Industry 4.0: An empirical analysis of its adoption in Wallonia

Joaquín Paseyro Mayol
PhD student | HEC Research - HEC Liège
Co-authors: Nicolas Neysen & Axel Gautier

October, 2020

Abstract

This paper studies the factors influencing the adoption of digital technologies in the manufacturing sector; the so called *Industry 4.0* phenomenon. We focus on the adoption of three particular technologies (Predictive Maintenance, Smart Production and Advanced Planning) in the Belgian region of Wallonia. In line with the claims of related qualitative studies, our findings suggest that smaller firms, which have a more restricted access to financial resources, are less prone to adopt these technologies. Our results are compatible with the notion that more digitally mature firms are more prone to be adopters. Moreover, we do not find evidence supporting the claim that more profitable firms are more likely to be adopters. Finally, we present indicative evidence regarding the efficacy of the regional governmental program which aimed to increase the diffusion of *Industry 4.0*.

Keywords— Industry 4.0; Technology diffusion; Wallonia; Made Different.

1 Introduction

Information technology has already revolutionized most of the sectors of the economy (transport, tourism, financial services, among others). Through the combination of sensors, data storage, software and connectivity, it is currently revolutionizing the manufacturing sector. This phenomenon, which was first called *Industry 4.0* by the German federal government in the 2011 Hannover Fair, implies the usage of Internet of Things, data science, robotics, etc. to achieve a competitive advantage either by lowering production costs (e.g. by decreasing the stoppage time of the machinery) or by offering enhanced products at a price premium (Porter and Heppelmann (2014)). A particular feature of this new technological wave is that it is being predicted *ex-ante* rather than observed *ex-post* (Hermann et al. (2015)). According to some related literature, it is expected that this revolution will entail enormous productivity gains (Hermann et al. (2016) and Schneider (2018)).

It is of no surprise, then, that many governments intend to foster the adoption of these technologies following the idea that an early adoption would put their firms at the forefront of this "new technological wave" and, ultimately, allow them to capture a larger market share. In particular, there are an increasing number of specific programs that focus on overcoming possible market failures that hinder technology diffusion, such as lack of information propagation, lack of skillful human resources, bureaucracy and economies of scale (Stoneman and Diederen (1994)). In this vein, there have been efforts to help to raise awareness of the existence of these technologies, like the pioneer "Industrie 4.0" program launched by the German authorities. In the last few years, these programs have been replicated in many industrialized countries: "Industrie du future" in France, "Fabbrica Intelligente" in Italy, the "Smart Industry Program" in the Netherlands, among others (Mariani and Borghi (2019)). Belgium also launched its analogous plan in 2013, called Made Different. According to the European Commission, its aim was to "increase the competitiveness of the manufacturing industry by supporting the digital transformation of production processes. The overall goal of this initiative is to transform manufacturing companies into 'Factories of the Future'. (...) The main activities of the Made Different initiative involve the organisation of awareness-raising events, the provision of tailored and long-term guidance services to companies willing to transform their production processes[1]." While it started exclusively in the Flemish region, in 2017 it was extended to Wallonia.

Overall, much has been said about the possible benefits of the *Industry 4.0* fast-growing phenomenon and, hence, about its expected evolution over time (Cusumano et al. (2014), Ghobakhloo (2018), Schneider (2018), Roblek et al. (2016) and Piccarozzi et al. (2018)) There are also a handful of qualitative studies analyzing possible driving forces and barriers to implement these technologies based on interviews with firms' CEOs (see, for example, Horváth and Szabo (2019)). Nevertheless, there is a lack of understanding of the actual degree of adoption of these technologies, their evolution over time and of the real existence of such drivers and barriers. Is the number of adopters increasing? If not, what are the barriers that are limiting the diffusion? Are there significant differences between SMEs and large firms in terms of *Industry 4.0* technology adoption? Are more profitable firms adopting these technologies more intensively than the rest? These questions, among others, are still unanswered. This study aims to fill this gap.

Our objective in this paper is to analyze the adoption of three specific *Industry 4.0* technologies (i.e. Predictive Maintenance, Smart Production and Advanced Planning), study their evolution over time and to evaluate the impact of certain firm characteristics (number of employees, profitability and location, among others) in their adoption. By exploiting a unique data set of the Walloon region for the years 2018 and 2020 that includes responses regarding the adoption of three *Industry 4.0* technologies, we shed some light to help to answer these questions. Additionally, we are able to provide indicative evidence of the efficacy of the Made Different program launched by the Agence du Numérique.

The rest of the paper is structured as follows. In Section 2 we review the related literature and we state our main hypothesis. Then, in Section 3 we describe the characteristics of our sample. In Section 4 we present the methodology used and in Section 5 we expose our results. Finally, in Section 6 we conclude.

[1]https://ec.europa.eu/growth/tools-databases/dem/monitor/content/belgium-%E2%80%9Cmade-different%E2%80%9D

2 Literature Review

The research objective of this article is linked to three main sources of literature. Firstly, there is the recent literature concerning the specific topic of the *Industry 4.0* phenomenon. Broadly speaking, the articles of this emerging field are mostly concerned to define the characteristics that differentiate this phenomenon from previous technological waves (Mariani and Borghi (2019), Santos et al. (2017) and Piccarozzi et al. (2018)), forecast the possible benefits of adopting these technologies (Ghobakhloo (2018), Cusumano et al. (2014), Schneider (2018) and Roblek et al. (2016)) and analyse the adoption of certain digital technologies by manufacturing firms (Horváth and Szabo (2019), Bettiol et al. (2020), Basl (2017), Kiel et al. (2017a), Kiel et al. (2017b), Müller et al. (2018)). Except for Bettiol et al. (2020), which provides an econometric analysis of *Industry 4.0* adoption in Italy associated to the ICT endowment of the firms, the rest of the papers address the technology adoption issue from a qualitative approach (interviewing CEOs, carrying out study cases, etc.). Although these studies are extremely valuable to have a first close up of the reasons that decision markers argue as to adopt or not adopt certain technologies, they do not provide rigorous statistical evidence that prove generalized barriers or drivers. In our study we intend to link the hypothesis of these studies with the evidence found in our data.

Secondly, our study is closely related to the broad literature of technology adoption and diffusion. Since the seminal work of Mansfield (1968), the question of why firms decide to adopt technologies at the moment in which they do has been a central question in economic research. Throughout the past decades a large number of researchers have focused on trying to disentangle the different factors that drive firms to adopt new technologies, in particular from an inter-firm perspective. As exposed by Karshenas and Stoneman (1993), there are four types of factors behind the decision of adopting a new technology; rank, stock, order and epidemic effects. While rank effects relate to the assumption that firms have different inherent characteristics (i.e. firm size) that lead them to obtain different results from the adoption of the new technology, stock and order effects capture the differential marginal benefits regarding the number of firms that already adopted it and the relative position of the firm under consideration. Lastly, the epidemic effect is linked to the assumption that information is spread in an increasing and parsimonious pattern; therefore, as information with respect of the potential benefits of the new technology is made available to more firms, the number of adopters would increase. The interplay of these effects are instrumental to explain the typical S-shaped pattern of technology diffusion (Götz (1999)).

