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Industry 4.0 Related Innovation and Firm Growth

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In this paper we explore the relationship between innovative firms that patent technology related to Industry 4.0 and their economic performance. By applying the new patent cartography developed by the EPO that identifies firm's 4.0 patents, this is one of the first large-scale, systematic studies on the impact of 4.0 technologies. Since 4.0 patents are more likely to be general purpose technologies, firms with 4.0 patents should be in a better position to increase their sales as 4.0 technology has on average a wider industrial applicability. Results of our Fixed Effects Least Squares regressions and Dynamic Panel Model suggest that 4.0 patent stock is positively associated to sales and that this effect is significantly larger than the effect of Non-4.0 patent stock. These effects are found to be decreasing with firm size.

Key Words: Industry 4.0, Patents, Firm Performance, Sales Growth.

JEL: L25, O14, O33.

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1 Introduction

On-going advancements in artificial intelligence, digitalization, connectivity, smart machines and the internet of things (IoT) are expected to bring forth a digital transformation that will mark a new era of technological development; the 4$^{\text{th}}$ Industrial Revolution (also known as Industry 4.0). It is expected to completely revolutionise production and operation procedures, boosting productivity and growth not just at the firm-level, but for the economy as a whole.

The benefits of the Industry 4.0 are expected to range from predicting and preventing major epidemics, to minimising waste, better forecasting of the supply chain and being able to deliver customised products on demand.[1] At the same time, concerns are being raised about job replacement, data security and the ethics of privacy (Arntz et al., 2017; Agrawal et al., 2018). The opportunities and threats of the digital transformation have made Industry 4.0 a topic high on the agenda of businesses and policy-makers alike (OECD, 2018).

Yet the influence that Industry 4.0 will have is not well understood. Little economic research on the topic exists and we often have to rely on the evidence at hand from the literature on IT. When looking at its impact on firm performance, this strand of literature tends to focus on very specific contexts of a 4.0 related technology that is adopted or implemented at one production plant. This makes them neither representative of all 4.0 technologies, nor does it facilitate extrapolation of their results. The most challenging obstacle for economists has been the lack of consensus as to what should be considered as 4.0-related and how to measure it.

This dissertation chapter is the first large-scale, systematic analysis on the impact of inventing 4.0 technology on firm performance. Using the newly developed (all-encompassing) 4.0 patent cartography of the EPO we are able to investigate all German firms that are patenting in 4.0 technology.[2] A comparison to other innovative German firms that are

[1] See Appendix A of the discussion paper by (McKinsey, 2017) for an elaborate description of five case studies on the application and benefits of artificial intelligence. The paper also reports the results of what is the most extensive firm survey that exists on AI.

[2] Henceforth, we will use the acronym '4.0' to either refer to Industry 4.0 or '4.0 technology' and '4.0 patents' to refer to technology and patents that are 4.0 related. It should also be noted that the EPO refers to the 4$^{\text{th}}$ Industrial Revolution, but Industry 4.0 is becoming a more widely accepted term, now also in the English language.

patenting but not in 4.0, allows us to quantify the additionality effect of 4.0 inventions. Innovative firms have a competitive advantage that enables them to survive and grow (Doms et al., 1995; Aghion et al., 2001) and patenting these inventions per definition offers them monopoly power via the right to exclude.

Diverging from the common approach in the literature, we study the impact of 4.0 technology on sales turnover, rather than productivity as the performance measure. Our main motivation for this is that the firms in our sample are *developers* of 4.0 technology rather than *adopters*, which means that they may not have large scale production plants to realise productivity gains. The sale of products or software solutions encompassing their 4.0 technology however, is a channel through which we can capture the economic gains that 4.0 *developers* might experience. This applies equally to licensing royalties. In fact, a firm's capability to produce general purpose technologies (GPTs) is an important determinant of licensing (Gambardella and Giarratana, 2013).[3] Strong arguments have been put forth that 4.0 technologies are general purpose technologies (GPTs), which is characterised by pervasive use in a wide range of sectors and has far reaching industrial applicability (Agrawal et al., 2018; Cockburn et al., 2018; Bresnahan and Trajtenberg, 1995). We therefore expect it to be easier for firms to generate sales turnover from 4.0 patents than from Non-4.0 patents.

The rest of the paper is structured as follows. We first describe the channels through which 4.0 patenting is expected to lead to higher sales turnover in section 2, give a short overview of the existing literature on the the relationship between ICT and patents on firm performance in the section 3. section 4 focuses on the data we use for our analysis, followed by the description of the econometric methodology in section 5 and the estimation results in section 6, before we draw our conclusions in section 7.

2 Channels of 4.0 Patenting to Higher Sales

The concept of Industry 4.0 is the application of modern information and communication technologies (ICT) in production facilities. 4.0 inventions are very closely related to ICT,

[3]Small firms license out 26% of their patents and leave 18% unused, while large firms license out only 10% and leave 40% of their patents unused Giuri et al. (2007).

with the addition of connectivity. It is a relatively recent term often used in the context of the productivity paradox, since ICT lead to a wave of productivity increases (Brynjolfsson and Hitt, 2003; Bloom et al., 2012; Hubbard, 2003; Bartel et al., 2007), which is not yet observed for the 4$^{\text{th}}$ Industrial Revolution (i.e. Industry 4.0). Sensors and the use of internet connection allow machines to communicate and exchange data with each other and with humans. These smart machines and smart production plants (also knows as cyber physical systems or more generally IoT; the internet of things), enable greater flexibility in production processes to react and adjust according to capacity constraints or specific demands of customers. A study that nicely shows how ICT-enhanced equipment allows for greater flexibility is one by Bartel et al. (2007). In the context of valve manufacturing, production plants that adopt new ICT-enhanced equipment are capable of producing more customised products. The introduction of the technology Bartel et al. look at - computer numeric controlled machines (CNC) - is in fact an early example of 4.0 technology, even though the authors do not define it as such. CNCs allow for more flexible production, improved quality control and reduced set up times.[4] Logic follows that these kind of efficiency gains can be expected for *adopters* of 4.0 technology.

The firms in our sample are not strictly speaking 4.0 *adopters* however. Our sample consists of the firms that file patent applications to protect the 4.0 technologies invented by them. In other words, our sample consists of 4.0 *developers* who do not necessarily implement the 4.0 technology in their own production facilities. Being an *adopter* is not mutually exclusive from being a 4.0 *developer*. Besides equipping machines with sensors and other components that allow transmission of data, these 4.0 *developers* write software solutions to assist production and the logistical system of their customers. They may not necessarily experience efficiency gains in their own production process, but may achieve higher sales either through licensing royalties, or by selling products encompassing 4.0 technologies, for which they will be able to attract a more diverse customer base, since 4.0 technologies - as general purpose technologies - can be applied to a broader range of industries. Since we cannot be sure that the 4.0 inventing firms of our sample are *adopers*, but we can be sure that they are *developers*, we decided to diverge from the

[4] An example of a CNC is the 5 axis multi-purpose milling, drilling, and boring machine T-30 manufactured by Cincinnati Milacron. The technology to this machine was patented in 1992 by General Electric Co (EP0545658A2) at the EPO. It's CPC class G05B 19 (now G05B 15) was classified by EPO's new patent cartography as being a 4.0 relevant technology.

traditional approach that looks at ICT on productivity, and instead look at sales turnover.

