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The Development of AI in Multinational Enterprises – Effects upon Technological Trajectories and Innovation Performance

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Abstract

This paper investigates how the development of AI-related inventions by Multinational Enterprises (MNEs) affects their technological trajectories and innovative performance. I combine a matched-pair analysis with an extension of the Difference-in-Difference method to analyse these effects over a novel panel dataset of MNEs. This dataset links over 30 thousand MNEs to more than 10 million patents that these companies owned directly or indirectly (i.e., through their subsidiaries) in the period from 2011 to 2019. The results indicate that MNEs introducing AI-related inventions increase the relatedness of subsequent inventions by about 10 per cent compared to a control group. These results are robust when accounting for a self-selection bias. AI is thus being used to reinforce the existing technological trajectories, rather than to disrupt them. The results also suggest that the number of subsequent inventions is about 40 per cent higher for MNEs that introduce AI during the observation period compared to the control group, without significant effects on the intensity of R&D expenditures per invention. It is argued that this increase in innovative performance is linked not only to knowledge dynamics created by learning about AI but also by AI's technical potential to be used for learning.

Keywords

Technological trajectory; Relatedness; Artificial Intelligence; Innovative performance

JEL Classifications

D22; O14; O33; L25

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1. Introduction

So far, the digital transformation has been manifesting itself primarily by the diffusion of information and communication technologies (ICTs) in business and society (Alcácer et al., 2016). The industrial diffusion of technologies related to Artificial Intelligence (AI) represents a qualitatively new development in this current ICT paradigm. AI's transformative qualities arguably offer new opportunities that could significantly change firms' processes of technological development.

First, AI is a digital technology, meaning that it has particular properties linked to convergence and generativity that allow, among other things, its embeddedness into non-physical products and the emergence of combinatorial innovations (Yoo et al., 2012). Firms can use AI to transform their existing nondigital products into digital ones, and recombine them to create further innovations with new functionalities. Second, due to its power of classification and prediction, AI is expected to be an Invention of a Method of Invention (IMI). This refers to AI's potential to serve as a tool of 'automated discovery' across many knowledge domains, where it could be used to expand the set of problems that firms can feasibly address (Cockburn et al., 2018). Third, AI functions as an intelligent autonomous agent and is a modular technology (Nilsson, 2009), which can affect organisations' functions, processes, product functionalities, and competencies (Paschen et al., 2020). As a result, AI can both enhance or devalue the existing knowledge and skills held by companies (ibid).

These particularities lead to great expectations about AI's potential. The mastering of this technology is expected to give countries advantages over global markets and industries (Cave & ÓhÉigeartaigh, 2018; Cockburn et al., 2018; Klinger et al., 2018). At the firm level, AI is expected to increase productivity gaps, potentially leading non-adopters to lose large market shares or even to go out of business (European Commission, 2017). AI is also linked to the risk of unemployment due to its automation potential (Goralski & Górniak-Kocikowska, 2020; Iscan, 2021; Su, 2018). But these expectations miss the point that AI will have very distinct impacts across industries. The main argument of this paper is that AI's true potential depends on how much this technology can change the technological trajectories of a broad set of firms. The underlying premise is that most of AI's impact will not come from the most obvious affected business (e.g., digital platforms such as Facebook, Uber, Airbnb, or more broadly, ICT-related companies), but rather from how it transforms the larger proportion of existing businesses.

The most recent empirical evidence highlights that AI is linked to an increase in firms' innovative performance in Rammer et al. (2021), improvement in wages (Genz et al., 2021), and that access to digital data contributes significantly to an increase in the number of AI innovations (Beraja et al., 2020). But there is a knowledge gap regarding how AI affects firms' technological trajectories. After all, is AI a new technological paradigm that allows firms to explore a completely new set of productive problems, or is it an extension of the current ICT paradigm?

Thereby, I focus on multinational enterprises (MNEs), since the current wave of AI adoption is skewed towards large and established firms (WIPO, 2019; Zolas et al., 2021). Firstly, I want to understand how firms' innovations change after AI adoption in comparison to their previous innovations. In particular, this paper suggests that the introduction of a proprietary AI innovation into an MNE's technological portfolio leads to the emergence of increasingly related innovations. I expect that MNEs will recombine their AI innovation with other technologies from their existing portfolio rather than aiming at new unrelated innovations or technological breakthroughs. Secondly, I want to confirm if AI adoption is linked to a change in firms' innovative performance, and if so, explore what are the mechanisms behind this change. Does AI affect firms' innovative performance due to the learning about this technology, or due to the use of this technology as an IMI? Given current evidence, I expect that the introduction of an AI innovation into MNEs' technological portfolio increases their innovative performance. Moreover, I expect that this result is not only linked to AI's potential as a new piece of knowledge, but also due to its potential as a learning tool.

These two main hypotheses are explored by applying a matching procedure to a novel dataset combining MNE and patent data for the observation period from 2011 to 2019. I match AI adopters to a control group based on industry, company size, age, and innovation output. AI effects are estimated considering the year that it was adopted by each firm using the extension of the Difference-in-Difference (DiD) method proposed in Callaway and Sant'Anna (2018, 2020). The estimated effects indicate that AI adopters develop innovations increasingly related to their knowledge bases, strengthening their existing technological trajectories. This result is consistent even for technological sectors that are unrelated to AI. I also find that AI adoption increases the performance of MNEs in terms of innovation output. Considering that even unrelated sectors increase their relatedness through AI adoption, I argue that both AI knowledge and its use as a learning tool contribute to the verified increase in firms' innovative performance. I also argue that AI is better linked to a continuous technological change within the current ICT technological paradigm than to a discontinuous change towards a new paradigm.

This paper is structured as follows: Section 2 provides the relevant theoretical background and specifies the research questions; Section 3 describes the creation of the dataset and the methodology; Section 4 presents the empirical findings; Section 5 discusses the main findings, contributions, and limitations of the paper.

2. Theoretical Background and Research questions

The evolutionary view of technological development highlights that knowledge production is a cumulative, path dependent, and interactive process (Dosi, 1982; Nelson & Winter, 1982). In principle, the adoption of digital technologies, such as AI, offers a technological opportunity that could lead firms to modify the way that they produce new knowledge. This change is understood to be the result of firms' progressing along their technological trajectories (Dosi, 1982).

2.1. Digital Technologies and AI

Emerging possibilities created by technological change give firms new windows of technological opportunity, allowing them to change their technological trajectories (Dosi, 1982). These changes can be continuous, if firms stay within their technological paradigms, or discontinuous if they make it possible for firms to enter into a new paradigm[1] (ibid). One of the most important recent technological developments is the ubiquitous use and diffusion of digital technologies (Alcácer et al., 2016). These technologies spawned novel value creation and value appropriation pathways, besides producing a new breed of innovations (Nambisan et al., 2017). They give a basis for combinatorial and distributed innovation (Yoo et al., 2012) which may provide firms with a technological opportunity to expand the domains of knowledge that they can explore and absorb efficiently.

The adoption and pervasive use of digital technologies also allow the emergence of affordances linked to generativity and convergence (Yoo et al., 2012), which are created through unique properties of digital technologies, namely reprogrammable functionality and data homogenisation. Generativity refers to the action potential of digital technologies for producing innovations characterised by unprompted change driven by large, varied, and uncoordinated actors. It causes digital technologies to become inherently dynamic and malleable. Convergence, in turn, refers to the action potential of embedding digital technologies in nondigital artefacts. This enables coupling several distinct products or tools into one. Both affordances also favour the emergence of combinatorial innovation, since distinct digital technologies, like software-based modules, can be integrated to produce further innovations (ibid)[2].

AI is arguably one of the most important advanced digital technologies (Zolas et al., 2021). Most of AI's current power comes from its use as a tool for prediction

[1] A technological paradigm comprehends the general outlook of the productive problems faced by firms (Dosi, 1982).

[2] The widespread diffusion of Application Programming Interfaces (APIs), which are used to connect distinct software, is an example of how digital innovations can even focus on integrating distinct digital-based systems to allow for the emergence of combinatorial innovation.

(Cockburn et al., 2018). Powered by digital inputs, AI can be used to find valuable patterns in large amounts of data, besides also making predictions and decisions accordingly. This refers to AI's potential to be an IMI, which could be used to expand the set of problems that firms can feasibly address (ibid). Through the automation of complex tasks, AI can help companies in finding new ways of creating value and enhance their knowledge and capabilities. But this very same power can also replace the existing knowledge and capabilities of firms (Paschen et al., 2020). AI could also arguably enable firms to discover a completely new set of productive problems, which would make it a bridging technology towards a new technological paradigm.

2.2. Relatedness and Innovative Performance

Relatedness was proposed based on the concept of absorptive capacity, which proposes that a firm's ability to explore new knowledge depends on how related it is to the firm's prior knowledge (Cohen & Levinthal, 1990). Extant research documented that large firms are multi-technology corporations that combine a usually greater number of technologies to develop and produce a lower number of products and services (Granstrand, 1998); corporate technological diversification changes only slowly over time (Cantwell & Andersen, 1996); and profiles of technological diversification differ across firms due to history, distinct initial conditions, market incentives, distinct institutional settings and other factors (Antonelli et al., 2010; Ivarsson et al., 2015; Le Bas & Sierra, 2002), despite being very similar among large firms producing similar products (Breschi et al., 2003; Teece et al., 1994).

Breschi et al. (2003) propose the concept of relatedness and present evidence that firms diversify their innovative activities mainly by exploring related technologies, with larger innovators being typically more coherent in their technological trajectories than smaller innovators. The importance of relatedness has been linked to knowledge dimensions of proximity, commonality, and complementarity. Knowledge proximity relates to firms' learning processes, which can be unintended or intended. Both are created by firms' focus on learning about technologies that are similar to what they know in terms of knowledge base. Knowledge commonalities imply that firms' innovative activities may span over more than one technology because the same type of knowledge is used in various technologies, whereas knowledge complementarity arises from the need to use distinct technologies together (ibid).

Subsequent studies provide evidence that firms innovating in related areas have higher survival rates (Colombelli et al., 2013), lower coordination costs (Nesta, 2008), and perform better in knowledge transfer and creation (Weber & Weber, 2010). Relatedness has been shown to moderate positively an inverted U-shaped relationship between technological diversification and technological performance (Kim et al., 2016; Leten et al., 2007). It eases the burden of having a widely diversified portfolio by reducing the costs of learning, but just to a limited extent. Too much diversification – despite offering further opportunities for cross-fertilisation and technology fusion – may hurt innovative performance due to higher coordination and integration costs (Leten et al., 2007). Harmful effects of excessive diversification can be attenuated by firms that develop sufficient competencies around their core technologies (Kim et al., 2016).

The relatedness concept was also extended to explain geographic patterns of innovation (Hidalgo, 2021; Hidalgo et al., 2007). Corresponding research documented that the exploration of related technologies is linked to higher knowledge production (Kogler et al., 2013) and innovative output of regions (Aarstad et al., 2016; Castaldi et al., 2015; Delgado et al., 2014; Solheim et al., 2018; Solheim et al., 2020). The diminishing returns of related innovations are also recognised (Antonelli et al., 2010; Ejdemo & Örtqvist, 2020). Conversely, the exploration of unrelated knowledge was linked to technological breakthroughs and radical innovations, but at higher costs of learning (Castaldi et al., 2015; Solheim et al., 2018; Solheim et al., 2020).

2.3. Hypotheses development

Given the possible influence of digital technologies on firms' absorptive capacity, the effects of introducing such technologies on MNEs' technological portfolios are closely examined. In particular, this paper analyses how the introduction of an AI innovation[3] – considered a type of advanced digital technology – affects the technological trajectories and innovative performance of MNEs.

These technological trajectories are identified through the concept of relatedness. If MNEs following innovations become technologically different from their previous innovations after the introduction of AI, MNEs' relatedness will decrease. If they are similar or fill close gaps of knowledge that the MNE has, relatedness will remain stable or increase, respectively.

Given the affordances of digital technologies, it is argued that the introduction of an AI innovation in a firm's portfolio will be followed by recombinations of this innovation to create further innovations. On the one hand, given the reduced costs of producing related innovations and the potential of AI for combinatorial innovations, MNEs might recombine their AI innovation with their existing portfolio rather than aiming at new

[3] It is worth highlighting what the 'introduction of AI' means in the context of this paper. The term, used throughout the paper, refers to the first moment when an MNE has ownership of an AI patent (directly, or through its subsidiaries). This ownership can happen through the self-development of this patent, or through acquisition (by buying the patent or a company that owns the patent). Hence, in the paper context, MNEs become AI adopters in the first year that they owned (directly or indirectly through one of their subsidiaries) an AI patent. Patents are the proxy for innovation, which is a limitation discussed in the final remarks of the paper.

unrelated innovations or technological breakthroughs. The convergence affordance of digital innovations suggests that MNEs can ‘transform’ their nondigital artefacts into digital ones by coupling them with AI, reinforcing their existing technological trajectories. In addition, it is noted that it is very hard to capture the value of digital innovations (Teece, 2018). This is due to difficulties in protecting digital innovations from being copied. Accordingly, it is also hard to reinforce intellectual property rights related to these innovations (ibid). Hence, the generativity aspect of digital innovations offers little direct economic benefits to upstream innovators. Still, these innovators may benefit from technological improvements made to their protected innovation in downstream sectors. This would allow them (i.e., the innovators who hold property rights over the original digital innovation) to produce additional improved versions of their innovations, increasing their technological relatedness. On the other hand, if relatedness decreases, it would indicate that MNEs use AI as an automated discovery tool to develop innovations in new knowledge domains. Considering that the first case is more likely than the second, I hypothesise:

(i) The introduction of an AI innovation into MNEs’ technological portfolio leads to the emergence of increasingly related innovations.

It can also happen that the introduction of an AI innovation has opposite effects across MNEs from distinct technological sectors. This would occur if the knowledge dynamics generated through learning about AI vary according to how distinct the new AI knowledge is from the firm’s existing knowledge base. For firms from technological sectors that are related to AI, the three dimensions of knowledge (i.e., knowledge proximity, commonalities, and complementarity) are to play out and affect the increase in relatedness. These technologically close sectors are to contain the companies most impacted by AI, e.g., the ICT-related sectors linked to companies like Facebook, Airbnb, and Uber. But for firms from sectors technologically distant from AI, AI knowledge will be a new piece of unrelated knowledge. Hence, only the knowledge complementarity dimension can arise. In this case, the new AI knowledge could only influence relatedness if it would be combined by the firm with another piece of its existing knowledge. This could happen, for example, in the cases where firms use AI to transform their nondigital products into digital ones.

But combinations of unrelated and related knowledge are very difficult and occur more seldomly (Castaldi et al., 2015). In these cases, relatedness would remain unchanged or even decrease at the moment that AI is first introduced. This is because at least one piece of unrelated knowledge will be contained in the firm’s following innovations. This piece of knowledge will only become related to the firm’s knowledge base by being repeated in further innovations[4]. Due to knowledge dimensions, the

[4] To understand how this happens, it is helpful to think about the implementation of the relatedness indicator. Using patents as a proxy for innovations, as it is done in this paper, the indicator compares how similar an innovation is to the existing knowledge base of a firm through

introduction of an AI innovation into MNEs' technological portfolio is to have distinct effects across firms from different technological sectors. Hence, I hypothesise:

(ii) MNEs from sectors that are close to AI's knowledge increase their relatedness, whereas MNEs from sectors more distant to AI's knowledge show no effect or decrease their relatedness after AI introduction.

