Technological innovation, digital adoption and firm performance*

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Abstract

This study investigates the impact of digital technology adoption on various firm outcomes. Using the Investment Survey of the European Investment Bank (EIBIS), we first show that the big and productive firms adopt digital technologies. To address the impact of adopting digital technologies on firms' outcome, we develop instruments that combine input-output linkages between country-industry groups and sector-specific digital patent stocks. Results suggest that the digital technology adoption leads to a significant increase in productivity and wages. In addition, we observe that digital technologies positively affect firms' training decisions and management practices as well as their investment in innovation. To strengthen our findings, we also present a positive causal effect of digital technology adoption on firms' outcome by using difference-in-differences technique with a propensity score matching.

JEL classifications: O10, O30, O33, D24.

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1 Introduction

Recent advances in digital technologies accelerated the discussions about the economic consequences of adopting these technologies. A major dimension of this debate is centered around the impact of advanced technologies, e.g., robot adoption, on employment. On one hand, it is claimed that the demand for labor increase due to productivity effect.[1] On the other hand, there are evidences showing that advanced technologies can affect the employment, wages and skill polarization (See e.g., Acemoglu and Restrepo, 2020; Acemoglu et al., 2020; Michaels et al., 2014 ; Dauth et al., 2018) due to displacement effect. The increased adoption of advanced technologies has an impact on other outcomes such as productivity (e.g., Graetz and Michaels, 2018; Dauth et al., 2018). Despite the importance of the topic, there is a limited systematic evidence at the firm level. In this paper, we aim to fill this gap by providing firm level evidence on the impact of digital adoption from 27 EU countries.

In this paper, we mainly examine the impact of digital technology adoption on various firm outcomes by using a unique firm level survey from the European Investment Bank (EIB). As in previous studies, we do not limit our analysis to only adopting robots but consider many different technology adoptions, such as robotics, big data analytics and 3D printing.[2] Since the impact of adopting various technologies is more comprehensive than the impact of just robot adoption, we mostly focus on the firm outcomes such as labor productivity, TFP and wages. In addition to these outcomes, we also investigate the impact on the investment in innovation, firms' management and training practices with respect to digital technology adoption. We first show that size and productivity are important determinants of digital technology adoption. Then, we establish a causal relationship between digital technology adoption and outcomes at the firm level by developing instruments that combine input-output linkages between country-industry groups and sector specific digital patent stocks.

Since the adoption of digital technologies is not a random decision, it poses an endogeneity problem. We address this endogeneity concern by providing an instrument in the spirit of shift-share instruments.[3] Our identification strategy utilizes input-output linkages across

[1] See e.g., Acemoglu and Restrepo (2020) ; Acemoglu and Restrepo (2019).

[2] The survey question includes different digital technologies. Details about the survey question are provided in Section 2.

[3] See e.g., Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022).

country-industry groups and digital patent stocks to quantify the effect of digital adoption on firms' outcomes. Particularly, using pre-existing (initial) input-output linkages, we construct two different share components: upstream and downstream shares. The digital patent stocks (lagged) at the industry and year level in other industries are used as a shift component. Combining these shifts and share parts, we create two different (upstream and downstream) weighted digital patent stock measures at the country-sector-year level as a proxy for digital adoption of firms.

To implement our empirical strategy, we combine comprehensive firm level survey with patent data. First, we use the EIB Investment Survey (EIBIS) to observe the digital adoption decisions of firms. In this survey, digital adoption is observable for the years between 2018-2021. The survey also provides standard information at the firm level, such as sectoral information, employment and fixed asset levels. We complement this firm level survey with the Intellectual Property data of World Top R&D Investors from JRC to calculate digital patent stocks at the industry-year level for the shift part of our instrument. We build our measure of digital innovation by classifying patents into digital and non-digital related categories.[4] Finally, we use input-output tables from Eurostat to construct upstream and downstream coefficients which constitute the share part of our instrument.

We present two main results. First of all, we show that bigger and productive firms are more likely to adopt digital technologies. Then, we claim that the upstream and downstream digital patent stocks at the industry-year level are legitimate proxies for the firms' digital adoption. Using 2SLS, our estimates suggest that digital technology uptake increases TFP and labor productivity more than %100. We also find a significant increase in average wages after digital adoption. In addition, we observe that the digital uptake affects firms' training and management practice decisions positively. Finally, we observe a positive relationship between firms' digital uptake and investment in innovation.

We perform many different robustness checks. In particular, we investigate results by using alternative controls and share of weighted digital patents instead of using the level of digital patent stocks as instruments. We also replicate results by limiting the sample to manufacturing firms and to specific country groups. Our results are robust to all of these

[4] We use the classification from Inaba and Squicciarini (2017).

checks. In addition, our results are robust using difference-in-differences techniques with a propensity score matching in the spirit of Guadalupe et al. (2012) and Koch et al. (2021).

Related Literature Our paper contributes to the literature examining the impact of the adoption of advanced technologies. Some of these studies mainly focus on robot adoption. By investigating the impact of computerisation, Frey and Osborne (2017) provides one of the first evidence on the impact of computerisation on employment. They claim that a significant part of total employment in the US is at risk. Also, Dauth et al. (2018) examines the effects of robot adoption on employment, wages and composition of jobs. They observe a noticeable alteration in the composition of jobs along with an increase in the labor productivity and a decrease in the labor share. Acemoglu and Restrepo (2020) also shows that robot adoption decreases wages and employment to population ratio by a considerable amount. Another important paper by Graetz and Michaels (2018) links a substantial increase in labor productivity growth and wages to robot adoption.Acemoglu et al. (2020) suggest that the firms adopting robots in France experience an increase in value-added and productivity while reducing the labor share. Using a firm level dataset from Spain, Koch et al. (2021) show a positive effect of robot adoption on firms' output and negative effect on labor share. Instead of solely focusing on only robot adoption, a few papers also explore the outcome of adopting advanced technologies from a broad perspective. For instance, Bessen et al. (2020) provide evidence from the Netherlands using firm level data and argue that automating firms experience faster employment and revenue growth than non-automating firms. In addition, Acemoglu et al. (2022) investigates the impact of the adoption of automation technologies by US firms across all economic sectors. They show that the adoption of these technologies mostly concentrates on large and young firms. They also claim that the adopters have higher labor productivity and lower labor shares.

Our paper, particularly the construction of our instrument, also relates to vast literature that links technology diffusion to economic growth and innovation.[5] A recent paper by Berkes et al. (2022) investigates the causal effect of innovation induced by international spillovers on value-added per worker and TFP at the sectoral level. Additionally, Ayerst et al. (2020) link diffusion of knowledge embedded in trade patterns to the patenting out-

[5] See e.g., Acemoglu et al., 2016 ; Oberfield, 2018 ; Liu, 2019.

comes by utilizing input-output linkages and international patent data. Cai and Li (2019) also examines the network of knowledge linkages between sectors and its impact on firm innovation and aggregate growth.