A study conducted on German firms by Saam et al. (2016) found that the motives for firms to adopt 4.0 technology was predominantly to increase efficiency or to achieve greater customisation, while 4.0 *developers* predominantly focus on product innovation that are software compatible. These software compatible products can in turn increase sales turnover as a result of higher demand for more flexible solutions. What is suggestive of this being a promising avenue is that after the introduction of software patents in the US firms in all ICT sectors invested in these patents (Hall and MacGarvie, 2010). In Europe, software patents are also experiencing steady growth.[5] In the last three years, the rate of growth for 4.0 patent applications was 54%. This far outpaces the overall growth of patent applications in the last three years of 7.65% (EPO, 2017). If we want our patent system to remain an effective institution that encourages innovation in a digital era, then we have to better understand the underlying mechanisms of software patents versus non-software patents, or 4.0 patents versus Non-4.0 patents.

There are some noteworthy underlying differences between 4.0 (or software) patents and more traditional patents. Software patents often protect parts of a process, for which it is harder to detect infringement.[6] Based on a small sample of software start-ups, Mann (2005) finds that it is relatively easy to invent around software patents, which might be why not many software firms acquire patents (Mann and Sager, 2007). Still, the firms in our sample do file software patents. The benefits are likely to lie in one of the following two reasons. One, is that the firm is indeed a 4.0 *developer* and *adopter* simultaneously and therefore seeks to commercialise it by selling products encompassing the 4.0 technology. The second reason is that the firm primarily wants to sell or license the intellectual property. Otherwise, secrecy would be a viable option.

[5]It is a common misconception that software cannot be patented in Europe. To make sure that software patents can be filed at the EPO, we got in contact with the examiner at the EPO who developed the 4.0 cartography. He told us that all 4.0 patents are software patents, practically by default because connectivity and data exchange is a prerequisite. They are however not termed as *software patents*, but instead are referred to as *computer implemented inventions because* they have to operate a device (though not necessarily a product).

[6]Increasing litigation of software patents has sparked a debate on the quality and uncertainty of software patents (Lerner, 2010). Given the willingness of the patent holder to initiate litigation procedures, the patents should be strong, enforceable patents. Yet Allison et al. (2011) finds that conditional on going to trial, software patents only win 13% of the cases.

3 Literature

In essence, this study is positioned in the strand of literature that attempts to quantify the private value of patents as well as the more recent literature on software patents, which is yet again closely related to prior literature on the returns to information technology (IT). The existing literature on the private returns of patents (to the firm) can be categorized into studies that look at three outcome variables; market value (sometimes measures as Tobin's Q), sales turnover and productivity. Towards the end of this section we will make a stronger link between the more recent literature on software patents and our 4.0 patenting firms, which is yet again closely related to prior literature on the returns to information technology (IT).

The first systematic assessment of the monetary private economic value of patents is that of Gambardella et al. (2008). They make use of a unique large-scale dataset (PatVal-EU) designed to represent the universe of European Patents in six EU countries. This European survey asked individual (EP) patent holders about the minimum price for which they would sell their patent. The mean value is estimated to be larger than 3 million euro. The median however, lies at around one-tenth of that, supporting prior findings on the skewness of the patent value distribution. Scherer (1998) and Silverberg and Verspagen (2007), find a similar skewed value distribution by looking at patent licensing royalties, patent profits (according to survey evidence), and a number of other measures of returns to innovation.[7] Hall et al. (2013) investigated whether patents have a positive effect on innovation-related turnover, conditional on the firm stating that it had introduced a product and/or process innovation. Using Community Innovation Survey data for the United Kingdom, their results suggest that patented innovations are more successful at generating sales.

Bloom et al. (2002) look at the impact of patents on two measures of company performance; productivity and market value. They find that citation weighted patent stock has an economically and statistically significant impact on firm-level productivity and market value. A doubling of the citation-weighted patent stock increases total factor productivity

[7]Successfully licensing a patent is facilitated if the patent has received many citations (Sampat and Ziedonis, 2005). However, citations were not good at predicting the amount of licensing revenue earned.

by 3%. While it takes time to have an affect on productivity, the effect is immediate upon market values. Patent citations are found to be more informative than the simple patent counts that have been used previously in the literature. This is in agreement with the pioneering study by Trajtenberg (1990), who was really the first to identify the importance of patent citations as a value measure. He exclusively examines one particular innovation - computed tomograbeen takephy scanners - and finds that patent citations are related to private value as well as social value. A few years later, Trajtenberg coauthored a paper, see Hall et al. (2005), that uses three variations of an explanatory variable of interest - citations to patents, patents to R&D and R&D to assets stocks - and find that each of these ratios significantly increases the firms' market value (measured as Tobin's Q). More concretely, one extra citation per patent is estimated to increases market value by 3% .

To a considerable extent, the literature on ICT is relevant for us due to the similarity of the arguments of how ICT impacts the firm and the impacts we expect 4.0 technology to have. Similar to the adoption of new IT, 4.0 technology can improve firm performance through the channels of higher flexibility (in the production process) and improved product quality or customization. Brynjolfsson and Hitt (1996) for example estimate a production function for large US firms over the period 1987 to 1991 including IT-capital as an input. They then test whether the contribution of IT-capital to output (sales) is positive and significantly different from zero using the output elasticity of IT-capital. The results show, that the output elasticity is indeed significantly positive.

The main way in which our approach diverges from the literature on IT is that we are not exclusively looking at adopters of 4.0 technology. We are looking at the developers of 4.0, who may or may not adopt these technologies at their own production plants.

A lack of evidence on the effects of patents/innovations on firm sales ceases to exist. This may be because the average firm only experiences very modest growth in sales. This point was made by Coad and Rao (2008) who therefore argue that it is not so interesting to look at regression techniques that focus on the average effects of the average firm. Rather, they perform quantile regressions focusing on incumbent US firms (from Compustat) in four commonly studied high-tech sectors. Indeed they find that the effects of innovation on growth are modest, on average, but that for the fast-growth firms at the upper quantiles, the coefficient on innovation rises sharply. In the lowest quantile, the effect is even negative but only significant for one of the four sectors.

4 Data and Descriptive Statistics

We use information from two different datasets for our analysis. The first, the Mannheim Enterprise Panel (MUP) is a dataset maintained by ZEW since 1992 in cooperation with Creditreform. It is the most extensive firm-level panel dataset for Germany (outside of official government statistics). Representing almost the entire German firm population, it contains information on the number of employees, sales, address, five-digit industry sector code (NACE rev. 2), date of foundation, date of closure, data of insolvency procedures, and shareholder structure. The second dataset we make use of is the worldwide patent statistical database (PATSTAT). This dataset contains rich information on all patents filed worldwide. We merge detailed information on the patent portfolios (from PATSTAT) to the firms in our MUP data. Using the patent cartography that the EPO produced, we classify these patents into 4.0 related or not. We restrict the patents considered in this study to patents filed at the European Patent Office because the 4.0 patent cartography is only available for these patents.

