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RESEARCH ARTICLE

Artificial intelligence and firm growth — catch-up processes of SMEs through integrating AI into their knowledge bases

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Abstract Artificial intelligence (AI) is seen as a key technology for future economic growth. It is labelled as a general-purpose technology, as well as an invention of a method for inventing. Thus, AI is perceived to generate technological opportunities and through these, innovations, and productivity growth. The leapfrogging hypothesis suggests that latecomer firms can use these opportunities to catch up. The aim of this paper is to provide insight into this catch-up process of latecomer firms through integrating AI into their knowledge portfolio and thereby creating new technological trajectories. The moderating effect of firm size is also analysed. Combining firm-level data with patent data, a regression at the firm level is conducted. Evidence is found that smaller firms experience productivity growth from AI when operating at the productivity frontier, indicating the opposite of the leapfrogging hypothesis. However, there is evidence for the positive impact of AI on firm innovation, which is higher for latecomer firms that are larger in size. In general, we find a diverging pattern of the influence of AI on productivity and innovation growth, indicating the need for a finer grained analysis that takes indirect effects - that also could explain the observed productivity paradox - into account.

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Plain English Summary Small frontier firms experience a higher labour productivity growth through AI integration. In contrast, large latecomer firms experience a higher innovative productivity growth. These effects are dependent on the type of AI. Artificial intelligence (AI) is seen as a key technology for future economic growth. It is labelled as a general-purpose technology, as well as an invention of a method for inventing. Thus, AI is perceived to generate innovations and productivity growth. This paper investigates the influence of different types of AI on smaller and larger firms that are either frontier or latecomer firms. We find that smaller frontier firms experience a higher labour productivity growth while larger latecomer firms experience a higher innovative productivity growth. This diverging impact has implications for scholars, as it could partially explain the productivity paradox and shows the need for research on specific types of AI. This impact also has implications for policy makers and practitioners alike that aim to strengthen frontier firms or to develop latecomer firms.

Keywords Artificial intelligence · Firm growth · Catch-up · Innovation · Productivity

JEL classification O31 · O32 · O33 · O47 · L25

1 Introduction

Digital technologies and digitalisation are currently key topics in policy, economics, and research. It seems that every product that has existed in the last century, from dishwashers to factory machines, has been upgraded to contain digital technology (Lee et al., 2005). One of the latest trends of this digitisation process is the technology of artificial intelligence (AI). Even though it is not a 'new' field of research dating back to the 1950s with the famous Turing-Test (Turing, 1950), since 2013 it has entered a recent boom that is based on machine learning (ML) and deep learning (DL) (Miyazaki et al., 2018). As a result, there has been an enormous growth in general-purpose ML tools that aim to minimise the amount of adjustments necessary for AI to work on different types of data (Taddy, 2018). Thus, it has become increasingly easier to apply AI to many different applications and fields, making AI seem to be a one-size-fits-all solution to various kinds of problems. Furthermore, AI and its subcategories ML and DL are not only being labelled emerging general-purpose technologies (GPTs) but also seem to be inventions of a method of inventing (IMI) (Cockburn et al., 2018). Applying these two theoretical frameworks, AI methods and AI applications are considered separately in this paper. AI methods generate new technological opportunities and inventions as IMIs increase the research output (Darby and Zucker, 2003). In comparison, AI applications can be seen as the application of a GPT in a firm, which should increase productivity (Bresnahan and Trajtenberg, 1995). Both concepts indicate an increase of technological opportunities across many different fields through the application and emergence of AI and thus can be considered an opportunity for latecomer firms to catch up with the frontier firms through utilising these technological opportunities. This is suggested by the leapfrogging thesis (Lee et al., 2005). Utilising emerging technological opportunities is an important factor in fostering the catch-up process (Perez and Soete, 1988; Freeman and Soete, 1997; Freeman, 1989, 1995). It facilitates latecomer firms in creating a new path instead of following frontier firms, thus allowing latecomers to leapfrog the gap between them and frontier firms (Lee and Lim, 2001).

This paper aims to provide insight into the catch-up process of latecomer firms through integrating AI into their knowledge portfolio and thereby creating new technological trajectories. Integrating AI into a firm's knowledge portfolio increases the technological opportunities of said firm. This has an impact on (a) the inventive output of a firm (Cockburn et al., 2018) and (b) the productivity of a firm (this relationship is highly discussed in the literature) (Raj and Seamans, 2018; Brynjolfsson et al., 2018). In addition, as barriers to entry for emerging technologies become smaller (Perez and Soete, 1988), latecomer firms have the opportunity to invest into these emerging technologies and thus catch up to the frontier firms as early movers in these emerging technologies. The influence of AI on the inventive output is expected to be greater on larger firms, as they can allocate more resources and capital into formal R&D (Rogers, 2002). In comparison, smaller firms are more flexible and less hierarchical in their structures, making them better at perceiving opportunities and integrating them into their portfolios (Goode and Stevens, 2000). This allows them to profit more from the implementation of AI into their knowledge bases. Smaller firms are then able to catch up to larger firms through enabling productivity growth. This follows the notion of AI acting as an external enabler for entrepreneurship (Obschonka and Audretsch, 2019). In this paper, we aim to determine to what extent the knowledge of AI fosters productivity and knowledge growth in a firm; specifically, we focus on the differences between small and medium enterprises (SMEs) and multinational enterprises and on the catch-up process of latecomer firms.

This paper contributes to the research of the impact of AI on firms, which is a field that has just recently started to receive theoretical (e.g. Raj and Seamans 2018; Cockburn et al., 2018; Brynjolfsson et al., 2018; Agrawal et al., 2019b) and empirical (e.g. Alderucci et al., 2020; Damioli et al., 2021) attention. We assess whether AI can facilitate productivity and innovative growth processes in firms and if it is able to generate catch-up processes, as there are only a limited number of studies addressing these issues (Raj and Seamans, 2018). Furthermore, this paper provides insight into the effects of a technology that is both a GPT and an IMI, which are 'dynamics that are as yet poorly understood or characterised' (Cockburn et al., 2018, p. 8) through conceptually dividing these two aspects. The remainder of this paper is organised into the following sections: Theory, Data and methods, Results, Interpretation and discussion, and Conclusion. Theory gives an overview of the history of AI and the theoretical background and provides the deduction of the hypotheses (Section 2).

Data and methods describes the data employed, operationalisation of variables and the methods employed (Section 3). Results (Section 4) and Interpretation and discussion (Section 5) respectively present and interpret the results of the study. Conclusion closes the paper with a discussion and prospects for further research.

2 Theory

2.1 AI as a general-purpose technology and an invention of a method of inventing

A GPT is a technology that has many different possible applications (Thoma, 2008). Following the GPT framework (Bresnahan and Trajtenberg, 1995; David, 1990), GPTs act as 'engines of growth' throughout the entire economy. They are characterised by three different aspects: pervasiveness, an innovation spawning effect and a scope for improvement (Helpman and Trajtenberg, 1994). Pervasiveness in this regard means that the technology or aspects of this technology are 'vital to the functioning of a large set of existing or potential products or production systems' (Youtie et al., 2008, p. 317). A GPT spawns innovation in each sector in which it is applied, as it offers new technological opportunities. It generates innovation complementarities which lead to productivity growth in the applied sector. For each sector in which a GPT is applied, feedback loops are generated, which lead to innovations and improvement in the GPT itself. These innovations lead to a further application utility of the GPT. Accordingly, a GPT needs a scope for improvement to enable these complementarities and feedback loops to increase the rate of innovation across all sectors. A GPT can thus be summarised into technological cumulativeness, dynamism and complementary innovations, as with each additional applied sector and innovation, additional innovations in the GPT are generated (Thoma, 2008), which ultimately leads to an increase of productivity (Bresnahan and Trajtenberg, 1995). AI has been identified as a GPT (Cockburn et al., 2018). With its latest boom and the rise of DL and ML, AI has become more and more general-purpose. Through recent innovations, it can be applied to many different data structures and applications, with less and less need for alteration (Yamakawa et al., 2016). As it can be applied in many different sectors, it has the opportunity to generate growth processes in each of these sectors. The chances for this growth process rise with each additional sector that uses AI, as innovation complementarities generate improvements in AI. This leads to further technological opportunities and enhances the set of possible products or production systems. Utilising these opportunities provides a firm with the potential to generate new trajectories that enable rapid growth processes and thus generate productivity growth (e.g. Czarnitzki et al., 2022; Damioli et al., 2021).

The concept of IMI was proposed by Griliches (1957). It describes an invention that is used in research to generate further inventions. An IMI can initiate waves of inventions. They create new technological opportunities and appropriability across a wide range of potential products (Darby and Zucker, 2003). This indicates an additional positive effect on technological opportunities and therefore growth. AI methods and techniques can be identified as IMIs (Cockburn et al., 2018) or as meta ideas (Agrawal et al., 2019), which follows the notion of an IMI. This means that AI can further generate technological opportunities and facilitate inventions if it is used as a method in the R&D process (e.g. Grashof and Kopka 2022; Rammer et al., 2022).

As described above, AI as an IMI and GPT generates technological opportunities, innovations, and inventions and both are closely related concepts. However, while the GPT framework focuses on the application of the technology (Bresnahan and Trajtenberg, 1995; David, 1990; Helpman and Trajtenberg, 1994), the IMI framework focuses on the methods that are used to generate new technological opportunities and inventions (Griliches, 1957; Darby and Zucker, 2003). Thus, the impact of AI knowledge on firms is twofold. AI knowledge based on its GPT characteristics enables productivity growth. Given the application-based nature of the GPT framework, this effect is based on application knowledge of AI. In comparison, AI knowledge based on its IMI characteristics enables further innovations. Given the method-based nature of the IMI framework, this effect is based on method knowledge of AI. Therefore, our first set of hypotheses are as follows:

1. **H1a:** Incorporating knowledge of AI applications into the knowledge base of a firm has a positive effect on the productivity of the firm.
2. **H2a:** Incorporating knowledge of AI methods into the knowledge base of a firm has a positive effect on the innovative output of the firm.

