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DIGITAL ADVANTAGE: EVIDENCE FROM A POLICY EVALUATION OF ADOPTION SUBSIDIES

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Abstract

Investments in advanced manufacturing technologies are expected to generate substantial gains for firms. The aim of this work is to evaluate the nature and extent of such gains. We use information on the "Nuova Sabatini" subsidy – an important policy measure adopted in Italy over the last few years – and employ a Difference-in-Differences methodology to estimate the effects of digital technologies on adopters relative to a first control group of applicants whose funding was revoked, and a second one obtained through statistical matching. The analysis exploits the rare opportunity of bringing together data from the Italian "National Register of State Aids" (NRA), confidential data from the Ministry of Economic Development (MiSE), and financial data from the complete business register of the Italian Chambers of Commerce (InfoCamere). Results show that new digital investments have positive effects on productivity and that the policy is effective in boosting the overall performance of treated firms. In addition, there is no evidence that digital adoption results in technological unemployment.[1]

Keywords: Advanced manufacturing; Industry 4.0; Technology diffusion; Adoption subsidies; Industrial strategy

JEL: D20; O33; O25

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1 Introduction

Investments in new technologies can generate significant improvements in the performance of firms. "Embodied technical change" (OECD and Eurostat, 2018) has long been recognised as a fundamental driver of productivity growth and economic development (Freeman, Clark, and Soete, 1982). Salter (1960), for example, stressed how heterogeneity in production efficiencies is influenced by the distribution of different vintages of capital equipment. A vast literature developed over time – both at the micro and macro levels – which used vintage capital models to emphasize the fundamental role of capital replacement and capital upgrading processes (Hulten, 1992; Greenwood, Hercowitz, and Krusell, 1997). Much has been written on the diffusion of information and communication technologies (ITC), and their effects on growth (Oulton, 2002; Van Ark, Inklaar, and McGuckin, 2003; Acemoglu et al., 2014). Similar emphasis is now being given to the diffusion of robotic technologies (see, among others, Bartel, Ichniowski, and Shaw, 2007; Acemoglu, Lelarge, and Restrepo, 2020; Koch, Manuylov, and Smolka, 2021; Domini et al., 2021; Dauth et al., 2021).

Technological upgrading is especially important in light of the growing divergence between "superstar" firms at the technological frontier – which have increased rapidly in recent decades – and the majority of small and medium enterprises (SMEs) – which have shown modest growth (Andrews, Criscuolo, and Gal, 2016). Indeed, weak capabilities in adopting and using new technologies have been identified as one of the causes behind the decline in productivity at the aggregate and at the firm level (Andrews, Criscuolo, and Gal, 2015). The case is especially compelling in relation to ICT (Acemoglu, Autor, et al., 2014), and the same argument could be made for new "Industry 4.0" technologies (Cirillo et al., 2023), which are very much connected to the ICT paradigm (Martinelli, Mina, and Moggi, 2021).

The potential to extract productivity gains from new technologies is contingent on the propensity to adopt and on country, sector and firm characteristics. In this work we consider the Italian economy, which has in recent years oriented part of its (limited) industrial policy towards the promotion of Industry 4.0 technologies – through the so-called "Industry 4.0" policy package. Empirical evidence on the effectiveness of this set of policies has so far been scant. This can be explained by the general weakness of public policy evaluation in Italy (Albanese et al., 2021), by the relative novelty of "Industry 4.0" technologies and policies, and above all by the lack of appropriate microdata for robust policy evaluation exercises.

In this paper we assess the effectiveness of one of the major policy schemes within the Italian Industry 4.0 plan, which gives us the opportunity to identify and estimate the effects of digital technology adoption on productivity, employment and wages in one of the largest European economies. We focus on the policy referred to as "Nuova Sabatini". Originally introduced in 2014, this scheme was designed to incentivize firm capital investments through the reduction of financial constraints. Importantly, from 2017 onward the policy specifically targeted investments in Industry 4.0 technologies. We use data from the "National Register of State Aids" (NRA), which includes information on all Italian firms that benefited from the policy scheme since 2017. We integrate these data with granular investment information provided by the Ministry of Economic Development (MiSE), and with financial data provided by the Italian business register database (InfoCamere). We apply a Difference-in-Differences (DiD) methodology with two different control groups: the first one is composed of firms that applied to the policy but whose funding was revoked; the second control group was obtained through statistical matching with InfoCamere (census) data. To obtain the "matched" control group, we implement a Nearest-neighbour matching with a Mahalanobis distance specification. By employing different and detailed data sources we can *ex-ante* remove confounding factors that could be related to "untreated" firms benefiting from policy schemes other than the "Nuova Sabatini" (e.g. we control for all types of government support that firms might be receiving – a rare advantage in this kind of analysis).

The work contributes to the existing literature in two related ways. On the one hand, the paper provides novel empirical evidence about the role of digital adoption on firm performance. In particular, results show that firms investing in 4.0 advanced technologies show higher productivity gains. Moreover, empirical evidence suggests that new digital investments do not result in technological unemployment. On the other hand, the work contributes to the literature studying the effects of innovation and industrial policies (Aghion et al., 2015; Bloom, Van Reenen, and Williams, 2019; Hünermund and Czarnitzki, 2019; Mulier and Samarin, 2021). In particular, results show positive effects of measures lowering credit constraints and favoring investments in new digital assets.

The remainder of the work is organized as follows. Section 2 reviews the existing literature on digital technology diffusion and the potential role of adoption for firm performance. Section 3 presents the Italian context and describes the policy. Sections 4 and 5 describe the data and methodology, respectively. Finally, Section 6 shows the results and Section 7 concludes.

2 Technology adoption and the new digital revolution

Technology diffusion is a complex and uneven process (Mansfield, 1961; Rosenberg, 1972; Dosi and Nelson, 2010). It is the cumulative outcome of adoption choices made by economic actors, which over time influence both the rate and direction of structural change in the economy, from the micro up to the meso- and macro- levels of analysis (Malerba and Orsenigo, 1996). The literature has stressed that technology adoption choices may depend on a variety of factors. It is possible to summarize the main findings in two broad set of drivers. Firms' choices may depend on both (i) firm-specific characteristics and (ii) external factors, broadly defined.

Regarding external factors, one may generally refer to the ensemble of supply-side and demand factors, associated with markets and production infrastructures, at the sector and regional/country level, as well as the institutional context in which firms operate (Mowery and Rosenberg, 1989). In particular, firms competing within the same sector may experience similar technological demand and supply shocks, thus moving along similar trajectories of technology choices. Moreover, the institutional quality – both at the national and regional levels – may shape the speed of adoption, since higher institutional quality is associated, *inter alia*, with higher business dynamism, better financial institutions, and higher-level skills in local labor markets.

Regarding firm-specific characteristics, adoption decisions may relate to firm size, the existence of credit-constraints, differences in human resources management (Bloom, Genakos, et al., 2012), knowledge-bases, capabilities and workforce skills. Firm size is indeed positively correlated to the speed of adoption (Mansfield, 1968; Davies et al., 1979). Also, diffusion processes generally involve "innovation for the user" (Freeman, Clark, and Soete, 1982) – i.e., learning – and modifications in the existing organization of production (Dosi, 1991). Indeed, for example, in many cases technology has to be adapted to individual firms' requirements (Gold, 1981) and, in addition, firms may need to invest in additional training. Firm pre-existing capabilities – e.g., skills, internal knowledge, managerial expertise, as well as existing technological endowments – co-determine adoption choices (David, 1990; Stoneman and Kwon, 1994).

Weaker capabilities in adoption and use of new embedded technologies, especially in relation to Information Communication Technologies (ICT), have been an important factor behind the declining productivity gains of small and medium-sized enterprises (SMEs) (Andrews, Criscuolo, and Gal, 2016). The recent emergence of a new cluster of digital technologies – often identified in Europe under the umbrella term of "Industry 4.0" – constitutes a new frontier of technical improvements after the diffusion of ICTs in the 1980s and 1990s.

The term "Industry 4.0" was launched for the first time at the Hannover Fair in 2011, as the outcome of an initiative put forward by the German Government. The final technical report (Kagermann, Wahlster, and Helbig, 2013) employed the term mainly (i) in reference to the development of strategic policy actions for German manufacturing and (ii) as a synonym of an alleged "Fourth industrial revolution". In general, the core idea was the emergence of a cluster of new technologies resulting from the convergence of new operational technologies with more conventional ICTs.Since then, the term has received great attention in academia, in business,[2] and in the policy domain.[3] The technologies typically included under the umbrella term "Industry 4.0" are: *Big Data/Industrial Analytics*, *Cloud Manufacturing*, *Artificial Intelligence (AI)*, *Internet of Things (IoT)*, *Robotics*, and *Additive Manufacturing*. Both policy-makers (ComEU, 2009) and the academic literature have stressed the "enabling" nature of these technologies (Martinelli, Mina, and Moggi, 2021) to capture their ability to improve processes, products and services systematically throughout the economy.

In general, major paradigmatic changes – as those occurring during industrial revolutions – are associated with the emergence of "General Purpose Technologies" (GPTs) (Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1996). These broad groups of technologies have pervasive use across sectors, have fast rates of improvement and show strong complementarities (Jovanovic and Rousseau, 2005). Enabling technologies such as "Industry 4.0" can be conceptualised as "early or emergent" GPTs (Martinelli, Mina, and Moggi, 2021), which could eventually trigger paradigmatic changes on a large scale (Dosi, 1982; Perez, 1985). While the full scale and scope of change associ-

[2] See Culot et al. (2020) for a systematic review.

[3] For example, in France, with the "*Nouvelle France Industrielle*"; "Smart Industry" in the Netherlands; "Connected Industry 4.0" in Spain. See EUCom (2017) for a list of policy cases.

ated with the new digital technologies is still unknown, there can be no doubt about their disruptive potential (Brynjolfsson and Hitt, 2003; Syverson, 2011; Ford, 2015; Dauth et al., 2021; DeStefano, Kneller, and Timmis, 2018; Calvino and Fontanelli, 2023).

3 Context and institutional setting

The Italian economy has been experiencing stagnating productivity growth since the 1980s. Pellegrino and Zingales (2017) have defined this growth problem as the "Italian disease". Many factors contribute to explain this dynamic, including low institutional quality, insufficient public investments, and low R&D expenditure – certainly interdependent. However, there is some consensus that the weakness of the Italian fragmented productive system and the low dynamism of firms have played a major role (Dosi et al., 2012; Dosi et al., 2021). For example, Calligaris et al. (2016) look at the distribution of firm productivity and find a thickening of the left tail, with a share of low-productivity firms increasing over time. More recently, Calvino et al. 2022 confirms the difficulty experienced by Italian firms in positioning themselves at the technological frontier through the exploitation of ICT and new technologies.

In this general context, industrial policy was neither entirely coherent nor very effective (Albanese et al., 2021). The "Industria 4.0" plan – launched in 2017 – arguably was the first policy package consistently designed to promote the recovery of productivity rates through the diffusion of new digital technologies in the Italian economy. The plan has included several components[4] which targeted technology diffusion, R&D, and innovation. In this paper we focus on the so-called "Nuova Sabatini" policy scheme.

3.1 The "Nuova Sabatini"

The "Beni Strumentali - Nuova Sabatini" (NS) promotes investments in capital goods (mainly equipment and machinery) for Micro, Small and Medium Enterprises (SMEs).[5] The policy works through the banking channel by facilitating access to credit. It provides for (i) subsidized loans

[4] Among others: Super-depreciation on Industry 4.0 assets, Hyper-amortization, and a Tax credit for R&D and innovation. See also Calvino et al. (2022) for related details.

[5] SMEs are identified following the EU Recommendation 2003/361/EC. A SME is defined as a firm having 1) less than 250 people with 2a) an annual turnover of less than EUR 50 million or whose 2b) annual total balance sheet does not exceed 43 million EUR. See section 5 for the potential methodological implications of such definition.

(or leasing) by banks and financial intermediaries and (ii) a public contribution (by the Ministry of Economic Development) in relation to the interest expenses on such loans.[6]

The measure was established in 2014, with its first operational cycle from 31/03/2014 to 31/12/2016. Subsequently, it was extended with the 2017, 2018, 2019 and 2020 budget laws, as well as amended and refinanced during the COVID-19 pandemic. With the 2017 budget law, the policy was aligned with the "Industry 4.0" Plan. An increased contribution was introduced for investments in "4.0" assets (3.575% compared to 2.75% for "ordinary" investments), defined in connection with Industry 4.0 technologies. The policy is compatible with other instruments of the "Industria 4.0" plan (e.g. the super-amortization), but the fact that it works through the debt channel allows us to study its direct effects of new investments.

In general, one can separate the operational phases of the policy in two periods: 2014-2016 and the one from 2017. Even though minor amendments have been implemented over time [7], the main policy change occurred in 2017 and the post-2017 phase is the one of interest (specifically, as explained in section 4, the year 2017). Industry 4.0 technologies were not explicitly included in the first phase of the policy. Moreover, the adoption of Industry 4.0 technologies have not been part of existing formal evaluation of the policy produced by Invitalia for the Ministry (Invitalia, 2020).

