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Digital technologies and firm performance: Industry 4.0 in the Italian economy

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ABSTRACT

Digital technologies and firm performance: Industry 4.0 in the Italian economy

New digital technologies can generate substantial gains for adopting businesses. In this paper we put to the test the effects that these technologies have on firm performance. More specifically, we analyse the impact of new technologies associated with the Industry 4.0 paradigm on labour productivity, average wages and sales growth. The analysis is based on data drawn from *Rilevazione Imprese e Lavoro* (RIL) Survey run by the Inapp (Istituto nazionale per l'analisi delle politiche pubbliche) on a large representative sample of Italian firms. We merge Inapp data with Orbis archive data covering the period 2010-2014-2018. By applying a Diff-in-Diff methodology, we show that the adoption of digital technologies exerts positive effects on labour productivity, wages and sales. The positive impact is strong across performance outcomes for small and medium-size firms, even though the effects appear to be concentrated among more mature rather than younger firms. These results are robust to the unobserved heterogeneity and endogeneity issues.

KEYWORDS: digital technologies, Industry 4.0, firm performance, labour productivity, wages

JEL CODES: D20, L23, O33

1. Introduction

There are great expectations on the performance-enhancing effects of investments in new digital technologies (Syverson 2011; Brynjolfsson and McAfee 2014). Digital technologies should enable firms to improve business processes, to automate routine tasks and to reduce costs of interactions with suppliers and customers, thus increasing firm productivity (Bartel *et al.* 2007; Akerman *et al.* 2013; Graetz and Michaels 2018). However, empirical evidence at the firm levels is still scant (NAS 2017; Raj and Seamans 2019). Moreover, the available evidence is overwhelmingly focused on robotics, which is only one of a broader cluster of new enabling technologies (Martinelli *et al.* 2021) and is not unanimous in reflecting the revolutionary expectations placed on this new production paradigm (Acemoglu *et al.* 2014; DeStefano *et al.* 2018; Cette *et al.* 2017; Gal *et al.* 2019).

The links between adoption of digital technologies and productivity are complex, and their empirical identification has remained a challenge because of the scarcity of appropriate microdata (Raj and Seamans 2019). This has made the analysis of firm-level effects of adoption difficult or altogether impossible in many economic contexts. This is unfortunate because only the use of firm-level data can shed light on productivity and performance dynamics of today's businesses, so that management can make informed strategic decisions and policy-makers design suitable measures to support technical change and/or adapt to possible unanticipated consequences of the digital transformation of production.

In this paper we aim to contribute to this research agenda and help to fill the gap in the micro-level evidence on the performance effects of new digital technologies. By using new and original data on a large sample of Italian firms, we assess how and to which extent new digital technologies (Internet of Things, Robotics, Big Data Analytics, Augmented Reality, and Cybersecurity) affect labour productivity, (average) wages and firm growth. The data are drawn from the *Rilevazione Imprese e Lavoro* (RIL for short), run by the Inapp (Istituto nazionale per l'analisi delle politiche pubbliche). We exploit specific questions contained in the 2018 wave of the survey, which collected detailed information on investments in digital technologies associated with the so called 'Industry 4.0' paradigm (Kagermann *et al.* 2013) in a representative sample of Italian firms. We merge these data with Orbis archive records over the period 2010-2014-2018 and obtain a panel of approximately 3,000 firms. We explore the relationship between technology adoption, productivity and wage performance, and run further tests to evaluate whether the introduction of Industry 4.0 (I4.0) technologies is associated with firm growth. A Diff-in-Diff approach allows us to mitigate concerns for unobserved heterogeneity and endogeneity. To foreshadow our main results, we find that the adoption of digital technologies exerts a positive effect on labour productivity, average wages and sales. In the terms of magnitude of the effect, the largest increment is recorded on productivity. Moreover, the positive impact of I4.0 appears to be especially strong for small and medium-size firms.

In section 2 we review the relevant literature. In section 3 we describe the data and provide initial insights from descriptive statistics. Section 4 illustrates our econometric strategy. Section 5 presents our main results and sensitivity analyses by firm size and firm age. Section 6 brings the contribution to a close by reflecting on the limitations of the study, on the possible lines of future research, and on the broader implications of our findings.

2. Background literature

Since the emergence of the ICT revolution, the complex interplay between advanced technologies and the dynamics of productivity, wages and employment has been the subject of a vast theoretical and empirical economic literature (Greenwood *et al.* 1997; Jorgenson 2001; Bresnahan *et al.* 2002; Brynjolfsson and Hitt 2003)[1]. The introduction of newer digital technologies and their convergence into a broader set of production and service delivery processes adds to the renewed interest in the role and effects of information technology in contemporary economic systems and their growth (Acemoglu *et al.* 2014).

It is indeed important to bear in mind the broad context of this debate, because the diffusion of digital technologies in many advanced economies has been accompanied by a significant slowdown in labour productivity growth and a decoupling between productivity and wage growth, with consequent distributional issues, such as the persistent decline in aggregate wage share (ILO and OECD 2015; OECD 2018; IMF 2017). Many contributions have been proposed in the literature on the technological drivers of these macroeconomic dynamics, through both theoretical and empirical investigations (Acemoglu 1998, 2002; Karabarbounis and Neiman 2014; Schwellnus *et al.* 2018; Pak and Schwellnus 2019). Evidence of these phenomena is also reflected in heterogeneous patterns of functional income distribution at both sector level (De Serres *et al.* 2001; Alvarez- Cuadrado *et al.* 2018; Beqiraj *et al.* 2019) and firm level (Schwellnus *et al.* 2018), with different paces of growth observed for labour productivity and for wages (Schwellnus *et al.* 2017).

Interestingly, the slowdown of aggregate productivity growth has been proceeding against increased adoption of new digital technologies, and this highlights a puzzling interplay between the new technologies and the aggregate performance patterns of economic systems. The weak aggregate productivity gains deriving from the increasing digitalization process of advanced economies has been defined as the "*modern productivity paradox*" (Gordon 2012; Acemoglu *et al.* 2014; Brynjolfsson *et al.* 2017).