One of the most studied relations between a firm's characteristic and the adoption of a new technology is the one concerning firm size. It has been broadly documented the fact that larger firms are more prone to adopt technologies earlier than smaller ones, *ceteris paribus*. As we will discuss in the following sections, this can be due to scale effects (Astebro (2002)), a larger stock of equipment (Romeo (1975)) and/or a larger financial resources availability (Stoneman (2001), Canepa and Stoneman (2007)), Gomez and Montoya (2009) and Czarnitzki and Binz (2008)). The ability of firms to assimilate and exploit information available in the environment is also largely documented to have a positive, significant impact on the decision of adopting a new technology (Cohen and Levinthal (1990)). In other words, the absorptive capacity can be seen as the readiness of firms to incorporate and exploit new technologies (Zahra and George (2002)). In line with this, we also expect that better informed firms would adopt earlier than others (Wozniak (1987)). In this sense, the Made Different program might have a positive impact on adoption given that it may equalize the access to information across firms and it may reduce the uncertainty of the profitability related to the adoption of technology (Jensen (1982)). There are other firm characteristics that have proved to be significant in this relation, such as: spatial location of the adopter (Foster and Rosenzweig (1995)), age of the firm (Czarnitzki and Delanote (2012)) and the market position (i.e. export orientation, Veugelers and Cassiman (1999) and Beneito (2003)).

Finally, our study is also related to several articles that aim to answer the technology adoption question in diverse fields using logit and ordered logit econometric models. Costa-Campi et al. (2015), Hochman and Timilsina (2017) and García-Quevedo and Massa-Camps (2019) analyze the adoption of energy efficient technologies, Brynjolfsson et al. (2011) and Brynjolfsson and Mcelheran (2016) study the adoption of data and business analytics related to firm performance and Veugelers and Cassiman (1999) use this framework to analyze the innovation degree of Belgian manufacturing firms, just to name a set of examples.

Since Horváth and Szabo (2019) provides a good summary of the existing literature at the moment concerning stated driving forces and barriers of *Industry 4.0*, we use it to identify the expected signs of the firms' characteristics with the technology adoption decision. In particular, we focus on the financial and performance factors as drivers (i.e. more profitable firms would invest more intensively in these technologies) and the lack of skilled human resources, shortage of financial resources and the difficulty of coordination across organizational units as barriers (i.e. firms with less skilled workforce, less access to financial markets and with more units would invest less intensively in these technologies). We also include other variables normally proved to have an impact on technology adoption such as the age of the firm, external commerce orientation, location of the plant and some characteristics of the CEO (age and educational level).

3 Data Description

The data used in this study stems from two sources. The main data set comes from the two editions of the ICT (Information and Communication Technologies) Surveys carried out by the Agence du Numérique in Wallonia (Belgium) in 2018 and 2020. This agency, as it claims in their institutional website[2], is "the public service body responsible for monitoring technological innovation and habits relating to digital technology". The samples of such surveys were built to be representative of the total population of private companies with headquarters in this Belgian region. Moreover, probability weights calculated regarding the size and sector of the firms were introduced to give the sample the natural distribution of the universe considered. The responses were collected by phone or via a web form.

[2]https://www.adn.be/en/agence-du-numerique-2/

Given that the main objective of these surveys was to study the digital maturity of Walloon enterprises, they include one specific block of questions related to Industry 4.0 technologies. This makes this data set particularly appealing for our purposes. Specifically, we focus on three questions of this block that asked whether the respondent firm adopt or did not adopt certain technologies:

- **Predictive Maintenance:** Are your production equipment capable of forecasting their maintenance needs by analyzing data independently for breakdowns?

- **Advanced Planning:** Does your company use advanced planning systems that aggregate internal and external (supplier, carrier, etc.) data to manage production operations?

- **Smart Production:** Are certain workstations or machines in your company capable of adapting their operation based on data transmitted by other workstations?

In our study we focus on the respondents of these three questions that belong to the Manufacturing sector (according to the NACE-BEL 2008 classification). We perform this filter to avoid including in our study firms that were not supposed to answer this block of questions but for some reason did. The fact that in the 2018 edition none of these questions were compulsory to finish the survey explains that we have different number of respondents for each question (as it is exposed in Table 1). Our data set, therefore, accounts for approximately 620 respondent firms for each cross-section. Besides the data already mentioned, the ICT surveys provide information of several firm characteristics, such as the number of employees, location, number of plants, etc.

Our main data set is complemented with information from the Belfirst database (provided by Bureau Van Dijk - A Moody's Analytics Company) which includes financial and legal data of Belgian firms. Table 4 offers a precise description of each variable and from which source it is extracted from.

In Table 1 we present a first approximation to the data, by showing the summary statistics of our main variables of interest. Since these are binary variables (that take the value 1 if the firm adopted the referred technology, and 0 otherwise), the mean can be taken as the degree of adoption of each technology for a given year. Although the adoption of these technologies is not widely spread across the sector yet, the number of adopters is not negligible either; between 3.6% and 8.2% of the firms have adopted some of them (taking both surveys into account). Despite the fact that for Predictive Maintenance and Smart Production the mean is lower in 2020 than in 2018, the size of the 95% confidence interval does not allow us to conclude if the adoption is effectively decreasing or not.

Another relevant approximation to the data is to observe the degree of adoption heterogeneity across sub-sectors. As we present in Table 2, the heterogeneity varies considerably in this dimension. While there are

Table 1: Summary statistics of adoption of Industry 4.0 technologies

Variable	Mean	Std. Dev.	95% Conf. Interval		Min.	Max.	N
Year of the Survey: 2018							
Predictive Maintenance	0.095	0.293	0.01	0.179	0	1	628
Smart Production	0.042	0.2	0.025	0.057	0	1	630
Advanced Planning	0.048	0.214	0.032	0.063	0	1	634
Year of the Survey: 2020							
Predictive Maintenance	0.069	0.254	0.038	0.1	0	1	615
Smart Production	0.031	0.172	0.017	0.043	0	1	615
Advanced Planning	0.052	0.221	0.028	0.075	0	1	615
Total							
Predictive Maintenance	0.082	0.275	0.036	0.128	0	1	1,243
Smart Production	0.036	0.187	0.025	0.046	0	1	1,245
Advanced Planning	0.05	0.218	0.035	0.063	0	1	1,249

sectors that seem to be at the forefront of this revolution (i.e. Manufacture of paper and paper products, Manufacture of rubber and plastic products, among others), there are some sectors that appear not to be involved at all (namely, Manufacture of tobacco products, Manufacture of leather and related products and Manufacture of wearing apparel). These marked dissimilarities could be explained by the differences in terms of the expected profitability of adopting such technologies but could also be related with the particular scheme of regulations of each sub-sector. In this sense, sub-sectors more implicated to adopt newer technology to meet environmental regulations (e.g. Manufacture of paper and paper products) might have stronger incentives to adopt these technologies. Accounting for these sub-sector specific particularities is fundamental for our statistic and econometric study of the determinants of *Industry 4.0* technology adoption.

In Table 3 we introduce a different perspective of technology adoption. Instead of focusing on the adoption of each technology, we present the weighted distribution of our sample regarding the number of *Industry 4.0* technologies adopted. This table allows us to observe that, overall, more than 13% of the firms adopted at least one of these technologies.