The "Nuova Sabatini" does not rely on formal selection mechanism. Indeed, the policy works through an interaction between banks and firms. The latter *de facto* select themselves into the policy. Banks then make a formal check on the requirements defined by the law. These mainly relate to the formal definition of SMEs and to the potential cumulability of other grants. Then, data on firms that obtain formal acceptance from financial intermediaries are sent to the Ministry of Economic Development. The Ministry finally grants the contribution. Importantly, firms which obtain the grant have to make and complete the investments within the following 12 months. This is a very important aspect for our analysis: one should observe effects – if any – which are not significantly delayed w.r.t. the granting of subsidies (especially as far as assets are concerned).[8]

[6]The grants can be configured as State Aid, within the limits specified by EU regulations (EC) no. 651/2014, n. 702/2014 and n. 1388/2014.

[7]Notably, the payment system for contributions was changed, from 6 separate instalments to a single one.

[8]This consideration is also coherent with the literature, which agrees on the lumpy nature of investments More than 50% of the allocations are made in the second half of the year (see Figure 7 in Appendix A), but it is safe to assume that average effects are observable at the end of 2017 given the relevant number of firms in the first half of the year. Also, we are going to estimate average effects across all post-treatment years, not only at year $t + 1$.

4 Data and variables

We perform a policy evaluation on the "Nuova Sabatini" policy scheme, and investigate if and how new investments – especially in Industry 4.0 technologies – promote productivity, sales and employment growth. To answer these research questions, we focus our analysis on the year 2017. This corresponds to the policy modification which aligned the "Nuova Sabatini" with the "Industry 4.0 plan". In this sense, first, it allows to study the specific role of Industry 4.0 technologies. Second, it constitutes a good starting point to study a homogeneous group of companies with respect to the "new" policy measure. Third, it allows to have a sufficient *ex-post* time span – 2017, 2018, 2019, 2020[9] – to measure policy effects.[10]

4.1 Data sources

To perform the policy evaluation, we accessed four different data sources. On the one hand, we used data provided by the Ministry of Economic Development (MiSE) about the "Nuova Sabatini" as well as information provided in the National Register of State Aids (NRA). The data provided by the Ministry relate to policy beneficiaries, in particular to firm investments. We use data collected in the NRA to understand which firms had simultaneous access to different policy instruments.

On the other hand, we accessed financial information from the Italian business register, the "InfoCamere" database, and its next best alternative, the Bureau van Dijk's Orbis database. Notably, the "InfoCamere" database – which we employ for the following analyses – maps Italian firms through the system of local chambers of commerce, and collects information on all firms operating in Italy and on all financial statements filed following the provisions of the law (information on coverage are available in Appendix A, Figure 8). A comparison between InfoCamere and Orbis data revealed that we would have missed approximately half of the firms in the treated group using Orbis, given its very uneven coverage of SMEs. The database not only allowed us to match detailed information with the NRA and MiSE data, but it also allowed us build a reliable control group for our estimations based on the universe of Italian firms.

[9]Since the year 2020 has been deeply affected by the Covid-19 economic crisis, in the following analyses we specify estimates without the year 2020. Nonetheless, we still provide graphical results for the year 2020.
[10]Also, most of data about beneficiary firms were already publicly available on the NRA database.

4.2 Variables and descriptive statistics on beneficiary firms

Tables 1 and 2 show descriptive statistics for firms which accessed the policy scheme in 2017.[11] We report the main variables for 2015 for firms which made Industry 4.0 investments (1) and ordinary investments (2).[12] We show the year 2015 since firms had to present financial statements at maximum two years before the policy. In this sense, we can immediately see that, for the year 2015, the maximum number of employees is lower than 250 for both groups (considering, e.g., Industry 4.0 firms, indeed $e^{5.41} \approx 223 < 250$), as required by the law (and EU Regulations; see Note 5). We compute Labor productivity considering total value added on total employment, and estimate TFP following the methodology proposed by Levinsohn and Petrin (2003).[13]

Table 1: "Industry 4.0" beneficiary firms in 2017 – data for 2015

	Mean	Median	Min	Max	Sd	1stQuart	3rdQuart	Obs.
log(Debts)	14.54	14.56	10.53	18.25	1.13	13.77	15.32	1651
log(Equity)	13.92	13.94	7.54	17.72	1.47	12.97	14.98	1651
log(Immat_Assets)	10.48	10.62	0.69	15.82	2.01	9.29	11.9	1651
log(Mat_Assets)	13.49	13.57	9.11	17.75	1.46	12.5	14.52	1651
log(Assets)	13.77	13.83	5.91	17.95	1.39	12.85	14.75	1651
log(TFP)	9.74	9.73	8.1	11.3	0.39	9.53	9.92	1651
log(Prod_Lab)	11.02	11.02	-0.21	13.21	0.5	10.78	11.25	1651
log(AvgWages)	10.56	10.59	8.12	12.89	0.32	10.41	10.74	1651
log(Sales)	14.15	14.17	3.04	16.61	1.02	13.52	14.86	1651
log(Emp)	3.13	3.14	0	5.41	0.86	2.56	3.74	1651
log(Costs_mat)	14.25	14.29	7.67	17.71	1.41	13.41	15.25	1651
Age	24.04	22	4	90	14.15	13	34	1651
i_roe	0.15	0.12	-4.37	1.04	0.26	0.05	0.23	1651
i_lev	3.08	1.77	0.05	20	3.43	0.81	3.89	1651

Notes: We show the year 2015 since firms must present financial statements at maximum two years before the policy. Note, in this sense, that maximum employment is below 250: indeed, $e^{5.41} \approx 223 < 250$. (recall section 3.1). Observations refer to the total number of firms available in the integrated database (see section 4.1). Nonetheless, some variables display missing values, which we omit in the computations.

Source: own elaboration on MiSE and InfoCamere data.

The two Tables show that firms belonging to the "Industry 4.0" group are on average bigger, more productive, more capital intensive, with higher sales. Also, we notice that they are – on average – older and with higher levels of debt. These findings are broadly in line with the literature. In

[11] Appendix A reports more extensive information on policy beneficiaries and investments across years.

[12] Appendix A shows additional statistics, such as the summary for the overall group in Table 14 (useful for estimations in section 6). In addition, Table 15 estimates a Linear Probability Model to disentangle the main structural differences across firms accessing the two different policy segments.

[13] We are aware of the recent developments about Total Factor Productivity estimation techniques (Ackerberg, Caves, and Frazer, 2015). Nonetheless, given the availability of data – especially regarding the workforce – and the specificity of the Italian context – see section 3 – we use the methodology by Levinsohn and Petrin (2003). We implement the estimation in R using the *prodest* package.

particular, they point out how firms which self-select into the "4.0" part of the policy are *ex-ante* more productive, and reasonably associated with higher static and dynamic capabilities.[14] Relatedly, the higher monetary incentive connected to this kind of investment (recall section 3.1) does not seem correlated to investment decisions.

In what follows, we describe the methodology we are going to implement to study policy effects.

Table 2: "Ordinary" beneficiary firms in 2017 – data for 2015

	Mean	Median	Min	Max	Sd	1stQuart	3rdQuart	Obs.
log(Debts)	14.29	14.32	9.35	18.09	1.23	13.47	15.12	5171
log(Equity)	13.41	13.42	2.77	18.38	1.49	12.35	14.48	5171
log(Immat_Assets)	10.19	10.33	0.69	16.72	2.13	8.76	11.73	5171
log(Mat_Assets)	13.12	13.21	1.61	18.04	1.62	12.08	14.24	5171
log(Assets)	13.41	13.5	2.3	18.34	1.53	12.44	14.44	5171
log(TFP)	9.65	9.62	8.22	11.27	0.38	9.43	9.87	5171
log(Prod_Lab)	10.93	10.91	6.95	14.92	0.47	10.68	11.15	5171
log(AvgWages)	10.49	10.55	4.23	14.12	0.41	10.34	10.71	5171
log(Sales)	13.79	13.77	9.21	17.43	1.06	13.1	14.51	5171
log(Emp)	2.86	2.83	0	5.52	0.93	2.3	3.5	5171
log(Costs_mat)	13.73	13.78	3.74	18.78	1.66	12.73	14.85	5171
Age	21.9	19	4	96	13.68	11	30	5171
i_roe	0.14	0.11	-6.84	1.85	0.3	0.03	0.24	5171
i_lev	3.65	2.28	0.04	20	3.78	1.05	4.86	5171

Notes: We show the year 2015 since firms must present financial statements at maximum two years before the policy. Note, in this sense, that maximum employment is below 250: indeed, $e^{5.52} \approx 249,6 < 250$. (recall section 3.1). Observations refer to the total number of firms available in the integrated database (see section 4.1). Nonetheless, some variables display missing values, which we omit in the computations displayed here.

Source: own elaboration on MiSE and InfoCamere data.

5 Methodology

5.1 The challenges of identification

The fundamental problem of policy evaluation concerns the identification of a suitable control group to perform an unbiased estimation of policy effects. Such an identification is mainly related to the institutional setting of the policy scheme (particularly to the assignment mechanism according to which the policy works). The institutional setting of the "Nuova Sabatini" does not provide for an *explicit* selection mechanism – based, e.g., on an external evaluation of a committee –, which is

[14] Table 15 in Appendix A estimates a Linear Probability Model to further disentangle the main structural differences across firms accessing the two different policy segments.

usually a very useful tool to perform a "Regression Discontinuity" (RDD) evaluation.[15] The policy still provides for a threshold according to which firms result eligible (or not). Indeed, following EU provisions (as recalled in section 3.1), only SMEs can access the scheme. This means that, e.g., firms with 250 employees can participate to the program while firms with 251 employees cannot.[16] Nonetheless, since the *formal* requirements of participation are *ex-ante* known to firms which apply, this reduces the number of observations near the threshold (and, in any case, this mechanism results to be at odds with the assumptions needed for RDD).[17]

Since the institutional setting of the policy rules out the possibility of using a RDD, the difference-in-difference approach results to be the best solution to conduct the policy evaluation.[18] The main challenge remains the correct identification of a suitable control group. We address this challenge in two ways. First, we exploit data on firms which received a formal revocation of the subsidy. This group of firms ("revocations") is very useful since it addresses the selection bias problem – as we explain below. Second, we build a comparable control group employing matching techniques. This enables the estimation of Average Treatment Effect on the Treated (ATT) by combining both matching and difference-in-differences methodologies. The next two sections describe the rationale and details of both approaches.

5.2 Revocations as counterfactual

As we have already noted, the "Nuova Sabatini" policy is not particularly selective. Applicants may receive a denial if they do not satisfy the formal "SME" requirements, a relatively uncommon outcome since (i) firms *ex-ante* know the basic requirements of the legislation and (ii) most Italian firms are actually SMEs.[19] Nevertheless, the policy provides for other cases in which applicants may result excluded from the scheme, while being formally eligible. These are shown in Table 3 ("Revoca Totale", "Rinuncia con revoca"), along with the absolute number of beneficiary firms

[15] A recent example is provided by Santoleri et al. (2022), which indeed exploit the assignment mechanisms of the European SME Instrument – a public R&D grant policy – to assess its impact on beneficiary firms.

[16] See Note 5 for the precise definition of "SME". See also descriptive statistics in section 4.2.

[17] Moreover, even in presence of a different assignment mechanism, estimations using the "SMEs" threshold would have a very low external validity, since the majority of Italian firms – both beneficiary and not – have sizes usually well below 250 employees (see section 3).

[18] The use of an Instrumental Variable approach presented major data limitations. Also, the policy setting does not present straightforward (exploitable) mechanisms to construct a valid instrument.

[19] Indeed, only 662 firms across the period 2014-2021 received a formal denial, despite the more than 100.000 firms financed (absolute number of firms, computed on MiSE data – see section 4.1).

("Erogazione").[20] Once firms have demanded access to the policy, they may (a) receive the grant ("Erogazione"), (b) renounce to the funding ("Rinuncia con revoca") or (c) have a formal revocation of the measure ("Revoca totale"). While in case (a) firms benefit from the policy, in case (b) and (c) they do not. However, in all three cases firms are formally eligible, as well as self-selected into the scheme.

Table 3: Policy outcomes - number of firms per year

Status	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Erogazione	2330	3419	8263	13096	18390	15020	17943
Revoca totale	613	554	672	1150	1746	884	225
Rinuncia con revoca	271	144	176	350	480	388	435

Notes: firms which have obtained resources through more than one decree are considered only once. "Erogazione" refers to firms which actually received the policy (i.e. beneficiaries). "Rinuncia con revoca" identifies firms which renounced to funding. "Revoca totale" refers to firms which had a formal revocation of funding.
Source: own elaboration on MiSE data (section 4.1).

This is a crucial point, since for all firms – treated and untreated – many of the *unobservable* factors which may influence, first, adoption of new technologies and, second (relatedly), self-selection into treatment, are controlled for. In other words, we solve the usual selection bias which may undermine the validity of a policy evaluation. The factors influencing self-selection (and adoption) may include strategic orientation, capabilities, management, and workforce composition; all factors which are difficult to deduce from balance sheet data, such as the ones we have. The possibility of relying on information about (i) self-selection plus eligibility and (ii) firms actually receiving funding is thus an important element for the analysis.

We further distinguish among firms which "renounce" to the scheme (group b) and firms which got a revocation (group c), ultimately relying on this latter group for the analysis (Table 4).

