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The impact of ICTs and digitalization on productivity and labor share: evidence from French firms*

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ABSTRACT

Taking advantage of an original firm-level survey carried out by the Banque de France, we empirically investigate how the employment of ICT specialists (in-house and external) and the use of digital technologies (cloud and big data) have an impact on firm productivity and labor share. Our analysis relies on the survey responses in 2018 of 1,065 French firms belonging to the manufacturing sector and with at least 20 employees. To tackle potential endogeneity issues, we adopt an instrumental variable approach as proposed by Bartik (1991, *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.). The results of our cross-section estimations point to a large effect: *ceteris paribus*, the employment of ICT specialists and the use of digital technologies improve a firm's labor productivity by about 23% and its total factor productivity by about 17%. Conversely, the employment of in-house ICT specialists and the use of big data both have a detrimental impact on labor share, of about 2.5 percentage points respectively.

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1. Introduction

Over the last decades, productivity growth has declined in most developed countries, regardless of their distance to the technological frontier. A few of them, such as the United States, benefited from a short revival between 1995 and 2005 explained by a rapid spread of Information and Communication Technologies (ICTs).[1] However, since the mid-2000s, rates of productivity growth have been the lowest observed outside of war periods since at least the second half of the nineteenth century. If these rates were to continue, such low productivity gains would make it very challenging to finance the changes needed to tackle the large headwinds we currently face, such as population ageing, rising inequalities, environmental risks or public indebtedness. Digitalization is often seen as the potential source of a huge and possibly long productivity revival able to address these challenges.[2] However, this productivity revival from digitalization seems to be taking its time to appear, which is indeed puzzling. The explanation from Van Ark (2016) is that '*the New Digital Economy is still in its "installation phase" and productivity effects may occur only once the technology enters the "deployment phase"*'. Hence, it seems important to better understand how ICTs and digitalization affect firms, in particular their productivity and labor share. France seems a good candidate for such an analysis, as it is an important economy that is close to the technological frontier, and for which firm-level data on ICTs and digitalization are available.

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An abundant literature has been devoted in the last decades to the quantification of the impact of ICTs on productivity (for a survey of the literature, see Gal et al. 2019a, 2019b; Anderton et al. 2020). Few papers focus on the impact of digitalization on productivity, and those that do mainly concern specific digital technologies, among them broadband access. They usually find that ICTs and digital technologies have a positive impact on productivity. Of the few papers that concern the productivity impact of digital technologies, DeStefano, Kneller, and Timmis (2019) is, to the best of our knowledge, one of the rare firm-level studies concerning the impact of the cloud. Relying on plant-level data for the United Kingdom, they show that younger firms that adopt cloud technology are more likely to benefit from higher productivity gains. This effect is less clear-cut for incumbent firms, which nevertheless reorganize to take advantage of emerging technologies when they use the cloud. Through a Dynamic Stochastic General Equilibrium (DSGE) model, Etro (2009) finds a significant contribution of the cloud to growth. This positive impact is explained by a reduction of the fixed costs of entry into ICT capital and the creation of numerous new small and medium-sized enterprises. While incumbent firms, as early adopters of cloud technology, face appropriation costs, younger firms, as later adopters, could benefit from such experience. Ultimately, this technology might foster the creation of new firms by lowering the fixed costs of entry. Using a similar DSGE approach, Tamegawa, Ukai, and Chida (2014, 2015) also find a positive impact of cloud adoption on productivity growth. They calculate that an increase of 10% in the rate of firms adopting cloud technology improves productivity by about 10%.

A large number of papers show that these favorable productivity impacts also depend on complementarity mechanisms between ICTs, digital technologies, intangible capital, worker skills, management quality, and distance from the technological frontier (see Andrews, Nicoletti, and Timiliotis 2018, for a survey and original estimates). There are also complementarity mechanisms between the use of ICTs, digital technologies and other innovations. For instance, the impact of ICTs on productivity has been boosted by the use of the internet. Malgouyres, Mayer, and Mazet (2019) provide evidence that the expansion of broadband internet had a positive impact on imports in France at the start of the 2000s, and suggest that this phenomenon might be a driving factor behind the beneficial effect of broadband on productivity.

However, very few papers have analyzed the impact of ICTs and digital technologies on labor share. Using US plant-level data, Dinlersoz and Wolf (2018) show that establishments that are more automated have a lower labor share, a greater long-term decline in the labor share, and fewer workers in production who receive higher wages and display higher labor productivity. More broadly, an abundant literature is devoted to explaining the decline in labor share observed over the last decades in several developed countries (for a survey, see Cette, Koehl, and Philippon 2019). Apart from measurement problems, different explanations of this decline are given, related to technological change. The one provided by Karabarbounis and Neiman (2014) hinges on an elasticity of substitution between labor and capital of more than one, and a decline in the investment price. For Acemoglu and Restrepo (2018), '*automation increases output per worker more than wages and reduces the share of labor in national income*'. In this regard, there is empirical evidence that the adoption of robots has a negative and significant impact on labor share (see, concerning the US, Acemoglu and Restrepo 2020 and concerning France, Acemoglu, Lelarge, and Restrepo 2020). Martinez (2018) builds a model where capital and labor are complementary and the aggregate production function displays a constant elasticity of substitution, but with endogenous weights influenced by automation. Opening trade to low-wage countries can also lower the equilibrium wage (at least for low skilled workers), which, with an elasticity of substitution of less than one, can lead to a lower labor share. Elsby, Hobijn, and Şahin (2013) emphasize the offshoring of the labor-intensive component of the US supply chain as a leading potential explanation of the decline in the US labor share. Autor et al. (2020) argue that the labor share decline could be the consequence of the growth of firms with low labor share technologies, especially in the digital economy. For Aghion et al. (2019), the growth of large firms with high productivity and low labor share is related to a decrease in the cost of running a higher number of product lines. In all these approaches and others, through within-firm or between-firm mechanisms, technological changes, and in particular ICTs, robotization and digitalization, have a negative impact on the global labor share.

The goal of this paper is to shed new light on the potential impact of the employment of ICT specialists (in-house and external) and the use of digital technologies (cloud and big data) on productivity and labor share. Our empirical analysis exploits the richness of two Banque de France (BdF hereafter) firm-level datasets. The first BdF database, called FIBEN, contains firm-level annual financial statements and makes it possible to calculate the levels of labor productivity (*LP* hereafter), total factor productivity (*TFP* hereafter) and labor share (*LS* hereafter). The second database is the BdF survey on factor utilization degrees (FUD hereafter), which has been carried out yearly since 1989 and targets French firms belonging to the manufacturing sector and with at least 20 employees. In addition to collecting original and unique FUD data, this survey also gathers information on topics of specific interest for policy makers. Interestingly for our purpose, in the survey conducted in 2018, firms were asked whether or not they employed in-house or external ICT specialists and used cloud and big data technologies, and if so for how long. After the usual data cleansing operations, our final dataset contains 1,065 observations. Although the size of the sample may appear small, other surveys of the same size have been used in a similar context (see for instance the Bloom and Van Reenen World Management Survey). Given that various types of fixed effects (related to the size, age and sector of the firm) need to be included to avoid specification biases in the estimates, this small number of observations implies that we cannot estimate models that are too sophisticated. We therefore estimate a simple relation where productivity (*LP* or *TFP*) or labor share (*LS*) is explained by the employment of ICT specialists and digital technologies. Our empirical approach is definitely a between-firm one. The information on how long these technologies have been used in each firm in our dataset also allows us to estimate learning-by-doing and second-mover advantage mechanisms, meaning that short-term effects could differ from medium-term ones.

To tackle endogeneity issues, which could have multiple sources, we adopt an instrumental variable (IV hereafter) approach, using a variant of the instruments proposed by Bartik (1991). More specifically, we use as an instrumental variable the leave-one-out mean of the employment of ICT specialists and the use of digital technologies at the sector level. Thanks to the inclusion of sector fixed effects in the regressions, the leave-one-out mean of the employment of ICT specialists and the use of digital technologies solely measures the average practices in terms of these technologies in the sector considered. Indeed, since the sector fixed effects capture all the other sectoral specificities, the individual adoption of these technologies is explained by the variation in the adoption of such technologies within the sector, *ceteris paribus*, and the only channel through which the leave-one-out mean of these technologies in the sector might affect these dependent variables is this individual adoption. For instance, the fact that a firm might be able to attract better management if there is a large pool of good managers in the sector will be captured by the sector fixed effects. Hence, with such an identification strategy, the presence of sectoral spillovers, external economies of scale and network effects are unlikely to affect the validity of the instrumental variables, either through the violation of the random assignment assumption, or through the violation of the exclusion restriction. As confirmed by descriptive statistics and tests of the validity of the instrumental variables, this instrumental variable approach therefore enables us to predict firm-level employment of ICT specialists and use of digital technologies in an exogenous way and hence to consistently estimate the impact of these firm-level technologies on labor productivity, total factor productivity and labor share.