Our paper differentiates from the papers investigating the impact of advanced technologies in two ways. First of all, we provide evidence by using unique firm level survey data from 27 EU countries. Second, existing papers using micro-level data mostly investigate the impact of robot adoption. We differentiate from these papers not only focusing on robot adoption but providing results on various other digital technology adoptions such as AI technologies, drones, 3D printing etc. In addition, we provide different firm level outcomes like investment in innovation or training. This paper also differentiates from the papers investigating the impact of international spillovers by particularly focusing on the impact of digital adoption. Our paper contributes to these various strands of the literature by first presenting the determinants of digital adoption at the firm level and then quantifying the impact of digital technology adoption using novel instruments.

The remainder of our paper is organised as follows. In Section 2 we describe the dataset and provide descriptive evidence. In Section 3 we analyse the determinants of digital technology adoption and in Section 4 we investigate the impact of digital adoption on firms' outcomes. In Section 5 we offer multiple robustness checks including difference-in-differences technique with a propensity score matching. Section 6 concludes.

2 Data

2.1 Data Sources

Firm level survey We use EIBIS survey which covers 12 000 firms each year across the EU27 since 2015. It provides rich and very detailed information mostly about investment decisions and investment finance choices of firms. This data offers an unique advantage by providing information on whether firms adopted any digital technologies. We exploit data across 4 years from 2018 to 2021. This the complete sample period which we can observe digital adoption of firms. In the first three waves the structure of the question slightly differs from the last wave. In particular, for the first three waves, question is stated as follows: 'Can you tell me for each of the following digital technologies if you have heard about them, not heard about them, implemented them in parts of your business, or whether your entire business is organised around them?'. While for the last wave, the question is re-framed and changed to the following structure: 'To what extent, if at all, are each of the following digital technologies used within your business? Please say if you do not use the technology within your business.' The definition of digital technologies differ from one sector to another slightly. If the firm operates in the Manufacturing sector the digital technologies include 3D printing , robotics, internet of things, big data analytics. Instead if firm operates in the service sector, the digital technologies include augmented or virtual reality, platform technologies, internet of things and big data analytics. Third, If firm operates in construction sector 3D printing, drones, augmented or virtual reality and internet of things. Finally, for the firms operates in the other sectors, the digital technologies include 3D printing, platform technologies, internet of things, big data analytics. Based on the responses, we create a binary indication variable which takes value of 1 if firm adopted digital technologies at the time t.

We can also observe/derive standard variables such as employment, value added, cost of employees and sector information for the years between 2018-2021. In addition, we can observe more detailed information on whether firms' investing in new product development and/or training. We also have information on whether they adopted new management practices. We deflate all the monetary values using Harmonised Indices of Consumer Prices (HICP) from Eurostat.

We use TFP and labor productivity as main outcomes. The total TFP is constructed by simply estimating sector specific regressions by using value-added, capital and labor levels of the firms using Cobb-Douglas formulation.[6]. After estimating the labor and capital coefficients, TFP is constructed as simply calculating the residual.[7] Alternatively, we use value-added per worker as an labor productivity measure. In addition, we consider wage per worker and binary outcome variables as dependent variables. In particular, we consider

[6] Since we do not observe any material costs, we can not apply advanced techniques such as Levinsohn and Petrin (2003) and Ackerberg (2015) to calculate TFP.

[7] Due to number of observations, for some sectors the TFP can not be constructed.

firms' training and advance management practices (whether firms adopt strategic business monitoring system). Finally, we investigate how digital adoption affects firms' investment decision in innovation. We follow simple cleaning procedures. We first drop negative and zero values in standard variables. Then we drop top one and bottom one percentage of standard variables such as employment, fixed-assets and wages. We also get rid of firms show extraordinary increase or decreases (top one and bottom one percentage) in labor productivity and value-added.

Patent Data We supplement firm level data with the world Top R&D Investors Intellectual Property database from JRC. This database consist of many different dataset including standard firm information like industry or location. It also includes patent portfolio of firms along with the patent class information. In particular, patent data includes publication authority, year of filing and patent classes such as IPC and WIPO. We use this data to calculate the patent stocks for each sector-industry-year group and create the shift part of our instrument.

Input Output Tables Additionally, we use Input-Output Tables from Eurostat. In particular, we use the FIGARO tables which includes EU inter-country Supply, Use and Input-Output tables. We specifically use 2017 Input Output Tables to construct the share part of our instrument.[8] After calculating the upstream (downstream) shares we use patent stocks to construct the country-sector-year instruments.

2.2 Descriptive Analysis

Before turning to the estimation part, we present the simple statistics from our sample. Table 1 in below show the firm level standard measures by separating firms into digital adopters and non-digital adopters. Different patterns are observed between digital technology adopter firms and non-digital technology adopter firms. First of all, firms adopting digital technologies are, on average, larger and more productive. Second, they have, on average, higher wages per worker. Finally, digital adopters are more likely to be Exporters and more likely to be investing in training and innovation.

To provide graphical evidence on the relationship between digital technology adoption and

[8] Construction of shares are explained in detail in the Section 4.1.

firm size/productivity, we plot the distribution of value added and value added per worker for firms adopt digital technologies versus firms do not adopt digital technologies. Figure 1 in above presents the distribution of firms' value-added per worker and size (log fixed assets) for the digital technology adopters vs non-digital technology adopters. Both of the firm size and labor productivity distribution of firms adopting digital technologies dominate the non-adopter firms.

3 Determinants of digital technology adoption

Before examining the impact of digital adoption on firms' outcome, in this section, we explore the determinants of digital technology adoption. In order to understand the direction of the selection, we formally analyse the determinants of the digital technology adoption.
To analyse the determinants of the digital technology adoption, we estimate the following equation.

$$DigitalAdoption_{i,c,s} = \boldsymbol{\psi F_{i,c,s,0}} + \mu_c + \delta_s + \epsilon_{i,c,s} \tag{1}$$

where dependent variable is 0/1 indicator variable for digital technology adoption which takes value of 1 if firm ever adopts digital technologies during the sample period. $\mathbf{F_{i,c,s,0}}$ denotes the vector of time-invariant (initial level) firm level controls: log of labor productivity, total assets, average wage and innovation investment share. We also control firms' exporter status and firm age category. μ_c, and δ_s denotes country, and sector fixed effects (CPA1), respectively.

Table 2 presents OLS estimates of equation 1. Standard errors are clustered at the country-industry level as in Berkes et al. (2022). We found that in all of these specifications, the impact of labor productivity and firm size (log fixed assets) is economically, statistically significant and positive. We also observe a positive correlation between wages and digital adoption. We also consider other specifications. In the Table A1 in Appendix, we also provide the results with probit model.