Table 4 offers an exhaustive definition of the variables we use in our study. A brief clarification has to be made with respect to the inclusion of the "EBITDA_Lagged" variable. While we would have preferred to include a better approximation of firms' profitability (for instance, by including the profit margin or a longer time period), the two-years lagged EBITDA was the variable by which we found more available data in the Belfirst data set. In case we used any other similar variable we would have lost too many observations on

Table 2: Adoption of Industry 4.0 adoption by Sub-Sector

Sub-Sector (2nd level of NACE-BEL 2008)	Pred. Main.	Smart Prod.	Adv. Planning
Other manufacturing	28.6%	2.1%	4.3%
Manufacture of paper and paper products	13.0%	11.7%	15.2%
Manufacture of machinery and equipment n.e.c.	12.5%	9.3%	11.4%
Manufacture of rubber and plastic products	11.6%	13.4%	24.4%
Manufacture of other non-metallic mineral products	11.3%	3.3%	3.0%
Manufacture of computer, electronic and optical products	9.7%	2.1%	10.5%
Manufacture of furniture	8.5%	1.4%	1.4%
Repair and installation of machinery and equipment	7.5%	7.1%	1.2%
Manufacture of fabricated metal products, except machinery and equipment	7.3%	5.5%	3.6%
Printing and reproduction of recorded media	6.5%	1.1%	3.3%
Manufacture of food products	4.9%	2.8%	7.7%
Manufacture of electrical equipment	4.4%	5.3%	5.3%
Manufacture of chemicals and chemical products	4.2%	3.6%	13.1%
Manufacture of basic metals	3.4%	5.8%	6.9%
Manufacture of motor vehicles, trailers and semi-trailers	3.3%	3.9%	5.3%
Manufacture of beverages	2.4%	1.9%	3.0%
Manufacture of textiles	1.7%	1.0%	1.6%
Manufacture of wood and of products of wood	1.3%	2.1%	1.8%
Manufacture of basic pharmaceutical products and pharmaceutical preparations	1.2%	8.7%	5.8%
Manufacture of other transport equipment	0.0%	1.0%	2.9%
Manufacture of wearing apparel	0.0%	0.0%	0.4%
Manufacture of leather and related products	0.0%	0.0%	0.0%
Manufacture of tobacco products	0.0%	0.0%	0.0%

Notes: According to the NACE-BEL 2008 classification, the Other manufacturing sub-sector includes the following activities: Manufacture of jewellery, bijouterie and related articles, Manufacture of musical instruments, Manufacture of sports goods, Manufacture of games and toys, Manufacture of medical and dental instruments and supplies and Manufacturing n.e.c.

the process. In any case, we believe it is a sound variable by which to approximate firms' profitability in an accurate way.

Table 3: Number of firms by number of Industry 4.0 technologies adopted

Number of technologies	Freq.	Percent
Year of the Survey: 2018		
0	533	85,18
1	75	12,01
2	13	1,99
3	5	0,82
Year of the Survey: 2020		
0	544	88,46
1	53	8,55
2	15	2,39
3	4	0,59
Total		
0	1,077	86,80
1	128	10,30
2	27	2,19
3	9	0,71

Table 4: Definition of variables

Dependent Variables	
Pred. Main.	Binary variable: 1 if the firm declares to have adopted predictive maintenance technologies, and 0 otherwise.
Smart Prod.	Binary variable: 1 if the firm declares to have adopted smart production technologies, and 0 otherwise.
Adv. Planning	Binary variable: 1 if the firm declares to have adopted advanced planning technologies, and 0 otherwise.
Explanatory Variables	
LSize	Number of employees in the firm (in log).
LAge	Age of the firm in years (in log).
LDevices_per_emp	Number of computers and tables per employees (in log).
Exports	Binary variable: 1 if the firm sells products/services to foreign countries, and 0 otherwise.
Made_Diff	Binary variable: 1 if the firm is aware of the "Made Different" program, and 0 otherwise.
Industrial_Zone	Binary variable: 1 if the firm is located in an industrial zone, and 0 otherwise.
Multiple_Plants	Binary variable: 1 if the firm is situated in more than one location, and 0 otherwise.
EBITDA_Lagged	EBITDA of the firm in millions of Euros (2 years lagged).
CEO_Age	Categorical variable: 1 if the CEO is less than 46 years old, 2 if he/she is between 46-55, and 3 if he/she is more than 55.
CEO_Education	Categorical variable: 1 if the highest level of formal education achieved by the CEO was School or High School (or equivalent), 2 if it was Bachelor (or equivalent), and 3 if it was Master or Doctorate.

Notes: All variables except for LSize, LAge and EBITDA_Lagged were extracted from the ICT Surveys carried out by Agènce du Numérique. The two latter variables, as well as the sub-sector of the firms, were taken by looking for the firm id numbers at the Belfirst database (provided by Bureau Van Dijk). For the case of LSize the data extracted from the Belfirst database was considered as the primary source; for the cases where the information was not available, the data provided at the ICT Survey was considered.

Table 5: Cross-correlation table

Variables	Pred. Main.	Smart Prod.	Adv. Planning
Pred. Main.	1.000		
Smart Prod.	0.378	1.000	
Adv. Planning	0.246	0.317	1.000
Size	0.117	0.034	0.144
Age	0.020	0.072	0.080
Dev_per_emp	-0.003	0.048	-0.045
Exports	0.104	0.134	0.210
Made_Diff	0.102	0.075	0.111
Industrial_Zone	0.111	0.175	0.200
Multiple_Plants	0.067	0.073	0.096
EBITDA_Lagged	0.089	0.003	0.080
CEO_Age	0.022	-0.017	-0.008
CEO_Education	0.065	0.074	0.154

Table 6: Profiles of adopters and non-adopters - Continuous explanatory variables

	Pred. Main.			**Smart Prod.**			**Adv. Planning**		
Variable	NO	YES	**Diff**	NO	YES	**Diff**	NO	YES	**Diff**
Size	6.44	26.19	19.753	7.05	34.76	27.718***	5.23	62.13	56.897***
	(0.48)	(13.94)	(13.911)	(1.08)	(7.35)	(7.409)	(0.37)	(21.16)	(21.133)
Dev_per_emp	2.35	3.33	0.986*	2.42	2.53	0.113	2.43	2.23	-0.199
	(0.08)	(0.51)	(0.516)	(0.10)	(0.53)	(0.537)	(0.10)	(0.33)	(0.343)
N	1105	138	1243	1089	156	1245	1039	210	1249
Age	18.70	17.26	-1.440	18.52	21.16	2.640	18.46	21.76	3.304*
	(0.78)	(1.72)	(1.880)	(0.75)	(2.28)	(2.400)	(0.76)	(1.79)	(1.947)
N	1104	138	1242	1088	156	1244	1038	210	1248
EBITDA_Lagged	0.26	3.87	3.610	0.58	2.35	1.778	0.17	6.92	6.754
	(0.05)	(3.58)	(3.567)	(0.38)	(1.04)	(1.107)	(0.02)	(5.14)	(5.131)
N	916	128	1044	897	149	1046	845	205	1050

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. The expressions "Yes" and "No" indicate whether the firms have adopted the technology or not. In the column "Diff" we present the difference of means and the statistical significance of the t-test of different means across groups of adopters and non-adopters.