If no difference is seen across technological sectors, it potentially means that AI effects don't come only from its potential as a new piece of knowledge. The effects could also come from using AI as a learning tool, through its IMI potential for example. To address this possibility, the effects on innovative performance are also analysed. It is suggested that AI innovations affect positively the innovative performance of MNEs due to: i) lower costs linked to the exploration and development of new related knowledge; ii) AI's potential for automating tasks and being a learning tool capable of extending firms' inventive capabilities; and iii) the malleable and dynamic aspects of AI as a digital technology.

The first mechanism refers to possible effects linked to learning about AI (i.e., absorption of AI as a piece of knowledge). Extant research at the regional level links the creation of increasingly related innovations to higher innovative performance (Aarstad et al., 2016; Castaldi et al., 2015; Kim et al., 2016; Leten et al., 2007). Thus I expect a similar relationship at the firm level. The second and third mechanisms refer to particular aspects of AI as a technology. AI has been described as an IMI, which would also lead to an increase in firms' innovative performance. Regarding this potential, Cockburn et al. (2018) highlight that it comes from AI being used as a tool to automate discovery. When applied over large datasets, AI can recognise important patterns and generate accurate predictions which help firms in the development of innovations. The greatest potential of AI as an IMI is that it could be used to learn patterns across very distinct technological sectors. This would allow firms to explore an enormous set of new knowledge (ibid). The literature on digital innovations also suggests that an improvement in innovative performance is expected due to the adoption of this type of technology (e.g., Hanelt et al. (2021); Huang et al. (2017); Khin and Ho (2019)). This is linked to the malleability

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the technological codes used to classify innovations (in the case of this paper, the 4-digits IPC codes). Consider a manufacturing company creating an autonomous car. The first innovations of the company may be mixing the existing knowledge (i.e., a technological code linked to 'cars') with a piece of knowledge represented by a code linked to software (used for making the car autonomous). If the firm never patented software (or did it seldomly), this innovation is only half related to the company knowledge base (thus, relatedness remain unchanged, or is reduced). But then, the company may innovate by improving the software of the car, creating further software-related innovations (which is made possible by the combinatorial aspect of digital innovations). As the company accumulates a considerable number of software-related codes in its knowledge-base, relatedness also starts to increase.

aspect of digital innovations, which allows them to be quickly improved or adapted to new contexts, which also favour the emergence of innovations.

But firms could also reduce their innovative performance due to the introduction of AI. This could happen if firms shift their technological trajectories to develop mainly unrelated innovations, which are linked to lower efficiency since such innovations are typically linked to higher R&D efforts (Solheim et al., 2020). In this case, mechanisms (ii) and (iii) would need to be strong enough to enable firms to increase their patent outputs at a higher rate than the increase in R&D expenditure. Hence, my last hypothesis is:

(iii) The introduction of an AI innovation into MNEs' technological portfolio increases their innovative performance.

I expect the overall impact of AI introduction on innovative performance to be positive due to the individual or combined potential effects of the three mentioned mechanisms.

3. Data & Method

3.1. Constructing the Dataset

The dataset combines three sources owned by Bureau van Dijk (BvD), namely Orbis, Orbis IP, and Orbis-Zephyr. All data was downloaded between July 2020 and March 2021. The construction of the company and patent datasets is done separately and merged through the unique standardised identifiers ('BvD ID number'). Details about the creation of the dataset are presented in Appendix A1.

The company dataset separates subsidiaries from their Global Ultimate Owners (GUOs) based on a minimum ownership threshold of 25.01%. This results in an ownership structure with up to 21 ownership levels, which is then filtered for corporate companies (see Appendix A1, Step I, pg. 33). M&D data is used to recursively extend the 2020 generated ownership structure backward, year by year. To this end, all M&A deals that relate to the GUOs or subsidiaries as of 2020 were downloaded from the Orbis-Zephyr database (Appendix A1, Step II, pg. 36). In the following step, a patent dataset is built by downloading from Orbis IP all priority filings[5] (granted or not) whose priority dates were within the period from 01/01/2000 to 31/12/2019 (Appendix A1, Step III, pg. 39). In this step, the AI patents are identified through a specific 'AI tag' that allows finding them later. The identification of AI patents adopts the list of keywords proposed in Leusin

[5] A priority filing is the first patent application filed to protect an invention. If the same patent is registered in other patent offices, the following registrations are called non-priorities, constituting a patent family linked through the priority filing.

et al. (2020), which is based on typical AI techniques. The authors report high accuracy of their proposed search strategy after comparing the quality of their results with alternative approaches (namely the ones proposed in Tseng and Ting (2013) and Fujii and Managi (2018)). All registers containing any of the considered AI-keywords in their titles, abstracts, claims, or description are identified as AI patents. For more details about the keywords adopted, see Appendix A1, Table A1.3 (Pg. 41).

Finally, the BvD ID of patent owners is used to link this patent dataset to the companies' ownership dataset (Appendix A1, Step IV, pg. 43). The patents are linked to their yearly owners, which allows accounting for changes in ownership due to patent or firm acquisitions, for example. As the ownership structure of companies covers only the 2011-2020 period, patents registered from 01/01/2000 to 31/12/2010 are linked to their owners using the ownership structures existent in 2011. These patents are used as the initial stock of companies. The year 2020 is dropped from the analysis due to the possibility of incomplete patent data.

3.2. Matching AI Adopters to Non-adopters

Matching methods offer causal inference with fewer assumptions, enabling higher robustness and less sensitivity to modelling assumptions (Ho et al., 2007). The premise is to construct a dataset where the treated group is as similar as possible to the control group, which means excluding data about units that are too divergent from their possible counterfactuals until a balance is reached. The evaluation of the matching procedure is then straightforward in the sense that the preferred generated dataset is the one that produces the best balance between distance (i.e., the difference between the control and treatment units regarding the considered criteria) and the number of excluded units.

In my case, the treatment is defined as the ownership of at least one AI patent in a given year, whereby both the development of an AI innovation by MNE units as well as the acquisition of an AI innovation (through buying a patent or acquiring a subsidiary that owns an AI patent) are considered. Therefore, the treatment considers all patents that are linked to the identified GUO directly or indirectly (i.e., through its subsidiaries)[6]. GUOs that adopted AI before 2011 are excluded. The criteria for matching the remaining GUOs are the number of patents owned per year, age, industry (NACE 4-digit level), and

[6] As a robustness test, an alternative measure considering only the patents owned directly by the GUO is also considered when looking at path dependency.

size class[7]. Except for the number of patents and age[8], the remaining criteria are applied through exact matching. Regarding number of patents, all years from the considered period (2011-2019) plus five years of pre-treatment control (i.e., from 2006 to 2010) are considered. This means that treated companies are matched to control companies throughout every year of the period from 2006 to 2019[9]. A caliper[10] of 0.10 standard deviations is used to define the limits of how 'similar' the number of patents has to be. Seldomly used NACE codes are put together under a created label 'Less used codes', which replaces the codes of companies that are found less than five times between AI adopters. Altogether, this label comprehends 20% of the considered NACE codes.

The matching implementation is done using the R package MatchIt (Stuart et al., 2011). The matching method with the most balanced results is based on a genetic algorithm. Once there are considerably more companies that didn't adopt AI than companies that did it, a ratio of 5 control units is applied in the matching to increase the size of the considered sample (i.e., five non-adopters are matched to one AI adopter for every 'matchable' treated GUO).

3.3. Estimating the Effects of AI Adoption

I use the extension of the Difference-in-Differences (DiD) model proposed in Callaway and Sant'Anna (2018, 2020) for estimating treatment effects with multiple time periods. It extends the classical model by adding two assumptions: The first is the 'Staggered treatment adoption assumption', which implies that once a unit participates in the treatment it remains treated. The second assumption restricts the DiD parallel trends assumption to consider that there is also no treatment effect heterogeneity across time, across groups receiving treatment in distinct time periods, or in the treatment

[7] According to Orbis classification, companies with 1,000 or more employees are 'Very large companies', companies with less than 1,000 but with 150 or more employees are 'Large companies', companies with less than 150 but with 15 or more employees are 'Medium sized companies', and the rest are considered 'Small companies'.
[8] Assuming that small age differences are more significant for newer companies than the oldest, I consider six periods for the age category: 0-1979, 1980-1999, 2000-2004, 2005-2009, 2010-2019. The last period considers more years due to the very limited number of companies created in the last five years considered.
[9] This is an important criterion to consider given the structure of my dataset, where the stock of patents of companies 'follows' them if they are acquired by other companies (in this way, if the number of patents of a company goes to 0 in a given year, it means the company was sold or stopped operating; given my matching criteria, such company would be matched only if there was another company that was also sold/stopped operating in the very same year).
[10] A caliper defines the number of standard deviations of the distance measure within which to draw control units.

sequence[11]. Through this extension, the treatment group can be further divided into smaller groups based on the period on which these distinct groups receive treatment. Thereby a generic treatment group G is divided into g(i) subgroups, with treated (d=1) and untreated (d=0) units. The units from each subgroup g(i) are treated in a distinct time period 'ti' and their group-specific counterfactuals (i.e., the control units where d=0) are assumed to follow parallel paths in all post-treatment periods t ≥ g. The treatment group is divided into 9 subgroups (i.e., i = 9), with each subgroup containing the treatment units that adopted AI in a distinct year t, which varies from 2011 to 2019.

Callaway and Sant'Anna (2018, 2020) also propose distinct aggregation schemes for highlighting treatment effect heterogeneity and pre-treatment estimates. For the former, I use the aggregation methods of 'Dynamic Treatment Effects' and 'Simple weighted average'. The pre-treatment estimates, in turn, refer to a 'pre-test' to check if the parallel trends assumption holds. The main idea behind these estimates is that they can be used to check if pre-treatment units are similar enough to treated units in the time periods before treatment. It is called a 'pre-test' because although the estimates are useful for the pre-treatment period, they can't say anything about the parallel trends assumption holding during the treatment and post-treatment periods. The parallel trends assumption in these periods, in turn, is fundamentally untestable. The authors point out that this 'pre-test' is an important piece of evidence on the credibility of the DiD design in a particular application. Accordingly, I present and discuss the results of this pre-test together with the estimation effects. All effects are estimated using the DID-R package presented in Brantly Callaway (2021).

3.4. Dependent Variables Considered

3.4.1. Path dependency

Path dependency is calculated following the relatedness density index proposed in Hidalgo et al. (2007) and adapted in Balland (2016) for patents. The implementation of the index is done through the EconGeo R package (Balland, 2017)[12]. Results lay

[11] There are two implementation options for this second assumption (i.e., the 'Parallel Trends Assumption based on not-yet treated units' and the 'Parallel Trends Assumption based on never-treated units'). The 'not-yet' option is particularly useful for cases where there is low availability of treatment units, as it allows these units to be used both as treatment i.e., in the time periods before they get treated) and as control (in the time periods in which they are treated. As a limited number of control units is not a particular problem of my dataset, I choose the 'never-treated' implementation option.

[12] The average relatedness density, implemented through the 'relatedness.density.int.avg' function, which in my case considers as input an incidence matrix with companies depicted in rows and their number of registers in each 4-digits IPC code in columns, and an adjacency symmetric matrix of IPC codes indicating the degree of relatedness between them.

between 0 and 100 percent, with higher values highlighting higher relatedness. The index is calculated as follows:

$$RD_{i,c,t} = \frac{\sum_{j \in c, j \neq i} xi * \varphi_{ij}}{\sum_{j \neq i} \varphi_{ij}} \times 100$$

Where 'i' stands for a technology (in my case, a 4-digits IPC code) found in the company 'c' at a time 't'. $'\varphi_{ij}'$ stands for the technological relatedness between two technologies 'i' and 'j', which is based on the premise that if two technologies co-occur more often than what would be expected by chance under the assumption of statistical independence, they are more related. These values are normalised following the cosine normalisation procedure (Eck & Waltman, 2009). $'xi'$, in turn, refers to a binary implementation of the Revealed Technological Advantage (RTA) index[13], taking the value of 1 if the company has a specialisation in technology 'i', and 0 otherwise.

The density equation works by capturing the average relatedness between the technologies in which the firm is specialised. Mathematically, the RTA equation makes it possible to develop specialisations only in a maximum of half of all activities explored by a firm. Considering the exemplary case of an increase in the density index, this may happen for two distinct reasons: The firm may have developed an additional specialisation that is in the average closer to the technological cluster in which the firm is, or the firm may have switched one of its previously existing specialisations for a specialisation in a technology that is closer to its technological cluster. Thus, the emergence of a more coherent technological path, proxied by relatedness, means that firms can be either adding close specialisations or switching to closer specialisations. New specialisations can be added just to a maximum limit of about half of the technologies the firm is patenting in, whereas switching specialisations can occur endlessly.

3.4.2. Innovative Performance

Three distinct proxies are considered for measuring innovative performance: i) the number of patents owned by the MNE; ii) the share between the number of patents owned by the MNE per unit of turnover (in thousands of USD), and iii) the share between the R&D expenditure (in thousands of USD) per number of patents owned by the MNE. These three proxies offer distinct perspectives over innovative performance: (i) focus directly on innovative output; (ii) considers how this output changes according to the firm's economic performance; and (iii) is closely linked to the idea of innovative efficiency, which is defined as the ability of firms to translate innovation inputs into outputs (Hollanders & Esser, 2007). These perspectives are complementary: if (i) increases,

[13] RTA = $\frac{patents_{c,t}(i) / \sum_i patents_{c,t}(i)}{\sum_c patents_{c,t}(i) / \sum_c \sum_i patents_{c,t}(i)}$, rounded to 1 if RTA ≥ 1, and 0 otherwise.

showing an improvement in innovative output, the shares (ii) and (iii) should decrease (showing a proportionally larger increase in economic performance and a decrease in R&D expending for developing patents, respectively) to corroborate (i).

4. Empirical Findings

4.1. Overview of Dataset

Overall, the dataset contains data for over 30 thousand GUOs, which are linked to more than 1 million subsidiaries. These companies own together more than 10 million patents, from which roughly 90 thousand are identified as being related to AI. The data also shows the rapid advancement of AI adoption in the considered period: from 5.6% of GUOs having at least one AI patent in 2011 to a share of 10.2% in 2019 (see Appendix A2 for an overview). It also shows a high concentration of large and old MNEs as the main AI adopters, with a high share of these coming from ICT-related sectors related. These results are very similar to the findings presented in Zolas et al. (2021), which are based on survey data on US companies. Additional information about the main AI adopters according to the number of AI patents owned is presented in Appendix 3 (which also includes a comparison with the data presented in Fujii and Managi (2018)).

The matching procedure drops most of the top AI adopters since many of them adopted AI before 2011. However, the distribution of firms considering the matching criteria adopted remains similar. AI adopters are primarily from ‘Computer programming activities’ (NACE 6201), 5829 ‘Other software publishing’ (NACE 5829), and ‘Manufacture of electronic components’ (NACE 2611), which together represent about 20% of the industry codes used by adopters. Further information comparing companies before and after applying the matching procedure is presented in Appendix A4.

