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Widening or closing the gap? The relationship between artificial intelligence, firm-level productivity and regional clusters

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Abstract

Artificial intelligence (AI) is seen as a key technology for economic growth. However, the impact of AI on firm productivity has been under researched – particularly through the lens of inequality and clusters. Based on a unique sample of German firms, filling at least one patent between 2013 and 2019, we find evidence for a positive influence of AI on firm productivity. Moreover, our analysis shows that while AI knowledge does not contribute to productivity divergences in general, it increases the productivity gap between laggard and all other firms. Nevertheless, this effect is reduced through the localisation in clusters.

Keywords
Artificial intelligence, Inequality, Productivity, Clusters, Patents, Firm-level

JEL Classifications
O18; O30; R11

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1. Introduction

Today's modern society is heavily influenced by digitalisation, which is an ongoing and transformative process (Alcácer et al., 2016; Andersen, 2006; Kopka & Grashof, 2022). The digitisation in the business context, especially in manufacturing, is summarized under the umbrella term of Industry 4.0, which can be traced back to an initiative of the German Government to secure the long-term competitiveness of the manufacturing industry (Kagermann et al., 2013). Generally, Industry 4.0 encompasses the application of digitisation, automation and robotics in manufacturing (Götz & Jankowska, 2017; Hervás-Oliver et al., 2019; Kagermann et al., 2013). Industry 4.0 therefore consists of different enabling technologies, such as the Internet of Things (IoT), robotics, artificial intelligence (AI) or additive manufacturing (Martínelli et al., 2021). The technology of AI in particular has received increased attention in recent years due to advances in machine and deep learning (Miyazaki et al., 2018), which bring AI one step closer to a general AI, since it can now be used in different contexts, while simultaneously reducing the costs for adaption (Taddy, 2018; Yamakawa et al., 2016). Consequently, researchers, politicians as well as entrepreneurs regard AI as a key technology for the prospective technological and economic growth (Aghion et al., 2017; Craglia et al., 2018; Goralski & Tan, 2020). Hence, and since the concept of Industry 4.0 is relatively broad and not settled yet (Götz & Jankowska, 2017; Götz, 2019; Künzel & Meier zu Köcker, 2015), we limit our analysis to one of the core underlying technologies of Industry 4.0, namely AI (Martínelli et al., 2021). Although there exists general consensus about the transformative potential of AI, the exact direction of these changes remains so far rather unclear (Hinks, 2019; Nam, 2019; Kopka & Grashof, 2022).

This holds also true for firm productivity, which can be seen as one major performance target for Industry 4.0 related initiatives (Liao et al., 2018). On the one hand, it is stressed that AI is a general-purpose technology (GPT) and an invention of a method of inventing (IMI) (Cockburn et al., 2019), suggesting that it acts as a bridging platform (inventions through innovation complementarities) and as a catalyst (generation of new inventions) both positively influencing productivity (Alderucci et al., 2020: Brynjolfsson et al., 2019; Damioli et al., 2021). On the other hand, it is also argued that the ongoing productivity slowdown characterising advanced economies since the 1970s[1] is permanent and cannot be reversed by current innovations such as artificial intelligence, which are less disruptive than previous general-purpose technologies (Gordon, 2016; Gordon, 2018). Despite these two streams of literature, there is indeed first empirical evidence for a productivity enhancing influence by Industry 4.0 technologies in general (Büchi et al., 2020; Dalenogare et al., 2018; Hervás-Oliver, 2021) and AI in particular (Alderucci et al., 2020; Damioli et al., 2021). However, more research on the firm-level,

[1] This phenomenon is also called “Productivity Paradox” (Brynjolfsson, 1993).

in different settings, is needed to provide a robust respond to the call of Raj & Seamans (2019) to investigate the relationship between AI and firm-level productivity.

This is all the more true as previous research in this context largely overlooks firm-specific differences and thereby also the consequences for possible convergence and divergence processes between firms. In view of an increasing productivity divergence across firms (e.g. Berlingieri et al., 2017; Cette et al., 2018; Faggio et al., 2010), this research gap is even more surprising. One popular explanation here for refers to the heterogenous diffusion patterns of new general-purpose technologies across firms (Andrews et al., 2019; Faggio et al., 2010). Following the core idea of the resource-based view (e.g. Barney, 1991), in general firms differ in their ability to adopt new technologies, e.g. through their financial abilities (e.g. Rogers, 2004), their absorptive capacities (e.g. Cohen & Levinthal, 1990) as well as their organisational structure (e.g. Goode & Steven, 2000). This also or especially applies to AI, whose potential benefits require large and costly, often intangible, investments (Accenture, 2019; Brynjolfsson et al., 2021; OECD, 2021). Despite the possible productivity-enhancing effect at the firm-level (e.g. Alderucci et al., 2020; Damioli et al., 2021), AI might therefore still hold the potential for increasing productivity divergence across firms. Thus, apart from investigating the influence of AI on firm productivity, in a second step, this paper aims to research to what extent AI influences the productivity gap between frontier and laggard firms.

Following an 'interactionist approach' (Beugelsdijk, 2007), we are additionally interested in the regional context that might moderate this relationship. Since one potential driver for the influence of AI on the inequality between firms refers to the unequal dissemination of technologies and knowledge (Andrews et al., 2015; Comin & Mestieri, 2018), we focus on regional clusters[2]. The benefits from co-locating with firms from the same industry have already been highlighted by Marshall (1920), who identifies four types of localisation externalities: access to a common specialized labour pool, access to specialized inputs, access to knowledge spillovers and access to greater demand by reducing consumer search costs (Grashof, 2021a; Marshall, 1920; McCann & Folta, 2008). Particularly, the eased knowledge exchange within clusters (Daft & Lengel, 1986; Jaffe et al., 1993) can be a crucial mechanism through which clusters may offer a beneficial environment particular for laggard firms (Shaver & Flyer, 2000), thereby preventing a potential increase in growth inequalities among firms through AI. Despite the fact that regional clusters are widespread and of economic importance (Grashof, 2020; Grashof, 2021a; Nathan & Overman, 2013), there are hardly any studies that investigate clusters in the context of industry 4.0. let alone in the context of artificial

[2] In line with Grashof and Fornahl (2021), the following cluster definition is applied: "Clusters are defined as a geographical concentration of closely interconnected horizontal, vertical and lateral actors, such as universities, from the same industry that are related to each other in terms of a common resource and knowledge base, technologies and/or product-market" (Grashof & Fornahl, 2021, p. 546).

intelligence.[3] Consequently, in a third step, we want to investigate whether AI knowledge leads to greater productivity divergence between companies located outside regional clusters than between companies located within regional clusters.

For the empirical analysis of these three research questions, we use and combine various data sources. In terms of firm-level data, we employ the extensive firm database ORBIS offered by Bureau van Djik (BvD). Furthermore, to identify the AI knowledge in firms, we use patent data from the patent database PATSTAT. There, we conducted a keyword search in the abstract and title of the patents as well as using the CPC and IPC classification. For the specific search strings, the WIPO report on artificial intelligence is used (World Intellectual Property Organization, 2019). Moreover, based on official employment data from 2012 in three-digit NACE Rev. 2 industries, we apply the actor-based method by Brenner (2017) in order to identify regional clusters in Germany (e.g. Grashof, 2021a).