2.2 Catch-up and leapfrogging of firms

The catch-up hypothesis, formulated by Abramovit (1986, p. 386), is based on the assumption that 'the growth rates of productivity during any long period tend to be inversely related to the initial levels of productivity. In the extant literature, the catch-up process of countries or firms to a global (or national) frontier is based on the theoretical construct of knowledge spillovers. These knowledge spillovers originate from the most productive technology. As long as the knowledge is non-rival and not fully appropriable, there is the possibility of an improved performance by learning from the frontier (Bartelsman et al., 2008). In general, this means, that the further a country or firm is from said frontier, the higher the benefits from the knowledge spillover, suggesting an automated convergence process that starts fast and then slows down (Abramovitz, 1986).

Lee and Lim (2001) identified three different patterns of catching-up. The first is *path-following catching-up*, where the latecomer firm (or nation) exactly follows the development path of the frontier. The second is *stage-skipping catching-up*, where firms skip certain parts of the trajectory. The third is *path-creating catching-up*, where firms create a new trajectory through perceiving technological opportunities and generating a higher growth than the frontier firms. In *stage-skipping catching-up*, latecomers may be able to leapfrog older technologies on the path, thereby avoiding heavy investments in those technological systems (Hobday, 1995). This leapfrog does not change the technological curve, it just skips part of it (Lee and Lim, 2001). *Path-creating catching-up* comes into play when new technological opportunities arise. Every country and firm is a beginner in terms of a newly emerging techno-economic paradigm. They serve as windows of opportunities, which implies the possibility of leapfrogging by latecomer firms (Lee et al., 2005) or newly industrialised economies (Freeman and Soete, 1997; Perez and Soete, 1988). Furthermore, machines and production facilities for this new technology do not exist yet and general-purpose machines with small production volumes are used. Thus, there is no barrier to entry associated with the scale of the economy, making entry into emerging technologies easier. In addition, catching-up firms or countries can be said to be in a rather advantageous position, as they are not locked into old technologies due to already-expended costs of investment (Perez and Soete, 1988). Another argument for path-creating catching-up is that it is impossible to exactly replicate technologies from the technological frontier, as there are always modifications required to tailor operations to the local circumstances (Malerba and Nelson, 2011).

Therefore, technological leapfrogging is a combination of learning from the frontier and integrating self-innovation and foreign advanced technology to not only jump over some phases of technological development but also create new paths to follow. It involves realisation of innovation and original intellectual property rights (Chen and Li-Hua, 2011). Furthermore, to create a new trajectory, it needs technological opportunities, such as an emerging techno-economic paradigm.

Studies on the catch-up process can be categorised into two groups: the macro group and the micro group. In the macro group, the productivity frontier of a nation is compared to the productivity of the global frontier country (see, e.g., Quah, 1996). In the micro group, studies use micro data of firms and compare this firm-level data against a national, global or sectoral frontier — or a combination of those (see, e.g., Nishimura et al., 2005; Bartelsman et al., 2008). Such firm-level analysis offers the advantage of allowing for in-group heterogeneity (Bartelsman et al., 2008). Defining just one global frontier undermines the fact that different firms operate under different framework conditions. The framework conditions between different sectors of the economy play an especially important role here. Taking into account sector-specific frontiers offers the possibility that different firms within a country can be frontier firms while others might be latecomers, as well as the fact that frontier firms can exist in non-frontier countries.

There are many reasons behind frontier firms having a competitive advantage over and an increased productivity growth compared to latecomer firms (e.g. Andrews et al., 2019). One possible explanation is the heterogeneous diffusion pattern of GPTs across firms (Andrews et al., 2019; Faggio et al., 2010). New GPTs diffuse at a decreasing rate between firms within an economy (Andrews et al., 2015; Bahar, 2018). Thus, firms that can adopt these technologies gain a competitive advantage, as they enable technological opportunities within the firm. Therefore, if a latecomer firm can adopt AI knowledge, AI as a technological opportunity can facilitate catch-up processes within these firms; we assume AI to be a GPT which should increase a firm's productivity (see Section 2.1). A GPT increases productivity through innovation complementarities and improvements of itself and thus the sector it is applied in. AI application knowledge is assumed to have a higher positive impact on latecomer firms, as these firms have more opportunities for productivity growth compared to firms already operating at the productivity frontier. In comparison, frontier firms have an advantage of being able to adopt new technologies, as firms differ in their ability to adopt new technologies depending on, for example, their financial abilities (Ayyagari et al., 2007; Dosi, 1988; Freeman and Soete, 1997) and their absorptive capacities (Cohen and Levinthal, 1990). Frontier firms are also better at seizing technological opportunities in a more formalised way. AI with its IMI features wields its greatest impact within formal R&D processes. AI method knowledge therefore has a more pronounced effect within frontier firms compared to latecomer firms because it is more reliant on an existing technology base and acts as a method to connect and generate new knowledge. We therefore derive the following hypotheses:

1. **H1b:** Incorporating knowledge of AI applications into the knowledge base of a firm has a greater positive effect on the productivity of latecomer firms.
2. **H2b:** Incorporating knowledge of AI methods into the knowledge base of a firm has a greater positive effect on the innovative output of frontier firms.

In summary, a latecomer firm has the potential to leapfrog under specific circumstances. A latecomer firm needs a certain distance to the global frontier to generate growth based on the convergence hypotheses. In addition, integrating technological opportunities provides a firm the chance to generate a new trajectory that can enable further growth. As latecomer firms are not locked into old technological systems, they are expected to better perceive these technological opportunities and to generate productivity growth. However, frontier firms have the ability to strengthen their lead through their competitive advantage regarding formal R&D processes and their abilities to adopt new technologies. Therefore, frontier firms are expected to better perceive technological opportunities to generate further innovation from these.

2.3 Benefits of AI with varying firm sizes

AI opens up many new technological opportunities and thus can be seen as an emerging techno-economic paradigm. This leads to the assumption that AI has an influence on path-creating catch-up processes. These effects not only differ between latecomer and frontier firms, but also between firm sizes. Smaller firms, which are more flexible and less hierarchical in their structure, are better at perceiving and integrating opportunities into their portfolio (Goode and Stevens, 2000). This characteristic is amplified by the rapid development of AI — a field that has a far-reaching potential but is very hard to predict (Grace et al., 2018) — giving smaller more flexible firms the ability to react faster to new developments. Furthermore, as data, not capital-intensive machinery, fuels AI (Agrawal et al., 2018), there are more opportunities for smaller firms. Therefore, we assume that the productivity of smaller firms benefits more from the integration of the technological opportunities arising from AI applications than that of larger firms. This argument is not without criticism, as data constraints for smaller firms could lead to incumbent advantages of large firms, such as Amazon AWS and Google.ai (Obschonka and Audretsch, 2019). In this paper, however, we follow the argument that big data concentration has limited possibilities for abuse (Nuccio and Guerzoni, 2019) and follow the notion of AI as an external enabler (Obschonka and Audretsch, 2019). Larger firms, in contrast to smaller ones, are able to allocate more resources and capital into formal R&D (Rogers, 2002). They can generate more inventions and innovative output than smaller firms from the integration of technological opportunities; however, larger firms lack the freedom to effectively integrate these technologies into their portfolio. Thus, integrating AI methods into their knowledge bases provides larger firms the advantage of knowledge creation and greater innovative output.

1. **H1c:** Incorporating knowledge of AI applications into the knowledge base of a firm has a greater positive effect on the productivity of smaller firms.
2. **H2c:** Incorporating AI methods into the knowledge base of a firm has a greater positive effect on the innovative output of larger firms.

There may also be an interaction between a firm's size and its position on the global, national or sectoral productivity distribution. Even though a firm's distance to the frontier and the size of a firm are often correlated (Hsieh and Klenow, 2009, 2014; Moral-Benito, 2018) and endogenous (Medrano-Adán et al., 2019), the distinction and comparison of these two are not as clear as assumed. Small and medium-sized firms experience less market friction and thus have an advantage over larger firms in innovating and reacting to changes in market environments. Díaz and Sánchez (2008) found that for SMEs in Spain, firm size negatively impacts efficiency. Similarly, Dhawan (2001) found that between 1970 and 1989, small firms in the United States were significantly more productive than large firms. Given this ambiguity, it is plausible to argue that being a latecomer firm and perceiving new technological opportunities might be more beneficial for a smaller firm because it is able to adapt faster to a change in the techno-economic paradigm. Another possible outcome is that frontier firms have the capital to invest in R&D, which might offset the negative aspects of being a small firm.

The influence of new opportunities in a market on growth and catch-up processes has been heavily investigated in the extant literature, focusing on macro-level economics (e.g. Freeman, 1989), specific industries (e.g. Lee et al., (2014); Yap and Rasiah, 2017), or regions (e.g. Henderson et al., 2007; Enflo and Hjertstrand, 2009; Badunenko and Tochkov, 2010). Even though there are studies targeting the integration of a digital technology into the market and thus creating a new trajectory (Lee et al., 2005), to our knowledge, there are no studies that discuss the effect of integrating AI into a firm's knowledge base. Recapitulating the above-mentioned concepts, we formulate the following hypotheses:

1. **H1d:** When incorporating knowledge of AI applications into the knowledge base of a firm, the positive moderating effect of being a latecomer firm on productivity is more pronounced for smaller firms.
2. **H2d:** When incorporating knowledge of AI methods into the knowledge base of a firm, the positive moderating effect of being a frontier firm on innovative output is more pronounced for larger firms.

