI may be applied (see Rammer et al., 2022 for more details). This data provides an ideal base for investigating the productivity impacts of the entire diversity of AI applications in firms.

The main findings of this paper are in line with the notion that AI is a productivity-enhancing technology. We find positive and significant associations between the use of AI and firm productivity. This finding holds for different measures of AI usage, i.e., an indicator variable of AI adoption, and the intensity with which firms use AI methods in their business processes. The general positive relationship between AI and firm productivity also holds both for sales-based and value-added-based productivity measures. In addition, our instrumental variables results suggest a potential direct relationship between the use of AI and productivity that is significantly higher in magnitude than our reduced-form results.

The rest of the paper is organized as follows. Section 2 relates this work to previous studies linking AI and productivity. Section 3 presents our empirical framework and model. Section 4 describes the data and model variables while Section 5 contains the results of our empirical analysis, including several robustness checks. Finally, Section 6 discusses the findings and identifies further research questions.

2. Artificial intelligence and productivity

2.1. AI as a productivity-enhancing technology or faltering innovation?

There are several potential channels by which AI can propel firm productivity. For example, machine learning advances have encouraged cheaper and better predictive analyses allowing the full automation of tasks (e.g., self-driving vehicles), larger access to new relevant knowledge that can be combined to produce new ideas and know-how, and the generation of innovations (Agrawal et al. 2019a; Agrawal et al., 2019b; Cockburn et al., 2019). As shown by Aghion et al. (2019) at a conceptual level, AI is an additional input in a firm's production process that can potentially change firm performance due to its effect on the generation of new ideas and technologies, and because it would become handy in solving difficult problems. According to Brynjolfsson et al. (2017), AI should be treated as additional intangible capital in the production function of firms as the expansion of investment in AI technology may increase productivity similarly to other types of factor inputs. The effective use of AI technologies would result in additional intangible assets such as datasets, firm-specific human skills, and establishing new firm processes. As for other new technology, productivity impacts of AI technologies may not be observed right after its implementation but with some time lag only (Brynjolfsson et al., 2017) as firms may have to adopt other processes and invest in complementary assets to fully leverage the productivity-enhancing potential of AI (Tambe et al., 2020). In addition, not all investments may be measured as such (particularly those related to data bases), resulting in a mismeasurement of the capital payments effect of intangible investment, which lowers measured productivity growth (Corrado et al. (2021). In a similar vein, Brynjolfsson et al. (2021) argue that the productivity-enhancing effect of AI will only show up in a later stage of AI development and diffusion.

Opposite to this strand of the literature, other economists have flagged the observed slowdown of productivity growth (Gordon 2014; 2018) and adopted a rather modest view on the transformative role of new (digital) technologies such as AI. Their arguments range from the notion that new ideas within firms are increasingly difficult to develop (Bloom et al., 2020) to the possible social, physical, and institutional constraints for accessing knowledge and data that are key to effectively exploiting AI techniques in business processes (see Agrawal et al., 2019b for a discussion).

Nonetheless, as claimed by Raj and Seamans (2018), until now there has not been a database available at the firm level that allows a rigorous study of the role of AI on productivity outcomes. Brynjolfsson et al. (2017) stressed the limitations of the currently available AI data and called for more comprehensive firm-level data on AI use. In that context, the literature reported above is rather speculative because it fundamentally lacks empirical evidence supporting either view. In the absence of measures that would cover the entire variety of AI use in firms, empirical research has so far mainly focused on three areas or approaches: (i) industrial robots and automation of tasks; (ii) patents or scientific publications related to AI; and (iii) data-driven managerial decisions or the use of big data.

2.2. AI, robots, and productivity

Early empirical work on likely productivity effects of AI used data on robots since automation through robots is increasingly using AI technology. However, not all robotization rests on AI technology, and AI-based robots represent only a small fraction of all AI use in firms (see the empirical part of the paper for evidence). In a pioneering paper, Graetz and Michaels (2018) analyzed industry-level data on industrial robots from the International Federation of Robotics (IRF) for six different countries from 1993 to 2007. These authors showed that country-industry pairs with a larger expansion in robot density were associated with larger benefits in labor productivity. Focusing on the German economy, Dauth et al. (2017) found that at the aggregate level, the industrial use of robots enhances labor productivity. More recently, relying on the same IRF data, Acemoglu and Restrepo (2020) showed that the penetration of robots for different periods had a positive effect on industry value-added measures. Other studies analyzing the impact of industrial robots at the aggregate level on productivity measures include, e.g., Humlum (2019) who estimated a structural model of a firm's robots adoption and found that firms expand the produced output when they embrace industrial robots (see also Fierro et al., 2022, Stiebale et al., 2020, and Acemoglu et al., 2020a for further evidence). A positive link between robotization and productivity was also found by Cathles et al. (2020).

Closely related, there is a strand of literature that focuses on the idea that technologies associated with AI (e.g., automatic guided vehicles or industrial robots) have the potential to automate tasks that are currently done by humans, and thus, possibly affect the labor market and productivity outcomes. For instance, Frey and Osborne (2017) used detailed information about tasks and occupations and estimated that around 47% of U.S. jobs were at high risk of automation given recent advances in computerization and machine learning methods (e.g., data mining or machine vision). According to the authors, for example, "telemarketers", "cargo and freight agents", or "watch repairers" would be at a dramatically high risk of automation whereas "recreational therapists" or "nutritionists" would be on the opposite extreme (see also Arntz et al. 2017). In a similar approach, Felten et al. (2021) classified industries concerning their AI exposure (AIIE) based on expert assessments. They find the highest AIIE scorings for financial services, legal, accounting and consulting services, and IT services, while the AIIE scores are rather low for most manufacturing industries except electronics (see as well Innocenti and Golin 2022).

By the framework developed by Acemoglu and Restrepo (2019a), AI-related or automation technologies could generate a strong displacement effect that may reduce the demand for labor, wages, and employment, hence, contracting the share of human labor in national income. Notwithstanding, labor demand could either be expanded in those industrial sectors which are being automated or change the task content by reinstating labor in a different and new way, generating a countervailing effect from automation that may boost productivity (see, e.g., Acemoglu and Restrepo 2019b for an empirical decomposition of these effects). However, not all robots or automation technologies are directly based on AI, and thus, this strand of the literature might not strictly identify the direct effect of AI adoption on productivity. As noted by Raj and Seamans (2018), the physical nature of robots, which makes them a tangible capital asset easy to measure and track, on top of the availability of public data (e.g., IRF data on industrial robots), has retained the attention on this area of most of the existing empirical work.

2.3. AI-related patents and productivity

Another stream of literature attempts to identify the impact of AI technologies through patent data. In general, patents are a relevant driver for the productivity growth and performance of firms. For example, Van Roy et al. (2020) analyzed the economic performance of European firms patenting on AI (i.e., "AI inventors") for the period 2000–2016. Using a keyword-based method for identifying AI patents,[1] the authors found significant growth in annual sales in AI inventors with at least

[1] See Table 1 in Van Roy et al. (2020) for multiple methods usually used by the literature to identify AI patents.

one granted patent – especially SMEs – compared to firms with only non-granted AI patent applications. Another recent study investigates the impact of patents associated with the so-called "Industry 4.0″ technologies, which would include AI methods, on the economic performance of firms. Behrens and Trunschke (2020) employed a panel dataset of German firms and found that the marginal effect of an additional "4.0 patent" would increase firms' sales by 8.3%, which diminishes by firm size (see as well Venturini (2022)). Further studies analyzing the contribution of AI adoption on firm performance using patent information are Yang (2022), De Prato et al. (2019), Cockburn et al. (2019), Alderucci et al. (2020), and Damioli et al. (2021).

2.4. AI-related jobs and productivity

Another way of measuring firm investment in AI is through analyzing jobs that require AI skills. Acemoglu et al. (2020b) used job posting data to assign a measure of AI exposure based on firms' occupation structure and analyzed the firms' labor demand. Following this approach, Babina et al. (2022) studied the impact of AI technologies on growth and product innovation, using worker resume data and job posting data related to AI skills as a proxy for firms' investment in AI. They find that AI-investing firms experience higher growth in sales, employment, and market valuations, which primarily emerges through increased product innovation. Bäck et al. (2022) use data on job advertisements related to AI skills for a sample of Finnish firms. They found that AI adoption increases productivity, but only for large firms. Early adopters do not experience productivity increases. There is evidence of at least three years delay between the adoption of AI and productivity effects.