Indeed, while both groups result untreated, in the "renounce" group the absence of treatment is voluntary and related to a decisions made by firms, while the "revocation" outcome stems from the formal implementation of the policy. This aspect is relevant to correctly asses and interpret policy effects. Indeed, firms may renounce to the scheme for a variety of reasons, such as applying to other – more convenient – policy schemes, facing an internal restructuring or simply not needing additional funding through debt. Given this possible heterogeneity, the magnitude and direction of

[20] There are also other administrative cases, which we omit to save space (since they have lower numerical and methodological relevance). "Erogazione" refers to firms which actually received the policy.

Table 4: "Revocations" control group in 2015

	Mean	Median	Min	Max	Sd	1stQuart	3rdQuart	Obs.
log(Debts)	14.32	14.33	10.45	17.22	1.23	13.5	15.2	496
log(Equity)	13.17	13.22	6.58	17.18	1.65	12.12	14.35	496
log(Immat_Assets)	10.3	10.42	3.09	15.11	2.06	9	11.76	496
log(Mat_Assets)	12.97	13.06	8.03	17.28	1.68	11.85	14.08	496
log(Assets)	13.3	13.42	8.54	17.3	1.57	12.22	14.27	496
log(TFP)	9.55	9.54	8.37	10.84	0.42	9.38	9.71	496
log(Prod_Lab)	10.88	10.86	8.79	12.91	0.46	10.62	11.09	496
log(AvgWages)	10.44	10.49	8.97	11.88	0.36	10.25	10.67	496
log(Sales)	13.66	13.64	8.79	16.5	1.1	12.91	14.41	496
log(Emp)	2.78	2.74	0	5.17	0.99	2.2	3.47	496
log(Costs_mat)	13.82	13.91	5.94	17.48	1.6	12.87	14.92	496
Age	20.84	17	4	90	13.5	10	30	496
i_roe	0.12	0.1	-8.54	0.9	0.5	0.03	0.23	496
i_lev	4.42	3.01	0.12	19.72	4.2	1.3	5.89	496

Notes: We show the year 2015 since firms must present financial statements at maximum two years before the policy. Note, in this sense, that maximum employment is below 250: indeed, $e^{5.17} \approx 175,9 < 250$. (recall section 3.1). Observations refer to the total number of firms available through InfoCamere (vs total revocations shown in Table 3). Some variables display missing values, which we omit in the computations displayed here.

Source: own elaboration on MiSE and InfoCamere data.

differential policy effects may result biased.

On the contrary, firms encounter a revocation if investments do not comply with law provisions. In particular, firms affected by revocation decrees are those which (i) planned investments before accessing the scheme or (ii) made investments not compliant with the law. In other words, the revocation control group is composed by firms which actually (all) invested. However, it includes firms which, in the former case (i), would have just "socialized costs"[21]; in the latter case (ii), made investments with, e.g., a lower technological intensity.[22]

Since this "revocations" control group is composed by firms which actually invested in new assets, it would not be suited to really find a "pure" treatment effect when compared to treated firms. Indeed, given that both treated and untreated firms made investments – an otherwise lumpy phenomenon – we expect to observe rather similar dynamics across the two groups. Notwithstanding, this is still a quite "useful" limitation. Indeed, first, one can assess if policy beneficiaries (1) show superior indirect effects on performance figures, possibly related to the higher technological content of investments performed/required under the policy; (2) show different direct effects regarding debt dynamics, implicitly targeted by the policy. Also, one can assess (3) if firms which got a revocation actually

[21] According to EU State Aids regulations (see Note 6), grants must be – at least in principle – "additional".

[22] This case is particularly important, especially w.r.t. "Industry 4.0" investments.

invested even absent the policy, hence investigating the screening capacity and effectiveness of the Ministry.

Even if the "revocations" control group solves relevant identification problems and may offer itself important policy conclusions, one is still interested in finding overall policy effects. As we stressed, the peculiarity and relevance of this control group resides in one of its limitations: being composed by firms which actually invested, as treated firms did (even with the differences highlighted above). In order to identify overall *differential* policy effects, we thus follow an additional approach, based on the construction of a comparable control group through matching techniques.

5.3 Counterfactuals through matching

In order to investigate overall policy effects, we build an additional control group using matching techniques (other than the one made out of "revocations", described in the previous section). Matching methods are aimed at neutralizing pre-treatment observed characteristics for treated and non-treated groups, in order to find control units which are *ex-ante* comparable to treated units. The selection of relevant covariates is thus the main identification challenge.

Following the argument of King and Nielsen (2019), we implement a Nearest neighbor matching with a Mahalanobis distance specification, including the following covariates: (i) immaterial assets, (ii) material assets, (iii) sales, (iv) size (employment) and (v) leverage (i.e. total debts on equity). We include each of these variables on a yearly base, for the (pre-treatment) years 2013, 2014, 2015, and 2016. Also, we perform first an exact matching on (vi) the 2-digit ATECO sectoral specification and (vii) the regional location of firms.

These choices are largely supported by the relevant literature, and related to the policy setting. Indeed, first, firms' technology adoption choices – such the ones related to Industry 4.0 under the policy – may depend on factors external to the firm, regarding market structure and production structure, at the sector and regional level (e.g. Mowery and Rosenberg, 1989), as well as to the institutional environment (e.g. North, 1990). The regional and sectoral dimensions are related not only to technology adoption, but also, generally, to different propensities/abilities/possibilities to access relevant information regarding national and regional policies. These aspects are crucial given the self-selection mechanism of the policy. While it is difficult to disentangle the extent to which technological adoption propensities and self-selection interact, these aspects are likely related to the regional and sectoral dimensions, on which we perform the above mentioned exact matching specification.[23]

Second, the Mahalanobis matching on the variables (i)-(v) enables to take account the specificities of the "Nuova Sabatini" (section 3.1). Indeed, firm characteristics such as size and sales are important performance indicators, which – taken together – may incorporate other relevant unobserved performance dimensions. Assets and leverage are relevant since the policy specifically targets investments through reduction in credit costs. Relatedly, capital configurations are likely correlated to firms' characteristics, which may be associated to different *ex-ante* propensities to apply to the policy.

Last but not least, we are confident about the reliability of our matching strategy since we employ the information provided in the "National Register of State Aids" (NRA) and can account for access to other policy instruments. Indeed, as shown in Table 5, in order to individuate our unbalanced control group we start by a firm universe composed by around 900.000 units. From this universe, we remove (i) all the firms with more than 250 employees in 2015/2016 (this is indeed coherent with the policy specification of the "Nuova Sabatini", see section 3.1). Also, we remove (ii) all the firms which applied to the "Nuova Sabatini" before or after 2017, to avoid matching with otherwise possibly treated firms. Finally, (iii) we remove all the firms which accessed other policy schemes between 2013 and 2019[24], as registered in the NRA.[25]

These steps result crucial to correctly identify causal effects. Notably, point (iii) enables to *ex-ante* removing effects which may be related to other policies accessed by the "untreated" units. Indeed, one of the major issues regarding public policy evaluation is having a precise mapping of which policy measures are used by firms. By simultaneously employing the NRA and MiSE data, we overcome this issue. According to our best knowledge, this is the first work which is able to combine such amount of data with the aim of isolating policy effects.

[23] We first factorized geographical and sectoral variables to perform the exact matching (Stuart, 2010; e.g. Mina et al., 2021 for a similar procedure).

[24] We do not consider years 2020 and 2021 since almost all Italian firms received emergency reliefs, registered in the NRA.

[25] Of course, these sets partly intersect. Hence, the resulting control group in Table 5 is equal to the universe minus the intersection of the other samples (we do not report here the numerosity of firms with less than 250 employees).

Table 5: (Unbalanced) control group identification using the NRA

Firms' universe accessible through InfoCamere	934.567
Firms in the NRA (excluding NS beneficiaries and firms registered in 2020/2021)	612.225
Firms which applied before/after 2017 to the Nuova Sabatini	49.736
Resulting (unbalanced) control group (<250 emp. in 2015/2016)	131.684

5.3.1 Obtaining appropriate controls

With these considerations in mind, we specify the matching algorithm and obtain our additional control group. As shown in Table 5, we start by an unbalanced control group constituted by 131.684 firms, which we associate to the group of treated firms (composed by the treated firms showed in Tables 1 and Tables 2 above).[26]

Figure 1 shows the results of the matching algorithm in terms of "standardized mean differences" (SDM). The latter represents the difference in the (standardized) means of each covariate between treatment groups[27], with SMDs close to zero indicating good balance, while higher values indicating unbalanced samples. As it is possible to see in both panel A and B, the unajusted sample is initially highly unbalanced (grey dots). By the specification of the first matching algorithm – without a caliper restriction – we obtain an improvement in terms of sample balance (see Panel A). Almost all the 6763[28] treated firms get a match (only 3 remains unmatched, due to exact matching constraints). Nonetheless, by looking at variance ratios VRs (reported in Appendix B), we notice that this specification generally does not perform well. The variance ratio indeed represents the ratio of variances of a given covariate between the two groups. In this sense, values close to 1 indicate good balance, i.e. similar variances across samples (Austin, 2009). With the specification in Panel A, we however obtain ratios between variances up to 17 times greater (i.e. a ratio of about 17). Hence, we decide to implement an algorithm with a caliper restriction. The latter represents the maximum allowed distance between two units (in terms of standard deviation units) w.r.t. specified covariates.[29] In this way, it enables to increase sample balance. With a caliper specification of 0.5

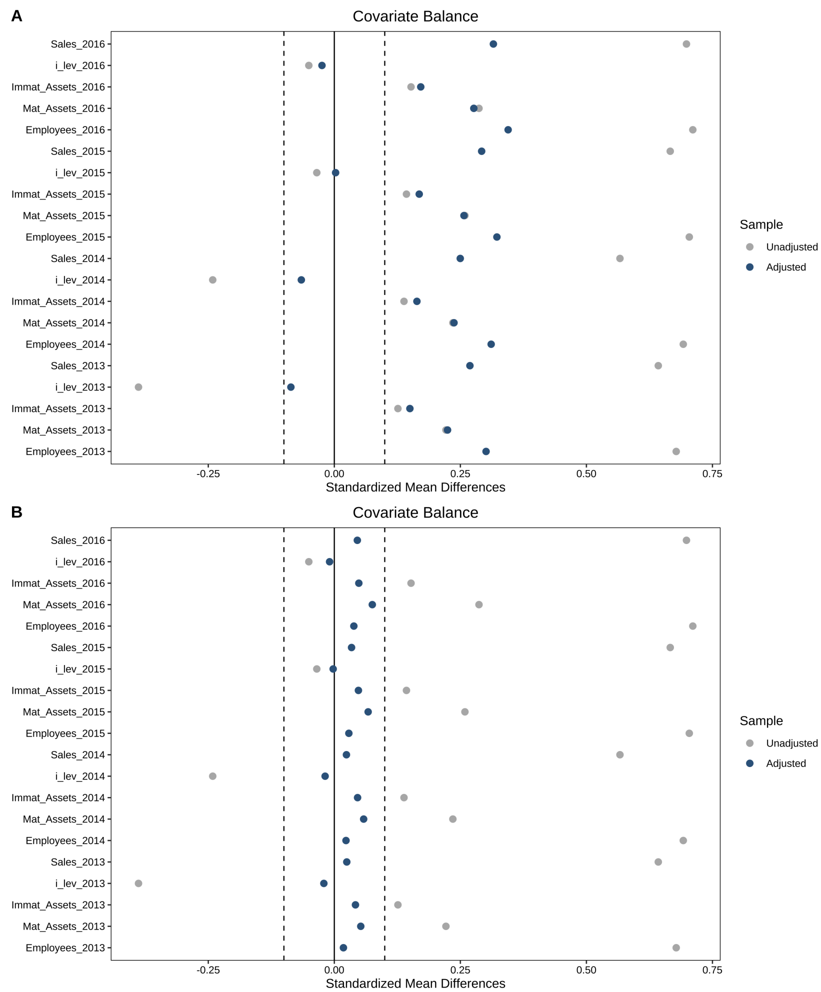
[26] We specify a matching without replacement with 1:1 matching, i.e. firms in the control group are paired only once (not "replaced in the untreated urn") and the output consists in only one control firm for each (matched) treated firm.

[27] We specify the standardization factor as the standard deviation of the covariate in the treated group.

[28] This number is slightly lower than the total number of firms treated (i.e. 6822) since some variables presented missing values.

[29] In other words, the caliper defines if units can be matched or not: if the distance among treated and untreated values of a given covariate is higher than the width of the caliper specification, units are not matched.

Figure 1: Sample(s) balance across two caliper specifications



Notes: Panel *A* shows the results of matching without the specification of a caliper. Panel *B* shows the results with a caliper equal to 0.5.
We do not report variables on which we perform exact matching, i.e. Regions and 2-digit ATECO sectors. For these variables, blue dots would be perfectly aligned on the vertical axis, with SMDs equal to zero.
Source: own elaboration on InfoCamere data.

on all matching variables, one can observe a substantial reduction in SMDs (panel *B*).[30]

All in all, from this matching specification we obtain 4211 matchings (Table 6), while 2552 firms remain unmatched. While this means that we are not going to find a "pure" ATT (see section 5) – since not all treated firms are effectively included into the treatment group – this is still a good

[30]From complementary statistics reported in Appendix B, one can assess how SMDs are all close to zero, while VRs display values close to 1, confirming the goodness of this specification. Similarly, eCDFs statistics, which summarize the differences in the empirical cumulative density functions of each covariate between groups, are all close to zero. Values close to zero mean almost perfectly overlapping CDFs, an indication of good balance. In Appendix B, we also report results of a third specification with a caliper of 0.3. Final results are coherent.