By empirically investigating these three research questions, we contribute to the recent literature stream dealing with the relationship between AI and firm-level productivity (e.g. Alderucci et al., 2020; Damioli et al., 2021) in two important aspects. First, besides analysing the influence of AI on firm productivity in Germany, we are particularly interested in the potential for increasing productivity divergence across firms. Apart from the performance effect of AI, we therefore also consider the socio-economic aspects of inequality and inclusive growth. Second, by following an ‘interactionist approach’ (Beugelsdijk, 2007), we are additionally investigating the potential moderating influence of regional clusters, thereby contributing to recent research that deals with regional clusters and Industry 4.0 (e.g. Grashof et al., 2020; Hervás-Oliver, 2021). Based on our findings, policy implications could also be derived aiming at supporting fundamental convergence processes, which in the end could contribute to a more inclusive rise in productivity and to a higher social well-being in general.

The remainder of this article is structured in the following way: The next section presents the underlying theoretical background. In the third section, the applied data and methodology is described. Hereafter, the fourth section shows the empirical analysis and the corresponding results, while the econometrical results are discussed and interpreted in the fifth section. The paper ends with concluding remarks, including future research endeavours.

[3] Some important exceptions refer for instance to Grashof et al. (2020), Götz and Jankowska (2017), Götz (2020), Hervás-Oliver et al. (2019) as well as Hervás-Oliver et al. (2021).

2. Theory

2.1. AI & Firm Growth 1

Artificial intelligence has been identified as both a GPT and an IMI (Cockburn et al., 2019). A GPT is a technology that is widely applicable (Thoma, 2008). They act as ‘engines of growth’ in the economy and are characterised by three key aspects: pervasiveness, an innovation spawning effect and a scope for improvement (Bresnahan & Trajtenberg, 1995; David, 1990; Helpman & Trajtenberg, 1994). GPTs are at the core of many different existing or potential products or production systems and thus can be found throughout the whole economy (Youtie et al, 2008). Through innovation complementarities, they are spawning additional innovations in each sector in which they are applied. Thus, they ensure productivity growth, as for each sector a GPT is applied, a feedback loop is created that increases the rate of innovation in all application sectors. Furthermore, IMIs (Darby & Zucker, 2003) also enable new innovations as they act as a new method to innovate in a specific area or field. Through a new method of inventing new possible products and processes are enabled. To sum up, AI therefore enables not only innovation in products and processes, it also opens up the opportunity for new technological paradigms, thus leading to rather radical innovations (Bresnahan & Trajtenberg, 1995; Ristuccia & Solomou, 2014).[4] These radical innovations emerge from the recombination of former unconnected knowledge (Fleming, 2001). If successful, they can help to build a strong competitive advantage (Castaldi et al., 2015) and serve as the basis for future sustainable economic growth (Ahuja & Lampert, 2001; Arthur, 2007).[5] Given these insights, firms that are implementing or researching AI should be able to generate innovations in products and processes as well as create completely new markets. Thus, they are expected to substantially grow in terms of innovativeness and revenue. Some studies therefore indeed find evidence for a positive impact of AI e.g. through product innovations (Babina et al., 2020), through new technological paradigms for example in health care start-ups (Garbuio & Lin, 2019) or entrepreneurs in general (Obschonka & Audretsch, 2020) as well as productivity gains concentrating in SMEs (Damioli et al., 2021). Nevertheless, there are also articles that question the direct positive impact of AI on productivity (e.g. Kopka & Fornahl, 2023), as productivity growth in general is stalling, which could be explained through a mismeasurement of AI - even though the evidence is small (Corrado et al., 2021) - or a low disruptiveness of today's innovations, compared to previous GPTs (Gordon, 2016; Gordon, 2018). In line with recent empirical results (e.g. Alderucci et al., 2020; Damioli et al., 2021), we however,

[4] Grashof & Kopka (2023) recently found evidence of firm- and technology-specific characteristics that change the direction of AI knowledge impact in this context.

[5] In view of the outstanding economic opportunities of radical innovations, they have become quite popular among policy makers (e.g. public agency for the promotion of radical innovations in Germany) as well as researchers (e.g. Grashof et al., 2020; Hesse & Fornahl, 2020).

assume that the adoption of AI in a firm has a positive influence on its labour productivity. We thus formulate the following hypothesis:

H1: AI knowledge has a positive impact on labour productivity.

2.2. AI & Productivity Gap between firms

While there are already some recent empirical studies dealing with the relationship between AI and firm productivity (e.g. Alderucci et al., 2020; Damioli et al., 2021), firm-specific differences and thereby also potential convergence and divergence processes between firms have been overlooked so far, despite an increasing productivity divergence across firms (e.g. Berlingieri et al., 2017; Cette et al., 2018; Faggio et al., 2010). For example, Andrews et al. (2019) show that between 2001 and 2013 manufacturing firms at the global productivity frontier have experienced an average annual growth rate of 2.8%, while laggard firms have only grown by an average rate of 0.6% per year. Previous research has offered different explanations to this rise in inequality (Andrews et al., 2019; Cette et al., 2018). One popular explanation refers to the heterogenous diffusion patterns of new general-purpose technologies across firms (Andrews et al., 2019; Faggio et al., 2010). Based on a large longitudinal sample of 25 technologies in 139 countries, Comin and Mestieri (2018) for instance show that the adoption lags for new technologies across countries have declined, while the divergence in the intensity of use of these technologies has increased. In other words, new technologies diffuse at an increasing rate between countries, but only at a decreasing rate between all firms within an economy (Andrews et al., 2015; Bahar, 2018). Following the core idea of the resource-based view, firms have different resource endowments[6] which can be used to achieve a competitive advantage (Barney, 1991; Newbert, 2007). As such, in general, firms also differ in their ability to adopt new technologies, depending for instance on their financial abilities (e.g. Rogers, 2004), their absorptive capacities (e.g. Cohen & Levinthal, 1990) as well as their organisational structure (e.g. Goode & Steven, 2000). AI is probably no exception in this context, because firms have different capabilities to realize and seize the potentials of AI (OECD, 2021). For instance, before realizing and seizing the potentials of AI, large and costly investments, e.g. in the data infrastructure but also in human capital, are needed (Accenture, 2019; Brynjolfsson et al., 2021; OECD, 2021). Furthermore, in order to fully exploit the possibilities of AI, the quantity as well as quality of the data is important. In comparison with larger firms, small and medium-sized enterprises (SMEs) may simply lack these types of data or the ability to collate, manage and protect the data (Bianchini & Michalkova, 2019; Cockburn et al., 2019; OECD, 2021). SMEs are therefore considered to be at a disadvantage compared

[6] In line with previous studies (e.g. Grashof, 2021), the widely used resource definition of Barney (1991) is here used, where resources are "(…) all assets, capabilities, organizational process, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness." (Barney, 1991, p. 101).

to larger companies in this technological transformation (Daor et al., 2020; OECD, 2021). Since frontier firms tend to be larger firms (e.g. Andrews, 2015), we assume that particular frontier firms are better able to adopt AI and consequently benefit more from this technology than laggard firms. Thus, increasing the gap between laggard and frontier firms. As such, we formulate the following hypothesis:

> **H2:** AI knowledge increases the productivity gap between leading and laggard firms.