3 Data and methods

3.1 Data

To analyse the hypotheses, two extensive databases are connected. For the analysis of the firm characteristics, the ORBIS database, containing enterprise data of over 300 million firms worldwide, is used. This database provides information on the size of firms as well as their growth in terms of the number of employees and revenue. To assess the knowledge base of firms and their integration of AI technologies, patent data retrieved from the European database PATSTAT is used.

We extract all patents applied for at the European Patent Office (EPO) from applicants with an address within the 28 member states of the European Union between the years 2010 and 2017. The analysis is based on the patent family level and not on the individual patent application level to avoid an exaggerated count of patents. The DOCDB family ID is used and describes simple patent families, where each family contains only equivalent documents (Kang and Tarasconi, 2016). In total, 764,856 patent families are observed. There are two different methods of identifying AI patents. One approach is based on the CPC or IPC classification of patents; the G06N category is generally used in this case (Tseng and Ting, 2013; Motohashi, 2018; Fujii and Managi, 2018). The other approach is a text-based approach (see, e.g., Cockburn et al., 2018; Miyazaki et al., 2018). To identify AI patents, we conduct a keyword search in the abstract and title of the patents as well as use the CPC and IPC classification. For the specific search string, the WIPO report on AI is used (World Intellectual Property Organization, 2019), which allows us to divide AI patents into AI methods and AI applications to account for the two theoretical frameworks applied in this paper. In total, 6,419 patent families are identified as AI patents.

To retrieve firm-level data via the ORBIS database, every patent application of the 764,856 patent families extracted from PATSTAT is used to identify the affiliated organisations of the specific patent in the ORBIS database. In total 79,698 firms are identified and downloaded. Based on the patent application number, the firms are matched with the corresponding family ID to identify patent and AI patent counts for each firm. The final dataset is a panel set of EU firms that applied for a patent between 2010 and 2017, with an entry for each firm and each year of the sample period.

3.2 Operationalisation

To assess the stated hypotheses, the productivity and the innovative output of firms have to be operationalised.

Productivity (*Prod*) is calculated as labour productivity, using the formula below, where a firm i in the year t generates a specific revenue (*Rev*) that is divided by the number of employees (*Emp*) in said year (1). The innovative output is measured through the number of patent applications in a year t per firm i ($Pat_{t,i}$). Although patent data is not a perfect measure of innovativeness or innovative output, it provides unique information to analyse the process of technical change (Griliches, 1990).

$$Prod_{t,i} = \frac{Rev_{t,i}}{Emp_{t,i}} \tag{1}$$

In this paper, we identify firms that integrate AI into their knowledge base through their patent portfolio. If a firm has an AI patent in a specific year, it is expected to have integrated the knowledge of AI into its own knowledge base. The number of AI patents indicates the amount of AI knowledge a firm has. Thus, two count variables are constructed, measuring the number of AI method patents ($AI\ method_{t,i}$) and AI application patents ($AI\ application_{t,i}$) of a firm.

To identify the global frontier and assess which firms are latecomer firms and which are frontier firms, sector-specific firm labour productivity is used. Following Iacovone and Crespi (2010), a 25% boundary is applied for the entire set of firms within each NACE Rev. 2 core industry for each individual year. This means that the upper 25% of all firms in the dataset are classified as a global frontier firm per year. Next, the distance of the individual $Prod_{t,i}$ of each firm in each year to the global frontier of its sector ($distGLOBAL_{t,i,s}$) is calculated, subtracting the individual labour productivity ($Prod_{t,i}$) from the breaking point of the 75% quantile of the global frontier per year ($BoundaryGLOBAL_{0,75,t}$).

$$\begin{aligned} disGLOBAL_{t,i,s} = &BoundaryGLOBAL_{0,75,t,s} \\ &- Prod_{t,i} \end{aligned} \tag{2}$$

Last, a variable indicating the size of a firm is included. This variable reflects the count of 1,000 employees ($N.\ of\ Employees\ in\ 1{,}000_{t,i}$) of a firm in a given year. The variable is included, as different productivity (Dhawan, 2001; Díaz and Sánchez, 2008) and patent (Goode and Stevens, 2000; Rogers, 2002) behaviour are expected for different firm sizes. The variable is also used to account for the assumed interaction effects in the hypotheses.

To account for influences outside of our hypotheses, we include control variables. First, the total patent count of a firm at the year *t-1* is included to control for the general innovativeness of a firm, as we expect that labour productivity is highly influenced by a firm's previous R&D effort (Hall et al., 2013). Second, we account for the age of a firm, subtracting the year of foundation from the year of observation ($Age_{t,i}$), as firms with different ages tend to have different patent activity (Huergo and Jaumandreu, 2004b) and productivity (Huergo and Jaumandreu, 2004a; Coad et al., 2013). We also do this to account for the fact that younger firms that undertake R&D activity possibly have a more volatile growth trajectory (Coad et al., 2016). Third, the industrial sector plays an important role in assessing trajectories and technological opportunities. Each sector differs regarding the used technologies, the nature of customers and the kind of competition (Malerba and Nelson, 2011). These characteristics together with the technological regimes are important for the catching-up of firms (Lee and Lim, 2001). Because of this, an additional control of the NACE Rev. 2 classification of sectors is used based on two digits ($NACE2_{t,i}$). Last, a dummy variable for each country is applied to account for country-specific circumstances and regimes, following Malerba and Nelson (2011), who highlight the importance of country-specific conditions.

3.3 Methods

First, we conduct a propensity score matching of firms (Rosenbaum and Rubin, 1983; Abadie and Imbens, 2016), as there are potential selectivity and simultaneity biases based on the possibility that productivity growth as well as AI inventions could be explained by firm size and other variables. While large firms have a higher liquidity and are therefore able to invest more in R&D (Rogers, 2002), there could be a problem of endogeneity. Firms with higher liquidity are firms that file AI patents and perform well in the market, thus making them the firms with the highest growth. To account for these biases, identical matches are identified for each AI-inventing firm, following Randolph and Falbe (2014). The matching employs a dummy variable as the dependent variable that indicates whether a firm

Table 1 Propensity score matching

	Means			Matched Means		
	Treated	Control	Difference	Control	Difference	Percent Improvement
Distance	0.1834	0.0052	0.1620	0.0388	0.1435	18.9
N. of Patents $_{t-1,i}$	168.7114	1.3214	167.3900	12.6255	145.2664	6.8
Prod $_{t,i}$	3311.5742	493.7950	2817.7792	1176.9376	2090.3660	24.2
Age $_{t,i}$	39.5503	23.3466	16.2037	30.5584	8.9919	44.5
N. of Employees in 1000 $_{t-1,i}$	25.8152	0.8784	24.9367	5.1740	9.2330	17.2

Table 2 Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Labour Productivity$_{t0,i}$	894	1238.880	11,330.850	1.451	124.046	354.407	259,187.400
N. of Patents$_{t0,i}$	894	7.628	37.584	0.000	0.000	0.750	542.750
AI methods$_{t-1,i}$	894	0.423	2.362	0	0	0	51
AI application$_{t-1,i}$	894	0.331	2.059	0	0	0	33
Dist. to Global Frontier$_{t-1,i,s}$	894	113.386	96.522	0.000	0.000	194.004	303.772
N. of Patents$_{t-1,i}$	894	38.640	208.947	0	0	3.5	3772
N. of Employees in 1000$_{t-1,i}$	894	8.614	41.549	0.001	0.018	1.054	628.115
Firm Age$_{t-1,i}$	894	32.0,57	45.076	0	9	40	679

has filed an AI patent application within the first years of the dataset (2010 to 2014). A logistic model is calculated, using the means of each individual firm for the first two years of the dataset as independent variables (2010 and 2011) to allow for a reasonable time lag between the matching and the final analysis. The following variables are used as independent variables to identify the matches: labour productivity, the number of patents, firm age, and the number of employees. The country and sector of a firm are included as well. Afterwards, a propensity score matching based on the nearest neighbour algorithm is applied with a ratio of 1 to 5, meaning that for every firm in the treatment group, five firms in the control group are selected. Table 1 shows the means of the treatment and control groups with and without the matching.[1] The matching results indicate an improvement of the mean difference between the control group and the treatment group. The distance of the groups is improved by 18%, having the greatest increase in the number of the employees. The dataset is structured as an unbalanced panel, as there are many missing values, especially for the number of employees and the revenue of a firm and therefore the labour productivity. To overcome the issues of missing values and the many problems that arise with using a panel regression within this dataset, an ordinary least squares (OLS) regression is conducted, which considers the sum of all AI application and method patents between 2010 and 2014 and the control variables based on the means of the years 2010 and 2011. To assess the two sets of hypotheses — one that concerns the influence of AI on innovative output and one that addresses the influence of AI on labour productivity — we conduct two sets of regressions. The first set of regression models includes the mean labour productivity of a firm in the years 2015 to 2018 as the dependent variable ($Prod_{t,i}$). As independent variables, the two constructed AI variables are also used as the mean-centred distance to the global productivity frontier and the number of employees. Additional controls are the number of patent applications and firm age as means in the years 2010 and 2011, as well as the country of a firm and its sector based on NACE Rev. 2 core sections. A dummy variable based on the BvD independence indi-

[1] To test the robustness of the propensity score matching employed here, it was also tested with different ratios (1 to 1 and 1 to 10). The results remain consistent.

cator showing whether a corresponding firm is independent and does not belong to a corporate structure (0) or not (1) is also included, following previous studies (e.g. Grashof, 2021; Grashof and Kopka, 2022). The independence indicator is measured by the number of shareholders and the percentage of their individual and collective holdings. The hypotheses also include two-way interaction effects (H1b and H1c), as well as three-way interaction effects (H1d).