Table 6: Matched control group in 2015

	Mean	Median	Min	Max	Sd	1stQuart	3rdQuart	Obs.
log(Debts)	13.38	13.41	8.56	18.2	1.11	12.66	14.16	4211
log(Equity)	12.69	12.77	7.01	17.11	1.47	11.7	13.78	4211
log(Immat_assets)	8.92	9.05	0	13.99	2.06	7.55	10.44	4211
log(Mat_assets)	11.79	11.89	2.71	16.01	1.77	10.67	13.1	4211
log(Assets)	12.12	12.23	1.61	17.2	1.67	11.09	13.29	4211
log(TFP)	10.28	10.29	6.13	12.43	0.44	10.05	10.54	4211
log(Prod_Lab)	10.81	10.81	6.57	13.48	0.47	10.55	11.07	4211
log(Wages)	10.44	10.5	5.48	12.42	0.43	10.26	10.69	4211
log(Sales)	13.16	13.24	7.13	15.46	0.87	12.67	13.76	4211
log(Emp)	2.35	2.4	0	4.34	0.74	1.95	2.83	4211
log(Costs_mat)	12.88	13.06	0.69	17.42	1.77	11.96	14.09	4211
Age	21.31	18	4	115	14.12	10	30	4211
i_roe	0.12	0.11	-7.22	6.76	0.41	0.03	0.24	4211
i_lev	3.19	1.64	0.03	19.95	3.87	0.68	4.03	4211

Notes: the maximum employment is well below 250: indeed, $e^{4.34} \approx 77 < 250$. (recall section 3.1). Observations refer to the total number of firms available (see section 4.1). Nonetheless, some variables display missing values, which we omit in the computations.
Source: own elaboration on MiSE and InfoCamere data.

number of observations.[31] Figure 2 shows the resulting distributional balance for the employment variable in 2015, [32] from which it is possible to notice that the resulting matched sample is composed generally by small(er) firms.[33]

In sum, the sample we obtain is rather balanced. Moreover, considering the initial exact matching specification on sectors and regions, we are confident that the two group of firms are *ex-ante* comparable.

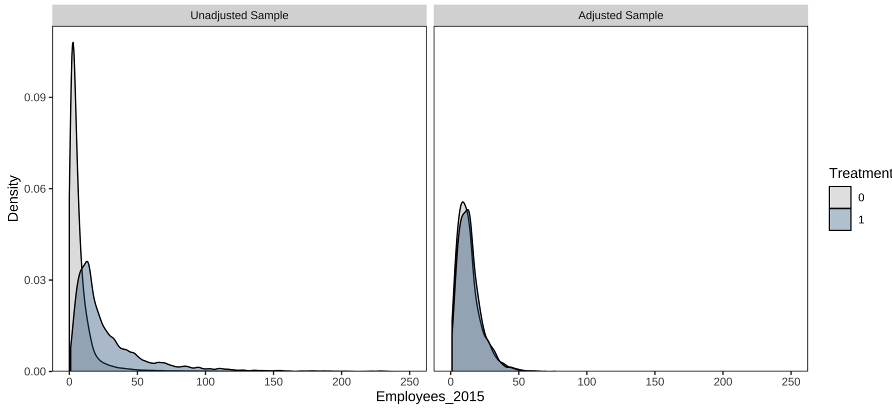
With these considerations in mind, we specify the econometric model we employ in the following analyses.

[31] This is also *ab origine* true considering available data (see section 4.1).

[32] Additional statistics are reported in Appendix B. Other distributional balances perform in the same way (since they reflect what is shown in Table 17), i.e. overall good sample balance (after matching).

[33] Given the fact that financial constraints are particularly binding for SMEs (e.g. Cosh, Cumming, and Hughes, 2009; Storey, 2016), in what follows we would expect high policy effects, if any. Indeed, SMEs usually are unlisted, may have less transparent track records, no collateral, and carry out activities which are more difficult to evaluate *vis-à-vis* larger firms. These factors transpose in a higher cost of external funds, i.e. a higher dependence on internal resources – so the potential emergence of financial constraint affecting investments (Berger and Udell, 2006; Revest and Sapio, 2012). The "Nuova Sabatini" acts precisely on the cost of credit, i.e. it should lower credit constraints.

Figure 2: Distributional balance for the "Employment" variable in 2015



Source: own elaboration on MiSE and InfoCamere data.

5.4 Econometric model

The econometric model we use in our DiD estimation is specified as follows:

$$Y_{i,t} = \alpha + \beta D_{i,t} + \delta time_{i,t} + \mu X_{i,t} + FE_i + \varepsilon_{i,t} \tag{1}$$

where, as described in section 4.2, our dependent variable $Y_{i,t}$ consists alternatively in the log of average wages, log of employment, and log of productivity. As we thoroughly explained, we are interested in these latter variables for answering our research questions. Nonetheless, since the policy scheme under consideration directly targets assets, we are going to consider also log of assets (and log of debts, since the policy works through the credit channel). In equation 1, $D_{i,t} = T_{i,t} \cdot time_{i,t}$ identifies the treated units in the post-period. Notably, $D_{i,t} = 1$ if unit i belongs to the treated group and it is observed *after* the implementation of the policy ($time_{i,t} = 1$); $D_{i,t} = 0$ otherwise. In our case, as described in section 3.1 and 4, 2017 is the "treatment" year, so that $time_{i,t} = 1$ for $t = 2017, 2018, 2019$[34] and $time_{i,t} = 0$ for $t = 2013, 2014, 2015, 2016$. $T_{i,t} = 1$ if firm i accessed the policy in 2017, and 0 otherwise. This model specification takes into account potential policy effects over multiple years. It follows that coefficient β – if parallel trends hold and there are no confounding effects – captures the ATT across all post-treatment years.

[34] As explained above, we exclude 2020 from model estimations, to avoid confounding related to the pandemic period (see Note 9).

$X_{i,t}$ represents instead a vector of control variables, which we described above (section 4.2). Those refer to geographical and sectoral characteristics as well as firms' legal form, age, and financial indicators. The age variable captures aging over years for each firm.

Indeed, one is interested in removing possible confounding elements which may correlate with *ex-post* outcomes. Given the panel specification of our linear model, unobserved units' constant factors are removed *ab initio*. However, the specification of additional controls can still increase error ($\varepsilon_{i,t}$) robustness. Regarding the latter, we specify robust errors clustered by group and time.

6 Empirical analysis and results

In order to assess possible effects of the policy, we implement a Diff-in-Diff methodology relying on two different control groups.

The first one is composed by firms whose funding were formally revoked. While this group takes care of the selection bias, it is composed mainly by firms that did invest. Notably, by (i) firms that had already planned investments and (ii) firms that made investments in asset types not covered by the "Nuova Sabatini" law (e.g., that did not satisfy the 4.0 requirement). In this sense, we expect to observe rather similar dynamics across the two groups, since they both invested (an otherwise lumpy phenomenon). Nonetheless, we can argue that firms in this control group have not invested in Industry 4.0 technologies. Hence, we are going to look at differential dynamics especially among "treated 4.0" and "untreated".[35]

Later, we will employ a second control group obtained through statistical matching to be *ex-ante* similar to treated firms. This helps us address self-selection biases in estimations. Matched firms (both treated and untreated) in the balanced sample are anyhow – on average – smaller than pre-matching ones.

[35] As an additional estimation, we compare labor productivity dynamica across "4.0" treated and "Ordinary" treated in 2017 (see Table 21 in Appendix and Section 6.3.2).

6.1 First control group: revocations

6.1.1 Parallel trends assumption

As we have explained in Section 3.1, the "Nuova Sabatini" provides for two different "treatments". Indeed, firms may invest in "Ordinary" assets or "4.0" assets.
Figure 3 shows the comparative dynamics of average variables for these two treated groups (in Tables 1 and 2 above) and for the "revocation" control group (Table 4). Notably, the red lines represent the dynamics for the untreated, the green lines for "Ordinary treated" while the blue lines for "Industry 4.0 treated".

The first stylized fact emerging from the Figure is the difference in *ex-ante* average levels across the two types of treatment (Ordinary and Industry 4.0). Indeed, here we can confirm that firms which invest in Industry 4.0 assets are bigger, more productive, with higher sales and higher labor productivity *vis-à-vis* firms that make "ordinary" investments.[36] These are already interesting findings on the firm characteristics *ex-ante* associated with self-selection into different types of treatment.

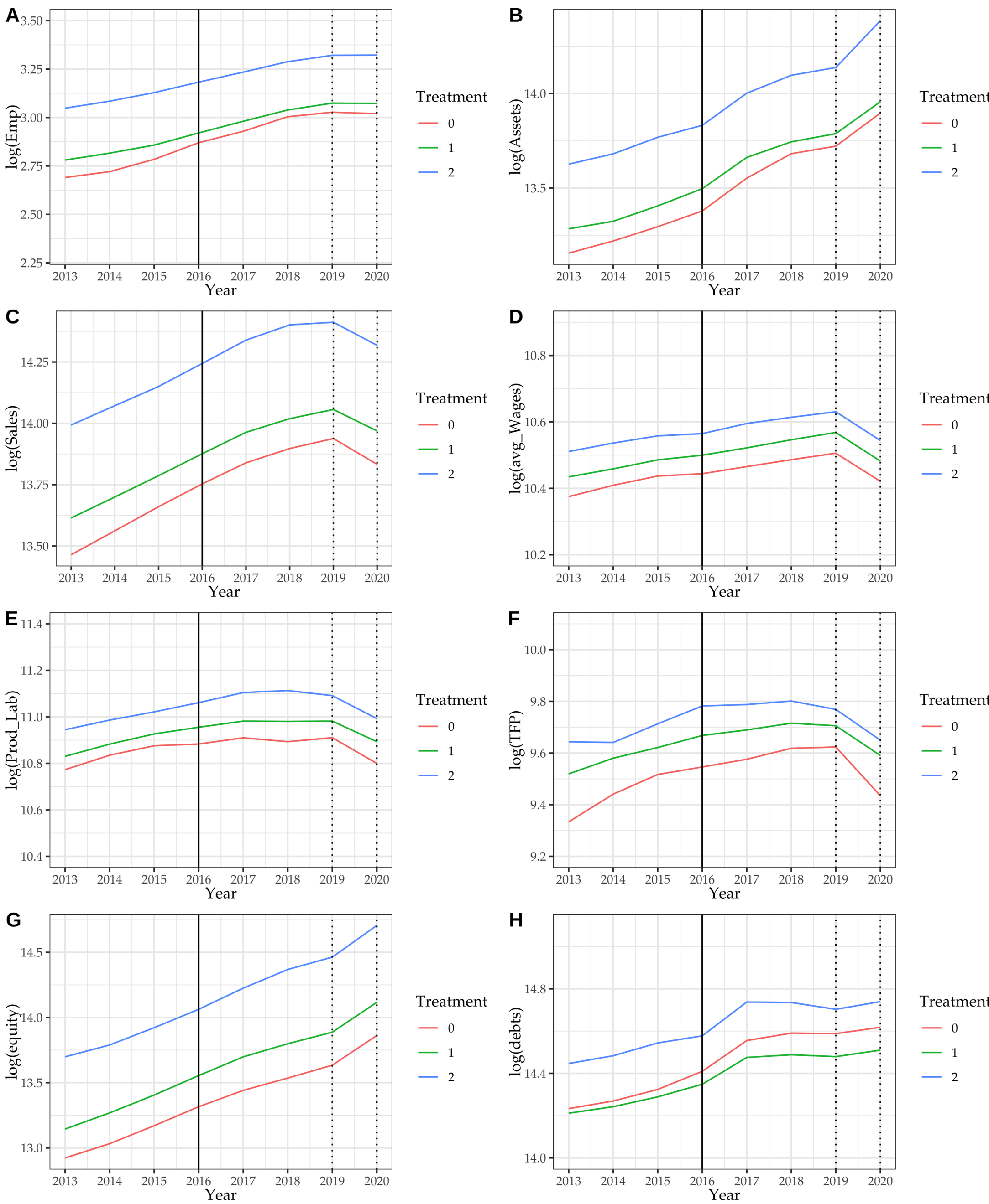
The Figure also reports the trends of 8 different variables. These are the logs of: employment (Panel A), assets (panel B), sales (panel C), average wages (Panel D), productivity of labor (Panel E), TFP (Panel F), equity (Panel G) and debts (Panel H).

From these *ex-ante* dynamics, we confirm the parallel trend assumption for all the variables except TFP (for group 2 *vis-à-vis* controls). This enables us to run further analyses, and specifically the Diff-in-Diff regression we described in section 5.4. Inspection of the graphs already gives us preliminary indications of *ex-post* dynamics as we can clearly see how the two main variables which should display close-to-the-break increases – i.e. assets and debts, given the policy setting (section 3.1) – do indeed experience *ex-post* increments. Importantly, this is not true only for the treated, but also for the untreated.

Recall indeed that also firms in this particular (untreated) control group make investments. Notably, the group is composed by firms which got "revocations", i.e. by firms which had planned investments before accessing the policy or that invested not in accordance with the policy. These are either firms that would have used the policy simply to externalize costs, thus producing crowding-

[36] Also, as we commented viewing Table 4, control firms show averages generally lower than the two treated groups.