Patent stocks were calculated using the perpetual inventory method as in the following equation $K_t = I_t + (1-\delta)K_{t-1}$, where K_t stands for the patent stock, I_t is the number of patent applications in year t and δ notes the depreciation rate, which we chose to be 15%, as established in the literature (Hall et al.).

Using all years available in the panel (1993-2017), our sample consists of 1,453 firms that hold at least one 4.0 patent and 17,759 firms that do not (see Figure 3 in the appendix). This is much lower than the total population of German firms because we only consider patenting firms, in order to rule out self selection into patenting. We also drop firms that are only observed once, as these cannot contribute to the estimation using panel data methods. We have a total number of 193,199 observations, meaning that we observe each firm for 10 years on average. The panel is unbalanced however, for years in which data on sales and employees was not available. We removed outliers by dropping the top one percentile of $Log(Sales)$ and $TotalPatStock$ (which is the sum of 4.0 and Non-4.0 patent stock) to ensure that our results are not driven by single outlier observations.

Table 1: Firm-Level Descriptive Statistics.

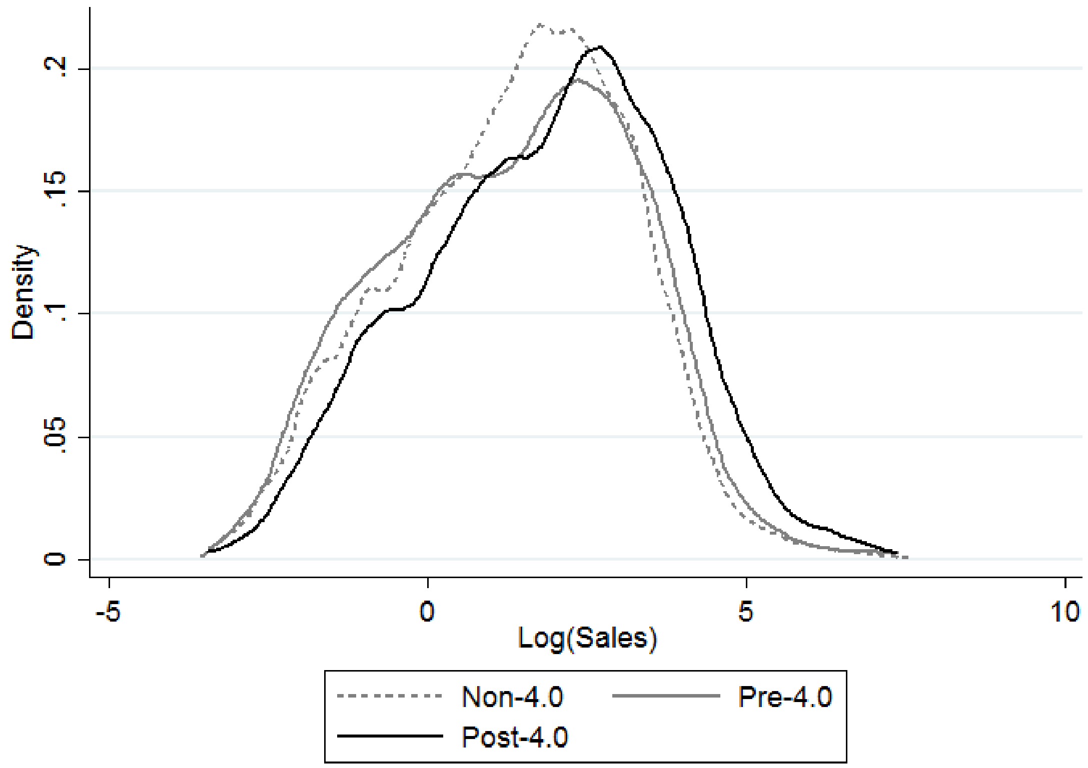
	(1) Non-4.0		(2) 4.0		(3) Mean Differences
	mean	sd	mean	sd	p
Firm Age	32.2234	(34.04)	23.0100	(26.54)	0.000
Sales (Mil.)	21.3818	(74.58)	34.1262	(108.00)	0.000
Log(Sales)	15.3889	(1.82)	15.6925	(1.96)	0.000
Employees	82.7679	(636.16)	117.1966	(345.96)	0.000
Total PatStock	0.9997	(2.36)	2.6200	(5.76)	0.000
4.0 PatStock	0.0000	(0.00)	0.5303	(1.00)	0.000
Non-4.0 PatStock	0.9997	(2.36)	2.0897	(5.48)	0.000
Sqr(4.0 PatStock)	0.0000	(0.00)	1.2799	(13.05)	0.000
Sqr(Non-4.0 PatStock)	6.5471	(62.22)	34.4262	(187.73)	0.000
Observations	176918		16281		193199

Table 1 presents firm-level summary statistics of the mean, standard deviation and the p-value on the test of differences in the means of 4.0 and Non-4.0 patenting firms. German firms that file patents related to 4.0 are on average younger than Non-4.0 patenting firms; 23 years of age compared to 32, respectively. 4.0 firms have a sales turnover of 34 million Euros on average, compared to 21 million Euros for Non-4.0 firms. The density distribution of the log-transformation of sales is depicted in Figure 1.[8] Comparing the sales distributions of Non-4.0 firms to 4.0 firms before they filed a 4.0 patent ("Pre-4.0") indicates that the values of $Log(Sales)$ were somewhat more volatile for 4.0 firms, as seen by the flatter and wider distribution. After filing a 4.0 patent ("Post-4.0") firms appear to experience higher sales, as observed by the clear shift to the right of the distribution.

Despite 4.0 firms being younger, they are significantly larger with 117 employees on average, compared to 83 employees for Non-4.0 firms. Our main variables of interest measures 4.0 and Non-4.0 patent stock of each firm each year. The logic for using stock

[8]Note that for the figure, sales values were deflated to account for inflation. Deflator values were obtained from The World Bank. Deflating the values is not necessary in the regressions as this is captured by the year fixed effects.

Figure 1: Kernal Density Distributions of Log(Sales).