For the second set of hypotheses that involves the influence of AI on the innovative output of a firm, the previously presented regression equation is altered; in this regression, the logged mean number of patent applications in the years 2015 to 2018 is used as the independent variable.[2] We do not change the controls. This approach follows Audretsch and Belitski (2020) very loosely, as it analyses innovation (through patents) and productivity (through labour productivity) separately, while including the impact of innovation on productivity in the productivity equation.[3] Table 2 reports the descriptive statistics of the final dataset after the propensity score matching with all employed variables. Next, the results of the analysis are presented, interpreted, and discussed.

4 Results

We first present a brief overview of patent development in the field of AI. Specifically, we discuss which types of firms file AI patents in terms of firm size and distance to the productivity frontier. Figure 1 shows the share of AI-inventing firms across all years based on the number of employees, split into AI application and AI method patents. Larger firms are more active in terms of AI patent applications, even though the number of larger firms is significantly smaller than that of smaller firms. Smaller firms, while being the largest group of firms, have the lowest AI patent activity in both areas. This first result shows a problem that will arise in the regression analysis. While trying to determine what effects AI patent applications have on a firm, it is equally important to determine who the AI-inventing firms are. As stated above, this why we conduct propensity score matching. Another expected result is the scarcity of AI patent applications across all firms. The share of AI-inventing firms ranges from 0.1% for the firms with only one employee up to a share of 15% for firms with more than 10,000 employees. Thus, AI patenting is still a very rare event, even during the rapid growth of the third boom, and is concentrated among larger firms.

When looking at the share of AI patent inventors across different distances to the global productivity frontier, the share of AI inventors is higher among firms that are closer to the global frontier. However, this relationship does not seem to be exactly linear. The share of AI inventors again increases among firms that are far away from the frontier. This effect can be found for both AI types, but is more pronounced for AI application patent inventors that are far away from the frontier. The general results support the above-mentioned concerns about selection and endogeneity biases, which implies the importance of the matching process undertaken (Fig. 2). Further visualisation of the sample can be found in the Appendix, which shows the distribution across countries as well as industries (see Appendix B).

To test the hypotheses, we next present and discuss the regression results. First, the hypotheses of H1 are analysed. Second, the results for the second set of hypotheses are shown (H2). For each of the sets of hypotheses, four models are calculated. Model (1) only includes the control variables. Model (2) includes the addition of both AI variables (AI method patents and AI application patents). In model (3), the different two-way interaction effects are considered. In model (4), the three-way interaction effects are considered.

Table 3 shows the results for the first set of hypotheses. First, when considering the control variables, the distance to the global frontier has a negative impact on labour productivity. In addition, the number of patents of a firm positively influences its labour productiv-

[2] We use the logged mean number of patent applications because the distribution of the variable follows a negative binomial pattern, even though it is not a count variable. As a robustness check, we include a negative binomial count model using the ceiling of the mean number of patent applications as the dependent variable. The results can be found in the Appendix. Furthermore, we check for zero-inflation with the Vuong test. The results of this test indicate that there is no zero-inflation. This can be explained through the matching process in which we match AI-inventing firms with non–AI-inventing firms.

[3] We calculate the variance inflation factor for each control variable in the second model to test for multicollinearity, as this model includes all explanatory and control variables but not the interaction effects. There is no indication of problems with multicollinearity. We observe the highest variance inflation factor of 2.64 for the number of patents. Including interaction effects in models (3) and (4) naturally increases the variance inflation factors.

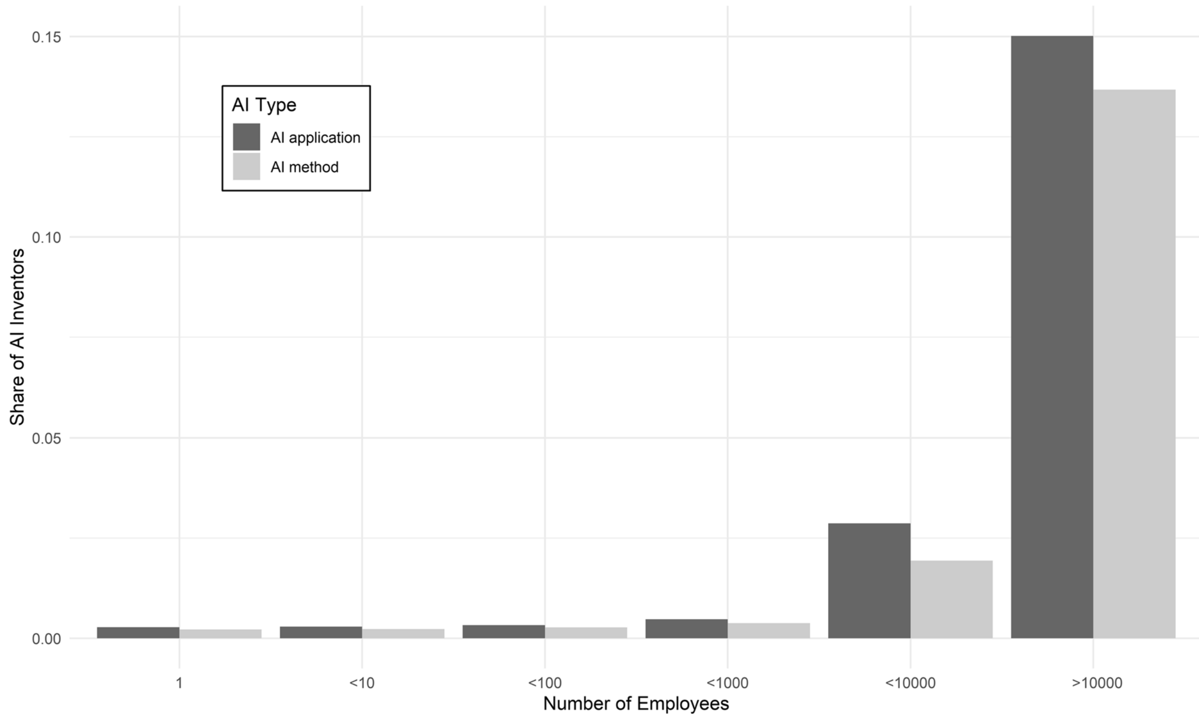


Fig. 1 Share of AI-inventing firms on all firms for specific firm sizes

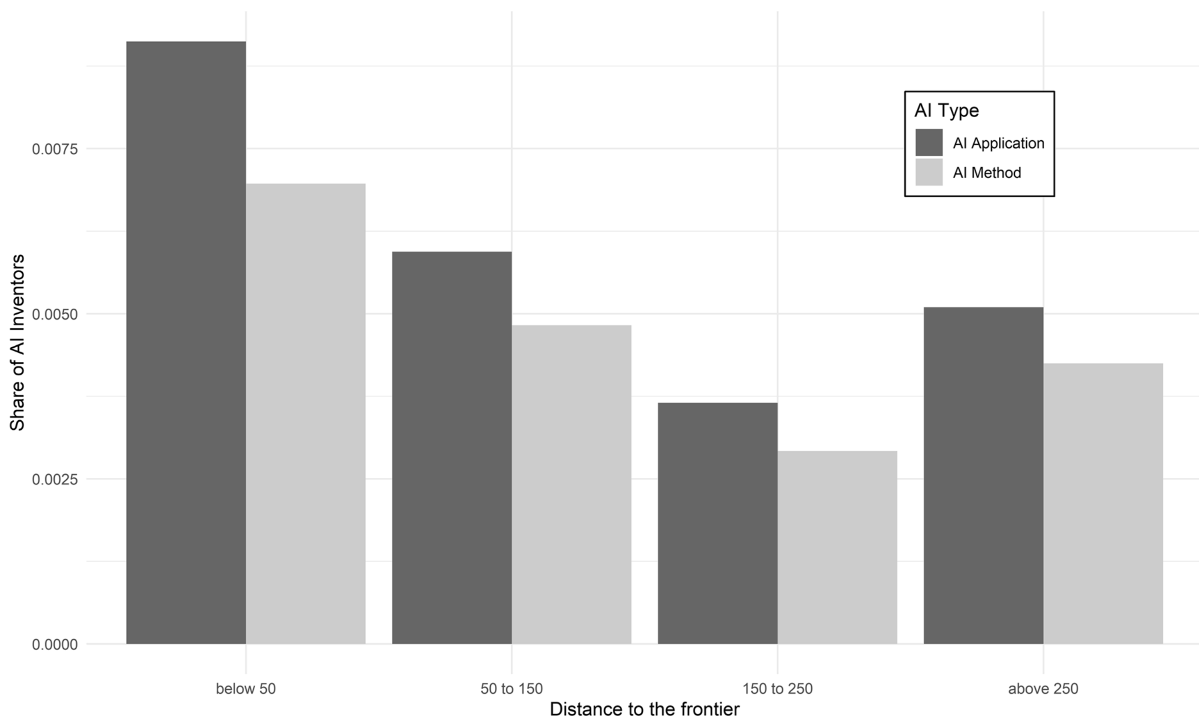


Fig. 2 Share of AI-inventing firms on all firms for specific distances to the frontier