Our empirical results confirm that the employment of ICT specialists and the use of digital technologies have a large impact on productivity. *Ceteris paribus*, the employment of ICT specialists (through internal and external employment) and the use of digital technologies (through the cloud and big data) could improve a firm's labor and total factor productivity by about 23% and 17% respectively. Our results also point to the existence of a learning by doing effect concerning the employment of external ICT specialists and the use of cloud, their effect starting to be beneficial for firm's productivity after five years. In contrast, the use of big data and the employment of in-house ICT specialists seem rather to be associated with a second mover advantage: the early adopters of such technologies face these appropriation costs and late adopters indirectly benefit from their experience. However, the employment of in-house ICT specialists and the use of big data both have a detrimental impact on labor share, of about 2.5 percentage points respectively. While various explanations for this phenomenon have been provided in the literature, one novelty of our study is that our estimations are *between* firms and not *within* firms. They suggest that ICTs and digitalization decrease workers' bargaining power. Overall, our results are consistent with the existing literature and confirm that ICTs and digitalization have a large impact on firm-level productivity and labor share.

This paper is structured as follows: Section 2 describes the dataset, Section 3 presents the estimated model and the identification strategy, Section 4 comments on the estimates and discusses the results, Section 5 concludes.

2. The dataset

In this section, we describe the construction of the French firm dataset used in the analysis (2.1.), provide some descriptive statistics (2.2.) and perform a multiple correspondence analysis (2.3.) on it.

2.1. A French firm dataset

In order to assess the impact of the employment of ICT specialists (in-house and external) and the use of digital technologies (cloud and big data) on productivity and labor share, we exploit two extremely rich and detailed datasets, namely the FIBEN database and the survey on factor utilization degrees (FUD). These two datasets are constructed by the Banque de France and provide information for each firm on a yearly basis.

FIBEN contains accounting data compiled from fiscal documents, including balance sheets and profit-and-loss accounts submitted as part of firms' annual tax statements. It features all French firms with an annual turnover exceeding €750,000 or with outstanding credit of over €380,000. Each year, these accounting data are available for about 200,000 firms. This dataset provides information on the characteristics of the firms, such as size, age, and various economic and financial outcomes. Using this information, we are also able to compute labor productivity, total factor productivity and labor share.

Labor productivity (*LP*) is calculated by dividing value added in real terms (*Q*, which is value added in nominal terms divided by the national value added deflator, at the sector level) by the employment level (*L*). This gives $LP = Q/L$. Total factor productivity (*TFP*) is calculated, assuming a Cobb–Douglas function with constant returns, by dividing value added in real terms (*Q*) by a geometric average of capital and labor (*K* and *L*) as production factors. This gives: $TFP = Q/(K^{1-\alpha}.L^{\alpha})$. The capital stock (*K*) is the sum of gross capital volumes for buildings and equipment. Gross capital at historical price (as reported in FIBEN) is divided by the national investment deflator, lagged by the mean age of gross capital (calculated from the share of depreciated capital in gross capital, at historical price). This measure corresponds to the volume of capital in fiscal statements, usually at the end of the fiscal year. For this reason, we introduce a one-year lag for capital stock to calculate total factor productivity. As regards the estimation of the Cobb–Douglas parameters, α corresponds to the labor share. The labor share is calculated by dividing the total labor cost (sum of wages and overall social contributions) by value added in nominal terms (production minus intermediate consumption). After removing outliers ($\alpha < 0$ or $\alpha > 1$), the overall average of α is 0.72.[3] However, to calculate *TFP*, we use sectoral values of α, equal to the average of the individual labor share at the sector level.

The FUD survey has been carried out each September since 1989, in order to assess the intensity of capital utilization in establishments belonging to the manufacturing sector (excluding manufacture of coke and refined petroleum products) and with at least 20 employees.[4] In this original and unique survey, establishments are questioned each year about their sector, their production capacity utilization rate, their employment level and the number of employees organized into shiftwork. Since 2015, a new section has been introduced in the survey which changes every year. This section focuses on a specific topic deemed relevant in the year under consideration from an economic policy perspective. In 2018, this part of the survey was dedicated to ICTs and digitalization. The ICTs considered were internet access and the employment of ICT specialists (in-house and external). Digitalization was measured by the use of cloud computing services and big data analysis.[5] For each of these technologies, the establishments were asked for how long they had been using them (different categories of number of years were proposed). More precisely, establishments answered the following questions:[6]

- 'For how many years have you been using an internet connection? What type of internet connection are you currently using (ADSL, SDSL, VDSL, fiber optic (FTTH), cable, WiMax, other, none)?'[7,8,9]
- 'Do you employ in-house ICT specialists? If yes, for how many years?'
- 'Do you employ external ICT specialists? If yes, for how many years?'
- 'Have you ever used cloud computing services? If yes, for how many years?'[10,11]
- *'Have you ever analyzed big data? If yes, for how many years?'*[12]

The Banque de France received 1,349 complete answers to these questions. In order to build our final database, we start by retrieving the variables of interest from FIBEN. The missing values of these variables are then interpolated by taking the average of their one-year-lag and one-year-lead observations. Then, in order to render the FUD survey comparable with FIBEN, we aggregate the former at the firm level. The employment level and the number of employees organized into shiftwork are added together at the firm level; the production capacity utilization rate is averaged using as weights the establishment shares in the firm's total employment, and the firm's use of ICTs and digitalization is computed as their maximum value at the firm level. In this respect, a firm is assumed to make use of a given ICT as soon as at least one of its establishments uses this ICT. Moreover, the number of years over which a firm is assumed to have used this ICT corresponds to the maximal length of use by its establishment(s).

Finally, in order to analyze the role of the employment of ICT specialists and the use of digital technologies, we restrict FIBEN and the FUD survey to the year 2018 and merge them together.[13] A clean-up of this database is also conducted in order to eliminate outliers. First, we restrict this dataset to the non-missing values of the variables considered. Second, we exclude from this dataset the observations belonging to the top and bottom 1% of labor productivity growth at the sector level and of total factor productivity growth at the sector level, to the bottom 1% of capital stock growth at the size level, and by applying a method developed by John Tukey (see Kremp 1995). This method removes values of labor productivity growth and total factor productivity located beyond the first (respectively third) quartile that are less (more) than three times greater than the interquartile range, at the sector level. Hence, the final dataset contains 1,065 observations (firms) belonging to the manufacturing sector and with at least 20 employees for the year 2018. To our knowledge, this firm-level database is unique for carrying out an empirical analysis of the impact of the employment of ICT specialists and the use of digital technologies on productivity and labor share in France.

One should note that firms are not equally distributed across size, age and sector categories in our database (see Table 1). Almost half of the firms employ between 50 and 249 workers (46%) and more than a third have between 20 and 49 workers (35%). The remaining 19% are distributed equally between firms with 250–499 employees and firms with 500 employees or more. Likewise, almost half of the firms are 36 years old or above (48%) and one-third of them are between 21 and 35 years old (34%). The remaining 18% of the firms are less than 21 years old. Regarding the sector

Table 1. Distribution of firms by size, age, sector and shiftwork use.

	Observations	Share (in %)
Distribution of firms by size		
20–49 employees	372	34.9
250–499 employees	105	9.9
50–249 employees	487	45.7
≥500 employees	101	9.5
Distribution of firms by age		
1–20 years old	192	18,00
21–35 years old	358	33.6
36–50 years old	227	21.3
51–70 years old	164	15.5
≥71 years old	124	11.6
Distribution of firms by manufacturing sector (11 categories)		
CA – Manufacture of food products, beverages and tobacco products	138	13
CB – Manufacture of textiles, wearing apparel, leather and related products	60	5.6
CC – Manufacture of wood and paper products; printing and reproduction of recorded media	113	10.6
CE – Manufacture of chemicals and chemical products / Manufacture of basic pharmaceutical products and pharmaceutical preparations	84	7.9
CG – Manufacture of rubber and plastics products, and other non-metallic mineral products	141	13.3
CH – Manufacture of basic metals and fabric. metal products, except machinery and equipment	226	21.2
CI – Manufacture of computer, electronic and optical products	44	4.1
CJ – Manufacture of electrical equipment	39	3.7
CK – Manufacture of machinery and equipment n.e.c.	108	10.1
CL – Manufacture of transport equipment	60	5.6
CM – Other manufacturing; repair and installation of machinery and equipment	52	4.9
Distribution of firms by shiftwork use		
No use	390	36.6
Use	675	63.4

Sources: FIBEN and FUD.
Scope: Firms for which at least one establishment belongs to the manufacturing sector and with at least 20 employees.

distribution, 21% of the firms are specialized in the manufacture of metals, and 13% either produce rubber and plastics products or food products, beverages and tobacco products. Approximately 10% of them are specialized in the manufacture of machinery and equipment or wood and paper products. Each remaining sector share is below 10%. Finally, Table 2 presents summary statistics regarding productivity, labor share and capital utilization rate of firms kept in the sample of analysis.