4 The Effects of Digital Technology Adoption

In this section, we aim to identify the impact of the digital adoption. Using instrumental variables strategy, we investigate the impact of the digital technology adoption mainly on the firms' productivity such as labor productivity and TFP. Additionally, we examine the effect on the average wages, training uptake, management practices, and innovation investment share.

Formally, we estimate the following equation. $Y_{i,c,s,t}$ is one of the following variables: log labor productivity, log TFP, log average wage, training and management practices[9],innovation investment (binary and share) for firm i in country c operating in sector s (CPA categories) at time t.

$$Y_{i,c,s,t} = \alpha + \beta DigitalAdoption_{i,c,s,t} + \boldsymbol{\tau X_{i,c,s,t}} + \mu_c + \gamma_t + \delta_s + \epsilon_{i,c,s,t} \tag{2}$$

where $DigitalAdoption_{i,c,s,t}$ refers to binary digital adoption variable which takes value of 1 if firm adopts digital technologies at time t. This variable is instrumented by using patent data and IO tables. $\mathbf{X_{i,c,s,t}}$ is a time varying vector of firm level controls including size, age and Exporter categories. μ_c,γ_t and δ_s denotes country, year, sector fixed effects (CPA1), respectively.

The main coefficient of interest is β. It relates the changes in firms' digital adoption at the firm-year level to the to the changes in firms' outcomes such as productivity and average wages. We include sector, country and year fixed effects. Country and sector fixed effects allows us to control time invariant country and sectors specific patterns since firms in different countries and industries might have different propensity in terms o digital adoption. While year fixed effects control for year specific trends.

We first present the main impacts on TFP, labor productivity and average wage. The baseline results uses 27 EU countries for the period between 2018-2021. Before turning into investigating causal relationship, we examine the simple correlation between firms' digital adoption and outcome. The detailed table of these estimations can be found in the Table 3.

[9] In the survey, firms are asked whether they adopted strategic business monitoring system or not. If they adopted this variable takes value of 1, 0 otherwise.

Results suggest that that the digital adoption increases labor productivity by around %9 while it increases TFP and average wage by %5 and %8, respectively. Linear probability model in column (4), (5) and (6) suggest that the there is a positive correlation between firms' digital adoption and training decisions, management practices and investment in innovation.

To establish causal relationship between digital adoption and firms' outcome, we need to identify variation in digital adoption that is orthogonal to unobserved factors that might affect digital adoption and outcome variables at the same time. Due to reverse causality and attenuation bias, the direction of bias is ambiguous. To deal with these biases, our methodology depends on the instrumental variables strategy. To further explain the details of our strategy, in the first stage of the estimation, we consider following equation.

$$DigitalAdoption_{i,c,s,t} = \boldsymbol{\rho Z_{c,s,t}} + \boldsymbol{\tau X_{i,c,s,t}} + \mu_c + \gamma_t + \delta_s + \epsilon_{i,c,s,t} \tag{3}$$

where $\mathbf{Z_{c,s,t}}$ denotes instrumental variables: log of weighted upstream and downstream digital patents at the country-industry-year level.[10] As before, $\mathbf{X_{i,c,s,t}}$ is a time varying vector of firm level controls including size, age and Exporter categories.[11]

4.1 Instrument Construction

In this section, we present our identification strategy in detail. We build an instrumental variable for a digital patenting activity at the country-sector-year level to determine the digital adoption of firms. Our instrument uses both pre-existing country-sector linkages and digital patent stocks similar to the shift-share design.[12] To construct the share terms of our instrument, we gather Input-Output table (2017) from Eurostat. We calculated upstream and downstream output-input coefficients as shares. In particular, for each country-sector of origin (c_o and s_o), we calculated the upstream and downstream shares using sector of destination, s_d. If the origin and destination sector equal to each other we equalize share to

[10] For the sake of notation we use the same industry index for the instrument and fixed effects. While the instrument is at the IO table industry level (CPA), the sector fixed effects are at the higher level (CPA1) and covers all the CPA categories.
[11] We also consider alternative controls in Section 5.
[12] Our measure is constructed in the spirit of Berkes et al. (2022).

zero. Formally, the construction of measures are given by,

$$Upstream(Downstream)Share_{c_o,s_o,s_d} = \frac{M_{c_o,s_o,s_d}}{\sum_{s_d,\forall d!=o} M_{c_o,s_o,s_d}}$$

where M_{c_o,s_o,s_d} refers to the output levels. Sectors in the instrument construction part refers to the CPA categories. Alternatively, $\frac{M_{c_o,s_o,s_d}}{\sum_{s_d,\forall d!=o} M_{c_o,s_o,s_d}}$ the shares represent the input required to produce one unit of production of country-industry c_o and s_o from industry s_d.

Then, we used patent data from JRC. This data allow us to observe the patent stock of world Top R&D Investor. Using firms industry information at the NACE level, we first match their industries to the CPA categories. Then we merge firm information with the patent portfolios where we classify patents into digital vs non-digital categories using their IPC codes.[13]. Then using yearly-digital patent information, stock of patents is calculated by simply summing up the number of digital patents.

Finally, we multiply stock of patents with the corresponding shares we constructed above and add them to construct a weighted-digital patents at the country-industry of origin-year level instruments. Formally,

$$Z_{c_o,s_o,t} = \sum_{s_d} Upstream(Downstream)Share_{c_0,s_o,s_d} \times \overbrace{(\sum_{t=t_0}^{t-1} DigitalPatents_{s_d,t})}^{PatentStock_{s_d,t}}$$

where $Z_{c,s,t}$ is the log of weighted digital patents (upstream and downstream separately) and where $DigitalPatents_{s_d,t}$ is stock of digital at the CPA categories and time t for each country. Since all of the upstream and downstream weighted patent measures are above zero, we can use the log of them without any transformation. Our instrument predicts digital adoption in the current period based on pre-existing (initial) input-output linkages across countries and industries and digital patenting activity at the sector-year level. Instead of considering log stock of weighted-digital patents, we also consider share of weighted digital patents. Our results are robust using this share of weighted patent measures. These results are presented in the Section 5.

[13] We use the classification from Inaba and Squicciarini (2017).

4.2 Baseline Results

The results of the baseline estimation is depicted in the Table 4. The first three column present results for the TPF, labor productivity and average wages without the controls, while the last three column controls for age, size and Exporter categories. The magnitude of the two-stage least squares regressions is stable to adding controls.[14] In all of the specifications, we observe positive and significant effects of digital technology adoption on firms' productivity. The coefficients in columns (4), (5) and (6) suggest that digital adoption increases labor productivity, TFP and average wage of firms' by more than %100.