Recent studies (see for example OECD 2018 and 2019) have pointed out how the discrepancy between digitalization and the effective productivity gains from such process may be due to deficiencies in key complementarities related to the diffusion of digital technologies, such as: i) complementarities among different technologies (Carlaw and Lipsey 2002); ii) complementarities at the level of firm capabilities, including managerial and organizational practices, adaptive routines, absorptive capacity (in line with Cohen and Levithal 1990; Winter 2003; Dosi *et al.* 2000); and iii) complementarities between policies with different objectives (OECD 2018). The weaker productivity dynamics has also led to a slowdown in average wage growth, especially in those economies where "decoupling" had already been observed during the past decades (OECD 2018), with a certain degree of dispersion of both productivity and wage dynamics at a firm-level (Berlingieri *et al.* 2017; Pieri *et al*. 2018; Cirillo and Ricci 2020).

Against this backdrop, Andrews *et al.* (2016) point to the uneven diffusion of digital technologies among firms, especially in ICT vs. non-ICT service sectors, as a potential source of the aggregate

[1] See also Jovanovic and Rousseau (2005) and Bresnahan (2010), for discussions of ICT as a general purpose technology.

slowdown of labour productivity. Gal *et al.* (2019) recently stressed how digitalization may represent a possible cause of the phenomenon due to greater difficulties faced by laggard and less productive firms in attracting high(er)-skilled labour, a likely complement to the use of new digital devices (Cirillo *et al.* 2020b)[2]. Gal *et al.* (2019) combine industry level-data on technology adoption with firm-level data on productivity. The technologies under investigation are high-speed broadband, digital planning systems, customer relationship management software, and cloud computing. Not all these technologies can be classed as 'new' digital technologies, but the analysis of their adoption is nonetheless relevant because it integrates the available evidence provided by studies that focus on robots through the use of aggregate sales data drawn from the International Federation of Robotics records (e.g. Graetz and Michaels 2018; Douth *et al.* 2018; and Acemoglu and Restrepo 2020). In reviewing this literature, Seamans and Raj (2018) have stressed the need for more firm-level analyses: while aggregate data can be useful to identify cross-country and cross-sectoral differences, they do not allow to say very much on micro-dynamics and within-sector productivity differentials.

Higher-quality microdata have appeared in very recent literature, even though they are mostly limited to the adoption of robotics technologies. Koch *et al.* (2021) use Spanish data from the ESEE Survey (*Encuesta Sobre Estregias Empresariales*) to study the effects of industrial robots in manufacturing. They find that robot adoption produces from 20 to 25% output gains, reduces labour costs and positively contributes to firm employment growth (at an average rate of approximately 10%). Acemoglu *et al.* (2020) and Domini *et al.* (2021) study the effects of investments in robots made by French firms. Acemoglu *et al.* (2020) show that adopting firms, while reducing the labour share and the share of production workers, increase their productivity and grow more than competitors; Domini *et al.* (2021) also find positive (employment) growth effects.

It is important to stress that the ongoing transformation of productive processes is not limited to the adoption of robots, and it is equally important to stress that robots may not even be the latest available technologies (they have been operating in manufacturing plants for decades now) unless we consider their convergence with newer technologies such as Big Data and Internet of Things[3]. This is fully reflected in the policy agenda that has emerged in several countries to foster the upgrading of productive systems through "smart" manufacturing technologies, clustered under the Industry 4.0 paradigm (Kagermann *et al.* 2013).

In this paper we extend the study of the effects of new digital technology adoption to a more comprehensive set of technologies, and draw evidence from new and original data on a large sample of Italian firms. The objective is to deepen our understanding of the micro-foundations of productivity

[2] Several contributions have focused on the impact of new digital technologies on employment and have devoted special attention to the effect of the automation on both the task content of occupations and aggregate outcomes in terms of job creation or destruction. The specific focus of this paper is on the effects of digital technology adoption on firm performance. As we cannot adequately cover here all existing literature on the relationship between new technologies (including robotics and artificial intelligence) on jobs, we refer the reader to Goos *et al.* (2014), Autor (2015), Brynjolfsson and McAfee (2016), Frey and Osborne (2017), Brynjolfsson *et al.* (2017), Felten *et al.* (2018), Balsmeier and Woerter (2019), Acemoglu and Resptrepo (2020), Domini *et al.* (2021), Cirillo *et al.* (2020a).

[3] One may be tempted to overemphasise the role of Artificial Intelligence in modern manufacturing, even though its application is still quite limited (Martinelli *et al.* 2021).

growth that is fuelled by technical change and to reflect on the joint effects of digital technologies on different dimensions of firm performance.

3. Data and descriptive statistics

The empirical analysis draws on data from the last three waves of the *Rilevazione Imprese e Lavoro* (RIL) conducted by Inapp in 2010, 2015 and 2018 on a representative sample of partnerships and limited liability firms[4].

Each wave of the survey covers over 25000 firms operating in non-agricultural private sector. A subsample of the included firms (around 40%) is followed over time, making the RIL dataset partially panel over the period under investigation.

The RIL-Inapp survey collects a rich set of information about the composition of the workforce, including the amount of investments in training, hiring and separations, the use of flexible contractual arrangements, the asset of the industrial relations and other workplace characteristics. Moreover, the data contains an extensive set of firm level controls, including management and corporate governance characteristics, productive specialization and other variables proxying firm strategies (such the introduction of product and process innovations and share of exports on value added).

The V wave of the RIL-Inapp survey includes a set of questions specifically designed to collect information on the introduction of new digital technologies.

The key question concerns investments over the period 2015-2017 ("In the period 2015-2017 did the firm invest in new technologies?"), and the respondent can choose among the following answers: Internet of things (IoT), Robotics, Big data analytics, Augmented reality and Cybersecurity. Although multiple answers are allowed, we adopt a dichotomous measure of Industry 4.0 investment and code a variable that is equal to 1 if a firm invested in at least one specific technology, 0 otherwise.

In order to investigate the impact of technology adoption on labour productivity, wages and employment, we merge RIL data with Orbis archive provided by Moodys' over the period 2010-2018 by tracking the identification code of companies.

