Structural Change and Economic Dynamics 72 (2025) 47–66

Contents lists available at ScienceDirect

Structural Change and Economic Dynamics

journal homepage: www.elsevier.com/locate/strueco

More technology, more loans? How advanced digital technologies influence firms' financing conditions

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ARTICLE INFO

JEL classification:
O33
G14

Keywords:
Digital technologies
Industry 4.0
Signaling effect
Credit rationing

ABSTRACT

The paper investigates the effects of the adoption of advanced digital technologies (i.e., Industry 4.0) on firms' credit conditions through a signaling effect. The empirical analysis exploits microdata from the Bank of Italy's "Survey on Manufacturing and Service Firms" available for the period 2015–2019, integrated with balance sheet information provided by Cerved. We use a binary endogenous treatment effect model and IV estimation strategy to determine the average effect of digital technology adoption on firms' financing variables. The results can be summarized as follows: (i) the adoption of digital technologies (DT) lowers the likelihood of being credit rationed; (ii) the adoption of DT is associated with a higher level of leverage but with a lower cost of debt; (iii) the increased firm's debt is associated with a composition effect resulting in an expansion of bank debt and a reduction in financial debt. These results, which are robust to a number of checks, suggest that digital technology adoption improves firms' financial conditions, with lower constraints and lower costs, and also influences the relationship between the firm and the financial institutions.

1. Introduction

The recent and wide diffusion of advanced digital technologies led to an analysis of the impact of their adoption in a variety of fields, with a major focus on their effects on economic performance, innovation mechanisms, and the labor market. The emergence of a new technological paradigm is, in fact, rapidly changing firms' and industries' dynamics, affecting the firm's ability to produce and capture value. The paper aims to understand whether and how the adoption of advanced digital technologies may affect firms' financial conditions and their ability to access credit.

Using a framework of imperfect financial markets, where innovative activities may exacerbate the firm's credit-rationing, we look at possible signals that help ease access to credit. From a theoretical point of view, the literature already assumes that some kinds of innovative activities—such as patents (Hottenrott et al., 2016) or innovation subsidies (Chiappini et al., 2022; Lazzaro and Romito, 2023)—may operate as a "signal" toward banks. Accordingly, we look at the adoption of digital technologies as a signal, given their potential to transform firms' technological capabilities and improve their performance. The literature on how technological change affects financial conditions has so far addressed mainly two aspects: the ability of a firm to invest when facing a financial constraints, and the relationship between financial constraints, innovation activities, and the firm's ability to finance them. The potential impacts of a new process adoption—here, through the diffusion of new technologies—on financing-related variables at the firm level seem to be an under-researched issue. Therefore, our focus is on how the adoption of digital technologies may affect the firm's ability to access credit.

As a matter of fact, the lack of funds is a major concern for a firm since it can impact its ability to invest, eventually hampering its survival. Firm's general financial conditions are relevant for firms' and industries' dynamics in terms of entry and exit on the markets and for the dimensional distribution (Ponikvar et al., 2018; Bottazzi et al., 2014). On the other hand, the digitalization of the economy is deeply changing firms' structures and markets' dynamics. The diffusion of advanced digital technologies, as those related to the *Industry 4.0* paradigm, affects the firms' organization, its innovation activities, the efficiency of production, and the value creation and appropriation mechanisms (Teece, 2018; Sung, 2018; Schwab, 2016).

The paper primarily aims to understand how the firm's adaptation to a new wave of technological change may have a signaling effect on the market and financial institutions, eventually improving its ability to access credit. The main research hypothesis is whether the adoption of advanced digital technologies (DT hereafter) works as a signal toward stakeholders affecting the bank–firm relationship, improving the firm's financial conditions through the easing of access to credit, lowering the

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https://doi.org/10.1016/j.strueco.2024.11.011
Received 10 May 2024; Received in revised form 3 October 2024; Accepted 23 November 2024
Available online 10 December 2024

probability of being credit-constrained and improving firms' credit conditions. Moreover, we investigate the impact on debt-related balance sheet variables.

The analysis is carried out using the Bank of Italy's "Survey on Manufacturing and Service Firms" (INVIND), a panel survey collecting a rich set of data on Italian firms with a focus on their relationship with financial institutions and on credit dynamics. Since 2015, the survey has introduced specific questions on the adoption of DT. Survey data are also linked to the firms' balance sheet data, drawn from the Cerved database. The time span covered by the data goes from 2015 to 2019. Since firms' self-selection or omitted variables can bias the OLS estimations of DT adoption and firm's credit conditions, we adopt an instrumental variable strategy based on two different instruments. The first one make use of a variable related to a policy intervention that took place in Italy in 2016–2017 (e.g., "Hyper-depreciation", part of the Italian Industry 4.0 National Plan). The second one is the firm's average exposure to investments in digitalization at the macroregion and NACE 2-digit level (using a firm-level leave-one-out cross validation).

Our empirical analysis provides novel evidence on the relationship between technology adoption—and namely, advanced DT—and firms' access to credit. The results can be summarized as follows: (i) the adoption of DT lowers the likelihood of being credit rationed, the latter being expressed by a self-reported variable built using the survey; (ii) the adoption of DT is associated with a higher level of leverage but with a lower cost of debt; (iii) the increased firm's debt is associated with a composition effect resulting in an expansion of bank debt and a reduction in financial debt.

The article is structured as follows: Section 2 presents the background literature, with a focus on technology adoption, signaling effects, and financing dynamics, along with the research hypotheses. In Section 3, we present the INVIND survey and the descriptive analysis, while the empirical analysis is developed in Section 4. Finally, the results are reported in Section 5, and Section 6 concludes.

2. Theoretical background and research hypotheses

The paper deals with two broad strands of literature. The first one relates to the relationship between access to credit, the signaling effect, and innovative activities at the firm level, while the second investigates the firm-level impact of the adoption of advanced DT.

With regards to access to credit, the Modigliani–Miller theorem proves that complete information and efficient markets make internal and external financing perfect substitutes, allowing investment decisions to be independent of their financing (Modigliani and Miller, 1958). However, financial sources cannot be considered perfect substitutes since information asymmetries or agency issues may arise, eventually resulting in cost differentials on credit sources and then financial constraints. This phenomenon is especially relevant for innovative investments, such as innovation activities (i.e., R&D and patenting) or the adoption of new technology, which can be considered a risky activity in a scenario of transition between technological paradigms.

To limit informational issues, firms may use "signals" to express some latent qualities of their business, displaying unobservable characteristics relevant to the investment, such as their capabilities, using a directly observable element. This "signal", from Spence's framework of "market signaling" (Spence, 1973), can also be used in the analysis of technology diffusion and of its impacts, with particular reference to some specific technologies, now at the center of the economic and social debate, such as in the case of *Industry 4.0* technologies.

Studying the diffusion of a technology, Stoneman and Battisti (2010) interpret the adoption as a message sent to the firm's competitors about its profitability. This positive signal induces competitors to adopt the technology, further increasing its diffusion. Other observable activities, such as patenting, R&D alliances, and team experience, are often used as signals, having a role in signaling the firms' attractiveness for venture capitalists (Hoenig and Henkel, 2015). The same effect is also found by Chiappini et al. (2022) regarding the access to innovation subsidies in French SMEs, where a signaling effect through the public subsidy is detected in relaxing firms' financial constraints. This signal works through a "certification effect" issued by the provider of the subsidy: other studies found a certification effect also in relation to venture capital (Islam et al., 2018) and equity (Söderblom et al., 2015). Moreover, firm-level innovation is found to play a role as a certification, which affects interest rates paid by firms, as found for Italy (Bellucci et al., 2023, 2014) and Portugal (Bonfim et al., 2021). Also, Hai et al. (2022) investigate the relationship between innovation and financial performance. Summarizing the literature on innovation and financial constraints, they find a nonlinear relationship: the hypotheses, already common in the literature, "*more innovation, more money*" and "*more innovation, less money*" are both likely to stand, depending on the firm's market positioning and the scale of production reached. Most of the literature focuses on the relationship between innovation (both subsidies and production) and financial structure, while the impact of the adoption of a new technology (embedding process innovations) on financial constraints seems to be an under-researched issue.

Finally, Geroski et al. (1993) distinguish direct and indirect effects of being involved in innovation activities and suggest that the indirect channel, i.e., not related to the production of a specific new product or process, signals a transformation of the firm's capabilities, eventually affecting permanently the ability to generate profits.[1]

This paper is the first contribution that studies whether the adoption of DT affects financing conditions of the firms through a signaling effect. The reason to focus on financial conditions is twofold: on the one hand, the need to collect the proper financial resources is crucial for many aspects of the firm's life. Financial resources are crucial to support growth opportunities and are a major determinant of firms' survival (Bottazzi et al., 2014; Carreira and Silva, 2010; Geroski et al., 2009), as well as an important factor in entry and exit dynamics (Ponikvar et al., 2018; Musso and Schiavo, 2008; Santarelli and Vivarelli, 2007), eventually influencing the firms' size distribution (Konings and Walsh, 2010; Cabral and Mata, 2003). At the same time, the presence of financial frictions is often related to the firms' innovative activities. The literature dealing with these aspects is mainly focused on R&D and the production of innovations, while some earlier contributions also show the positive role of ICT adoption on access to credit for small firms (Dalla Pellegrina et al., 2017) in terms of the quality of information transmitted to banks. In this paper, we draw attention to the role of advanced digital technologies[2] and firms' technological capabilities in influencing credit allocation.