2.2. A first descriptive analysis of the employment of ICT specialists and the use of digital technologies

The FUD survey enables a number of new stylized facts to be drawn regarding internet, the employment of ICT specialists and the use of digital technologies (see Figure 1) in France. Firms make extensive use of internet and ICT specialists, but tend to have less recourse to other digital technologies such as cloud computing services and big data analysis.

Almost all firms have access to internet (98%), and the majority have used it for 6 years or more (96%). Likewise, almost three-quarters of the firms employ ICT specialists (73%), either in-house or

Table 2. Summary statistics of the dependent variables and the capital utilization rate.

	Mean	St.D.	Min	Max
Log of labor productivity	4.196	.414	2.448	5.881
Log of total factor productivity	2.747	.397	1.516	4.054
Labor share	.722	.164	.215	1
Capital utilization rate	.768	.167	.1	1

Sources: FIBEN and FUD survey (Banque de France).
Scope: Firms for which at least one establishment belongs to the manufacturing sector and with at least 20 employees.

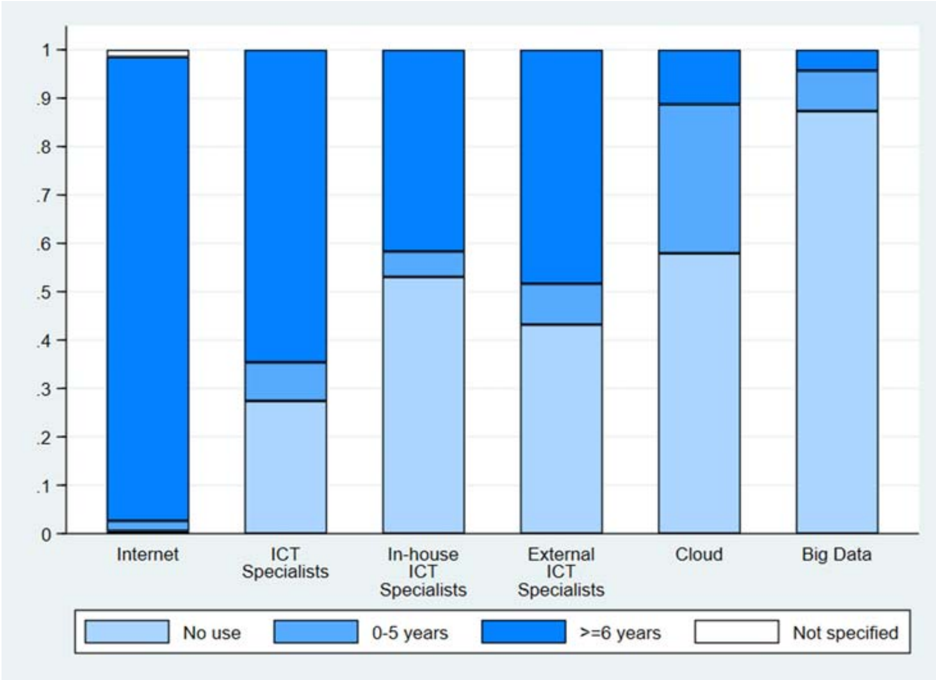

Figure 1. Employment of ICT specialists and use of digital technologies. Sources: FIBEN and FUD survey (Banque de France). Scope: Firms for which at least one establishment belongs to the manufacturing sector and with at least 20 employees. Key: 98% of firms have access to internet, less than 2% have had internet access for 0–5 years, and 96% have had access for 6 years or more.

externally, and more than half of them have done so for at least 6 years (65%). Moreover, since the proportion of firms employing ICT specialists at the aggregate level is greater than the respective proportions of firms employing ICT specialists in-house or externally, these two resources appear to be used by firms both as substitutes and complements. Conversely, less than half of the firms use cloud computing services (42%) and almost one-third have been purchasing such services for less than 5 years (31%). Finally, very few firms perfom big data analysis (13%), and in general those that do have done so for less than 5 years (8%).

These characteristics vary however across firm sizes and sectors. ICT adoption and digitalization tend to increase with the size of the firm. Firms from the computer, electronic and optical products industries as well as the transport equipment industry appear particularly advanced. In contrast, firms from the electrical equipment, metals and food products industries have the lowest propensity to employ ICT specialists, or use cloud computing services and big data.

These descriptive statistics can be compared to the results drawn from the Eurostat ICT survey. This survey was launched by Eurostat in 2004 and is conducted every year within each Member State of the European Union (EU). In France, it is conducted by the French National Institute of Statistics and Economic Studies (INSEE) on firms belonging to the market sector excluding agriculture, finance and insurance, and with at least 10 employees. For the sake of comparability, the summary statistics presented hereafter correspond to the firms covered by the Eurostat ICT survey and belonging to the manufacturing sector. Although the descriptive results from the 2018 Eurostat ICT survey on internet access and big data analysis are very similar to the ones from our database, they differ regarding the employment of ICT specialists and the use of cloud computing services.[14] In this respect, 99% of the firms covered by the Eurostat ICT survey (i.e. belonging to the manufacturing sector and with at least 10 employees) have access to internet, and 13%

analyze big data from any data sources. However, 19% of these firms employ ICT specialists and 12% purchase cloud computing services, against respectively 73% and 42% in the FUD survey. These differences might stem from the fact that the firms covered by the FUD survey have at least 20 employees and hence might be more liable to use ICTs and digital technologies than the smaller-sized firms that are also included in the Eurostat ICT survey. These differences might also be amplified by the sampling method. Indeed, the Eurostat ICT survey sample is drawn from the exhaustive INSEE SIRENE database using a stratified random sampling method based on the sector, size and revenue of the firm. Hence, large-sized firms are potentially overrepresented in the FUD survey relative to the Eurostat ICT one. Moreover, although the ICT and digitalization definitions underlying the FUD and Eurostat ICT survey questions are almost identical, the two surveys have different objectives. The FUD survey focuses on the use of specific ICTs and digital technologies, whereas the Eurostat ICT survey aims at providing a comprehensive picture of ICTs and digitalization. Not only does this survey document the use of a broader range of ICTs such as e-commerce, 3D printing and websites, it also asks detailed questions about their specific use. Hence, the resulting formulation of the questions potentially leads to diverging answers. Therefore, the results of these two surveys complement each other and provide a broad picture of the use of ICTs and digital technologies by French firms. Furthermore, in both surveys, the results display a significant amount of variability across firm sizes and sectors.

2.3. A multiple correspondence analysis

We perform a multiple correspondence analysis in order to compute a principal component that will be used as a composite index of ICT use summarizing the different degrees of employment of ICT specialists (in-house and external) and use of digital technologies (cloud and big data). The adoption rates of these technologies are statistically significant and positively correlated, suggesting potential complementarities from their joint use (see Table 3). Hence, performing a multiple correspondence analysis on these technologies provides several principal components, which are defined as linear combinations of employment of ICT specialists and use of digital technologies that account for the largest fractions of the total variation of these adoption rates. These components are successively computed so as to account for this largest fraction in descending order of importance and are constructed in such a way as to be independent from one another.

The first principal component of this multiple correspondence analysis explains a high fraction of the overall variation in the employment of ICT specialists and the use of digital technologies (43%) and is statistically significantly and positively correlated with each of these technologies (see Table 4). In contrast, the other principal components explain a much lower fraction of this overall variation. Moreover, the second principal component displays lower correlation levels with the employment of ICT specialists and the use of digital technologies than the first one. Additionally,

Table 3. Correlation between the employment of ICT specialists and the use of digital technologies.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Comp1	1.000					
(2) Comp2	0.544***	1.000				
(3) In-house ICT Specialists	0.461***	0.017	1.000			
(4) External ICT Specialists	0.083***	−0.757***	0.211***	1.000		
(5) Cloud	0.574***	−0.007	0.355***	0.225***	1.000	
(6) Big Data	0.922***	0.547***	0.281***	0.133***	0.257***	1.000

Sources: FIBEN and FUD survey (Banque de France).
Scope: Firms for which at least one establishment belongs to the manufacturing sector and with at least 20 employees.
Keys:

- Comp1 and Comp2 correspond respectively to the first and second principal components of the multiple correspondence analysis.
- The *t* statistics are reported as follows: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 4. Eigenvalue, proportion and cumulative proportion of each principal component of the multiple correspondence analysis.

	Eigenvalue	Proportion	Cumulative Proportion
Comp1	.426	42.61	42.61
Comp2	.225	22.483	65.092
Comp3	.188	18.76	83.852
Comp4	.161	16.148	100

Sources: FIBEN and FUD survey (Banque de France).
Scope: Firms for which at least one establishment belongs to the manufacturing sector and with at least 20 employees.
Key: Comp1, Comp2, Comp3 and Comp4 correspond respectively to the first, second, third and fourth principal components of the multiple correspondence analysis.

although the employment of ICT specialists and the use of digital technologies appear to be important contributors to the first principal component, the employment of in-house ICT specialists appears to be the major driving force behind this component (32%), closely followed by the use of the cloud (31%), see Table 5.