4.2. Estimated effects

4.2.1. Effects on Relatedness

I use the matched dataset to estimate the aggregated treatment effects of AI adoption (see Table 1). The ‘Simple weighted average’ highlights the weighted average of all considered groups with weights being proportional to the size of each group. One disadvantage of this kind of measure is that early-treated groups are observed for more time periods. The second method, namely ‘Dynamic Treatment Effects’, avoids this limitation by weighting the average treatment effects according to the different lengths of exposure to the treatment (Callaway & Sant’Anna, 2018, 2020).

In the matched dataset I still have some MNEs classified as holding companies (NACE 6420) and head offices (NACE 7010). Both codes could include firms with quite different industrial profiles, which might be an issue for estimating treatment effects. To account for that, MNEs linked to these two sectors are excluded as a robustness check in (b). Overall, the effects of AI on MNEs' technological relatedness are significant at the 95% confidence interval for all calculations. The effect becomes stronger when head offices and holdings are dropped (see Table 1, column b). The value of 1.037 means an increase of 10.3% over the average relatedness of 10.095 for non-AI adopters; the value of 1.153, in turn, means an increase of 11.4% over the average relatedness of non-AI adopters[14].

Table 1: Estimates for the aggregate treatment effects of AI adoption on firms' relatedness.

		a) MNE's relatedness	b) MNEs relatedness without considering holdings and head offices
Simple Weighted Average	Estimated effect	1.037	1.114
	Standard error	0.169	0.179
	Conf. interval	from 0.7054 to 1.3689*	from 0.7625 to 1.4657*
Dynamic Treatment Effects	Estimated effect	1.153	1.253
	Standard error	0.261	0.281
	Conf. interval	from 0.6409 to 1.6643*	from 0.7032 to 1.8036*
Number of treated units considered		1,155	1,054

The 'Dynamic Treatment Effects' method can be further disaggregated across subgroups (see Figure 1). Particularly, length of exposure equal to 0 provides the average effect of participating in the treatment across subgroups in the time period when they first participate in the treatment (instantaneous treatment effect). Negative lengths of exposure correspond to time periods before subgroups first participate in the treatment, and lengths of exposure equal to or above 1 correspond to the time periods after initial exposure to the treatment (being 1 the first year after treatment). Grey bars with negative values refer to the estimators from the pre-treatment test proposed in Callaway and Sant'Anna (2018, 2020). This test can detect a broad set of violations

[14] As an additional robustness check, similar results hold when considering GUOs' direct ownership of patents only: the estimated effects are 0.639 under the simple weighted average, which is significant from 0.2672 to 1.0115*, and 0.504 for dynamic treatment effects, which is non-significant for the dynamic treatment effects with a confidence interval from -0.0599 to 1.0679. 871 treated units are included in the sample when only GUOs' direct ownership is considered.

against the conditional parallel assumption, which in turn form the basis for all the considered estimation procedures. The interpretation is that for values of 0 within the considered confidence band (in my case, 95%), this assumption is held.

It is seen in Figure 1 that the parallel trends assumption holds for all pre-treatment years, meaning that the considered treated and control companies are similar enough before treatment across groups (given the considered criteria)[15]. The corresponding effect of AI adoption increases for the first 5 years after adoption, before it starts to decline albeit remaining positive. The exclusion of MNEs classified as holding companies and head offices does not change this trend (see Figure 1b).

[15] These pre-treatment values go until -12 to pick the maximum number of years that one subgroup stayed in the sample without being treated (in this case, the Subgroup 2019, which wasn't treated during the 4 years following the initial year of analysis, which is also reflected for all groups [i.e., considering the 4 years following 2006 until 2010] plus 8 years [from 2011 to 2018] in which this particular Subgroup was not treated whereas all the other subgroups were). Once the data goes just until 2019, the effects of the 9th group (i.e., companies that adopted AI firstly in 2019) are considered just for the immediate effect (i.e., at the length of exposure 0).

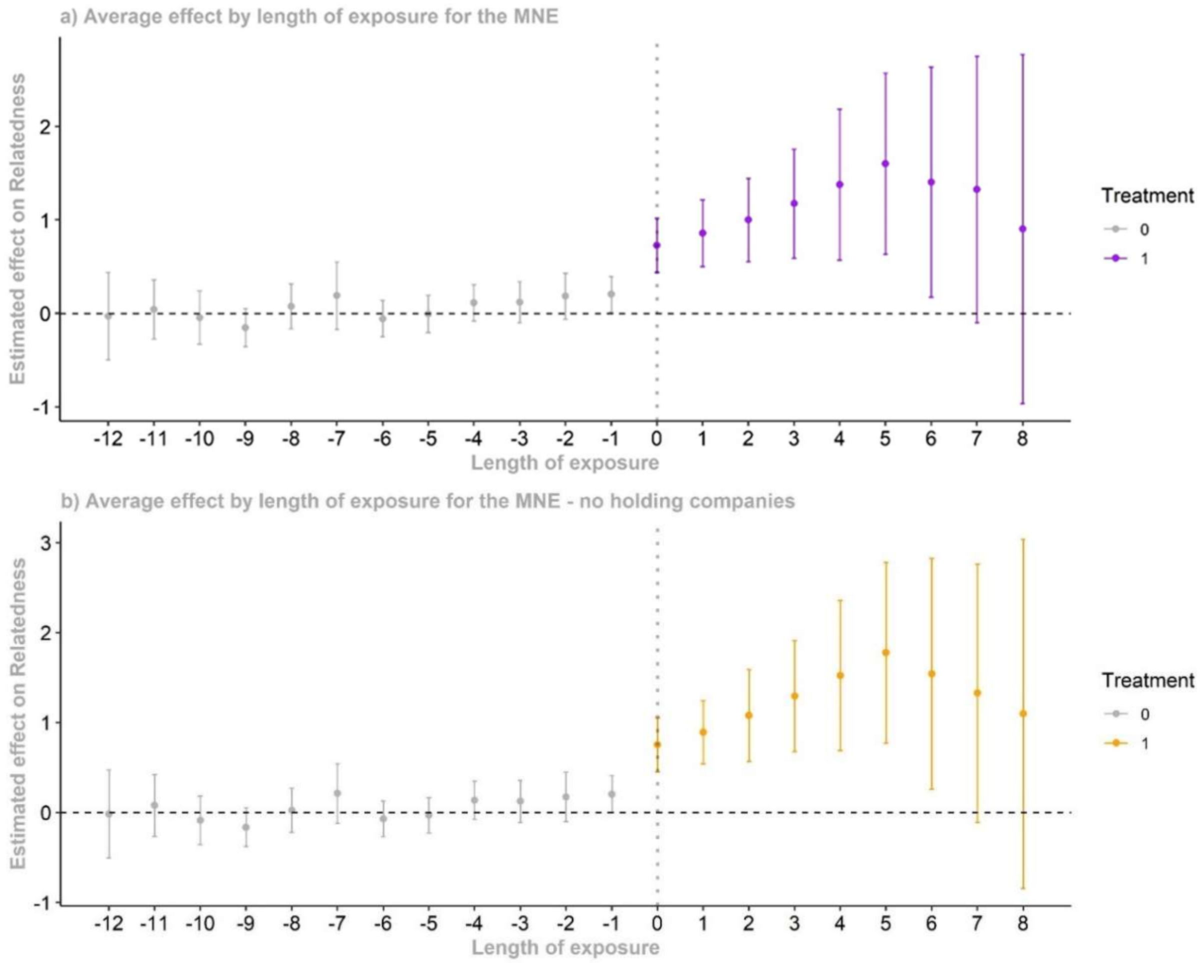

Figure 1: Estimated Dynamic Treatment Effects of AI adoption on the relatedness of all MNEs (a) and when holdings and head offices are excluded (b).

4.2.2. Relatedness effects across sectors and the self-selection bias

Using a nonrandomised sample for estimating the effects of AI may raise concerns regarding a self-selection bias. Although the 'pre-test' may pick differences across MNEs before they receive treatment for the considered criteria, a self-selection problem may still exist if AI adopters are inherently different from non-adopters in a relevant but unaccounted way. I foresee two main situations where a self-selection would occur in the considered context. It may happen i) if AI-adopters and non-adopters differ in regards to their innovation strategy, or ii) if adopting AI requires such a low effort that firms do it for trivial reasons (e.g., as a way to signalise something to competitors, investors, to the company itself, etc.). Although the dataset does not allow accounting for innovation strategies and other potentially relevant parameters, it is argued that the effects on firms' relatedness would have significant differences according to firms' knowledge distance to AI.

In the first case, in which AI adoption is driven by the effects of different 'perceptions' towards AI, AI adopters are to increase their number of AI innovations. This could happen because of the favourable view towards AI, or to create a head start over competitors[16]. In this situation, the knowledge distance to AI would lead companies from far away sectors to rapidly decrease their relatedness. Or, at the very least, companies from these sectors don't substantially change their innovation patterns (e.g., despite the AI strategy, innovative efforts are minimal), and relatedness doesn't change significantly due to AI adoption. The reason is straightforward: the technological 'movement' towards AI for companies with knowledge bases close to AI means creating innovations that are relatively similar to the ones that these companies already had (increase in relatedness), whereas for companies distant to AI this would lead to the creation of innovations that are unrelated from what the companies had so far (decrease in relatedness). The effect would be similar for the second possible self-selection bias, albeit for a distinct reason. Some AI adopters could enter in the treatment just because the effort is minimal, but the costs would be greater the larger the distance is to AI (i.e., unrelated knowledge is more expensive to learn). Accordingly, firms with knowledge bases that are distant to AI aren't likely to create several costly AI innovations for trivial reasons, and no effects should be seen on relatedness.

Hence, I disentangle the matched pairs of treated and non-treated MNEs into three subgroups with distinct knowledge distances to AI. In doing so, I also verify the validity of the second proposed hypothesis. I apply two options to calculate distances: First, a very simplistic one in which all companies that belong to ICT-related sectors (NACE 5829, 6201, 6311, 6312, 6391, and 6399) are put in the closest to AI category, MNEs previously classified into the "Less used codes" (which comprehends the 20% NACE codes less used by AI adopters) are put in the category with the greatest distance to AI, and all remaining MNEs are put in a median group. In the second option, the average distance of every NACE code to the 'AI cluster' is measured, and quartiles are used to create three distinct categories (see for a detailed description in Appendix A5)[17].

The results of the new estimations considering the three distance groups across the two distinct distance measures are presented in Table 2. Figures for the disaggregation across groups under the 'Dynamic Treatment Effects' are presented separately in Appendix A6. Overall, the positive results are maintained for all groups, with the 'Median group' being the only exception with non-significant results for the estimations based on knowledge distance and Dynamic effects. It is noted, however, that the magnitude of the effect changes across the considered groups. Particularly, closer

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[16] Considering that patents offer the possibility of protecting the use of an invention, AI adopters could create several AI-related patents in a defensive way to protect knowledge seen as potentially having future economic value, for example.

[17] The proposed measure seems to perform well in putting 'digital MNEs' in the top quartile. The reference for this assessment is based on the Technical Annex entitled "The Top 100 Digital MNEs" made by (available at https://unctad.org/system/files/official-document/wir2017ch4_Annex_en.pdf), which identifies companies related to internet platforms, IT and Telecom companies, and other sectors as the main adopters of digital technologies.

subgroups present effects that are up to 7 times stronger. Regarding Appendix A6, the results are also very similar to the trend seen previously: The effects on relatedness are increasingly positive in the first years after adoption, and then decline albeit staying positive. A particular difference is that the increasing trend remains longer for closer groups in comparison to the other two groups. Considering the assumption that a self-selection bias would be reflected in companies from sectors distant to AI showing no effects on relatedness, I assume that the consistency of significant results is indicative of no self-selection bias.

Table 2: Results estimated for the self-selection bias across the considered two distinct knowledge distances to AI.

			Closer group (1)	Median group (2)	Farthest away group (3)
Check 1: Based on codes' usage in the treated units	Simple Weigh. Avg.	Estim. effect	2.426	0.761	0.622
		Stand. error	0.465	0.213	0.310
		Conf. interval	from 1.5152 to 3.3368*	from 0.3439 to 1.1772*	from 0.0137 to 1.2299*
	Dyn. Treat. Effects	Estim. effect	2.888	0.807	0.571
		Stand. error	0.590	0.327	0.466
		Conf. interval	from 1.731 to 4.0449*	from 0.1665 to 1.4483*	from -0.3413 to 1.484
	N. of treated units considered		204	655	302
Check 2: Based on tech-nolo-gical distan-ce to the AI cluster	Simple Weigh. Avg.	Estim. effect	1.990	0.249	0.777
		Stand. error	0.297	0.302	0.243
		Conf. interval	from 1.4078 to 2.5713*	from -0.3429 to 0.8417	from 0.2997 to 1.2535*
	Dyn. Treat. Effects	Estim. effect	2.413	-0.016	0.856
		Stand. error	0.446	0.439	0.378
		Conf. interval	from 1.5389 to 3.2863*	from -0.8775 to 0.8451	From 0.1152 to 1.5977*
	Number of treated units considered		400	368	387

4.2.3. Effects on Innovative Performance

Orbis provides company data for an up to 10-years span in its online version. This limitation affects two of the three considered proxies for innovative performance, namely Turnover and R&D expenditures. In addition, there is very often missing data for these indicators for some years[18]. Therefore, I extended the data backward and then forward to fill the missing values of individual companies for these two indicators. All MNEs with available data for 2 or fewer years (2011-2019) are excluded. Furthermore, I excluded the group treated in 2011 when considering these two variables due to the lack of data for 2010, required for pre-testing before treatment. As R&D expenditure is more frequently missing than Turnover data, the final samples used for each proxy are slightly different (see Appendix A7). Particularly, very large MNEs are overrepresented due to their more complete availability of data. To understand how much this potentially affects the results, I estimate the effects on the number of patents owned by the entire MNE for the sample of companies from the Turnover dataset (i.e., complete matched dataset minus the 38.5% companies lost in the Turnover sample). Table 3 summarises the estimation effects for this additional estimation, together with the other three considered proxies used to measure innovative performance. Estimations with holdings and head offices excluded from the samples are shown within square brackets.

Table 3: Estimated effects for the three distinct dependent variables related to innovative performance.

		No. of patents owned by the MNE	No. of patents owned by the MNEs with Turnover data	No. of patents owned by the MNE/ Turnover	R&D expenses/No. of patents owned by the MNE
Simple Weigh. Avg.	Estimat. effect	25.01	32.134 [31.54]	-0.007 [-0.013]	-29,865.73 [-30,110.03]
	Stand. error	4.99	6.58 [7.79]	0.0144 [0.014]	18,008.61 [17,407.32]
	Conf. interval	from 15.23 to 34.80*	from 19.24 to 45.02* [from 16.27 to 46.82*]	from -0.035 to 0.021 [from -0.041 to 0.015]	from -65,161.96 5,430.50 [from -64,227.76 to 4,007.69]
Dyn. Treat. Effects	Estimat. effect	35.48	43.95 [44.77]	-0.013 [-0.013]	-27,061.3 [-27,347.35]
	Stand. error	7.05	9.66 [11.55]	0.014 [0.012]	18,619.97 [17,481.74]
	Conf. interval	from 21.66 to 49.30*	from 25.01 to 62.89* [from 22.13 to 67.42*]	from -0.041 to 0.016 [from -0.037 to 0.010]	from -63,555.77 9,433.17 [from -61,610.93 to 6,916.23]
N. of treated units considered		1155	690 [620]	690 [669]	444 [442]

[18] 46.7% of the Turnover data is missing for at least one year; this share increases to 62.7% when R&D expenses data is considered.