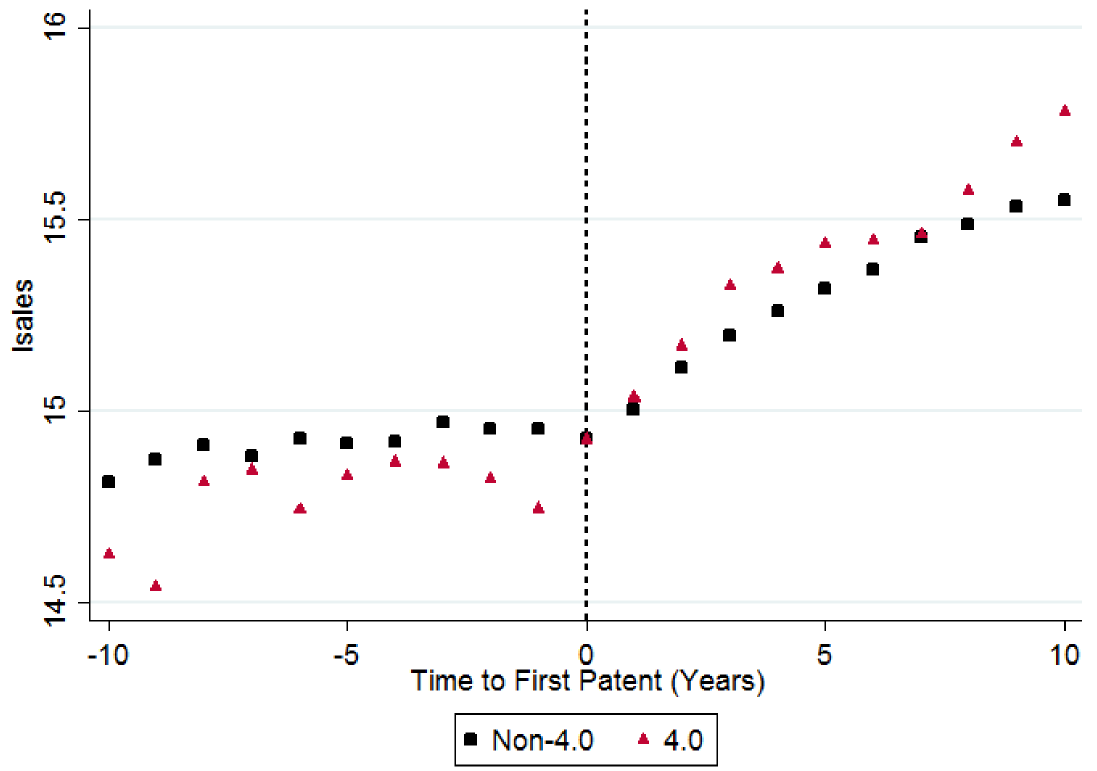
measures rather than counting the number of patent application filed each year is that the benefits of patents are likely to persist into the following years. Following convention, we depreciate all our patent stock measures by 15% per annum. Treated firms have an average $TotalPatStock$ of 2.6 patents and control firms just under 1. For 4.0 patenting firms, one fifth of the patent stock is 4.0 related; a 4.0$PatStock$ of 0.5 on average. For control firms, 4.0$PatStock$ is by definition zero.

The impact patenting has for both groups can be clearly observed in Figure 2, where we plot the yearly averages of $Log(Sales)$ for 10 years before and after filing the first patent. In Figure 2 we exclude firms whose first patent was not a 4.0 patent to make a comparison between the firms fair.[9] Both groups reveal a rather flat trend in average $Log(Sales)$ before filing their first patent, with 4.0 firms having lower and more volatile average values. After filing their first patent average sales for both groups substantially increase. 4.0 patenting firms however seem to benefit more because their average sales values lie for the subsequent years strictly above the average of the Non-4.0 patenting

[9]The first patent filed was also a 4.0 patent for about 81% of 4.0 firms.

firms.

Figure 2: Average Log(Sales) Before and After Patent Filing. Excluding 4.0 Firms whose first patent was not 4.0.



To make sure that the trend we observe for the 4.0 firms is not driven by the sample selection that we make, we plot the same graph for all 4.0 firms (including those whose first patent is not necessarily a 4.0 patent), to be found in the appendix; Figure 4.

5 Econometric Methodology

The choice to engage in 4.0 innovation, and to patent these innovations is left to the firm, which raises concern of selection bias. Another concern is that firms might differ systematically from one another in unobservable ways that affect the outcome of interest. Confounding factors like these, influencing both the dependent and independent variable cause a spurious and unidentified relationship between the two. An example of a confounding factor in our case may be a firms' absorptive capacity. Absorptive capacity is likely to affect both the likelihood of a firm to engage in 4.0 innovation (and to patent it), but also its ability to commercialise it and generate sales from it (Cohen and Levinthal, 1990). When panel data is available, fixed effects are frequently used to limit selection bias. By using only the within-firm variation, the Fixed Effects Least Squares model reduces selection bias by eliminating these time-invariant confounding factors. Another channel of endogeneity may arise because the past performance of a firm (or even anticipated growth) may enable it to better commit resources to subsequent sales. Dynamic models that include a lagged dependent regressor on the right hand side at least partially alleviates this problem and controls for the potentially confounding effects of time-invariant effects. We perform both, Fixed Effects Least Squares and a Dynamic Fixed Effects Panel Model. Our econometric approach will be described in this section, along with the advantages and disadvantages of both methodologies.

5.1 Fixed Effects Least Squares

To analyze whether 4.0 patenting firms achieve higher sales, we first estimate a fixed-effects model using the following specification:

$$\begin{aligned} Log(Sales)_{it} = \alpha + \beta_1\ 4.0\ PatStock_{it} + \beta_2\ Non\ 4.0\ PatStock_{it} \\ +\beta_3\ FirmAge_{it} + \tau_t + \mu_i + \nu_{it} \end{aligned} \tag{1}$$

where our dependent variable is the log-transformed sales recorded for firm i at time t. β_1 is our main coefficient of interest and measures the effect of 4.0 $PatStock_{it}$ on sales. Due to its cumulative nature of counting patents (depreciated at a yearly rate of 15%), it allows patents filed in previous periods to effect sales in the current period. In order to see whether the effect is due to 4.0 patents rather than patents more generally speaking, we need to somehow account for the Non-4.0 patents filed by the firm. Calculated using the same perpetual inventory method as for 4.0 patent stock, we include Non 4.0 $PatStock_{it}$ in the model. This enables us to make a direct comparison between the two to test whether 4.0 patents have a stronger or weaker impact on sales compared to Non-4.0 patents. τ_t are time invariant and unit invariant regressors that reflect changing intercepts due to macroeconomic conditions common to all firms. They enter the regression via 24 time dummies for each survey year. τ_{1993} is dropped from the regression and is in essence the "baseline" intercept.

$\mu_i + \nu_{it}$ combined is the error term, where the first component, μ_i is the firm specific error term at time t and is the firm fixed effect of the equation. The remainder of the disturbance, ν_{it} is assumed to be stochastic and iid. Patent stock and firm age is assumed to be independent of ν_{it} for all i and t. α (a scalar) and μ_i are not estimable separately and together capture the unobserved firm-specific effects. These could be things such as the firms absorptive capacity and general ability to bargain in licensing agreements or to commercialise 4.0 inventions.

What the FE Least Squares approach does is to eliminate unobserved firm-specific heterogeneity by demeaning Equation 1, as follows

$$Log(Sales)_{it} - \overline{Log(Sales)}_i = \tau_t + \beta\left(\mathbf{X}_{it} - \overline{\mathbf{X}}_i\right) + \left(\nu_{it} - \overline{\nu}_i\right) \tag{2}$$

Here the three regressors 4.0 $PatStock$, Non 4.0 $PatStock$ and $FirmAge$ are summarised into one $\mathbf{X}$ vector for simplicity. This is the model that corresponds to our regression results in Table 2, which will be interpreted in the next section. This FE Least Squares model allows for arbitrary dependence and heterogeneity across t within a given firm i. Since the error terms for firm i may still be correlated to the error terms of the same firm in any other period, we cluster our standard errors at the firm level.