2.3 AI & Productivity Gap between firms & clusters

Following an 'interactionist approach' (Beugelsdijk, 2007), we are additionally interested in the regional context that might moderate this relationship. Given the conceivable differences in the use of AI (e.g. Rammer et al., 2022), regional clusters seem to be of particular importance due to localisation externalities, such as knowledge spillovers (Marshall, 1920). The benefits from co-locating with firms from the same industry, for instance in terms of more innovation (e.g. Baptista & Swann, 1998), have already been highlighted by Marshall (1920), who identifies four types of localisation externalities: access to a common specialized labour pool, access to specialized inputs, access to knowledge spillovers and access to greater demand by reducing consumer search costs (Grashof, 2021a; Marshall 1920; McCann & Folta 2008). As a result, both academics and politicians have been intensively dealing with regional clusters (Lazzeretti et al., 2014; Martin & Sunley, 2003; Zenker et al., 2019). Despite the widespread assumption that these benefits can be realised automatically (Grashof & Fornahl, 2021; Lee, 2018; Martin & Sunley, 2003), the recent results of the meta-analysis by Grashof (2020) indicate that it rather depends on the particular circumstances of each individual company. Consequently, it is also likely that laggard and frontier firms, which are characterised by different firm-specific attributes (Andrews et al., 2015), gain heterogeneously from being located in a cluster. For laggard firms, the eased knowledge exchange within clusters (Daft & Lengel 1986; Jaffe et al., 1993) might be a crucial mechanism through which these firms can gain access to AI-related knowledge and thereby prevent potential divergence processes in terms of productivity. In general, it has been highlighted that firms need to have absorptive capacities in order to recognise, process and finally integrate the knowledge coming from collocated firms (Cohen & Levinthal, 1990; McCann & Folta, 2011). Since frontier firms have in general also higher absorptive capacities than laggard firms (e.g. Andrews et al., 2015), this would implicate that clusters rather promote the performance gap between them (Grillitsch & Nilsson, 2019). However, if absorptive capacities are too high, there is also a high risk of unintentional knowledge spillovers to competitors, which in turn continuously reduces a firm´s relative competitive advantage over other firms (Grashof, 2021a; Hervás-Oliver et al., 2018; Knoben et al., 2016; Shaver & Flyer, 2000). Consequently, we assume that particularly laggard firms profit from the available knowledge spillovers within clusters, which is in line with the adverse selection effect stressed by Shaver and Flyer (2000). As such, clusters are argued to offer a beneficial environment through which particular laggard firms can have access to AI-related knowledge and thereby clusters contribute to decreasing the productivity divergence between companies. Thus, we formulate the following hypothesis:

> **H3:** The diverging effect of AI knowledge on the firm productivity gap is reduced by being located in a cluster.

3. Data & Method

3.1 Data

In order to analyse the three proposed research hypotheses, we created a unique dataset that combines the following main data sources. First, in order to identify the AI knowledge of firms, we used patent data based on the database PATSTAT. There we extracted all patents that are issued by firms based in Germany from 2013 to 2019. In order to identify AI patents within this dataset we used keywords as well as CPC codes based on the search algorithm provided by the WIPO (2019).

Second, to account for the firm specific characteristics and the productivity performance, we assessed data from the exhaustive firm database ORBIS. We extracted firm specific information (e.g. founding year) on all firms located in Germany within 2013 and 2019. In order to match these two extensive databases, the ORBIS patent database (ORBIS IP) is used, which combines patent information (e.g. application id) from PATSTAT with firm-level information from ORBIS (BvD ID).

Third, since we are additionally interested in the moderating influence of clusters on the effect of AI on productivity, information on whether a firm is located in a cluster or not is needed. For this purpose, we follow previous studies (e.g. Grashof, 2021a) and use the actor-based cluster identification method according to Brenner (2017). Based on official IAB employment data from 2012 in three-digit NACE Rev. 2 industries, we estimate a cluster index for each firm on the municipality level ("Gemeindeebene"). Compared with traditional indicators used in this regard, the actor-based cluster indicator has the advantage that a) it is not subject to the modifiable area unit problem as it is a border-free indicator and b) it avoids a potential overvaluation of large firms because the travel distance to all other firms of the same industry is additionally considered as a weight (Brenner, 2017; Grashof, 2021a; Scholl & Brenner, 2016). However, the main disadvantage of this approach is that a relatively extensive information about a set of locations (L), their travel distances (D), the activity level at each location (v_l), a set of actors (A) and their locations (l_a) is needed (Brenner, 2017; Grashof, 2021a). Based on this information the actor-based cluster index can be calculated in the following way:

$$C_a = \frac{\sum_{l \in L}\left(v_l\, f\left(d_{l,l_a}\right)\right) \Big/ \sum_{l \in L}\left(w_l\, f\left(d_{l,l_a}\right)\right)}{\sum_{l \in L}(v_{Ger}) \Big/ \sum_{l \in L}(w_{Ger})} \qquad (1.)$$

where f(d) is a log-logistic decay function, which decreases to one half for 45 minutes travel distance. In other words, the log-logistic decay function expresses how the relevance of activity v (employment in industry i in the municipality l) and w (total employment in the municipality l) decreases with increasing geographical distance. Similar to usual location quotient, national values for whole Germany (v_{Ger} and w_{Ger}) are additionally considered (Brenner, 2017; Grashof, 2021a). Our threshold, indicating whether a company is part of a cluster, was set at 1.9, which is almost in accordance with the threshold of two of the European Cluster Observatory (European Cluster Observatory, 2018; European Commission, 2008).[7] Based on the unique firm-identifier (BvD-ID), we then match this information with our final firm-level database. In total, our sample consists of 16.083 firms located in Germany, that have filed at least one patent between 2013 and 2019.

3.2 Operationalisation

Based on our comprehensive database, we constructed the following variables. Our two dependent variables are firm labour productivity (see H1 and H3) and the distance to the production frontier (see H2). First, to identify the productivity of firms, in line with previous studies (e.g. Alderucci et al., 2020; Damioli et al., 2021) we have determined labour productivity by calculating the natural logarithm of the revenue per employee (Log_Labour Productivity). Second, similar to previous approaches (e.g. Andrews et al., 2019) we define the (national) productivity frontier by the log labour productivity levels of the top 5% of companies, within each one-digit industry sector and each year. By taking the difference between firms' labour productivity and the (national) productivity frontier we then calculate the distance to the frontier for each firm and each year (Log_Distance to Frontier).