In line with the literature, we claim that the average wage in firms adopting digital technologies increases since digital adoption has implication on the skill composition of workers. In particular, if firms hire more skilled-workers after adopting digital technologies we expect to observe an increase in the average wage.[15] First stage coefficients and Kleibergen-Paap Wald F statistics are reported under the Table 4. We found a positive impact of our instrument on firms' digital technology adoption. In particular, we observe that %10 increase in the weighted upstream patents increases the digital adoption by around 0.2 percentage points across many specifications. While this number is slightly lower for the weighted upstream patents.[16] Since, the Kleibergen-Paap Wald F statistics in the baseline regressions is above 40, weak instrument concerns are ruled out. The estimated 2SLS coefficients are larger than OLS coefficients. This results might suggest that the OLS estimates suffer from attenuation bias. Alternatively, raising market concentration of market leaders might explain the downward bias in the OLS estimates.[17]

Other Impacts We turn to the impact on firms adopting digital technologies on firms' training uptake and management practices. Due to adopting digital technologies, it is expected to observe a change in the training and management practices after digital technology

[14] We also consider additional control variables and lag control variables. These results can be found in Section 5.

[15] Unfortunately, we can not observe the employment levels depending on skill composition.

[16] We also use downstream and upstream weighted patents separately in the first stage. The results are robust to this specification.

[17] See e.g., Akcigit and Ates (2021).

adoption. Table 5 above presents these results.

First two column present the results without the control variables while the last two column shows the results with the control variables. Results suggest digital adoption increases the probability of investing in training and adopting new management practices by 68 and 26 percentage points, respectively. Since we use binary indicator as a dependent variable, we also consider probit estimation with instrumental variable strategy. Results of these estimations can be found in the Table A2 in Appendix.

Finally, we turn to the impact of digital adoption on firms' innovation decisions. We consider both binary and continuous measures of innovation uptakes: whether there is a positive investment in innovation and share of innovation investment to total investment. Table 6 presents the results of these estimations. As before the first two column present the results without the controls and the last column shows the estimations with control variables. As expected we observe an increase in the share of innovation investment. Digital adoption increases the probability of investing in innovation by almost 41 percentage points and increases share of innovation investment by 0.35.

5 Robustness Check

In this section, we present the results of the different robustness checks. We first show that our estimates are robust to using lag control variables and rest of the patent stocks. Then we show results where we replace the log weighted digital patent levels with the share of weighted digital patents. Finally, we limit our sample to only manufacturing firms. Our results are robust to all of these specifications. We also perform alternative robustness checks. The results of these robustness checks can be found in the Appendix.

Alternative Controls As a first robustness check, we use lag control variables such as lag of log capital intensity (capital/employment), lag log employment in addition to Exporter status and age categories. First three column of Table 7 presents these results. We also consider non-digital weighted patent stocks as control variable in addition to Exporter status, age and size categories. The last three reports of Table 7 presents these results. Our results robust to all of these specifications.

We also consider other outcome variables with alternative controls. These results can be found in the Table A3 and Table A4 in the Appendix.

Manufacturing firms and alternative instruments We also consider alternative instruments. Instead of focusing on levels of digital patents, we use share of weighted digital patents in total patents. First three columns of Table 8 presents the results of an estimation when sample is restricted to only manufacturing firms. Alternatively, we use upstream and downstream share of weighted patent stocks instead of the log of the patent stocks. These results are given in the last three column of Table 8. The baseline results are robust across all of these specifications.

We also consider other outcome variables by using only manufacturing firms and alternative instruments. All of the outcome variables are robust to these specifications. These results can be found in the Table A5 and Table A6 in the Appendix.

Finally, We also consider alternative digital patent classification and we check the impact of digital adoption for different country groups. These results can be found in Table A7, Table A8, Table A9 and Table A10.

Propensity Score Matching (PSM) In order to strengthen our results, we investigate the causal relationship between digital technology adoption and firm outcomes, with propensity score matching similar to Koch et al. (2021) and Guadalupe et al. (2012). We use propensity score matching to construct similar distribution of key variables across digital adopters and non-adopters. We estimate propensity scores by pooling treatment and control groups across 27 EU countries, running probit regressions for treatment on one year lag of log total assets, log labor productivity growth and log value-added growth, age categories, sector and Exporter dummies. We also consider year dummies and one year lag of innovation investment share in total yearly investment.[18] After extracting weights from the propensity score matching, we estimate the impact of digital adoption on firms' outcome. Table 9 presents these results. First two column presents the results for TFP and labor productivity. Third column shows the results for the wage per worker while last three columns present results for the firms' training and management practices adoption along with firms' innovation investment decisions.

[18] We do not consider any main dependent variables as a control variables in the matching.

Results suggest that the digital adoption increases the labor productivity,TFP and average wage around %5 to %4. Figure 2 provide visual representation of the reduced deviation between treated and control groups. We also check the distribution of the dependent variables with respect to treatment after PSM. We also provide both t-tests across digital adoption categories. These can be found in Table A11.

Figure 3 provides the propensity score distributions before and after matching. We observe that after matching the propensity scores distributes similarly across treated and control groups.

6 Conclusion

This paper provides novel evidence on the impact of digital adoption on firm level outcomes. By using unique firm level data from 27 EU countries, we first show that big and more productive firms are more likely to adopt digital technologies. Then we construct novel instruments by leveraging pre-existing input-output linkages across countries-industry groups and digital patent stocks at industry-year levels. Our 2SLS estimates suggest that the digital adoption leads to significant increases in TFP, labor productivity and wages. Additionally, we observe that the firms' training, management practices and investment in innovation are positively impacted by digital adoption.

We show that our results are robust to many alternative specifications and robustness checks. We first show that our results are not affected by the control variables. Then we find that our results are robust using alternative instruments. Additionally, we provide evidence suggesting that our results are not driven by particular industry groups such as manufacturing. Finally, we consider difference-in-difference technique with propensity score matching and observe a positive causal impact of digital adoption on firms' outcomes.

Our findings, which focus on broader concepts of advanced technologies, provide novel evidence on how digital adoption can affect firm outcomes. Our results indicate that digital adoption has a significant impact on firm outcomes. Our findings, and more specifically our instruments, highlight an important determinant of digital uptake at the firm level: the importance of the innovation stock in upstream and downstream industries. Policies aimed at increasing firm productivity and controlling the employment effects of digital technology adoption should consider the impact of upstream and downstream partners as well as the firm itself.