The highly risky nature of the innovation activities is likely to affect the firm's innovative capabilities in the presence of financial constraints (Mina et al., 2013; Hottenrott and Peters, 2012). These latter may be exacerbated by issues such as adverse selection (Akerlof, 1970), information asymmetries (Myers and Majluf, 1984), and capital market imperfections. On the other hand, financial constraints are also identified as one of the hindrances to the adoption of new technologies, affecting the availability of internal resources (Gomez and Vargas, 2009; Canepa and Stoneman, 2005). The presence of excessively perceived economic risks or their high cost may impact access to credit for firms willing to invest in new technologies (Hoffmann and Nurski, 2021; Stoneman and Battisti, 2010), while in high-tech sectors, firms might have lower realizable assets due to intangible goods produced. In this case, there may be difficulties in evaluating risks since there is no

[1] Moreover, Geroski (1991) underlines that the use of an innovation—DT adoption in our case—rather than the production of an innovation (i.e., patenting activities) seems to have a stronger impact on the firm's productivity and profits.

[2] The technologies here studied, and which are discussed in the remainder of the paper, display characteristics of higher sophistication compared to those of the first wave of digitalization (e.g., ICT).

prior experience to compare with (European Investment Bank, 2019). The same applies to SMEs and younger firms, which are more exposed to financial constraints due to lower collateral and a shorter period of operations.

To conclude, most of the literature focuses on the relationship between innovation and economic performance or financial structure, while the impact of the adoption of new technologies (embedding process innovations) on financial constraints and access to credit seems to be an under-researched issue. Moreover, when analyzing the finance-innovation nexus, most of the studies analyze the "production" of innovations rather than the "use", i.e., the adoption of a new technology. In this perspective, the paper aims to broaden the scope of the analysis by combining the market signaling framework with the impacts of new process adoption, represented by the DT related to the *Industry 4.0* paradigm.

The spread of *Industry 4.0* technologies is rapidly modifying the production process and improving firms' performance (Cirillo et al., 2022; Büchi et al., 2020). The pervasiveness of digital technologies affects many interconnected economic processes, starting from the digitalization of processes and products to the firms' choices on the degrees of specialization, diversification and to internalize or externalize tasks (Ietto-Gillies and Trentini, 2023). These technologies allow for lower production costs by increasing efficiency, improving the firm's resilience (Marcucci et al., 2022; Bertschek et al., 2019) and agility in the production, as well as increasing the monitoring and control activities over the production process, to achieve a lean system and a tense production flow (Cirillo et al., 2021), eventually affecting value creation and value capture dynamics (Frank et al., 2019; Nambisan et al., 2019; Müller et al., 2018; Teece, 2018). Since DT adoption is directly linked to improved performance, adopters will be evaluated as having higher creditworthiness by banks.

In this light, our underlying assumption is that DT allow firms to improve their performance through an increase in operative efficiency or through the introduction of new processes or products that eventually affect the firm's profitability. The evolution of the firm's technological capabilities, enabled and signaled by the adoption of DT, allows banks and stakeholders to expect improved performance. Concerning access to credit, this process translates into a lower likelihood of being credit-rationed and possibly into improved debt conditions. The literature on relationship lending suggests that banks can acquire soft information from borrowers through a number of channels to monitor their performance and creditworthiness (see, e.g., Rajan, 1992, Petersen and Rajan, 1994 and, for a review, 2004). Banks can gather this information during the process of lending, monitoring cash flows and payments, providing financial services, contacting borrowers directly, or using other informal channels. These channels are able to transmit to the banks also information on the distinctive technologies adopted by the firms. Thus, we argue that continuous firm–bank relationships can provide banks with valuable information on firm's investment, productive processes, and key business activities, including digital technology adoption.

Therefore, the first hypothesis we put forward is that the adoption of advanced DT may "signal" to stakeholders, and particularly financial institutions, a change in the firm's technological capabilities:

Hypothesis 1. Adopting DT indirectly signals the improvement of the firm's technological capabilities, resulting in a lower likelihood of being credit-rationed.

Since advanced DT improve firms' performance, their adoption may signal a transformation in the firms' profitability (Geroski et al., 1993). For these reasons, we investigate whether the adoption of DT may improve the firm's creditworthiness, allowing it to get better credit conditions, which is our second hypothesis:

Hypothesis 2. Lower costs and higher value produced through the adoption of DT positively affect the firm's credit conditions, i.e., the cost of debt.

Finally, asymmetric information and potential adverse selection may affect price differentials between different sources of financing (Myers and Majluf, 1984; Akerlof, 1970). Since the adoption of DT may "signal" the transformation of the firm's technological capabilities (*Hypothesis* 1), price differentials on debt's cost may be affected accordingly since the different sources of financing may not be perfect substitutes (Modigliani and Miller, 1958).

This peculiar kind of signal, that is, the adoption of a specific technology, may not be accessible in a balanced and agile manner to all financial stakeholders (e.g., financial intermediaries and banks). To disclose the signal, the firm should produce an adequate campaign to disseminate this information, and this may be costly, especially for smaller and younger firms. Then, it may hold that institutions, such as banks, which have a closer relationship with firms—also in geographical terms—are more able to read the signal.

Therefore, we test the possible composition effect between different financing sources, that is our third hypothesis:

Hypothesis 3. DT adoption increases information among agents, affecting the cost of financing and then leading to a composition effect between bank debt and financial debt.

All the hypotheses are tested with the empirical model illustrated in the next Section.

3. Data and descriptive statistics

3.1. The bank of Italy's INVIND survey

The dataset used in the empirical analyses is the Bank of Italy's *Survey on Industrial and Service Firms* (INVIND), a panel survey collected each year by the local branches of the Bank of Italy on a stratified sample of Italian manufacturing and services firms.

The survey covers firms with at least 20 employees from all manufacturing sectors (including energy and extractive industries).[3] Since 2002, it also includes non-financial private firms, except NACE sectors referring to "financial intermediation and insurance, general government, school and health sectors, and other social and personal public services" (Bank of Italy, 2017).

The sample analyzed is a balanced panel of about 2200 firms, observed over the period 2015–2019. The sample is matched with the Cerved database, a data source collecting balance sheets for Italian firms,[4] including the rating evaluated by Cerved itself.

The firms in the sample (Table 1) are located for about 42% of the total firms in the North-Western regions, 20% come from the North-Eastern regions, and 18% is the relative proportion, for both, of firms from the center and the south. From a dimensional point of view, about 38% of the sample is represented by small enterprises (according to Eurostat definition[5]), 46% of firms are classified as medium, while 14% are large firms.

The sections of the survey collect information on employment and wages; investments, sales, and pricing strategies; sources of productive inputs and export dynamics; access to credit; and financing dynamics. In each section, some questions do not change and are regularly asked every year, but they also present some variable parts, allowing us to go in depth into transitory, temporary, or new phenomena. In fact, since 2015, the investment section has been integrated with questions about advanced DT.

[3] The firms from the construction sector, also included in the survey for those having 10 or more employees, are discarded from the analysis.

[4] Cerved collects information only on limited liability companies, which are those included in our sample.

[5] "EC Commission Recommendation of 6 May 2003 concerning the definition of micro, small, and medium-sized enterprises, no. 2003/361/CE".

Table 1
Sample composition by size class and NUTS-1 region.

	Size			NUTS-1	
	N	%		N	%
Large	327	14.86	North-West	925	42.05
Medium	1024	46.56	North-East	451	20.50
Small	849	38.58	Center	413	18.76
			South	411	18.69

Weights applied.

The sections relevant to our analysis are those surveying technology adoption and the firm's credit and financing. With respect to the first dimension, we draw from the survey information on the adoption of six DT, which are: advanced robots, 3D printing, cloud computing, Internet of Things, Artificial Intelligence, and big data analytics. Moreover, the use of fiscal incentives for technology adoption is also surveyed.

Using the survey, we build a self-reported credit constraints variable, which represents the dependent variable used to test the first hypothesis. The other outcome variables—the firm's debt and quantity, cost, and composition—are drawn from the balance sheet data and are presented in the next section.

3.2. Model's variables

See Table 2.

3.2.1. The dependent variables: measuring credit and financial conditions

The measurement of firms' financial conditions is based on different sources. The dependent variables used are: (i) the firm's self-reported credit constraints; (ii) debt and credit variables from balance sheet data drawn from Cerved.

The self-reported credit constraints variable (*credconst*) is built following the literature (Ferri et al., 2019; Bond et al., 2015; Minetti and Zhu, 2011). Relying on the INVIND survey, we use two specific questions: (a) whether the firm applied for new financing in the year preceding the survey (1/0); and (b) whether the application was rejected or partially accepted (1/0). The two questions are combined, and the firm is defined to be credit-rationed when both conditions hold, with the variable taking the value of 1 and 0 otherwise.[6] We expect that the signaling exerts a direct (negative) effect on this variable, implying a more favorable assessment of the firm's creditworthiness, then leading to a lower likelihood of being credit constrained.