[7] Unfortunately, we cannot use exactly the same threshold as the European Cluster Observatory, because the proxy for firms' AI-related knowledge base would then be omitted due to collinearity. However, since our chosen threshold is not far from that of the European Cluster Observatory, we are still confident in our cluster identification.

One of our main independent variables is the AI-related knowledge of firms. To operationalise the AI knowledge of firms we use patents. Although patents have some well-known drawbacks (e.g. Griliches, 1990), they offer quite extensive information that is often used as a proxy for the knowledge base of regions and firms (Buarque et al., 2020; Grashof et al., 2020; Xiao & Boschma, 2021). In line with previous studies (e.g. Damioli et al., 2021), we therefore use the number of AI patent families on the firm-level per year as a proxy for the AI-related knowledge base of firms (AI). Moreover, to further investigate potential differences in the influence of AI on labour productivity across firms, we also consider different firm types (FirmType). In more concrete terms, based on the labour productivity level, we differentiate between frontier firms (located at the productivity frontier), near-to-frontier firms (5%-20% productivity percentile) and laggard firms (lower 80%). As already indicated in section 3.1., based on the actor-based cluster identification approach, we create a dummy variable, indicating whether a firm is located in a cluster or not (Clusterdummy).

To account for other factors that might influence our dependent variables, control variables are additionally included. First, since patent activities tend to vary across firm age (Huergo & Jaumandreu, 2004), we follow previous studies (e.g. Grashof et al., 2020) and include firm age (years since foundation) as a control variable. Second, in line with previous studies (e.g. Damioli et al., 2021), the total non-AI patent count is included (Pat). This proxies the general knowledge stock of firms. A higher knowledge stock within a firm is likely to increase the chance of AI knowledge generation by pure chance, given the recombinant nature of innovations (Weitzman, 1998). Lastly, to control for the technological diversity of a firm, which might lead to benefits in terms of cross-fertilization (Granstrand, 1998; Leten at al., 2007), we use the Herfindahl-Hirschman Index based on CPC 4-digit codes of all patents a firm has applied (e.g. Garcia-Vega, 2006; Leten et al., 2007). This index is measured by counting the number of patents of each 4-digit CPC code in each firm and then calculating the share of each CPC code. These shares are squared and added up which generates the Herfindahl-Hirschman Index (HHI). Table 1 shows the corresponding descriptive statistics for all main variables.[8] A first interpretation of these descriptive statistics yields the following results. First, we observe that the mean distance to the productivity frontier increases between the two time periods, indicating that frontier firms were able to increase their productivity advantage even more in comparison with laggard firms. Furthermore, it is obvious that AI knowledge generation is a rare event with a relatively small share of firms that innovate in the area of AI, while the patenting activity of firms generally is more widespread. Both AI knowledge generation as well as the general non-AI patent activity seem to be clustered events indicated through a high standard deviation in comparison with their mean. Finally, while the mean age of firms in our full sample is roughly 31 years, we observe some differences

[8] The pairwise correlation matrix for all variables is presented in Appendix 1.

between the groups of AI patenting and Non-AI patenting firms. On average AI patenting firms are 8 years older (39 years) than Non-AI patenting firms (31 years).

Table 1: Descriptive Statistics

	Full Sample			Period 2013-2015		Period 2016-2019	
Variable	Obs	Mean	SD	Mean	SD	Mean	SD
Log_Labour Productivity	37046	12.28	0.976	12.309	0.947	12.265	0.989
Log_Distance to Frontier	37046	1.479	1.025	1.44	1.001	1.498	1.036
AI	110535	0.002	0.061	0.003	0.081	0.001	0.041
Pat	110535	1.594	21.017	1.933	25.352	1.35	17.240
Age	110157	30.561	32.741	29.29	32.778	31.474	32.684
HHI	110535	0.052	0.182	0.107	0.251	0.012	0.091
FirmType	37046	1.249	0.534	1.262	0.539	1.243	0.532
Clusterdummy	110535	0.134	0.340	0.135	0.342	0.133	0.340

Unfortunately, due to data limitations in the ORBIS database, we had to made the decision not to consider the capital stock of firms. This might bias our results. However, the information about the capital stock is not equally given for all firms in our sample, but only for a limited number – in particular large manufacturing firms. Using the limited information about the capital stock would consequently lead to a significant reduction in the number of observations (in some cases even more than half of our observations), which might create a sampling bias – especially in the analysis of different firm types. As a trade-off between these two potential biases, we decided to leave the capital stock out. Nevertheless, as a robustness check we also control for the capital stock, which is measured through the working capital per employee.[9] The corresponding results remain thereby robust and are shown in Appendix 4.

3.3 Method

As indicated in section 3.1., our dataset has a (unbalanced) panel structure consisting of patenting firms in Germany between 2013 and 2019. To test H1 and H2, we run the following two dynamic panel models (in a stylized form):

[9] In the case of the third and fourth regression model (see Table 2), where different firm types are investigated, the inclusion of the capital stock reduces the number of observations so much (more than half of the observations are lost – especially from smaller firms) that we decided not to include it here, as it would bias the results to such an extent that an analysis of different firm types would not be meaningful.

$$\text{Log}(\text{Prod}_{it}) = \alpha + \beta1\text{AI}_{it-1} + \beta2\text{Pat}_{it-1} + \beta3\text{Age}_{it} + \beta5\text{HHI}_{it} + \beta6\text{Log}(\text{Prod}_{it-1}) + \delta_t + \varepsilon_{it} \quad (2.)$$

$$\text{Log}(\text{Distance}_{it}) = \alpha + \beta1\text{AI}_{it-1} + \beta2\text{Pat}_{it-1} + \beta3\text{Age}_{it} + \beta5\text{HHI}_{it} + \beta6\text{Log}(\text{Prod}_{it-1}) + \delta_t + \varepsilon_{it} \quad (3.)$$

where our dependent variable is either the log-transformed labour productivity or the log-transformed distance to the (national) productivity frontier for firm i at time t. Similar to previous research (Ernst, 2001, Artz et al., 2010), we do not expect that an AI patent application is immediately integrated in a firm's knowledge base. As such, our main explanatory variable AI knowledge of firms, is included with a one-year time lag (AI_{it-1}). In order to control for the overall patent activities, we additionally include the general number of patents for firm i at time t-1. Moreover, the age (Age_{it}) and the technological diversity of a firm (HHI_{it}) are also included as control variables. Finally, α is the intercept, δ_t represents year dummies and ε_{it} is the error term. To address potential endogeneity concerns when including the one year lagged dependent variable as an explanatory variable ($LogProd_{it-1}$), we follow previous research (e.g. Boschma et al., 2014; Santoalha, 2019) and estimate the relevant coefficients of equation (2.) and (3.) using the difference-generalized method of moments (Diff-GMM)[10] with two-step robust standard errors (Arellano & Bond, 1991; Windmeijer, 2005). For the implementation we use the Stata xtabond2 command (Roodman, 2009a). In this context, similar to previous studies (e.g. Behrens & Trunschke, 2020), we consider age, year dummies and additionally the technological diversity of a firm as strictly exogenous.[11]

In a second step, to further disentangle the influence of AI on labour productivity across firms, we consider different types of firms: frontier firms, near-to-frontier firms and laggard firms. In general, the variable FirmType captures not only firm´s own (past) labour productivity, but also the (past) labour productivity of all other firms, because it is constructed based on the distance to the productivity frontier (see section 3.2.). As such, due to collinearity we removed the one year lagged dependent variable as an explanatory variable ($LogProd_{it-1}$). In a stylized form, the corresponding equation can be expressed in the following form:

[10] The System GMM (e.g. Blundell & Bond, 1998) failed to reject the nonexistence of an autocorrelation of order 2. Furthermore, the Hansen test of overidentifying restrictions (Hansen, 1982) is rejected.