The Orbis records offer comprehensive information on the balance sheets of the vast majority of Italian companies operating in the private sector. The merged dataset contains yearly values of financial variables such as revenues, value added, net profits, book value of physical capital, total wage bill and expenditures in raw-materials. Thus, we have information on labour productivity (value added per employee), sales (total revenues from sales per employee), wages (total labour cost per employee), fixed capital (the total amount of physical assets per employees) and other balance sheet variables (raw material expenditures, net profits ecc.). We exclude from the RIL-Orbis merged dataset firms with less than 5 employees, and firms with missing information for key variables.

[4] The RIL-Inapp survey sample is stratified by size, sector, geographical area and the legal form of firms. Inclusion depends on firm size, measured by the total number of employees. This choice has required the construction of a "direct estimator" which is defined for each sample unit (firm) as the inverse of the probability of inclusion in the sample. For more details on RIL questionnaire, sample design and methodological issues see: <http://www.inapp.org/it/ril>.

The resulting (longitudinal) RIL-Orbis sample consists of approximately 3,000 firm-year observations over the 2010-2018 period.

3.1 Descriptive statistics

Table 1 shows mean and standard deviation of labour productivity, average wages and sales per employee for two groups of firms. The first one includes firms that invested in digital technologies over the period 2015-2017, and which can thus be defined as "treated". The second group – defined as the "control" – includes firms that did not make digital investments. Both the treated and the control groups are observed at three points in time: 2010, 2015 and 2018. Bearing in mind that the treatment event (i.e. adoption) is recorded in 2018, we report for each period, corresponding to one RIL-Inapp survey wave, also the distribution of covariates in the treatment and control groups before and after treatment.

The figures indicate that on average adopting firms present a higher share of tertiary and upper secondary educated workers; are less likely to be managed by family owners while they have a higher incidence of tertiary educated management.

Treated firms are more likely to operate in international markets, to sign foreign trade agreements, to introduce product and process innovations, to sign second level bargaining agreements. These firms are more likely located in Northern Italian regions and less likely to be microenterprises. Furthermore, there are differences between the two groups of firms at the level of their managerial characteristics. In the treatment group we detect a declining trend in the share of firms with lower secondary-educated management, whereas the opposite occurs in the control group: in the latter, over the 2010-2014 period, lower secondary-educated management grew by 4 percentage points, whereas tertiary educated and upper secondary educated management fell by 3 percentage points.

The share of firms whose management is more than 54 years old grew by almost 10 percentage points in the control group, while the share of firms whose managers are young (less than 35 years old) declined by 6 percentage points. Different trends between the two groups can also be observed for other workforce characteristics (share of blue collars) and vacancies. The groups are instead similar in the dynamics over time of tertiary, secondary and lower secondary educated workers, and their share of female, old and middle-aged workers[5].

The data are very rich, and therefore informative, but the identification strategy will have to take into explicit consideration firm heterogeneity between groups.

[5] For the interested reader, table A1 in the appendix shows the incidence of I4.0 investments by firms' size, macro-region, sector of activity and age separately for the cross-section and for the panel component. In terms of coverage by size, age and sector, the statistics show satisfactory coverage and good balance between smaller vs. larger firms, older vs. younger firms and across sectors of activities. Overall, figures of table A1 describe a larger diffusion of investments in new enabling technologies among large and young manufacturers located in Northern Italy.

Table 1. Descriptive statistics for explanatory variables, by sample year and treatment status