Table 7: Profiles of adopters and non-adopters - Categorical explanatory variables

	Pred. Main.			Smart Prod.			Adv. Planning		
Variable	NO	YES	**F-test**	NO	YES	**F-test**	NO	YES	**F-test**
Exports									
No	0.54	0.05	0.02	0.58	0.01	7.72^{***}	0.58	0.01	15.35^{***}
Yes	0.37	0.03		0.38	0.02		0.37	0.04	
Made_Diff									
No	0.90	0.07	3.03^{*}	0.94	0.03	2.82^{*}	0.92	0.05	1.92
Yes	0.02	0.01		0.03	0.00		0.03	0.00	
Industrial_Zone									
No	0.76	0.06	1.25	0.80	0.02	20.06^{***}	0.80	0.03	22.06^{***}
Yes	0.16	0.02		0.15	0.01		0.16	0.02	
Multiple_Plants									
No	0.84	0.07	1.26	0.88	0.03	3.75^{*}	0.87	0.04	$8,57^{***}$
Yes	0.08	0.01		0.08	0.01		0.08	0.01	
CEO_Age									
Less than 46	0.29	0.04		0.32	0.01		0.31	0.02	
Between 46-55	0.28	0.01	1.19	0.29	0.01	0.43	0.28	0.02	1.01
More than 55	0.34	0.03		0.36	0.01		0.35	0.01	
N			1,243			1,245			1,249
CEO_Education									
Low	0.44	0.02		0.45	0.01		0.44	0.01	
Medium	0.27	0.04	1.91	0.31	0.01	1.87	0.32	0.01	11.72^{***}
High	0.20	0.02		0.20	0.01		0.20	0.02	
N			1,045			1,046			1,049

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. The expressions "Yes" and "No" indicate whether the firms have adopted the technology or not. In the column "F-test" we present the value of the of the F-Pearson design-based test.

In Table 5 we show the Pearson correlations between the three dependent variables and the explanatory ones. A few observations have to be made. Firstly, the correlations between the dependant variables are positive in every case, which is obvious given their binary nature. The correlation between Predictive Maintenance and Smart Production is stronger than the one between the former and Advanced Planning. Secondly, some explanatory variables behave as expected (Size, Exports, Made_Diff, among others). Other independent variables present ambiguous results (in particular, Dev_per_emp and CEO_Age). All in all, it is not possible to derive sound conclusions from this table. Given the different nature of our variables (continuous and categorical), a better way of observing if there are substantial differences between adopters and non-adopters with regard to our explanatory variables is by carrying out difference of means t-tests for the continuous variables and F-Pearson design-based tests for the categorical ones. In Tables 6 and 7 we present the results of these tests.

Based on the figures shown in Table 6, we do reject the null hypothesis of equal means across groups of adopters vs. non-adopters in terms of size for Smart Production and Advanced Planning, devices per employees for Predictive Maintenance and age of the firm for Advanced Planning (the two latter at a 10% statistical significance).

The third column of each dependent variable of Table 7 shows the value of the F-Pearson test and its statistical significance. This test is the analogous version for weighted samples of the chi-squared test, which checks if the distribution of the two categorical variables are related or not. In this case, we reject the null hypothesis of non-existence of a relationship between Smart Production and Advanced Planning and several explanatory categorical variables (i.e. Exports, Industrial_Zone and Multiple_Plants).

These results give us some hints of which variables may prove to be statistical significant when running the regressions in the following sections.

4 Methodology and estimation strategy

Given the binary nature of our dependent variables, we find it suitable to use a logit model. Therefore, we estimate the probability of the firm i to adopt a certain technology conditioned on a series of its characteristics and year fixed effects.

Our basic econometric model is the following:

$$\begin{aligned} Pr(Y_i = 1|X) = \Theta(\alpha_0 + \beta_1 LSize_i + \beta_2 LDev\_per\_emp_i + \beta_3 LAge_i + \delta_1 Exports_i + \delta_2 Made\_Diff_i + \\ \delta_3 Industrial\_Zone_i + \delta_4 Multiple\_Plants_i + \delta_5 CEO\_Age\_46\_55_i + \delta_6 CEO\_More\_55_i + \\ \delta_7 Year\_2020_i + \epsilon_i) \end{aligned} \tag{1}$$

Being:

- $\Theta = \frac{exp(X'\beta)}{1+exp(X'\beta)}$
- $Y_i = 1$ if the firm i adopted such technology. $Y_i = 0$ otherwise.

In a second step we incorporate sub-sector fixed effects (at the second level of the NACE-BEL 2008 classification) to capture all the differences in technology adoption across sub-sectors. We choose not to include them in the first model because we would lose observations due to the sample non-adoption of certain sub-sectors for some technologies. By including them from the second model onward we are able to check the robustness of the results of our first estimation. This is our preferred model for inferring results.

$$
\begin{aligned}
Pr(Y_i = 1|X) = \Theta(&\alpha_0 + \beta_1 LSize_i + \beta_2 LDev\_per\_emp_i + \beta_3 LAge_i + \delta_1 Exports_i + \delta_2 Made\_Diff_i + \\
&\delta_3 Industrial\_Zone_i + \delta_4 Multiple\_Plants_i + \delta_5 CEO\_Age\_46\_55_i + \delta_6 CEO\_More\_55_i + \\
&\delta_7 Year\_2020_i + \sum Sub\_SectorFE_i + \epsilon_i)
\end{aligned} \tag{2}
$$

In a third step, we include two dummy variables to check for the importance of the educational level of the CEO to adopt these technologies.

$$
\begin{aligned}
Pr(Y_i = 1|X) = \Theta(&\alpha_0 + \beta_1 LSize_i + \beta_2 LDev\_per\_emp_i + \beta_3 LAge_i + \delta_1 Exports_i + \delta_2 Made\_Diff_i + \\
&\delta_3 Industrial\_Zone_i + \delta_4 Multiple\_Plants_i + \delta_5 CEO\_Age\_46\_55_i + \delta_6 CEO\_More\_55_i + \\
&\delta_7 Year\_2020_i + \sum Sub\_SectorFE_i + \delta_8 CEO\_Ed\_Medium_i + \delta_9 CEO\_Ed\_High_i + \epsilon_i)
\end{aligned} \tag{3}
$$

Finally, we estimate a model including financial information of the firms. By including the EBITDA two years lagged we intend to test if there is a statistical significant correlation between the decision to adopt these technologies and the profitability of the firms. The scarce availability of information with respect to the whole data set is the reason why we present these two models separately from the previous ones.

$$
\begin{aligned}
Pr(Y_i = 1|X) = \Theta(&\alpha_0 + \beta_1 LSize_i + \beta_2 LDev\_per\_emp_i + \beta_3 LAge_i + \delta_1 Exports_i + \delta_2 Made\_Diff_i \\
&+ \delta_3 Industrial\_Zone_i + \delta_4 Multiple\_Plants_i + \delta_5 CEO\_Age\_46\_55_i + \delta_6 CEO\_More\_55_i + \\
&\delta_7 Year\_2020_i + \sum Sub\_SectorFE_i + \beta_4 EBITDA\_Lagged_i + \epsilon_i)
\end{aligned} \tag{4}
$$