[11] As a further robustness check and in line with previous studies (e.g. Damioli et al., 2021), we also estimate equation (2.) and (3.) in fixed effects models with clustered standard errors (see Appendix 2). Although FE estimates control for unobserved individual effects, they only serve as approximate results here, because they may still be affected by the endogeneity of the lagged dependent variable (Damioli et al., 2021), Nevertheless, the corresponding results of the fixed effects models are in line with our findings presented in Table 2. Furthermore, since a too high number of instruments can cause biased coefficient and standard error estimates (Roodman, 2009b), we also limit the number of lags as instruments. The corresponding results remain stable and can be provided upon request.

$$Log(Prod_{it}) = \alpha + \beta 1 AI_{it-1} + \beta 2 FirrmType_{it-1} + \beta 3 (AI \times FirmType)_{it-1} + \beta 4 Pat_{it-1} + \beta 5 Age_{it} + \beta 6 HHI_{it} + \delta_t + \varepsilon_{it} \quad (4.)$$

The equation differs in two important aspects from equation (2.). First, we introduce $FirmType_{it-1}$ and its interaction term with the lagged number of AI knowledge (AI_{it-1}) in order to further test H2 and H3. Second, by removing the lagged labour productivity from the right-hand sight of the equation (i.e. the dynamic component of firm´s labour productivity), we use an alternative panel estimation approach. Based on the results of the robust Hausman test (e.g. Schaffer & Stillman, 2010; Wooldridge, 2002), we choose to run a fixed effect panel regression. Following previous studies (e.g. Hoechle, 2007; Kopka & Grashof, 2022), the standard errors are clustered around the NUTS-3 regions in Germany in order to control for heteroscedasticity and autocorrelation. Finally, since we are also interested in a potential influence of regional clusters (see H3), we calculate equation (4.) for the full sample as well as the cluster sample (i.e. all firms located in regional clusters in Germany).[12]

4. Results & Discussion

The corresponding fixed-effects and Diff-GMM estimation results are shown in Table 2. Regarding our control variables, our results are somewhat surprising. We assumed that the patent activity of a firm has a positive impact on its labour productivity as well as its distance to the frontier. Nevertheless, we found no evidence for a direct impact of the non-AI patent count of a firm on the labour productivity nor the distance the frontier. This could be either due to the fact that formal R&D is very costly and uncertain, and therefore the effect on the revenue is (at least initially) offset by the investments needed, e.g. in human capital, thus decreasing the revenue while at the same time increasing the number of employees. The age has a positive impact on the overall labour productivity of a firm, meaning the older the firm, the more productive the firm tends to be. On the other hand, there is no direct influence of the firms age on its distance to the productivity frontier. Additionally, we controlled for the firms' diversity through the Herfindal-Hirschman Index. Here we observe no direct impact of the firms' knowledge diversity on the firms labour productivity as well as its distance to the frontier. A high knowledge diversity may therefore be conducive to the innovativeness of firms (e.g. Garcia-Vega, 2006), but not necessarily to their productivity, as the costs of a rather diversified knowledge base, e.g. greater coordination and communication expenses (Granstrand, 1998), may counteract the positive influences.

[12] As a further robustness check, we tested equation (4.), both for the full sample and the cluster sample, with varying definitions of the near-to-frontier and laggard firms. In total, we estimated three different models, with a broader definition of frontier firms (5%-25% productivity percentile and 5%-35% productivity percentile) and more narrow definition (5%-15% productivity percentile). The corresponding results remain robust and are presented in Appendix 3.

After describing the results of our control variables, we now analyse our hypotheses. Firstly, we assumed that AI knowledge in a firm has a positive impact on the labour productivity of the firm. Here we found that there is indeed a significant direct and positive impact of AI on firms' labour productivity (see Model 1). Therefore, we have no evidence to reject hypothesis H1. In line with recent empirical studies (e.g. Damioli et al., 2021; Yang, 2022), we thus find no evidence for an "excess automation" hypothesis (Acemoglu & Restrepo, 2018), where more automation leads to inefficiencies slowing down productivity growth.

Table 2: Regression results

	Log_Labour Productivity	Log_Distance to Frontier	Log_Labour Productivity	Log_Labour Productivity
	Difference GMM	Difference GMM	Fixed effects	Fixed effects
	(1)	(2)	(3)	(4)
AI_{t-1}	0.086** (0.037)	-0.061 (0.046)	-0.115 (0.073)	1.909*** (0.033)
Pat_{t-1}	0.0002 (0.0002)	-0.0003 (0.0002)	0.0003 (0.0004)	-0.0001 (0.0004)
Age	0.018*** (0.003)	-0.011*** (0.003)	0.012*** (0.002)	0.017*** (0.005)
HHI	0.022 (0.020)	-0.029 (0.020)	0.012 (0.019)	0.012 (0.023)
$LogLabourProd_{t-1}$	0.171*** (0.051)	-0.126*** (0.046)		
$FirmType_{t-1}$			0.059*** (0.022)	0.039 (0.051)
AI_{t-1} X $FirmType_{t-1}$			0.122*** (0.032)	-0.956*** (0.028)
Constant			11.77*** (0.105)	11.44*** (0.314)
Time-fixed effects	Yes	Yes	Yes	Yes
Full Sample	Yes	Yes	Yes	Cluster Sample
Observations	18916	18916	25676	4224
R^2 (Within)			0.010	0.014
AR(1) – p value	0.000	0.000		
AR(2) – p value	0.427	0.839		
Hansen test – p value	0.184	0.145		
Nr. of Instruments	51	51		

Note: Two-step robust standard errors (GMM)/Clustered standard errors (Fixed Effect) in parentheses; * p<0.10, ** p<0.05, *** p<0.01

But instead, our empirical results rather go in line with two alternative arguments. First, through increased efficiency in automation in production (e.g. Rajawat et al., 2021), firms experience labour productivity growth, which on the other hand might increase the job automation risk (e.g. Foster-McGregor et al., 2021). Second, through its GPT and IMI characteristics, AI enables (radical) innovations thereby generating new market opportunities which ultimately result in a higher productivity (Ahuja & Lampert, 2001; Bresnahan & Trajtenberg, 1995; Ristuccia & Solomou, 2014).