Table 3 Regression results — Part I

	Dependent variable: Prod$_{t,i}$			
	(1)	(2)	(3)	(4)
AI methods$_{t-1,i}$		156.761 (223.202)	1804.839*** (397.808)	2528.727*** (403.623)
AI application$_{t-1,i}$		−524.188** (220.893)	−1037.408** (475.507)	−1062.168* (560.866)
Dist. to Global Frontier$_{t-1,i}$	−13.210*** (4.113)	−13.010*** (4.105)	−7.597* (4.118)	−6.166 (4.058)
N. of Patents$_{t-1,i}$	6.507*** (1.940)	8.140*** (2.605)	8.320** (3.278)	19.044*** (3.712)
N. of Employees in 1000$_{t-1,i}$	−29.581*** (10.015)	−28.888*** (10.017)	−26.556*** (10.015)	−20.259 (19.413)
Firm Age$_{t-1,i}$	3.783 (8.468)	6.724 (8.546)	6.522 (8.395)	0.838 (8.291)
BvD Independence$_i$	642.068 (1127.491)	674.877 (1126.776)	839.671 (1106.915)	120.745 (1083.834)
AI methods$_{t-1,i}$*N. of Employees in 1000$_{t-1,i}$			4.052** (1.585)	−27.382*** (4.922)
AI application$_{t-1,i}$*N. of Employees in 1000$_{t-1,i}$			−2.671 (2.749)	3.216 (7.711)
AI methods$_{t-1,i}$*Dist. to Global Frontier$_{t-1,i}$			−29.558*** (5.104)	−39.860*** (5.246)
AI application$_{t-1,i}$*Dist. to Global Frontier$_{t-1,i}$			11.430* (5.926)	14.877** (6.671)
Dist. to Global Frontier$_{t-1,i}$ *N. of Employees in 1000$_{t-1,i}$				0.026 (0.094)
AI methods$_{t-1,i}$*Dist. to Global Frontier$_{t-1,i}$ *N. of Employees in 1000$_{t-1,i}$				0.288*** (0.043)
AI application$_{t-1,i}$*Dist. to Global Frontier$_{t-1,i}$ *N. of Employees in 1000$_{t-1,i}$				−0.120* (0.067)
Constant	535.989 (5148.972)	263.907 (5139.561)	−908.616 (5012.821)	194.139 (4889.982)
Country	Yes	Yes	Yes	Yes
NACE Rev. 2	Yes	Yes	Yes	Yes
Observations	894	894	894	894
R^2	0.243	0.248	0.289	0.327
Adjusted R^2	0.216	0.220	0.259	0.296
Residual Std. Error	10,030.430 (df = 863)	10,009.240 (df =861)	9756.138 (df= 857)	9508.153 (df = 854)
F Statistic	9.219*** (df = 30; 863)	8.856*** (df = 32; 861)	9.654*** (df = 36; 857)	10.620*** (df = 39; 854)

*p<0.1; **p<0.05; ***p<0.01

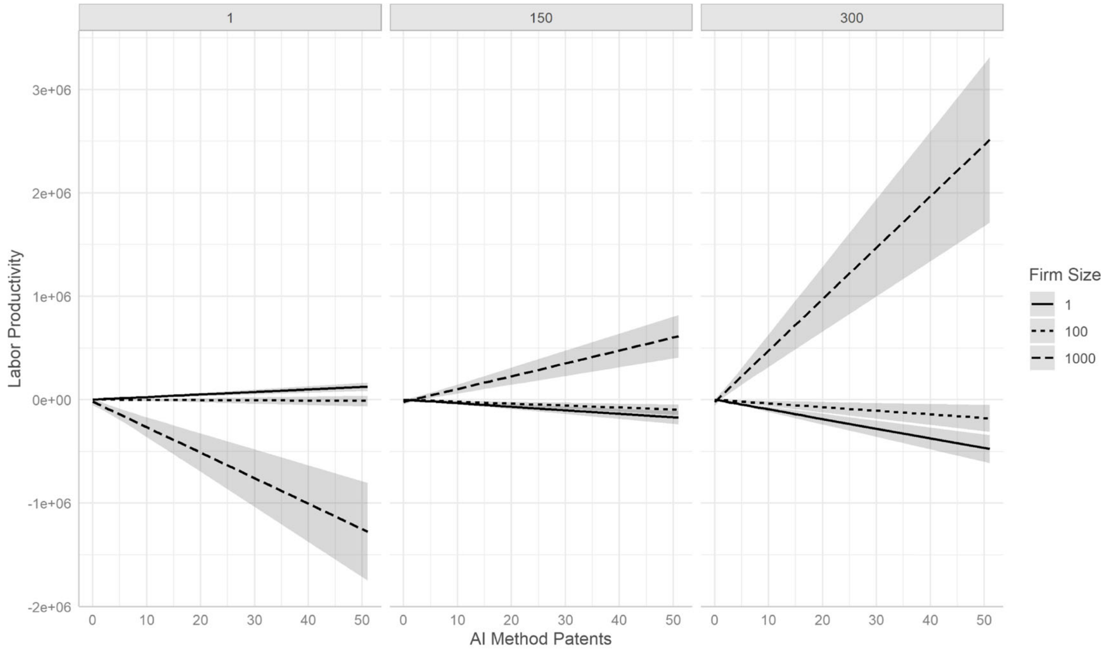
ity while the number of employees negatively impacts labour productivity. All these results are expected by the extant theory presented in Section 2. Interestingly, we did not find a significant impact of firm age nor of the independence dummy of a firm on labour productivity.

Regarding the first hypothesis (H1a) about the influence of AI application patents, there is no evidence of a direct positive influence. Moreover, all three models show a negative and significant impact of AI application patents on productivity. However, if we consider the two-way and three-way interactions, there seems to be a hidden mechanic in place, when just looking at the direct influence of AI application patents. In summary, there is no evidence to support H1a.

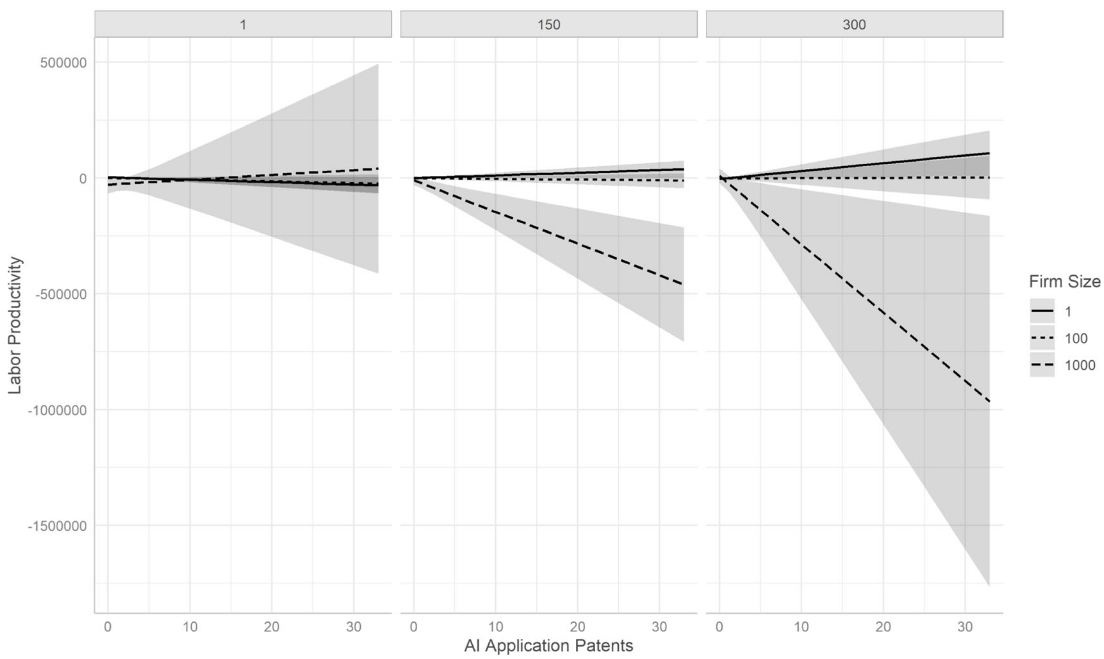
H1b and H1c consider the two-way interaction effects between AI application knowledge and firm distance to the global frontier, as well as firm size. When looking at the third model, which includes the two-way interactions, the effect of AI application knowledge becomes clearer. The first result shows that there is no indication of a two-way interaction effect between firm size and additional AI application patents of a firm. Therefore, hypothesis H1c must be rejected, as including knowledge of artificial Intelligence applications into the knowledge base of a firm does not have a higher positive effect on the productivity of smaller firms in comparison to larger firms. However, the interaction effect between the distance to the global frontier and AI application patents is significant and positive (at a 10% significance level), indicating that the further away a firm operates from the global frontier, the more positive the impact of AI on labour productivity becomes; thus, there is evidence in support of H1b.