2.5. AI, big data in the business, and productivity

A further group of papers studies the impact of data-driven decisions or the use of big data on firm performance. AI-related methods such as machine learning algorithms and deep neural networks are usually used to analyze the ever-increasing amount of data that firms use and produce as part of their business activities (Taddy 2019). Given the essential role of data for AI technologies, many scholars looked at the impact that the use of big data might have on firms' decisions and performance. Brynjolfsson et al. (2011) analyze the impact of managerial decision-making based on big data on U.S. firm productivity for the period 2005 to 2009. They show that firms adopting data-driven decisions are more productive than competitors that do not use big data methods. More recently, Niebel et al. (2019) employed representative data of German manufacturing and services firms to analyze the effect of big data use on innovation performance such as the sales shares of new products. They show that the use of big data is related to a higher propensity and intensity to innovate (see Ghasemaghaei and Calic 2019 and Lozada et al., 2019 for related works). Notwithstanding the close relationship between big data and AI, not all big data analyses involve the development and adoption of AI, nor do the different varieties of AI applications in firms necessarily involve big data analysis.

2.6. AI measured through firm surveys

In recent years, firm surveys have been used to collect data on the adoption of AI technologies by firms. While these surveys are useful to inform about the diffusion of AI technologies (see Montagnier et al., 2020), they have very rarely been made available to researchers yet for analyzing the performance impacts of AI. One exception is Cathles et al. (2020) who used data from the European Investment Bank's Investment Survey (EIBIS) covering EU member states and the U.S. The survey includes an item on whether firms use big data analytics and AI. Cathles et al. found a positive relationship between adopting these technologies and both employment growth and labor productivity. Other papers investigating AI use and firm performance based on survey data include Lee et al. (2022), Morikawa (2020) and Chatterjee et al. (2021).

This paper also uses firm-level survey data, exploiting information on the use of various AI applications in a representative sample of German firms from manufacturing and services industries, collected through the German part of the CIS (see Rammer et al., 2022). We aim to extend the empirical evidence about firm-level productivity impacts of AI in three ways. First, we cover all types of AI methods and technologies used for any kind of production process or output, overcoming the limitations of existing studies which focused on specific AI-related technologies such as robots or big data use. Secondly, we consider all types of active use of AI in a firm, regardless of whether the AI technology was developed by the AI using firm or by others. By covering also the adoption of AI, we extend existing studies that focused on the development of novel AI technologies as indicated by patents. Thirdly, we analyze the role of how intensively a firm is using AI, by developing a measure of the breadth of AI use in a firm, i.e., the variety of different AI methods employed in different AI application areas.

3. Empirical framework

We follow the standard approach to analyze firm productivity by linking inputs and outputs within a production function approach (Berndt 1991).[2] The production function (f) of firms describes the association between a firm's output (Y),

[2] See Bartelsman and Doms (2000) and Syverson (2011) for literature reviews on studies analyzing the determinants of firm's productivity.

measured by annual sales, and total factor productivity (A) as well as a set of inputs, such as capital (K), labor (L), and intermediate inputs such as materials, energy and purchased services (M). We will accommodate this framework and add an additional input to the production function that represents AI adoption (AI). This approach is similar to previous studies analyzing the role of IT or innovation technologies on a firm's productivity. For instance, Brynjolfsson and Hitt (2003) estimated a production function with a firm's computer capital stock as an additional production input.[3] Assuming that AI is a type of intangible asset that can be accumulated and is depreciable, and that firms can employ to generate output (Brynjolfsson et al., 2017), the production function for firm i in period t is defined as

$$Y_{it} = f(A_{it}, K_{it},\ L_{it}, M_{it}, AI_{it}), \tag{1}$$

with $i = 1, \ldots, N$. For simplicity, we assume that the functional form of the production function follows a four-input Cobb-Douglas form as

$$Y_{it} = A_{it} K_{it}^{\alpha_k} L_{it}^{\alpha_l} M_{it}^{\alpha_M} AI_{it}^{\alpha_{ai}} \tag{2}$$

or, equivalently,

$$lnY_{it} = lnA_{it} + \alpha_k lnK_{it} + \alpha_l lnL_{it} + \alpha_m lnM_{it} + \alpha_{ai} lnAI_{it}, \tag{3}$$

where α_k, α_l, α_m, and α_{ai} are unknown parameters to be estimated. The term A, the total factor productivity (TFP), accounts for variations in productivity that are not due to observed inputs but that operate through the production function (Syverson 2011).

In order to get an empirical equation that can be estimated, we introduce stochastic disturbances, which represent random, nonsystematic shocks when firms seek to modify the amount of inputs employed to reach the necessary requirements for profit maximization (Zellner et al. 1966). Thus, for firm i in period t, we have the following estimable equation

$$lnY_{it} = \lambda_i + \alpha_k lnK_{it} + \alpha_l lnL_{it} + \alpha_m lnM_{it} + \alpha_{ai} lnAI_{it} + X_{it}\beta +\ \varepsilon_{it}, \tag{4}$$

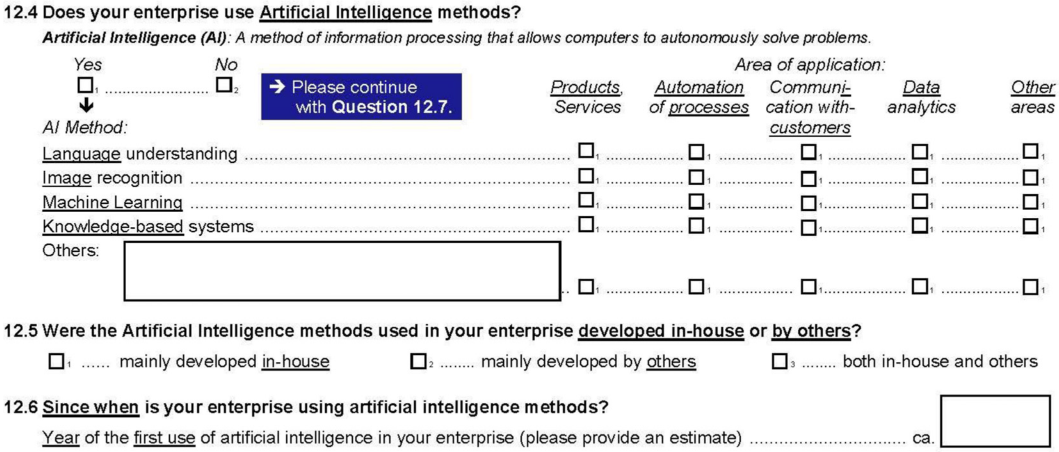
where $\lambda_i + X_i\beta + \varepsilon_i = lnA_{it}$, X_{it} is a matrix of firm's characteristics that are described below, λ_i is a firm-specific time-invariant productivity term, and ε_{it} is a random, unobserved error with mean zero. The coefficient of interest is α_{ai}, the ceteris paribus impact of AI adoption. Of course, we could conceptually also consider that AI is not a factor input but that it rather affects total factor productivity, and would thus be included in the term lnA. We would arrive at the same equation to be estimated.

In the literature on production function estimation, it is commonly hypothesized that the firm-specific term λ_i is known to the firm but unobserved to the researcher, and that the firm chooses its factor input optimally based on its knowledge of λ_i which gives rise to an endogeneity concern in econometric estimations. Several approaches have been suggested to overcome that problem. Among others, the most prominent examples are the works of Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015), and most recently Gandhi et al. (2020).