Secondly, our next hypothesis is that there is an increasing impact of AI on the distance to the labour productivity frontier, in other words laggard firms are benefiting less from AI knowledge than frontier firms. However, our empirical results indicate an insignificant effect of AI knowledge in firms on their distance to the productivity frontier (see Model 2). Thus, in general AI does not statistically increase the productivity gap. In order to further disentangle the influence of AI on labour productivity across firms, we extend our empirical approach and consider different firm types: frontier firms, near-to-frontier firms and laggard firms (see section 3.2.). In Model 3, the corresponding interaction term between AI knowledge and firm type is highly significant and positive, indicating that particularly frontier (and near-to-frontier) firms benefit in terms of labour productivity from AI knowledge. For a better visualisation of these firm-specific differences, Figure 1 shows graphically the average marginal effects of AI on the labour productivity across the three different firm types.

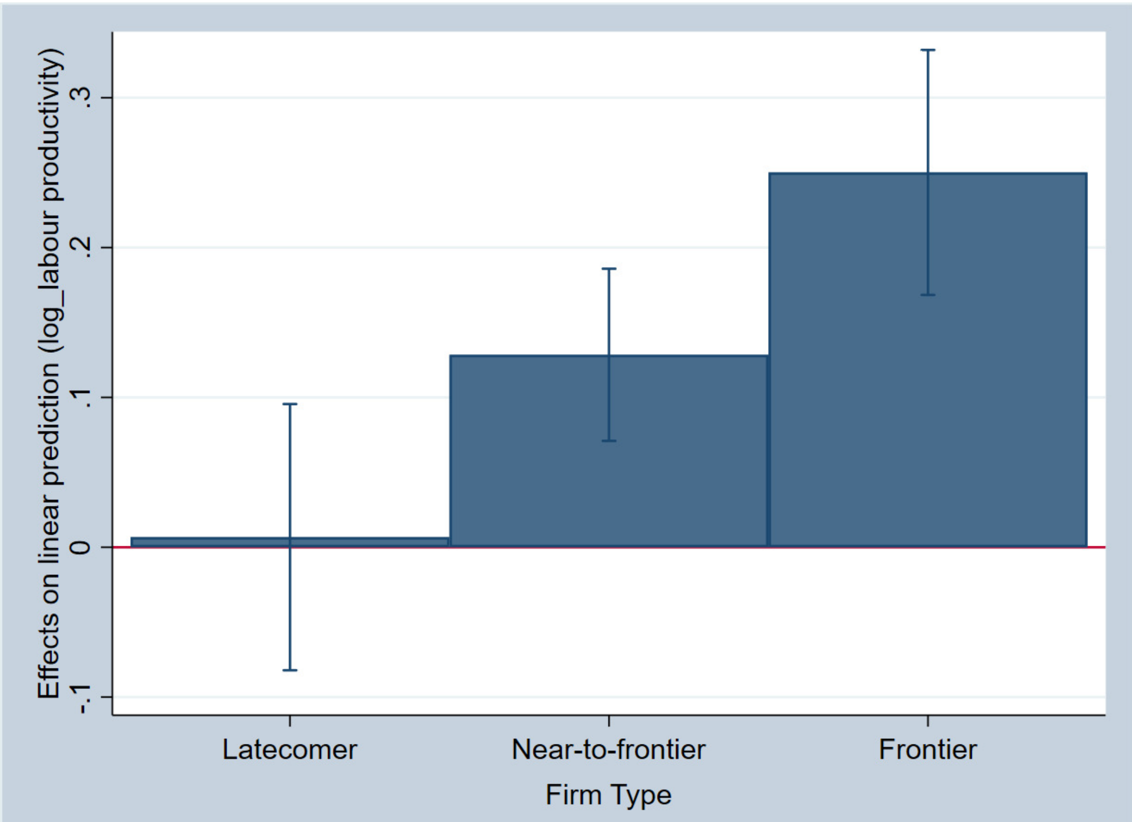

Figure 1: Average marginal effects of lagged AI on logged labour productivity in full sample (with 95% CIs)

Here, we can observe that, on the one hand, for both frontier and near-to-frontier firms more AI knowledge significantly fosters the labour productivity, with the highest average marginal effect for frontier firms. However, on the other hand, for laggard firms the effect of AI knowledge on labour productivity is not statistically significant. In summary, our results (from Model 2, Model 3 and Figure 1) therefore indicate that while AI knowledge does not significantly contribute to productivity divergences on average, its positive influence on labour productivity plays only out for frontier and near-to-frontier firms, thereby specifically widening the productivity gap between laggard firms and all other firms. Hypothesis H2 can therefore only partially be accepted.

The found firm-specific differences between frontier, near-to-frontier and laggard firms can be explained by the different resource endowments highlighted within the RBV (Barney, 1991; Newbert, 2007). For instance, firms differ in their ability to adopt new technologies depending, among other things, on the financial abilities (e.g. Rogers, 2004), the absorptive capacities (Cohen & Levinthal, 1990) and the organisational structure (e.g. Goode & Steven, 2000). With regard to AI, this means that a sufficiently equipped data infrastructure, well trained human capital as well as data management competencies are essential to realize and seize the potentials of AI (Accenture, 2019; Brynjolfsson et al., 2021; OECD, 2021). Particularly SMEs are considered to face a lack of these resources (Bianchini & Michalkova, 2019; Cockburn et al., 2019; OECD, 2021). Since frontier firms tend to be larger firms (e.g. Andrews, 2015) and tend to have more human capital (Bartelsmann et al., 2014), it is reasonable that this type of firms is thus also better capable to harvest the benefits of AI on production automation compared to laggard firms, all other things being equal.

Nevertheless, thirdly, we theorized that being located in a cluster reduces the diverging effect of AI. To assess this hypothesis, we further split our dataset into cluster firms and non-cluster firms to calculate a model only with cluster firms (see Model 4). Similar to Model 1, we can observe that AI also has a direct significant positive influence on the labour productivity of firms located within clusters. However, in contrast to the previous Model 3, the interaction term between AI knowledge and firm type is highly significant and negative, meaning that within clusters particularly laggard firms profit from AI knowledge. Similar to Model 3, we also graphically plot the corresponding average marginal effects of AI on the labour productivity within clusters. Contrary to the full sample, Figure 2 shows that within clusters particularly laggard firms benefit from AI knowledge within their knowledge base, while in the case of frontier firms we even find evidence for a negative influence of AI knowledge. Therefore, we can accept hypothesis H3, that the diverging effect of AI knowledge on firms' productivity gap is reduced by being located in a cluster.