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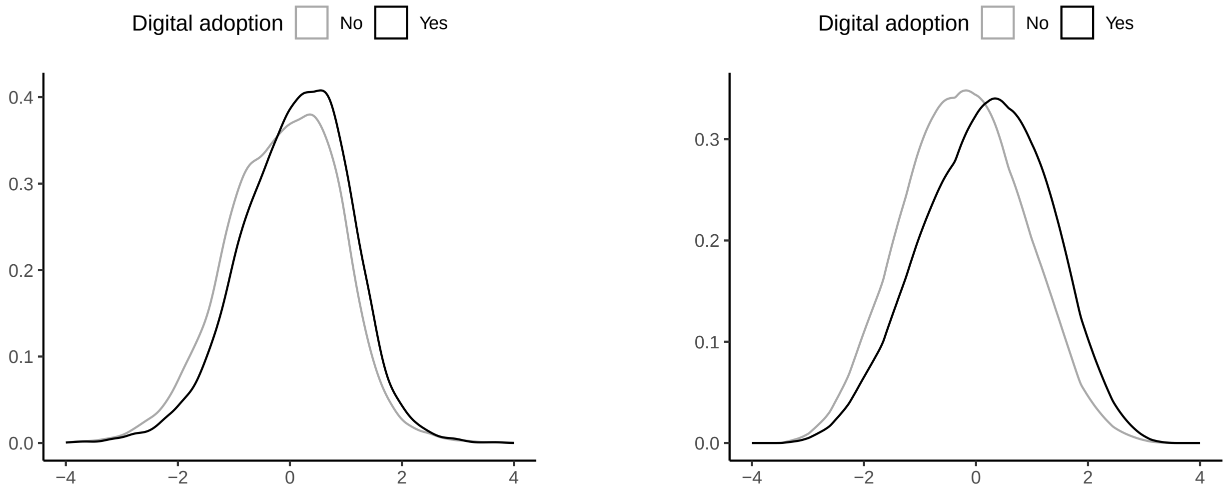
Tables and Figures

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Median	Pctl(25)	Pctl(75)
				Digital Adopters		
Log(FixedAssets)	20,836	14.243	2.230	14.444	12.603	15.815
Log(Value-Added)	19,741	14.248	1.652	14.300	12.975	15.553
Log(Value-Added/Emp)	19,741	10.308	0.836	10.363	9.764	10.885
Log(TFP)	18,948	8.445	0.924	8.468	7.824	9.079
Employment	22,756	132.236	219.731	53	14	150
Log(Wage/Emp)	21,215	10.052	0.800	10.113	9.558	10.639
Exporter(Binary)	22,698	0.555	0.497	1	0	1
Age(Category)	22,754	3.485	0.800	4	3	4
Investment in Innovation(Binary)	19,521	0.474	0.499	0	0	1
Innovation Investment Share	19,521	0.189	0.288	0.000	0.000	0.300
Training Binary	20,276	0.561	0.496	1	0	1
Management Practices Uptake	22,235	0.567	0.495	1	0	1
Digital Patents(Downstream)	22,756	15,162.420	13,319.190	10,724.040	5,753.027	21,009.120
Digital Patents(Upstream)	22,756	6,204.222	5,879.814	4,773.565	2,467.383	7,682.188
				Non-Digital Adopters		
Log(FixedAssets)	17,539	13.332	2.147	13.291	11.798	15.019
Log(Value-Added)	16,372	13.467	1.536	13.342	12.361	14.529
Log(Value-Added/Emp)	16,372	10.115	0.869	10.160	9.532	10.727
Log(TFP)	15,480	8.376	0.936	8.405	7.730	9.026
Employment	19,885	70.633	145.609	20	9	70
Log(Wage/Emp)	18,125	9.858	0.826	9.911	9.339	10.469
Exporter(Binary)	19,818	0.382	0.486	0	0	1
Age(Category)	19,879	3.426	0.835	4	3	4
Investment in Innovation(Binary)	15,680	0.327	0.469	0	0	1
Innovation Investment Share	15,680	0.131	0.261	0.000	0.000	0.100
Training Binary	17,861	0.418	0.493	0	0	1
Management Practices Uptake	19,402	0.335	0.472	0	0	1
Digital Patents(Downstream)	19,885	12,787.330	12,495.260	8,174.711	4,336.243	16,986.070
Digital Patents(Upstream)	19,885	5,736.456	4,916.021	4,860.641	2,466.898	6,837.781



(a) Standardized log value-added per worker

(b) Standardized log fixed assets

Figure 1: Panel (a) depicts the distribution of standardized log value-added per worker with digital technology separation. The black line presents the density of value-added per worker for digital technology adopters while gray line presents the density of value-added per worker for non-digital technology adopters. Panel (b) shows the same as panel (a) using standardized log fixed assets.

Table 2: Determinants of Digital Adoption

Dependent Variable:	Digital			
Model:	(1)	(2)	(3)	(4)
Variables				
ln(Va/emp)	0.0700***	0.0433***	0.0289***	0.0164*
	(0.0056)	(0.0052)	(0.0081)	(0.0086)
ln(T.Asset)		0.0375***	0.0372***	0.0347***
		(0.0020)	(0.0020)	(0.0019)
ln(wage/emp)			0.0204**	0.0246***
			(0.0080)	(0.0088)
Fixed-effects				
CPA1	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Other Controls				Yes
Fit statistics				
Observations	23,777	22,672	22,672	19,612
R^2	0.0724	0.0967	0.0969	0.1079

Notes: Column 4 includes also exporter status, innovation investment share and age categories. Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01.

Table 3: Baseline Impact without IV

Dependent Variables:	ln(Va/emp)	ln(TFP)	ln(wage/emp)	Training	Mngmt Prac.	Innovation(Binary)	Innovation(Share)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Digital	0.0964***	0.0547***	0.0851***	0.1186***	0.1492***	0.1126***	0.0434***
	(0.0086)	(0.0088)	(0.0067)	(0.0058)	(0.0055)	(0.0066)	(0.0037)
Fixed-effects							
Wave	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	36,058	34,379	39,275	38,066	41,529	35,135	35,135
R^2	0.4271	0.4966	0.4912	0.1256	0.1882	0.0847	0.0662

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. Controls include Exporter status, age and size categories.

Table 4: Effect of digital adoption on firms' outcome

Dependent Variables:	ln(Va/emp)	ln(TFP)	ln(wage/emp)	ln(Va/emp)	ln(TFP)	ln(wage/emp)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Digital	1.613***	2.026***	1.670***	1.484***	1.971***	1.661***
	(0.4104)	(0.4636)	(0.3392)	(0.4013)	(0.4490)	(0.3429)
Fixed-effects						
Wave	Yes	Yes	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes
Fit statistics						
Observations	36,113	34,428	39,340	36,058	34,379	39,275
			First-Stage Estimates			
Ln(Upstream(Digital) Patent)	0.0219***	0.0235***	0.0211***	0.0232***	0.0246***	0.0227***
	(0.0074)	(0.0076)	(0.0074)	(0.0067)	(0.0068)	(0.0066)
Ln(Downstream(Digital) Patent)	0.0260***	0.0253***	0.0272***	0.0226***	0.0223***	0.0238***
	(0.0070)	(0.0070)	(0.0071)	(0.0068)	(0.0068)	(0.0069)
R^2 (1st stage)	0.0650	0.0656	0.0660	0.1089	0.1075	0.1122
F-test (1st stage)	43.355	42.563	48.391	40.491	40.280	45.827