Unfortunately, our data do not allow the application of the most commonly used estimator, as our main database is a cross-section of surveyed firms. We, therefore, have to limit the current analysis to simpler estimation techniques but offer a number of variations of the specification and conduct robustness tests to the extent possible with the current database. In particular, we estimate the following models:

1. Our base models are cross-sectional OLS regressions where we use a dummy variable indicating whether a firm uses any AI technology in its production along with the factor inputs K, L, and M. We have to introduce the restriction that $\lambda_i =\ \lambda_0\ \forall\ N$ but use a number of controls (X) to mitigate possible endogeneity concerns arising from omitted variable bias and unobserved heterogeneity, such as industry dummies, firms' age, and variables on general innovation activity as well as information on past investments into IT architecture (cf., among others, Brynjolfsson and Hitt 2003). The variables are described in detail in the subsequent data section.
2. We run IV regressions (2SLS) where we instrument the AI variable to address the concern that the more productive firms are those investing in AI. Unfortunately, our database is not rich enough to also instrument the common factor inputs L, K, and M.
3. We implement an entropy balancing procedure as a further approach to address a likely bias due to unobserved heterogeneity. Entropy balancing is a method that ensures that the three moments of each matching variable (mean, standard deviation, skewness) are identical for the group of treated firms (i.e., AI adopters) and for the control group (i.e., firms not using AI). This is achieved by weighting the observations of non-users of AI in a way that the weighted observations produce the same moments as one finds for the group of AI adopters (see Hainmueller 2012). Entropy balancing is more flexible than propensity score matching methods since it uses all available control group observations and is therefore less contingent on outliers. For the balancing, we use all covariates from the main regression, i.e., L, K, M, and X. Applying entropy balancing implies that the effect of AI on productivity is not driven by structural differences between AI adopters and firms not using AI.

[3] Stiroh (2005) and Draca et al. (2006) provide surveys of studies considering IT technologies in firm's production functions. In a recent survey, Abrardi et al. (2021) review studies that consider AI as a new input of production.


12.4 Does your enterprise use Artificial Intelligence methods?

Artificial Intelligence (AI): *A method of information processing that allows computers to autonomously solve problems.*

Yes ☐1 .... *No* ☐2 → Please continue with **Question 12.7.**

AI Method: | *Area of application:*

	Products, Services	*Automation of processes*	*Communication with customers*	*Data analytics*	*Other areas*
Language understanding	☐1	☐1	☐1	☐1	☐1
Image recognition	☐1	☐1	☐1	☐1	☐1
Machine Learning	☐1	☐1	☐1	☐1	☐1
Knowledge-based systems	☐1	☐1	☐1	☐1	☐1
Others:	☐1	☐1	☐1	☐1	☐1

12.5 Were the Artificial Intelligence methods used in your enterprise developed in-house or by others?

☐1 ...... mainly developed in-house ☐2 .... mainly developed by others ☐3 .... both in-house and others

12.6 Since when is your enterprise using artificial intelligence methods?

Year of the first use of artificial intelligence in your enterprise (please provide an estimate) .... ca.

Fig. 1. Question of AI use in the German Innovation Survey 2019.

4. To further address the concern of unobserved heterogeneity, we constructed a very small panel with $T = 2$, such that we can estimate the production function in first differences, i.e., we regress ΔlnY on ΔlnL, ΔlnK, ΔlnM, and the AI dummy variable. The firm-fixed effect λ_i is thus accounted for by first-differencing. We run both OLS and IV regressions, where we instrument the AI dummy in the latter. As the AI dummy is just available from one cross-section of the survey, we cannot take the first difference though. We have to modify the interpretation slightly: in the first-difference fixed effects regression, the AI dummy is assumed to approximate that the firm invested in AI in the recent period rather than interpreting the dummy as a stock. The investment assumption is plausible as most AI-using firms have only recently started to develop or adopt this technology. If they thus indicated in the survey that they have been using AI in the recent three-year period, it is also likely that they invested.
5. We also offer some robustness tests of the specifications described above.
   a. Instead of the AI dummy variable, we will also use an AI index that measures the intensity of AI use in the firm.
   b. Instead of using sales as the output variable, we also use value-added (and then omit M from the right-hand side of the production function).

4. Data

4.1. Data source

We use cross-section as well as panel data of firms taken from the German contribution to the Community Innovation Survey (CIS) of the European Commission. Different from other national innovation surveys, the German survey is designed as a panel survey and is conducted every year, called the 'Mannheim Innovation Panel' (MIP, see Peters and Rammer 2013 for more details). The information collected is representative of all firms in Germany with at least 5 employees in manufacturing, mining, utilities, and business-oriented service sectors (wholesale trade, transportation, financing and insurance, information and communication, professional, scientific, technical, administrative, and support services). The MIP follows the methodological guidelines of the CIS as laid down by the Statistical Office of the European Commission (Eurostat) in terms of sampling, data processing, and quality control. The survey is based on a stratified random sample. Data is collected through a standardized questionnaire that can be answered both on paper and online. The response rate of the MIP is between 25 and 35%. A likely bias among responding firms is analyzed through an extensive non-response survey (see Peters and Rammer 2013).

4.2. AI variables

The German Innovation Survey conducted in the year 2019 (reference year 2018) included questions on the use of AI which allow us to separate AI-using from not AI-using firms (see Fig. 1).[4] A first question asked in a matrix format whether a firm uses AI methods at the time of the survey and the application areas for which the methods were used. The questions distinguished four broad AI methods related to language understanding, image recognition, machine learning, and knowledge-based systems. In terms of application areas, five areas were distinguished: products/services, process automation, customer interaction, data analytics, and any other area. Further questions were asked on whether the AI used in the firm was developed in-house or by others, and in which year the firm used AI for the first time.

[4] Note that this question was not included in any other national CIS.

Table 1
Definitions and summary statistics of model variables.

		Non-users of AI (5442 obs.)				AI users (409 obs.)			
Variable	Definition	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
AI	1 if a firm used, by 2018, at least one AI method in at least one application area, 0 otherwise	0	0	0	0	1	0	1	1
AIint	Number of combinations of AI methods and AI applications areas, divided by the maximum possible number (20)	0	0	0	0	0.129	0.097	0.050	0.750
SALES	Turnover in 2018 in million €	33.549	114.480	0.097	1950.56	114.47	289.91	0.136	2151.41
EMP	Number of full-time employees, average of year 2018	84.476	219.665	1	2897	244.55	517.56	2	3150
MAT	Purchase of material, energy, services and other production inputs in 2018 in million €	15.041	53.103	0.005	791.133	32.651	77.198	0.007	617.418
CAP	Stock of fixed capital at the start of 2018 in million €	17.206	131.423	0.001	6625.51	28.304	99.763	0.003	1098.98
ΔlnSALES	First difference the log value of *SALES**	0.037	0.140	−0.579	0.722	0.054	0.147	−0.493	0.559
ΔlnEMP	First difference the log value of *EMP**	0.019	0.105	−0.470	0.510	0.046	0.116	−0.405	0.510
ΔlnMAT	First difference the log value of *MAT**	0.049	0.228	−1.276	1.330	0.021	0.260	−1.321	1.098
ΔlnCAP	First difference the log value of *CAP**	0.053	0.213	−0.571	0.980	0.069	0.210	−0.559	0.911
RDCON	1 if a firm conducted research and development activities during 2016 to 2018 on a continuous base, 0 otherwise	0.192	0.394	0	1	0.498	0.500	0	1
TECHIMP	1 if a firm acquired technology during 2016 and 2018 that was new or improved compared to the technology used by the firm at the beginning of 2016, 0 otherwise	0.586	0.493	0	1	0.777	0.416	0	1
lnAGE	Number of years since the firm started business (log values)	3.279	0.673	1.098	6.811	3.205	0.700	1.098	6.926
AI_IND	Number of German firms having introduced AI during 2011 and 2017 by two-digit NACE industry	10.307	12.572	0	58	20.599	18.042	0	58
PASTINNO	Average annual expenditure for innovation activities during 2011 and 2017 per full-time employee in million €	0.003	0.007	0	0.066	0.007	0.010	0	0.055
RESIST	1 if firm reported that internal resistance against innovation lead to discontinuation, delay or not-starting of innovation activities during 2016 and 2018, 0 otherwise	0.148	0.355	0	1	0.254	0.435	0	1
lnVA	Log value of gross value added (SAL minus MAT) in 2018 (measured in million €)**	1.245	1.685	−4.291	7.491	2.088	2.129	−3.241	7.646
lnPASTSOFT	Log value of software expenditure in 2017 (measured in million €)	- 2.354	3.107	−8.804	2.639	−1.253	2.242	−8.804	3.526
lnAVGSOFT	Log value of average annual software expenditure during 2011 and 2017 (measured in million €)	−3.213	3.266	−9.986	1.099	- 1.975	2.448	−9.986	1.098

Notes: D: dummy variable; $N = 5851$ ($^*N = 5569$; $^{**}N = 5693$). Sources: German CIS reference year 2018.