The last hypothesis in this set considers the three-way interaction between the firm size, the distance to the frontier and the number of AI application patents (H1d). Figure 3 shows the marginal effects of this three-way interaction effect as well as the three-way interaction effect with the variable for AI method patents for comparison. This figure shows in the case of AI application patents, that there is a diverging trend for different firm sizes and distances to the frontier. The greater the distance to the frontier and the larger the firm, the more negative the impact of AI application patents is on the labour productivity of a firm. In contrast, smaller firms experience a positive impact if their distance to the frontier is large enough. Therefore, larger firms tend to be negatively impacted by AI application patents when they operate further from the frontier, while smaller firms tend to be positively impacted when they are considered as latecomers. This result in itself is interesting enough, but the marginal effects of the other three-way interaction effect for AI method patents show completely opposite behaviour. Larger firms tend to benefit greatly from AI method patents if they operate at a larger distance to the global frontier, while suffering a negative impact when they operate closer to the frontier. The opposite effect can be observed for smaller firms, even though it is smaller in scale. In summary, H1d cannot be rejected, as there is strong evidence of a three-way interaction between a firm's size, its distance to the frontier and its number of AI application patents.

The second set of hypotheses addresses the influence of AI knowledge on the general innovativeness of a firm. Table 4 shows the regression results of this analysis. Starting with the control variables, the distance to the global frontier shows a negative and significant influence on the number of patents in all models, while the number of patents has a positive and significant effect in all models. Hence, firms further from the frontier file fewer patents, while those already active in patenting remain active. In models (3) and (4) the size of the firm shows evidence of positively impacting the patent count of firms. This effect, however, is not robust across all models. Firm age does not significantly influence a firm's patent count at all. In addition, not being independent negatively influences a firm's patent count in some of the models (1+2). Considering the hypotheses, the expected results are different from the previous regression analysis using labour productivity as the dependent variable. In contrast to AI applications, AI method patents are expected to have a positive impact on the innovative output of a firm, as these could enhance innovativeness as IMIs. The results of the direct effect of AI method patents do not support hypothesis H2a. The variable is only positively significant in model (4), but not without the interaction effects in model (2). Hence, there does not seem to be a direct effect of AI method knowledge on firm innovativeness in terms of a higher patent output. Thus, H2a must be rejected. In addition, the results for the two-way interaction between the distance to the global frontier and the number of AI method patents show that the higher the distance to the frontier, the higher the impact of AI method patents. Thus, the results are opposite of the expected outcome formulated in H2b, resulting in the rejection of this

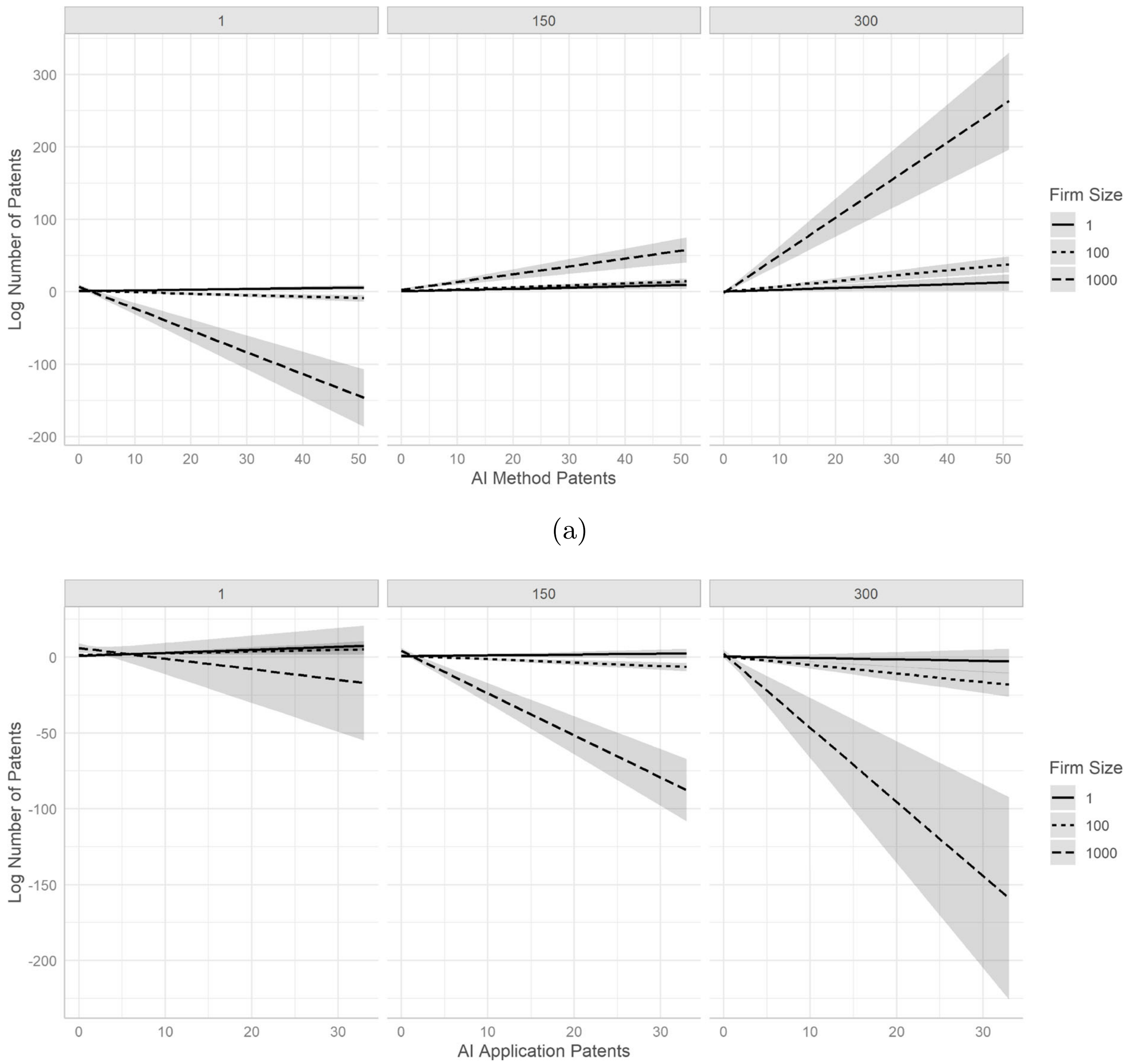


(a)



(b)

Fig. 3 The first plot (a) shows the marginal three-way interaction effects with AI method patents, while plot (b) shows the effects with AI application patents. The three lines indicate different firm sizes based on the number of employees. The subplots show the moderating effects of the firm size on the predicted labour productivity over different distances to the global frontier (1 = nearly at the frontier, 150 = medium distance, 300 = large distance)



(b)

Fig. 4 Marginal effects of the three-way interactions for regression results — Part II

hypothesis. The next hypothesis addresses the moderating effect of firm size on the effect of AI method patents on the number of patents of a firm. The coefficient is not significant in model (3) and is negative and significant in model (4). Thus, there is either no effect or a negative effect of AI method patents for larger firms on the patenting activities. Therefore, H2c must be rejected. As the last hypothesis in the second set, the three-way interaction between the firm size, the distance to the frontier and the number of AI method patents is analysed (H2d). Figure 4 shows the marginal effects of this interaction effect together with the three-way interaction effect of AI application patents to compare the results. Both interaction effects are significant in model (4). Figure 4 clearly shows that the previous results regarding the conditional effects of AI method patents have to be relativised. There is a diverging trend for the conditional effect, based on firm size and distance to the frontier. For firms that are close to the frontier, firm size negatively moderates the effect of AI method patents on the number of patents of a firm; conversely, with increasing distance, the moderating effect becomes positive. In comparison, the effect of AI application patents is opposite to this observed behaviour, even though for the case of frontier firms it is not as strong, indicating more variance through the confidence intervals of large firms. However, the further a firm is from the frontier, the greater the negative effect of AI application patents, with this becoming even more pronounced for larger firm sizes. The results show an opposing trend when examining AI method and AI application patents, which is the same behaviour shown in the previous results regarding labour productivity. Ultimately, H2d has to be rejected, as large frontier firms experience a negative impact of AI method patents on their patent count. Nevertheless, there is strong evidence of a three-way interaction between a firm's size, its distance to the frontier and its number of AI method patents.

5 Interpretation and discussion

Assessing the first set of hypotheses regarding the labour productivity, we do not observe a direct positive impact of AI application patents on labour productivity — on the contrary, we find a negative direct impact. There are several possible reasons for this finding. First, due to the integration of AI into the knowledge base of a firm, additional highly qualified human capital is required to operate the technology, as AI and specifically DL and ML are new technologies. Any positive effects on the revenue of a firm through the integrating of AI into the knowledge base may be offset by the need for additional human capital. This could be an explanation for the lack of a direct impact of AI patents on labour productivity in the short run, even if there are assumed positive effects on the revenue. Second, the short timeframe of the study must be considered. Given the fact that the third boom of AI is a recent phenomenon, and consequently the short timeframe in the study, efficiency improvements through integrating AI into the knowledge base of a firm may need additional time to come to fruition. The tacit knowledge of AI must first diffuse within a firm, leading to a plateau in the productivity growth during the learning phase. This effect can be observed, for example, in the integration of new platform technologies within an organisation (Blancett, 2002). Third, GPTs tend to lead to productivity slowdowns in their early stage of diffusion and only after surpassing a specific threshold do they generate productivity growth (David, 1990). The last two interpretations follow the work of Brynjolfsson et al. (2018), who associated the stagnation in production growth with the time lag between the implementation and effect of AI. While Damioli et al. (2021) actually did find a significant impact of artificial intelligence patents in general on the labour productivity of firms, this effect applies mostly in the service sector. Furthermore, they did not differentiate between method and application patents, and we find that AI method patent applications do increase labour productivity. Rammer (2020) found that the implementation of AI increases the labour demand and revenue does not necessarily increase with the usage of AI. This paper follows the argument of Brynjolfsson et al. (2018).