The results indicate that AI adoption significantly increases the innovative output of firms regarding the number of patents owned (see first two columns of Table 3). This effect is stronger for the sample with larger companies. The estimated effect of 25.017 for the simple weighted method in the complete dataset represents an increase of 40.0% over the average number of patents owned by non-treated MNEs (average of non-treated: 62.48; treated: 108.52); the estimated effect of 32.134 in the Turnover-related sample, which has the larger companies, represents an increase of 35.7% over the average number of patents owned by non-treated units (average of non-treated: 89.90, average of treated: 162.58). The effects, therefore, are relatively smaller for the sample with larger companies (despite being larger in absolute values). The dynamic effects for the number of patents across these two distinct samples are shown in Figure 2. It is seen that, compared to relatedness, innovative output increases more steeply and consistently. There is a drop in the last three years, but it is very little and the results remain significantly positive except for the last considered year.

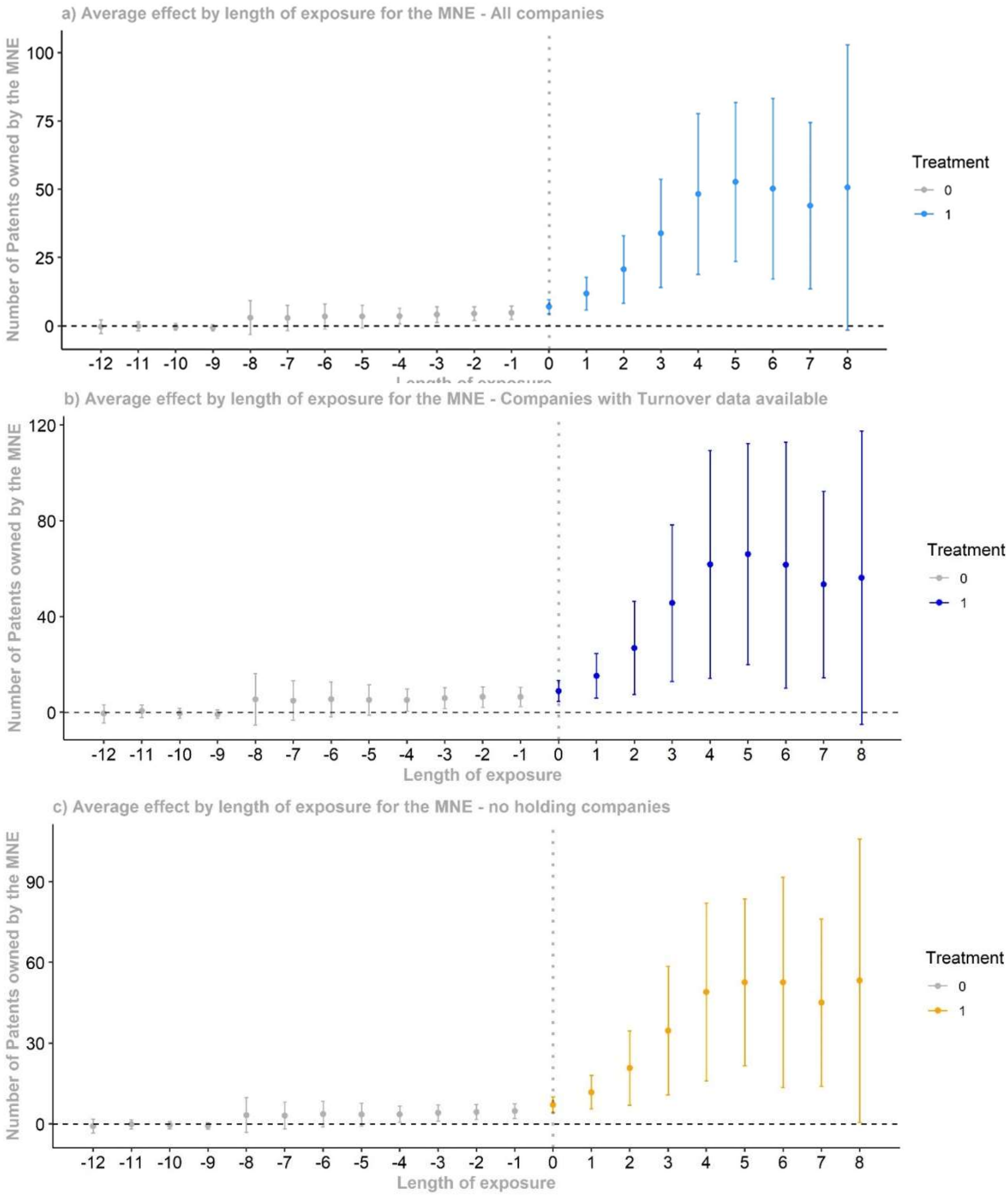

Figure 2: Estimated effects for the number of patents owned by the entire MNE for the entire (a) and for the smaller samples with larger companies (b and c). Please note: treated units don't pass the pre-test up to 4 years before receiving treatment (for the complete sample) and 3 years for the larger-companies sample (b and c), meaning they may be different from non-treated units and, accordingly, results should be considered with caution. Overall, the trend is very similar for the three considered samples.

The results for the other two considered proxies show that AI adoption decreases insignificantly both the number of patents owned by the MNE per unit of turnover and the share of R&D expenses per patent (see Table 3). The estimated negative effect of 0.007 for the simple weighted method represents a decrease of 83.42% over the average number of patents per unit of Turnover (which is 0.0084 for non-treated units, and 0.0098 for treated). The estimated negative effect of 29,865.73 for the same method represents a decrease of 80.25% over the average share between R&D expenditures and the number of patents owned (which is 37,215.73 for non-treated units, and 112,120.46 for treated). The dynamic effects for these indicators are shown in Figure 3.

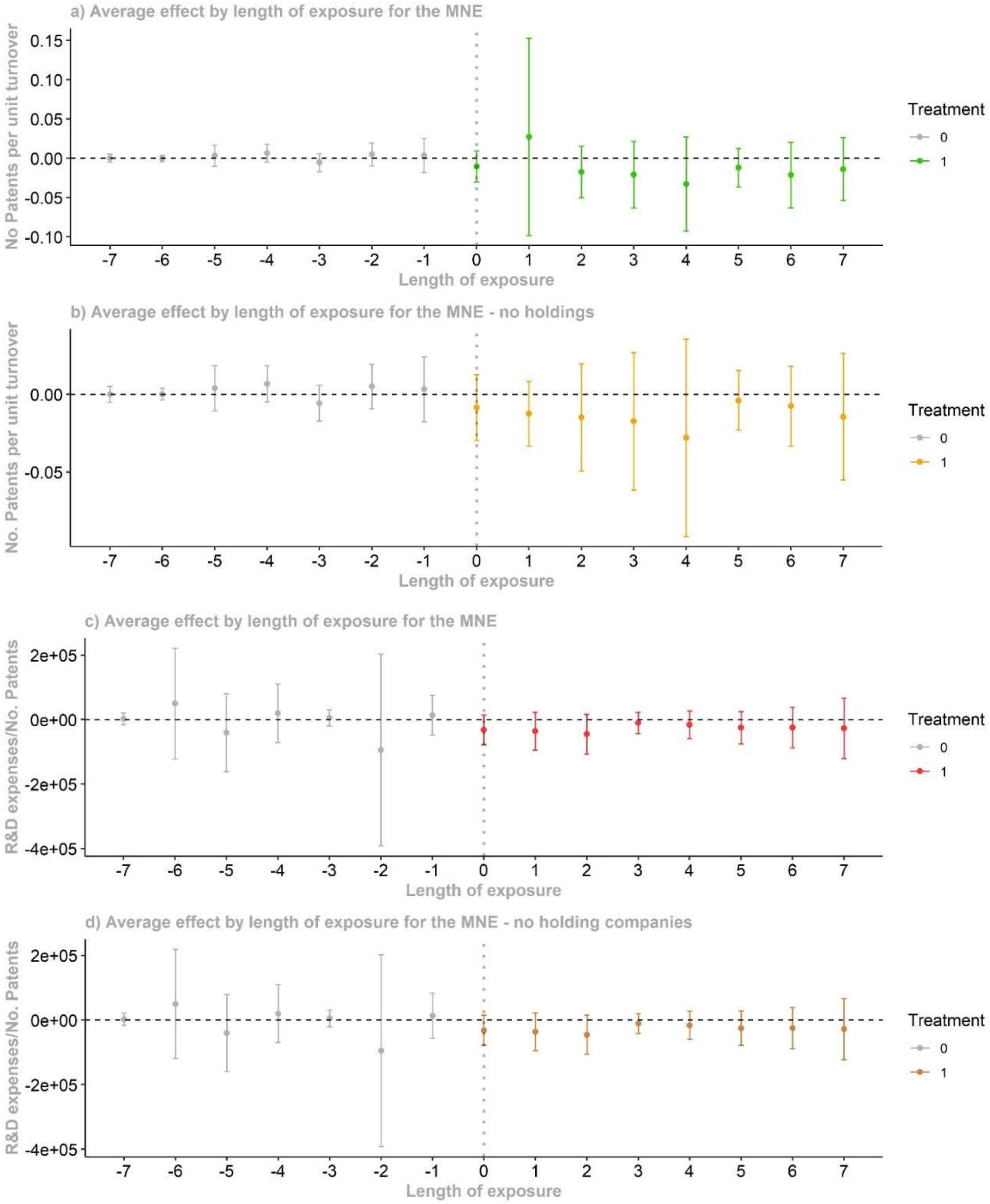

Figure 3: Estimated effects for Number of patents per unit of turnover (a and b) and R&D expenses per patent (c and d). Note: There is data available only for the last 10 years for both of these parameters, the pre-test for the parallel trends assumption goes only until -7 (instead of -12 as in the previous figures). Also, as the 2011 group is dropped from both samples, the length of exposure goes only until 7 years instead of 8. Particularly regarding the exclusion of holdings and head offices, it is seen that the exposure for the first proxy seems more consistent after the exclusion (b), whereas for the second proxy it seems to make no difference. Moreover, in comparison with the previous proxies, the negative effects seen here are relatively stable over time rather than increasing over time for some years and just then stabilising or diminishing.

5. Discussions and Conclusions

5.1. Discussion

Summing up, the results indicate that MNEs introducing AI-related innovations increase the relatedness of their subsequent innovations by about 10 to 11 per cent. The corresponding effect increases over the first 5 years after the introduction, before declining albeit remaining positive. The result seems robust when accounting for a possible self-selection bias. It is also seen that AI effects on relatedness remain positive across sectors with knowledge bases far away from AI knowledge. This means that even companies from sectors unrelated to AI increase the relatedness of their following innovations after its introduction. The evidence also indicates that MNEs increase by about 40 per cent the number of innovations they own after the introduction of an AI innovation. This effect grows steeply and considerably stronger over time in comparison to the effect seen for relatedness. This increase is also shown to occur without significantly changing the intensity of R&D expenditures per innovation. Thus, the empirical findings are in line with hypotheses (i) and (iii).

Particularly, the first hypothesis refers to AI's potential to increase firms' relatedness. It is confirmed that the introduction of an AI innovation is associated with such an effect, increasing firms' technological coherence. Thus, rather than being used as a tool to automate knowledge discovery across distant technological domains (Cockburn et al., 2018), AI reinforces the learning of related knowledge. This finding corroborates the anecdotal evidence presented in Brock and Von Wangenheim (2019) that AI is being deployed mostly to support companies' existing businesses. Taking AI as an example of advanced digital technology allows better understanding how the most recent wave of technological developments is potentially affecting firms' innovative activities. The evidence indicates the increasing role of absorptive capacity in the current information age. This finding is somewhat puzzling. Some aspects of digital innovations could arguably lead firms to become less path dependent as they become digitalised, e.g., digital innovations are reprogrammable (which makes them 'malleable' to changes as highlighted in Yoo et al. (2012)), and digital resources allow companies to reduce their sunk costs related to physical goods. But these very same aspects are also to reinforce path dependency of technological sectors unrelated to digital technologies. It is very unlikely that firms from the mining industry, manufacture, or linked to agriculture – i.e., sectors that are shown in Appendix A5 to be far away from the AI knowledge cluster – would change their technological trajectories due to digitalisation. Digital technologies will be used by these firms to innovate within their technological trajectories.

Additional evidence to confirm this assumption comes from the findings linked to the second hypothesis. This hypothesis suggests that the introduction of an AI innovation may have distinct effects across MNEs, depending on their knowledge distance to AI. I expected that MNEs from sectors that are close to AI's knowledge would increase their relatedness, whereas MNEs from sectors more distant to AI's knowledge would show no effect or decrease their relatedness after AI introduction. However, the results indicate that the effects are consistently positive across all technological sectors, the only difference being the intensity of the effect. But hypothesis (ii) considers solely the possible effects of AI as being introduced as a new piece of knowledge. The dimensions of knowledge can explain why the effects on relatedness are larger for firms that are closer to AI (i.e., the three dimensions are to play out, whereas for unrelated firms the only effects are to come from AI being used as a knowledge complementarity), but cannot explain how the introduction of unrelated knowledge leads to an immediate and significant increase in the production of related knowledge. However, the introduction of an AI innovation does not comprehend only the knowledge aspect. AI is also a technology that can be used to discover patterns in large amounts of digital data. This technological use is at the core of AI's expected IMI potential (Cockburn et al., 2018).

The fact that AI adoption is linked to an increase in firms' innovative performance[19] is additional evidence of AI's specific technological potential. This finding is associated with the third hypothesis presented. This hypothesis considers that AI can increase firms' innovative performance by being a valuable new piece of knowledge and due to its technological particularities. As a new piece of knowledge, AI increases firms' relatedness, which is associated in the geographic view of relatedness with higher innovative performance. AI's power as a technology, in turn, is created by its digital affordances and IMI potential. When used as a technology, AI can help firms to learn from digital data and to create 'malleable' adaptable innovations suited to recombination to other contexts. But the ability to recognise which data and contexts are valuable to explore is dependent on firms' existing knowledge bases. The data available to a firm is also to be specific to the firm's current operations, which also determines what kind of innovations can be deployed[20]. This specificity of data and the path dependence of firms in judging the value of opportunities explain why the introduction of AI is linked to an increase in knowledge relatedness. AI innovations are thus path dependent on existing knowledge bases: Firms innovate according to the data and accumulated knowledge they have.