Figure 3: Parallel trend assumption and post-treatment average dynamics for treated group(s) and CG 1 (revocations)



Notes: the red lines represent the dynamics for untreated, the green lines for "Ordinary" treated while the blue lines for "Industry 4.0" treated.
Source: own elaboration on MiSE and InfoCamere data.

out of private resources, or firms whose investments did not concern assets covered by the provision of the Law. Hence, as a first approximation, we can already appreciate that – given the *ex-post* trends of both treated and untreated groups – the Ministry of Economic Development rightly excluded firms present in this control group. Moreover, we notice that firms in the control group of firms which did not invest in Industry 4.0 technologies show worse dynamics for several variables, suggesting the superiority of "embedded technology" associated with the Industry 4.0 cluster.

6.1.2 Effects on firm performance

Table 7 shows the DiD effects on treated *vis-à-vis* untreated (revocations), where the group of treated firms include both those which made ordinary investments and those that made Industry 4.0 investments.[37] These results indicate that there are no significant *differential* effects across groups w.r.t. employment, sales, wages, and assets. These effects are captured by our *DiD* coefficient, which is indeed not significant for those variables. This "insignificance" reflects (or transposes) to the overall parallel dynamics of the variables – across groups – both before and after the implementation of the policy, shown in Figure 3.

Table 7: DiD results for treated firms (both Ordinary and 4.0) *vis-à-vis* revocations control group

	Dependent variable:					
	log(Sales)	log(ProdLab)	log(Emp)	log(Wages)	log(Assets)	log(Debts)
	(1)	(2)	(3)	(4)	(5)	(6)
DiD	−0.002	0.023*	−0.024	0.003	−0.022	−0.049***
	(0.016)	(0.012)	(0.015)	(0.008)	(0.028)	(0.018)
time	0.010	−0.035***	0.044***	−0.003	0.129***	0.142***
	(0.015)	(0.012)	(0.014)	(0.008)	(0.027)	(0.017)
Firm ch	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral ch	Yes	Yes	Yes	Yes	Yes	Yes
Regional ch	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Robust errors	Yes	Yes	Yes	Yes	Yes	Yes
Panel method	Within	Within	Within	Within	Within	Within
Observations	48,986	48,980	49,030	48,895	49,296	49,079
R^2	0.290	0.059	0.240	0.094	0.188	0.155

*p<0.1; **p<0.05; ***p<0.01

Notes: Firms characteristics include Age, i_{roe}, i_{lev}, legal form. i_{lev} is not included for assets and debts. The complete list of coefficients is available in Appendix C (Table 19).

Source: own elaboration on MiSE and InfoCamere data.

[37] Parallel trends are indeed respected also when considering the averages for the overall group.

Conversely, we can appreciate substantial developments in the assets and debts variables across pre/post treatment periods. More precisely, by looking at the *time* coefficient, we notice how assets are in the post-implementation period (i.e. from 2017) around 13% higher than in the pre-tretment period. Similarly, debts are on average about 14% higher in 2017-2018-2019 *vis-à-vis* 2013-2014-2015-2016. This is true in general, both for treated and untreated firms. In fact, the *time* coefficient identifies the general differences among treatment periods for variables under consideration, across all groups. Notably, there is a general increase in assets, while there is no differential effect between groups. In other words – considering just assets – one can judge the screening phase made by the Ministry as effective. Indeed, both groups do invest, but the one whose policy incentives were revoked did that without externalizing any cost to the State.

On the other hand, one can appreciate a differential effect on debts. Indeed, while average debts increase for all firms (*time* coefficient), we see that the *DiD* coefficient for the debt variable is negative and statistically significant. This means that firms which accessed the policy experienced a lower increase in debts *vis-à-vis* firms which received a revocation. We deduce that the latter firms, in order to finance investments, increased debts more than treated firms. This is indeed plausible, since the policy *de facto* aims to lower debt burdens. Finally, while we observe a general decrease in the productivity of labor for the post-treatment period, we notice a small differential effect (significant at 10%) for the treated group. We further inspect this dynamic in the next two Tables, where we split the sample of treated firms according to their respective treatments (i.e. Ordinary or Industry 4.0).

Table 8 shows results for the subgroup of firms which invested in Industry 4.0 technologies. Interestingly, we notice how effects on productivity are still positive, but higher and statistically stronger w.r.t. Table 7. Conversely, effects for firms which invested in "Ordinary" capital are overall not significant, as shown in Table 9. We interpret these results as indications of the relatively higher impact of Industry 4.0 investments *vis-à-vis* ordinary ones. More specifically, we can imagine that firms whose incentives were revoked actually invested in a form of capital comparatively "more similar" to the ordinary type, rather than to the Industry 4.0 type. Indeed, we observe differential effects only for firms which made the second type of investment, while DiD effects for ordinary investments are null. This interpretation is coherent with the composition of our control group,

Table 8: DiD results for 4.0 treated firms *vis-à-vis* revocations control group

	Dependent variable:					
	log(Sales)	log(ProdLab)	log(Emp)	log(AvgWages)	log(Assets)	log(Debts)
	(1)	(2)	(3)	(4)	(5)	(6)
DiD	0.005	0.037***	−0.031**	0.005	−0.016	−0.043**
	(0.017)	(0.013)	(0.015)	(0.009)	(0.030)	(0.019)
time	0.019	−0.023**	0.041***	0.002	0.121***	0.145***
	(0.014)	(0.011)	(0.013)	(0.008)	(0.025)	(0.016)
Firm ch	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral ch	Yes	Yes	Yes	Yes	Yes	Yes
Regional ch	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Robust errors	Yes	Yes	Yes	Yes	Yes	Yes
Panel method	Within	Within	Within	Within	Within	Within
Observations	14,466	14,466	14,479	14,460	14,512	14,493
R^2	0.328	0.104	0.283	0.121	0.210	0.183

*p<0.1; **p<0.05; ***p<0.01

Notes: Firms characteristics include Age, i_{roe}, i_{lev}, legal form. i_{lev} is not included for assets and debts.

which includes mainly (i) firms that had already planned investments before accessing the policy and (ii) firms that did invest but without making investments as required by the "Nuova Sabatini" law (see again section 3.1). As a robustness w.r.t. previous discussions, we still notice in both Tables how debts are comparatively lower for firms which accessed the policy, for both types of investments.

Table 9: DiD results for Ordinary treated firms *vis-à-vis* revocations control group

	Dependent variable:					
	log(Sales)	log(ProdLab)	log(Emp)	log(AvgWages)	log(Assets)	log(Debts)
	(1)	(2)	(3)	(4)	(5)	(6)
DiD	−0.004	0.018	−0.021	0.004	−0.019	−0.051***
	(0.016)	(0.012)	(0.015)	(0.008)	(0.028)	(0.018)
time	0.006	−0.037***	0.042***	−0.006	0.130***	0.137***
	(0.015)	(0.012)	(0.014)	(0.008)	(0.027)	(0.017)
Firm ch	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral ch	Yes	Yes	Yes	Yes	Yes	Yes
Regional ch	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Robust errors	Yes	Yes	Yes	Yes	Yes	Yes
Panel method	Within	Within	Within	Within	Within	Within
Observations	37,835	37,829	37,871	37,750	37,950	37,907
R^2	0.284	0.055	0.230	0.092	0.182	0.154

*p<0.1; **p<0.05; ***p<0.01

Notes: Firms characteristics include Age, i_{roe}, i_{lev}, legal form. i_{lev} is not included for assets and debts.
Source: own elaboration on MiSE and InfoCamere data.

Finally, Tables 8 and 9 illustrate how firms which invested in Industry 4.0 experienced a lower increase in employment *vis-à-vis* controls (which did invest, but plausibly not in Industry 4.0 technologies). Indeed, while the *time* coefficient is positive (indicating an increase in employment across groups), the DiD coefficient is negative and significant. We explain this effect as strictly related to the productivity effect we described above. Indeed, we can interpret Industry 4.0 technologies as having a higher *marginal* role in process innovation and economies of scale, potentially related to a lower increase in employment *vis-à-vis* controls. We will briefly return on this aspect in section 6.3, where we address heterogeneous effects for the matched control group.

6.2 Second control group: matching

6.2.1 Parallel trends assumption

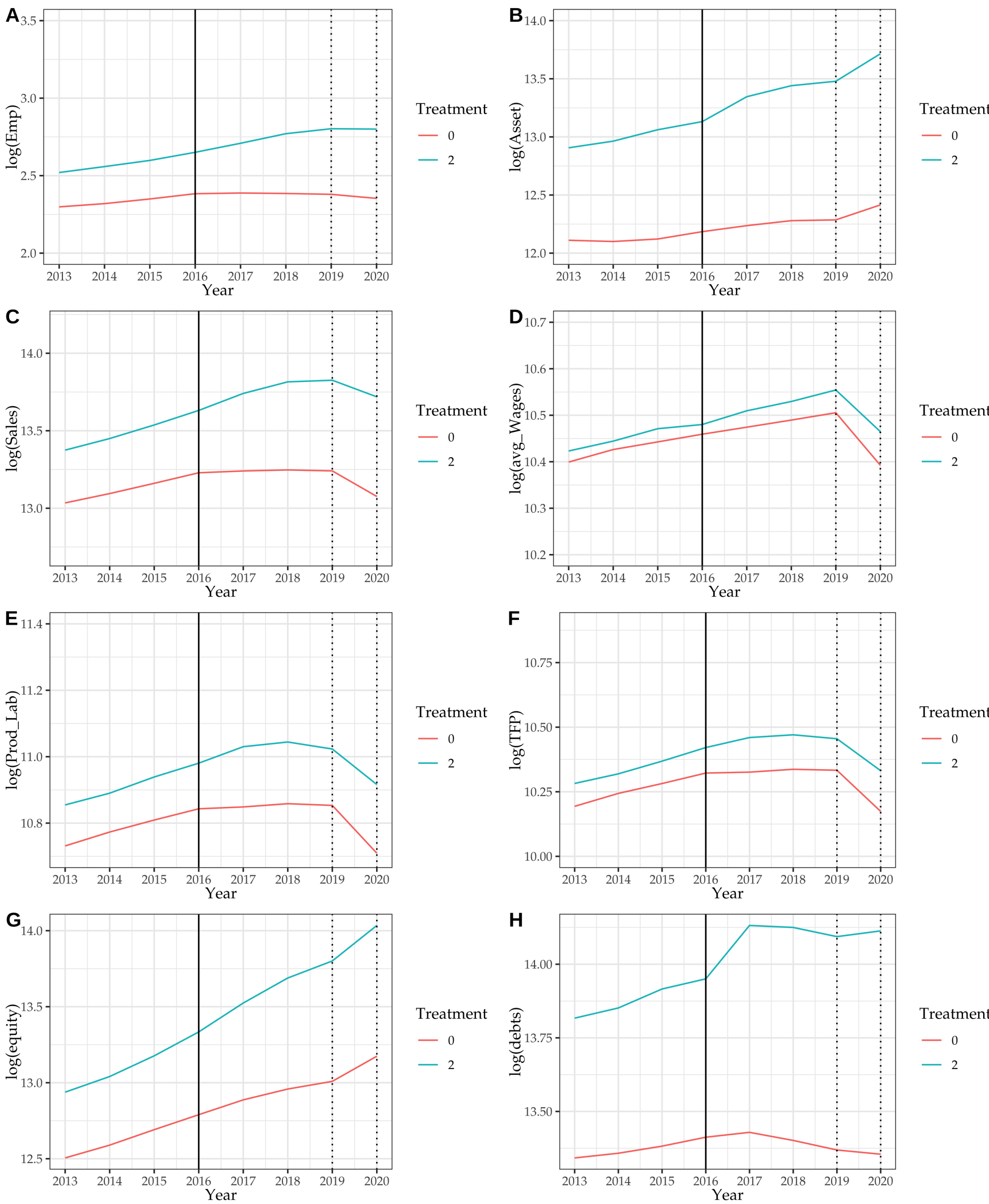
Figure 4 shows the dynamics of treated "Industry 4.0" firms *vis-à-vis* controls, identified through statistical matching (section 5.3). We notice that parallel trends are satisfied in the case of employment (Panel A), assets (panel B), sales (panel C), productivity of labor (Panel E), debts (Panel H), equity (Panel G), TFP (Panel F) and average wages (panel D). From this Figure we can already tentatively identify *ex-post* effects, firstly, on the two variables which are indeed directly affected by the policy – assets and debts – and secondly on employment, sales, productivity and wages.

6.2.2 Effects on firm performance

Table 10 shows results for the group of "Industry 4.0" firms *vis-à-vis* the matched control group (cfr. Table 6 above). There are strong positive effects of Industry 4.0 technologies. Closer inspection of the results reveals generally positive and significant effects on Assets and Debts. Recall that the policy primarily targets assets, which did indeed increase in the post-implementation period. Relatedly, the policy facilitated access to external financing, which coherently transposes in a higher level of debts. Naturally, these two coefficients have different signs *vis-à-vis* the ones we found before (Tables 7, 8, 9). This is reasonable and expected because here our control group is composed by firms which did not apply to the "Nuova Sabatini". Also, these firms did not access any other policy schemes in 2017 or in the post-implementation period, as we could verify through the "National Register of State Aids".

Conversely, we observe close-to-the-break increments for the treated group, as shown in Figure 4

Figure 4: Parallel trend assumption and post-treatment average dynamics for 4.0 treated group and CG 2 (matching)



Notes: the red lines represent the dynamics for the untreated (matched) group, while the blue lines for "Industry 4.0" treated.
Source: own elaboration on MiSE and InfoCamere data.