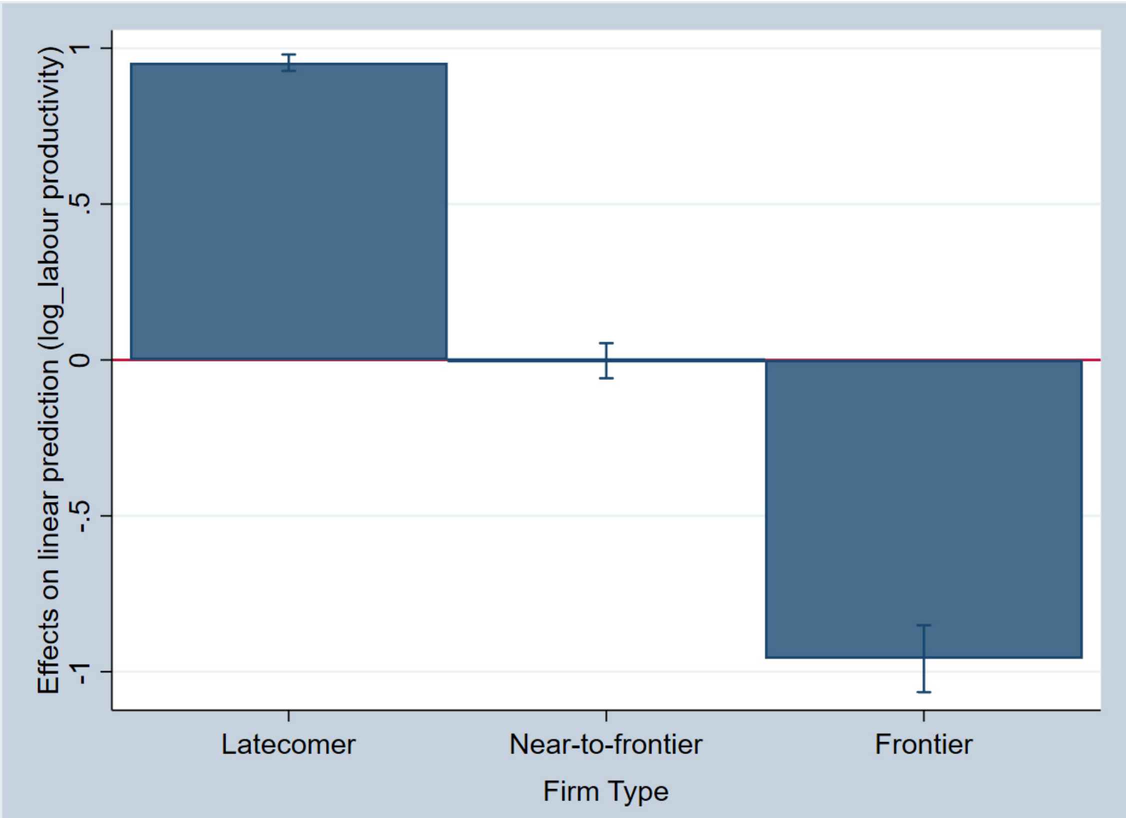

Figure 2: Average marginal effects of lagged AI on logged labour productivity in cluster sample (with 95% CIs)

The opposing results between firms located in clusters and outside clusters can be explained by the special circumstances in clusters, for instance the localization externalities (e.g. Marshall, 1920). In particular, the eased transfer of (tacit) knowledge among co-located firms appears to be highly relevant in this context (Daft & Lengel, 1986; Jaffe et al., 1993). While in general it has been highlighted that firms need to own sufficiently high absorptive capacities in order to recognise, process and finally integrate the knowledge (Cohen & Levinthal, 1990; McCann & Folta, 2011), recent evidence suggests that too high absorptive capacities are also not conducive to the (innovative) performance of companies (e.g. Grashof, 2021a; Hervás-Oliver et al., 2018). In an environment of reinforced knowledge exchange, such as regional clusters, firms with high absorptive capacities have a high risk of unintentional knowledge spillovers to competitors, which in turn continuously reduces firms' relative competitive advantage leading to an adverse selection process (Grashof, 2021; Knoben et al., 2016; Shaver & Flyer, 2000). Our empirical results seem to go in line with this argument of an adverse selection process. Frontier firms, that have in general higher absorptive capacities than laggard firms (e.g. Andrews, 2015), are the ones that have much less to gain and actually lose part of their relative competitive advantage due to unintentional knowledge spillovers. Contrary, laggard firms profit from these knowledge outflows by having access to highly relevant AI-related knowledge and eventually also human capital, due to the high labour mobility within clusters (Bienkowska et al., 2011; Erikson & Lindgren, 2009). The common specialized labour pool within regional clusters (Krugman, 1991; Marshall,

1920) can help to reduce the great difficulty, particularly for laggard firms (Gal et al., 2019), to attract high-skilled labour, being an essential complement to realize and seize the opportunities of AI (Brynjolfsson et al., 2021; Cirillo et al., 2021; OECD, 2021).

5. Conclusion

Although there are high expectations about Industry 4.0 in general (De Propis & Bellandi, 2021; Hervás-Oliver et al., 2019) and in particular about AI (e.g. Craglia et al., 2018), as one of the core underlying technologies of Industry 4.0 (Martínelli et al., 2021), the empirical assessment of the actual impact of AI on firm productivity, being one major target of Industry 4.0 related initiatives (Liao et al., 2018), has been rather limited so far, despite some important recent exceptions (e.g. Alderucci et al., 2020; Damioli et al., 2021). This is all the more true as previous research has largely overlooked firm-specific differences, thereby ignoring the potential for convergence and divergence processes, as well as the regional context which might moderate the relationship between AI and firm productivity, e.g. through localisation externalities. By combining patent data, firm-level data and regional employment data in three-digit NACE Rev. 2 industries, this paper therefore investigates (1.) the influence of AI knowledge on firm productivity in Germany, (2.) the extent to which AI knowledge influences the productivity gap between firms, (3.) the moderating influence of being located in a cluster on the diverging effect of AI knowledge on the firm productivity gap.

Our results suggest that first and foremost AI knowledge does have a positive impact on the productivity of German firms, which goes in line with previous theoretical papers (e.g. Brynjolfsson et al., 2019; Cockburn et al., 2019) and recent empirical studies in different research settings (e.g. Alderucci et al., 2020; Damioli et al., 2021). One potential explanation of this finding refers to the GPT and IMI characteristics of AI. As such, AI act as a bridging platform (inventions through innovation complementarities) and as a catalyst (generation of new inventions) which promotes the emergence of (radical) innovations and thereby new market opportunities, ultimately leading to a higher productivity. Secondly, we found that AI knowledge does not significantly contribute to productivity divergences in general, but it increases in specific the productivity gap between laggard and frontier firms, thus being a driver of inequality between laggard firms and all other firms. This also seems to partially explain the productivity paradox (Brynjolfsson et al., 2019) as generally frontier firms benefit more from an internal AI knowledge base. Lastly, we assumed that the diverging effect of AI knowledge on the firm productivity gap is reduced by being located in a cluster, due to localisation externalities (Marshall, 1920), particularly knowledge spillovers/leakages, from which especially laggard firms might profit. Our empirical results indeed find evidence for such an adverse selection effect (Shaver & Flyer, 2000). Frontier firms, having in general higher absorptive capacities than laggard firms (e.g. Andrews, 2015), have much less to gain within regional clusters and actually lose part of their relative competitive advantage due to unintentional knowledge spillovers, while laggard firms profit from these knowledge outflows and eventually also from the high labour mobility within clusters (Bienkowska et al., 2011; Erikson & Lindgren, 2009; Grashof, 2021a).