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. Firm controls include Exporter status, size and age categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table 5: Effect of digital adoption on firms' training and management practices

Dependent Variables:	Training	Mngmt Prac.	Training	Mngmt Prac.
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.6655***	0.2338	0.6767***	0.2525*
	(0.1504)	(0.1433)	(0.1588)	(0.1353)
Fixed-effects				
Wave	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Fit statistics				
Observations	38,137	41,637	38,066	41,529
		First-Stage Estimates		
Ln(Upstream(Digital) Patent)	0.0277***	0.0231***	0.0288***	0.0244***
	(0.0076)	(0.0075)	(0.0069)	(0.0068)
Ln(Downstream(Digital) Patent)	0.0291***	0.0277***	0.0257***	0.0244***
	(0.0071)	(0.0068)	(0.0070)	(0.0065)
R^2 (1st stage)	0.0658	0.0662	0.1131	0.1126
F-test (1st stage)	62.535	55.390	59.264	52.370

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. Firm controls include Exporter status, size and age categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table 6: Effect of digital adoption on firms' innovation

Dependent Variables:	Innovation(Binary)	Innovation(Share)	Innovation(Binary)	Innovation(Share)
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.4718***	0.3859***	0.4103***	0.3439***
	(0.1430)	(0.0925)	(0.1442)	(0.0867)
Fixed-effects				
Wave	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Fit statistics				
Observations	35,201	35,201	35,135	35,135
	First-Stage Estimates			
Ln(Upstream(Digital) Patent)	0.0176**	0.0176**	0.0196***	0.0196***
	(0.0076)	(0.0076)	(0.0070)	(0.0070)
Ln(Downstream(Digital) Patent)	0.0318***	0.0318***	0.0286***	0.0286***
	(0.0074)	(0.0074)	(0.0070)	(0.0070)
R^2 (1st stage)	0.0686	0.0686	0.1111	0.1111
F-test (1st stage)	48.901	48.901	46.529	46.529

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. Firm controls include Exporter status, size and age categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table 7: Effect of digital adoption on firms' outcome

Model:	Lag controls			Alternative controls		
Dependent Variables:	ln(Va/emp)	ln(TFP)	ln(wage/emp)	ln(Va/emp)	ln(TFP)	ln(wage/emp)
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Digital	0.8924**	1.124***	1.116***	1.865***	2.720***	2.124***
	(0.3440)	(0.3809)	(0.2871)	(0.7095)	(0.9232)	(0.6199)
Fixed-effects						
Wave	Yes	Yes	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes
Fit statistics						
Observations	16,004	15,395	17,029	36,058	34,379	39,275
			First-Stage Estimates			
Ln(Upstream(Digital) Patent)	0.0257***	0.0277***	0.0242***	0.0460***	0.0468***	0.0442***
	(0.0093)	(0.0095)	(0.0092)	(0.0154)	(0.0157)	(0.0148)
Ln(Downstream(Digital) Patent)	0.0324***	0.0319***	0.0343***	0.0104	0.0121	0.0156
	(0.0077)	(0.0079)	(0.0079)	(0.0214)	(0.0225)	(0.0205)
R^2 (1st stage)	0.1189	0.1180	0.1212	0.1090	0.1076	0.1123
F-test (1st stage)	30.702	30.658	33.727	11.472	11.560	12.544

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. First three column includes the lag employment, lag capital intensity, Exporter status and age categories. The last three column uses add the log of non-digital upstream and downstream weighted patents as controls along with Exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table 8: Effect of digital adoption on firms' outcome

Model:	Manufacturing Firms			Alternative instruments		
Dependent Variables:	ln(Va/emp)	ln(TFP)	ln(wage/emp)	ln(Va/emp)	ln(TFP)	ln(wage/emp)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Digital	1.054***	1.537***	1.240***	1.643***	2.447***	1.875***
	(0.2693)	(0.2841)	(0.2134)	(0.5833)	(0.7586)	(0.4747)
Fixed-effects						
Wave	Yes	Yes	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes
Fit statistics						
Observations	11,363	10,917	12,278	36,058	34,379	39,275
First-Stage Estimates						
Ln(Upstream(Digital) Patent)	0.0197**	0.0214**	0.0189**			
	(0.0082)	(0.0088)	(0.0083)			
Ln(Downstream(Digital) Patent)	0.0409***	0.0399***	0.0425***			
	(0.0096)	(0.0093)	(0.0096)			
Share of Upstream(Digital) Patent				0.1837**	0.1872**	0.1737**
				(0.0724)	(0.0741)	(0.0698)
Share of Downstream(Digital) Patent				0.1835*	0.1903*	0.2072**
				(0.0943)	(0.0983)	(0.0936)
R^2 (1st stage)	0.1225	0.1199	0.12746	0.1077	0.1062	0.1109
F-test (1st stage)	55.550	53.680	62.646	15.413	15.506	17.545

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. Controls include Exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table 9: Effect of digital adoption on firms' outcome-PSM

Dependent Variables:	ln(Va/emp)	ln(TFP)	ln(wage/emp)	Training	Mngmt Prac.	Innovation(Binary)	Innovation(Share)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Digital	0.055***	0.040***	0.039***	0.239***	0.364***	0.291***	0.045***
	(0.014)	(0.012)	(0.013)	(0.032)	(0.028)	(0.034)	(0.007)
Fixed-effects & Controls							
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	8,218	8,218	7,944	7,867	8,092	7,463	7,465
R^2	0.485	0.580	0.585				0.046

Notes: Clustered (Country & Sector) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. Controls include Exporter status, age and size categories. Column 4, 5 and 6 reports probit estimates while the other columns report OLS estimates.