To evaluate the second hypothesis—the impact of DT adoption on financing costs—we look at two balance sheet variables using Cerved data. The financial indicators selected are the debt level and its cost. We use (in natural log): the leverage[7] (*leverage*), and the cost of debt (*debtcost*), the latter defined as the ratio between financial costs and the total debts.

Regarding the third hypothesis, we use the share of bank debts (*bankdebt*) and the share of financial debts (*findebt*), both in natural log and defined on the firm's total debts. Using these variables, we look at the possible composition effect arising from the signal due to DT adoption.

3.2.2. The treatment variable: the adoption of DT

Since the 2015 round, the INVIND survey has also collected information about the adoption of six DT: advanced robots, 3D printing, cloud computing, Internet of Things, artificial intelligence, and big data analytics.

The survey presents single dummies in each year in which the question is asked, namely, starting from 2015, every two rounds (2015, 2017, 2019). Since we can consider DT as capital goods and not consumable goods, we presume the firm keeps the technology in the following years, even if in successive years the question about the adoption is not asked or its reply is negative.[8] Then we build a treatment variable, assuming the value of one if the firm adopted at least one DT from the year of first adoption onward and zero otherwise (explanatory variable "At Least 1 DT", *AL1*).

The technology variables are also aggregated according to their characteristics. We distinguish two groups of technologies: Operational DT (i.e., advanced robotics, 3D printing) is related to the physical production process, while Information DT (i.e., cloud computing, IoT, AI, and big data analytics) is related to data production, collection, and exploitation.

Therefore, the Operational DT variable (*OPR*) assumes a value of 1 if at least one technology is adopted among advanced robotics and 3D printing (additive manufacturing) and 0 if none of them are adopted. The Information DT variable (*INF*) assumes a value of 1 if at least one technology among cloud computing, IoT, AI, or big data analytics is adopted, and 0 if none of them were adopted.

3.2.3. Control variables

To mitigate endogeneity concerns that may arise, all the variables are lagged up to three periods, excluding the simultaneous correlation. Moreover, we are able to control for a large set of control variables, which are: the (log of) investments (*investments*); the (log of) market share in terms of value added (*marketshare*)[9]; the share of exported turnover (*exports*); the Cerved rating (*rating*); the (log of) labor productivity (total value added per employee, *labprod*). These variables should allow for control of other factors affecting the firm's ability to get credit, the latter also related to the firm's performance (productivity, exported turnover), size (market share, investments), and probability of default (Cerved rating).

The latter variable is an important control at our disposal. It is a synthetic indicator of the probability of default, built by Cerved using

[6] To identify financially constrained enterprises, we chose to utilize a direct self-reported survey-based measure rather than others inferred from "prior lending relationship" (i.e., "servizio di prima informazione") used in the literature, taking into account our sample's firm size. Banks that receive a loan request can obtain information on the possible new borrower's credit condition from the whole banking system by inquiring about "prior lending relationships" with the Credit Register. Access to this service is voluntary and costly for banks, therefore it is only activated if the bank believes it is valuable. Some studies define a constrained firm as one that: (a) at least one bank inquires about the prior lending connection and (b) the firm does not receive a loan from the requesting bank (see: Jiménez et al., 2012; Jiménez et al., 2014). Because the bank has the option to request the service but it is not obligated, this system is prone to measurement errors. For example, if a corporation borrows from a bank that did not request the services, it may be incorrectly indicated as constrained if some other banks requested the service, but it is not (see for a discussion: Carmignani et al., 2021). Note that the measurement error would occur even if the bank denies the loan without first requesting the prior lending service. In principle, the measurement error will increase as the firm's number of bank relationships increases. Since the number of the bank relationships grows with firm size, we expect that the measurement error is positively correlated with the size of the firms (Kosekova et al., 2023). Our sample includes medium and large enterprises (with at least 20 employees), hence we believe this measure of credit constraints does not fit well with our firms' sample. Overall, we believe that in our case, the measure of credit constraints self-reported by enterprises in the survey is preferable to an indirect estimate based on prior lending relationship.

[7] The leverage is computed and reported by the Cerved database as follows: "Is the ratio between financial debts and the sum of the same financial debts and the equity".

[8] A negative reply for the adoption variable that follows a positive reply in a previous round is interpreted as a lack of new adoptions without affecting previous investments.

[9] The market share is defined here as the ratio between the value added produced by the firm and the total value added of the 2-digit NACE sector in which the firm operates.

Table 2
Variables' description.

	Variable	Ref. time	Description	Source
Treatment var.	$AL1$	t	At Least 1 DT (1/0)	
	OPR	t	Operational DT: at least 1 among adv. robots, 3D printing (1/0)	INVIND
	INF	t	Information DT: at least 1 among cloud, IoT, AI, big data (1/0)	
	$AL1\_L1$	t−1	At Least 1 DT (1/0), lagged (t−1) variable	
	OPR_L1	t−1	Operational DT (1/0), lagged (t−1) variable	INVIND
	INF_L1	t−1	Information DT (1/0), lagged (t−1) variable	
Dependent var.	$credconst$	t	Self-reported credit constraints (1/0)	
	$leverage$	t	(ln) Leverage	
	$debtcost$	t	(ln) Debt cost: Total financial expense on total debts	CERVED
	$bankdebt$	t	(ln) Bank debt (share): Bank debts on total debts	
	$findebt$	t	(ln) Financial debt (share): Financial debts on total debts	
Instrumental var.	$HypDep$	t	Use of Hyper-Depreciation (1/0)	INVIND
	$HypDep\_F1$	t+1	Use of Hyper-Depreciation (1/0)	
Control	$investments\_L1$	t−1		
	$investments\_L2$	t−2	(ln) Investments	INVIND
	$investments\_L3$	t−3		
Control	$marketshare\_L1$	t−1		
	$marketshare\_L2$	t−2	(ln) VA market share: Firm's value-added over total 2-digit NACE value added	CERVED
	$marketshare\_L3$	t−3		
Control	$rating\_L1$	t−1		
	$rating\_L2$	t−2	Cerved rating (Altman score)	CERVED
	$rating\_L3$	t−3		
Control	$exports\_L1$	t−1		
	$exports\_L2$	t−2	Exported turnover (share): Exported turnover over total annual turnover	INVIND
	$exports\_L3$	t−3		
Control	$labprod\_L1$	t−1		
	$labprod\_L2$	t−2	(ln) Labor productivity: Total firm's value-added per employee	CERVED
	$labprod\_L3$	t−3		

balance sheet data and based on the Altman algorithm (Altman et al., 1994). Firms are assigned to ten risk classes: the safest classes (scores 1–4), the vulnerable (scores 5–6), and the riskier classes (scores greater than 7). The higher the probability of default, the higher the firm's risk in terms of rating, and the higher the probability of being credit constrained or getting higher debt costs. Hence, the rating variable is negatively correlated with our dependent variables.

Moreover, we also control for a set of firms' characteristics: age, legal form, geographical region of establishment (NUTS-2 level), and the dummies obtained by the interaction between sectors and years to capture time effects related to sectoral trends.

3.3. Descriptive statistics

The sample under analysis is composed to a large extent of medium and large firms, which account for 60% of the observations, while small firms (with at least 20 employees) represent about 40% of the sample.

Looking at the distribution of the dependent variables, i.e., the financial variables, across size classes (Table 4, panel A), we observe the same value for the firm's self-reported credit constraint, with an average value of 4% of firms being credit constrained in both size classes (i.e., SME and large). When we look at the debt quantity in terms of leverage and cost, we find a differentiated picture. On the one hand, the debt quantity, that is, the leverage, is different between SME and large firms, with the latter displaying a lower value (40.997 against the 43.894 of SME). On the other hand, the difference in means is not statistically different when we look at the debt cost. Finally, the debt composition displays an expected pattern, with SME being more exposed to bank debt and having a share of bank debt of more than 80%, against the 65% of large firms.

With regard to DT, adoption increases with the firm's size (Table 4), with 78% of large firms adopting at least 1 DT, against the 69% of SME in the sample. Moreover, adopting firms also show slightly worse financial conditions (Table 4, panel B), with a higher share of firms credit constrained (4% of adopters against 3% of non-adopters), higher leverage (43 against 41 for non-adopters), and higher debt cost (0.27 against 0.18). It is worth highlighting that all the differences in mean between DT adopters and non-adopters are statistically non-significant. At first glance, DT adoption seems to be linked to poorer financial conditions. This appears to be consistent with the larger financial liabilities undertaken by firms to fund investments in digital transformation (see Table 3).

4. Empirical strategy

The empirical model aims to assess how the adoption of DT affects the firm's financial condition, namely, if the adoption, in previous periods,[10] of (at least one) DT signals a transformation of the firm's technological capabilities, improving its credit conditions.

We use a treatment effect model, considering technology adoption as the treatment (with a binary nature) and the firm's credit and financial conditions as the dependent variable. The latter is represented, in turn, by (i) the binary self-reported credit constraints variable and (ii) balance sheet variables built using Cerved data (see Section 3.2.1 for details).

The baseline relationship to be estimated is represented by the following equation:

$$Y_{jit} = \alpha_0 + \beta DT_{kit-1} + \sum_{p=1}^{3} \Gamma_p \mathbf{Controls}_{it-p} + \gamma_4 NUTS2_i + \gamma_5 NACE_i \times Year_t + \varepsilon_{it} \tag{1}$$

The dependent variable Y_{jit} measures the firm's financial conditions. Each measure is identified by the subscript j for the firm i in the period t.