5.2 Dynamic Panel Model

Since the firms' current sales may be explained by sales of the previous period (presence of state dependence) we would want to run a regression that allows sales to be dynamic in nature. There are two types of state dependence: true state dependence and spurious state dependence. In the former, one would include the lagged dependent variable for its own sake. An example of this may be salary, which is determined by the previous salary with an adjustment. In spurious state dependence, the lagged dependent variable is not just included for its own sake but also to account for unobservables μ_i or $\nu_{i,t-1}$, which is our motivation for its inclusion. One can exploit panel data to better understand this dynamic relationship between sales. This is typically done by including a lagged dependent variable as a regressor on the right hand side of the equation, as follows:

$$\begin{gathered} Log(Sales)_{it} = \gamma \; Log(Sales)_{i,t-1} + \beta_1 \; 4.0 \; PatStock_{it} \\ +\beta_2 \; Non \; 4.0 \; PatStock_{it} + \beta_3 \; FirmAge_{it} + \tau_t + \epsilon_{it} \end{gathered} \tag{3}$$

Assuming a one-way error component model, $\epsilon_{it} = \mu_i + \nu_{it}$, where μ_i and ν_{it} are both iid and independent of each other. γ is a scalar and the lagged dependent variable encompasses the effects of the entire time path of the independent variable(s). When we use $Log(Sales)_{i,t-1}$ as a regressor on the right hand side, the interpretation of the coefficients changes, where the γ now measures the effect of a change in $Log(Sales)$ of the previous period on the change in $Log(Sales)$ of the current period.

However, there are some limitations to this dynamic approach. Since $Log(Sales)_{it}$ is a function of μ_i, it immediately follows that the lagged response variable $Log(Sales)_{i,t-1}$ is also a function of μ_i, and therefore endogenous, rendering the OLS estimator biased and inconsistent even if the ν_{it} are not serially correlated. In the FE Least Squares model, the μ_i is eliminated as a result of demeaning all regressors on a firm level (the within transformation). However, the fixed effects approach still does not lead to consistent estimates here because $Log(Sales)_{i,t-1}$ will still be correlated with $(\nu_{it} - \overline{\nu}_i)$ because $Log(Sales)_{i,t-1}$ is correlated with $\overline{\nu}_i$ by construction.[10] As discussed in Baltagi (2005), Arellano and Bond (1991) propose a generalized method of moments (GMM) procedure in which firm specific effects are eliminated by first differencing Equation 3 to get:

$$\begin{aligned} Log(Sales)_{it} - Log(Sales)_{i,t-1} = \gamma \left[Log(Sales)_{i,t-1} - Log(Sales)_{i,t-2} \right] \\ +\tau_t + \beta \left(\mathbf{X}_{it} - \mathbf{X}_{i,t-1} \right) + \left(\epsilon_{it} - \epsilon_{i,t-1} \right) \end{aligned} \tag{4}$$

Then using lagged regressors as instruments leads to consistent estimates of the beta

[10]The consistency of the within estimator will depend on the T being large (Nickell, 1981). It is also worth noting that the inclusion of a lagged regressor increases model fitness (higher R^2) and tends to result in error terms with little serial correlation. This is because $Log(Sales)_{i,t-1}$ contributes the most to R^2. Furthermore, including a lagged response variable makes most time-invariant regressors useless, but as we are not interested in these regressors, it does not pose a limitation for us.

parameters. The three regressors 4.0 $PatStock$, Non 4.0 $PatStock$ and $FirmAge$ are again summarised into one $\mathbf{X}$ vector for simplicity. An important part of the model specification is the assumptions we make about the correlation between the the regressors $\mathbf{X}$ and the error term ϵ. We assume that $E(PatStock_{it}\epsilon_{is}) = 0,\ \forall s \geq t$ and $E(PatStock_{it}\epsilon_{is}) \neq 0,\ \forall s < t$, for both 4.0 and Non-4.0 patent stock, which means that $\mathbf{X}$ can be correlated with past error terms but not with contemporary or future error terms. Assuming a predetermined relationship for patent stock makes sense, as the cumulative nature of patent stock at any given time t will depend on past patent stock (except in the t where the first ever (4.0) patent is filed). We implement this estimation as a two-step GMM regression as this is asymptotically efficient when errors are heteroskedastic.

6 Results

Results to the FE Least Squares model are presented in Table 2. Since our dependent variable is log-transformed, coefficients on patent stock are to be interpreted as semi-elasticities. Column (1) corresponds to results on the complete sample of all firm sizes and indicates that one more 4.0 patent in a given period (which can also result from several discounted 4.0 patents of previous periods) is associated with a 8.3% increase in sales. The coefficient on $Non - 4.0 PatStock$ is also positive and statistically significant at the 1% level, yet it is comparatively lower with an estimated increase in sales of 3.0%. The difference between the two coefficients, β_1 and β_2 is statistically significant (p-value of 0.009) and supports our hypothesis that the benefits (increased sales) of commercialising 4.0 patents are greater than for Non-4.0 patents, believed to be due to the greater industrial applicability of these inventions, allowing firms to target a larger market and more heterogeneous customers.

Columns (2)-(4) present the regression results according to firm size, in ascending order. Sales of small firms (1-10 employees) increase even more on average than the total population average, for both 4.0 and Non-4.0 patents. As firms get larger, the effect of 4.0 patent stock decreases; from 10.5% for small firms, to 6.6% for medium sized firms (11-50 employees), to 5.5% for large firms (51-250 employees). Results become a little

Table 2: Fixed Effects Least Squares Regression Results.

	(1) Log(Sales) Total	(2) Log(Sales) Small	(3) Log(Sales) Medium	(4) Log(Sales) Large
4.0 PatStock	0.0831***	0.108***	0.0660**	0.0551**
	(4.30)	(2.92)	(2.25)	(2.33)
Non-4.0 PatStock	0.0296***	0.0482***	0.0268***	0.0149***
	(6.74)	(5.32)	(3.92)	(4.06)
Log(Age)	0.552***	0.643***	0.393***	0.139***
	(33.24)	(25.05)	(13.33)	(5.80)
Constant	13.51***	12.57***	14.02***	15.79***
	(276.56)	(160.38)	(164.49)	(204.91)
Within R^2	0.149	0.144	0.227	0.229
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	193199	97460	47298	48441

t statistics in parentheses

Notes: Each column gives the results of a linear fixed effects regression where the dependent variable is $Log(Sales)$. Column 1 estimates the model for the full sample and columns 2-4 include the results for the sample of small, medium and large firms respectively.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

more uncertain for medium and large firms as the significance level drops to 5%, despite the within R^2 increasing to above 22%. The coefficient estimates on $Log(Age)$ tells us that sales also increase with firm age but deteriorating with firm size.