Table 10: DiD results for 4.0 treated firms *vis-à-vis* matched control group

	Dependent variable:						
	log(Sales)	log(ProdLab)	log(Emp)	log(AvgWages)	log(TFP)	log(Assets)	log(Debts)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DiD	0.179***	0.052***	0.126***	0.018***	0.047***	0.253***	0.201***
	(0.011)	(0.008)	(0.009)	(0.006)	(0.009)	(0.023)	(0.013)
time	−0.063***	−0.030***	−0.032***	−0.006**	−0.030***	0.023**	−0.013**
	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.010)	(0.006)
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral ch	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional ch	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel method	Within	Within	Within	Within	Within	Within	Within
Observations	34,391	34,384	34,449	34,302	24,834	34,472	34,571
R^2	0.139	0.056	0.079	0.057	0.089	0.056	0.040

*p<0.1; **p<0.05; ***p<0.01

Notes: Firms characteristics include Age, i_{roe}, i_{lev}, legal form. i_{lev} is not included for assets and debts. Table 20 in Appendix C shows the complete list of coefficients.

Source: own elaboration on MiSE and InfoCamere data.

and captured by the DiD coefficients for assets and debts. Recalling the content of Figure 2, which reported the distributional balance of the post-matching sample, we know that our control group (and treated group) is composed by firms which are on average smaller than pre-matching. Hence, we interpret the magnitude of this DiD coefficients as the particular ATT on this subgroup of smaller firms. Moreover, the noticeable effects we find appear in line with the idea that financial constraints are particularly binding for smaller firms, in line with the literature and with our expectations.

Table 10 reports generally positive effects on employment, productivity (TFP and Labor), wages and sales. We interpret these results as the manifestation of process innovations following new investments. More specifically, we can argue that new capital, incorporating new technology, brings about higher productivity, leading to higher sales and higher wages (over the three year post treatment period). Importantly, this dynamic does not translate in a reduction of employment, but rather its increase (we further analyze these aspects in the next section). The control group – recall Figure 4 – shows instead a rather constant dynamic from 2017 onward. In particular, sales seem to flatten while employment remains overall constant. Labor productivity and TFP also fall. All in all, we can say that by lowering of credit constraints, the policy successfully improves employment, productivity, and sales.

6.3 Additional estimations

6.3.1 Heterogeneous effects by sector

In Table 11 we show results for selected variables for firms belonging to (A) Low-Tech/Medium Low-Tech and Less Knowledge intensive sectors and to (B) High-tech, Medium High-Tech and Knowledge intensive sectors. We confirm two main intuitions. First, results are coherent with those shown in Table 10. Second, they confirm our hypothesis about productivity effects. Indeed, we find that the effects regarding both labor productivity and TFP are not significant for firms belonging to HT/MHT/KIS sectors, while they are significant for firms belonging to lower-tech sectors. Notably, labor productivity increases by around 5% points in the post-treatment period for firms belonging to group A, whereas TFP increases by ca. 5% points. Employment grows for both groups, suggesting that the role of new investments is expansionary across the two macro-sectors.

6.3.2 Robustness checks

The analyses performed in previous sections point out for general effects related to the policy. Notably, (i) given the particular composition of our two control groups, and (ii) the coherence of results across different specifications, we are confident that we correctly identified policy effects. Nonetheless, the magnitudes of our coefficients may be biased, notably for estimations which rely on the matched control group. Indeed, the matching technique we exploit does not fully take into account the differences in capabilities which may characterize (pre-treatment) firms. Moreover, the control group is built taking as a reference point the entire population of treated firms, i.e. also firms which invest in "Ordinary capital". In other words, we compare firms which invest in "4.0" with matched firms which are *ex-ante* similar not only to them, but also to firms which invest in ordinary capital. In this sense, effects may be magnified by pre-existing differences across groups. This constitutes a possible source of bias.

However, the reverse argument can also apply. What happens to firms which invested in *ordinary capital* relatively to our control group? Put differently, do we observe any effects in firms which invested in ordinary capital *vis-à-vis* the controls? In this case, we would compare ordinary firms with matched firms that are not only *ex-ante* similar to them, but also to firms which invested in Industry 4.0. As we know from the descriptive analyses, these firms are *ex-ante* (e.g.) more productive[38]. Hence, we should expect a *downward bias* in estimations, but if the policy generally works, we should still find positive effects. This is indeed the case. Table 12 shows Diff-in-Diff results[39] for firms which invested in ordinary capital *vis-à-vis* the matched control group. Coefficients are positive and significant.[40]

[38] See also Table 15 in Appendix A.

[39] Parallel trends are satisfied for all variables except for wages. The figures are not included in the paper but are available from the Authors upon request.

[40] Table 21 in Appendix C further disentangles differences among Ordinary treated and 4.0 treated, finding positive differential labour productivity effects for (larger) firms investing in 4.0 assets.

Table 11: DiD results for 4.0 treated firms *vis-à-vis* matched control group across HT/LT sectors

	Dependent variable:									
	LT/MLT/LKIS (A)					HT/MHT/KIS (B)				
	log(ProdLab)	log(Emp)	log(Assets)	log(Debts)	log(TFP)	log(ProdLab)	log(Emp)	log(Assets)	log(Debts)	log(TFP)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DiD	0.056***	0.125***	0.262***	0.204***	0.049***	0.018	0.122***	0.212***	0.167***	0.027
	(0.009)	(0.010)	(0.025)	(0.015)	(0.009)	(0.021)	(0.019)	(0.054)	(0.031)	(0.022)
time	−0.032***	−0.032***	0.022**	−0.015**	−0.030***	−0.009	−0.033***	0.026	0.002	−0.023*
	(0.005)	(0.004)	(0.010)	(0.006)	(0.005)	(0.011)	(0.009)	(0.029)	(0.016)	(0.012)
Firm ch	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral ch	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional ch	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel method	Within	Within	Within	Within	Within	Within	Within	Within	Within	Within
Observations	29,602	29,665	29,704	29,781	21,128	4,782	4,784	4,768	4,790	3,788
R^2	0.050	0.068	0.052	0.036	0.077	0.151	0.148	0.054	0.071	0.145

*p<0.1; **p<0.05; ***p<0.01

Notes: Firms characteristics include Age, i_{roe}, i_{lev}, legal form. i_{lev} is not included for assets and debts. The Table with complete list of coefficients is not reported in Appendix and it is available upon request.
Source: own elaboration on MiSE and InfoCamere data.

Table 12: DiD results for Ordinary treated firms *vis-à-vis* matched control group

	Dependent variable:					
	log(Sales)	log(ProdLab)	log(Emp)	log(TFP)	log(Assets)	log(Debts)
	(1)	(2)	(3)	(4)	(5)	(6)
DiD	0.160***	0.025***	0.134***	0.029***	0.234***	0.180***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.016)	(0.009)
time	−0.088***	−0.032***	−0.056***	−0.036***	−0.008	−0.034***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.010)	(0.006)
Firm ch	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral ch	Yes	Yes	Yes	Yes	Yes	Yes
Regional ch	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Robust errors	Yes	Yes	Yes	Yes	Yes	Yes
Panel method	Within	Within	Within	Within	Within	Within
Observations	50,331	50,318	50,408	37,509	50,440	50,549
R^2	0.186	0.053	0.133	0.086	0.087	0.068

*p<0.1; **p<0.05; ***p<0.01

Notes: Firms characteristics include Age, i_{roe}, i_{lev} legal form. i_{lev} is not included for assets and debts. Table with complete coefficients is not reported in Appendix and it is available upon request.
Source: own elaboration on MiSE and InfoCamere data.

7 Conclusions

The paper addressed the effects of new "Industry 4.0" technologies on firm performance. We exploited data on the "Nuova Sabatini" policy scheme, and analyzed the effects of investments on adopters. We reach two main conclusions. Firstly, the policy is effective in promoting asset growth (its main objective). Secondly, and most importantly, we find evidence of positive effects of new "Industry 4.0" capital investments on productivity, sales and wages growth. Results also show that technological upgrading does not result in "technological unemployment".

The Difference-in-Differences methodology we applied alleviates endogeneity concerns and the set of controls we have used considerably limits problems of unobserved heterogeneity. The rich data we have used – particularly the 7 million observations on policies available through the NRA – allowed us to remove *ex-ante* important confounding factors related to any policy schemes accessed by "untreated" firms other than policy under investigation. To the best of our knowledge, this is the first paper that can make this claim.

Results are robust to different estimations and to the use of different control groups as counterfactuals. The use of different control groups allowed us to obtain further interesting results. Firstly, the control group associated with the "revocations" of incentives enabled us to ascertain that the Ministry rightly excluded this group of firms from the policy scheme, saving public resources. Secondly, the composition of our post-matching control group allowed us to confirm that smaller firms – which are much more inclined than larger firms to suffer from financial constraints – experience substantial gains from the policy. As an underlying mechanism, this follows closely the credit channel through which the policy is implemented.

In terms of self-selection into treatment, pre-existing differences among firms matter. When we distinguish firms that made investment in "Ordinary" from firms that invested in Industry 4.0 technologies, we notice how – regardless of the value of the subsidy rates – firms that are *ex-ante* (on average) more productive self-select into "Industry 4.0" investments, while less productive firms self-select into the "Ordinary" segment. Hence, while we assessed that the policy is effective in increasing investments and performances for treated groups, we also showed how it does not reduce differences across groups. Therefore, two aspects of the problem are worth mentioning: first, there is a possible divergence-inducing role of policies that work through incentives, such as "Nuova Sabatini", and more generally EU State Aids; second, there might additional room for more direct industrial policies, if the policy maker's objective is to reduce the gap between superstar firms and laggards. Further research might be able to assess the medium- to long-term adaptation of the economy to the digital revolution, and to identify new policy gaps.

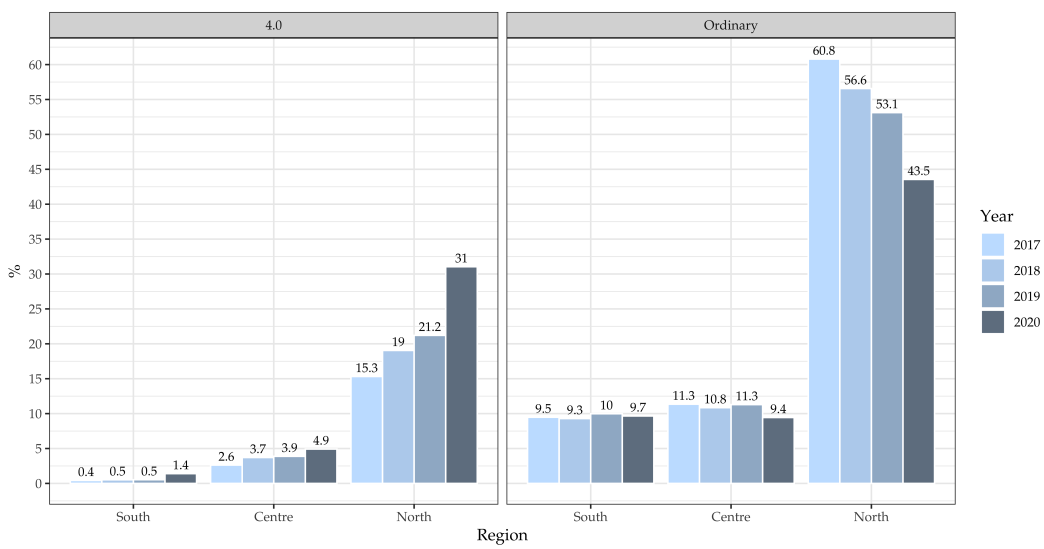
Appendix A: Additional information on policy beneficiaries

Table 13: "Nuova Sabatini" at a glance

Year	**2014**		**2015**		**2016**		**2017**		**2018**		**2019**		**2020**		**Total**	
	Units	%	Units	%	Units	%	Units	%	Units	%	Units	%	Units	%	Units	%
Total	2330		3419		8263		13096		18390		15020		17943		78461	
Medium	680	29%	835	24%	1597	19%	2105	16%	2598	14%	2173	14%	2250	13%	12238	16%
Small	1066	46%	1716	50%	3909	47%	6032	46%	8089	44%	6471	43%	6571	37%	33854	43%
Micro	584	25%	868	25%	2757	33%	4959	38%	7703	42%	6376	42%	9122	51%	32369	41%
Non-individual	2217	95%	3156	92%	7309	88%	11406	87%	15651	85%	12514	83%	13537	75%	65790	84%
Individual	113	5%	263	8%	954	12%	1690	13%	2739	15%	2506	17%	4406	25%	12671	16%
North-east	777	33%	1438	42%	3612	44%	5158	39%	6927	38%	5580	37%	6506	36%	29998	38%
North-west	907	39%	1325	39%	2869	35%	4809	37%	6981	38%	5583	37%	6878	38%	29352	37%
Centre	415	18%	416	12%	1070	13%	1832	14%	2678	15%	2279	15%	2575	14%	11265	14%
South	174	7%	162	5%	444	5%	926	7%	1313	7%	1221	8%	1518	8%	5758	7%
Islands	57	2%	78	2%	268	3%	371	3%	491	3%	357	2%	466	3%	2088	3%
HT	35	2%	32	1%	62	1%	102	1%	133	1%	89	1%	93	1%	546	1%
MHT	245	11%	357	10%	639	8%	1019	8%	1244	7%	900	6%	786	4%	5190	7%
MLT	714	31%	1150	34%	2442	30%	3680	28%	4662	25%	3351	22%	2869	16%	18868	24%
LT	477	20%	593	17%	1211	15%	1767	13%	2430	13%	1700	11%	1585	9%	9763	12%
KIS	131	6%	96	3%	148	2%	263	2%	360	2%	292	2%	303	2%	1593	2%
LKIS	470	20%	852	25%	2741	33%	4188	32%	5677	31%	4665	31%	4863	27%	23456	30%
Other	258	11%	339	10%	1020	12%	2077	16%	3884	21%	4023	27%	7444	41%	19045	24%
Manufacturing	1471	63%	2132	62%	4354	53%	6568	50%	8469	46%	6040	40%	5333	30%	34367	44%
Services	258	11%	339	10%	1020	12%	2077	16%	3884	21%	4023	27%	7444	41%	19045	24%
Other	601	26%	948	28%	2889	35%	4451	34%	6037	33%	4957	33%	5166	29%	25049	32%
Ordinary inv							10689	82%	14107	77%	11173	74%	11240	63%	47209	74%
4.0 inv							2407	18%	4283	23%	3847	26%	6703	37%	17240	26%