[19] The gains in innovative performance linked to AI corroborate the findings presented in Rammer et al. (2021), which were based on survey data. Considering that AI is a type of digital technology, these gains in innovative performance contradict the findings presented Usai et al. (2021). The authors combine survey data about ICT usage in European firms and their innovation performance. One possible reason for these distinct results is that Usai et al. (2021) focus on the use of digital innovations, whereas I focus on the ownership of these innovations via intellectual property rights.

[20] Beraja et al. (2020) give an example of how deterministic data is to the emergence of AI innovations. The authors show that the availability of surveillance camera network data has a causal effect on the emergence of AI software linked to facial recognition.

Thereby, AI's technological potential to be a learning tool can create additional knowledge spillovers of related knowledge. Spillovers generated through learning processes are typically linked to the dimension of knowledge proximity (Breschi et al., 2003). But in the AI's case, these spillovers are generated from using AI as a technology, rather than due to the learning process generated through its absorption as a new piece of knowledge. This use of AI as a learning technology explains why the results on relatedness are consistent even across sectors that are unrelated to AI. This effect cannot be explained by other technological particularities of AI, as its digital aspects of generativity and convergence[21].

This finding allows understanding the concept of absorptive capacity as an ability that can be changed by firms' technological choices. Despite the recognition in the literature that some technologies give firms specific benefits or advantages (as explored here in the case of digital technologies following the arguments presented in Yoo et al. (2012)), this possibility was not yet explored. MNEs that introduced AI extended their innovative activities also as a result of particular technological potentialities that AI offers. This is in addition to changes linked to learning about AI as a new piece of knowledge. Breschi et al. (2003) highlight that firms extend their innovative activities in knowledge-related domains as a consequence of their learning processes and due to specific features of knowledge and its links. This paper adds to that view by showing that the adoption of some specific technologies may also impact firms' ability to explore knowledge-related domains. This finding is particularly interesting because it shows that even unrelated technologies can be used to create related knowledge.

Therefore, digitalisation seems to reinforce the aspect of knowledge production as being a cumulative, path dependent, and interactive process (Dosi, 1982; Nelson & Winter, 1982). In this context, AI seems associated with continuous technological change (Dosi, 1982) within the existing ICT technological paradigm, rather than a discontinuous change towards a new paradigm. The fact that AI reinforces existing technological trajectories also highlights that this technology is not being applied yet to its full potential as an IMI. AI is not being used to develop unrelated knowledge. This corroborates similar findings from Bianchini et al. (2020) regarding the potential use of AI as an IMI in science. The authors find that scientists use AI to explore scientific areas that are related to their knowledge domains. In the way that AI is being deployed (i.e., to strengthen

[21] Generativity stresses the role of unprompted change driven by large, varied, and uncoordinated actors. Uncoordinated actors are not likely to produce knowledge that fill the gaps from technologically distant firms. Convergence, in turn, refers to the action potential of embedding digital technologies in nondigital artefacts. This affordance is to have a negative effect on relatedness particularly for firms from sectors technologically distant from digital technologies. This technological distance would lead relatedness to be reduced at least in the first moments after AI introduction, when the firm is transforming its related nondigital artefacts into unrelated digital innovations. The dynamic effects for relatedness across distinct sectors show that this is not the case (See Appendix A6, Figures A6.1 and A6.2).

technological trajectories), it also seems that firms are using this technology to enhance their existing competencies instead of replacing them (Paschen et al., 2020). Nevertheless, AI's potential to be a competence-destroyer technology can play out through competition between firms as AI enhances competences within firms. AI adopters may be using AI to deploy functions that replace what other firms offer.

5.2. Contributions

This paper analysed the effects that affordances provided by digital technologies may have on firms' technological trajectories. For AI as an example of an advanced digital technology, I show that AI adoption is linked to a significant increase in the technological coherence and innovative performance of MNEs. Given the consistency of AI effects on relatedness across distinct sectors, I argue that sectors technologically distant from AI manage to increase their technological relatedness by using AI as a tool for learning rather than by just using AI as a new piece of knowledge. This has implications for the concept of absorptive capacity, linking it to a changing ability that can be influenced by firms' technological decisions. As a result, not only knowledge dimensions, as suggested by Breschi et al. (2003), but also technologies hold the potential to influence the emergence of relatedness.

5.3. Limitations and future research

There are several limitations I need to acknowledge: First, I consider inventions as a direct proxy of innovations. However, only a fraction of AI innovations is patented. Innovators may not patent their innovations for several reasons, e.g., to avoid disclosing technical aspects of their inventions and/or avoid copying, due to difficulties in proving the invention's novelty, due to prices related to patenting, etc. In addition, patent applications do not reflect activities by MNEs in open source software development, which might be a relevant aspect of AI development by firms. Second, I use patent applications rather than granted patents, which might introduce a quality bias. Third, there are missing values for two out of the three indicators considered for innovative performance in the dataset, which may compromise the analysis related to these particular indicators.

Future work is particularly needed – with a focus on alternative technologies – to understand whether the effects measured for AI are part of a broader aspect of how firms' technological trajectories change when they learn about a new technology, or not. In this sense, a detailed analysis of how specific technologies impact sectors from distinct knowledge distances would be particularly interesting. Future research could also focus on alternative data sources to measure innovation and on the possible effects of AI's adoption in the competition between firms (i.e., to understand AI's competence-destroyer potential).

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Appendix

A1: Constructing a dataset combining Patents and Multinational Enterprises data (2011-2019)

The creation and matching of the firm and patent data presented in this paper consists of four main steps, which can be summarised as follows:

1) Construct a dataset of corporate Global Ultimate Owners and their subsidiaries as of 2020;
2) Recreate ownership structures of the past 10 years by adding M&A data and incorporation dates;
3) Create a patent dataset containing the historical ownership of patents;
4) Matching of firm- and patent data and creation of additional firm-level variables;

The construction of the complete dataset was developed in R. Each of the steps carried in the dataset development is detailed in the subsections below.

Step I: Creating a dataset of corporate Global Ultimate Owners and their subsidiaries as of 2020

This step combines a bottom-up identification of Multinational Enterprises (MNEs) on Orbis, followed by a top-down approach used to download data to complement the coverage of the companies considered. Both approaches are based on data downloaded from Orbis between 17/07/2020 and 25/01/2021. In the bottom-up approach, foreign subsidiaries are linked to their immediate parents and, ultimately, their respective global ultimate owners (GUOs). All subsidiaries with foreign shareholders were extracted from Orbis with an *ownership criterion of 25.01%*. The files were downloaded in the following format:

Set 1: Files "GUO" - 2,803,941 companies: Subsidiaries and related ownership data

Company name Latin alphabet	MNE-BvD ID Number	GUO_BvD ID Number	ISH_BvD ID Number (Immediate parent)
Siemens GmbH	DE10001		
Flender GmbH	DE10012	DE10001	LU10002
Siemens Mechanical Drives GmbH	LU10002	DE10001	DE10011

Building on this data structure, a *vlookup* function[22] was used to extend the ownership levels upwards (look for subsidiaries that are parents of other subsidiaries) and downwards (look for parents that are subsidiaries of other subsidiaries). This resulted in an ownership network structure for each of the subsidiaries consisting of a maximum of 21 ownership levels. The search for more subsidiaries/parents stopped when there were no more subsidiaries of a company and when the parent equalled the GUO. This leads to a first outcome file with the following structure:

[22] This vlookup function is applied through the expss package. It looks for a vector of looked up values in a reference column of a data frame, returning the corresponding values from this data frame (https://cran.r-project.org/web/packages/expss/expss.pdf). In the current implementation, the vector values are a list of individual BvD ID Numbers.

Outcome 1: "Interim1" / 2,609,242 companies: Ownership Network of MNEs (bottom-up)

GUO	Own 1	Own 2	Own 3	Own 4	Own 5	Own 6	Own7
DE10001		DE10011	LU10002	DE10012			
DE10001			DE10011	LU10002	DE10012		
DE10002		DK10003	DE10021	DE10022			
DE10002			DK10003	DE10021	DE10022	DE10023	

As this method only allows the connection of subsidiaries across borders and not all subsidiaries might be captured, this initial dataset was then complemented with a top-down search for shareholders with foreign subsidiaries. Thus, the shareholders and *all* their subsidiaries were downloaded in the following format:

Set 2: Files "Sharehoders" - 3,152,693 companies: Shareholders and related subsidiary data

Company name Latin alphabet	Subsidiary-BvD ID Number	GUO_BvD ID Number	Shareholder_BvD ID Number
Siemens GmbH	DE10001		
Flender GmbH	DE10012	DE10001	LU10002
Siemens Mechanical Drives GmbH	LU10002	DE10001	DE10011

By treating the shareholder as the parent company, a *vlookup* function was then used to establish the ownership levels of each company, leading to a second Outcome file with the following structure:

Outcome 2: "Interim2" / 1,752,876 companies: Ownership Network of MNEs (top-down)

GUO	Own 1	Own 2	Own 3	Own 4	Own 5	Own 6	Own7
DE10001		DE10011	LU10002	DE10012			
DE10001			DE10011	LU10002	DE10012		
DE10002		DK10003	DE10021	DE10022			
DE10002			DK10003	DE10021	DE10022	DE10023	

As both data structures are incompatible to match due to differences in the final ownership structures, the bottom-up data frame is used as a basis, which is then complemented with the shareholder data. Therefore, a data string of all shareholders and subsidiary relations across all ownership level was established and merged to each ownership level of Interim 1. An overview of how this Structure-based output is created is presented below.

Match 1: "Structure" / 3,212,537 companies: Ownership Network of multinational enterprises

GUO	Own 1	Own 2	Own 3	Own 4	Own 5	Own 6	Own7
DE10001		DE10011	LU10002	DE10012			
DE10001			DE10011	LU10002	DE10012		
DE10002		DK10003	DE10021	DE10022			
DE10002			DK10003	DE10021	DE10022	DE10023	

GUO	Own 1
DE10011	LU1002
DE10002	DE10012
DE10003	DE10021

After removing duplicates and empty columns, this new dataset contains data from all shareholders and all of their subsidiaries – domestic and foreign –, which add up to 21 ownership levels for the longer firm's ownership structure. As the focus is on identifying *corporate GUOs* only, the original bottom-up Orbis search was modified by *filtering for different types of GUOs*. This set *(Set 3: Files "Diverse" - 2.803.941 companies)* had the same structure as the first set but was bundled by the types of GUOS including Banks, Insurance, Private Equity Funds, Hedge Funds, Mutual and Private Equity Funds, Research Institutes, Public Agencies, Individuals, Employees, and Corporations. By loading these datasets into R and matching them with the ownership structure dataset, it was possible to create a 'type' variable for each company. This led to a dataset with all multinational enterprises, their global structure and a column indicating non-corporate GUOs, with the structure presented below.

Outcome 3: "Type" / 2,609,982 companies: Ownership Network of MNEs with Type

GUO	Own 1	Own 2	Own 3	Own 4	Own 5	Own 6	Type
DE10001		DE10011	LU10002	DE10012			
DE10001			DE10011	LU10002	DE10012		
DE10002		DK10003	DE10021	DE10022			
DE10002			DK10003	DE10021	DE10022	DE10023	

To avoid non-corporate GUOs in the dataset, ownership structures were moved down if the GUO was not a corporate company. This means that states or holdings having an ownership share in several corporations were excluded and corporations were made the highest entity in the corporate network. This resulted in a dataset of 342,787 corporate GUOs representing the top node of the ownership structure as of 2020.

Step II: Recreating ownership structures of the past 10 years by adding M&As and dates of incorporation

After establishing the corporate network ownership structure, two data frames were constructed to allow extending the 2020 ownership structure backwards with additional M&A historical data. First, one data frame consisting of all GUOs in one column and all subsidiaries in the second column (as well as one duplicate of the GUO) was created. Based on this structure, GUOs without subsidiaries or subsidiaries located only in the home country were removed, leaving 280,206 unique GUOs and 1,815,997 subsidiaries. This data serves as the basis for matching all data to all companies in the dataset while still allowing the aggregation to the (corporate) GUO level. To do so, the dataset was split into many GUO-ownership-level data frames, recombined, and cleaned for duplicates. Second, a two-column string of all company subsidiary relations was established by splitting the corporate network data across all ownership levels. This helps defining the subsidiaries of every single nod, which is important if a company (and its subsidiaries) is acquired by another firm. The structure of these two files is presented below.

Outcome 4: "Own" (2,096,203) & "Subs" (3,770,613): Company strings

GUO	Subsidiaries
DE10011	LU1002
DE10002	DE10012
DE10003	DE10021

Company	Subsidiaries
DE10011	LU1002
LU1002	DE10012
DE10003	DE10021

To establish past ownership structure, all M&A deals that relate to the GUOs or subsidiaries as of 2020 were downloaded from the Orbis-Zephyr database. These files included deal and company characteristics, particularly the target, vendor and acquiror information, and were downloaded in the following format:

Set 4: Files "DealsX" - 486,770 transactions: Mergers and acquisitions (since 2010) + company data

Deal Number	Target BvDID	Acquiror BvDID	Vendor BvDID	Deal Type	Deal date	Deal value
351998	DE10015	DE10001	LU10002	Acquisition 50%	2011	n.a.
352048	DE10015	DE10011	UK10001	Acquisition 50%	2015	n.a.
352061	LU10004	LU10002	LU10003	Minority Stake unknown%	2014	n.a.

After excluding deals that are not relevant to ownership changes (unknown % or acquisitions below 25%), *32.334 deals* were left for the period between 2010 and 2020. To calculate the ownership structure backwards, subsidiaries that were sold in year t were added to the ownership structure in year t-1. This was done to identify companies that only belonged to the ownership structure in previous years and to capture all subsidiaries that belonged to the GUO during the examination period. This structure was treated as a basis of 2010 to adjust the ownership structure through forward calculation in three main ways:

1. Merge by target: If the subsidiary as of 2010 was target of a deal in 2011, a vlookup function is used to Check if the acquiror of the target may still be in the ownership group according to the 2020 dataset. If the acquiror's GUO was not the same as the target GUO

(indicating an inter-company acquisition), the company-subsidiary string was matched to detect all companies related to the acquired company. After re-checking if the acquiror belonged to the corporate group, all targets and their related subsidiaries were deleted from the 2010 structure to arrive to a new the 2011 structure.

2. Merge by acquiror: If a company within the GUOs ownership structure of 2010 acquired a new subsidiary in 2011, the target company was added to the ownership structure in 2011, Therefore, the match by acquiror displayed all targets that were added by the company in 2011. Then, the company-subsidiary string was added to identify all subsidiaries of the acquired company. Then, if the acquiror of the targets belonged to the same ownership group, all targets and their subsidiaries were added to the new corporate group of the acquiror.
3. Merge by vendor: If a company within the GUOs ownership structure of 2011 (resulting string of the previous two steps) sold a subsidiary in 2012, the target company and its subsidiaries were added post hoc to the ownership structure in 2011.

In this way, the ownership structures were calculated from 2011 to 2019 and the company-subsidiary data was also updated synchronously to generate a complete picture of ownership structures based on their acquisition deals. The validity of the process is also demonstrated by the consistency of the original Orbis structure and the resulting 2020 ownership structure as there is only a minor *difference of 40.000 companies*, which can be explained with lacking updates of the Orbis data and deletion of companies with a 25.01% ownership change. The following illustration shows the process of removing and adding new subsidiaries.