Any firm that uses at least one AI method by 2018 is considered an AI user (*AI*), including all firms that adopted AI at any year before 2018. Both firms that developed AI applications in-house and firms that use AI methods developed by others are included. Note that this measure of AI represents a stock variable (similarly to a capital stock) and not the investment made by a firm in AI during a certain period of time. In order to consider the scope of AI use in an AI-using firm, we construct a measure of AI intensity (*AIint*). *AIint* represents the sum of different AI methods and AI application areas that are used by a firm, divided by the maximum possible number, which is 20 (as there are 4 methods and 5 application areas distinguished in the questionnaire). The measure is similar to that used by Lee et al. (2022) who construct an AI intensity index based on the use of natural language processing, computer vision, and machine learning AI technologies in the production or development of goods and services.

As shown in Table 1, our cross-sectional sample contains 5851 firms out of which 409 can be classified as AI users (about 7%). Among the AI-using firms, the average value of our AI intensity variable amounts to 12.9%, i.e., the average firm used 2.5 out of the 20 possible combinations of AI methods and areas of application. About 60% of AI-using firms used AI in products or services, 56% for the automation of processes, 34% for data analysis, and 22% for the interaction with clients (see Rammer et al., 2022).

4.3. Other variables in the production function

The production function is estimated for the financial year 2018. Output is measured by annual sales (*lnSALES*) and, alternatively, by value added, i.e., sales minus intermediate inputs (*lnVA*). Inputs to the production function, which are all measured as natural logarithms, include the number of full-time employees (annual average) (*lnEMP*), the volume of intermediate inputs such as material, energy and purchased services (*lnMAT*), and the stock of tangible assets (*lnCAP*). Information on all input and output variables is obtained from respective questions in the questionnaire. As mentioned, we also estimate a first-differentiated fixed-effects production function, denoting the first difference as $\triangle$*lnSALES,* $\triangle$*lnVA,* $\triangle$*lnEMP,* $\triangle$*lnMAT,* and $\triangle$*lnCAP*.

In order to separate the likely productivity effect of AI from the possible effects of other innovative and technological assets of the firm, we allow the TFP term, *A* in Eq. (3), to vary with some further firm-specific variables (*X)*. First, firms that perform R&D on a permanent basis may possess a larger stock of technological knowledge both from their own R&D activities and from absorbing relevant external knowledge (Cohen and Levinthal 1989), which both may lead to a higher TFP level compared to non-R&D-performers, or firms that conduct R&D only occasionally. We thus include a dummy, *RDCON,* which equals 1 if the firm is performing R&D on a continuous basis.

Second, since firms may also benefit from supplier-induced innovation and technical progress embedded in acquired machinery or equipment, we include the variable *TECHIMP* which equals 1 if the firm has adopted, from 2016 to 2018, new or improved production technology relative to their machinery and equipment that has been used prior to the survey period (i.e., before 2016).

Third, as a further explanatory variable, we use the natural logarithm of a firm's age (*lnAGE*). It could be expected that more mature firms had more opportunities to optimize their production more than younger firms and therefore achieve higher TFP, all else constant.

Fourth, as a firm's overall progress towards digitalization can be assessed through its investments in software and databases, we follow Brynjolfsson and Hitt (2003), and consider firms' past software expenses to account for the general IT architecture of the firm. We use two alternative versions: a lag of software expenses per employee (*lnPASTSOFT*) and the average of the firm's software expenses between 2011 and 2017 (*lnAVGSOFT*). We cannot calculate a stock variable as there are many gaps in the time series. Thus, we average the expenses across the years that we observe between 2011 and 2017.

Finally, 17 industry dummies control for unobserved TFP variation across sectors that are not yet captured by any of the structural variables described so far. The 17 sectors are industry-aggregates based on NACE 2-digit definitions. See Table 9 in the Appendix for further information regarding the industry categories considered and the corresponding number of AI-using firms and non-AI users per industry.

In the panel fixed effects regressions, unobserved TFP heterogeneity is captured by firm-specific effects.

4.4. Endogeneity of AI

When extending the methodological application from cross-sectional OLS regressions to IV regressions in order to address the potential endogeneity of AI, we require instrumental variables. There are several ways in which the impact of AI on productivity might be biased due to an endogenous (non-random) nature of the decision to employ AI methods. First, firms could decide to implement AI technologies as a consequence of higher profits or larger available economic resources. In this case, a firm's productivity level might drive the decision to use AI. Secondly, given the data at hand, omitted covariates not included in our estimated specifications might be correlated with the use of AI, leading to biased estimates. For example, AI investment decisions might be associated with the broader digitalization efforts of a firm or with the general expansion of a firm's technological infrastructure.

Therefore, we need a set of instruments that must be correlated with AI usage but not with unobserved productivity shocks. The following instruments are considered in the estimation process. First, as the MIP questionnaire also collects information on the year of first use of AI by the firms, we construct a measure of investment into AI at the industry level during the period between the years 2011 to 2018 (*AI_IND*); that is, we consider the number of firms using AI methods by sector (at the two-digit NACE code) for the years 2011 to 2018. The frequency of AI use at the sector level may induce the focal firm to also employ AI, but the sector-level usage should not depend on a single firm's choice.

Second, making use of panel data, we compute the firms' average annual innovation expenses per employee for the period 2011 to 2017 (*PASTINNO*). Innovation expenditure covers internal and external R&D as well as other innovation-related expenses (e.g., acquisition of new equipment and external knowledge, training, marketing, design, and engineering work for innovations). We expect that the more a firm invested in innovation in the past, the more likely it is to use AI at some point. We measure the past innovation expenditure per employee in the regressions to avoid multicollinearity with firm size.

Lastly, as firms may be reluctant to employ AI methods in case they face organizational rigidities and reluctance to new technologies among the workforce, we construct a dichotomous variable that equals 1 if "internal resistance" was stated as an obstacle to the firm's innovation activities (*RESIST*). This instrument is much in the spirit of some of the instruments used by Brynjolfsson et al. (2011). They instrumented the impact of data-driven managerial decisions on firm productivity by barriers to IT adoption within the firm.

We believe that these variables could be valid exclusion restrictions as (i) the industry-level AI use should not have an independent effect on the focal firm's productivity as we control the firm's own AI use, (ii) the past innovation expenditure should not have an own, independent effect on productivity as we control for permanent R&D (RDCON) and realized technological innovation (possibly through these past expenses) by the variable TECHIMP; (iii) the RESIST variable refers to resistance to innovation and should only affect productivity through RDCON and TECHIMP, i.e. own R&D or technology adoption, for which we control. These conceptual thoughts are also supported by overidentification test results (Hansen's J) that we show in the regression tables.

4.5. Descriptive statistics

After removing observations with missing values, erroneous responses, and outliers, we end up with a sample size of 5851 firms. Table 1 provides summary statistics for all model variables.

We generally observe that firms that use AI are, on average, larger in all dimensions, i.e., sales and value-added as output and employment, capital and materials as inputs. For instance, the average AI user realizes sales of about 114 million EUR and has 245 employees. For non-users, these numbers are about 33 million EUR in sales and 84 employees. We also find that AI users' sales grow faster. The growth rates amount to about 5.4% versus 3.7% (see $\triangle$*lnSALES*). The adopters also engage more in R&D and innovation as can be seen from the share of firms engaging in R&D on a permanent basis (the mean of *RDCON* is 50% versus 19%) and the share of firms acquiring improved machinery and equipment (*TECHIMP* is 78% versus 59%). The means of past R&D and innovation expenses per employee are also higher for AI users than for other firms. Interestingly, there is no difference in age between AI users and other firms, and AI users face higher internal resistance against innovation than other firms; 25% versus 15%.

5. Estimation results

5.1. Main results: cross-sectional regressions

Table 2 presents the results for the cross-sectional regressions using the AI dummy (*AI*) as the main variable of interest. First, we can see that the ceteris paribus effect of AI use on productivity based on sales as output measure (*lnSALES*) is positive and significant in all specifications. Looking at column (1) for the OLS results of the most parsimonious specification of the production function without additional covariates, AI use is associated with higher productivity: AI users annually sell, on average, 13.9% more than non-users. We also find a positive and significant relationship between AI use and productivity after controlling for age (*lnAGE*), innovation engagement (*RDCON* and *TECHIMP*), investments in software and databases (*lnPASTSOFT* or ln*AVGSOFT*), and sectoral heterogeneity by industry dummies (see columns (2) and (3)). The marginal effect then implies about 5.5 – 5.7% higher sales.