	Pre-treat				Pre-control				Post treat		Post control	
	2010		2015		2010		2015		2018			
	Mean	**std dev**	**Mean**	**std dev**	**Mean**	**std dev**	**Mean**	**std dev**	**Mean**	**std dev**	**Mean**	**std dev**
Labour productivity	10.8	0.49	10.8	0.7	10.7	0.48	10.7	0.52	11.0	0.50	10.8	0.56
Average Wages	10.4	0.37	10.5	0.40	10.3	0.39	10.4	0.49	10.56	0.33	10.43	0.44
Sales per employee	12.11	0.81	12.05	0.77	12.02	0.86	11.95	0.94	12.07	0.90	11.91	0.84
Management												
Tertiary ed	0.28	0.45	0.28	0.45	0.26	0.44	0.23	0.42	0.28	0.45	0.24	0.43
Upper secondary ed	0.56	0.50	0.57	0.49	0.56	0.50	0.53	0.50	0.58	0.49	0.55	0.50
Lower secondary ed	0.16	0.37	0.15	0.36	0.19	0.39	0.23	0.42	0.14	0.35	0.21	0.41
Share of women	0.10	0.30	0.11	0.32	0.14	0.35	0.16	0.37	0.13	0.34	0.16	0.37
Age>54	0.30	0.46	0.31	0.46	0.27	0.45	0.37	0.48	0.34	0.47	0.36	0.48
34<age<55	0.30	0.46	0.29	0.45	0.30	0.46	0.25	0.43	0.20	0.40	0.19	0.39
Age<35	0.07	0.25	0.03	0.16	0.11	0.31	0.05	0.23	0.03	0.17	0.04	0.20
Family ownership	0.85	0.35	0.85	0.35	0.88	0.33	0.91	0.29	0.86	0.35	0.88	0.33
Dynastic management	0.86	0.35	0.86	0.35	0.91	0.29	0.90	0.31	0.85	0.36	0.91	0.29
Workforce												
Tertiary ed	0.10	0.16	0.12	0.20	0.09	0.17	0.10	0.20	0.13	0.20	0.12	0.21
Upper secondary ed	0.50	0.28	0.52	0.28	0.46	0.29	0.47	0.29	0.53	0.28	0.50	0.31
Lower secondary ed	0.40	0.31	0.36	0.30	0.45	0.32	0.42	0.32	0.34	0.29	0.38	0.33
Share of women	0.34	0.26	0.38	0.27	0.32	0.26	0.35	0.28	0.35	0.25	0.35	0.28
Share of workers >50	0.16	0.14	0.24	0.18	0.16	0.16	0.26	0.22	0.32	0.23	0.31	0.23
Share of workers 35-50	0.51	0.21	0.51	0.21	0.52	0.23	0.50	0.24	0.45	0.22	0.44	0.24
Executives	0.04	0.08	0.04	0.07	0.04	0.10	0.04	0.10	0.04	0.08	0.04	0.09
White collars	0.43	0.30	0.47	0.32	0.36	0.28	0.39	0.30	0.44	0.31	0.39	0.32
Blue collars	0.53	0.32	0.49	0.33	0.59	0.31	0.56	0.32	0.52	0.32	0.57	0.33
Share of temporary w.	0.10	0.15	0.08	0.16	0.10	0.16	0.07	0.14	0.12	0.17	0.12	0.18
Share of migrants	0.05	0.10	0.05	0.09	0.05	0.10	0.04	0.11	0.05	0.11	0.05	0.10
Firms												
Vacancy	0.15	0.35	0.15	0.36	0.10	0.29	0.06	0.23	0.24	0.43	0.15	0.36
Foreign markets	0.43	0.49	0.40	0.49	0.27	0.45	0.28	0.45	0.46	0.50	0.26	0.44
Multinationals	0.02	0.13	0.03	0.18	0.02	0.15	0.01	0.12	0.02	0.12	0.02	0.15
Foreign trade agree.	0.21	0.40	0.18	0.38	0.15	0.35	0.10	0.31	0.25	0.43	0.13	0.34
Foreign direct inv	0.05	0.22	0.02	0.15	0.01	0.12	0.02	0.12	0.04	0.20	0.01	0.10
Outsourcing	0.02	0.13	0.06	0.24	0.01	0.08	0.03	0.16	0.01	0.11	0.00	0.06
Employers' association	0.64	0.48	0.63	0.48	0.59	0.49	0.58	0.49	0.59	0.49	0.56	0.50
II level bargaining	0.12	0.33	0.12	0.32	0.06	0.24	0.04	0.20	0.17	0.38	0.07	0.25
Product innov	0.51	0.50	0.49	0.50	0.39	0.49	0.30	0.46	0.50	0.50	0.26	0.44
Process innov	0.48	0.50	0.39	0.49	0.31	0.46	0.24	0.43	0.47	0.50	0.21	0.41
Irap tax cut	0.00	0.00	0.07	0.25	0.00	0.00	0.03	0.17	0.06	0.23	0.02	0.15
Firms' age (in years)	24.07	18.26	27.60	13.99	21.86	14.99	26.28	13.85	31.64	14.81	29.85	14.75
N of empl<10	0.26	0.44	0.38	0.49	0.44	0.50	0.51	0.50	0.30	0.46	0.47	0.50
9< n of empl<50	0.58	0.49	0.51	0.50	0.49	0.50	0.46	0.50	0.58	0.49	0.49	0.50
49<n of empl<100	0.08	0.28	0.06	0.23	0.04	0.19	0.02	0.13	0.06	0.24	0.02	0.14
99<n of empl<250	0.05	0.21	0.03	0.17	0.02	0.13	0.01	0.10	0.03	0.16	0.01	0.10
N of empl>249	0.03	0.16	0.02	0.14	0.01	0.08	0.00	0.06	0.02	0.14	0.00	0.07
ln (phy capital pc)	9.97	1.61	9.87	1.64	10.00	1.65	9.75	1.82	10.11	1.63	9.72	1.81
North Ovest	0.36	0.48	0.48	0.50	0.29	0.45	0.39	0.49	0.49	0.50	0.42	0.49
North East	0.32	0.47	0.29	0.46	0.27	0.44	0.28	0.45	0.29	0.46	0.26	0.44
Centre	0.19	0.40	0.15	0.36	0.24	0.43	0.19	0.39	0.16	0.37	0.21	0.41
South	0.12	0.33	0.08	0.27	0.21	0.41	0.15	0.36	0.06	0.23	0.11	0.31
N of obs	1,082		1,208		1,168		1,301		1,140		1,146	

Note: sampling weights applied.
Source: our calculations on RIL-Orbis merged sample

4. Econometric strategy

To assess the impact of digital technology adoption on firm performance, we estimate the following linear relationship:

$$Y_{i,t} = \alpha+\beta_1 \, I4.0_i+\beta_2 \, year\ 2018+\beta_3 I4.0_i{*}year2018 + \gamma M_{i,t}+\delta W_{i,t}+\lambda F_{i,t}+\mu_i+\varepsilon_{i,t} \quad [1]$$

where $Y_{i,t}$ indicates alternatively the (log of) labour productivity, the (log of) average wages, and the (log of) sales per employees for each *i* firm at the sample year t=[2010, 2014,2018]. Our key explanatory variable $I4.0_i$ is a dummy equal to 1 whether the firm invested in at least one digital technology among Internet of things (IoT), Robotics, Big data analytics, Augmented reality and Cybersecurity over the 2015-2017 period, and 0 otherwise. The year 2018 is a time indicator for the "post-treatment" period while the interaction term $I4.0_i{*}$year2018 identifies the Diff-in-Diff effect of digital investments over the period 2015-2017 on firms' performance. Among the other controls, vector $M_{i,t}$ includes managerial and corporate governance characteristics, $W_{i,t}$ represents the workforce composition while $F_{i,t}$ captures a rich set of firms' productive characteristics, geographical location and sectoral specialization (for further details see table 1). Furthermore, the parameters μ_i are firm fixed-effects capturing time-invariant unobserved heterogeneity, while $\varepsilon_{i,t}$ is the idiosyncratic error term.

To begin with, we perform Pooled OLS regressions of the equation [1] by imposing the parameter β_3=0. In this case the coefficient estimates associated with β_1 are expected to be unbiased if time invariant unobserved heterogeneity and endogeneity issues play no significant role in shaping the impact of digital investment on firms' performance.