DT is the key explanatory variable, measuring the adoption of DT. It is the binary treatment variable, and the subscript k identifies the

[10] To account for the treatment's anticipation with respect to the outcome.

Table 3
Descriptive statistics.

Variable	N	Mean	SD	Median	Min	Max
$AL1\_L1$	2200	0.671	0.470	1	0	1
OPR_L1	2200	0.142	0.350	0	0	1
INF_L1	2200	0.648	0.478	1	0	1
$credconst$	723	0.038	0.190	0	0	1
$leverage$	2200	3.268	1.401	3.715	−8.111	5.344
$debtcost$	2170	−3.531	1.132	−3.551	−10.168	5.050
$bankdebt$	2002	−0.218	0.713	−0.002	−13.167	0
$findebt$	1459	−2.503	2.136	−1.992	−10.989	0
$HypDep\_F1$	2200	0.311	0.463	0	0	1
$investments\_L1$	2200	5.675	1.808	5.670	0	14.980
$investments\_L2$	2200	5.555	1.827	5.565	0	14.780
$investments\_L3$	2200	5.487	1.784	5.485	0	14.784
$marketshare\_L1$	2200	−1.442	1.149	−1.443	−5.101	4.247
$marketshare\_L2$	2200	−1.485	1.141	−1.507	−4.477	4.514
$marketshare\_L3$	2200	−1.516	1.143	−1.545	−4.7	4.514
$rating\_L1$	2200	3.527	1.632	4	1	8
$rating\_L2$	2200	3.645	1.661	4	1	9
$rating\_L3$	2200	3.722	1.639	4	1	9
$exports\_L1$	2200	0.233	0.299	0.065	0	1
$exports\_L2$	2200	0.232	0.300	0.059	0	1
$exports\_L3$	2200	0.229	0.299	0.051	0	1
$labprod\_L1$	2200	4.197	0.565	4.136	1.339	8.156
$labprod\_L2$	2200	4.166	0.557	4.096	1.976	8.182
$labprod\_L3$	2200	4.142	0.560	4.082	0.711	8.309

form assuming: it is, in turn, At Least 1 DT ($AL1$); Operational DT (OPR); and Information DT (INF). The vector $Controls$ contains a set of control variables of the firms' characteristics, which are presented in Section 3.2.3 and lagged up to three periods, while Γ is the associated vector of parameters.

We also control for the regional fixed effects ($NUTS2$) and the interaction between NACE 2-digit sector and year to account for sectoral trends ($NACE \times Year$). Finally, ϵ_{it} is the error term.

The empirical model is estimated by applying a Probit-2SLS procedure, which is a binary treatment model with an endogenous treatment that accounts for the idiosyncratic average effect (Cerulli, 2014).

This model combines different steps. In the very first stage, an instrumental variable is identified and used in a probit model to predict the probability of getting the treatment, along with the set of controls. The propensity score obtained from the first probit model is used in a classic Two Stage Least Square estimation, using the propensity score as the instrument.

This model allows for dealing with reverse causality, which is the major concern of endogeneity to be addressed. Moreover, it allows the treatment to start with differentiated timing, as occurs for the firms in our sample.

The reverse causality arises since the adoption of DT is not costless and requires financing. The firm's digital transformation implies investments in new durable goods, both tangibles (i.e., physical technologies) and intangibles (i.e., software and algorithms), as well as complementary investments in training and skill upgrading (Brynjolfsson et al., 2021; Brynjolfsson and Hitt, 2000; Goldin and Katz, 1998).

The firm facing a credit constraints will find it difficult to finance the investments needed, and then its ability to access credit will also influence the possibility of adopting DT, giving rise to the reverse causality. To avoid that, we use lagged control variables and an exogenous instrumental variable, as shown in the identification section.

4.1. Identification

Our strategy relies on the identification of an instrumental variable. This variable is then used to build the probability of getting the treatment, which is then used as an instrument in a 2SLS procedure, following Cerulli (2014). In this Section we present the first instrumental variable, while we will use a further different IV in Section 5.4 for the robustness analysis.

Our first preferred IV identified reports access to a fiscal incentive related to the adoption of DT, forwarded at time $t + 1$. The fiscal incentive is the "Hyper-Depreciation", part of the *National Plan Industry 4.0*.[11] This incentive allows the firms buying the capital goods (a specific category of digital capital goods, listed in the annexes to the law[12]) to use a "hyper-depreciation" rate in the balance sheets—that is, a depreciation rate for digital-related capital goods higher than 100%—thus lowering the taxable income and eventually paying lower corporate taxes. There is no other eligibility criteria or evaluation mechanism to access the incentive: all enterprises that acquire capital goods counted in the *Industry 4.0* program, automatically benefit from the tax credit.

Looking at the relevance of the instrument, we assume that the use of hyper-depreciation in time $t + 1$ can be considered a proxy of the firm's technological capabilities in the previous periods. Due to the structure of the incentive, when the firm buys a new digital-related capital good at time t, it is allowed to report in the balance sheet an increased depreciation value of $t+1$. Since the investments are planned by the firm according to a multi-year perspective, we can assume that if the firm used the incentive in time $t+1$, the technology was adopted the year before (at time t). Moreover, the adoption of new technology requires complementary investments to fully exploit its benefits (Teece, 2010), such as workforce training, organizational adjustments, and, in general, an adequate absorptive capacity (Stornelli et al., 2021; Nicoletti et al., 2020; Gal et al., 2019). All these complementarities should be already planned and most likely carried out in the periods immediately prior. Finally, the firm's investment plan is not determined by the incentive, which may only affect the magnitude or the possible additional resources (Brachert et al., 2018; Cerqua and Pellegrini, 2014).

In conclusion, we can consider the variable "use of hyper-depreciation" ($HypDep$) at time $t + 1$ as a proxy for the overall firm's capabilities and hence an instrumental variable for the readiness to adopt technology in $t - 1$. This variable will then be used in the first probit step of the model to build the probability of being treated, that is, the instrument for the 2SLS.

To assess the exogeneity of the instrumental variable, we rely on both the institutional scheme of the incentive and the timing of the variables in the survey. The hyper-depreciation incentive started in 2016 and does not require any selection mechanism to access it. It follows that all the firms, reporting the use of the incentive, bought (at least one) capital good related to *Industry 4.0*.

Since the aim of the incentive is to lower (and thus artificially alter) the firm's taxable income, using the contemporaneous relation between the incentive and financial conditions variable could give rise to a reverse causality concern. The latter can be discarded thanks to the use of the probability to get "the treatment", given the use of the incentive at time $t + 1$. This mechanism has two advantages: the first is that the forwarded variable excludes the possibility that the dependent variable can be directly affected.[13] The second advantage is that we do not use

[11] "Hyper-depreciation", along with "Super-depreciation", was introduced in 2016 as part of the *National Plan Industry 4.0* by the Italian Ministry for Economic Development. These incentives were specifically tailored to foster the accumulation of new capital goods to enhance firms' technological and digital transformation.

[12] The measure was introduced by the 2017 Italian Budget Law (Law no. 232/2016).

[13] The use of the forwarded variable is useful to mechanically exclude the effect of the "altered" – i.e., higher – value of the digital investment on the balance sheet's items. Otherwise, the use of the contemporaneous or lagged value of the incentive would for sure affect the balance sheet through the construction of the incentive scheme.

Table 4
Main variables by size classes and DT adoption.

	(A) by size classes					(B) by DT adoption				
	N. obs.		Mean		Signif.	N. obs.		Mean		Signif.
	Large	SME	Large	SME		Non-adopt.	Adopters	Non-adopt.	Adopters	
Credit constraints	272	451	0.037	0.037		201	522	0.030	0.040	
Leverage	853	1347	40.977	43.894	**	611	1589	41.789	43.138	
Debt cost	853	1347	0.265	0.235		611	1589	0.182	0.272	
Bank debt (share)	853	1347	0.653	0.843	***	611	1589	0.784	0.764	
DT adoption (at least 1)	853	1347	0.777	0.687	***					

Bank debt as a share of total debt. Financial debt = 1 − Bank debt. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 5
Correlation matrix.

	Pr($AL1$)	Pr(Opr)	Pr(Inf)	Leverage	Debt cost	Bank debt	Fin. debt
Pr(AL1)	1,00						
Pr(Opr)	0.39***	1.00					
	0.00						
Pr(Inf)	0.96***	0.24***	1.00				
	0.00	0.00					
Leverage	0.10***	−0.12***	0.11***	1.00			
	0.00	0.00	0.00				
Debt cost	−0.03	−0.05***	−0.02	−0.47***	1.00		
	0.15	0.00	0.24	0.00			
Bank debt	−0.07***	−0.15***	−0.09***	0.05***	0.03***	1.00	
	0.00	0.00	0.00	0.00	0.01		
Fin. debt	0.04	0.09***	0.03	−0.25***	0.09***	−0.47***	1.00
	0.11	0.00	0.13	0.00	0.00	0.00	

Pairwise correlations (first lines) and p-values (second lines) between dependent variables and the IV, i.e., $Pr(DT = 1|HypDep_t + 1, Ctrl)$. See Eq. (2) and Section 4.2 for details. Significance levels at 1%. Variable other than Pr(DT) are in natural logarithm.

as IV the access to the subsidy, but the probability that the firm adopts a DT given the future access to the incentive, also considering other firm-level control variables. The probability to be treated that we get from the "subsidy anticipation" mechanism represents the firm-level readiness—i.e., the technological capabilities—to adopt a DT.