With the intention to provide a more general outlook of the *Industry 4.0* phenomenon, that overcomes the individual technology perspective, we include estimations of ordered logit models that replicate the four previous logit ones. We assume that there is a latent variable Y^* (namely, the variation in expected profits of a firm by adopting more *I4.0* technologies) that depends on a set of variables X and we redefine Y as the number of *I4.0* technologies adopted. Hence,

$$
\begin{aligned}
Pr(Y_i = 0|X) &= Pr(Y^* \leq 0|X) = \Theta(-X'\beta) \\
Pr(Y_i = 1|X) &= Pr(0 < Y^* \leq c_1|X) = \Theta(c_1 - X'\beta) - \Theta(-X'\beta) \\
Pr(Y_i = 2|X) &= Pr(c_1 < Y^* \leq c_2|X) = \Theta(c_2 - X'\beta) - \Theta(c_1 - X'\beta) \\
Pr(Y_i = 3|X) &= Pr(Y^* \geq c_2|X) = 1 - \Theta(c_2 - X'\beta)
\end{aligned}
$$

5 Results

Tables 8, 9 and 10 contain our main results. They show the average marginal effects of a group of logit regressions using Predictive Maintenance, Smart Production and Advanced Planning as dependent binary variables, respectively. While the first column of each table presents the results of the baseline regressions, the second one shows the regression that includes sub-sector fixed effects. It is relevant to notice that once we include sub-sector fixed effects, the statistical significance of our results remain. In columns 3 and 4 we expand our initial specifications by including variables regarding the education level of the CEO and the EBITDA of the firm (lagged two years). Given that this data was not available for all firms in our sample, the number of observations varies in each regression. In the Appendix we present the actual values of the parameters for each regression and the Log-Likelihood and Pseudo-R-squared (Mc-Fadden) values.

We begin our analysis by focusing on the first two columns of the tables exposed. The first point to highlight is that, in line with our expectations, the number of employees of a firm is a relevant predictor of the likelihood of adopting each of these technologies. The larger the firm, the more likely it is that it has adopted any of the three technologies included in this study. There are multiple mechanisms by which this variable operates. As summarized in Gomez and Montoya (2009) it could be explained, among other reasons, by scale effects, a larger stock of equipment or a relative major availability of funds. The first explanation relates to the notion that larger firms would be able to spread the investment cost in more units, therefore making the adoption of technology more profitable in comparison to smaller firms. The second explanation is related to the idea sustained by Romeo (1975) that larger firms are expected to have more equipment and, hence, a higher need to replace a share of it with newer technology. Finally, certain market failures provoke that smaller firms have more difficulties to gather funds to finance their investments on new technologies. As explained by Canepa and Stoneman (2007) and Stoneman (2001), reasons concerning high uncertainty regarding future cash flows, large information asymmetries between firm managers and potential financers and the need to invest part of the funds in firm-specific assets, make it easier to firms with more internal financial sources to adopt these technologies. In our study we attempt to corroborate the relevance of financial constrains by checking the statistical relation with the EBITDA variable. Nevertheless, we are aware that, given the characteristics of our data set, it is not possible to isolate completely this effect in such variable and, hence, the size of the company may be capturing certain part of this mechanism.

Secondly, the number of devices per employees is also statistical significant and presents the expected sign in all cases. As we explained in the second section, we use this variable as a proxy of the digital maturity of the firm to adopt *Industry 4.0* technologies. Simply put, firms with more devices per employee are expected to have employees with better capacities to incorporate these technologies in their production processes. It can also be related to the absorptive capacity of the firm as defined by Cohen and Levinthal (1990) and summarized in Gomez and Montoya (2009): the “ability of a firm to recognize the value of new, external information, assimilate it and apply it to commercial ends”. Nevertheless, we cannot discard an opposite

Table 8: Average Marginal Effects of Logit Regressions - Predictive Maintenance

	(1) Baseline	(2) Sub-Sector_FE	(3) CEO_Ed	(4) EBITDA
LSize	0.036***	0.039***	0.044***	0.037***
	(0.012)	(0.0091)	(0.0094)	(0.012)
LDev_per_emp	0.085**	0.084***	0.095***	0.10***
	(0.042)	(0.028)	(0.025)	(0.031)
LAge	0.012	0.0062	0.0077	0.0038
	(0.020)	(0.016)	(0.013)	(0.021)
Exports	-0.037	-0.0073	-0.0043	0.0089
	(0.047)	(0.036)	(0.033)	(0.045)
Made_Diff	0.069	0.091	0.041	-0.071
	(0.059)	(0.059)	(0.055)	(0.074)
Industrial_Zone	0.033	0.041	0.050	0.046
	(0.031)	(0.029)	(0.032)	(0.037)
Multiple_Plants	0.018	0.033	0.042	0.0082
	(0.035)	(0.032)	(0.034)	(0.044)
CEO_Age				
Between 46-55	-0.071	-0.056	-0.045	-0.082*
	(0.058)	(0.038)	(0.030)	(0.049)
More than 55	-0.038	-0.0026	0.020	-0.046
	(0.064)	(0.049)	(0.043)	(0.059)
CEO_Education				
Medium			0.051	
			(0.032)	
High			0.030	
			(0.039)	
EBITDA_Lagged				0.0051
				(0.0031)
Year_FE	YES	YES	YES	YES
Sub-Sector_FE	NO	YES	YES	YES
Observations	1242	1212	1016	1022

Standard errors in parentheses

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

relationship in terms of firms adopting more devices once they have decided to adopt these technologies. Thirdly, there is a group of variables that, although not at the center of our study, deserves a detailed

Table 9: Average Marginal Effects of Logit Regressions - Smart Production

	(1) Baseline	(2) Sub-Sector_FE	(3) CEO_Ed	(4) EBITDA
LSize	0.030***	0.031***	0.033***	0.035***
	(0.0054)	(0.0052)	(0.0057)	(0.0061)
LDev_per_emp	0.017**	0.018**	0.023***	0.026***
	(0.0077)	(0.0072)	(0.0069)	(0.0093)
LAge	-0.013*	-0.014**	-0.013**	-0.0099
	(0.0076)	(0.0073)	(0.0064)	(0.011)
Exports	0.0066	0.012	0.012	0.014
	(0.012)	(0.012)	(0.012)	(0.018)
Made_Diff	0.018	0.026	-0.018	-0.013
	(0.027)	(0.028)	(0.013)	(0.016)
Industrial_Zone	0.0073	-0.000078	0.0062	0.018*
	(0.0077)	(0.0096)	(0.0085)	(0.0098)
Multiple_Plants	-0.026**	-0.022**	-0.015*	-0.018
	(0.011)	(0.010)	(0.0089)	(0.012)
CEO_Age				
Between 46-55	0.0078	0.0035	0.0061	-0.0010
	(0.013)	(0.014)	(0.013)	(0.017)
More than 55	0.011	0.011	0.0058	-0.00046
	(0.015)	(0.016)	(0.012)	(0.018)
CEO_Education				
Medium			-0.00035	
			(0.016)	
High			-0.017*	
			(0.010)	
EBITDA_Lagged				-0.000060
				(0.000039)
Year_FE	YES	YES	YES	YES
Sub-Sector_FE	NO	YES	YES	YES
Observations	1244	1230	1031	1036

Standard errors in parentheses

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

focus. The Age variable allow us to conclude that for two of the three technologies being considered (smart production and advanced planning) the average marginal effects are statistically significant. This result implies that younger firms adopt these technologies more intensively than older ones *ceteris paribus*. This finding relates to Czarnitzki and Binz (2008), a study that evidences the existence of *Young Innovative Companies* in the Belgian Flemish region with a higher growth rate than the rest of the firms.