We also ran a nonlinear version of this regression, in which we include squared patent stock regressors, as shown in Table 3. Including nonlinear parameters of patent stock does not increase the within R^2 but the coefficients on the $Non-4.0\ PatStock$ roughly double in magnitude compared to the linear model in Table 2. Across all firm size categories, $Non-4.0\ PatStock$ reveals a concave relationship with sales, meaning that after a certain stock size is reached further increases do not contribute to an increase in sales. This turning point for small firms for instance, is $\frac{0.0838}{2\times0.00122} = 34.3$. Therefore, once a small firm accumulates a $Non-4.0\ PatStock$ of 34.3 patents, additional Non-4.0 patents will not further increase sales, on average.[11] 4.0 PatStock remains positive across all firm size categories, statistical significance decreases with firm size. Interestingly, the nonlinear

[11]The maximum $Non-4.0\ PatStock$ for small firms was 55.6 patents.

relationship in column (4) shows no evidence of 4.0 *PatStock* reaching a turning point, rather it is increasing, but insignificant.

Table 3: Nonlinear Fixed Effects Least Squares Regression Results.

	(1) Log(Sales) Total	(2) Log(Sales) Small	(3) Log(Sales) Medium	(4) Log(Sales) Large
4.0 PatStock	0.107***	0.163***	0.0799*	0.0464
	(4.55)	(3.99)	(1.83)	(1.49)
4.0 PatStock^2	-0.00289***	-0.00514***	-0.00215	0.00121
	(-2.70)	(-3.37)	(-0.38)	(0.33)
Non-4.0 PatStock	0.0546***	0.0838***	0.0589***	0.0285***
	(9.26)	(6.68)	(6.07)	(6.50)
Non-4.0 PatStock^2	-0.000868***	-0.00122***	-0.00120***	-0.000459***
	(-5.12)	(-3.53)	(-5.63)	(-2.98)
Log(Age)	0.544***	0.630***	0.381***	0.135***
	(32.71)	(24.37)	(12.96)	(5.66)
Constant	13.51***	12.58***	14.03***	15.79***
	(277.16)	(160.52)	(165.74)	(205.60)
Within R^2	0.150	0.145	0.229	0.231
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	193199	97460	47298	48441

t statistics in parentheses

Notes: Each column gives the results of a linear fixed effects regression where the dependent variable is $Log(Sales)$. This model includes a quadratic term of both 4.0 and Non-4.0 patent stock. Column 1 estimates the model for the full sample and columns 2-4 include the results for the sample of small, medium and large firms respectively.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We now turn to the results from the Dynamic Panel Model, first the results that correspond to Equation 3 as shown in columns (2)-(5) of Table 4 and afterwards we turn to the Two-Step GMM regression results. Naturally, the number of observations drops as the earliest observation of each firm cannot enter the regression as a result of using the lagged dependent variable as a regressor.[12] For this reason, we also report the Fixed Effects Least Squares estimates in column (1) using the smaller sample to ensure that results still hold, and indeed they are unmistakably similar to column (1) of Table 2. The magnitudes of the patent stock variables are lower in the dynamic panel model, but the overall finding

[12] Observations actually drop by more than the total number of firms (19,212) because of the restriction that the lagged regressor has to be observed in $t-1$ and since we have an unbalanced panel, some firms sales are not observed in $t-1$.

that the effect of patent stock decreases with firm size, and that 4.0 patent stock has a larger effect than Non-4.0 patent stock holds.

Table 4: Dynamic Panel Model Regression Results.

	(1) Log(Sales) Total	(2) Log(Sales) Total	(3) Log(Sales) Small	(4) Log(Sales) Medium	(5) Log(Sales) Large
4.0 PatStock	0.0845***	0.0401***	0.0578***	0.0411***	0.0183
	(4.24)	(3.75)	(2.83)	(2.64)	(1.28)
Non-4.0 PatStock	0.0288***	0.0101***	0.0160***	0.00749**	0.00449**
	(6.23)	(5.03)	(3.61)	(2.38)	(2.50)
Log(Age)	0.552***	0.0249**	0.0906***	0.0292*	-0.0334**
	(22.93)	(1.98)	(4.01)	(1.66)	(-2.16)
L.Log(Sales)		0.638***	0.630***	0.697***	0.647***
		(104.27)	(87.14)	(55.58)	(44.51)
Constant	13.73***	5.458***	5.261***	4.591***	5.848***
	(226.53)	(61.79)	(50.13)	(26.26)	(25.37)
Within R^2	0.124	0.518	0.501	0.616	0.573
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Clustered SE	✓	✓	✓	✓	✓
Observations	138454	138454	63311	36820	38323

t statistics in parentheses

Notes: This table gives the results of the dynamic panel model where the dependent variable is $Log(Sales)$. Column 1 restates the results from the linear fixed effects model on the new sample. Column 2 estimates the model for the full sample and columns 3-5 include the results for the sample of small, medium and large firms respectively. Standard errors are clustered at the firm level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Two-Step GMM regression results are presented in Table 5. Finding valid instruments though was quite challenging partly because of the long time series dimension of the data. But after restricting the number of potential instruments and playing with the assumption on the correlation between the explanatory variables and the idiosyncratic error term, we find a set of valid instruments for all three firm sizes, albeit only marginally significant for small firms as indicated by the p-value of the Hansen test. For small and large firms, we even get a statistically significant effect; a one unit increase in 4.0 $PatStock$ is associated with a 4.29% growth for small and 1.98% growth for large firms' sales in the short-run, significant at the 5% and 10% level respectively, ceteris paribus. The estimated effect of $Non - 4.0\ PatStock$ is a sales growth of 3.48% for small, and around 0.8% for medium and large firm. Somewhat surprising is the negative and significant effect of $Log(Age)$, but as the coefficient is to be interpreted as an elasticity, the magnitude is small; a 1% increase in firm age is associated with a 0.0669% reduction in sales (column 1).

Table 5: Two-Step GMM Regression Results.