To mitigate the endogeneity concerns, we look at the correlation between the probability of being treated and the dependent variables. As reported in Table 5, the correlation between the two variables (the use of the incentive and the generated probability) and the dependent variables is very low. Moreover, to assess the exogeneity of the instrumental variable to the dependent variables, some fixed effects regressions are performed that show the non-significant effect on the dependent variables.[14]

Finally, a comprehensive scheme of the identification strategy is depicted in Fig. 1. The instrumental variable $HypDep$ in time $t+1$ is exogenous with respect to the outcome, Y, in time t. The latter is, in turn, the firm's financial constraints, the overall financial conditions, or the debt quantity (leverage), cost, or composition (bank or financial debt share). DT adoption is the explanatory variable, predicted with the $HypDep$ variable (i.e., the IV), along with the other lagged controls, using the probit model. From this, we get the predicted probabilities that are used in the 2SLS model, where, in the first stage, DT is regressed on the generated instrument (i.e., the propensity score), then we get the fitted values that are used in the second stage, obtaining the unbiased coefficient for the treatment.

[14] Tables with the regressions to assess the exogeneity of the instrumental variable are available in Appendix.

4.2. The probit-2SLS model

The model proposed is built following Cerulli (2014),[15] which allows to estimate a binary treatment model with heterogeneous average treatment effect and treatment endogeneity.[16]

In fact, the baseline relationship presented in Eq. (1) faces a selection into treatment (i.e., the adoption of digital technology) due to both observable and unobservable characteristics, and a potential reverse causality may also hold. Therefore, the use of an IV approach is required to restore consistency for the estimation of the causal effect.

Let Y be the financial dependent variables, DT the treatment (technology adoption), and $Controls$ the set of control variables up to three lags.

In the first step, we run a probit model with the instrumented binary-treatment variable as a dependent over the instrumental variable—the use of hyper-depreciation in t+1 ($HypDep\_F1$)—and the set of lagged controls.

$$Pr(DT_{it-1} = 1) = \phi(HypDep_{t+1}, \sum_{p=1}^{3} \mathbf{Controls}_{it-p}) \tag{2}$$

From Eq. (2), we obtain the propensity score for the selection into treatment (i.e., the probability of adopting DT, i.e., $\widetilde{DT_{it}}$). This is used in the second step of the model, the 2SLS procedure, where the first stage is run with a probit model to account for the binary nature of the dependent variable.

[15] The methodology builds on Wooldridge (2010), Heckman et al. (1999), and Angrist et al. (1996).

[16] Following Imbens and Angrist (1994), and Angrist and Pischke (2009), the IV model with binary treatment and the binary instrument—such as our Probit-2SLS model—can also be considered an estimator for the Local Average Treatment Effect.

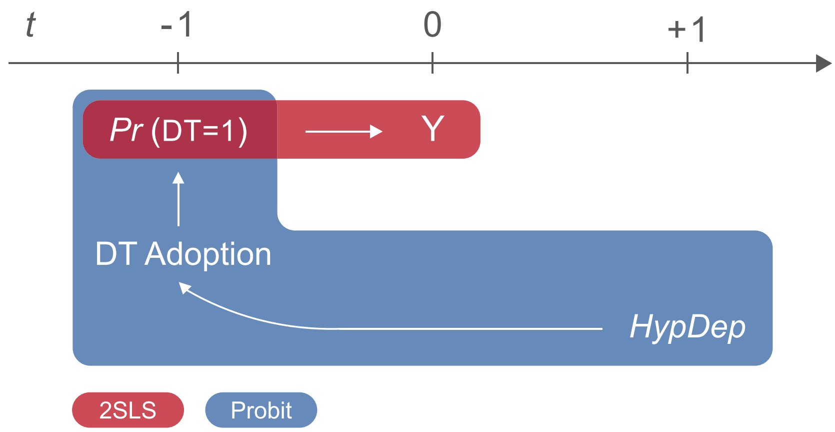

Fig. 1. The Probit-2SLS model - Identification strategy.

$$DT_{it-1} = \mu_0 + \delta \widetilde{DT}_{it} + \sum_{p=1}^{3} \Theta_p \mathbf{Controls}_{it-p} + \theta_4 NUTS2_i + \theta_5 NACE_i \times Year_t + v_{it} \quad (3)$$

$$Y_{it} = \alpha_0 + \beta \widehat{DT}_{it-1} + \sum_{p=1}^{3} \Gamma_p \mathbf{Controls}_{it-p} + \gamma_4 NUTS2_i + \gamma_5 NACE_i \times Year_t + \phi \widetilde{DT}_{it} + \varepsilon_{it} \quad (4)$$

In the first stage of the 2SLS (Eq. (3)), the treatment variable is regressed on the propensity score and the set of control variables. We then obtain the fitted values ($\widehat{DT}_{it}$) that are used as a regressor in the final stage (Eq. (4)). Following Cerulli (2014), the previously generated regressor $\widetilde{DT}_{it}$ is also included, and then robust standard errors are computed to correct heteroskedasticity.

4.2.1. Self-reported credit constraints: Heckman correction

It is worth noting that the variable $credconst$, i.e., the self-reported credit constraints, suffers from a non-random sampling issue. It is in fact reported only by the firms that asked for new funds, which may then result in being credit-constrained if the application was unsuccessful (or partially approved).

To correct for the non-randomness bias, we apply to Eq. (1) the Heckman correction, following Cerulli (2014) and Wooldridge (2010) and using the same dependent, explanatory, and control variables.

Operationally, a two-step procedure is applied. The first stage is the same as the one previously explained, that is, a probit regression is run for the treatment (DT adoption) on the instrumental variable ($HypDep\_F1$) and the set of controls. Then, the second stage is an OLS regression corrected with the Inverse Mills' ratio (Cerulli, 2014) to get an unbiased estimation of the treatment effect (the β coefficient).

5. Results

5.1. Self-reported credit constraints

In Table 6, we report the results of the Heckit model on the binary credit-constraints variable. In Columns 1, 4, and 7, we also report the results for the baseline estimation on the full sample with a logit model.[17] Looking at the results of the full sample, which includes both manufacturing and service firms, the adoption of at least one digital technology in the period before the application for new funds lowers the likelihood of being credit-constrained by half a point (−0.58%).

Moreover, a heterogeneous effect is detected by looking at different groups of technologies. Differentiating the DT, the impact is far larger for the Information DT compared to the operational ones. The adoption of Information DT lowers the likelihood of being credit-constrained by 0.77%, vis-à-vis the −0.23% of Operational DT.

These results are consistent with two relevant aspects of the analysis. After controlling for several relevant variables—and most importantly for rating, market shares, and productivity—the coefficient of adoption has a strong negative impact, both in magnitude and significance. This can be interpreted as the signaling effect of the firm's transformation of technological capabilities due to the adoption of new technologies in the production process. Furthermore, the coefficient is stronger in magnitude for the Information DT that are at the core of the current technological transformation. These DT direct firms toward business models centered on the use of data to optimize the production process or support decision-making, eventually reducing waste and increasing productivity.

5.2. Debt level, cost, and composition

The results on leverage and debt cost may be read and interpreted in combination Table 7.[18] The adoption of DT is associated with a greater level of the firm's leverage but, simultaneously, with a lower level of debt cost.[19] The increase in the probability of adopting a DT is associated with an increase in the firm's leverage of 4.19% for the adoption of at least 1 DT on the full sample (Table 7, panel A). The magnitude of the effect varies from 1.38% for the Operational DT to 6.12% for Information DT.

On the other hand, the higher leverage found for technology adoption is associated with a lower debt cost for adopting firms (Table 7, panel B). The overall adoption (at least 1 DT) decreases the debt cost by 3.56%, with an effect stronger for Information DT (−5.14%), while Operation DT decreases the debt cost by 1.45%.

Looking at the nature of the firm's debt, a composition effect arises (Table 8).[20] The adoption of at least 1 DT increases the bank debt by 2.75% for the firms in the full sample, but no significant effect are found when we look at differentiated technologies.

At the same time, the adoption is associated with a strong decrease in financial debt (−6.64% for the full sample). The results, again, are

[17] Detailed tables with the results of the baseline logit regression are available upon request.

[18] In Table 7 we also report the results for the baseline OLS estimation. The results are consistent with the Probit-2SLS model, which is explained and commented on in the text. Extended results for the OLS are available upon request.

[19] Here, it is defined as the ratio between financial expenses and the total of financial and bank debts.

[20] Similarly to the Table on debt level and cost, we also report the estimation for the corresponding baseline OLS model.

Table 6
Self-reported credit constraints.