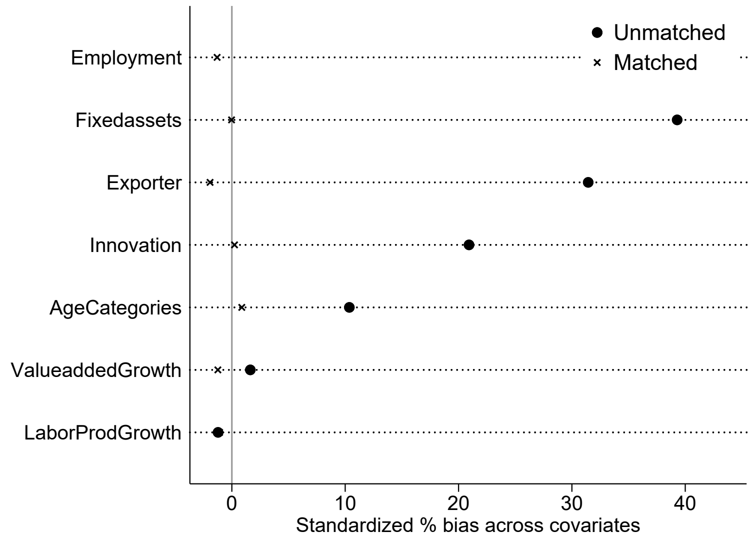


Figure 2: Reduction of bias after matching

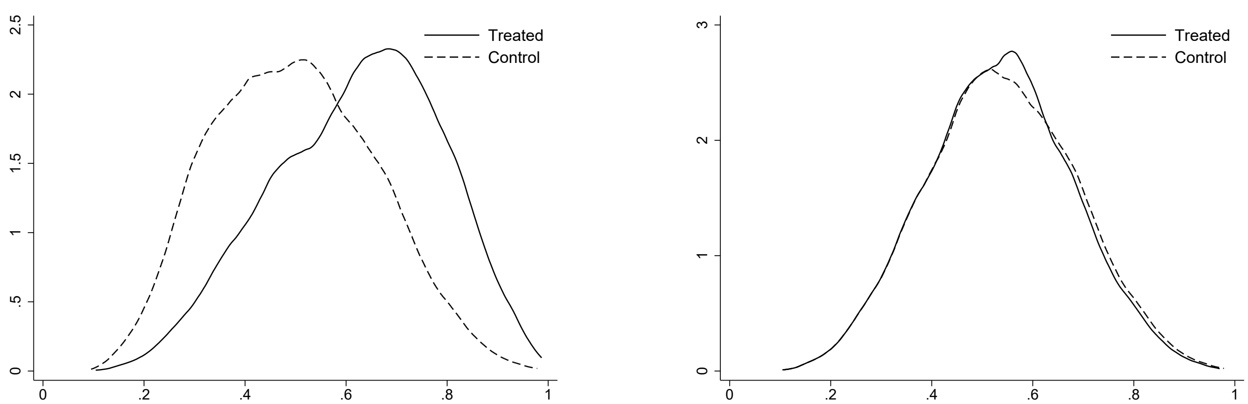


Figure 3: Distribution of propensity scores. Panel (a) depicts the distribution of propensity scores before matching while Panel (b) presents the propensity score distribution after matching.

Appendix

Table A1: Determinants of digital adoption-Probit

Dependent Variable:	Digital			
Model:	(1)	(2)	(3)	(4)
Variables				
ln(Va/emp)	0.1896***	0.1186***	0.0795***	0.0450*
	(0.0157)	(0.0146)	(0.0229)	(0.0251)
ln(T.Asset)		0.1045***	0.1038***	0.0987***
		(0.0056)	(0.0056)	(0.0056)
ln(wage/emp)			0.0556**	0.0699***
			(0.0225)	(0.0254)
Fixed-effects				
CPA1	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls				Yes
Fit statistics				
Observations	23,772	22,667	22,667	19,607
Pseudo R^2	0.0562	0.0759	0.0760	0.0863

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01.

Table A2: Effect of digital adoption on firms' training & management practices & innovation-IVProbit

	(1)	(2)	(3)
VARIABLES	Training	Mngmt Prac.	Innovation(Binary)
Digital	1.919***	0.726***	1.076***
	(0.295)	(0.280)	(0.295)
Observations	38,062	41,525	35,133
Controls	Yes	Yes	Yes
Country	Yes	Yes	Yes
Sector	Yes	Yes	Yes
Year	Yes	Yes	Yes

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. The table reports the estimates from IV-Probit. Controls include Exporter status, age and size categories.

Table A3: Alternative Controls-Effect of digital adoption on firms' training & management practices

Model:	Lag controls		Alternative controls	
Dependent Variables:	Training	Mngmt Prac.	Training	Mngmt Prac.
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.4007***	0.2008	0.9894***	0.3739
	(0.1337)	(0.1540)	(0.3363)	(0.2797)
Fixed-effects				
Wave	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Fit statistics				
Observations	16,422	17,251	38,066	41,529
	First-Stage Estimates			
Ln(Upstream(Digital) Patent)	0.0309***	0.0253***	0.0523***	0.0427***
	(0.0096)	(0.0095)	(0.0154)	(0.0146)
Ln(Downstream(Digital) Patent)	0.0360***	0.0348***	0.0199	0.0225
	(0.0082)	(0.0078)	(0.0205)	(0.0200)
R^2 (1st stage)	0.1232	0.1217	0.1132	0.1127
F-test (1st stage)	40.968	35.688	17.073	13.964

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. First two column includes the lag employment, lag capital intensity, Exporter status and age categories. The last two column uses add the log of non-digital upstream and downstream weighted patents as controls along with Exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table A4: Alternative Controls-Effect of digital adoption on firms' innovation

Model:	Lag controls		Alternative controls	
Dependent Variables:	Innovation(Binary)	Innovation(Share)	Innovation(Binary)	Innovation(Share)
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.3155**	0.2806***	1.388***	0.8675***
	(0.1495)	(0.0708)	(0.3965)	(0.2441)
Fixed-effects				
Wave	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Fit statistics				
Observations	15,271	15,271	35,135	35,135
	First-Stage Estimates			
Ln(Upstream(Digital) Patent)	0.0240***	0.0240***	0.0406**	0.0406**
	(0.0090)	(0.0090)	(0.0158)	(0.0158)
Ln(Downstream(Digital) Patent)	0.0375***	0.0375***	0.0257	0.0257
	(0.0084)	(0.0084)	(0.0220)	(0.0220)
R^2 t (1st stage)	0.1188	0.1188	0.1112	0.1112
F-test (1st stage)	34.358	34.358	11.733	11.733

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. First two column includes the lag employment, lag capital intensity, Exporter status and age categories. The last two column uses add the log of non-digital upstream and downstream weighted patents as controls along with Exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table A5: Effect of digital adoption on firms' training & management practices

Model:	Manufacturing Firms		Alternative instruments	
Dependent Variables:	Training	Mngmt Prac.	Training	Mngmt Prac.
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.6141***	0.2998***	0.6637**	0.2303
	(0.1263)	(0.0976)	(0.2685)	(0.2333)
Fixed-effects				
Wave	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Fit statistics				
Observations	11,791	12,830	38,066	41,529
	First-Stage Estimates			
Ln(Upstream(Digital) Patent)	0.0263***	0.0192**		
	(0.0092)	(0.0089)		
Ln(Downstream(Digital) Patent)	0.0444***	0.0435***		
	(0.0096)	(0.0085)		
Share of Upstream(Digital) Patent			0.2104***	0.1653**
			(0.0738)	(0.0690)
Share of Downstream(Digital) Patent			0.2412**	0.2333***
			(0.0934)	(0.0899)
R^2	0.1286	0.1265	0.1114	0.1112
F-test (1st stage)	75.327	67.681	23.728	19.785