Match 2: "Own" + "Deals": Matching ownership structures with M&A data

Structure 2010
(Basis for match)

BvDID	Subsidiaries
DE10001	DE10001
DE10001	DE10011
DE10001	DE10012
DE10001	DE10013
LU10001	LU10001
LU10001	LU10002

Company	Subsidiaries
DE10001	DE10001
DE10001	DE10011
DE10001	DE10012
DE10001	DE10013
DE10013	DE10011
LU10001	LU10001
LU10001	LU10002
LU10002	LU10003

Match by target

BvDID	Subsidiaries	Acquiror	GUO1	Subsidiaries	Acquiror	GUO2	Delete
DE10001	DE10001						
DE10001	DE10011	DE10012	DE10001				
DE10001	DE10012				LU10001	LU10001	1
DE10001	DE10013	LU10001	LU10001				1
LU10001	LU10001						
LU10001	LU10002	DE10012	DE10001	LU10003			1
LU10001	LU10003				DE10012	DE10001	1

Match by acquiror

BvDID	Subsidiaries	Target	Subsidiaries	Acquiror GUO	Add	Delete
DE10001	DE10001					
DE10001	DE10011			DE10001		
DE10001	DE10012	DE10011		DE10001		
DE10001	DE10012	LU10002	LU10003	DE10001	1	
DE10001	DE10013	LU10001	LU10001			1
LU10001	LU10001	DE10013	DE10011		1	
LU10001	LU10002					1
LU10001	LU10003					1

BvDID	Subsidiaries
DE10001	DE10001
DE10001	DE10012
DE10001	DE10013
DE10001	LU10002
DE10001	LU10003
LU10001	LU10001
LU10001	DE10011

Match by vendor in 2020

BvDID	Subsidiaries	Target
DE10001	DE10001	DE10014
DE10001	DE10012	
DE10001	DE10013	
DE10001	LU10002	
DE10001	LU10003	
LU10001	LU10001	
LU10001	DE10011	AD10011

BvDID	Subsidiaries
DE10001	DE10001
DE10001	DE10012
DE10001	DE10013
DE10001	LU10002
DE10001	DE10014
DE10001	LU10001
LU10001	LU10001
LU10001	DE10013
LU10001	AD10011

Structure 2011

This process resulted in nine separate ownership files (one for each year considered between 2011-2019), which were further refined through the inclusion of the date of incorporation. The data of incorporation allows differentiating between the foundation of new subsidiaries (greenfield investment) from acquisitions (brownfield investment). This additional data was downloaded in the following format:

Set 5: Files "Date_data" - 2.463.340 (605,532 NAs) companies: Date of incorporation data

Company name Latin alphabet	BvD ID Number	Date of incorporation
Siemens GmbH	DE10015	08/12/2014
Flender GmbH	DE10015	23/06/2005
Siemens Mechanical Drives GmbH	LU10004	12/03/1956

This data was matched to each yearly dataset and companies that were founded after the last considered year were excluded. Plus, companies that were founded in the specific year of interest were indicated with a dummy variable. The resulting dataset has the following structure:

Match 3: "Full20xx" + "Date_data": Matching companies and their dates of incorporation

BvDID	Subsidiaries
DE10001	DE10001
	DE10011
	DE10012

Match by BvDID

BvDID	Subsidiaries	Greenfield
DE10001	08/12/2020	0
DE10011	23/06/2011	1
DE10012	n.a.	0

The changes of the forward ownership calculation and date match are summarised in Tables A1.1 and A1.2.

Table A1.1: Forward Calculation of ownership structures (Original 2020 value 2,096,203)

Year	Companies	By vendor
'20	2,096,203	/
'19	2,096,252	663 (2,999)
'18	2,096,254	995 (3,297)
'17	2,096,262	972 (3,857)
'16	2,096,258	987 (4,154)
'15	2,096,265	915 (3,542)
'14	2,096,225	1,034 (3,783)
'13	2,096,229	881 (3,313)
'12	2,096,239	746 (2,517)
'11	2,096,239	707 (2,277)
'10	2,096,242	704 (2,253)

Year	Companies	By target	By acquiror	By vendor
'10	2,096,242			
'11	2,089,584	1,228 (2,995)	2,272 (3,597)	1,327 (4)
'12	2,086,754	1,299 (2,838)	2,290 (3248)	1,566 (18)
'13	2,084,039	1,363 (1,229)	2,331 (2,897)	1,701 (91)
'14	2,080,873	1,764 (2,958)	2,921 (4,018)	3,480 (138)
'15	2,075,449	2,170 (3089)	3,281 (6,593)	1,563 (218)
'16	2,071,648	2,035 (2,722)	2,939 (9,206)	1,624 (158)
'17	2,066,043	2,138 (3,740)	3,025 (5,263)	1,657 (48)
'18	2,060,179	2,133 (4,124)	2,947 (7,848)	2,004 (73)
'19	2,055,048	1,937 (4,409)	2,698 (8,543)	1,309 (134)
'20	2,055,977	1,223 (3,013)	1,694(3,773)	/

Table A1.2: Forward Calculation of ownership structures (New 2020 value: 2.055.977)

Year	'11	'12	'13	'14	'15	'16	'17	'18	'19
Companies	1,649,863	1,696,713	1,747,034	1,798,762	1,852,586	1,907,127	1,958,278	2,006,336	2,044,415
Difference	+46,850	+50,321	+51,728	+53,824	+54,541	+51,151	+48,058	+38,080	+51,728

Step III: Creating a dataset of patent applications with historical ownership data

One additional dataset with patent data applications was collected from Orbis IP. The development of the patent dataset is divided into five steps, which refer to the creation of a general patent dataset (step 1), creation of a complementary dataset containing additional information about patents with changes in ownership (step 2), creation of an additional AI tag to identify AI patents (step 3), filtering and merging of these three datasets (step 4), and the slicing of the final patent dataset into yearly data (step 5). The details of each step are presented below.

Creating a complete dataset of priority patents

First a dataset based on all patent filings (granted or not) whose priority dates were within the period between 01/01/2009 and 31/12/2019 is created. Particularly, the year 2020 was excluded due to the existing lag in the application process of patents. The initial 45,183,514 patents attending this criterion were further filtered for priorities. Orbis IP allows filtering priorities through the "Families" option, where the filter "Most representative family member only" can be applied. This filter reduces the original dataset of patents from 45,183,514 registers to 27,415,475 priorities registered at the date of the search (11/11/2020). It is still worth highlighting that the option ""Complete" family (DOCDB definition - extended approach)" is the one chosen (conversely to the option ""Simple" family (invention based)". These 27,415,475 priorities were downloaded in the following format:

Set 6: Files "Priorities" - 27,415,475 priority filings: Patents applications with priority dates (2009-2019)

Publication number	Priority date	Current direct owner(s) BvD ID	Applicant(s) BvD ID	IPC code (main)	IPC code	Granted
AP2016094D0	02/09/2015	HK0022459176	HK0022459176	n.a.	n.a.	
AM170U	05/06/2009			n.a.	n.a.	Yes
AT12187U3	19/04/2009	DE2190544304	DE2190544304	E04H12/04	…	Yes
BG111715A	05/03/2014			D01H4/02	…	

Creating a complete dataset of priority patents with change in ownership

In the second step, additional patent information for the patents that had a change in ownership after the first considered year of 2009 is downloaded. There are 773,721 patents that attend to those criteria, and they were downloaded in the following format:

Set 7: Files "OwnershipChange" - 773,721 Priority filings: All patent applications with a change in ownership (2009-2019)

Publication number	Current direct owner(s) BvD	Previous direct owner(s) BvD ID	Vendor BvD ID Number	Acquiror BvD ID Number	Transaction date
AT12626U1	CHCHE10592			US133668641	16/10/2018
				CHCHE1059295	16/10/2018
AT12628U1	AT91108193	AT91105013	AT91105013	AT9110819336	23/10/2014
AU201124213	FI10942595	AU096768704	FI15380325	SE5565878054	13/07/2020
		SE5565878054	FI15380325	FI120464	13/08/2020
		FI120464	AU0967687	FI15380325	07/02/2019

Due to some issues with ambiguous and duplicated data in Orbis IP, additional filterers and checks were employed to separate irrelevant data from the relevant transactions useful for the analysis. In short, four filters were applied for cleaning the data: i) one for identifying changes where the current owner[23] is also the acquirer of the patent or the applicant (if the vendor

[23] It is worth mentioning that Orbis IP allows for the possibility of a patent having more than one owner, which is also considered in the creation of the patent dataset presented here.

information is not available); ii) one for counting the number of changes that actually happened, based on the dates (i.e., excluding the possibility of several changes occurring in the same day); iii) one for selecting which of the repeated data should be selected (based on the acquiror/vendor and owner/applicant information); and iv) one for identifying different owners and applicants, so that data about any of these companies is not missed. After applying these filters and dropping irrelevant data, a total of 694,859 patents are identified as having at least one ownership change in the considered period. These are further filtered for priorities and expired patents by merging this dataset to the priority's dataset, created in the last step (unmatched registers are dropped). The resulting dataset contains information about ownership changes for 429,227 priority patents.

Creating an 'AI' tag

As the current paper has a particular focus on AI technologies, these are additionally tagged in the patent dataset. The identification of these patents follows the keyword-based search proposed in Leusin et al. (2020). The list of keywords considered is also presented in Table A1.3.

Table A1.3: Keywords proposed in Leusin et al. (2020) for identifying AI patents

AI Technique Keyword	Additional Wikipedia Synonym Keyword
%neural network%	No additional synonym
%machine learn%	No additional synonym
%artificial intelligence%	%machine intelligen%
%expert system%	No additional synonym
%support vector machin%	%support vector network%
%fuzzy logic%	No additional synonym
%graphical model%	%structured probabilistic model%
%pervised learn%	No additional synonym
%deep learn%	%deep structured learn% and %hierarchical learn%
%classification tree% OR %regression	%decision tree learn%
%reinforced learn%	%reinforcement learn%
%logic programming%	No additional synonym
%rule learn%	%rule induction%
%probabilistic reason%	%probability logic% and %probabilistic logic%
%task learn%	No additional synonym
%logical learn% OR %relational learn%	No additional synonym
%latent represent%	No additional synonym
%bio-inspired approach%	%bio-inspired comput% and %biologically inspired
%instance-based learn%	%memory-based learn%
%ontology engineer%	No additional synonym
%description logistic%	Keyword not found

Conversely to Leusin et al. (2020), which identifies as AI patents all registers containing any of the mentioned AI-keywords in the titles or abstracts, also the <u>claims and description</u> of the patents are considered in this paper. These criteria resulted in 717,860 identified AI patents, which are further filtered for priorities, resulting in a final "AI tag" added to 440,698 priorities.

Filtering and merging patent datasets

Next, the patents with a change in ownership are extracted from the general comprehensive priorities' dataset. Priorities without any information about current owners are also excluded from the main dataset, remaining 17,581,241 priorities (and 429,227 priorities in the unchanged "Dataset with changes in ownership"). Both datasets are further filtered for withdrawn or abandoned patents by dropping the ones containing the status of "Expired" in Orbis IP. Considering the usual expiration time of 20 years and the time frame considered between 2009 and 2019, no expired patents should be found in the considered period, meaning that applications with this status were very likely withdrawn or abandoned by the applying companies. Therefore, they don't represent any significant innovation results and are excluded from the patent dataset.

To allow for the direct matching o the patent data with the MNEs' ownership structure later on, a structure with the yearly ownership data information of patents throughout each year of the considered period is created. For patents without any change in ownership, the owner information is repeated for each year and each owner for the number of times that the patent has existed in the considered period. For the dataset with changes in ownership, distinct criteria for selecting the owners of the patents in distinct periods of time are applied, based on the dates in which the changes in ownership occurred. More precisely, until the first change in ownership, the owners of the patents are assumed to be the applicants of the patent. For the period after the last change in ownership of a patent, the owners of the patent are defined to be the current owners of the patents. For all changes of ownership occurring between these two periods, the owners of the patents are defined based on the "Acquiror BvD ID Number" information of each ownership change transaction. In addition, if there is missing information about applicants, owners or acquirors in the years that this information is used for defining the owners, the patents are not dropped but just stay without an owner until the next transaction without missing data happens.

Finally, these two datasets were merged with the "AI tag" using the Publication number information. In this way, AI patents gain additional identification information to separate them from the rest of the patents. The final dataset has the following structure:

Outcome 6: "Patents" / 1,527,441 companies: Ownership Structures with firm-and country variables

Publication Number	Curr. Owner BvDID	Prior. Year	Diff 1	Owner	Cur. Year	IPC main	IPC other	Grant	No of family mem.	AI tag
CN2082366U	CN9387053	2018	2	CN9387053	2019	NA	NA	NA	NA	NA
CN2082366U	CN9387053	2018	2	CN9387053	2018	NA	NA	NA	NA	NA
CN2082367U	CN31995PC	2018	2	CN31995PC	2019	NA	NA	NA	NA	NA
CN2082367U	CN31995PC	2018	2	CN31995PC	2018	NA	NA	NA	NA	NA
CN2082375U	CN9371220	2017	3	CN9371220	2019	NA	NA	NA	NA	NA

"Diff1" refers to how many years the patent existed in the period 2009-2019. "CurrYear" refers to each year of "existence" of the patent in this period. The column "Owner" refers to the owner of the patent in a given year. Finally, for AI patents, the last column, namely "AI", indicates if the register is an AI patents ("Yes") or not (NA). Descriptive information about the generated patent ownership data is presented in Table A1.4.

Table A1.4: Characteristics of the patent dataset

Description	Full Dataset	
Total number of priority patents for the period 2009-2019 including withdraw/abandoned patents	18,010,468	
Detailed results:	**Considering the period 2011-2019:**	
Total number of non-expired priority patents	15,735,583	100%
Total number of non-expired priority patents with no changes in ownership	15,438,678	98.1%
Total number of non-expired priority patents with no changes in ownership and with just one owner	14,582,343	92.7%
Total number of non-expired priority patents with no changes in ownership and with more than one owner	856,335	5.4%
Total number of non-expired priority patents with changes in ownership	296,905	1.9%

Finally, to complement the patent stock, additional patent data is downloaded. But this time, the data is downloaded focusing on the relevant BvD IDs identified. This means that the ownership structure of GUOs as of 2010 is used as input to collect additional patents that were owned by these companies before the year 2011. This additional patent stock data was downloaded in 02/03/2021. In total, 13,545,086 additional priorities were identified. All these patents (plus the patents from 2009 to 2010) were aggregated to the 2010 ownership structure, which served as the basis for the patent stock variables.