	Full sample		Manufact.	Full sample		Manufact.	Full sample		Manufact.
	Logit (1)	Heckit (2)	Heckit (3)	Logit (4)	Heckit (5)	Heckit (6)	Logit (7)	Heckit (8)	Heckit (9)
At Least 1 DT	−0.28***	−0.58***	−0.07						
	(0.07)	(0.18)	(0.11)						
Operational DT				−0.35	−0.23**	−0.17*			
				(0.46)	(0.09)	(0.10)			
Information DT							−0.27*	−0.77***	−0.07
							(0.15)	(0.24)	(0.11)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
NACE × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	2149	742	480	2149	742	503	2149	742	503

Results in columns 1, 4, and 7 are the baseline estimations of a logit model on the full sample. Columns 2, 3, 5, 6, 8, and 9 report the results for the Two-step model with Heckman correction. Explanatory variable DT_{t-1}, SE in brackets (for the logit results, SE are bootstrapped with 50 replications). Full tables with all the variables used are available in the Appendix. Controls included (up to three lags): investments, market share, Cerved rating, exported turnover, and labor productivity. Regional (NUTS-2) FE included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7
Leverage and Debt cost.

Panel A, dependent variable: **(ln) Leverage**									
	Full sample		Manufact.	Full sample		Manufact.	Full sample		Manufact.
	OLS (1)	P2S (2)	P2S (3)	OLS (4)	P2S (5)	P2S (6)	OLS (7)	P2S (8)	P2S (9)
At Least 1 DT	0.10**	4.19***	3.50***						
	(0.04)	(1.35)	(1.09)						
Operational DT				0.11**	1.38***	2.32***			
				(0.04)	(0.52)	(0.80)			
Information DT							0.08**	6.12**	5.07**
							(0.04)	(2.70)	(2.05)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
NACE × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	6444	2200	1529	6444	2180	1522	6444	2200	1529
Panel B, dependent variable: **(ln) Debt cost**									
	Full sample		Manufact.	Full sample		Manufact.	Full sample		Manufact.
	OLS (1)	P2S (2)	P2S (3)	OLS (4)	P2S (5)	P2S (6)	OLS (7)	P2S (8)	P2S (9)
At Least 1 DT	−0.11***	−3.56***	−2.38***						
	(0.04)	(1.17)	(0.84)						
Operational DT				−0.11***	−1.45***	−1.51**			
				(0.04)	(0.47)	(0.62)			
Information DT							−0.12***	−5.14**	−3.43**
							(0.03)	(2.23)	(1.46)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
NACE × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	6357	2171	1512	6357	2152	1505	6357	2171	1512

Results in columns 1, 4, and 7 are the baseline estimations of an OLS model on the full sample. Columns 2, 3, 5, 6, 8, and 9 report the results for the Probit−2SLS model (P2S). Explanatory variable DT_{t-1}, SE in brackets (for the OLS results, SE are bootstrapped with 50 replications). Full tables with all the variables used are available in the Appendix. Controls included (up to three lags): investments, market share, Cerved rating, exported turnover, and labor productivity. Regional (NUTS-2) FE included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

stronger for Information DT, where the negative coefficient on financial debt is about 4 times larger than the coefficient of the Operational DT (−8.90% against −1.94% for Operational DT, columns 5 and 3, Table 8, panel B).

Although the results on the (log of) bank debt present a weak significance, it seems to emerge with clarity a composition effect.[21] Then, the increase in leverage associated with DT adoption (Panel A, Table 7) results in a reduction of the financial debt collected on the financial markets, and in an increase in the bank debt.

These results have a strong implication on the functioning of the signaling and the mechanism by which firms try to overcome their financial constraints.

The signaling mechanism needs the interaction between two age nts—the firm and the financial intermediary here—where the first sending of an (unintentional[22]) signal to increase its reliability and creditworthiness, while the second should read and interpret the signal and offer accordingly the service (the credit, here) with a cost determined as a function of the available information set.

Since technology adoption is an unintentional signal strictly related to the firm's production process, it may be true that the generalist

[21] An analysis on the level of bank debt has also been carried out (with the ratio between bank debt and total debt as a dependent variable). The results show a statistically significant increase in bank debt (and a reduction in financial debt, as it complements the unit). However, the results are not significant for the bank debt if we consider its logarithm. The results are available upon request.

[22] Spence's framework (Spence, 1973) also allows the signal to be unintentional. In fact, technology adoption is not directly aimed at signaling to a stakeholder some firm's qualities but is just meant to be part of the (new) firm's production process.

Table 8
Debt composition, bank vs. financial debt.

Panel A, dependent variable: **(ln) Bank debt, share**

	Full sample		Manufact.	Full sample		Manufact.	Full sample		Manufact.
	OLS (1)	P2S (2)	P2S (3)	OLS (4)	P2S (5)	P2S (6)	OLS (7)	P2S (8)	P2S (9)
At Least 1 DT	0.02	2.75*	2.45**						
	(0.03)	(1.46)	(1.08)						
Operational DT				0.02	−0.08	0.14			
				(0.03)	(0.46)	(0.56)			
Information DT							0.01	6.04	6.01
							(0.03)	(5.22)	(3.68)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
NACE × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	5837	2003	1397	5837	1985	1390	5837	2003	1397

Panel B, dependent variable: **(ln) Financial debt, share**

	Full sample		Manufact.	Full sample		Manufact.	Full sample		Manufact.
	OLS (1)	P2S (2)	P2S (3)	OLS (4)	P2S (5)	P2S (6)	OLS (7)	P2S (8)	P2S (9)
At Least 1 DT	−0.30***	−6.64***	−4.03***						
	(0.07)	(2.23)	(1.31)						
Operational DT				−0.14**	−1.94***	−3.33***			
				(0.07)	(0.71)	(1.14)			
Information DT							−0.27***	−8.90**	−6.12***
							(0.07)	(3.93)	(2.29)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
NACE × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	4419	1460	979	4419	1449	984	4419	1460	979

Results in columns 1, 4, and 7 are the baseline estimations of an OLS model on the full sample. Columns 2, 3, 5, 6, 8, and 9 report the results for the Probit-2SLS (P2S) model. Explanatory variable DT_{t-1}, SE in brackets (for the OLS results, SE are bootstrapped with 50 replications). Full tables with all the variables used are available in the Appendix. Controls included (up to three lags): investments, market share, Cerved rating, exported turnover, and labor productivity. Regional (NUTS-2) FE included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

financial market is not able to understand the firm's signal. In fact, the distance[23] between the market and the firm is wider compared to the distance between the bank and the firm. To access financial markets and use the technology as a signal, the firm should produce an adequate campaign to disseminate information to the stakeholders. But, on the other hand, it may be cheaper to apply for bank credit, as the bank is more able to read the signal with respect to the market, given its proximity.

Then, this set of results may be read as the higher potentiality of the banks to read the signals from the firm, given their lower distance. This will result in a composition effect that favors bank credit, with an expansion of the firm's leverage and eventually a lower debt cost due to the firm's improved capabilities, resilience, and performance.

5.3. Heterogeneity analysis

The adoption of DT may affect firms differently according to their capabilities, structures, and organizational complexity. To analyze possible heterogeneous impacts, we look at the effects according to the macro-industry in which the firms operate. In Tables 6–8, we report the results for DT adoption on manufacturing firms. Regarding the self-reported credit constraints, manufacturing firms show a significant negative impact only for the adoption of Operational DT, which are more commonly used in the macro-sector. Here, the coefficient of Operational DT adoption is slightly lower than the one in the full sample (−0.17 against −0.23), while no significant value is found for Information DT. When we look at the leverage and debt cost (Table 7, panels A and B), we find that different types of DT have differentiated effects on firms in the full sample and on manufacturing firms. Both for leverage and debt cost, the effect of Operational DT is larger for manufacturing firms rather than the full sample (2.32 vs. 1.38 for leverage, −1.51 vs. −1.45 for debt cost), while the effect of Information DT is larger on the full sample rather than manufacturing firms, suggesting that the effect may be driven by service firms. Looking at the debt composition (Table 8), we do not detect a statistically significant effect when we differentiate the types of DT for bank debt (panel A), while the difference is relevant when we look at the financial debt (panel B). In this case, again, the impact is stronger for Operational DT in manufacturing (−3.33 against −1.94 in the full sample), while the opposite holds for Information DT (with the coefficient for the full sample larger than manufacturing: −8.90 vis-à-vis −6.12).

The comparison between the full sample estimations and the results on the manufacturing sub-sample seems to suggest that Operational DT, which are related to lower costs and productivity enhancement, are more relevant for manufacturing firms, a sector in which Operational DT are more widespread and where the average firm's size is smaller, and therefore the marginal effect of adopting a new DT may be relatively higher compared to larger firms. On the other hand, service firms seem to be more able to seize the benefits from the adoption of Information DT.[24]

To delve into the differentiated impacts of technologies due to different capabilities and organizational complexity, we also perform a heterogeneity analysis looking at the effect of adopting a DT across different size and age classes. We hypothesize that the signal triggered by the DT adoption is stronger for smaller and younger firms that are more prone to credit constraints due to informational problems. We use the definition of size made by Eurostat (aggregating small and medium firms into one category), which classifies firms according to a

[23] Here, the closeness is meant as the degree of "relationship lending" between agents, and not in a geographical meaning.

[24] Since the survey only collects information for firms having more than 20 employees, the average firm's size for manufacturing is 92 employees, while 130 is the average for service firms (sampling weights applied).

Table 9
Marginal effects by size classes - At least 1 DT.