Contrary to our previous expectations and to some related literature (Veugelers and Cassiman (1999) and Beneito (2003)), the export-oriented feature of a firm is not an important characteristic for the adoption of these technologies. One could expect that firms involved in international markets have to deal with more intense competition and that it would lead to a higher propensity to adopt technology. Nevertheless, in the case of Belgian firms, it might not be so relevant given that the local market is very small and integrated with the neighboring countries (mainly France, Germany and the Netherlands).

In our predictions we also stated that those firms that have better information with respect to the benefits and adoption methods of these technologies would be expected to adopt them in a more intensive manner. But it is not the case. Firms that are aware of the Made Different program are not more prone to adopt any of these technologies. This can be interpreted in different ways. One could say that there was no informational barrier in the first place, that once the firms got the information of the technology they rationally decided not to adopt them or plainly that the program was not effective on its purposes. More evidence is needed to disentangle these explanations. In principle, we can state the the evidence does not support the achievement of the goals of such program.

In contrast to our expectations, firms located in industrial zones are not more prone than others to adopt these technologies. We would expect that being close to other innovative firms could be determinant to learn from them similarly to what is exposed in Foster and Rosenzweig (1995) regarding technical change in agriculture. However, there seems to be no "learning spillovers" in the *Industry 4.0* phenomenon.

The Multiple_Plants variable aimed at capturing the coordination problems that may arise when one firm has several facilities (based on Gomez and Montoya (2009). In line with what we expected, firms with more than one plant adopt Smart Production technology less intensively. In the other two technologies the variable proved not to be relevant. The weakness of our explanatory variable is a caveat for the robustness of this result.

Fourthly, we were intrigued to check if the characteristics of the CEO concerning its age and educational level could determine the propensity of the firm to adopt new technology. We find no evidence supporting these claims.

Finally, the EBITDA_Lagged variable introduced in the fourth regressions is not statistically significant for any of the three technologies. This suggests that more profitable firms, with presumably better access to financial resources, do not adopt these technologies more intensively. Interpretations regarding the non-existence of financial barriers have to be derived carefully. In the first place because the variable we are using has several caveats (not a precise approximate of access to financial funds, only one year is taken into account, etc.) and, in the second place because, as we pointed out earlier, we may be capturing some of the financial barriers effect in the Size variable.

On Table 11 we present the results of the ordered logit regressions. Our discrete dependent variable is the number of technologies adopted by firm i (which can be 0, 1, 2 or 3). The utility of running these regressions is to overlook the peculiarities of each technology and analyze the phenomenon *Industry 4.0* as a whole. In line with the results of the three previous tables, the number of employees and the number of devices per employee are the only statistically significant variables to determine if a firm would adopt these technologies. In other words, firms with more employees and more devices per employees are more prone to adopt a higher number of *Industry 4.0* technologies.

Table 10: Average Marginal Effects of Logit Regressions - Advanced Planning

	(1) Baseline	(2) Sub-Sector_FE	(3) CEO_Ed	(4) EBITDA
LSize	0.034***	0.031***	0.033***	0.045***
	(0.0053)	(0.0047)	(0.0048)	(0.0064)
LDev_per_emp	0.018**	0.016*	0.017**	0.016*
	(0.0089)	(0.0090)	(0.0082)	(0.0097)
LAge	-0.0053	-0.0078	-0.0097*	-0.035***
	(0.0069)	(0.0070)	(0.0057)	(0.013)
Exports	0.022	0.026	0.017	0.055**
	(0.018)	(0.018)	(0.016)	(0.025)
Made_Diff	-0.0039	0.0083	0.012	0.036
	(0.018)	(0.017)	(0.018)	(0.025)
Industrial_Zone	0.0093	0.0061	0.0068	0.0070
	(0.011)	(0.012)	(0.012)	(0.016)
Multiple_Plants	-0.0030	0.0043	0.0011	-0.0063
	(0.020)	(0.021)	(0.021)	(0.025)
CEO_Age				
Between 46-55	0.0092	0.0087	0.0053	0.017
	(0.016)	(0.016)	(0.012)	(0.022)
More than 55	-0.0017	-0.00033	0.010	0.017
	(0.018)	(0.020)	(0.018)	(0.031)
CEO_Education				
Medium			-0.033***	
			(0.013)	
High			-0.010	
			(0.026)	
EBITDA_Lagged				0.000038
				(0.000094)
Year_FE	YES	YES	YES	YES
Sub-Sector_FE	NO	YES	YES	YES
Observations	1248	1243	1043	1044

Standard errors in parentheses

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

Table 11: Ordered Logit Regressions - All Technologies

	(1) Baseline	(2) Sub-Sector_FE	(3) CEO_Ed	(4) EBITDA
LSize	0.83***	0.82***	1.05***	0.80***
	(0.12)	(0.12)	(0.15)	(0.13)
LDev_per_emp	1.03***	0.98***	1.29***	0.98***
	(0.34)	(0.27)	(0.30)	(0.27)
LAge	0.034	-0.038	-0.065	-0.17
	(0.22)	(0.18)	(0.19)	(0.21)
Exports	-0.30	0.039	-0.012	0.41
	(0.47)	(0.41)	(0.43)	(0.45)
Made_Diff	0.74	1.13	0.66	-0.12
	(0.66)	(0.71)	(0.69)	(0.64)
Industrial_Zone	0.41	0.37	0.59	0.43
	(0.33)	(0.34)	(0.40)	(0.36)
Multiple_Plants	0.17	0.44	0.56	0.075
	(0.40)	(0.39)	(0.45)	(0.40)
CEO_Age				
Between 46-55	-0.70	-0.65	-0.68*	-0.68
	(0.52)	(0.41)	(0.41)	(0.42)
More than 55	-0.56	-0.35	-0.16	-0.60
	(0.58)	(0.49)	(0.50)	(0.52)
CEO_Education				
Medium			0.33	
			(0.43)	
High			0.062	
			(0.50)	
EBITDA_Lagged				0.023
				(0.029)
Constant	-2.83***	-4.02***	-5.21***	-3.59***
	(0.42)	(0.79)	(1.00)	(0.88)
Year_FE	YES	YES	YES	YES
Sub-Sector_FE	NO	YES	YES	YES
Observations	1240	1235	1037	1036
Pseudo-R^2	0.136	0.205	0.236	0.241
Log-Likelihood	-97.31	-89.35	-75.82	-61.99

Standard errors in parentheses

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

6 Conclusions

This paper has analysed the degree of adoption of three *Industry 4.0* technologies (Predictive Maintenance, Smart Production and Advanced Planning) in Wallonia. By applying logit econometric models on survey data from the Walloon region for 2018 and 2020, we have studied the impact of several firm characteristics on the decision to adopt these technologies. We were able to contrast some of the assumed drivers and barriers of adoption.