The *v*-test statistics allow us to compare and rank by order of importance the employment of ICT specialists and the use of digital technologies within each principal component. Indeed, a positive (respectively negative) v-test means that the technology considered is over-represented (respectively under-represented) in a given group. In this respect, the employment of ICT specialists and the use of digital technologies display strictly positive v-tests and hence are over-represented in the first principal component of the multiple correspondence analysis, ranking from employment of in-house ICT specialists, use of the cloud, big data analysis to employment of external ICT specialists (see Table 6).

Using data from the Eurostat ICT survey, Gal et al. (2019a) perform a similar exercise at the country-sector level and find comparable results. Their multiple correspondence analysis is based on the following ICTs and digital technologies: high-speed broadband, enterprise resource planning, customer relationship management, cloud computing and complex cloud computing. The first principal component derived from this multiple correspondence analysis explains an even higher

Table 5. Contribution of the employment of ICT specialists and the use of digital technologies on each principal component of the multiple correspondence analysis.

	In-house ICT Specialists	External ICT Specialists	Cloud	Big Data
Comp1	31.817	13.668	30.979	23.536
Comp2	1.67	80.051	1.026	17.253
Comp3	12.524	6.277	22.577	58.622
Comp4	53.99	.003	45.419	.588

Sources: FIBEN and FUD survey (Banque de France).
Scope: Firms for which at least one establishment belongs to the manufacturing sector and with at least 20 employees.
Key: Comp1, Comp2, Comp3 and Comp4 correspond respectively to the first, second, third and fourth principal components of the multiple correspondence analysis.

Table 6. V-tests of the employment of ICT specialists and the use of digital technologies on each principal component of the multiple correspondence analysis.

	In-house ICT Specialists	External ICT Specialists	Cloud	Big Data
Comp1	24.02	15.744	23.702	20.66
Comp2	3.997	−27.676	3.134	12.849
Comp3	−10	7.079	−13.426	21.634
Comp4	−19.263	.152	17.668	2.011

Sources: FIBEN and FUD survey (Banque de France).
Scope: Firms for which at least one establishment belongs to the manufacturing sector and with at least 20 employees.
Key: Comp1, Comp2, Comp3 and Comp4 correspond respectively to the first, second, third and fourth principal components of the multiple correspondence analysis.

fraction of the overall variation in the ICTs and digital technologies (61%). Moreover, the use of the cloud displays the highest correlation with the first principal component.

The significant and positive correlation between the employment of ICT specialists and the use of digital technologies might imply a multicollinearity issue, therefore preventing their joint inclusion in regressions. The first principal component computed based on the multiple correspondence analysis can be seen as a composite index summarizing the different degrees of employment of ICT specialists and use of digital technologies. Hence, this index can be directly used in our regressions as an explanatory variable in order to assess the impact of the employment of ICT specialists and the use of digital technologies on productivity and labor share while simultaneously taking into account the potential correlations existing between these technologies.

3. Estimated model and identification strategy

In this section, we present the estimated model (3.1.) and the identification strategy (3.2.).

3.1. Estimated model

The main estimated model corresponds to the relation (1):

$$Y_i = \beta_1.DIG_i + \beta_2.CUR_i + \beta_3.Shiftwork_i + \beta_4 + \delta_S i + \delta_{A_i} + \delta_{I_i} + \varepsilon_i \quad (1)$$

Where the index *i* indicates that the variable concerns the firm *i*, *Y* is the variable of interest, *DIG* is either the employment of ICT specialists (in-house or external) or the use of digital technologies (cloud or big data), *CUR* is the capacity utilization rate, *Shiftwork* is a dummy variable indicating the use of shiftwork (*Shiftwork = 1* if the firm uses shiftwork, 0 otherwise), δ_S, δ_A, *and* δ_I correspond to size, age and sector (industry) fixed effects, and ε is the idiosyncratic error term.

The variable of interest *Y* can be the log of labor productivity (*LP*), the log of total factor productivity (*TFP*) or the level of labor share (*LS*).

The explanatory variable *DIG* aims to capture the impact of the employment of ICT specialists and the use of digital technologies on productivity and labor share. As stated in the introduction, numerous papers have already estimated the impact of ICT on productivity using such types of specification, but few have estimated the impact of digitalization, because of a lack of data on this topic. Equation (1) is successively estimated using as the explanatory variable *DIG*:

- The composite index (*Comp1*), which summarizes the different degrees of employment of ICT specialists (in-house and external) and use of digital technologies (cloud and big data) and corresponds to the first principal component computed, based on the multiple correspondence analysis;
- Each raw component of the employment of ICT specialists (in-house or external) and the use of digital technologies (cloud or big data), which are directly obtained from the answers to the FUD survey and denoted hereafter as follows: employment of in-house ICT specialists (*Int. ICT*), employment of external ICT specialists (*Ext. ICT*), use of the cloud (*Cloud*) and use of big data (*Big data*). These raw components are successively included one by one and all together in the estimation of equation (1);
- Each raw component of the length of the employment of ICT specialists (in-house or external) and the use of digital technologies (cloud or big data), which are also directly obtained from the answers to the FUD survey and denoted hereafter as follows: length of the employment of in-house ICT specialists of less than five years (*Int. ICT* $<=5$), length of the employment of in-house ICT specialists of more than five years (*Int. ICT* >5), length of the employment of external ICT specialists of less than five years (*Ext. ICT* $<=5$), length of the employment of external ICT specialists of more than five years (*Ext. ICT* >5), length of the use of cloud of less than five years (*Cloud* $<=5$), length of the use of cloud of more than five years (*Cloud* >5), length of

the use of big data of less than five years (*Big data* $< = 5$), length of the use of big data of more than five years (*Big data* > 5). These raw components are successively included one by one and all together in the estimation of equation (1).

The capacity utilization rate is expected to have a positive impact on productivity: with a higher (respectively lower) capacity utilization rate, the same quantity of factors produces more (less) output, which means a higher (lower) productivity level. Conversely, it is expected to have a negative impact on the labor share: *ceteris paribus*, with a higher (lower) capacity utilization rate, the same global factor costs are associated with more (less) output, which means a lower (higher) labor share. Evidence regarding the existence of such relations has been confirmed by numerous previous studies.[15]

It appears interesting to take into account the use of shiftwork. As the use of shiftwork is usually more frequent when the capital to labor ratio is high, we expect a positive coefficient for the estimates of labor productivity, which corresponds to this positive capital deepening impact on labor productivity. At the same time, the average working time of shiftworkers is usually shorter than that of other workers (as a result of state regulations or collective agreements). For this reason, we expect the use of shiftwork to be associated with a lower total factor productivity level.[16]

Various size, age and sector fixed effects are included in equation (1) in order to capture all the potential age, size and sector specificities highlighted in Section 2. In this respect, we distinguish 4 size categories (20–49 employees; 50–249 employees; 250–499 employees; 500 employees or more), 5 age categories (20 years old or less; 21–35 years old; 36–50 years old; 51–70 years old; 71 years or above) and 11 categories of manufacturing industries (CA – Manufacture of food products, beverages and tobacco products; CB – Manufacture of textiles, wearing apparel, leather and related products; CC – Manufacture of wood and paper products, printing and reproduction of recorded media; CE – Manufacture of chemicals and chemical products / Manufacture of basic pharmaceutical products and pharmaceutical preparations; CG – Manufacture of rubber and plastics products, and other non-metallic mineral products; CH – Manufacture of basic metals and fabricated metal products, except machinery and equipment; CI – Manufacture of computer, electronic and optical products; CJ – Manufacture of electrical equipment; CK – Manufacture of machinery and equipment n.e.c.; CL – Manufacture of transport equipment; CM – Other manufacturing, repair and installation of machinery and equipment). Estimations are performed on the 1,065 available observations.

3.2. Identification strategy

The goal of this paper is to assess the impact of the employment of ICT specialists and the use of digital technologies on productivity and labor share. However, this empirical exercise is far from being trivial. On the one hand, productivity and labor share might also affect the employment of ICT specialists and the use of digital technologies, since most productive firms or firms that have lower labor share are also more likely to adopt such technologies. On the other hand, there might be confounding factors linked to the employment of ICT specialists and the use of digital technologies also influencing productivity and labor share. For instance, firms with a better management quality have a greater propensity to use such technologies and are also potentially more productive for this same reason.[17]

Hence, to consistently estimate equation (1), several identification issues must be resolved. First, because the dependent variables (labor productivity, total factor productivity and labor share) have an impact on the employment of ICT specialists and the use of digital technologies, we have to deal with a simultaneity problem. Second, and even more importantly, these technologies are also likely to be correlated with the error term ε of equation (1) because unobserved confounding factors can influence both the dependent variables and these technologies. In particular, the employment of ICT specialists and the use of digital technologies by firms might be influenced by managerial practices, which are also likely to affect their labor productivity, their total factor productivity and their labor share. Indeed, if firms adopting these technologies are also those more likely to have high labor productivity, high total factor productivity and low labor share, the ordinary least square estimates of equation (1) will be biased.