Slicing the Patent dataset into yearly data and creation of additional variables

The "Patent dataset" created in the previous step is further separated by year into 10 slices, which covers a stock file (with data from 2000 to 2010) plus yearly ownership information from 2011 to 2019. The created variable "Owner" is used to create the following additional variables: sum of patents (NoPat), sum of new patents per year (App), sum of AI patents (AINoPat), sum of new AI patents per year (AInew) These variables are aggregated to the owner and include all MNEs and non-MNEs that patented in the examination period. The yearly dataset has the following structure:

Outcome 7: "Full11" / 1.527.441 companies: Patent dataset for 2011

BvDID Owner	Year	No Pat	App	AINoPat	AIApp	AInew
GB000414	2011	254	0	0	0	0
UG800100	2011	0	0	0	0	0
GB054441	2011	0	0	0	0	0

Step IV: Matching corporate and Patent data, and download of additional variables

Finally, the patent data was matched with the GUO-subsidiary data based on the owners BvD IDs, so that the patent-related variables per company were attached to the different entities of the MNEs. As the main interest is on the top node of the MNE hierarchy, the patent variables were aggregated up to the corporate GUO. Then, the list of GUOs considered was uploaded to Orbis as a search criterion, so that additional specific firm-level variables could be downloaded for each MNE. The following additional variables were downloaded from Orbis: 'NACE Rev. 2, core code (4 digits)', 'Country ISO code', 'Size classification' (which follows Orbis classification), 'Operating revenue (Turnover) th USD' (one column of data for each year within the period 2011-

2019), 'R&D expenses/Operating revenue (%)' (also one additional column of data for each year within the period 2011-2019), in addition to the variables 'age' and 'Type of entity', which were already downloaded in the previous steps. This additional data was downloaded on 26/03/2021.

To further reduce the sample, exclusion criteria on the number of total patents (<1), foreign subsidiaries (<1), employees (<50.000) and revenue (<50.000.000) were applied. These criteria comply with the definition of large companies according to the European Commission. This step also ensures the comparability of firms in the dataset. General information about the complete dataset is presented on Appendix A2.

A2: General descriptives of the complete dataset. Note: Both total number of AI patents accumulated and total number of AI patents identified consider an initial stock from 2000 to 2010.

Indicator	**Year**								
	2011	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
General information about number of GUOs and their subsidiaries									
Total number of GUOs considered	30,228	31,551	32,756	33,806	34,992	36,210	37,279	38,103	38,168
Total number of subsidiaries	785,931	817,887	848,821	880,528	911,233	943,850	974,776	1,003,895	1,016,299
Total number of subsidiaries with at least one patent (and share in relation to total number of subsidiaries)	59,067 (7.5%)	62,653 (7.7%)	66,040 (7.8%)	69,078 (7.8%)	72,121 (7.9%)	75,146 (8.0%)	77,964 (8.0%)	80,325 (8.0%)	80,857 (8.0%)
General information about patents									
Total number of patents identified	6,026,034	6,590,477	7,155,959	7,739,903	8,370,595	9,001,192	9,571,261	10,168,201	10,303,302
Total number of patents owned by GUOs	3,737,247	4,018,636	4,285,994	4,554,733	4,820,442	5,092,258	5,302,449	5,522,523	5,479,364
Total number of patents owned by subsidiaries (and share in relation to total)	2,288,787 (38%)	2,571,841 (39%)	2,869,965 (40%)	3,185,170 (41%)	3,550,153 (42%)	3,908,934 (43%)	4,268,812 (45%)	4,645,678 (46%)	4,823,938 (47%)
Total number of GUOs with direct ownership of patents	17,165 (57%)	17,870 (57%)	18,557 (57%)	19,154 (57%)	19,775 (57%)	20,436 (56%)	21,010 (56%)	21,401 (56%)	21,399 (56%)
Total number of GUOs with direct or indirect ownership of patents	18,760 (62%)	19,692 (62%)	20,513 (63%)	21,253 (63%)	22,075 (63%)	22,903 (63%)	23,660 (63%)	24,242 (64%)	24,335 (64%)
Information about AI patenting									
Total number of GUOs without AI patents	28,523	29,656	30,675	31,520	32,472	33,405	34,101	34,370	34,271
Total number of GUOs with at least one AI patent (and share related to the total number of GUOs with direct or indirect ownership of patents)	1,705 (5.6%)	1,895 (6%)	2,081 (6.4%)	2,286 (6.8%)	2,520 (7.2%)	2,805 (7.7%)	3,178 (8.5%)	3,733 (9.8%)	3,897 (10.2%)
Total number of AI patents identified owned by the considered GUOs	15,265	17,793	21,068	25,509	32,224	41,625	56,131	79,469	91,742
Total number of AI patents owned at the GUO level	9,247	10,448	11,912	13,910	16,511	20,603	26,766	35,823	39,193
Total number of AI patents owned at the subsidiary level (and share in relation to total)	6,018 (39%)	7,345 (41%)	9,156 (43%)	11,599 (45%)	15,713 (49%)	21,022 (51%)	29,365 (52%)	43,646 (55%)	52,549 (57%)

In particular, the role of subsidiaries in patenting seems to grow over time, although the number of subsidiaries that create at least one patent changes just marginally. The number of patents owned by subsidiaries related to the considered GUOs increases from 38% in 2011 to 47% in 2019, whereas the total number of subsidiaries with at least one patent changes from 7.5% to 8.0%. When AI patents are considered separately, the increase in subsidiaries' relevance is even more expressive: their ownership share grow from owning 39% of the AI patents related to the GUOs in 2011 to a share of 57% in 2019. Note the difference between the three indicators presented in the table: the indicator named 'Total number of GUOs considered' considers the accumulated number of Global Ultimate Owners (GUOs) that appear in my dataset. It comprehends both companies that still exist and companies that are no longer active (due to mergers or other reasons). The two indicators 'Total number of GUOs with direct ownership of patents' and 'Total number of GUOs with direct or indirect ownership of patents', in turn, allow differentiating the number of active companies in a given year. This differentiation is possible through the structure of my dataset: as patents 'follow' their previous owners once they are acquired by other companies, a GUO that has no ownership over any patent is not active or was merged to another GUO. Finally, the higher values seen for 'Total number of GUOs with direct or indirect ownership of patents' over 'Total number of GUOs with direct ownership of patents' mean that in some cases the GUOs didn't register any patent in the considered period, although subsidiaries related to them did.

A3: Data about 30 larger AI adopters in 2016 (Table C1) and 2019 (Table C2).

No.	Name of the GUO	No. of patents owned	No. of AI patents owned	Country
1	Microsoft Corporation	49,912	1,754	US
2	Samsung Electronics Co., Ltd.	65,999	1,343	KR
3	International Business Machines Corp	85,963	1,183	US
4	Alphabet Inc.	31,602	970	US
5	Softbank Group Corp	15,608	884	JP
6	Siemens Ag	52,783	845	DE
7	Intel Corp	50,365	677	US
8	Sony Corporation	92,139	555	JP
9	Qualcomm Inc	43,850	534	US
10	Koninklijke Philips N.V.	33,878	493	NL
11	General Electric Company	47,308	488	US
12	Hitachi Ltd	144,544	455	JP
13	Fujitsu Limited	78,317	440	JP
14	Nec Corporation	69,580	389	JP
15	Nokia Oyj	45,775	385	FI
16	Naspers Limited	10,680	385	ZA
17	Toshiba Corporation	139,962	344	JP
18	Halliburton Co	12,568	344	US
19	Panasonic Corporation	218,691	314	JP
20	Mathworks Inc	1,004	305	US
21	Mitsubishi Electric Corporation	105,359	297	JP
22	Canon Incorporated	165,658	287	JP
23	Ford Motor Co	19,176	269	US
24	Facebook, Inc.	5,642	260	US
25	Ericsson (Telefonaktiebolaget Nl) Ab	33,658	247	SE
26	Zte Corporation	37,475	241	CN
27	Hp Inc.	30,430	238	US
28	Robert Bosch Industrietreuhand Kommanditgesellschaft	40,219	212	DE
29	Boeing Company (The)	14,949	187	US
30	General Motors Company	25,382	173	US

Table A3.1: Main AI adopters identified in 2016. In comparison to the results presented in Fujii and Managi (2018), Table 3, one can see significantly higher numbers here. All top 10 AI adopters presented in Fujii and Managi (2018) are also seen here, although in slightly distinct positions (these top 10 are highlighted in the above table). Please note that Alphabet is the parent company of Google. When the top 15 are considered, Yahoo and D-Wave don't appear here. When the top 20 are considered, SAP and Xerox don't appear.

No.	Name of the GUO	No. of patents owned	No. of AI patents owned	Country
1	Softbank Group Corp	29,727	3,137	JP
2	Naspers Limited	20,529	2,752	ZA
3	Microsoft Corporation	51,903	2,719	US
4	Samsung Electronics Co., Ltd.	82,699	2,638	KR
5	Siemens Ag	59,342	1,747	DE
6	Alphabet Inc.	33,012	1,736	US
7	Intel Corp	52,849	1,524	US
8	International Business Machines Corp	77,273	1,513	US
9	Koninklijke Philips N.V.	35,334	983	NL
10	Sony Corporation	93,803	972	JP
11	Lg Corp.	102,404	889	KR
12	Fujitsu Limited	83,578	833	JP
13	Hitachi Ltd	157,540	813	JP
14	General Electric Company	48,639	778	US
15	Nokia Oyj	48,228	750	FI
16	Gree Electric Appliances, Inc. Of Zhuhai	51,911	742	CN
17	Qualcomm Inc	47,882	724	US
18	Robert Bosch Industrietreuhand Kommanditgesellschaft	51,863	722	DE
19	Nec Corporation	71,228	717	JP
20	Mitsubishi Electric Corporation	122,082	644	JP
21	Fujifilm Holdings Corporation	119,637	600	JP
22	Canon Incorporated	180,316	571	JP
23	Jd. Com Incorporated	5,797	566	KY
24	Panasonic Corporation	226,173	542	JP
25	Ericsson (Telefonaktiebolaget Nl) Ab	38,329	538	SE
26	Apple Inc.	25,351	457	US
27	Xiaomi Corporation	12,302	452	KY
28	Hp Inc.	31,585	444	US
29	Ford Motor Co	24,256	438	US
30	Halliburton Co	14,166	421	US

Table A3.2: Main AI adopters of 2019. In comparison to the previous table, the overall number of AI patents increases considerably, with 8 players owning now more than 1,000 patents, in comparison to 3 seen in 2016. Particularly some smartphone manufacturers come into the picture, seen with the first appearance of Apple, LG, and Xiaomi.

A4: Data about AI adopters before and after matching. The three most used Nace codes are the same before and after the matching, although the code 6201 in particular has a considerably higher share for the matched sample. Size classes are also very similar for both samples (C2), as well as Age (C3) and Year of first adoption (C5). For countries, the three leaders hold some distance from the rest of the countries for both samples, whilst Japanese companies overcome Chinese ones in the matched sample. Overall, the considered AI adopters are overwhelmingly very large companies, usually from the sectors 6201 (Computer programming activities), 5829 (Other software publishing) and 2611 (Manufacture of electronic components), which concentrate 22.5% of the Nace sectors. AI adopters are also mostly companies created before 2001 (63%), situated in the USA, China or Japan (51%), and 41% of them adopted AI in 2017 or 2018.

Data pre-matching (n = 1798)		Data post-matching (n = 871)	
Nace code	Representativeness (%)	Nace code	Representativeness (%)
6201	6.9%	6201	11.4%
5829	5.8%	5829	6.3%
2611	5.3%	2611	4.8%
6420	5.3%	2120	3.8%
6209	3.3%	6209	3.3%
2120	2.6%	2899	3.1%
2899	2.6%	2651	2.8%
2630	2.4%	6420	2.5%
2651	2.4%	7112	2.1%
2620	2.1%	2630	2.0%

Table A4.1: Nace codes' representativeness before and after the matching procedure.

Size class	Representativeness Pre-Matching (%)	Representativeness Post-Matching (%)
Very large company	72%	73%
Large company	13%	11%
Medium sized company	10%	8%
Small company	6%	8%

Table A4.2: Size class' representativeness before and after the matching procedure.

Age category	Representativeness Pre-Matching (%)	Representativeness Post-Matching (%)
(0,1980]	23%	25%
(1980,2000]	32%	38%
(2000,2005]	15%	12%
(2005,2010]	13%	12%
(2010,2021]	16%	13%

Table A4.3: Age categories' representativeness before and after the matching procedure.

Data pre-matching (n = 1798)		Data post-matching (n = 871)	
Country	**Representativeness (%)**	**Country**	**Representativeness (%)**
USA	24%	USA	28%
China	15%	Japan	13%
Japan	11%	China	11%
Germany	5%	Germany	6%
United Kingdom	4%	Taiwan	4%

Table A4.4: Main countries' representativeness before and after the matching procedure.

Year first AI adoption	Representativiness Pre-Matching (%)	Representativiness Post-Matching (%)
2011	7%	7%
2012	9%	9%
2013	7%	6%
2014	9%	8%
2015	9%	8%
2016	12%	14%
2017	16%	16%
2018	24%	25%
2019	7%	8%

Table A4.5: Distribution groups (based on the year of AI adoption) before and after the matching procedure.

A5: Average distance of every Nace sector to the AI technological cluster.

Below it is presented the estimated distance for all Nace codes available, from the technologically closest ones (subgroup 1) to the most distant ones (subgroup 3). The calculation of these distances is done in the following way: i) patents are separated into their subclasses (4-digits IPC codes) and aggregated in the Nace sectors of the companies that own them; ii) the relatedness density of all AI patents considered is calculated; iii) the relatedness density between the considered Nace sectors to the AI density cluster is calculating, generating a matrix in which each Nace sector presents values between 0 and 100 for every subclasses of technologies existent; iv) the Mean Absolute Error (MAE) for every sector from their density matrix to the AI cluster is calculated and used as final measure for knowledge distance. The implementation of step 2 and 3 is done using the EconGeo package, through the formulae “relatedness.density.int” and “relatedness.density.ext”, respectively.