	Credit const. (1)	(ln) Leverage (2)	(ln) Debt cost (3)	(ln) Bank debt (4)	(ln) Fin. debt (5)
SME	−0.14*	1.65***	−1.63***	0.64*	−2.78***
	0.08	0.49	0.47	0.33	0.99
Large	−0.17*	1.86***	−1.83***	0.75*	−2.84***
	0.09	0.55	0.53	0.39	1.01
Obs.	642	2117	2092	1935	1387

Elasticities/SE of dependent variables with respect to the adoption of at least 1 DT. Size categories according to Eurostat definition. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10
Marginal effects by size and age classes - At least 1 DT.

	Credit const. (1)	(ln) Leverage (2)	(ln) Debt cost (3)	(ln) Bank debt (4)	(ln) Fin. debt (5)
SME#Young	−0.14*	1.64***	−1.63***	0.65*	−2.84***
	0.08	0.48	0.47	0.33	1.01
SME#Old	−0.15*	1.67***	−1.65***	0.64*	−2.72***
	0.08	0.49	0.48	0.33	0.96
Large#Young	−0.17*	1.85***	−1.81***	0.75*	−2.85***
	0.10	0.54	0.53	0.39	1.01
Large#Old	−0.17*	1.87***	−1.85***	0.74*	−2.82***
	0.09	0.55	0.54	0.38	1.00
Obs.	642	2117	2092	1935	1387

Elasticities/SE of dependent variables with respect to the adoption of at least 1 DT. Size categories according to Eurostat definition and age classes defined over the median of the sample. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11
Adoption intensity.

	Credit const. (1)	Leverage (2)	Debt cost (3)	Bank debt (4)	Fin. debt (5)
Low: DT = 1, t−1	−0.10	2.11**	−2.21**	0.30	−2.94**
	(0.17)	(0.82)	(0.87)	(0.55)	(1.45)
High: DT ≥ 2, t−1	−0.11*	1.87***	−2.00***	1.04*	−2.69***
	(0.06)	(0.72)	(0.61)	(0.55)	(1.01)
Controls	✓	✓	✓	✓	✓
Obs.	445	1499	1479	1370	921

Probit-2SLS model with IV (Use of Hyper-Depreciation in $t+1$). Robust standard errors in parentheses. Regional, sectoral, year, and sector-year FE included. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Detailed tables are available upon request.

Table 12
Alternative IV.

	Credit const. (1)	Leverage (2)	Debt cost (3)	Bank debt (4)	Fin. debt (5)
At least 1 DT	−0.06	1.37**	−1.11*	−0.00	0.03
	(0.10)	(0.64)	(0.60)	(0.47)	(1.35)
N	2037	6189	6103	5583	4209
R2	0.10	0.15	.	0.18	0.18
Operational DT	0.01	−0.41	−0.07	−1.46***	1.18**
	(0.06)	(0.33)	(0.31)	(0.30)	(0.47)
N	2075	6060	5982	5486	4088
R2	0.12	0.25	0.10	.	0.13
Information DT	−0.01	1.40**	−1.12*	−0.61	0.63
	(0.12)	(0.63)	(0.60)	(0.45)	(1.28)
N	2112	6189	6103	5583	4221
R2	0.10	0.13	.	0.13	0.15
Controls	✓	✓	✓	✓	✓
NACE × Year	✓	✓	✓	✓	✓

Coefficients for the main variable of interest and SE (in round brackets) are reported. Results in Column 1 are estimated with the Probit-2SLS model augmented with the Heckman correction, while Columns 2 to 5 are estimated with the Probit-2SLS model. Dependent variables in columns 2-5 are in natural log. Alternative IV: Average value for the dummy "Investment in DT for at least 20.1% out of the total firms' investment" by NUTS-1 region, NACE 2-digit sector, year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13
IV relevance.

	At Least 1 DT		Information DT		Operational DT	
	Full samp. (1)	Manufact. (2)	Full samp. (3)	Manufact. (4)	Full samp. (5)	Manufact. (6)
$HypDep\_F1$	0.21***	0.28***	0.12*	0.17**	0.38***	0.31***
	(0.07)	(0.09)	(0.07)	(0.08)	(0.08)	(0.09)
investments_L1	0.03	0.04	0.03	0.04	0.07**	0.07*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
investments_L2	−0.02	−0.00	−0.02	−0.00	0.01	0.03
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
investments_L3	−0.01	−0.01	0.00	0.00	0.04	0.04
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
marketshare_L1	0.69**	0.60*	0.70**	0.64*	0.15	0.33
	(0.29)	(0.35)	(0.29)	(0.34)	(0.35)	(0.38)
marketshare_L2	−0.41	−0.31	−0.38	−0.26	0.13	0.03
	(0.31)	(0.33)	(0.30)	(0.31)	(0.29)	(0.28)
marketshare_L3	−0.21	−0.21	−0.24	−0.29	−0.24	−0.34
	(0.22)	(0.26)	(0.22)	(0.26)	(0.21)	(0.27)
rating_L1	0.06*	0.03	0.06*	0.02	−0.07*	−0.04
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
rating_L2	−0.00	0.04	−0.00	0.04	0.02	−0.02
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
rating_L3	−0.01	−0.02	−0.01	−0.02	0.03	0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
export_L1	0.33	0.41	0.26	0.37	0.77*	0.40
	(0.38)	(0.43)	(0.37)	(0.41)	(0.41)	(0.44)
export_L2	−0.34	−0.33	−0.27	−0.20	0.09	0.06
	(0.35)	(0.39)	(0.35)	(0.39)	(0.37)	(0.38)
export_L3	0.14	0.24	−0.03	0.01	0.08	0.04
	(0.30)	(0.33)	(0.30)	(0.33)	(0.30)	(0.34)
labprod_L1	−0.77**	−0.65*	−0.78***	−0.68*	−0.24	−0.48
	(0.30)	(0.36)	(0.29)	(0.36)	(0.37)	(0.40)
labprod_L2	0.49	0.39	0.48	0.37	−0.00	0.12
	(0.30)	(0.31)	(0.29)	(0.30)	(0.27)	(0.25)
labprod_L3	0.20	0.13	0.23	0.19	0.09	0.21
	(0.22)	(0.26)	(0.22)	(0.25)	(0.21)	(0.25)
2017.year	0.00	0.00	0.01	0.01	−0.04*	−0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
_cons	0.72	0.99	0.40	0.27	−1.22**	−0.33
	(0.47)	(0.79)	(0.45)	(0.74)	(0.53)	(0.77)
NACE × Year	✓	✓	✓	✓	✓	✓
N	2446	1701	2446	1701	2424	1694

Probit model estimations to test IV relevance. Explanatory variable (instrumental variable): $HypDep\_F1$, dependent variables: DT adoption in $t-1$; SE reported in brackets. All the (continuous) control variables are in natural log. Regional (NUTS2) FE included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

combination of the number of employees and the firm's turnover, and we then evaluate the marginal effects (i.e., the elasticity[25]).

Results for the elasticities of adopting at least 1 DT according to the size classes are reported in Table 9.[26] The effects are generally smooth across size categories, with point estimates slightly larger for large firms but eventually comparable in terms of magnitude with SMEs' coefficient. Moreover, all the results remain consistent and significant across the size classes. A 1% increase in the likelihood of adopting at least 1 DT reduces the credit constraints of SMEs' of 0.14%, against the −0.17% for large firms. Again, the adoption increases the leverage of 1.65% for SMEs', against the 1.86% for large firms (column 2), while the debt cost decreases of −1.63% for SMEs and −1.83% for large firms (column 3). The composition effect between different sources of financing is confirmed (Table 9, columns 4 and 5), with an expansion of bank debt (0.64% for SMEs and 0.75% for large firms) and a reduction of financial debt (−2.78 for SMEs, and −2.84 for large firms).

The same exercise is performed also looking at the interaction between the size and the firm's age, being this interaction a proxy of both firms' technological capabilities and for entities in principle more credit-rationed. To define age classes, we use as a threshold the sample weighted median, and we define two categories for firms above and below it. Being the age median of the sample of 34 years, the firms are categorized as "young" if they are below, and "old" if they are above the threshold. We then combine the age classes with the two Eurostat size classes, obtaining four categories for size-age, and we evaluate the elasticities upon them.

The results of the analysis on size-age classes are reported in Table 10 and are consistent with those on size classes. Distinguishing firms' classes according to the interaction size-age (Table 10), the previous results are confirmed both in terms of sign and significance. Looking at the elasticities, the coefficients are slightly higher for large firms with respect to the SME regardless of age, which seems not to play a mediator role.

In conclusion, it is worth emphasizing two main results arising from the heterogeneity analysis. The first evidence is that when the impacts of DT adoption are disentangled by size and size-age classes, we find a slightly larger effect for firms with more than 250 employees, but we cannot detect a strong difference between SME and large firms. Moreover, when we interact the size class with the age, the latter does not seem to play a relevant role in differentiating the effect, but this

[25] The marginal effects here evaluated are the derivatives of the log of the dependent variable with respect to the log of the explanatory variable, i.e., DT adoption, among different size classes (SME vs. large firms).

[26] Descriptive statistics for the heterogeneity classes used in the analyses of this section are reported in the Appendix, Table 20.