Given these results, we also have to acknowledge some limitations to this article, which can serve as a starting point for future research. First, we only focus on firms within Germany thus limiting our productivity gap to a group of firms that tend to be (in comparison to firms worldwide) closer to the frontier. Future research may therefore consider additional countries in order to get a broader picture and to control for potential country effects. Second, due to the recent developments of AI our time horizon is rather small, giving not enough space to analyse long-term effects which could be interesting to investigate in the future. Third, the limited data availability of employment data in three-digit NACE Rev. 2 industries on the municipality level has only allowed us to calculate the actor-based cluster index for the year 2012. Thus, for future research it may be promising to calculate the actor-based cluster index for a longer time period in order to investigate the dynamic evolution across the cluster life cycle (e.g. Menzel & Fornahl, 2010). Fourth, AI technologies should not be considered as a whole, but at least separated between their IMI and their GPT function, as these might have different effects on the productivity. However, given the limited geographical scale of this article, such an approach was not feasible.

Nevertheless, in general our paper is able to give part of the answer on the highly discussed topic of firm productivity through AI – especially through the lens of inequality and cluster effects. Our results suggest that policy makers should indeed support the development of AI knowledge within firms in order to increase the productivity. However, at the same time, policy makers should also address the AI-related problem of increasing inequality between laggard firms and all other firms. Apart from supporting firm´s R&D activities and human capital (Edler et al., 2016), for instance through continuous vocational trainings (Borrás & Edquist, 2015; CEDEFOP, 2011), particularly cluster policies seem to be promising for laggard firms in reaping the benefits of AI. As such, a more targeted approach is needed (Grashof, 2021b). By doing so, AI can, in the end, contribute to a higher productivity across all firms and thereby also meet the high expectations about its impact (e.g. Craglia et al., 2018).

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Appendix

A1: Pairwise correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Log_Labour Productivity	1.000							
(2) Log_Distance to Frontier	-0.938***	1.000						
(3) AI	0.050***	-0.044***	1.000					
(4) Pat	0.031***	-0.043***	0.235***	1.000				
(5) Age	0.053***	-0.096***	0.008**	0.079***	1.000			
(6) HHI	0.051***	-0.072***	0.016***	0.028***	0.067***	1.000		
(7) FirmType	0.681***	-0.684***	0.031***	0.037***	-0.013***	0.039***	1.000	
(8) Clusterdummy	0.014***	-0.085***	0.005	0.039***	0.124***	0.029***	0.039***	1.000

*** p<0.01, ** p<0.05, * p<0.1

A2: Fixed effects models with clustered standard errors (equation 2 and 3)

	Log_Labour Productivity	*Log_Distance to Frontier*
	Fixed effects	Fixed effects
	(1)	(2)
AI_{t-1}	0.119* (0.062)	-0.079 (0.068)
Pat_{t-1}	0.001 (0.0004)	-0.001 (0.001)
Age	0.011*** (0.002)	-0.011*** (0.003)
HHI	0.011 (0.019)	-0.029 (0.020)
$LogLabourProd_{t-1}$	0.067* (0.039)	-0.063 (0.040)
Constant	11.07*** (0.477)	2.66*** (0.484)
Time-fixed effects	Yes	Yes
Full Sample	Yes	Yes
Observations	25676	25676
R^2 (Within)	0.013	0.012

A3a: Fixed effects models with frontier firms defined by the 5%-25% productivity percentile (equation 4)

	Log_Labour Productivity	*Log_Labour Productivity*
	Fixed effects	Fixed effects
	(1)	(2)
AI_{t-1}	-0.110 (0.074)	1.879*** (0.029)
Pat_{t-1}	0.0003 (0.0004)	-0.00004 (0.0004)
Age	0.016*** (0.002)	0.017*** (0.004)
HHI	0.017 (0.018)	-0.001 (0.021)
$FirmType_{t-1}$	0.051*** (0.020)	0.048 (0.043)
AI_{t-1} X $FirmType_{t-1}$	0.121*** (0.033)	-0.940*** (0.026)
Constant	11.62*** (0.089)	11.45*** (0.232)
Time-fixed effects	Yes	Yes
Full Sample	Yes	Cluster Sample
Observations	25676	4224
R^2 (Within)	0.008	0.012

A3b: Fixed effects models with frontier firms defined by the 5%-35% productivity percentile (equation 4)

	Log_Labour Productivity	*Log_Labour Productivity*
	Fixed effects	Fixed effects
	(1)	(2)
AI_{t-1}	-0.100 (0.064)	1.810*** (0.061)
Pat_{t-1}	0.0004 (0.0004)	0.0003 (0.0004)
Age	0.016*** (0.002)	0.017*** (0.004)
HHI	0.017 (0.019)	-0.001 (0.021)
$FirmType_{t-1}$	0.030* (0.018)	0.020 (0.044)
AI_{t-1} X $FirmType_{t-1}$	0.113*** (0.031)	-0.862*** (0.080)
Constant	11.65*** (0.090)	11.49*** (0.240)
Time-fixed effects	Yes	Yes
Full Sample	Yes	Cluster Sample
Observations	25676	4224
R^2 (Within)	0.007	0.010

Appendix 3c: Fixed effects models with frontier firms defined by the 5%-15% productivity percentile (equation 4)

	Log_Labour Productivity	*Log_Labour Productivity*
	Fixed effects	Fixed effects
	(1)	(2)
AI_{t-1}	-0.107 (0.071)	1.878*** (0.030)
Pat_{t-1}	0.0003 (0.0004)	-0.00003 (0.0004)
Age	0.016*** (0.002)	0.017*** (0.004)
HHI	0.018 (0.018)	0.002 (0.022)
$FirmType_{t-1}$	0.079*** (0.025)	0.060 (0.063)
AI_{t-1} X $FirmType_{t-1}$	0.121*** (0.031)	-0.938*** (0.027)
Constant	11.59*** (0.093)	11.42*** (0.252)
Time-fixed effects	Yes	Yes
Full Sample	Yes	Cluster Sample
Observations	25676	4224
R^2 (Within)	0.009	0.012

*Note: Clustered standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01*

Appendix 4: GMM models with control for capital stock

	Log_Labour Productivity	*Log_Distance to Frontier*
	Difference GMM	Difference GMM
	(1)	(2)
AI_{t-1}	0.058** (0.026)	-0.080 (0.059)
Pat_{t-1}	0.001** (0.0002)	-0.001* (0.0003)
Age	0.009** (0.004)	-0.001 (0.004)
HHI	-0.016 (0.022)	0.010 (0.023)
$LogLabourProd_{t-1}$	0.156** (0.070)	-0.080 (0.061)
LogCapital	0.094** (0.037)	-0.063** (0.025)
Time-fixed effects	Yes	Yes
Full Sample	Yes	Yes
Observations	9284	9284
AR(1) – p value	0.012	0.018
AR(2) – p value	0.757	0.100
Hansen test – p value	0.392	0.173
Nr. of Instruments	71	71

*Note: Two-step robust errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01*

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