The results suggest that larger firms are more likely to have adopted any of these technologies analysed in this study. Larger scale, more stock equipment or less financial constraints are all reasons compatible with this finding. The last of these explanations goes in line with one of the main barriers for adoption that claimed by firms' CEOs (i.e. shortage of financial resources). We also found that the number of digital devices per employee is a strong predictor of adoption. We can interpret this finding as a proxy of the readiness for adoption of the firms (or absorptive capacity, as it is called in the literature). Given that firms with more devices per employee can be assumed to have more capable personnel, this interpretation matches with the lack of skillful human resources as a major setback proposed in the literature. Additionally, we do not find evidence to support that more profitable firms are more prone to adopt these technologies than the rest.

Furthermore, we provide indicative evidence that the Made Different program was not successful to encourage firms to adopt such technologies. Although it may have helped to overcome the informational barrier and to diffuse the benefits of these technologies to a group of firms, the presence of financial and labour barriers may have hindered the outcomes of such program. Probably, a more complete action, that includes financial resources as well as staff training, may deliver better results.

The main limitation of this article is the cross-sectional nature of the data. A panel data structure would allow us to disentangle in a better way the existence of drivers and barriers and to address unanswered questions such as the profitability impact of adopting these technologies. More precise data on the firms (i.e. educational level of the personnel, more extensive financial data, precise location, etc.) as well as a larger pool of respondents would prove helpful to increase the robustness of our findings. Finally, enhanced data and an appropriate methodology design would allow us to provide a causal policy assessment of the Made Different program.

Further questions are still open regarding why the adoption of these *Industry 4.0* technologies has not increased between 2018 and 2020 in Wallonia. Better data would prove useful to answer the existence of drivers and barriers of adoption in a more precise way. It would also be interesting to extend this study to other regions as to compare the findings.

Overall, the present study provides the first available evidence of the existence of drivers and barriers to adopt *Industry 4.0* technologies in the manufacturing sector. Despite the particularities of the Walloon market, its results should be taken into account for policy makers who seek to foster the adoption of such technologies. It should prove useful by firms wanting to understand what drivers and barriers are present in the market in the process of *Industry 4.0* technology adoption.

7 Appendix

Table 12: Logit Regressions - Predictive Maintenance

	(1) Baseline	(2) Sub-Sector_FE	(3) CEO_Ed	(4) EBITDA
LSize	0.52***	0.59***	0.70***	0.46***
	(0.14)	(0.14)	(0.16)	(0.16)
LDev_per_emp	1.23***	1.26***	1.52***	1.27***
	(0.45)	(0.36)	(0.35)	(0.37)
LAge	0.17	0.093	0.12	0.047
	(0.27)	(0.24)	(0.21)	(0.26)
Exports	-0.53	-0.11	-0.069	0.11
	(0.63)	(0.54)	(0.54)	(0.55)
Made_Diff	1.01	1.36	0.65	-0.89
	(0.83)	(0.87)	(0.88)	(0.91)
Industrial_Zone	0.48	0.61	0.80	0.57
	(0.46)	(0.44)	(0.51)	(0.46)
Multiple_Plants	0.26	0.50	0.68	0.10
	(0.51)	(0.48)	(0.54)	(0.55)
CEO_Age				
Between 46-55	-1.08	-0.94*	-0.84	-1.00*
	(0.67)	(0.56)	(0.53)	(0.56)
More than 55	-0.47	-0.033	0.27	-0.49
	(0.73)	(0.62)	(0.57)	(0.63)
CEO_Education				
Medium			0.81	
			(0.49)	
High			0.51	
			(0.64)	
EBITDA_Lagged				0.063*
				(0.037)
Constant	-3.53***	-5.69***	-8.56***	-4.94***
	(0.54)	(1.23)	(1.99)	(1.34)
Year_FE	YES	YES	YES	YES
Sub-Sector_FE	NO	YES	YES	YES
Observations	1242	1212	1016	1022
Pseudo-R^2	0.12	0.20	0.25	0.23
Log-Likelihood	-72.0	-64.4	-55.6	-46.9

Standard errors in parentheses .

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

Table 13: Logit Regressions - Smart Production

	(1) Baseline	(2) Sub-Sector_FE	(3) CEO_Ed	(4) EBITDA
LSize	0.98***	1.00***	1.35***	1.00***
	(0.12)	(0.12)	(0.15)	(0.14)
LDev_per_emp	0.56**	0.59***	0.96***	0.72***
	(0.24)	(0.22)	(0.27)	(0.25)
LAge	-0.41*	-0.46**	-0.53**	-0.28
	(0.22)	(0.22)	(0.23)	(0.29)
Exports	0.21	0.39	0.48	0.40
	(0.40)	(0.39)	(0.48)	(0.49)
Made_Diff	0.59	0.85	-0.76	-0.35
	(0.86)	(0.87)	(0.54)	(0.44)
Industrial_Zone	0.24	-0.0025	0.26	0.50*
	(0.27)	(0.31)	(0.37)	(0.30)
Multiple_Plants	-0.85***	-0.70**	-0.61*	-0.49
	(0.30)	(0.30)	(0.35)	(0.31)
CEO_Age				
Between 46-55	0.27	0.12	0.26	-0.029
	(0.42)	(0.47)	(0.53)	(0.46)
More than 55	0.36	0.34	0.25	-0.013
	(0.47)	(0.50)	(0.52)	(0.51)
CEO_Education				
Medium			-0.012	
			(0.55)	
High			-0.79*	
			(0.44)	
EBITDA_Lagged				-0.0017
				(0.0011)
Constant	-3.83***	-3.43***	-4.34***	-4.48***
	(0.63)	(0.91)	(1.10)	(0.80)
Year_FE	YES	YES	YES	YES
Sub-Sector_FE	NO	YES	YES	YES
Observations	1244	1230	1031	1036
Pseudo-R^2	0.17	0.22	0.27	0.23
Log-Likelihood	-37.4	-34.8	-25.5	-24.3

Standard errors in parentheses

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

Table 14: Logit Regressions - Advanced Planning

	(1) Baseline	(2) Sub-Sector_FE	(3) CEO_Ed	(4) EBITDA
LSize	0.83***	0.78***	1.03***	0.84***
	(0.14)	(0.14)	(0.21)	(0.14)
LDev_per_emp	0.45**	0.40*	0.55**	0.30*
	(0.20)	(0.22)	(0.26)	(0.17)
LAge	-0.13	-0.20	-0.31*	-0.65***
	(0.17)	(0.18)	(0.17)	(0.22)
Exports	0.53	0.66	0.54	1.02**
	(0.43)	(0.43)	(0.48)	(0.40)
Made_Diff	-0.096	0.21	0.39	0.67
	(0.45)	(0.42)	(0.56)	(0.46)
Industrial_Zone	0.23	0.15	0.21	0.13
	(0.27)	(0.32)	(0.38)	(0.31)
Multiple_Plants	-0.073	0.11	0.036	-0.12
	(0.50)	(0.51)	(0.66)	(0.47)
CEO_Age				
Between 46-55	0.22	0.21	0.18	0.33
	(0.38)	(0.39)	(0.41)	(0.43)
More than 55	-0.043	-0.0088	0.32	0.33
	(0.47)	(0.54)	(0.56)	(0.57)
CEO_Education				
Medium			-1.18***	
			(0.36)	
High			-0.27	
			(0.73)	
EBITDA_Lagged				0.00071
				(0.0017)
Constant	-4.21***	-4.45***	-4.80***	-3.37***
	(0.51)	(0.90)	(1.19)	(0.92)
Year_FE	YES	YES	YES	YES
Sub-Sector_FE	NO	YES	YES	YES
Observations	1248	1243	1043	1044
Pseudo-R^2	0.17	0.22	0.27	0.25
Log-Likelihood	-47.6	-44.5	-33.7	-34.9