On the other hand, recent literature (Bessen *et al.* 2019; Domini *et al.* 2021) has pointed out that investments in advanced manufacturing technologies tend to be lumpy, and their effect may be difficult to observe unless this aspect is taken into account. In the design of our study we are helped by the timing of the 2018 survey, which followed the implementation of the Italian 'National Enterprise Plan 4.0', an incentives scheme introduced by the Italian Government to lower financial constraints to investment and accelerate the diffusion of digital technologies through tax credits. This exogenous discontinuity is very useful for analytical purposes. Moreover, because all firms were eligible to the scheme and all of them automatically received the incentive if they invested, the policy was 'neutral' with respect to firm characteristics and did not involve any external selection into the scheme.

It must nevertheless be acknowledged that the identification of post-adoption effects poses both theoretical and empirical challenges. First of all, it is difficult to fully take into account the complex interplay between technology and productivity, and the strong complementarities between technology, labour and work organisation. Second of all, there is a risk of endogeneity resulting from both reverse causality and common factors influencing productivity and adoption. As stated in Gal *et al.* (2019), reverse causality arises from the fact that digital adoption may be easier for relatively more productive firms that have resources to invest in new digital technologies. In addition, potential drivers of digital adoption such as workforce and managerial skills, institutional or industrial relations, or favourable business environments can impact productivity directly, and indirectly through digital adoption. This could lead to upward bias in the estimates.

In order to tackle these issues we apply Diff-in-Diff models on the equation [1] by exploiting the three-period structure of the RIL-Orbis sample and a very rich set of firm level observational data on both treatment and a control groups in the pre- and post-investment periods. In this framework the treatment group are those firms declaring to have invested in I4.0 over 2015-2017 (I4.0=1) while the control group contains those firms that did not invest in I4.0 in the same time span (I4.0=0). Then the Diff-in-Diff fixed effect estimates of the parameter β_3 is expected to identify the causal impact of Industry 4.0 investments on productivity, wages and sales.
It is worth to notice that the crucial assumption to obtain unbiased estimates of β_3 is the so-called Common Trend Assumption (CTA). This implies that we should observe parallel trends in the outcome of treated and control firms in absence of treatment. If CTA holds, compared to the fixed effects estimator, the Diff-in-Diff estimator has the advantage of removing any common period effects influencing the treatment and control group in identical ways (see Gebel and Vossemer 2014). Further, in order to avoid potential biases due to omitted variables, we include a broad set of controls for managerial, organisational and corporate features, as well as firm internationalization and innovation. Different streams of literature have highlighted that divergences in firm performances can be linked to (i) management and corporate governance characteristics that are important sources of firm unobserved heterogeneity (Damiani *et al.* 2020; Bloom and Van Reenen 2011); (ii) highly idiosyncratic technological-organizational capabilities, rooted in the procedural knowledge of the organizations (firms), which manifest themselves using highly complementary inputs (Costa *et al.* 2020). Since we are able to include several proxies for these covariates we are confident that potential bias stemming from omitted variables is reduced and effects of digital technologies on firm performance are correctly identified.

5. Results

Table 2 shows the pooled OLS and Diff-in-Diff Fixed Effects estimates of equation [1] for the whole sample.
The pooled OLS results reported in the first column of table 2 indicate a positive correlation (+6%) between investment in digital technologies and labour productivity, with respect to firms not investing in new enabling technologies. As discussed before, the OLS estimates may be biased due to time-invariant unobserved heterogeneity and reverse causality, even though we control for a wide set of observed explanatory variables. The Diff-in-Diff FE estimates displayed in the second column reveal that this is not the case: here we find that digital investments increase by 5% labour productivity, a figure in line with the OLS estimates. Note that the validity of the common trend assumption is confirmed: the coefficient for the interaction between the I4.0 dummy variable and the indicator for pre-treatment year 2014 is statistically not significant. In other words, controlling for confounding factors related to firm time-invariant unobserved heterogeneity and endogeneity risk, we observe that the positive impact generated on labour productivity by the adoption of digital technologies still holds. This result supports the hypothesis that new enabling technologies bring about higher efficiency of production, as was suggested by Bartel *et al.* (2007), Brynjolfsson *et al.* (2008) and Akerman *et al.* (2013).

When we focus on average wages, the pooled OLS estimates in the third column of table 2 indicate a positive association between the adoption of digital technologies and wages (1,9%). The Diff-in-Diff FE estimate of the interaction term I4.0*year 2018 – in the fourth column of table 2 – confirms in both statistical significance and magnitude the pooled OLS results. This suggests that at least some of the productivity gains are reflected in firm-level wage dynamics. Again, the common trend assumption holds – the interaction term I4.0*2014 has a statistically non-significant coefficient.
Finally, table 2 indicates a positive impact of digital investments on firm sales. The latter have increased, on average, by 4% due to the adoption of new enabling technologies. In this case too, the non-significant interaction between the adoption dummy variable and the 2014 time dummy supports the validity of the Common Trend Assumption. In other words, there is a parallel trend in sales per employee between firms in the treated and in the control groups up until the technology adoption event recorded in the 2018 survey.

Table 2. Main estimates

	Labour productivity		**Average wage**		**Sales per employee**	
	OLS	DIFF-FE	OLS	DIFF-FE	OLS	DIFF FE
Ind 4.0	0.058***		0.019*		0.041*	
	[0.019]		[0.012]		[0.027	
Ind 4.0*year 2018		0.051**		0.018*		0.048**
		[0.020]		[0.011]		[0.021]
Ind 4.0*year 2014		0.027		-0.009		0.014
		[0.019]		[0.011]		[0.018]
year 2018	-0.023	0.015	-0.009	0.052***	-0.020	-0.036*
	[0.016]	[0.017]	[0.010]	[0.010]	[0.023]	[0.020]
year 2014	-0.035***	-0.02	-0.015**	0.028***	-0.043***	-0.042***
	[0.011]	[0.015]	[0.007]	[0.009]	[0.014]	[0.015]
Management ch	Yes	Yes	Yes	Yes	Yes	Yes
Workforce ch	Yes	Yes	Yes	Yes	Yes	Yes
Firms ch	Yes	Yes	Yes	Yes	Yes	Yes
constant	9.853***	9.778***	10.048***	10.005***	10.528***	11.048***
	[0.088]	[0.189]	[0.064]	[0.130]	[0.131]	[0.243]
N of Obs	6971	6963	7251	7240	7244	7244
R2	0.378	0.105	0.455	0.183	0.421	0.104

Note: managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects. Clustered standard errors in parentheses: * statistical significance at 10%, ** at 5%, *** at 1%.
Source: our elaborations on RIL-Orbis merged sample

5.1 Heterogeneity of effects by firm size

The adoption of new enabling technologies may have different effects on small and large firms due to different opportunities and challenges in adopting and extracting gains from digital investments. According to the OECD (2019), small and medium firms can take advantage of digital technologies to improve access and use of skills and in the outsourcing of key business functions (integrated production processes) that improve firm performance. There are indeed conspicuous differences in the uptake of digital technologies among firms of different sizes, as also documented in Cirillo *et al.* (2020b), who point out that the rate of adoption of new enabling techs more than doubles among large companies with respect to small firms.