In order to tackle these endogeneity issues, we adopt an instrumental variable approach, using instruments inspired by Bartik (1991). Bartik instruments, proposed by Bartik (1991) and popularized by Blanchard and Katz (1992), are defined as weighted averages of a common set of shocks (i.e. national sectoral growth rates), where the share weights (i.e. local sectoral shares) account for the heterogeneous shock exposures. These shift-share designs have been used to estimate the effect of a wide range of shocks. In these two seminal papers, the shift-share designs are used to analyze the impact on local labor markets of shifters measured as changes in national sectoral employment. In line with these papers, shift-share strategies have been applied to investigate the local labor market impact of various shocks, including technological change (Acemoglu and Restrepo 2020, 2019).

The validity of such shift-share instrumental variables (SSIV) regressions also relies on the exogeneity assumption of at least one of the components of these instruments, i.e. either exogenous shocks, or exogenous exposure share weights. In this respect, three papers have studied the statistical properties of SSIV from these two perspectives. They derive the conditions under which their orthogonality assumption holds and propose tests to be applied to the most suitable framework for the setting.

On the one hand, Borusyak, Hull, and Jaravel (2019) assume that the validity of SSIV regressions relies on the quasi-random assignment of shocks conditional on the exposure share weights. Moreover, SSIV regressions yield consistent estimates when the number of shocks is large, uncorrelated and sufficiently dispersed in terms of their average exposure. They show that SSIV regression coefficients are equivalently obtained from a shock-level instrumental variable regression in which the instrument is the shock, and the outcome and the endogenous treatment variables are averaged using exposure shares as weights. Furthermore, according to Adão, Kolesár, and Morales (2019), such shock-level regressions are associated with valid (i.e. exposure robust) standard errors, while conventional clustered standard errors are generally invalid in SSIV regressions because observations with similar exposure share weights are likely to have correlated residuals due to the presence of unobserved shift-share terms. Such correlations are not accounted for by the inference procedures typically used in SSIV, leading to an underestimation of the variance of the OLS coefficient estimates and hence their over-rejection.

On the other hand, Goldsmith-Pinkham, Sorkin, and Swift (2020) formalize a different framework based on the random assignment of the exposure share weights conditional on the shocks. They show that SSIV regression coefficients coincide with a generalized method of moments estimation with exposure share weights as multiple excluded instruments. They argue that researchers are likely to be using such a research design based on the exogeneity assumption of exposure share weights if they (i) describe their research design as reflecting differential exogenous exposure to common shocks, (ii) emphasize a two-sector example, and/or (iii) emphasize shocks to specific sectors as central to their research design. They derive two solutions in order to assess the exogeneity of the exposure share weights. First, correlates of these weights highlight potential other channels through which they might affect outcomes. Second, following Rotemberg (1983), the exposure weight shares might be directly used as instruments and tested in order to highlight the subset of instruments to which the coefficient estimate is the most sensitive to misspecification (i.e. endogeneity).

In our paper, we assume that our estimation is identified through exogenous exposure share weights. Such an assumption is less intuitive *a priori*, for two main reasons. First, the exogeneity of exposure share weights might be difficult to justify, especially if there are any unobserved shocks that affect outcomes through shares (such as unobserved automation trends). Second, SSIV identification is generally better understood through the quasi-random assignment of a single instrument (shocks) rather than through a large set of invalid instruments (exposure share weights). However, our research design has the desirable properties in terms of exogenous exposure share weights. Indeed, our identification relies on differential exogenous exposure to common shocks of a limited number of manufacturing industries.

More specifically, we use as an instrumental variable the leave-one-out mean in the sector, defined as: $\overline{DIG_i} = \left(\sum j \neq i\ DIG_j/N - 1\right)$, where DIG_j denotes the explanatory variable *DIG* of firm *j* belonging to the same sector as firm *i*. This leave-one-out mean is computed on the same variables as the ones considered for DIG_i. The sector decomposition used to construct these instrumental variables corresponds to that of the sector fixed effects included in equation (1).

Hence, the employment of ICT specialists (in-house and external) and the use of digital technologies (cloud and big data) of firm *i are* predicted by the leave-one-out mean of these technologies in its sector:

$$DIG_i = \gamma_1.\overline{DIG_i} + \gamma_2.CUR_i + \gamma_3.Shiftwork_i + \gamma_4 + \gamma_S i + \gamma_{A_i} + \gamma_{I_i} + \varepsilon_i \qquad (2)$$

In order to be valid, an instrumental variable must be both exogenous and relevant. An instrumental variable is said to be exogenous if it is correlated with the dependent variable only through the endogenous variable and if it is therefore uncorrelated with the error term. An instrumental variable is said to be relevant if it is correlated with the endogenous variable.

We are quite confident about the exogeneity of the instrumental variables used. First, thanks to the inclusion of sector fixed effects in the regressions, the leave-one-out mean of the employment of ICT specialists and the use of digital technologies solely measures the average practices in terms of these technologies in the sector considered. Indeed, since the sector fixed effects capture all the other sector specificities, the individual adoption of these technologies is explained by the variation in the adoption of such technologies within the sector, *ceteris paribus*, and the only channel through which the leave-one-out mean of these technologies in the sector might affect these dependent variables is this individual adoption. Hence, with such an identification strategy, the presence of sectoral spillovers, external economies of scale and network effects are unlikely to affect the validity of the instrumental variables, either through the violation of the random assignment assumption, or through the violation of the exclusion restriction. For instance, the fact that a firm might be able to attract better management if there is a large pool of good managers in the sector will be captured by the sector fixed effects and the instrumental variable will remain uncorrelated with the error term. In a similar way, large adoption rates for a specific technology might foster the creation of a supplier network for this technology, reducing input costs and creating a mechanical link between sectoral adoption rates and firm value added. Again, such sectoral phenomena should also be taken into account by the sector fixed effects, and the instrumental variable should only capture the extent to which the firms belonging to the sector considered deviate from the mean. Finally, one should bear in mind that the firms considered in our sample appear distant from one another both in terms of geography and inputs, ruling out the possibility of sectoral spillovers or network effects from this perspective.[18]

Moreover, the results of the first-stage regressions also highlight the relevance of our instrumental variables. All the coefficients associated with the instrumental variables are high and statistically significant, pointing toward a strong impact of the instrumental variables on the endogenous ones. The proportion of variance of the endogenous variables explained by the explanatory variables of the model, measured by R^2, is also systematically high (greater than 75%), and underlines the quality of the prediction. The F-statistic associated with these regressions is always greater than 10, providing further evidence of the strength of the instrumental variables.[19]

Hence, the individual employment of ICT specialists and use of digital technologies are correlated with their leave-one-out mean counterparts, which are unlikely to have a direct impact on the dependent variables. Therefore, these leave-one-out means are used as instrumental variables for the individual employment of ICT specialists and use of digital technologies. Equation (2) implies that the individual employment of ICT specialists and use of digital technologies are explained by their leave-one-out mean counterparts. Assuming that the error term of equation (1) is uncorrelated with these leave-one-out means, equation (1) can be consistently estimated by two-stage least squares, using $\overline{DIG_i}$ as instrument for DIG_i.

4. Impacts of the employment of ICT specialists and the use of digital technologies on productivity and labor share

We detail the empirical estimate results of the impact of the employment of ICT specialists and the use of digital technologies on productivity, through the composite index of ICT use corresponding to *Comp1*, the first principal component of the multiple correspondence analysis (4.1.) and through each raw component of the employment of ICT specialists and of the use of digital technologies (4.2.). We then highlight the potential learning-by-doing and second-mover advantage mechanisms underlying the length of use of each of these raw components (4.3.). Then, we present the estimate results of the impact of the composite index of ICT use and of each raw component of employment of ICT specialists and of digital technologies use on labor share (4.4.). Finally we interpret and discuss the implications of our results (4.5).

4.1. Impact of the employment of ICT specialists and the use of digital technologies on productivity: first principal component estimate results[20]

We first estimate the impact of the employment of ICT specialists (in-house and external) and the use of digital technologies (cloud and big data) on productivity through the composite index of ICT use (*Comp1*) corresponding to the first principal component derived from the multiple correspondence analysis presented above.[21] Using this synthetic indicator, we estimate equation (1) for labor productivity (*LP*) or total factor productivity (*TFP*), with or without the capacity utilization rate (*CUR*) and the use of shiftwork (*Shiftwork*) as control variables, and with Instrumental Variable (IV) approaches.[22] The results of these estimates are presented in Table 7.

The coefficient of the index of ICT use (*Comp1* variable) is always positive and statistically significant. This confirms the positive impact of the employment of ICT specialists and the use of digital technologies on productivity – both on labor productivity *(LP)* and total factor productivity (*TFP*).

Table 7. Results of the impact of the employment of ICT specialists and the use of digital technologies on productivity (LP and TFP in log, IV estimates).