Standard errors in parentheses

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

References

Astebro, T. (2002). Noncapital investment costs and the adoption of cad and cnc in u.s. metalworking industries. *The RAND Journal of Economics*, 33(4):672–688.

Basl, J. (2017). Pilot study of readiness of czech companies to implement the principles of industry 4.0. *Management and Production Engineering Review*, 8.

Beneito, P. (2003). Choosing among alternative technological strategies: an empirical analysis of formal sources of innovation. *Research Policy*, 32(4):693–713.

Bettiol, M., Capestro, M., Maria, E. D., and Micelli, S. (2020). At The Roots Of The Fourth Industrial Revolution: How ICT Investments Affect Industry 4.0 Adoption. "Marco Fanno" Working Papers 0253, Dipartimento di Scienze Economiche "Marco Fanno".

Brynjolfsson, E., Hitt, L., and Kim, H. (2011). Strength in numbers: How does data-driven decisionmaking affect firm performance? *SSRN Electronic Journal*, 1.

Brynjolfsson, E. and Mcelheran, K. (2016). Data in action: Data-driven decision making in u.s. manufacturing. *SSRN Electronic Journal*.

Canepa, A. and Stoneman, P. (2007). Financial constraints to innovation in the UK: evidence from CIS2 and CIS3. *Oxford Economic Papers*, 60(4):711–730.

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1):128–152.

Costa-Campi, M. T., García-Quevedo, J., and Segarra, A. (2015). Energy efficiency determinants: An empirical analysis of Spanish innovative firms. *Energy Policy*, 83(C):229–239.

Cusumano, M., Kahl, S., and Suarez, F. (2014). Services, industry evolution, and the competitive strategies of product firms. *Strategic Management Journal*, 36.

Czarnitzki, D. and Binz, H. L. (2008). R&D Investment and Financing Constraints of Small and Medium-Sized Firm. Technical report.

Czarnitzki, D. and Delanote, J. (2012). Young innovative companies: The new high-growth firms? *SSRN Electronic Journal*, 22.

Foster, A. D. and Rosenzweig, M. R. (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of Political Economy*, 103(6):1176–1209.

García-Quevedo, J. and Massa-Camps, X. (2019). Why firms invest (or not) in energy efficiency? A review of the econometric evidence. Technical report.

Ghobakhloo, M. (2018). The future of manufacturing industry: a strategic roadmap toward industry 4.0. *Journal of Manufacturing Technology Management*, 29:910–936.

Gomez, J. and Montoya, P. (2009). The effect of financial constraints, absorptive capacity and complementarities on the adoption of multiple process technologies. *Research Policy*, 38:106–119.

Götz, G. (1999). Monopolistic competition and the diffusion of new technology. *The RAND Journal of Economics*, 30(4):679–693.

Hermann, M., Pentek, T., and Otto, B. (2015). Design principles for industrie 4.0 scenarios: A literature review.

Hermann, M., Pentek, T., and Otto, B. (2016). Design principles for industrie 4.0 scenarios. *2016 49th Hawaii International Conference on System Sciences (HICSS)*, pages 3928–3937.

Hochman, G. and Timilsina, G. R. (2017). Energy efficiency barriers in commercial and industrial firms in Ukraine: An empirical analysis. *Energy Economics*, 63(C):22–30.

Horváth, D. and Szabo, R. (2019). Driving forces and barriers of industry 4.0: Do multinational and small and medium-sized companies have equal opportunities? *Technological Forecasting and Social Change*, 146:119–132.

Jensen, R. (1982). Adoption and diffusion of an innovation of uncertain profitability. *Journal of Economic Theory*, 27(1):182–193.

Karshenas, M. and Stoneman, P. L. (1993). Rank, stock, order, and epidemic effects in the diffusion of new process technologies: An empirical model. *The RAND Journal of Economics*, 24(4):503–528.

Kiel, D., Arnold, C., and Voigt, K.-I. (2017a). The influence of the industrial internet of things on business models of established manufacturing companies – a business level perspective. *Technovation*, 68:4 – 19.

Kiel, D., Müller, J., Arnold, C., and Voigt, K.-I. (2017b). Sustainable industrial value creation: Benefits and challenges of industry 4.0 [rewarded with ispim best student paper award].

Mansfield, E. (1968). *Industrial Research and Technological Innovation*. Norton, New York.

Mariani, M. and Borghi, M. (2019). Industry 4.0: A bibliometric review of its managerial intellectual structure and potential evolution in the service industries. *Technological Forecasting and Social Change*, 149(C).

Müller, J. M., Buliga, O., and Voigt, K.-I. (2018). Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. *Technological Forecasting and Social Change*, 132(C):2–17.

Piccarozzi, M., Aquilani, B., and Gatti, C. (2018). Industry 4.0 in management studies: A systematic literature review. *Sustainability*, 10:3821.

Porter, M. E. and Heppelmann, J. E. (2014). How smart, connected products are transforming competition. *Harvard Business Review*.

Roblek, V., Meko, M., and Krape, A. (2016). A complex view of industry 4.0. *SAGE Open*, 6.

Romeo, A. A. (1975). Interindustry and Interfirm Differences in the Rate of Diffusion of an Innovation. *The Review of Economics and Statistics*, 57(3):311–319.

Santos, C., Mehrsai, A., Barros, A., Araújo, M., and Ares, E. (2017). Towards industry 4.0: an overview of european strategic roadmaps. *Procedia Manufacturing*, 13:972 – 979. Manufacturing Engineering Society International Conference 2017, MESIC 2017, 28-30 June 2017, Vigo (Pontevedra), Spain.

Schneider, P. (2018). Managerial challenges of industry 4.0: an empirically backed research agenda for a nascent field. *Review of Managerial Science*, 12.

Stoneman, P. (2001). *The economics of technological diffusion*. Wiley-Blackwell.

Stoneman, P. and Diederen, P. (1994). Technology Diffusion and Public Policy. *Economic Journal*, 104(425):918–930.

Veugelers, R. and Cassiman, B. (1999). Make and buy in innovation strategies: evidence from belgian manufacturing firms. *Research Policy*, 28(1):63 – 80.

Wozniak, G. D. (1987). Human Capital, Information, and the Early Adoption of New Technology. *Journal of Human Resources*, 22(1):101–112.

Zahra, S. and George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *The Academy of Management Review*, 27.