Table 3 reports pooled OLS and Diff-in-Diff FE estimates of labour productivity generated by separate regressions for small and medium firms (with less than 50 employees) and medium-large and large companies (with at least 50 employees). Perhaps surprisingly, the estimates suggest that productivity gains are more likely to occur in small and medium firms compared to medium-large and large companies. In the short-run SMEs register a 6% increase in labour productivity, whereas no effects are detected among larger companies. This may be explained by a different time span of realization of productivity gains: in large companies the adoption of new technologies may require long adjustments of existing production processes and therefore it is highly likely that in these more complex organisations productivity gains induced by I4.0 investments take longer to realise.

Table 3. Estimates labour productivity by firms size

	N of employees <50		**N of employees >49**	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	0.070***		0.038	
	[0.023]		[0.033]	
Ind 4.0*year 2018		0.066***		0.029
		[0.024]		[0.035]
Ind 4.0*year 2014		0.033		0.067
		[0.021]		[0.047]
Year 2018	-0.016	0.015	-0.023	0.032
	[0.019]	[0.020]	[0.032]	[0.031]
Year 2014	-0.031**	-0.006	-0.039*	-0.063
	[0.014]	[0.016]	[0.023]	[0.045]
Management ch	Yes	Yes	Yes	Yes
Workforce ch	Yes	Yes	Yes	Yes
Firms ch	Yes	Yes	Yes	Yes
Constant	10.069***	10.110***	9.467***	9.722***
	[0.097]	[0.184]	[0.157]	[0.328]
Obs	4873	4873	2090	2090
R2	0.32	0.07	0.49	0.138

Note: managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects. Clustered standard errors in parentheses: * statistical significance at 10%, ** at 5%, *** at 1%.
Source: our elaborations on RIL-Orbis merged sample

Wages in small and medium-small companies mirror labour productivity dynamics: they are positively associated to digitalization only in those firms with less than 50 employees. Investment in digital technologies increases firm average wage by 2.3% in small and medium-small firms, whereas it does not affect wages in medium-large and large companies (table 4). It is possible that the lack of effects among larger companies is due not only to longer productivity and wage adjustment periods (note that the result is in line with the effect recorded for productivity gains in larger firms), but also to possible internal wage dispersion over a much bigger range between top and bottom-level salaries. The second interesting point that can be made on this result is that, even though we observe some redistribution in the groups where productivity gains are observed, the labour share is smaller compared to the productivity growth figures that we can attribute to digital technology adoption. The difference is almost 3 percentage points. This is arguably an indication of weak redistribution of returns to technological change, in line with the dominant pattern of wage-productivity decoupling detected in several countries over the last decade (OECD 2018).

Table 4. Estimates average wage by firms' size

	N of employees <50		**N of employees >49**	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	0.031**		-0.010	
	[0.014]		[0.020]	
Ind 4.0*year 2018		0.023*		-0.004
		[0.014]		[0.018
Ind 4.0*year 2014		-0.011		0.014
		[0.013]		[0.019]
year 2018	-0.019	0.044***	0.027	0.075***
	[0.012]	[0.012]	[0.021]	[0.018]
year 2014	-0.010	0.034***	-0.012	0.005
	[0.009]	[0.010]	[0.012]	[0.017]
Management ch	Yes	Yes	Yes	Yes
Workforce ch	Yes	Yes	Yes	Yes
Firms ch	Yes	Yes	Yes	Yes
constant	10.118***	10.006***	10.047***	10.163***
	[0.071]	[0.134]	[0.125]	[0.175]
Obs	5105	5105	2135	2135
R2	0.378	0.126	0.613	0.276

Note: managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects. Clustered standard errors in parentheses: * statistical significance at 10%, ** at 5%, *** at 1%.
Source: our elaborations on RIL-Orbis merged sample

Table 5 provides the estimates of the relationship between I4.0 investments and firms' profitability expressed as sales per employee. Also this result goes hand in hand with labour productivity, and indicates an increase of about 6% in those firms investing in new technologies compared to firms that do not invest. However, the relationship between technology adoption and sales is particularly strong in medium and medium-small companies with less than 50 employees, but disappears in medium-large and large firms. One possible explanation is again that it may take longer for larger firms to capture returns from investment, possible because they need to complete a longer plan of upgrading through replacement of a larger installed base of manufacturing equipment. It could also be the case the smaller companies, which may cover their whole production with one-off discrete investments in new technologies, can also take advantage of the fact that many of these enabling technologies (e.g. 3D printing, cloud, and cybersecurity) can offer immediate cost advantages that are not conditional on economies of scale (Weller *et al.* 2015).