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. Controls include Exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table A6: Effect of digital adoption on firms' innovation

Model: Alternative instruments	Manufacturing Firms			
Dependent Variables:	Innovation(Binary)	Innovation(Share)	Innovation(Binary)	Innovation(Share)
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.3855***	0.2780***	1.061***	0.6816***
	(0.1307)	(0.0729)	(0.2684)	(0.1677)
Fixed-effects				
Wave	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Fit statistics				
Observations	11,172	11,172	35,135	35,135
	First-Stage Estimates			
Ln(Upstream(Digital) Patent)	0.0222**	0.0222**		
	(0.0101)	(0.0101)		
Ln(Downstream(Digital) Patent)	0.0436***	0.0436***		
	(0.0101)	(0.0101)		
Share of Upstream(Digital) Patent			0.1548**	0.1548**
			(0.0731)	(0.0731)
Share of Downstream(Digital) Patent			0.2706***	0.2706***
			(0.0976)	(0.0976)
R^2	0.1198	0.1198	0.1097	0.1097
F-test (1st stage)	64.245	64.245	19.073	19.073

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. Controls include Exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table A7: Effect of digital adoption on firms' outcome

Model:	Alternative digital patent specification						
Dependent Variables:	ln(Va/emp)	ln(TFP)	ln(wage/emp)	Training	Mngmt Prac.	Innovation(Binary)	Innovation(Share)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Digital	1.487***	2.027***	1.698***	0.6798***	0.2406*	0.4563***	0.3692***
	(0.4105)	(0.4637)	(0.3509)	(0.1614)	(0.1404)	(0.1531)	(0.0918)
Fixed-effects							
Wave	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	36,058	34,379	39,275	38,066	41,529	35,135	35,135
	First-Stage Estimates						
Ln(Upstream(Digital) Patent)	0.0236***	0.0251***	0.0231***	0.0292***	0.0249***	0.0200***	0.0200***
	(0.0067)	(0.0068)	(0.0067)	(0.0070)	(0.0069)	(0.0071)	(0.0071)
Ln(Downstream(Digital) Patent)	0.0218***	0.0215***	0.0231***	0.0253***	0.0238***	0.0283***	0.0283***
	(0.0070)	(0.0070)	(0.0070)	(0.0071)	(0.0067)	(0.0072)	(0.0072)
R^2	0.1088	0.1073	0.1121	0.1130	0.1125	0.1110	0.1110
F-test (1st stage)	38.423	38.266	43.578	57.272	50.177	45.151	45.151

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. Controls include Exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table A8: Effect of digital adoption on firms' outcome-Western & Northern Europe and Southern Europe

Model:	Western & Northern Europe			Southern Europe		
Dependent Variables:	ln(Va/emp)	ln(TFP)	ln(wage/emp)	ln(Va/emp)	ln(TFP)	ln(wage/emp)
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Digital	0.8780	2.174	1.416**	1.544***	1.858***	1.381***
	(0.8769)	(1.338)	(0.6103)	(0.5040)	(0.5814)	(0.3885)
Fixed-effects						
Wave	Yes	Yes	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes
Fit statistics						
Observations	13,782	12,993	15,032	7,559	7,280	8,286
First-Stage Estimates						
Ln(Upstream(Digital) Patent)	0.0214**	0.0213**	0.0237***	0.0259**	0.0286**	0.0229*
	(0.0086)	(0.0090)	(0.0086)	(0.0115)	(0.0115)	(0.0119)
Ln(Downstream(Digital) Patent)	0.0096	0.0089	0.0125	0.0330**	0.0340***	0.0335***
	(0.0110)	(0.0112)	(0.0115)	(0.0129)	(0.0126)	(0.0126)
R^2	0.1343	0.1337	0.1373	0.0927	0.0891	0.0954
F-test (1st stage)	6.8244	6.0979	10.176	14.771	15.773	15.199

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. Controls include Exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table A9: Effect of digital adoption on firms' outcome-Western & Northern Europe and Southern Europe

Model:	Western & Northern Europe		Southern Europe	
Dependent Variables:	Training	Mngmt Prac.	Training	Mngmt Prac.
	(1)	(2)	(3)	(4)
Variables				
Digital	0.8381**	-0.2607	0.6476**	0.5211**
	(0.3979)	(0.3976)	(0.2982)	(0.2173)
Fixed-effects				
Wave	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Fit statistics				
Observations	14,763	16,223	7,789	8,461
	First-Stage Estimates			
Ln(Upstream(Digital) Patent)	0.0226**	0.0243***	0.0290**	0.0252**
	(0.0087)	(0.0084)	(0.0115)	(0.0119)
Ln(Downstream(Digital) Patent)	0.0159	0.0135	0.0360***	0.0337***
	(0.0116)	(0.0112)	(0.0126)	(0.0115)
R^2	0.1374	0.1378	0.0971	0.0936
F-test (1st stage)	11.109	11.675	18.149	16.289

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. Controls include Exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table A10: Effect of digital adoption on firms' outcome-Western & Northern Europe and Southern Europe

Model:	Western & Northern Europe		Southern Europe	
Dependent Variables:	Innovation(Binary)	Innovation(Share)	Innovation(Binary)	Innovation(Share)
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.1302	0.3978*	0.4116*	0.3483**
	(0.2705)	(0.2289)	(0.2137)	(0.1647)
Fixed-effects				
Wave	Yes	Yes	Yes	Yes
CPA1	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Fit statistics				
Observations	13,721	13,721	7,156	7,156
	First-Stage Estimates			
Ln(Upstream(Digital) Patent)	0.0183*	0.0183*	0.0224	0.0224
	(0.0099)	(0.0099)	(0.0138)	(0.0138)
Ln(Downstream(Digital) Patent)	0.0179	0.0179	0.0362***	0.0362***
	(0.0114)	(0.0114)	(0.0131)	(0.0131)
R^2	0.1344	0.1344	0.0896	0.0896
F-test (1st stage)	9.6020	9.6020	15.060	15.060

Notes: Clustered (Country & Industry (CPA1)) standard-errors in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01. Controls include Exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table A11: PSM T-test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fixedassets	0.000532						
	(0.0447)						
Employment		0.0172					
		(0.0283)					
Innovation			-0.0640				
			(0.585)				
Exporter				0.00949			
				(0.0110)			
LaborProdGrowth					0.00537		
					(0.0110)		
ValueaddedGrowth						0.00566	
						(0.0102)	
AgeCategories							-0.00631
							(0.0162)
Observations	8218	8218	8218	8218	8218	8218	8212

Notes: The table presents the t-test results of the variables used in the matching. There is no statistically significant difference among treated and control group.