Adding explanatory variables regarding innovation engagement and software expenditures helps to isolate the productivity impact of AI usage more convincingly from the impact of other digitalization efforts on the firm's productivity. At the same time, however, the software expenses might also include specific AI investments and therefore we might also underestimate the AI effect. As we cannot fully separate the AI effect from the given data, we decide to present two versions of software and databases expenditures.

As we do only have the lagged software expenses for about half of the sample, we generate a dummy variable indicating when the information is a missing value, *D*(*MISSING*), and we impute zeros in the software variable in order to not lose these observations for the regressions. The dummy captures the effect of imputing zeros and the estimated slope coefficient of *lnPASTSOFT* is obtained from the non-missing values. As an alternative approach, we use the average past software expenses as we can then use information from more than one previous survey. As the data may now stem from different years, and the available frequencies per firm vary, we average the software expenses across the different years and create the variable *lnAVGSOFT*. We again combine this with a missing value indicator to keep the observations for which no software information is available.

The positive impact of AI on productivity also holds when we address the potential endogeneity of AI by instrumenting the variable with the sectoral AI adoption level, past innovation expenses, and the internal resistance against innovation (see columns (4) and (5)). A first-stage F-test of the excluded instruments rejects the null hypothesis, and the absolute F-value is also higher than 10 which does not lead to a concern about weak instruments (Staiger and Stock 1997). The Hansen J-test on the instruments' validity does not reject the null in columns (4) and (5). The first-stage results are shown in Table 3. Overall, the three instruments strongly correlate with AI usage and have the expected sign.

In terms of the control variables, we find the expected results. The coefficients of labor, capital, and intermediate inputs do roughly add up to 1. An F-test does not reject constant returns to scale. We also find that productivity is positively associated with firm age, permanent R&D, software expenses, and to a weaker extent with investment in innovative machinery and equipment. Interestingly, the coefficients of lagged software expenses remain significant even after addressing the endogeneity issues of AI (see columns (3) and (5)). This is virtually the same when we include the annual average of software expenses for the period 2011 to 2017. The coefficients for AI use become slightly smaller in the IV regressions compared to

Table 2
Productivity effects of AI use (based on sales as output measure) including past software expenses variables: results of OLS and 2SLS regressions ($N = 5851$).

Dependent variable:	OLS			IV (2SLS)		IV (2SLS) with entropy balancing	
lnSALES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI	0.139***	0.057*	0.055*	1.231***	1.179***	0.299*	0.332**
	(0.029)	(0.029)	(0.029)	(0.292)	(0.290)	(0.156)	(0.160)
lnEMP	0.603***	0.586***	0.584***	0.558***	0.557***	0.711***	0.713***
	(0.011)	(0.013)	(0.013)	(0.015)	(0.015)	(0.027)	(0.027)
lnCAP	0.057***	0.062***	0.061***	0.063***	0.062***	0.054***	0.054***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.014)	(0.014)
lnMAT	0.368***	0.368***	0.367***	0.374***	0.372***	0.295***	0.297***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.019)	(0.019)
lnAGE	–	0.034***	0.030***	0.048***	0.044***	−0.002	0.003
	–	(0.012)	(0.012)	(0.014)	(0.013)	(0.029)	(0.029)
RDCON	–	0.047**	0.047**	−0.054	−0.051	0.002	−0.002
	–	(0.020)	(0.020)	(0.034)	(0.034)	(0.036)	(0.036)
TECHIMP	–	0.027*	0.025	−0.006	−0.006	−0.008	−0.009
	–	(0.016)	(0.016)	(0.019)	(0.019)	(0.040)	(0.040)
lnPASTSOFT	–	–	0.030***	–	0.026***	–	0.016
	–	–	(0.005)	–	(0.005)	–	(0.011)
lnAVGSOFT	–	0.027***	–	0.022***	–	0.030**	–
	–	(0.005)	–	(0.005)	–	(0.012)	–
D(MISSING)	–	−0.163***	−0.189***	−0.157***	−0.177***	−0.133**	−0.078
	–	(0.028)	(0.027)	(0.032)	(0.031)	(0.058)	(0.055)
R-squared	0.904	0.910	0.910	0.885	0.887	0.938	0.937
F-stat. on joint sig. of IVs in 1st stage	–	–	–	17.138***	16.886***	17.838***	17.001***
Hansen's J, *p*-value	–	–	–	0.605	0.563	–	–
Industry dummies	No	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors are in parentheses. All regressions include an intercept. In the IV regressions, we use the following instruments: industrial investment in AI (*AI_IND*), past innovation expenses per employee (*PASTINNO*), and internal resistance to innovation (*RESIST*). The *D(MISSING)* corresponds to a dummy that is equal to 1 if a missing value was imputed by a 0 in the corresponding software expenses variable. To test the joint significance of the instruments, the following statistic was computed: F(5,5816).

*** $p<0.01$,.

** $p<0.05$,.

* $p<0.1$.

Table 3
First-stage regressions on AI use. See Table 2 for the second-stage results. ($N = 5851$).

Dependent variable:	IV (2SLS)		IV (2SLS) with entropy balancing	
AI	(1)	(2)	(3)	(4)
lnEMP	0.024***	0.024***	−0.002	−0.002
	(0.004)	(0.004)	(0.018)	(0.018)
lnCAP	−0.001	−0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.011)	(0.011)
lnMAT	−0.004	−0.004	0.005	0.005
	(0.002)	(0.002)	(0.012)	(0.012)
lnAGE	−0.011**	−0.011**	0.005	0.005
	(0.005)	(0.005)	(0.022)	(0.022)
RDCON	0.061***	0.061***	−0.053	−0.053
	(0.011)	(0.011)	(0.033)	(0.033)
TECHIMP	0.026***	0.026***	−0.0005	−0.0005
	(0.006)	(0.006)	(0.032)	(0.032)
lnPASTSOFT	0.002	–	0.0008	–
	(0.003)	–	(0.009)	–
lnAVGSOFT	–	0.002	–	0.0005
	–	(0.001)	–	(0.009)
PASTINNO	3.322***	3.276***	8.501***	8.169***
	(0.720)	(0.723)	(1.613)	(1.609)
AI_IND	0.002***	0.002***	0.005***	0.005***
	(0.0005)	(0.0005)	(0.001)	(0.001)
RESIST	0.035***	0.035***	0.079***	0.081***
	(0.010)	(0.010)	(0.032)	(0.032)
Industry dummies	Yes	Yes		

Robust standard errors are in parentheses. All regressions include an intercept. * $p<0.1$.

*** $p<0.01$,.

** $p<0.05$,.

Table 4
Productivity effects of AI intensity (based on sales as output measure) including past software expenses variables: results of OLS and 2SLS regressions. ($N = 5851$).

Dependent variable:	OLS		IV (2SLS)	
lnSALES	(1)	(2)	(3)	(4)
AIint	0.271*	0.272*	8.715***	8.285***
	(0.160)	(0.164)	(2.178)	(2.142)
lnEMP	0.586***	0.584***	0.559***	0.558***
	(0.013)	(0.013)	(0.016)	(0.016)
lnCAP	0.062***	0.061***	0.063***	0.062***
	(0.007)	(0.006)	(0.007)	(0.007)
lnMAT	0.368***	0.367***	0.371***	0.370***
	(0.009)	(0.009)	(0.010)	(0.010)
lnAGE	0.033***	0.030***	0.048***	0.044***
	(0.012)	(0.012)	(0.014)	(0.013)
RDCON	0.049**	0.049**	−0.038	−0.035
	(0.020)	(0.020)	(0.034)	(0.033)
TECHIMP	0.028*	0.025	−0.008	−0.009
	(0.016)	(0.016)	(0.020)	(0.020)
lnPASTSOFT	0.027***	–	0.020***	–
	(0.005)	–	(0.006)	–
lnAVGSOFT	–	0.031***	–	0.026***
	–	(0.005)	–	(0.005)
D(MISSING)	−0.162***	−0.189***	−0.139***	−0.175***
	(0.028)	(0.027)	(0.037)	(0.033)
R-squared	0.910	0.910	0.874	0.878
F-stat. on joint sig. of IVs in 1st stage	–	–	12.817***	12.564***
Hansen's J, p-value	–	–	0.757	0.707
Industry dummies	Yes	Yes	Yes	Yes

Robust standard errors are in parentheses. All regressions include an intercept. In the IV regressions, we use the following instruments: industrial investment in AI (*AI_IND*), past innovation expenses per employee (*PASTINNO)*, and internal resistance to innovation (*RESIST*). The *IMPUTED-SOFT* corresponds to a dummy that is equal to 1 if a missing value was imputed by a 0 in the corresponding software expenses variable. To test the joint significance of the instruments, the following statistic was computed: F(3,5823).