The hypothesis stating that especially small firms can gain productivity from investing in AI application patents cannot be confirmed when only two-way interactions are considered. This can again be explained by the relatively costly investments in highly qualified human capital, which might disproportionally increase costs for small firms. However, the distance to the frontier positively moderates the effects of AI application patents on productivity, as we assume in our hypothesis. Although global frontier firms presumably already have a higher stock of human capital (Vandenbussche et al., 2006), even these firms might need to employ more specialised human capital to be able to integrate AI applications and increase turnover. However, the leapfrogging effect for firms far from the technological frontier seems to be extremely high. This shows up again in the three-way interaction. Small firms far from the frontier should aggressively invest in AI application patents — they have a flat internal structure and high flexibility to change their business model in a way that allows them to gain the most from AI applications. The opposite holds true for large firms far from the frontier. As large firms are often more hierarchical and adapt to new possibilities slower than small firms (Rogers, 2002), the observed negative mediating role could be explained due to the newness of AI and the recent advances made in this field. This is especially true when one considers the fact that AI is not widespread at the moment (see Figs. 1 and 2) and thus smaller firms may better perceive the changes that are arising. The path dependencies in these firms regard-

Table 4 Regression results — Part II

	Dependent variable: log($Pat_{t,i}$ + 1) (1)	(2)	(3)	(4)
AI methods$_{t-1,i}$		0.024 (0.020)	0.034 (0.033)	0.108*** (0.034)
AI application$_{t-1,i}$		0.030 (0.020)	0.241*** (0.040)	0.204*** (0.047)
Dist. to Global Frontier$_{t-1,i}$	−0.003*** (0.0004)	−0.003*** (0.0004)	−0.002*** (0.0003)	−0.002*** (0.0003)
N. of Patents$_{t-1,i}$	0.003*** (0.0002)	0.002*** (0.0002)	0.004*** (0.0003)	0.005*** (0.0003)
N. of Employees in 1000$_{t-1,i}$	0.001 (0.001)	0.001 (0.001)	0.003*** (0.001)	0.007*** (0.002)
Firm Age$_{t-1,i}$	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	−0.00002 (0.001)
BvD Independence$_i$	−0.222** (0.102)	−0.214** (0.102)	−0.077 (0.093)	−0.140 (0.090)
AI methods$_{t-1,i}$*N. of Employees in 1000$_{t-1,i}$			−0.0002 (0.0001)	−0.003*** (0.0004)
AI application$_{t-1,i}$*N. of Employees in 1000$_{t-1,i}$			−0.002*** (0.0002)	−0.001 (0.001)
AI methods$_{t-1,i}$*Dist. to Global Frontier$_{t-1,i}$			0.001*** (0.0004)	0.0005 (0.0004)
AI application$_{t-1,i}$*Dist. to Global Frontier$_{t-1,i}$			−0.002*** (0.0005)	−0.001* (0.001)
Dist. to Global Frontier$_{t-1,i}$*N. of Employees in 1000$_{t-1,i}$				−0.00002*** (0.00001)
AI methods$_{t-1,i}$*Dist. to Global Frontier$_{t-1,i}$				0.00003*** (0.00000)
*N. of Employees in 1000$_{t-1,i}$				
AI application$_{t-1,i}$*Dist. to Global Frontier$_{t-1,i}$				−0.00001** (0.00001)
*N. of Employees in 1000$_{t-1,i}$				
Constant	1.307*** (0.464)	1.316*** (0.463)	1.231*** (0.421)	1.282*** (0.407)
Country	Yes	Yes	Yes	Yes
NACE Rev. 2	Yes	Yes	Yes	Yes
Observations	894	894	894	894
R^2	0.460	0.463	0.559	0.590
Adjusted R^2	0.441	0.443	0.541	0.572
Residual Std. Error	0.904 (df = 863)	0.902 (df = 861)	0.819 (df = 857)	0.791 (df = 854)
F Statistic	24.479***	23.224***	30.235***	31.569***
	(df = 30; 863)	(df = 32; 861)	(df = 36; 857)	(df = 39; 854)

*p<0.1;**p<0.05; ***p<0.01

ing structures, processes and markets are opposing the effective integration and use of AI applications leading to higher costs due to investments in AI application patents without increasing turnover accordingly.

Considering the second set of results of the analysis regarding innovativeness, a straightforward interpretation of the direct impact of AI method patents on the number of patents of a firm is not possible. Neither the AI applications patents as discussed above, nor the AI method patents have a direct influence. This is an important finding since it shows that firms should not follow the herd and blindly invest in AI applications or methods, but should instead thoroughly analyse their specific situation.

In the twofold analysis we cannot identify a moderating effect of firm size on AI method patents and patenting activities. Hence, firm size does not matter. However, the distance to the frontier is a relevant moderating variable. Regarding the distance to the frontier, latecomer firms benefit more from the integration of AI method knowledge into their knowledge base. This gives credit to the theory that latecomer firms can technologically catch up to the frontier because of being able to pursue technological opportunities better.

Large firms far from the frontier are able to use the knowledge of AI methods to generate new innovations that are built upon or use the knowledge in a knowledge creation process. Thus, we can assume that for these firms, AI can be seen as an IMI and has a strong impact on the innovative process. A reason for this finding can be based on the potential of large firms to organise R&D processes. This capability can now be combined with AI methods leading to an increase in the number of patents. Latecomer firms, in contrast, have the potential to venture into new markets and fields, leading to the combination of more diverse knowledge and thus to more innovations. One explanation for the lack of benefit for large frontier firms could be that they already are more innovative than latecomer firms and have already accumulated a great amount knowledge, which makes further advancements in their field more difficult (Bloom et al., 2020).

The diverging results between AI method and AI application patents in the mediating effect of firm size and distance to the frontier are very interesting. First, large latecomer firms strongly benefit from investing in AI methods to increase both productivity and innovative output. Second, smaller firms can profit from investments in AI methods and through this can at least increase their patent counts — the stronger the further away from the frontier they are. Third, firms of all sizes at the frontier — or at least firms that are not latecomers — can gain the most in terms of productivity and patents if they invest in AI applications. These frontier firms may be more capable of reaping the benefits of learning-by-doing, as they likely have more human capital as well as more established heuristics, leading to them being able to generate innovations from these learning processes.

In summary, we can conclude that the integration of AI into the knowledge base of a firm does not always have positive effects on labour productivity or the innovative output. The interplay between the distance to the frontier, the type of technology that is integrated and the size of the firms play a major role here. AI method knowledge does behave differently and even opposite to the AI application knowledge.

6 Conclusion

This paper advances the growing body of theoretical literature on the impacts of AI (Brynjolfsson et al., 2018; Agrawal et al., 2019b; Cockburn et al., 2018; etc.) with empirical evidence by analysing the effects of the integration of AI into the knowledge base of smaller and larger firms on their labour productivity and patent behaviour while considering the position of the firm in relation to the productivity frontier. As, empirical research on the impact of AI has just recently gained attention (see, e.g., Alderucci et al., 2020; Damioli et al., 2021), to our knowledge, no study in the extant literature has combined the theoretical background of AI with the catch-up hypothesis and firm size arguments.

This paper follows the theory that AI can be considered both a GPT as well as an IMI. These two theoretical constructs imply that AI methods as IMIs generate inventions, while AI applications as GPTs generate productivity growth through revenue or increased efficiency. Thus, we analyse AI methods and AI applications separately.

A particular emphasis is placed upon the catch-up potential of smaller and latecomer firms through integrating AI into their knowledge bases, which opens up the possibility of generating growth through emerging technologies. We discover several interesting findings. First, AI as a technology is still at an early stage of diffusion, as AI patent applications are rare events and the patents are mostly filed by larger firms. Second, there is no indication of a general positive productivity effect from the integration of AI application knowledge into the knowledge base of a firm for all firms, but some firms that are more distant to the global frontier can generate labour efficiency improvements through integrating AI application knowledge into their knowledge base. This only holds true for smaller firms. One possible explanation is that latecomer firms generally lack the human capital necessary for the implementation of AI application knowledge, but smaller firms are flexible enough to adapt to AI nevertheless, thus opening an opportunity to catch-up. We also find opposite diverging mediating effects of firm size and distance to the frontier for AI methods and AI applications, providing another possible explanation for the productivity paradox (Brynjolfsson et al., 2018), as it is possible that we do not observe productivity effects due to the heterogeneity of the effect of AI on productivity.

There is no evidence of a positive direct influence of the integration of AI into the knowledge base of a firm on its innovative output. However, the further away from the frontier a firm operates, the greater the positive impact of AI method patents on the innovative output. This effect becomes more pronounced with an increase in firm size. Here, we again observe this diverging pattern between AI application and AI method patents, showing the need for a finer grained analysis on the effects of AI as they seem not to be distinctly positive or negative.

In conclusion, our results suggest that large latecomer firms benefit the most from AI methods in terms of both productivity and innovativeness. In the case of AI applications, the impact becomes more negative the farther away a firm operates from the frontier and the larger it is. These two effects offset each other, leading to a weak observed direct effect of AI overall.

Some limitations must be considered regarding the findings of this paper. First, the data set employed in this study only provides information on the patent activity of a firm, this being a proxy for knowledge integration. This proxy could be misleading as there is no information reporting whether the patented inventions lead to different processes within firms. Second, the sample size is relatively small. With a higher number of observations and a longer timeframe, more robust results could be generated. Third, due to heteroscedasticity problems, all results must be taken with a grain of salt. Future research should try to address the obvious data problem, first regarding the operationalisation of the integration of AI into the knowledge base of a firm and second, regarding the short period of time that is analysed in this paper. In addition, questions remain about the drivers of adoption of AI knowledge, as well as the characteristics of AI-inventing firms. Furthermore, the presented research opens many implications for the specific influence of AI on different firm sizes and frontier or latecomer firms. In future research these implications should be assessed and analysed in more detail.