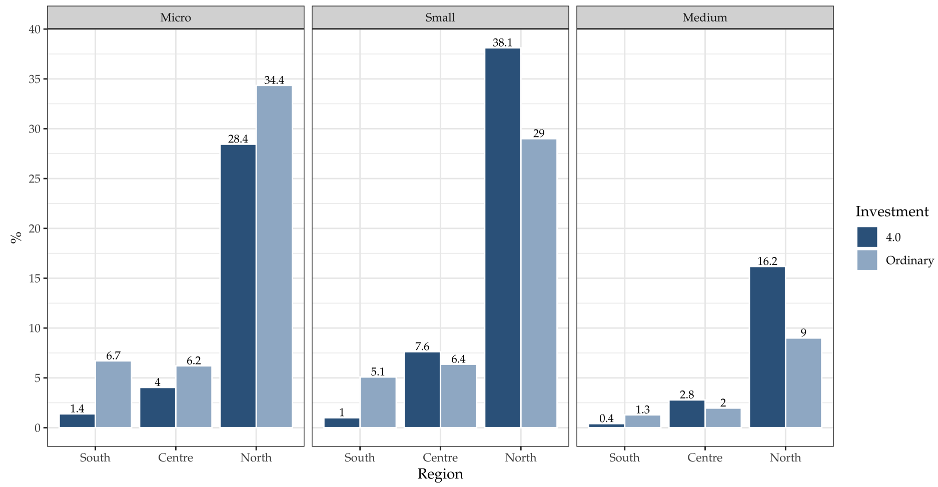
Notes: Medium/Small/Micro refer to firm dimension. Individual/non-individual to legal form. HT stands for High-tech, MHT for Medium HT, LT for Low tech, KIS for Knowledge Intensive Sectors, LKIS for Less KIS. "Other" refers to sectors non classifiable according to the Eurostat nomenclature. A detailed description of the Eurostat classification is provided in Appendix A. Firms which have obtained resources through more than one decree are considered only once.
Source: own elaboration on MiSE data. See also section 4.1.

Figure 5: Yearly distribution of NS beneficiaries by region and by type of investment (2017-2020)



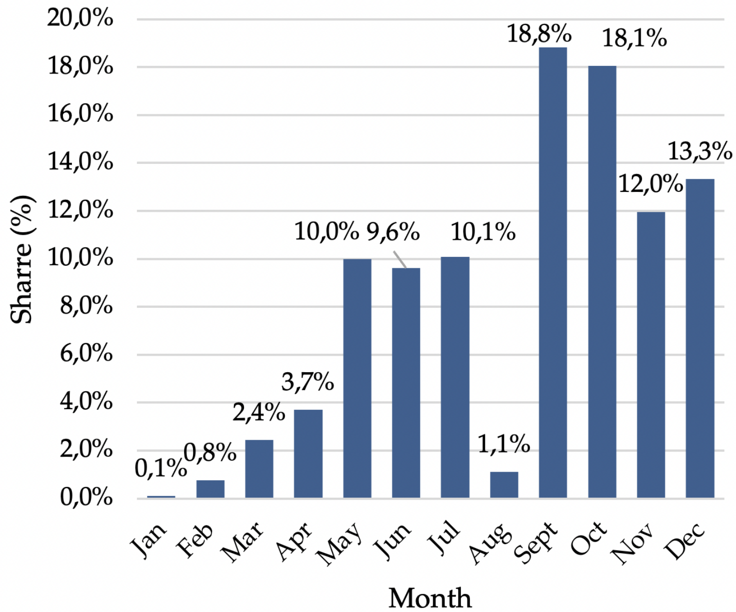
Source: own elaboration on MiSE data.

Figure 6: Investment types according to geographical area and firm dimension (2017-2020)



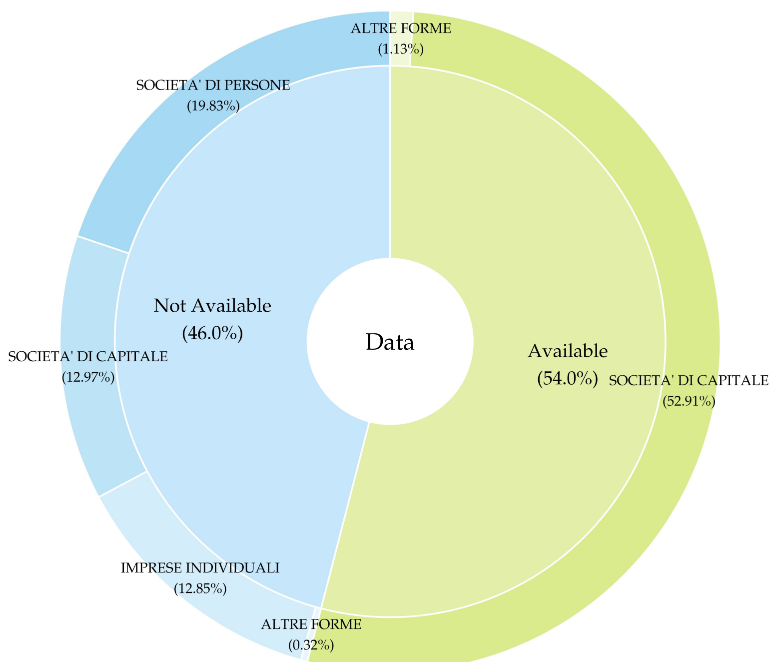
Source: own elaboration on MiSE data.

Figure 7: Distribution of "Nuova Sabatini" approval decrees by month (year 2017)



Source: own elaboration on MiSE data.

Figure 8: Financial data available within the InfoCamere database according to firms' legal form and analysis specification



Notes: The category "Altre forme" (other forms of companies) includes: "Consorzio", "Società cooperativa", "Società consortile", "Cooperativa sociale".
Source: own elaboration on InfoCamere and MiSE data.

Table 14: Overall beneficiary firms in 2015

	Mean	Median	Min	Max	Sd	1stQuart	3rdQuart	Obs.
log_TFP	9.67	9.64	8.1	11.3	0.39	9.45	9.88	6822
log_Prod_Lab	10.95	10.94	-0.21	14.92	0.48	10.7	11.18	6822
log_debts	14.35	14.38	9.35	18.25	1.22	13.53	15.19	6822
log_Equity	13.53	13.54	2.77	18.38	1.5	12.47	14.62	6822
log_IntAssets	10.26	10.41	0.69	16.72	2.1	8.88	11.78	6822
log_TanAssets	13.21	13.3	1.61	18.04	1.59	12.21	14.32	6822
log_Assets	13.49	13.59	2.3	18.34	1.51	12.55	14.53	6822
log_AvgWages	10.5	10.56	4.23	14.12	0.39	10.36	10.72	6822
log_Sales	13.87	13.87	3.04	17.43	1.06	13.2	14.6	6822
log_Emp	2.92	2.89	0	5.52	0.93	2.3	3.56	6822
Age	22.42	20	4	96	13.83	11	31	6822
log_IntCosts	13.85	13.92	3.74	18.78	1.62	12.85	14.96	6822
i_roe	0.14	0.11	-6.84	1.85	0.29	0.04	0.24	6822
i_lev	3.51	2.14	0.04	20	3.71	0.97	4.65	6822

Notes: We show the year 2015 since firms must present financial statements at maximum two years before the policy. Note, in this sense, that maximum employment is below 250: indeed, $e^{5.52} \approx 249,6 < 250$. (recall section 3.1). Observations refer to the total number of firms available (see section 4.1). Nonetheless, some variables display missing values, which we omit in the computations displayed here.
Source: own elaboration on MiSE and Infocamere data.

Table 15: Linear probability model, adoption of "Industry 4.0" vs "Ordinary capital"

	Dependent variable:							
	Adoption of I4.0							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(L)	0.031***	0.030***	0.032***		0.034***			0.037***
	(0.005)	(0.005)	(0.005)		(0.005)			(0.007)
log(W)				0.040***	0.012			
				(0.014)	(0.015)			
log(K)						0.016***	0.011***	−0.005
						(0.003)	(0.003)	(0.005)
log(VA/L)		0.072***	0.059***				0.052***	0.065***
		(0.010)	(0.011)				(0.011)	(0.012)
i_{fi}			0.119***	0.149***	0.157***	0.128***	0.107***	0.120***
			(0.024)	(0.023)	(0.023)	(0.022)	(0.024)	(0.024)
Age	0.0002	−0.00000	−0.0003	0.0004	−0.0002	−0.0001	0.00000	−0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Sect. 2-digit FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,537	8,156	8,152	8,151	8,114	8,475	8,188	8,140
R^2	0.147	0.151	0.154	0.147	0.151	0.149	0.151	0.154

*p<0.1; **p<0.05; ***p<0.01

Notes: the table reports results for the estimation of a linear probability model ($I4.0_i = \alpha + \beta X_i + FE_i + \varepsilon_i$). The dependent variable is a dummy ($I4.0_i$) equal to 1 if the firm invests in 4.0 capital in 2017 and 0 if it invests in Ordinary capital. X_i is the vector of adoption drivers (mean log values for 2012-2016). In particular, log(L) is employment, log(W) is average wages, log(K) is capital, log(VA/L) is labour productivity, i_{fi} is the index of financial independence, computed as equity over total assets. Results highlight two main conclusions. In terms of self-selection into treatment, *ex-ante* (on average) larger and more productive self-select into "4.0" investments, while smaller and less productive firms tend to opt for the "Ordinary" segment. Moreover, we find that 4.0 technologies tend to be installed by financially healthier firms, while ordinary capital by less financially independent firms.
FE_i represents region and firm fixed effects. Region and sector fixed effects coefficients are not reported. The constant is omitted. Robust standard errors are shown in parentheses.
Source: own elaboration on MiSE and InfoCamere data.

Appendix B: Matching control group statistics

Table 16: Balance statistics for matching without caliper

	SMD	VR	Mean eCDF	Max eCDF	SPD
Sales_2016	0.32	2.01	0.06	0.19	0.36
i_lev_2016	-0.02	15.12	0.07	0.13	0.08
Immat_Assets_2016	0.17	4.55	0.17	0.23	0.26
Mat_Assets_2016	0.28	2.07	0.15	0.25	0.41
Employees_2016	0.34	2.17	0.04	0.20	0.49
Sales_2015	0.29	1.97	0.06	0.17	0.35
i_lev_2015	0.00	17.44	0.07	0.14	0.06
Immat_Assets_2015	0.17	4.84	0.16	0.22	0.26
Mat_Assets_2015	0.26	2.12	0.15	0.24	0.40
Employees_2015	0.32	1.98	0.04	0.19	0.49
Sales_2014	0.25	2.57	0.06	0.16	0.30
i_lev_2014	-0.07	0.42	0.06	0.13	0.42
Immat_Assets_2014	0.16	5.08	0.16	0.22	0.26
Mat_Assets_2014	0.24	2.08	0.14	0.22	0.39
Employees_2014	0.31	1.91	0.04	0.18	0.49
Sales_2013	0.27	1.84	0.06	0.16	0.33
i_lev_2013	-0.09	0.11	0.06	0.13	0.62
Immat_Assets_2013	0.15	4.95	0.15	0.21	0.24
Mat_Assets_2013	0.22	1.97	0.14	0.22	0.39
Employees_2013	0.30	1.90	0.04	0.17	0.49

Notes: SMD stands for standardized mean difference; VR for variance ratio; SPD for standardized pair difference.
Source: own elaboration on MiSE and InfoCamere data.
Go back to Section 5.3.1.