*** $p<0.01$,.

** $p<0.05$,.

* $p<0.1$.

the estimations excluding past software expenses. This may partly reflect that some software expenses are related to implementing AI technology, implying that a part of the AI productivity effect is captured by software expenses, or that the AI variable in column (1) is picking up some effect of the general digitalization efforts measured by software investment. The fact that the AI coefficient remains positive and significant, however, supports our confidence in the presence of a genuine contribution of AI to firm-level productivity. Estimation results without controlling for any software expenditure variable are presented in the Appendix.

The estimated AI coefficients in the IV regressions shown in columns (4) and (5) in Table 2 are somewhat high, i.e., above unity. While possible, such high coefficients do not seem intuitive. The results may partly stem from the presence of unobserved heterogeneity that the IV regression cannot take into account. This motivates our further econometric applications. First, we estimate entropy balancing weighted regressions in columns (6) and (7) of Table 2. Subsequently, as explained below, we also estimate panel regressions to account for possible unobserved heterogeneity.

In columns (6) and (7) of Table 2, we combine, respectively, the IV regressions of columns (4) and (5) with entropy balancing, i.e., we perform weighted regressions such that firms not using AI are similar in their production inputs to AI users. The results of the entropy-balanced IV regressions in columns (6) and (7) (the other weighted regressions are omitted for reasons of brevity) largely confirm the earlier results of a positive and significant coefficient of AI use. However, the marginal effect amounts to about 29 - 33%. This corresponds, on average, to roughly 12 million EUR higher sales (the unconditional average of sales is about 40 million EUR).

5.2. Cross-sectional regressions using AI intensity

Table 4 reports the regression results considering AI intensity as a variable of interest (*AIint*), i.e., the breadth with which a firm applies AI methods across application areas. Similarly to our baseline estimates, increasing the fraction of AI methods or areas would have, on average, a significant and positive ceteris paribus impact on productivity.

In terms of the magnitude of the marginal effect, we find similar results to the specification using the dummy variable. When looking at the IV results in columns (4) and (5), the estimated coefficients are about 8.2 – 8,7. A firm that uses one AI technology in one application area (which corresponds to the majority of AI users) would have a value of $AIint = 0.05$ (1 out

Table 5
Productivity effects of AI use (based on sales as output measure): results of first difference fixed effect panel regressions, 2017–2018 ($N = 5569$).

Dependent variable: $\Delta lnSALES$	OLS (1)	IV (2SLS) (2)	IV (2SLS) with entropy balancing (3)
AI	0.012*	0.062**	0.044**
	(0.007)	(0.030)	(0.020)
$\Delta lnEMP$	0.363***	0.355***	0.397***
	(0.021)	(0.022)	(0.042)
$\Delta lnCAP$	0.013	0.012	0.056***
	(0.008)	(0.008)	(0.018)
$\Delta lnMAT$	0.198***	0.201***	0.150***
	(0.012)	(0.012)	(0.020)
R-squared	0.214	0.206	0.191
F-stat. on joint sig. of IVs in 1st stage	–	51.755***	127.682***
Hansen's J, *p*-value	–	0.527	–

Robust std. err. in parentheses. All regressions include an intercept. In the IV regressions, we use as instruments: industrial investment in AI (*AI_IND*), past innovation expenses per employee (*PASTINNO)*, and internal resistance to innovation (*RESIST*). To test the joint significance of the instruments, the following statistic was computed: F(3,5562).
*** $p<0.01$,.
** $p<0.05$,.
* $p<0.1$.

Table 6
Productivity effects of AI intensity (based on sales as output measure): results of first difference fixed effect panel regressions, 2017–2018 ($N = 5569$).

Dependent variable: $\Delta lnSALES$	OLS (1)	IV (2SLS) (2)
AIint	0.040	0.440**
	(0.042)	(0.211)
$\Delta lnEMP$	0.364***	0.353***
	(0.021)	(0.022)
$\Delta lnCAP$	0.013	0.012
	(0.008)	(0.008)
$\Delta lnMAT$	0.199***	0.201***
	(0.012)	(0.012)
R squared	0.214	0.200
F-stat. on joint sig. of IVs in 1st stage	–	36.707***
Hansen's J, *p*-value	–	0.595

Robust std. err. in parentheses. All regressions include an intercept. In the IV regressions, we use as instruments: industrial investment in AI (*AI_IND*), past innovation expenses per employee (*PASTINNO)*, and internal resistance to innovation (*RESIST*). To test the joint significance of the instruments, the following statistic was computed: F((3,5562). * $p<0.1$.
*** $p<0.01$,.
** $p<0.05$,.

of 20 combinations of AI technology and area). It would thus realize about 42% higher sales than non-users (0.05×8.45), all else constant. Note that the weighted entropy balancing regressions require as a treatment indicator a binary variable (which is not the case with *AIint*). The first-stage results for the IV regressions in Table 4 are presented in the Appendix.

5.3. Robustness checks

We conduct two robustness checks to our main results. First, to assess for further unobserved heterogeneity that the IV regressions cannot account for, we estimate fixed effects panel regressions. Second, instead of annual sales as an output measure, we use value-added defined as the logarithm of annual sales net of intermediate inputs (*lnVA*).

5.3.1. Fixed effects panel regressions

When inspecting our IV regressions carefully, one might be concerned that the estimated marginal effects are much higher than in the OLS regressions. This is a phenomenon that often arises in IV regressions and in our case, the benefits of AI seem possibly unintuitively high. Even though the regression diagnostics do not suggest a weak instrument bias or endogeneity of instruments, remaining unobserved heterogeneity among firms might still result in biased estimates. Therefore, we constructed a panel database to check the robustness of the results once we account for unobserved heterogeneity by including firm-fixed effects. Unfortunately, the AI data is so recent in the survey that we can only build a panel with

Table 7
Productivity effects of AI use (based on value-added as output measure) results of OLS and 2SLS regressions ($N = 5693$).

Dependent variable: *lnVA*	OLS (1)	(2)	IV (2SLS) (3)	IV (2SLS) with entropy balancing (4)
AI	0.146***	0.053	1.603***	0.490**
	(0.037)	(0.038)	(0.376)	(0.208)
lnEMP	0.903***	0.900***	0.866***	0.995***
	(0.012)	(0.013)	(0.017)	(0.026)
lnCAP	0.144***	0.138***	0.140***	0.097***
	(0.007)	(0.008)	(0.009)	(0.018)
lnAGE	–	0.039***	0.061***	0.012
	–	(0.015)	(0.018)	(0.038)
RDCON	–	0.101***	−0.038	0.003
	–	(0.026)	(0.046)	(0.046)
TECHIMP	–	0.029	−0.016	−0.004
	–	(0.021)	(0.025)	(0.051)
R-squared	0.827	0.837	0.788	0.886
F-stat. on joint sig. of IVs in 1st stage	–	–	17.113***	18.181***
Hansen's J, p-value	–	–	0.710	–
Industry dummies	No	Yes	Yes	Yes

Robust standard errors are in parentheses. All regressions include an intercept. In the IV regressions, we use the following instruments: industrial investment in AI (*AI_IND*), past innovation expenses per employee (*PASTINNO)*, and internal resistance to innovation (*RESIST*). To test the joint significance of the instruments, the following statistic was computed: F(3,5668). * $p<0.1$.
*** $p<0.01$,.
** $p<0.05$,.

Table 8
Productivity effects of AI intensity (based on value-added as output measure) results of OLS and 2SLS regressions ($N = 5693$).