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Appendix A: Sample distributions

A Agriculture, forestry and fishing; **B** Mining and quarrying; **C** Manufacturing; **D** Electricity, gas, steam and air conditioning supply; **E** Water supply; sewerage, waste management and remediation activities; **F** Construction; **G** Wholesale and retail trade; repair of motor vehicles and motorcycles; **H** Transportation and storage; **I** Accommodation and food service activities; **J** Information and communication; **K** Financial and insurance activities; **L** Real estate activities; **M** Professional, scientific and technical activities; **N** Administrative and support service activities; **O** Public administration and defence; compulsory social security; **P** Education; **Q** Human health and social work activities; **R** Arts, entertainment and recreation; **S** Other service activities; **T** Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use; **U** Activities of extraterritorial organisations and bodies;

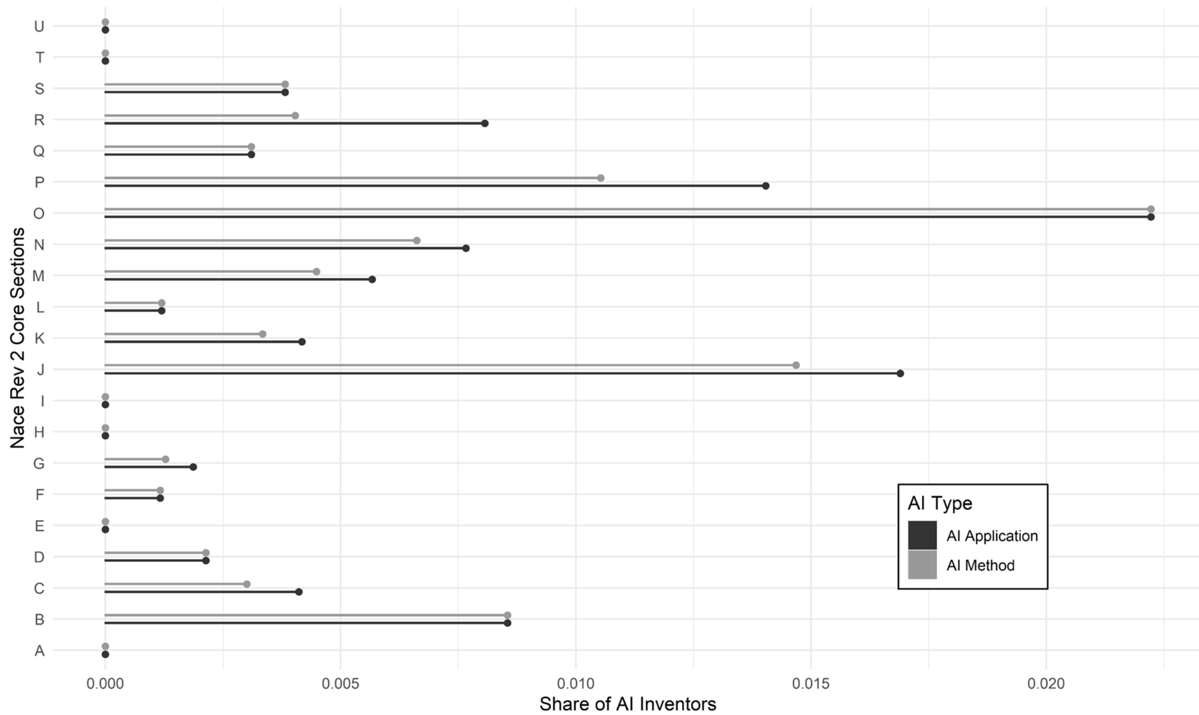

Fig. 5 Share of AI-inventing firms on all firms for each NACE Rev 2 Core sector

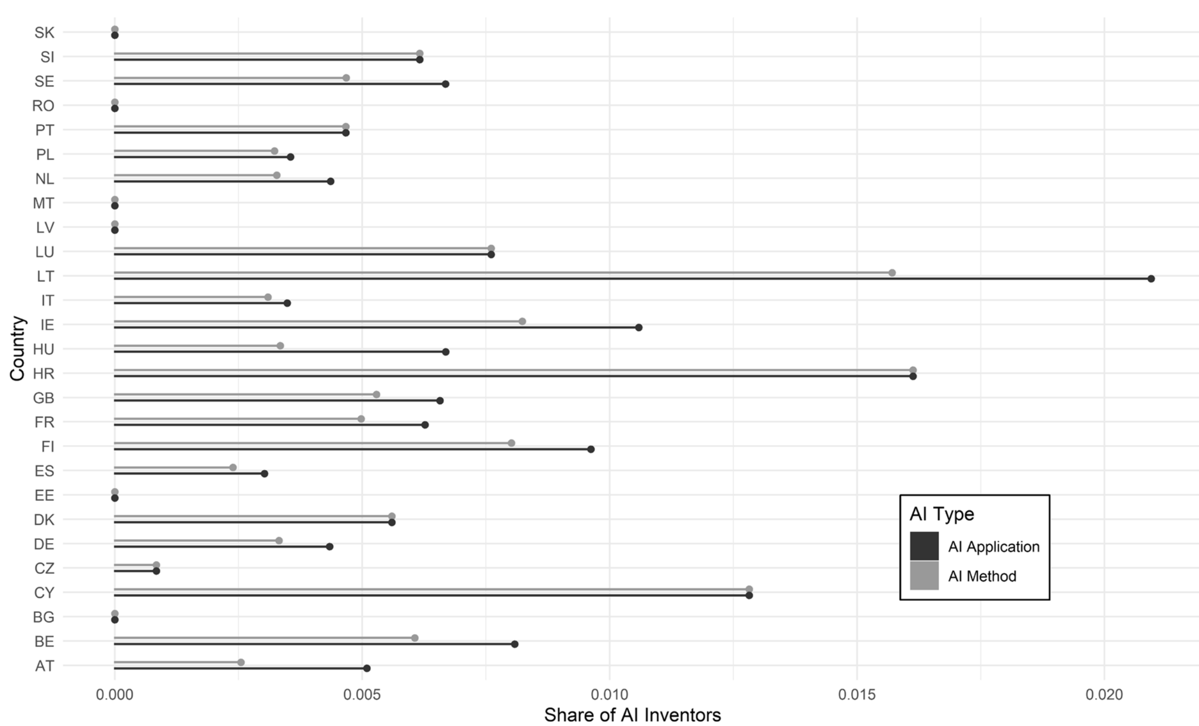

Fig. 6 Share of AI-inventing firms on all firms for each country

Appendix B: Negative binomial count model results

Table 5 Regression results - Part II

	Dependent variable: $\mathrm{Pat}_{t,i}$ (1)	(2)	(3)	(4)
AI methods$_{t-1,i}$		0.140*** (0.037)	0.250*** (0.064)	0.349*** (0.065)
AI application$_{t-1,i}$		0.017 (0.037)	0.178** (0.079)	0.041 (0.093)
Dist. to Global Frontier$_{t-1,i}$	−0.005*** (0.001)	−0.005*** (0.001)	−0.005*** (0.001)	−0.005*** (0.001)
N. of Patents$_{t-1,i}$	0.010*** (0.0003)	0.009*** (0.0004)	0.010*** (0.001)	0.011*** (0.001)
N. of Employees in 1000$_{t-1,i}$	0.004** (0.002)	0.003 (0.002)	0.008*** (0.002)	0.024*** (0.003)
Firm Age$_{t-1,i}$	0.002 (0.001)	0.003* (0.001)	0.002 (0.001)	0.001 (0.001)
BvD Independence$_i$	−0.086 (0.213)	−0.076 (0.213)	−0.102 (0.205)	−0.091 (0.204)
AI methods$_{t-1,i}$*N. of Employees in 1000$_{t-1,i}$			−0.001*** (0.0003)	−0.011*** (0.001)
AI application$_{t-1,i}$*N. of Employees in 1000$_{t-1,i}$			−0.004*** (0.0004)	0.003** (0.001)
AI methods$_{t-1,i}$*Dist. to Global Frontier$_{t-1,i}$			0.001 (0.001)	0.0002 (0.001)
AI application$_{t-1,i}$*Dist. to Global Frontier$_{t-1,i}$			0.0004 (0.001)	0.001 (0.001)
Dist. to Global Frontier$_{t-1,i}$*N. of Employees in 1000$_{t-1,i}$				−0.0001*** (0.00002)
AI methods$_{t-1,i}$*Dist. to Global Frontier$_{t-1,i}$				0.0001*** (0.00001)
*N. of Employees in 1000$_{t-1,i}$				
AI application$_{t-1,i}$*Dist. to Global Frontier$_{t-1,i}$				−0.0001*** (0.00001)
*N. of Employees in 1000$_{t-1,i}$				
Constant	1.255 (0.928)	1.223 (0.926)	1.265 (0.894)	1.090 (0.872)
Country	Yes	Yes	Yes	Yes
NACE Rev. 2	Yes	Yes	Yes	Yes
Observations	894	894	894	894

Table 5 continued

	Dependent variable: $\text{Pat}_{t,i}$ (1)	(2)	(3)	(4)
Log Likelihood	−1572.592	−1568.328	−1542.708	−1528.064
θ	0.373***	0.377***	0.418***	0.449***
	(0.026)	(0.026)	(0.030)	(0.032)
Akaike Inf. Crit.	3207.184	3202.656	3159.416	3136.127

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