	(1) Log(Sales) Total	(2) Log(Sales) Small	(3) Log(Sales) Medium	(4) Log(Sales) Large
4IR PatStock	0.0256**	0.0429**	0.0111	0.0198*
	(2.53)	(2.06)	(0.90)	(1.84)
Non-4IR PatStock	0.0183***	0.0348***	0.00740**	0.00855***
	(5.38)	(5.54)	(2.46)	(3.98)
Log(Age)	-0.00669	-0.0249**	-0.0361***	-0.0180***
	(-0.56)	(-2.00)	(-10.21)	(-6.34)
L.Log(Sales)	0.893***	0.794***	0.925***	0.896***
	(39.97)	(20.61)	(28.28)	(28.25)
Constant	1.757***	3.244***	1.347**	1.904***
	(5.63)	(5.93)	(2.56)	(3.44)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	138454	63311	36820	38323
Nr. of Groups	17796	10214	3782	3800
Nr. of Instruments	201	201	195	200
Hansen P-Value	0.0972	0.0905	0.668	0.388
AR(2) P-Value	0.00103	0.0736	0.00120	0.00227

t statistics in parentheses

Notes: This table gives the results of the dynamic panel model where the dependent variable is $Log(Sales)$. These models were estimated using a 2-step GMM approach. Instruments used: $4IR\ PatStock$ and $Non-4IR\ PatStock$ as predetermined, and $Log(Age)$ and year dummies as strictly exogenous, all with three lags from $t-1$ to $t-3$. Column 1 estimates the model for the full sample and columns 2-4 include the results for the sample of small, medium and large firms respectively. P-values for the Hansen test on overidentifying restrictions reports the validity of the instruments.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Comparing the magnitude of the coefficients on both patent stocks in column (2) and (4) again confirms all our previous results that the benefit from patent stock decreases with firm size, and that 4.0 $PatStock$ provides a greater advantage compared to $Non-4.0\ PatStock$. The lagged dependent regressor $L.Log(Sales)$ is informative of the persistence of sales turnover. The coefficient on the total sample for instance, was estimated to be 0.89, which indicates that even when a firm has zero patent stock, one can expect the sales in year t to be 89% of the size of sales in the previous period, $t-1$.

7 Conclusion

The 4^{th} Industrial Revolution has the potential to completely revolutionize the functioning of our economy. Its impacts are not yet well understood however, as little economic research on this topic exists due to a lack of consensus as to what should be considered as 4.0-related and how to measure it. Using a newly developed cartography by the EPO, this study is one of the first large-scale, systematic analysis on all European 4.0 Patents filed by German firms.

We focus on *developers* (or inventors) of 4.0-related technology (rather than *adopters*) and investigate the effect that 4.0 patents have on the economic performance of the innovating firm. We outline two channels of (sales) growth based on the findings of the closely related literature on ICT, patents and firm performance. A 4.0 developing firm can boost sales turnover through (1) selling products encompassing their 4.0 technology, and/or (2) licensing royalties or sale of the patent itself. As a general purpose technology (GPT), 4.0 technology has wider industrial applicability, which allows 4.0 firms to boost sales turnover more so than their Non-4.0 counterparts.

To empirically examine if patenting in 4.0 technology has the awaited positive effect on the firm's economic performance we conducted a treatment effects analysis using both linear fixed effects regressions and a dynamic panel approach. The results of our fixed effects models of 4.0 patent stock on the development of sales suggest that innovating in the area of Industry 4.0 affects the firm's sales positively. This effect is estimated to be higher than for Non-4.0 technology. However, the importance of holding these patents diminishes with firm size. Suspecting sales to have a dynamic effect, we additionally estimated models including sales of the previous period. The results of these models differ in size and significance but not in the qualitative interpretation of the effect.

Hence, the main conclusion of our analysis is that innovating in 4.0 technology effects the firms' sales positively and that it does so to a larger extent than innovating in other technology fields.

Appendix

Figure 3: Firm Observations by Size.

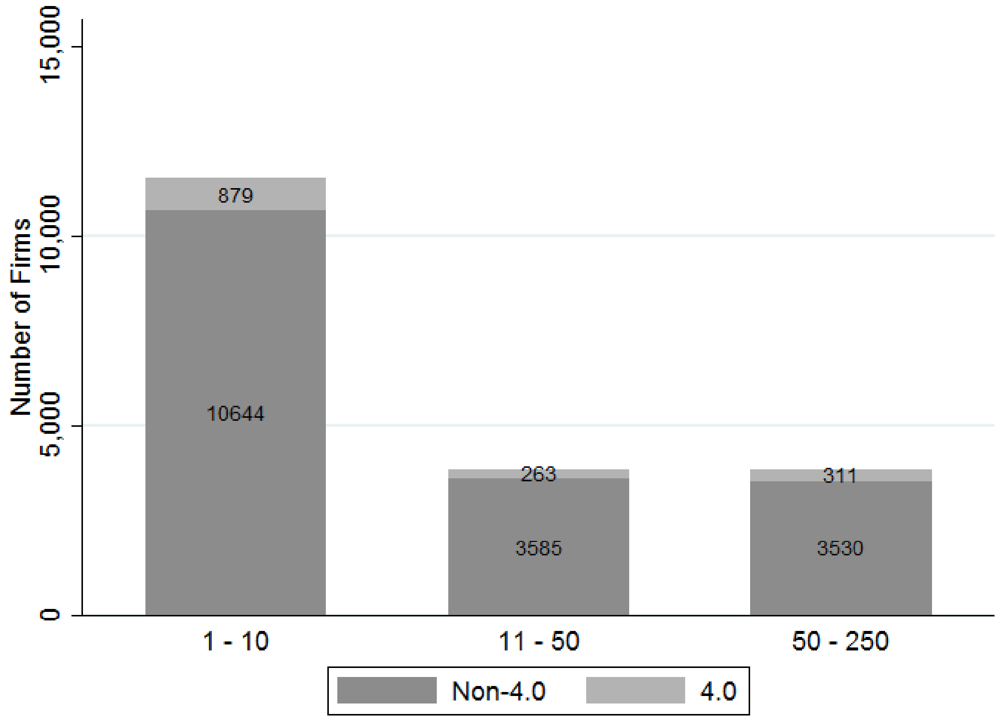


Figure 4: Average Log(Sales) Before and After 4.0 Patent Filing (Only 4.0 Firms)

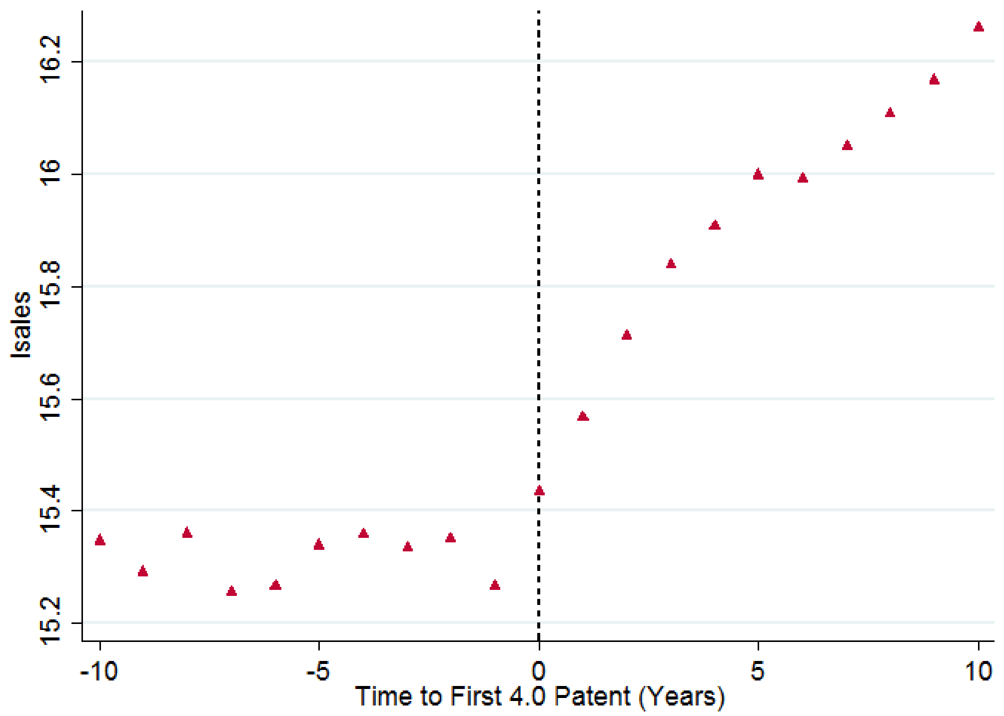


Table A.1: Patent-Level Descriptive Statistics.