	(1)	(2)	(3)	(4)
Explained Var.	Log(LP)	Log(LP)	Log(TFP)	Log(TFP)
Comp1	0.00837***	0.00823***	0.00502***	0.00546***
	(0.00167)	(0.00166)	(0.00151)	(0.00138)
CUR		0.219**		0.240***
		(0.0938)		(0.0790)
Shiftwork		0.0510		−0.0831**
		(0.0373)		(0.0342)
Constant	3.624***	3.464***	2.779***	2.611***
	(0.0795)	(0.0896)	(0.0720)	(0.0812)
Nb. Obs.	1,065	1,065	1,065	1,065
R^2	0.210	0.221	0.201	0.218
Size FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Sect. FE	Yes	Yes	Yes	Yes

Notes: Measurement of the employment of ICT specialists and use of digital technologies by the first principal component of the multiple correspondence analysis. Comp1 is an index of ICT use. It corresponds to the first principal component of the multiple correspondence analysis.

Robust standard errors clustered at the sector level (11 categories of manufacturing industries) are reported between parentheses

The t statistics are reported as follows: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

The way the index of ICT use is constructed renders the economic interpretation of its associated coefficient level impossible, but using the coefficient estimates from columns (2) and (4), it appears that an increase in this synthetic indicator of one standard deviation would correspond to an increase of 5.9% in *LP* and of 3.9% in *TFP*. This means that the employment of ICT specialists and the use of digital technologies may have a large productivity impact.

The inclusion of the capacity utilization rate and shiftwork as control variables does not affect the coefficient associated with the technology variable of interest. Hence, the impact of the technology variable does not channel through these variables. However, capacity utilization rate and shiftwork appear to be by themselves important determinants of labor productivity and total factor productivity. In this respect, the coefficient of the control variable *CUR* is positive and statistically significant for the estimates for both *LP* and *TFP*. An increase of 1 percentage point in the capital utilization rate would increase labor productivity or total factor productivity by 0.22% to 0.24%. This result corresponds to those obtained in other analyses (see for instance Cette, Lecat, and Jiddou 2016a, 2016b). The coefficient of the control variable *Shiftwork* is positive but non-significant for the *LP* estimates, and negative and significant for the *TFP* estimates. It corresponds to what is expected (see above).

4.2. Impact of the employment of ICT specialists and the use of digital technologies on productivity: component estimate results

We now estimate the impact of the employment of ICT specialists and the use of digital technologies on productivity through the four raw components introduced first individually and then simultaneously. The results of IV regressions are presented in Table 8 for *LP* and in Table 9 for *TFP*.

All estimated coefficients have the expected positive sign: the use of each of the four technologies improves productivity – both *LP* and *TFP*. The employment of in-house ICT specialists (*Int. ICT*) substantially improves productivity: it is associated with an improvement of 13.2% in *LP* (column 5 in Table 8) and of 8.0% in *TFP* (column 5 in Table 9). The employment of external ICT specialists (*Ext. ICT*) also improves productivity, but to a smaller extent, and the corresponding

Table 8. Results of the impact of the employment of ICT specialists and the use of digital technologies on labor productivity (LP in log, IV estimates).

	(1)	(2)	(3)	(4)	(5)
Int. ICT	0.157***				0.132***
	(0.0213)				(0.0225)
Ext. ICT		0.0464***			0.0216
		(0.0177)			(0.0197)
Cloud			0.0678***		0.0239
			(0.0167)		(0.0152)
Big data				0.141***	0.104***
				(0.0346)	(0.0339)
CUR	0.212**	0.203**	0.211**	0.213**	0.222**
	(0.0960)	(0.100)	(0.0955)	(0.0967)	(0.0943)
Shiftwork	0.0447	0.0578	0.0532	0.0561	0.0404
	(0.0350)	(0.0386)	(0.0374)	(0.0387)	(0.0352)
Constant	3.784***	3.800***	3.790***	3.800***	3.750***
	(0.0766)	(0.0843)	(0.0787)	(0.0779)	(0.0752)
Nb. Obs.	1,065	1,065	1,065	1,065	1,065
R^2	0.224	0.210	0.210	0.218	0.232
Size FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Sect. FE	Yes	Yes	Yes	Yes	Yes

Notes: Measurement of the employment of ICT specialists and use of digital technologies by each of the 4 components. Robust standard errors clustered at the sector level (11 categories of manufacturing industries) are reported between parentheses The t statistics are reported as follows: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 9. Results of the impact of the employment of ICT specialists and the use of digital technologies on total factor productivity (TFP in log, IV estimates).

	(1)	(2)	(3)	(4)	(5)
Int. ICT	0.102***				0.0797***
	(0.0244)				(0.0262)
Ext. ICT		0.0483***			0.0309*
		(0.0166)			(0.0184)
Cloud			0.0606**		0.0314
			(0.0246)		(0.0242)
Big data				0.0894***	0.0617***
				(0.0241)	(0.0231)
CUR	0.236***	0.229***	0.237***	0.235***	0.243***
	(0.0801)	(0.0841)	(0.0799)	(0.0813)	(0.0788)
Shiftwork	−0.0870***	−0.0795**	−0.0833**	−0.0796**	−0.0916***
	(0.0334)	(0.0346)	(0.0333)	(0.0351)	(0.0329)
Constant	2.823***	2.825***	2.819***	2.834***	2.787***
	(0.0547)	(0.0624)	(0.0573)	(0.0559)	(0.0590)
Nb. Obs.	1,065	1,065	1,065	1,065	1,065
R^2	0.219	0.217	0.216	0.217	0.225
Size FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Sect. FE	Yes	Yes	Yes	Yes	Yes

Notes: Measurement of the employment of ICT specialists and the use of digital technologies by each of the 4 corresponding components. Robust standard errors clustered at the sector level (11 categories of manufacturing industries) are reported between parentheses.
The t statistics are reported as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

coefficient is not always significant, as is the case when all raw components are introduced simultaneously: it is associated with an improvement of 2.2% in *LP* and of 3.1% in *TFP*. The same phenomenon appears for the use of the cloud (*Cloud*). The corresponding coefficient is not always significant, and it is associated with an improvement of 2.4% in *LP* and of 3.1% in *TFP*. The use of big data (*Big data*) also improves productivity to a greater extent, and the corresponding coefficient is always quite significant. The use of big data is associated with an improvement of 10.4% in *LP* and of 6.2% in *TFP*. These results confirm the large impact of these technologies on productivity.

The coefficient of the control variable *CUR* is positive and statistically significant for the estimates of *LP* (Table 8) and *TFP* (Table 9). The coefficient of the control variable *Shiftwork* is positive and non-significant for the *LP* estimates, and negative and significant for the *TFP* estimates for the same reason as previously explained.

4.3. Employment of ICT specialists and use of digital technologies: learning-by-doing or second-mover advantage

It is interesting to estimate whether there is a learning-by-doing effect (LDE hereafter) or a second-mover advantage (SMA hereafter) regarding the impact on productivity of the employment of ICT specialists and the use of digital technologies. An LDE arises when firms initially face appropriation costs for adopting such technologies and hence only start benefiting from them after a while. This LDE would mean that the medium-term impact of the employment of ICT specialists and the use of digital technologies would be greater than the short-term impact. An SMA arises when the early adopters of such technologies face these appropriation costs and late adopters indirectly benefit from their experience. This SMA would mean that the medium-term impact of the employment of ICT specialists and the use of digital technologies would be lower than the short-term impact. We estimate the same equation (1) as in the previous section, but for each of the four raw components, we identify whether the employment of ICT specialists and the use of digital technologies have lasted more or less than five years. The results of these estimates are presented in Table 10 for

Table 10. Results of the impact of the length of the employment of ICT specialists and of the use of digital technologies on labor productivity (LP in log, IV estimates).

	(1)	(2)	(3)	(4)	(5)
Int. ICT ≤ 5	0.140***				0.139***
	(0.0379)				(0.0361)
Int. ICT > 5	0.160***				0.126***
	(0.0237)				(0.0259)
Ext. ICT ≤ 5		−0.0428			−0.0491
		(0.0414)			(0.0350)
Ext. ICT > 5		0.0654***			0.0370*
		(0.0162)			(0.0194)
Cloud ≤ 5			0.0548***		0.0172
			(0.0191)		(0.0175)
Cloud > 5			0.104***		0.0455*
			(0.0243)		(0.0245)
Big data ≤ 5				0.154***	0.117***
				(0.0459)	(0.0454)
Big data > 5				0.118***	0.0644
				(0.0337)	(0.0395)
CUR	0.212**	0.191*	0.213**	0.214**	0.215**
	(0.0967)	(0.101)	(0.0954)	(0.0962)	(0.0943)
Shiftwork	0.0443	0.0594	0.0528	0.0561	0.0423
	(0.0350)	(0.0392)	(0.0378)	(0.0386)	(0.0357)
Constant	3.785***	3.813***	3.792***	3.799***	3.760***
	(0.0781)	(0.0838)	(0.0801)	(0.0776)	(0.0771)
Nb. Obs.	1,065	1,065	1,065	1,065	1,065
R^2	0.223	0.212	0.211	0.218	0.234
Size FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Sect. FE	Yes	Yes	Yes	Yes	Yes

Notes: Measurement of the length of the employment of ICT specialists and of the use of digital technologies by each of the 4 corresponding components. Robust standard errors clustered at the sector level (11 categories of manufacturing industries) are reported between parentheses

The t statistics are reported as follows: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

labor productivity (*LP*) and in Table 11 for total factor productivity (*TFP*). We comment mainly on the results in the columns (5) of these two Tables.