Table 5. Estimates sales per employees by firm size

	N of employees <50		N of employees >49	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	0.069**		0.001	
	[0.032]		[0.054]	
Ind 4.0*year 2018		0.067***		0.006
		[0.025]		[0.035]
Ind 4.0*year 2014		0.021		0.002
		[0.020]		[0.034]
Year 2018	-0.018	-0.039*	0.000	-0.012
	[0.026]	[0.020]	[0.051	[0.037]
Year 2014	-0.046***	-0.043***	-0.019	-0.022
	[0.017]	[0.016]	[0.027]	[0.028]
Management ch	Yes	Yes	Yes	Yes
Workforce ch	Yes	Yes	Yes	Yes
Firms ch	Yes	Yes	Yes	Yes
Constant	10.826***	11.277***	10.059***	9.995***
	[0.141]	[0.231]	[0.258]	[0.443]
Obs	5106	5106	2138	2138
R2	0.376	0.053	0.522	0.129

Note: managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects. Clustered standard errors in parentheses: * statistical significance at 10%, ** at 5%, *** at 1%.
Source: our elaborations on RIL-Orbis merged sample

5.2 Heterogeneity of effects by firm age

According to the Digital Transformation Scoreboard (2018), young European firms (under 5 years old) and mid-aged firms (between 10 and 15 years old) register that the highest frequency of technology adoption, while firms aged between 6 and 10 years and over 15 years have the lowest share of adoption. These discontinuities are not easy to explain and there is scant empirical evidence on the relationship between firm age and digital technology adoption. On the one hand, there is an argument that modern young firms are “born digital” (Nambisan 2017) and in the aftermath of their formation it is unlikely that they will immediately change their technology of production or business model. On the other hand, young firms typically face more financial constraints compared to more mature firms, and these constraints may prevent, via barriers to technology adoption, the exploitation of opportunities to better manage information flows, enter new markets and challenge the competitive position of larger incumbents (OECD 2019).

Table 6 shows pooled OLS, Diff-in-Diff FE estimates for labour productivity by performing separate regressions for the subsample of firms with less than 15 years old in 2018 (i.e., less than 10 years old in 2014) and those with 15 or more years old in 2018. Results show that younger firms investing in digital technologies did not register statistically significant productivity gains, whereas more mature firms recorded increases in productivity of about 6%.

Table 6. Estimates labour productivity by firms age

	Firms age 2018 <15		**Firms age 2018 >14**	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	-0.119		0.071***	
	[0.078]		[0.019]	
Ind 4.0*year 2018		-0.085		0.060***
		[0.078		[0.020]
Ind 4.0*year 2014		0.001		0.032
		[0.072		[0.020]
Year 2018	0.105*	0.053	-0.034**	0.012
	[0.062]	[0.061]	[0.017]	[0.017]
Year 2014	0.008	-0.011	-0.037***	-0.023
	[0.045]	[0.054]	[0.012]	[0.015]
Management ch	Yes	Yes	Yes	Yes
Workforce ch	Yes	Yes	Yes	Yes
Firms ch	Yes	Yes	Yes	Yes
Constant	9.356***	9.516***	9.886***	9.797***
	[0.380]	[0.396]	[0.091]	[0.197]
Obs	426	424	6545	6539
R2	0.468	0.332	0.376	

Note: managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects. Clustered standard errors in parentheses: * statistical significance at 10%, ** at 5%, *** at 1%.
Source: our elaborations on RIL-Orbis merged sample

The evidence seems to indicate that there is merit in the suggestion that increments in the digital endowments of young firms does not fundamentally change their productivity dynamics because the productive assets with which these firms are born is much closer to the technological frontier compared to older firms[6]. At the same time, we cannot rule out that strong complementarities are required between digital technologies and organizational capabilities (Dosi 2012; Costa *et al.* 2020),

[6] Unfortunately, we cannot test this speculative argument because we do not have any information about the type of productive assets firms have at birth.

managerial and human capital skills (Brynjolfsson and Hitt 2000; Basu *et al.* 2003; Bugamelli and Pagano 2004; Bloom *et al.* 2012); and R&D and intangible investments (Corrado *et al.* 2017; Mohnen *et al.* 2018). Complementarities might require longer periods of adjustment and co-development, and this factor might play a role in generating comparatively weaker productivity gains among less mature firms.

If we turn to wages, consistently with results we obtained for labour productivity, table 7 shows a positive effect of I4.0 investment among more mature firms (more than 14 years old in 2018). More precisely, a firm that has invested in digital technologies experienced on average an increase of firm average wage of about 2.6%. Once again, while we notice that some redistribution of productivity gains due to digital investments is taking place, productivity gains are more than double the magnitude of wage growth.

Table 7. Estimates average wage by firm age

	Firms age 2018 <15		**Firms age 2018 >14**	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	-0.067 [0.062]		0.025** [0.012]	
Ind 4.0*year 2018		-0.062 [0.061]		0.026** [0.012]
Ind 4.0*year 2014		-0.073 [0.058]		-0.001 [0.011]
Year 2018	0.098* [0.052]	0.114** [0.048	-0.018* [0.011	0.047*** [0.01
Year 2014	0.015 [0.045]	0.054 [0.043]	-0.013* [0.007]	0.024*** [0.008]
Management ch	Yes	Yes	Yes	Yes
Workforce ch	Yes	Yes	Yes	Yes
Firms ch	Yes	Yes	Yes	Yes
Constant	9.699*** [0.355]	9.539*** [0.350]	10.076*** [0.065]	10.042*** [0.112]
Obs	450	448	6798	6792
R2	0.371	-0.299	0.464	-0.367

Note: managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects. Clustered standard errors in parentheses: * statistical significance at 10%, ** at 5%, *** at 1%.
Source: our elaborations on RIL-Orbis merged sample

Finally, we find that investments in new enabling technologies increase average sales by about 5% (table 8), but this increment is concentrated among more mature companies. When we take together the results of tables 6 and 8, those presented in tables 3 and 5, the message is that the greatest performance improvements which can be directly related to the new technologies cluster among the smaller and more mature businesses in our sample. It is possible that minimal exogenous relaxation of constraints to technology adoption, which coincide with the policy framework of the treatment event we are studying, may generate the most pronounced improvements in the firms that were relatively more distant from the production frontier. At the same time, it is possible that the introduction of radical (process) innovation in the form of digital production machinery is hindered by some forms of "organizational inertia" or inability of organizations to adapt their strategy and structure (Hannan and Freeman 1984). This problem is particularly relevant in larger and older organizations. This interpretation is also compatible with the view that complex organizational capabilities can generate economic returns in the long, rather than in the short run, because their development is slow and costly (Nelson and Winter 1982; Hannan and Freeman 1984). Only the availability of long-term performance indicators will be able to delve deeper into the lag structure of outcomes in the presence of firm heterogeneity.