	(1) Non-4.0		(2) 4.0		(3) Mean Differences
	mean	sd	mean	sd	p
Number of Applicants	1.0963	(0.37)	1.1573	(1.86)	0.061
Number of Inventors	2.0665	(1.44)	2.2271	(2.35)	0.000
Geographical Coverage	4.8355	(3.48)	3.8457	(2.51)	0.000
Claims	7.5862	(7.89)	6.3456	(7.61)	0.000
Patent Scope	1.7570	(1.07)	1.9247	(1.15)	0.000
Observations	86959		3293		90252

References

Aghion, P., C. Harris, P. Howitt, and J. Vickers
2001. Competition, imitation and Growth with Step-by-Step Innovation. *Review of Economic Studies*, 68(3):467–492.

Agrawal, A. K., J. Gans, and A. Goldfarb
2018. *The Economics of Artificial Intelligence: An Agenda.*

Allison, J. R., M. A. Lemley, and J. H. Walker
2011. Patent Quality and Settlement among Repeat Patent Litigants. *The Georgetown Law Journal*, 99:677–712.

Arellano, M. and S. Bond
1991. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2):277–297.

Arntz, M., T. Gregory, and U. Zierahn
2017. Revisiting the Risk of Automation. *Economics Letters*, 159:157–160.

Baltagi, B. H.
2005. Econometric Analysis of Panel Data. *Third Edit. John Wiley & Sons, Ltd.*

Bartel, A., C. Ichniowski, and K. Shaw
2007. How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills. *The Quarterly Journal of Economics*, 122(4):1721–1758.

Bloom, N., R. Sadun, and J. Van Reenen
2012. Americans do IT better: US Multinationals and the Productivity Miracle. *American Economic Review*, 102(1):167–201.

Bloom, N., J. Van Reenen, and J. V. Reenen
2002. Patents, Real Options and Firm Performance. *The Economic Journal*, 112(478):C97–C116.

Bresnahan, T. F. and M. Trajtenberg
1995. General Purpose Technologies 'Engines of growth'? *Journal of Econometrics*, 65:83–108.

Brynjolfsson, E. and L. Hitt
1996. Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending. *Management Science*, 42(4):541–558.

Brynjolfsson, E. and L. M. Hitt
2003. Computing Productivity: Firm-Level Evidence. *Review of Economics and Statistics*, 85(4):793–808.

Coad, A. and R. Rao
2008. Innovation and firm growth in high-tech sectors: A quantile regression approach. *Research Policy*, 37(4):633–648.

Cockburn, I. M., R. Henderson, and S. Stern
2018. The Impact of Artificial Intelligence on Innovation. *NBER Working Paper Series.*

Cohen, W. M. and D. A. Levinthal
1990. Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, 35(1):128–152.

Doms, M., T. Dunne, and M. J. Roberts
1995. The Role of Technology Use in the Survival and Growth of Manufacturing Plants. *International Journal of Industrial Organization*, 13:523–542.

EPO
2017. Patents and the Fourth Industrial Revolution: The Inventions Behind Digital Ttransformation. *European Patent Office Working Paper*.

Gambardella, A. and M. S. Giarratana
2013. General Technological Capabilities, Product Market Fragmentation, and Markets for Technology. *Research Policy*, 42:315–325.

Gambardella, A., D. Harhoff, and B. Verspagen
2008. The Value of European Patents. *European Management Review*, 5:69–84.

Giuri, P., M. Mariani, S. Brusoni, G. Crespi, D. Francoz, A. Gambardella, W. Garcia-Fontes, A. Geuna, R. Gonzales, D. Harhoff, K. Hoisl, C. Le Bas, A. Luzzi, L. Magazzini, L. Nesta, Ö. Nomaler, N. Palomeras, P. Patel, M. Romanelli, and B. Verspagen
2007. Inventors and Invention Processes in Europe: Results from the PatVal-EU Survey. *Research Policy*, 36:1107–1127.

Hall, B., A. Jaffe, and M. Trajtenberg
2005. Market Value and Patent Citations. Technical Report 1.

Hall, B. H., C. Helmers, M. Rogers, and V. Sena
2013. The Importance (Or Not) of Patents to UK Firms. *Oxford Economic Papers*, Pp. 603–629.

Hall, B. H. and M. MacGarvie
2010. The private value of software patents. *Research Policy*, 39:994–1009.

Hall, B. H., G. Thoma, and S. Torrisi
. The Market Value of Patents and R&D: Evidence from European Firms. *A European Commission Project*.

Hubbard, T. N.
2003. Information, Decisions, and Productivity: On-Board Computers and Capacity Utilization in Trucking. *The American Economic Review*, 93(4):1328–1353.

Lerner, J.
2010. The Litigation of Financial Innovations. *The Journal of Law & Economics*, 53(4):807–831.

Mann, R. J.
2005. Do Patents Facilitate Financing in the Software Industry. *Texas Law Review*, 83(4):961–1030.

Mann, R. J. and T. W. Sager
2007. Patents, Venture Capital, and Software Start-Ups. *Research Policy*, 36:193–208.

McKinsey
2017. Artificial Intelligence – The Next Digital Frontier? *McKinsey & Company*.

Nickell, S.
1981. Biases in Dynamic Models with Fixed Effects. *Econometrica*, 49(6):1417–1426.

OECD
2018. OECD Science, Technology and Innovation Outlook 2018: Adapting to Technological and Societal Disruption. *OECD Publishing, Paris.*

Saam, M., S. Viete, and S. Schiel
2016. Digitalisierung im Mittelstand: Status Quo, Aktuelle Entwicklungen und Herausforderungen. *ZEW (Forschungsprojekt im Auftrag der KfW Bankengruppe).*

Sampat, B. and R. H. Ziedonis
2005. Patent Citations and the Economic Value of Patents. In *Handbook of Quantitative Science and Technology Research*, Pp. 277–98.

Scherer
1998. The Size Distribution of Profits from Innovation. *Annales d'Économie et de Statistique*, (49/50):495–516.

Silverberg, G. and B. Verspagen
2007. The Size Distribution of Innovations Revisited: An Application of Extreme Value Statistics to Citation and Value Measures of Patent Significance. *Journal of Econometrics*, 139:318–339.

Trajtenberg, M.
1990. A Penny for Your Quotes: Patent Citations and the Value of Innovations. *RAND Journal of Economics*, 21(1):172–187.

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