Regarding labor productivity (Table 10), the employment of external ICT specialists is associated with a learning by doing effect (LDE) as the coefficient is larger for years > 5 than for years ≤ 5, while nothing appears clearly for the employment of internal ICT specialists. Interestingly the use of cloud is also associated with a LDE effect. However, the use of big data is associated with a second mover advantage (SMA) as the corresponding coefficient is larger for years ≤ 5 than for years > 5.

Regarding *TFP* (Table 11), results are relatively similar as the employment of external ICT specialists and the use of cloud are also associated with a LDE. However, in this case, the employment of internal ICT specialists and the use of big data are associated with a SMA.

4.4. Impact of the employment of ICT specialists and the use of digital technologies on labor share

We first estimate the impact of the employment of ICT specialists and the use of digital technologies on labor share using the composite index of ICT use corresponding to the first principal component derived from the multiple correspondence analysis presented in the Section 2.[23] Using this synthetic indicator, we estimate equation (1) with labor share (*LS*) as the explained variable, with or without the *CUR* and *Shiftwork* as control variables. The results of these IV regressions are presented in Table 12.

Table 11. Results of the impact of the length of the employment of ICT specialists and of the use of digital technologies on total factor productivity (TFP in log, IV estimates).

	(1)	(2)	(3)	(4)	(5)
Int. ICT ≤ 5	0.124***				0.118***
	(0.0318)				(0.0301)
Int. ICT > 5	0.0972***				0.0698*
	(0.0316)				(0.0358)
Ext. ICT ≤ 5		0.00227			−0.00847
		(0.0323)			(0.0270)
Ext. ICT > 5		0.0581***			0.0394**
		(0.0179)			(0.0187)
Cloud ≤ 5			0.0495*		0.0205
			(0.0274)		(0.0268)
Cloud > 5			0.0920***		0.0609**
			(0.0241)		(0.0296)
Big data ≤ 5				0.120***	0.0933**
				(0.0382)	(0.0386)
Big data > 5				0.0336	−0.00785
				(0.0243)	(0.0251)
CUR	0.236***	0.223***	0.238***	0.239***	0.244***
	(0.0800)	(0.0832)	(0.0799)	(0.0815)	(0.0776)
Shiftwork	−0.0864**	−0.0787**	−0.0837**	−0.0796**	−0.0898***
	(0.0340)	(0.0347)	(0.0336)	(0.0348)	(0.0335)
Constant	2.821***	2.831***	2.821***	2.831***	2.790***
	(0.0542)	(0.0600)	(0.0574)	(0.0563)	(0.0574)
Nb. Obs.	1,065	1,065	1,065	1,065	1,065
R^2	0.220	0.217	0.216	0.220	0.230
Size FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Sect. FE	Yes	Yes	Yes	Yes	Yes

Notes: Measurement of the length of the employment of ICT specialists and of the use of digital technologies by each of the 4 corresponding components. Robust standard errors clustered at the sector level (11 categories of manufacturing industries) are reported between parentheses

The t statistics are reported as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12. Results of the impact of the employment of ICT specialists and the use of digital technologies on labor share (LS in level, IV estimates).

	(1)	(2)
Comp1	−0.00157***	−0.00147***
	(0.000565)	(0.000542)
CUR		−0.0897***
		(0.0314)
Shiftwork		−0.0314***
		(0.00986)
Constant	0.838***	0.904***
	(0.0279)	(0.0332)
Nb. Obs.	1,065	1,065
R^2	0.092	0.108
Size FE	Yes	Yes
Age FE	Yes	Yes
Sect. FE	Yes	Yes

Notes: Measurement of the employment of ICT specialists and the use of digital technologies: First principal component of the multiple correspondence analysis. Comp1 corresponds to the first principal component of the multiple correspondence analysis. Robust standard errors clustered at the sector level (11 categories of manufacturing industries) are reported between parentheses.

The t statistics are reported as follows: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

It appears that the coefficient of the composite index (*comp1* variable) is always negative and statistically significant. This indicates that the employment of ICT specialists and the use of digital technologies have a negative impact on *LS*. Here again, the economic interpretation of the coefficient

Table 13. Results of the impact of the employment of ICT specialists and the use of digital technologies on labor share (*LS* in level, IV estimates).

	(1)	(2)	(3)	(4)	(5)
Int. ICT	−0.0315***				−0.0292**
	(0.0100)				(0.0118)
Ext. ICT		−0.00719			−0.00351
		(0.00877)			(0.00964)
Cloud			−0.00227		0.00742
			(0.00744)		(0.00733)
Big data				−0.0299***	−0.0248**
				(0.0116)	(0.0125)
CUR	−0.0888***	−0.0868***	−0.0870***	−0.0889***	−0.0895***
	(0.0326)	(0.0320)	(0.0316)	(0.0317)	(0.0326)
Shiftwork	−0.0299***	−0.0327***	−0.0328***	−0.0322***	−0.0300***
	(0.00951)	(0.0101)	(0.00975)	(0.0100)	(0.00940)
Constant	0.848***	0.844***	0.841***	0.845***	0.850***
	(0.0249)	(0.0260)	(0.0239)	(0.0234)	(0.0259)
Nb. Obs.	1,065	1,065	1,065	1,065	1,065
R^2	0.111	0.107	0.106	0.109	0.114
Size FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Sect. FE	Yes	Yes	Yes	Yes	Yes

Notes: Measurement of the employment of ICT specialists and the use of digital technologies by each of the 4 corresponding components. Robust standard errors clustered at the sector level (11 categories of manufacturing industries) are reported between parentheses.
The t statistics are reported as follows: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

level is not straightforward, but using the coefficient estimates from column (2), it appears that an increase in the composite index of one standard deviation would correspond to a 1.1 percentage-point decrease in *LS*. This means that digitalization may have a large impact on *LS*.

The inclusion of capacity utilization rate and shiftwork as control variables does not affect the coefficient associated with the technology variable of interest. Hence, the impact of the technology variable does not channel through these variables. However, capacity utilization rate and shiftwork appear to be by themselves important determinants of labor share. In this respect, the coefficient of the control variable *CUR* is negative and statistically significant. Indeed, the intensity of capital use generally decreases the cost of using capital and hence the labor share. An increase of one percentage point in the capital utilization rate would, on average, decrease the labor share by almost 0.1 percentage point. This result is consistent with previous analyses (see Cette, Lecat, and Jiddou 2016a, 2016b). The coefficient of the control variable *Shiftwork* is negative and significant. As the use of shiftwork is usually more frequent when the capital to labor ratio is high,[24] this negative coefficient estimate seems logical.

We now estimate the impact of the employment of ICT specialists and the use of digital technologies on *LS* through the four raw components, introduced first individually and then simultaneously. The results of these IV regressions are presented in Table 13. We comment mainly the results from column 5 when all the raw components are simultaneously introduced (column 5).

The employment of in-house ICT specialists (*Int. ICT*) and the use of big data (*Big data*) significantly decrease *LS*: their respective use is associated with a drop of 2.9 percentage points and 2.5 percentage points in *LS*. The employment of external ICT specialists (*Ext. ICT*) and the use of the cloud (*Cloud*) have no significant impact on *LS*. These results confirm the impact of the use of ICT and digital technologies on *LS*.

4.5. Discussion

The goal of this subsection is to summarize and discuss our main findings.

First, our empirical results indicate that the employment of ICT specialists and the use of digital technologies at the firm level have a positive and significant impact on productivity. *Ceteris paribus*, the employment of ICT specialists (through internal and external employment) and the use of digital technologies (through the cloud and big data) could improve a firm's labor and total factor productivity by about 23% and 17% respectively. Overall, such results are in line with other studies concluding to a positive impact on productivity of digital technology adoption. Gal et al. (2019b) exploit cross-country firm level data on multifactor productivity to investigate the impact of digital technology adoption at the industry rather than at the firm level. Their results suggest that a 10% increase in high speed broadband or cloud computing would be associated after 5 years with a 5.6% higher level of *TFP* for the average firms. Tamegawa, Ukai, and Chida (2014, 2015) also find a positive impact of cloud adoption on productivity growth. According to their studies, an increase of 10% in the rate of firms adopting cloud technology improves productivity by about 10%.