Dependent variable: *lnVA*	OLS (1)	(2)	IV (2SLS) (3)	IV (2SLS) with entropy balancing (4)
AIint	0.965***	0.454**	11.159***	3.121**
	(0.209)	(0.207)	(2.780)	(1.325)
lnEMP	0.903***	0.900***	0.864***	0.984***
	(0.012)	(0.013)	(0.017)	(0.027)
lnCAP	0.144***	0.138***	0.139***	0.096***
	(0.007)	(0.008)	(0.009)	(0.018)
lnAGE	–	0.040***	0.060***	0.018
	–	(0.015)	(0.018)	(0.038)
RDCON	–	0.101***	−0.016	0.012
	–	(0.026)	(0.044)	(0.047)
TECHIMP	–	0.028	−0.019	−0.029
	–	(0.021)	(0.026)	(0.053)
R-squared	0.827	0.837	0.773	0.884
F-stat. on joint sig. of IVs in 1st stage	–	–	12.463***	10.679***
Hansen's J, p-value	–	–	0.691	–
Industry dummies	No	Yes	Yes	Yes

Robust standard errors are in parentheses. All regressions include an intercept. In the IV regressions, we use the following instruments: industrial investment in AI (*AI_IND*), past innovation expenses per employee (*PASTINNO)*, and internal resistance to innovation (*RESIST*). To test the joint significance of the instruments, the following statistic was computed: F(3,5668). * $p<0.1$.
*** $p<0.01$,.
** $p<0.05$,.

two time periods, 2017 and 2018. We implement the fixed effect regressions as a first-differences approach (1D-FE) where we regress the first difference of *lnSALES* on the first differences of the factor inputs and the AI dummy, i.e., we consider the growth rates of sales and factor inputs between 2017 and 2018. Compared to the cross-sectional regressions, the interpretation of the estimated AI effect has to be adapted accordingly: an AI dummy of 1 is now assumed to indicate that the firm invested in AI in the survey period (flow interpretation) rather than employing AI technology (stock interpretation). Consequently, the estimated coefficient now refers to the productivity growth associated with recent AI investments.

In order to account for any potential correlation between the error term and our covariates, i.e., a violation of the strict exogeneity assumption, we also estimate IV FE regressions.

Tables 5 and 6 report the results of FE regressions using AI use (*AI*) and AI intensity (*AIint*), respectively. The estimates of interest show the percentage change or growth over time in firm productivity when employing AI methods. The 1D-FE regression for AI use shows a significant impact of AI use on productivity. The marginal effect amounts to about 6.2% in the IV regression and to 4.4% when entropy balancing is used additionally.

When considering AI intensity, we also find a positive coefficient. On average, the AI firms realize about 5,2% higher sales based on the IV regression results (0.440 × 0.12, where the latter is the mean of *AIint* among AI users).

5.3.2. Value-added as an output measure

As shown in Tables 7 and 8, using value-added as an output indicator produces results that are consistent with the ones presented above based on sales. For reasons of space, we only show regressions controlling for firms' innovation engagement. Note that our sample is slightly smaller than in the main results because of some missing values in the value-added measure. The ceteris paribus effect of AI use is positive and significant in almost all specifications. The estimation result in column (1) of Table 7, suggests that AI users achieve 14.6% higher value-added. In the IV regressions, the magnitude of the estimated coefficients increases again as in the case where sales were used as the dependent variable. This increase is reduced, however, if the IV regression is run with weights obtained from entropy balancing. We observe some consistent findings in Table 8 when using AI intensity instead.

6. Conclusion

This paper studied the extent to which the use of Artificial Intelligence (AI) technologies by firms contributes to the firms' productivity. We used firm-level panel data from the German innovation survey which provides rich information on firms' performance and technological activities. Most importantly, the data contain information on the use of different AI methods and the business areas in which AI methods have been applied. This database allows to derive measures of AI use that overcome shortcomings in the existing literature. So far, most studies on AI and productivity either relied on specific technologies related to AI (e.g., robots and big data analysis) or employed patent data, which are limited to those firms that develop and patent AI technologies and miss firms that either adopt AI developed by others or use un-patented own AI (see Graetz and Michaels 2018; Acemoglu and Restrepo 2020; Brynjolfsson et al., 2011; Niebel et al., 2019; Ghasemaghaei and Calic 2019). Although these studies obtained important insights into how AI may drive productivity, they failed to capture the entire variety of how AI is used by firms, including firms that are mere adopters of AI technology, and the intensity of AI use. Our study tried to close this gap.

Using both a dichotomous and a continuous measure of AI usage, we examined the impact of AI on productivity using sales and value-added as alternative output variables. Our model considers AI as an intangible asset that enables firms to obtain a higher level of output. To overcome potential endogeneity issues of AI use, we employed instrumental variable regressions using the local diffusion of AI at the industry level, the firm's past investment in R&D and innovation, and organizational rigidities as instruments.

We found that employing AI technologies has a positive and significant impact on firm productivity. In particular, we showed that both the use of AI and the intensity with which firms exploit the potential of AI significantly increase both sales and value-added. This effect remains robust after controlling for several technological features of the firm. The evidence presented in this paper, therefore, confirms what has previously been hypothesized in the literature, i.e., AI use contributes positively to firms' productivity (Abrardi et al., 2021).

Our results provide evidence that AI is a productivity-enhancing technology; at least in the short run. This finding has important policy implications. Fostering the adoption of AI in firms could lead to substantial productivity gains. However, a common preoccupation about the diffusion of AI-related technologies is their possible impact on jobs and inequality, as AI may displace workers and affect low-skilled jobs more than high-skilled ones (see Lane and Saint-Martin 2021; Arntz et al. 2017). As pointed out by Agrawal et al. (2019b), policy measures in education or taxation may be required to counterbalance such developments. At the same time, policy measures should encourage firms to use AI on a broader scale, by tackling barriers related to AI use such as a lack of specialized skills, insufficient IT infrastructure (e.g., scarcity of access to secure cloud computing or low digit rates), and privacy regulation on data usage (see Agrawal et al., 2019b; Reim et al., 2020; Nolan 2020). Our results also suggest that managers need to be better aware of the potential of AI for increasing productivity, as only a small fraction of firms are currently using AI (see Montagnier et al., 2020).

Our empirical findings are subject to several limitations. First, we rely on data from one country and we can currently construct only a very short panel database. While currently unique, our data has several shortcomings. For instance, we cannot employ state-of-the-art techniques to estimate production functions where one can appropriately account for the endogeneity of (all) factor inputs. We can only offer to estimate IV regressions in which we account for the possible endogeneity of AI use. Even though our IV regressions pass the common specification tests, the estimated coefficients of AI use seem somewhat high in cross-sectional regressions. We addressed this issue by applying entropy balancing methods and fixed effect panel regressions to account for unobserved heterogeneity. In addition, we control for additional covariates, including past software expenses as a measure of intangible assets related to digitalization, to mitigate the further risk of omitted variable bias. However, it would be desirable to compile a database that enables the application of more sophisticated production function estimation methodologies.

A broader country coverage and time-series data on AI use would be highly useful to better identify the causal contribution of AI to productivity in a quasi-experimental setting. For example, one could capitalize on policy changes in the regulation of AI or utilize data on technological shocks (e.g., the emergence of new features in AI methods). To pin down the channels by which the adoption of AI is boosting firm productivity, we would have to complement our data with more detailed information, particularly on a firm's labor force as well as its innovative capacity and strategy. For policy, it would be highly important to disentangle the productivity impact of AI into a labor-saving (e.g., from automation) and a business expansion one. For example, AI could increase labor productivity by complementing human labor and automating specific tasks (Acemoglu and Restrepo 2019a). AI could also be contributing to the creation of new types of innovation or business models that will lead to new sales and increase productivity through output growth (Rammer et al., 2022).