Sector	Avg. Dist.	Subgroup number
6209	11.38	1
4743	11.79	1
4761	11.79	1
6190	11.84	1
5829	11.93	1
6020	12.34	1
6201	12.36	1
6311	12.59	1
5320	12.60	1
5121	12.63	1
6202	12.64	1
5819	12.75	1
8020	12.82	1
8010	12.92	1
8623	13.00	1
2630	13.26	1
6411	13.26	1
4791	13.28	1
2740	13.30	1
6399	13.34	1
7711	13.45	1
7722	13.50	1
8510	13.60	1
8621	13.61	1
9411	13.63	1
4648	13.65	1
8610	13.65	1
4332	13.72	1
4651	13.75	1
7420	13.77	1
8220	13.82	1
8291	13.84	1
7312	13.87	1
7911	13.87	1
2600	13.89	1
6391	13.89	1
6120	13.89	1
4532	13.90	1
6200	13.93	1
8422	13.94	1
5010	14.00	1
2640	14.08	1
8219	14.19	1
5221	14.19	1
3513	14.24	1
6203	14.24	1
6491	14.25	1
8559	14.25	1
4312	14.32	1
9523	14.33	1
4774	14.36	1
9002	14.37	1
8413	14.40	1
6130	14.41	1
6312	14.52	1
9603	14.53	1
4742	14.55	1
8790	14.60	1
2620	14.61	1
4939	14.61	1
9312	14.62	1
4520	14.63	1
4222	14.66	1
4212	14.69	1
9602	14.70	1
9329	14.70	1
5223	14.70	1
4730	14.73	1
9200	14.73	1
4637	14.73	1
9313	14.77	1
7820	14.78	1
7733	14.79	1
4931	14.83	1
5914	14.84	1
9003	14.86	1
5813	14.86	1
8560	14.86	1
2100	14.89	1
6010	14.89	1
5912	14.90	1
2811	14.97	1
7021	14.98	1
9319	15.00	1
8430	15.04	1
7912	15.04	1
7110	15.06	1
6110	15.06	1
6900	15.06	1
6611	15.06	1
5814	15.07	1
8424	15.11	1
8421	15.15	1
8622	15.15	1
3240	15.16	1
1391	15.17	1
6622	15.20	1
5913	15.25	1
6629	15.25	1
7220	15.27	1
9512	15.30	1
8230	15.30	1
1412	15.30	1
9601	15.32	1

2823	15.35	1
4762	15.36	1
4531	15.38	1
0162	15.38	1
4631	15.40	1
6530	15.40	1
4540	15.41	1
1813	15.42	1
3320	15.42	1
4510	15.43	1
7311	15.45	1
2822	15.46	1
4665	15.46	1
4615	15.47	1
1390	15.48	1
4310	15.49	1
7731	15.49	1
0142	15.51	1
4772	15.51	1
8292	15.52	1
3821	15.52	1
7200	15.53	1
0123	15.55	1
6610	15.55	1
5629	15.56	1
9604	15.57	1
2700	15.58	1
6800	15.59	1
4777	15.60	1
8899	15.61	1
4775	15.61	1
2540	15.61	1
9311	15.61	1
4932	15.62	1
2731	15.63	1
7020	15.64	1
3220	15.65	1
4619	15.67	1
4770	15.69	1
4940	15.69	1
2500	15.69	1
7400	15.71	1
3040	15.71	1
4765	15.72	1
4331	15.73	1
0990	15.73	1
8730	15.75	1
0620	15.76	1
2651	15.76	1
5920	15.76	1
4799	15.77	1
7800	15.78	1

3812	15.78	1
1700	15.79	2
5630	15.80	2
582	15.81	2
9104	15.81	2
4910	15.82	2
4750	15.83	2
3530	15.87	2
2572	15.87	2
4613	15.88	2
3314	15.88	2
7000	15.88	2
8425	15.88	2
2312	15.89	2
0150	15.89	2
9420	15.89	2
2349	15.89	2
4213	15.90	2
0240	15.90	2
4776	15.90	2
0129	15.90	2
2360	15.91	2
2440	15.91	2
4636	15.91	2
2840	15.91	2
4622	15.91	2
5000	15.91	2
4100	15.91	2
4511	15.92	2
7712	15.92	2
4313	15.93	2
0160	15.93	2
1410	15.94	2
4700	15.94	2
0125	15.94	2
4664	15.95	2
2310	15.95	2
3020	15.95	2
5030	15.95	2
4612	15.96	2
16	15.96	2
3523	15.96	2
0721	15.96	2
3311	15.97	2
2443	15.97	2
4290	15.97	2
5040	15.97	2
9810	15.97	2
3315	15.97	2
0124	15.97	2
0146	15.97	2
3800	15.97	2

691	15.97	2
7310	15.97	2
7735	15.97	2
7830	15.97	2
8290	15.97	2
9524	15.97	2
4610	15.97	2
8122	15.97	2
7729	15.98	2
0164	15.99	2
4110	15.99	2
803	15.99	2
4670	15.99	2
2344	15.99	2
3250	15.99	2
9600	16.00	2
4291	16.01	2
2510	16.01	2
7430	16.01	2
4643	16.02	2
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3510	16.21	2

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0112	16.23	2
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1030	16.23	2
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2040	16.43	2
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2790	16.44	2
1411	16.45	2
4778	16.45	2
9321	16.46	2
4660	16.47	2
2591	16.47	2
2512	16.54	2
2815	16.54	2
3822	16.54	2
2810	16.54	2
0114	16.56	2

1092	16.57	2
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7810	16.58	2
0119	16.60	2
1071	16.60	2
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2733	16.61	2
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6400	16.72	2
7990	16.74	2
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7490	16.76	2
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4623	17.69	2

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2017	17.79	2
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6832	17.84	2
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2369	17.86	2
2820	17.87	2
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1414	17.88	2
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4633	18.70	3
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1722	18.76	3
1395	18.79	3
1082	18.79	3
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6920	18.85	3
9412	18.87	3
2314	18.87	3
2453	18.88	3
2059	18.89	3
5911	18.91	3
4759	18.91	3
2445	18.96	3
4641	18.97	3
3700	18.98	3
2015	18.99	3
1020	18.99	3
2041	19.00	3
0510	19.02	3
2319	19.03	3
1013	19.03	3
2562	19.07	3
0111	19.09	3
2014	19.09	3
2529	19.10	3
2891	19.10	3
4752	19.12	3
2892	19.14	3
2920	19.14	3
4690	19.14	3
2521	19.16	3
8541	19.17	3
1081	19.19	3
2341	19.21	3
1330	19.25	3
2813	19.26	3
2013	19.30	3
2561	19.31	3
0893	19.33	3
1920	19.33	3
5110	19.36	3
7210	19.36	3
2229	19.37	3
2219	19.39	3
2016	19.40	3
2432	19.41	3
1712	19.42	3
1310	19.42	3
2313	19.42	3
4711	19.44	3
1031	19.46	3
8412	19.48	3
4672	19.50	3
6831	19.53	3
4519	19.53	3
0811	19.54	3
4614	19.56	3
1041	19.57	3
1107	19.57	3
2343	19.57	3
2311	19.59	3
0210	19.61	3
4674	19.61	3
5229	19.61	3
7740	19.64	3
2454	19.65	3
8411	19.65	3
1091	19.68	3

6910	19.70	3	4634	20.04	3	3011	20.58	3
5610	19.70	3	1910	20.07	3	6430	20.61	3
2442	19.71	3	4950	20.07	3	4221	20.84	3
2060	19.73	3	2351	20.10	3	2899	20.88	3
8552	19.75	3	2814	20.13	3	6820	21.10	3
2223	19.78	3	2391	20.17	3	1629	21.11	3
5510	19.79	3	2011	20.17	3	6420	21.17	3
2221	19.80	3	4669	20.20	3	2829	21.24	3
6500	19.81	3	6492	20.21	3	4941	21.26	3
0729	19.82	3	6810	20.25	3	4618	21.47	3
2420	19.84	3	4673	20.28	3	7410	21.47	3
1011	19.85	3	2800	20.40	3	2599	21.81	3
2732	19.86	3	1399	20.41	3	0899	22.02	3
4329	19.89	3	2020	20.42	3	4671	22.04	3
4675	19.93	3	2593	20.47	3	7112	22.23	3
1420	19.97	3	2399	20.49	3	7010	22.31	3
2550	19.98	3	2511	20.50	3	6499	22.31	3
3811	19.98	3	6630	20.51	3	4649	22.55	3
3600	20.04	3	0891	20.55	3	7219	22.98	3

A6: Dynamic effects for the self-selection analysis for the first (Figure A6.1) and second (Figure A6.2) classification methods used.

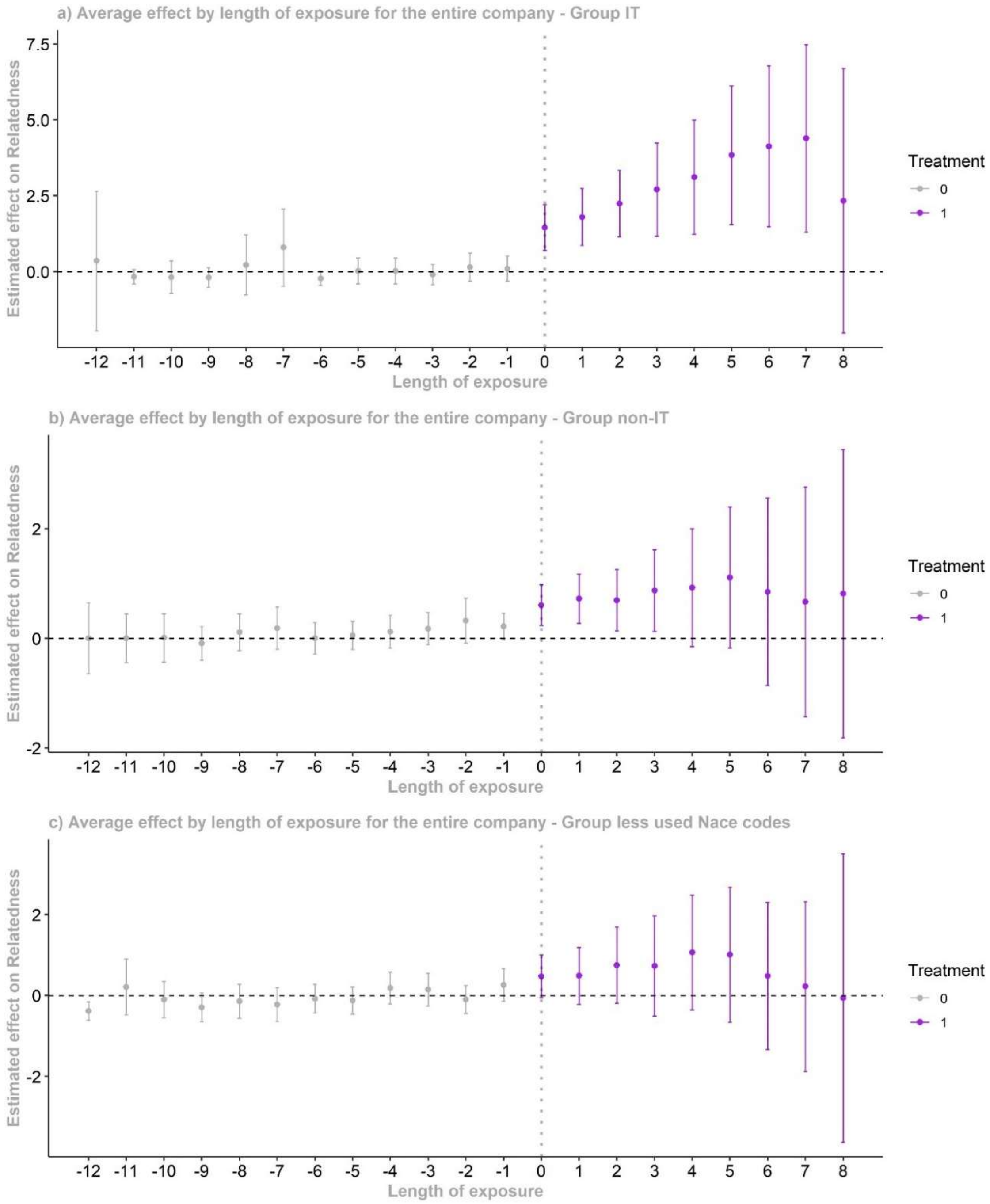

Figure A6.1. Estimated effects on firms' relatedness considering Nace-based classification

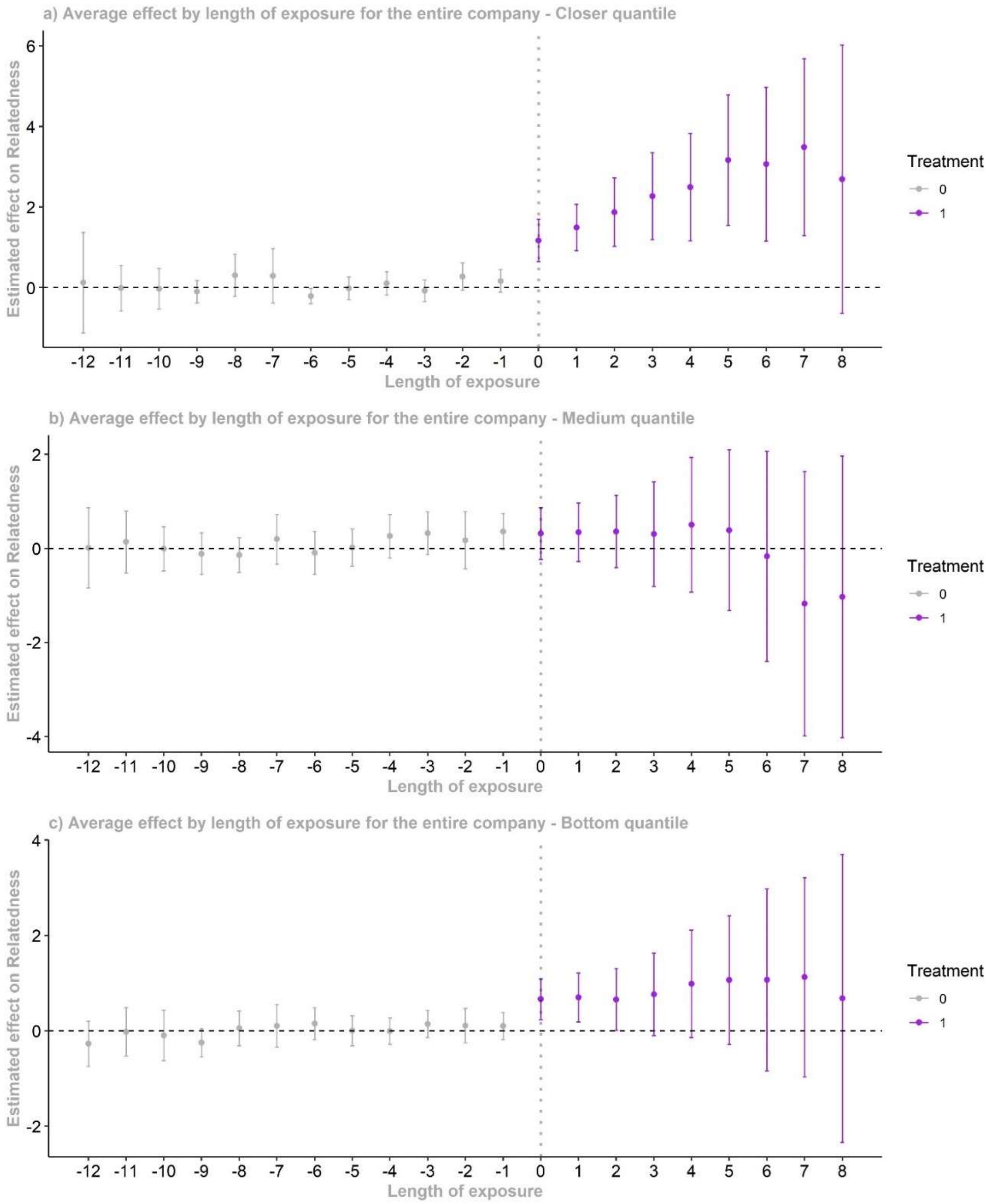

Figure A6.2. Estimated effects on firms’ relatedness considering knowledge distance-based classification

A7: Distribution of distinct considered samples regarding the size of the companies.

Size	Distribution all matched companies	Distribution companies with Turnover data	Distribution of companies with R&D expenses data
Very large company	73%	87.6%	99.5%
Large company	11%	7.6%	0.5%
Medium sized company	8%	3.8%	0.0%
Small company	8%	1.0%	0.0%
Number of MNEs in the sample	6,930	4,259	2,649
Units lost in comparison to the total		38.5%	61.9%

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