Table 17: Sample balance – statistics with caliper

	SMD	VR	Mean eCDF	Max eCDF	SPD
Sales_2016	0.05	1.02	0.04	0.10	0.07
i_lev_2016	-0.01	0.48	0.06	0.12	0.05
Immat_Assets_2016	0.05	2.24	0.12	0.21	0.09
Mat_Assets_2016	0.08	1.27	0.12	0.22	0.16
Employees_2016	0.04	1.01	0.01	0.08	0.10
Sales_2015	0.03	0.96	0.03	0.09	0.07
i_lev_2015	0.00	0.55	0.06	0.11	0.04
Immat_Assets_2015	0.05	1.96	0.12	0.20	0.09
Mat_Assets_2015	0.07	1.23	0.12	0.21	0.15
Employees_2015	0.03	0.97	0.00	0.06	0.10
Sales_2014	0.02	0.96	0.03	0.08	0.06
i_lev_2014	-0.02	0.64	0.06	0.11	0.37
Immat_Assets_2014	0.05	1.76	0.12	0.20	0.10
Mat_Assets_2014	0.06	1.19	0.11	0.19	0.15
Employees_2014	0.02	0.98	0.00	0.05	0.10
Sales_2013	0.02	0.96	0.03	0.07	0.07
i_lev_2013	-0.02	0.44	0.06	0.11	0.56
Immat_Assets_2013	0.04	1.83	0.11	0.18	0.09
Mat_Assets_2013	0.05	1.17	0.10	0.18	0.15
Employees_2013	0.02	0.95	0.00	0.04	0.10

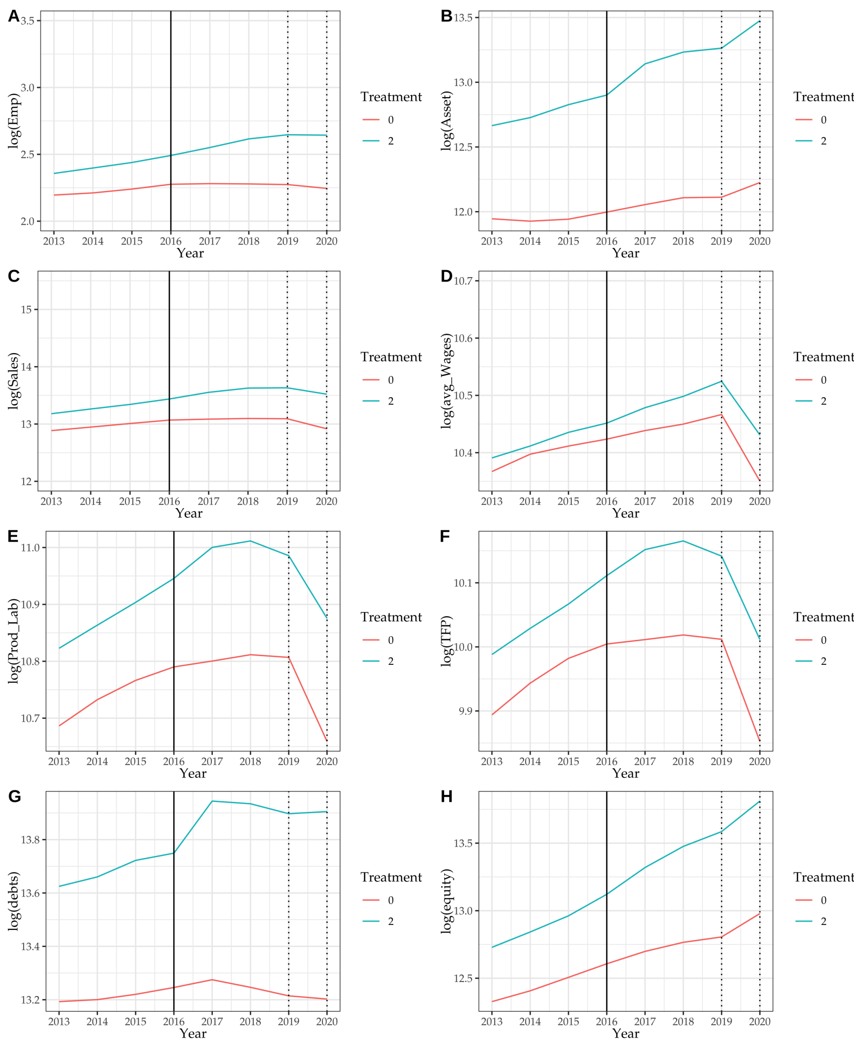
Notes: SMD stands for standardized mean difference; VR for variance ratio; SPD for standardized pair difference.
Source: own elaboration on MiSE and InfoCamere data.
Go back to Section 5.3.1.

Table 18: % Balance Improvements after matching (caliper = 0.5)

	SMD	VR	eCDF Mean	eCDF Max
Sales_2016	93.46	98.53	90.52	83.67
i_lev_2016	81.46	78.41	1.42	-4.30
Immat_Assets_2016	68.06	47.35	44.36	36.95
Mat_Assets_2016	73.75	85.29	65.00	57.42
Employees_2016	94.55	99.22	94.53	85.94
Sales_2015	94.87	96.84	91.25	85.23
i_lev_2015	93.40	79.76	-6.78	-8.55
Immat_Assets_2015	66.60	60.19	43.11	36.49
Mat_Assets_2015	74.10	87.25	64.89	57.19
Employees_2015	95.91	98.38	95.79	89.11
Sales_2014	95.76	97.65	92.50	87.14
i_lev_2014	92.43	94.71	-10.75	-4.30
Immat_Assets_2014	66.62	67.48	43.15	36.19
Mat_Assets_2014	75.26	88.86	66.68	59.96
Employees_2014	96.65	98.51	96.53	91.09
Sales_2013	96.16	96.68	92.89	88.34
i_lev_2013	94.65	90.06	-18.18	-10.73
Immat_Assets_2013	66.76	62.93	44.41	39.76
Mat_Assets_2013	76.31	90.03	68.44	61.67
Employees_2013	97.34	96.29	96.90	92.13

Notes: SMD stands for standardized mean difference; VR for variance ratio.
Source: own elaboration on MiSE and InfoCamere data.
Go back to Section 5.3.1.

Figure 9: Parallel trend assumption and post-treatment average dynamics for 4.0 treated group and matched control group (caliper = 0.3)



Notes: the red lines represent the dynamics for untreated (matched control group), while the blue lines for "Industry 4.0" treated.
Source: own elaboration on MiSE and InfoCamere data.

Appendix C: Additional estimations

Table 19: DiD results for treated firms (both Ordinary and 4.0) *vis-à-vis* revocations control group – complete Table

	Dependent variable:					
	log(Sales)	log(ProdLab)	log(Emp)	log(Wages)	log(Assets)	log(Debts)
	(1)	(2)	(3)	(4)	(5)	(6)
DiD	−0.002	0.023*	−0.024	0.003	−0.020	−0.049***
	(0.016)	(0.012)	(0.015)	(0.008)	(0.028)	(0.018)
time	0.010	−0.035***	0.044***	−0.003	0.130***	0.142***
	(0.015)	(0.012)	(0.014)	(0.008)	(0.027)	(0.017)
Age	0.073***	0.028***	0.045***	0.021***	0.067***	0.031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
i_roe	0.0005**	0.0004**	0.00005	−0.0002**	−0.0001***	0.0001***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.00001)	(0.00001)
i_lev	0.00005	0.0001**	−0.00000	−0.00002		
	(0.00003)	(0.00002)	(0.00005)	(0.00002)		
Firm ch	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral dummy	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Robust errors	Yes	Yes	Yes	Yes	Yes	Yes
Panel method	Within	Within	Within	Within	Within	Within
Observations	48,986	48,980	49,030	48,895	49,135	49,079
R^2	0.290	0.059	0.240	0.094	0.187	0.155

Go back to Table 7.

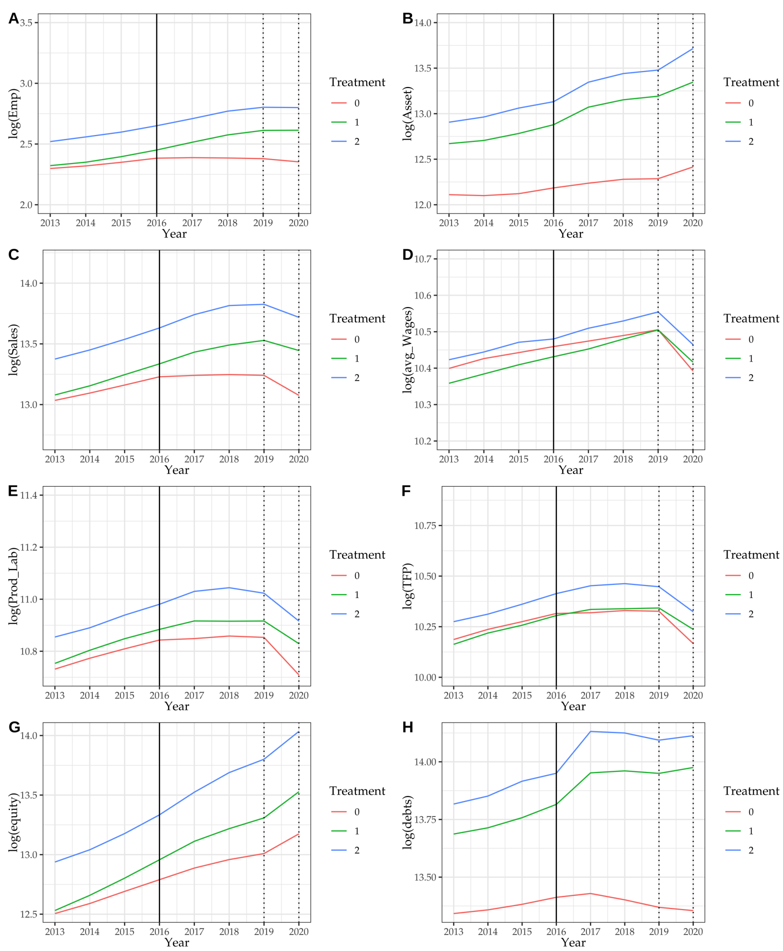
*p<0.1; **p<0.05; ***p<0.01

Table 20: DiD results for 4.0 treated firms *vis-à-vis* matched control group – complete Table

	Dependent variable:						
	log(Sales)	log(ProdLab)	log(Emp)	log(AvgWages)	log(TFP)	log(Assets)	log(Debts)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DiD	0.179***	0.052***	0.126***	0.018***	0.046***	0.253***	0.201***
	(0.011)	(0.008)	(0.009)	(0.006)	(0.009)	(0.023)	(0.013)
time	−0.063***	−0.030***	−0.032***	−0.006**	−0.030***	0.023**	−0.013**
	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.010)	(0.006)
Age	0.050***	0.027***	0.022***	0.019***	0.026***	0.032***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
i_roe	0.003*	0.003	−0.0001	0.0002	0.031***	0.0003	0.0002
	(0.002)	(0.002)	(0.0004)	(0.0002)	(0.008)	(0.0002)	(0.0002)
i_lev	0.0001	0.0001	−0.00000	0.00001	−0.0003		
	(0.0001)	(0.0001)	(0.00002)	(0.00001)	(0.0003)		
Firm ch	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral ch	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional ch	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel method	Within	Within	Within	Within	Within	Within	Within
Observations	34,391	34,384	34,449	34,302	24,834	34,472	34,571
R^2	0.139	0.056	0.079	0.057	0.089	0.056	0.040

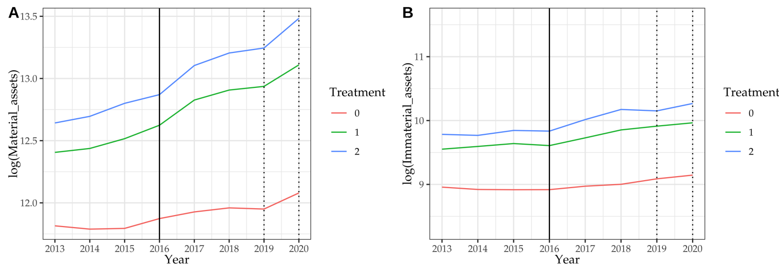
Go back to Table 10. *p<0.1; **p<0.05; ***p<0.01

Figure 10: Parallel trend assumption and post-treatment average dynamics for 4.0 treated group and CG 2 (matching)



Notes: the red lines represent the dynamics for untreated, while the blue lines for "Industry 4.0" treated.
Source: own elaboration on MiSE and InfoCamere data.

Figure 11: Parallel trend assumption for material and immaterial assets (4.0 and Ordinary treated and matched control)



Notes: the red lines represent the dynamics for untreated, the blue lines for "Industry 4.0" treated, while the green lines for "Ordinary" treated.
Source: own elaboration on MiSE and InfoCamere data.

Table 21: Labor productivity dynamics in 2017-2019 vs 2012-2016, for 4.0 firms vs Ordinary firms, for whole and splitted sample (size)

	Dependent variable:			
	Log(VA/L)			
	All	Size 0-19	Size 20-49	Size 50-250
	(1)	(2)	(3)	(4)
DiD	0.011	0.007	0.028**	0.024**
	(0.007)	(0.012)	(0.012)	(0.012)
time	0.184***	0.193***	0.190***	0.109***
	(0.011)	(0.011)	(0.009)	(0.021)
Age	0.001	0.001	0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
i_{fi}	0.194	0.479***	0.049	0.550***
	(0.118)	(0.050)	(0.041)	(0.159)
Firm char	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Sectoral 2-dig FE	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Robust errors	Yes	Yes	Yes	Yes
Panel method	Within	Within	Within	Within
Observations	64,344	35,287	19,687	9,323
R^2	0.088	0.101	0.114	0.121

*p<0.1; **p<0.05; ***p<0.01

Note: year, region, and sector fixed effects coefficients not reported. Constant omitted.
Source: own elaboration on MiSE and InfoCamere data.

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