In order to better understand the contribution of AI to productivity, more in-depth analysis of the link between AI use and other firm assets would be useful. So far, little is known about how these complementary assets might affect the relationship between AI adoption and firm performance (see Kim et al., 2021). In a recent study, Lee et al. (2022) showed for a sample of Korean firms that the performance gains from AI use tend to be larger among firms that invested in cloud computing and database systems. Other complementarities may be linked to the use of external knowledge from technology suppliers or consultants when using AI applications in the firm. Another important complementary variable is human capital. Acemoglu et al. (2020a), Babina et al. (2022) and Bäck et al. (2022) showed that the AI use requires specific skills, and firms increasingly employ workers with knowledge in AI technologies such as deep learning, machine learning and natural language processing. In order to analyze whether investment in certain AI skills changes the productivity impact of AI use, detailed data on the human capital side of AI would be needed. Such data could be established, for example, by linking survey data on AI (as has been used in this paper) with data on job postings and worker resume (as used by Babina et al., 2022 and Bäck et al., 2022).

Another topic for future research is to investigate the time dimension of the link between AI and productivity. In this paper, we considered all firms that were using AI actively in their business processes or products, regardless of the year they first started with applying AI technologies. Rammer et al. (2022) have shown that the experience of a firm with AI (i.e., the number of years since the first-time use of AI) is an important variable for explaining heterogeneity in the innovation output of AI-using firms. In this paper, we were not able to analyze a likely experience effect due to the limited number of observations on AI using firms in our cross-section data base. Future research should aim at establishing time-series data on AI use in order to capture likely differences in productivity impacts resulting from AI experience and investigate time lags between adopting AI technologies and obtaining higher firm performance from AI.

Declaration of Competing Interest

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Data availability

The data can be accessed for research and replication purposes at the Research Data Center of ZEW Mannheim, Germany. Please see: https://www.zew.de/en/research-at-zew/zew-research-data-center-zew-fdz

Appendix

Tables 9, 10, 11

Table 9
Industries and number of firms per industry, by AI use.

Industry group	Non-users	AI users	All firms
Crop and animal production; hunting; fishing; and manufacture of food products, beverages, tobacco products.	233 (4.28%)	5 (1.22%)	239 (4.07%)
Manufacture of textiles, wearing apparel, leather and related products, wood and products of wood and cork except furniture, and articles of straw and plaiting materials.	216 (3.97%)	3 (0.73%)	219 (3.74%)
Manufacture of chemicals and chemical products, and of basic pharmaceutical products and pharmaceutical preparations.	148 (2.72%)	15 (3.67%)	163 (2.79%)
Manufacture of rubber and plastic products, other non-metallic mineral products, basic metals, and fabricated metal products, except machinery and equipment.	727 (13.37%)	35 (8.56%)	762 (13.03%)
Manufacture of computer, electronic and optical products, and electrical equipment.	315 (5.79%)	40 (9.78%)	355 (6.07%)
Manufacture of machinery and equipment n.e.c., motor vehicles, trailers and semi-trailers, other transport equipment; and repair and installation of machinery and equipment.	486 (8.94%)	43 (10.51%)	529 (9.04%)
Manufacture of furniture, other manufacturing, paper and paper products; printing and reproduction of recorded media; and repair of computers and personal and household goods.	285 (5.24%)	13 (3.18%)	298 (5.09%)

(*continued on next page*)

Table 9 (*continued*)

Industry group	Non-users	AI users	All firms
Manufacture of coke and refined petroleum products; mining of coal and lignite; extraction of crude petroleum and natural gas; mining of metal ores; other mining and quarrying; mining support service activities; electricity, gas, steam and air conditioning supply; construction of buildings; civil engineering; and specialized construction activities.	314 (5.78%)	7 (1.71%)	321 (5.49%)
Water collection, treatment, supply, and material recovery; sewerage; and remediation activities and other waste management services.	261 (4.80%)	6 (1.47%)	267 (4.56%)
Wholesale and retail trade and repair of motor vehicles and motorcycles; wholesale trade, except of motor vehicles and motorcycles; and retail trade, except of motor vehicles and motorcycles.	302 (5.55%)	10 (2.44%)	312 (5.33%)
Land transport and transport via pipelines; water transport; air transport; warehousing and support activities for transportation; and postal and courier activities.	353 (6.49%)	13 (3.18%)	366 (6.26%)
Publishing activities; motion picture, video and television program production, sound recording and music publishing activities; programming and broadcasting activities; and printing and reproduction of recorded media.	212 (3.90%)	15 (3.67%)	227 (3.88%)
Telecommunications; computer programming, consultancy and related activities; and information service activities.	241 (4.43%)	68 (16.63%)	309 (5.28%)
Financial service activities, except insurance and pension funding; insurance, reinsurance and pension funding, except compulsory social security; activities auxiliary to financial services and insurance activities.	126 (2.32%)	20 (4.89%)	146 (2.50%)
Architectural and engineering activities; technical testing and analysis; scientific research and development; education; human health activities; residential care activities; creative, arts and entertainment activities; libraries, archives, museums, other cultural activities.	456 (8.39%)	44 (10.76%)	500 (8.55%)
Legal and accounting activities; activities of head offices; management consultancy activities; advertising and market research; and public administration and defense; compulsory social security.	309 (5.68%)	52 (12.71%)	361 (6.17%)
Accommodation; food and beverage service activities; real estate activities; other professional, scientific and technical activities; administrative and support service activities; other services.	458 (8.42%)	20 (4.89%)	478 (8.17%)

Source: NACE Rev. 2, Statistical classification of economic activities in the European Community.

Table 10
Productivity effects of AI use (based on sales as output measure), without software expenditures: results of OLS and 2SLS regressions ($N = 5851$).

Dependent variable:	OLS		IV (2SLS)		IV (2SLS) with entropy balancing
lnSALES	(1)	(2) incl. additional covariates	(3)	(4) incl. additional covariates	(5) incl. additional covariates
AI	0.139***	0.060**	1.373***	1.356***	0.376**
	(0.029)	(0.030)	(0.172)	(0.306)	(0.158)
lnEMP	0.603***	0.592***	0.547***	0.560***	0.702***
	(0.011)	(0.013)	(0.014)	(0.016)	(0.025)
lnCAP	0.057***	0.064***	0.070***	0.065***	0.057***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.014)
lnMAT	0.368***	0.370***	0.379***	0.376***	0.295***
	(0.008)	(0.009)	(0.009)	(0.010)	(0.018)
lnAGE	–	0.035***	–	0.052***	0.017
	–	(0.012)	–	(0.014)	(0.025)
RDCON	–	0.052***	–	−0.062*	−0.005
	–	(0.020)	–	(0.036)	(0.034)
TECHIMP	–	0.033**	–	−0.006	−0.009
	–	0.060**	–	1.356***	0.376**
R-squared	0.904	0.910	0.867	0.883	0.939
F-stat. on joint sig. of IVs in 1st stage	–	–	51.496***	16.879***	17.412***
Hansen's J, p-value	–	–	0.027	0.762	–
Industry dummies	No	Yes	No	Yes	Yes

Robust standard errors in parentheses. All regressions include an intercept. In the IV regressions, we use the following instruments: investment in AI per sector (*AI_IND*), past innovation expenses per employee (*PASTINNO*), and a dummy indicating internal resistance to innovative activities (*RESIST*). To test the joint significance of the instruments we compute the following statistic: F(5,5844) for the unweighted IV regressions and F(3,5825) for the IV with entropy balancing.

*** $p<0.01$,.

** $p<0.05$,.

* $p<0.1$.

Table 11
First-stage regressions on AI intensity. See Table 4 for the second-stage results. (N = 5851).

Dependent variable:	IV (2SLS)	
AIint	(1)	(2)
lnEMP	0.003***	0.003***
	(0.0007)	(0.0007)
lnCAP	−0.0001	−0.0001
	(0.0004)	(0.0004)
lnMAT	−0.0002	−0.0002
	(0.0001)	(0.0001)
lnAGE	−0.001*	−0.001*
	(0.0008)	(0.0008)
RDCON	0.006***	0.006***
	(0.001)	(0.001)
TECHIMP	0.004***	0.004***
	(0.0009)	(0.0009)
lnPASTSOFT	0.0006	–
	(0.0004)	–
lnAVGSOFT	–	0.0003
	–	(0.0003)
PASTINNO	0.449***	0.447***
	(0.109)	(0.111)
AI_IND	0.0003***	0.0003***
	(0.0001)	(0.0001)
RESIST	0.005***	0.005***
	(0.001)	(0.001)
Industry dummies	Yes	Yes

Robust standard errors are in parentheses. All regressions include an intercept. ** $p<0.05$,.
*** $p<0.01$,.
* $p<0.1$.

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