Table 8. Estimates sales per employees by firm age

	Firms age 2018 <15		**Firms age 2018 >14**	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	-0.203 [0.134]		0.063** [0.027]	
Ind 4.0*year 2018		0.013 [0.114]		0.053*** [0.020]
Ind 4.0*year 2014		-0.040 [0.110]		0.019 [0.018]
Year 2018.	0.210* [0.111]	0.015 [0.086]	-0.044* [0.023]	-0.037** [0.016]
Year 2014	-0.011 [0.067]	0.002 [0.080]	-0.047*** [0.014]	-0.047*** [0.014]
Management ch	Yes	Yes	Yes	Yes
Workforce ch	Yes	Yes	Yes	Yes
Firms ch	Yes	Yes	Yes	Yes
Constant	9.849*** [0.627]	10.343*** [0.522]	10.545*** [0.127]	11.166*** [0.179]
Obs	451	449	6801	6795
R2	0.460	-0.307	0.426	-0.494

Note: managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects. Clustered standard errors in parentheses: * statistical significance at 10%, ** at 5%, *** at 1%.
Source: our elaborations on RIL-Orbis merged sample

6. Conclusions

In this paper we contribute to the growing literature on the effects of new digital technologies on firm performance. We have answered the call made by Seamans and Raj (2018) to provide micro-level evidence on the ongoing process of industrial transformation. We have done so through a detailed analysis of new Italian data that contains rare information of investments in technologies associated with the Industry 4.0 paradigm. The main findings reveal that the adoption of these new technologies has a positive effect on labour productivity, on average wages, and on sales. The economic size of the effect on productivity and sales is approximately twice as large as the effect on average wages. We interpret this as an indication of weak redistribution of gains from technology adoption, in line with the dominant pattern of wage-productivity decoupling detected in several countries over the last decade.

Even though we use novel and highly relevant data and are able to apply an econometric strategy that limits unobserved heterogeneity and endogeneity concerns, our study has course limitations that only newer data and further research could address. Firstly, we observe only short-term performance effects of technology adoption, and it would be extremely interesting to extend the observation of outcomes to a longer period. A potential problem in this direction is the set of effects that the unfolding Covid-19 pandemic is producing on the economic performance of firms, regions and countries. Secondly, even though data on general investments are available with a panel structure, information on specific digital technologies investments is only recorded for the later period by the 2018 survey wave. Repeated observations of specific investments in advanced technologies would be extremely useful for further empirical investigations. Thirdly, the employment implications of technology adoption are certainly among the most important outcomes and an obvious next step in this research agenda. Matched employer-employee data could shed new light on wage dispersion dynamics – arguably polarisation – within firms, but these data are not yet available in connection with firm-level observations of new technology adoption, and in this study we have limited our analysis to average wages, leaving for further research the important problem of the broader workers-level implications (e.g. quality of work, task structure of work, new hiring and separations, and of course wages). Fourthly, this study has been conducted in a specific context – the Italian economy – and more comparative data are needed to qualify the ability to generalise our findings. When we compare our results with related studies about the performance effects of new technology in France (Acemoglu *et al.* 2020; Domini *et al.* 2021) and in Spain (Koch *et al.* 2021), we all find evidence of a positive impact. In the Italian case, it is very interesting to observe that over the period that we have considered, the most noticeable increments in productivity are observed among firms that in the pre-adoption period were likely the most distant from the technological frontier. This reinforces the case that, despite the challenges posed by radical process innovation, Industry 4.0 technologies can indeed renew the productive capacity of an economy. It is important to maintain realistic expectations in light of the still limited diffusion of the most advanced technologies, but our findings show demonstrable improvements after adoption, and this arguably strengthens the case for targeted policy support behind this slow and complex process of technological upgrading.

Appendix

Table A1. Descriptive statistics on I4.0 technologies by firms' size, sector, macro-region and age

	Panel component			Cross sectional component		
	Mean	std dev	N	Mean	std dev	N
Firms' size						
4<n of emp<10	0.292	0.455	355	0.299	0.458	1965
9< n of empl<50	0.431	0.495	1210	0.393	0.488	6863
49<n of empl<100	0.673	0.470	310	0.581	0.493	2442
99< n of empl<250	0.647	0.479	231	0.645	0.479	1753
N of empl>249	0.757	0.430	185	0.755	0.430	1008
Macroregion						
North Ovest	0.429	0.495	811	0.396	0.489	3955
North East	0.418	0.494	713	0.417	0.493	3718
Centre	0.328	0.470	428	0.392	0.488	2860
South	0.252	0.435	339	0.258	0.438	3498
Sector of activity						
Mining, public utilities	0.386	0.489	145	0.533	0.499	698
Food, etc	0.408	0.493	176	0.387	0.487	824
Textile, furniture, papers	0.478	0.501	170	0.401	0.490	1035
Chemistry, metallurgy etc	0.499	0.501	261	0.461	0.499	1605
Mechanics et al	0.592	0.493	245	0.517	0.500	1415
Other manufacturing	0.511	0.501	175	0.462	0.499	870
Construction, real estate	0.268	0.444	310	0.218	0.413	1687
Retail and wholesale trade	0.353	0.479	190	0.367	0.482	2012
Transportation	0.363	0.482	146	0.322	0.467	858
Hotels, restaurants, tourism	0.171	0.379	80	0.237	0.426	541
Information and communication	0.525	0.502	88	0.549	0.498	754
Insurance, banking and financial services	0.679	0.477	25	0.588	0.494	119
Other business services	0.221	0.417	114	0.373	0.484	923
Social, education and health private services	0.368	0.484	166	0.274	0.447	690
Firms' age						
> 9 years (in 2010)	0.394	0.489	2157	0.415	0.493	10827
< 10 years (in 2010)	0.358	0.481	134	0.294	0.456	3204
Total	0.391	0.488	2291	0.369	0.483	14031

Note: sampling weights applied; statistics are referred to the final sample – with no missing values – used for econometric analysis.
Source: our elaboration on RIL-Orbis merge sample 2018

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