In as much as they are comparable, the orders of magnitude associated with our results appear quite large. First of all, one should keep in mind that empirically assessing the causal impact of digital technology adoption is particularly challenging. Some recent papers have relied on quasi natural experiments to exploit exogenous variation in the access of firms to broadband internet. Akerman et al. (2015) rely on a public Norwegian program in which broadband access points were progressively rolled-out in different municipalities and different points in time to assess the causal impact of adoption of broadband internet on labor productivity and wages at the firm level. Malgouyres et al. (2019) exploit the gradual spread of broadband internet in French municipalities over time to assess its causal impact on the importing behavior of firms. Unfortunately, we are not aware of similar programs that could give rise to exogenous variation in access to cloud or to big data at the firm level. We therefore relied on Bartik (1991) instrumental variable suggestions to try to overcome endogeneity issues, an approach which is common in the literature. Nevertheless, while our survey on ICT employment and digital technology adoption is quite novel in the detailed information it provides at the firm level, we must acknowledge that it is quite limited regarding its size and cross sectional dimension. It would therefore be useful to be able to compare our results to other studies relying on such reliable methods or on other instrumental variables. Moreover, a number of studies have shown that the effect of digitalization could be stronger in manufacturing firms or in industries where the share of routine tasks is higher (Dhyne, Konings, and Vanormelingen 2018; Gal et al. 2019b). Given that our empirical analysis relies on a sample of firms of more than 20 employees in the manufacturing sector, it would be worth investigating whether the effects are of the same order of magnitude when considering a larger sample of firms or a broader range of industries (especially service industries).

Second, in line with recent literature (DeStefano, Kneller, and Timmis 2019), we find that there are important appropriation costs associated with the employment of ICT specialists and with the adoption of cloud and big data. However, our results suggest that they differ according to the type of technology considered. The employment of external ICT specialists and the use of cloud are associated with learning by doing effects, their effect starting to be beneficial for firm's productivity after five years. In contrast, the use of big data and the employment of in-house ICT specialists seem rather to be associated with a second mover advantage: the early adopters of such technologies face these appropriation costs and late adopters indirectly benefit from their experience. A potential rationale for such result could be that external ICT specialists and cloud services may contain capabilities, which are by nature 'out' of the firm. A time for adaptation to the firm specificities is therefore necessary before it translates into productivity effect. In contrast, the use of big data and the employment of 'in house' ICT specialists can be an advantage in the short term but then rather benefits second movers who can for instance hire experienced ICT specialists and benefit from their experience.

Finally, extensive literature has been devoted to identifying the potential drivers of the observed decline in labor share in several countries. Several explanations have been proposed including automation, robotization and digitalization. In the case of France, Acemoglu, Lelarge, and Restrepo (2020) provide evidence that firms which adopted robots between 2010 and 2015 experienced significant declines in labor share. Disentangling which of these driving forces dominate and identifying how they potentially interact is well beyond the scope of this paper. Nevertheless, our results suggest that digital technology adoption regarding cloud and big data could also play a role in the decline in labor share.

5. Conclusion

Using answers to an original Banque de France survey carried out in 2018 on French firms belonging to the manufacturing sector and with at least 20 employees, we analyzed the empirical impact of the employment of ICT specialists (in-house and external) and the use of digital technologies both on productivity and labor share. The database we used contains 1,065 observations. To avoid endogeneity problems, which could have multiple sources, we adopted an instrumental variable approach using Bartik-variant instruments, as proposed by Bartik (1991).

The estimates confirm a potentially large impact of the employment of ICT specialists (in-house and external) and the use of digital technologies (cloud and big data) on productivity. *Ceteris paribus*, the employment of ICT specialists and the use of digital technologies could improve firms' labor productivity and total factor productivity by about 23% and 17% respectively. Results also point to the existence of a learning by doing effect concerning the employment of external ICT specialists and the use of cloud, their effect starting to be beneficial for firm's productivity after five years. In contrast, the use of big data and the employment of in-house ICT specialists seem rather to be associated with a second mover advantage: the early adopters of such technologies face these appropriation costs and late adopters indirectly benefit from their experience. The use of in-house ICT employment and big data have a detrimental impact on labor share, of about 2.5 percentage points respectively.

If confirmed by further firm-level studies, these results would suggest that the employment of ICT specialists and the use of digital technologies might correspond to a third industrial and technological revolution. It would be the way to escape from the dangerous prospect of a secular stagnation characterized by low productivity gains. It would also allow us to finance the changes necessary to tackle the major headwinds we currently face, such as population ageing, rising inequalities, environmental risks or public indebtedness. Without this financing solution, after a long period of low productivity growth, developed countries would soon enter into a period full of risks regarding the sustainability of their economic organization, their social system and possibly their institutions.

In the context of the COVID-19 threat, national lockdown strategies have in all likelihood boosted the use of digital technologies by firms and households. This could be the starting point for an acceleration of ICT and digital diffusion. We could therefore expect significant productivity improvements after the exit of the lockdown periods. This is one possible non-negative impact of the pandemic event, which would open more widely the door to the third industrial revolution.

Notes

1. Concerning this long productivity growth decline in developed countries, see for instance Bergeaud, Cette, and Lecat (2016, 2017). Concerning the US productivity revival from the mid-1990s related to the spread of ICTs, see for instance Jorgenson, Ho, and Stiroh (2008).
2. Concerning these expectations from digitalization, see the seminal book from Brynjolfsson and McAfee (2014).
3. This average labor share level corresponds to the value calculated by Cette, Koehl, and Philippon (2019) for the French non-financial business sector with data from national accounts.
4. These establishments are the ones usually covered by the Banque de France monthly survey on the business climate.
5. Establishments were also asked on the use of industrial and service robots. Since the variables relative to robots suffer from measurement biases, they are not considered further in our empirical investigation.
6. For more details, see Nevoux et al. (2019).

7. The xDSL technologies (ADSL, followed by the new, more powerful SDSL and VDSL generations) use copper connection lines (telephone or other) and rely on the traditional telephone network. The cable technology consists in a signal broadcast via a cable from a fiber located a short distance away; it is more powerful than the xDSL technologies. The optical fiber (FTTH) technology relies on optical data transmission via glass or plastic wires, and is even more powerful than the xDSL and cable technologies. The WiMax technology relies on wireless data transmission at high frequencies and over long distances.
8. The categories of number of years for internet access and the employment of ICT specialists are the following: 0–2 years; 3–5 years; 6–10 years; 11–15 years; 16–20 years; 21 years or more.
9. 97% of all firms have internet access. Among those firms, 86% either use DSL or fiber optic as their internet connection type (respectively 44% and 43%). In contrast, cable and WiMax are used by only 2% of firms. The remaining 12% didn't specify their internet connection type.
10. Cloud computing services are computer services used on the internet to access software, computing power, and storage capacity.
11. The categories of number of years for cloud computing services and big data analysis are the following: 0–1 year; 2–3 years; 4–5 years; 6–7 years; 8–10 years; 11–15 years; 16 years or more.
12. Big data are generated by activities executed electronically and between machines. Big data analysis refers to the use of techniques, technologies, algorithms and software to analyze big data from institutional, corporate or other sources.
13. This merged dataset contains 1,287 observations.
14. For more details, see INSEE (2019a, 2019b, 2019c).
15. See Cette, Lecat, and Jiddou (2016a 2016b) for a review of the literature and estimates on the same type of data.
16. On this topic of shiftwork and its impact on productivity, see Anxo et al. eds. (1995).
17. The density and evolution of the dependent variables by employment of ICT specialists, use of digital technologies and their length are available upon request from the authors.
18. Stylized facts on the geography and inputs of firms are available upon request from the authors.
19. The corresponding estimate tables are available upon request from the authors.
20. According to Dinlersoz and Wolf (2018), establishments that are more automated have a lower labor share, a greater long-term decline in the labor share, and fewer workers in production who receive higher wages and display higher labor productivity. In order to check a more complex relation between digitalization and productivity, acting partly through the labor share, additional regressions were run including labor share as a supplementary control variable when considering labor productivity as dependent variable. Their conclusion is confirmed by our empirical findings. The impact of the employment of ICT specialists and the use of digital technologies on labor productivity partly channels through the reduction of labor share. However, this indirect effect appears quite small, as the estimated direct impact of these technologies on productivity is only very slightly changed. The results of these estimates are available upon request from the authors.
21. When we add the second principal component as an explanatory variable, the corresponding coefficient is never statistically significant, which is not surprising if we consider the weak part of the dispersion of the employment of ICT specialists and the use of digital technologies explained by this second component (see Section 2.3).
22. To ease readiness, OLS results are not presented in the paper and are available upon requests from the authors.
23. When we add the second principal component as an explanatory variable, the corresponding coefficient is again never statistically significant, for the same reason as for productivity: this second component explains a weak part of the dispersion of the employment of ICT specialists and the use of digital technologies (see Section 2.3).
24. On this topic of shiftwork and its impact on productivity, see Anxo et al. eds. (1995).

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