Table 14
IV exogeneity.

	Credit constraints		(ln) Leverage		(ln) Debt cost		(ln) Bank debt (share)		(ln) Fin. debt (share)	
	Full samp. (1)	Manufact. (2)	Full samp. (3)	Manufact. (4)	Full samp. (5)	Manufact. (6)	Full samp. (7)	Manufact. (8)	Full samp. (9)	Manufact. (10)
$HypDep\_F1$	−0.04**	−0.02	−0.02	−0.05	0.01	0.00	0.05	0.02	−0.05	−0.04
	(0.02)	(0.02)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.09)	(0.11)
investments_L1	−0.00	0.01	0.04**	0.02	−0.04*	−0.03	−0.01	−0.00	0.00	−0.07
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.05)	(0.06)
investments_L2	−0.00	−0.02**	0.00	−0.01	0.01	−0.01	−0.01	−0.00	0.08*	0.08
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.05)	(0.06)
investments_L3	−0.02**	−0.01*	0.00	−0.01	−0.01	0.01	0.01	−0.01	0.05	0.03
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)	(0.06)
marketshare_L1	0.12	0.03	−0.10	0.40**	−0.16	−0.25	−0.16	−0.36**	−0.63*	−0.96**
	(0.11)	(0.10)	(0.16)	(0.19)	(0.18)	(0.21)	(0.15)	(0.16)	(0.34)	(0.40)
marketshare_L2	0.02	0.00	−0.05	−0.13	0.20	0.36*	0.21	0.18	0.30	0.34
	(0.08)	(0.07)	(0.17)	(0.19)	(0.19)	(0.21)	(0.15)	(0.16)	(0.33)	(0.36)
marketshare_L3	0.13*	0.08	0.03	−0.08	−0.40**	−0.46**	−0.17	−0.21	−0.22	−0.49
	(0.07)	(0.07)	(0.14)	(0.16)	(0.16)	(0.18)	(0.13)	(0.14)	(0.28)	(0.31)
rating_L1	0.02**	0.02**	0.05**	0.03	0.06**	0.09***	0.03	0.04	−0.02	−0.01
	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.05)	(0.06)
rating_L2	0.00	0.02*	−0.04*	−0.04	0.07***	0.08***	−0.01	−0.00	−0.01	−0.00
	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.05)	(0.06)
rating_L3	0.00	−0.01	0.03	0.02	−0.05*	−0.04	0.00	−0.03	0.07	0.13**
	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.05)	(0.06)
export_L1	0.36***	0.00	0.30	0.34	−0.34	−0.39	0.11	0.19	−0.03	0.80
	(0.12)	(0.14)	(0.24)	(0.28)	(0.27)	(0.31)	(0.23)	(0.25)	(0.47)	(0.56)
export_L2	−0.10	−0.01	−0.01	0.04	−0.10	−0.35	0.16	0.25	0.73	1.06*
	(0.15)	(0.14)	(0.22)	(0.26)	(0.25)	(0.29)	(0.20)	(0.22)	(0.48)	(0.56)
export_L3	0.05	0.07	−0.04	−0.13	−0.06	−0.02	0.17	−0.02	−0.50	−0.31
	(0.11)	(0.10)	(0.21)	(0.23)	(0.23)	(0.26)	(0.20)	(0.21)	(0.47)	(0.50)
labprod_L1	−0.11	0.04	0.09	−0.42**	0.07	0.19	0.22	0.42***	0.12	0.36
	(0.11)	(0.11)	(0.16)	(0.19)	(0.18)	(0.21)	(0.15)	(0.16)	(0.33)	(0.38)
labprod_L2	−0.04	−0.04	0.09	0.11	−0.14	−0.25	0.03	0.14	−0.42	−0.50
	(0.07)	(0.06)	(0.16)	(0.18)	(0.18)	(0.20)	(0.15)	(0.16)	(0.32)	(0.34)
labprod_L3	−0.12	−0.06	0.07	0.10	0.24	0.29	0.05	0.09	0.03	0.23
	(0.07)	(0.07)	(0.14)	(0.16)	(0.16)	(0.18)	(0.13)	(0.14)	(0.27)	(0.30)
_cons	1.74**	0.38	3.94***	6.14***	−1.90	−2.90	−2.08	−4.14***	−1.51	−4.92
	(0.78)	(0.76)	(1.34)	(1.65)	(1.51)	(1.82)	(1.27)	(1.44)	(3.03)	(3.70)
NACE × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	1139	772	3189	2204	3151	2184	2910	2027	2063	1384

FE regression to test IV exogeneity. Explanatory variable (instrumental variable) $HypDep\_F1$, SE reported in brackets. All the (continuous) control variables are in natural log. Regional (NUTS-2) fixed effects included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

could be affected by the quite large threshold we have selected (i.e., the median firms' age is 34 years).

The second evidence is the robustness of the main results. When the impacts are disentangled using size and size-age classes, larger and older firms—which are theoretically more capable of getting financing at better conditions—do not drive the results. This evidence ensures that the results are not affected by the influence of firms located on the right-hand side of the age and size distributions and supports the idea that the adoption of advanced DT may signal the transformation of the firms' technological capabilities.

In conclusion, these results seem to suggest that, restricted to the firms in our sample, there is no threshold in terms of a firm's size or age that activates the positive effects of digital technologies. It may be the case that there are other dimensions to consider as impacting the heterogeneous effects of the adoption, such as the availability of infrastructure, a trained workforce and managers, or industry-level technological opportunities (e.g., the extent to which that technology can permeate the industries' processes).

5.4. Robustness checks

To verify the robustness of our main results, we perform a series of robustness analyses. First of all, we introduce a set of other control variables, to account for local- and industry-specific time trends. We estimate a specification of the main equation with the Probit-2SLS model also adding $NUTS3 \times ATECO2$ (province-industry 2-digit fixed effect) and $NUTS2 \times Year$ (region-year fixed effect) variables. The results become a little bit conservative in magnitude but remain fully consistent in terms of sign and significance for all the explanatory and dependent variables.[27]

A further robustness analysis concerns the number of DT adopted by the firm. We may posit that the intensity of DT adopted (e.g., the number) may influence the impact on the dependent variables. Then we consider two explanatory variables identifying the intensity of the treatment, in a binary form. The first one—for "Low-digital firms"—takes value of one when the firm adopts only one DT, while the second one—for "High-digital firms"—takes the value of one for the adoption of at least 2 DT. If the results are driven by "massive adopters", the results should be larger for the latter category, that is, adopters of at least 2 DT. In Table 11 we report the results for the main coefficients of interest (i.e., the differentiated level of DT adoption). The overall results are confirmed in sign and in magnitude, and display a higher magnitude for the "low-digital firms", whenever the coefficients are significant (i.e., except for the self-reported credit constraint and bank debt, even though the signs are consistent with main results). The results support the idea that the results are not driven by "massive adopters", and also that the marginal benefit of the adoption is higher for those firms at the beginning of the process of digital upgrading (i.e., for the first DT adopted) and decrease with the increase in the number.

[27] Detailed tables using further interacted fixed effects variables are available upon request.

Table 15
Self-reported credit constraints.

	At least 1 DT		Operational DT		Information DT	
	Full samp. (1)	Manufact. (2)	Full samp. (3)	Manufact. (4)	Full samp. (5)	Manufact. (6)
DT adoption	−0.58***	−0.07	−0.23**	−0.17*	−0.77***	−0.07
	(0.18)	(0.11)	(0.09)	(0.10)	(0.24)	(0.11)
investments_L1	−0.01	0.00	0.00	0.00	−0.02*	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
investments_L2	0.03**	−0.01	0.01	−0.01	0.03**	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
investments_L3	−0.01	0.01	0.00	0.01	−0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
marketshare_L1	0.00	−0.06	−0.04	−0.01	0.08	−0.05
	(0.07)	(0.06)	(0.07)	(0.05)	(0.08)	(0.06)
marketshare_L2	0.03	0.02	0.01	−0.02	0.01	0.00
	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.08)
marketshare_L3	−0.01	0.04	0.02	0.01	−0.06	0.04
	(0.06)	(0.05)	(0.05)	(0.05)	(0.07)	(0.05)
rating_L1	0.05***	0.03**	0.03**	0.03*	0.06***	0.03**
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
rating_L2	−0.00	0.01	0.00	0.00	−0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
rating_L3	0.01	−0.01	−0.00	−0.01	0.01	−0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
export_L1	0.54**	0.10	0.34*	0.06	0.58***	0.08
	(0.21)	(0.15)	(0.19)	(0.11)	(0.22)	(0.15)
export_L2	−0.66***	−0.12	−0.34**	−0.11	−0.70***	−0.10
	(0.22)	(0.13)	(0.16)	(0.10)	(0.22)	(0.12)
export_L3	0.07	0.02	0.03	0.07	0.02	0.02
	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
labprod_L1	0.03	0.08*	0.03	0.02	−0.05	0.07
	(0.06)	(0.05)	(0.06)	(0.05)	(0.07)	(0.05)
labprod_L2	−0.05	−0.07*	−0.05	−0.05	−0.01	−0.06
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
labprod_L3	0.04	−0.02	0.02	−0.00	0.08	−0.02
	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)
_ws_ident	−0.00	0.00	−0.00	−0.00	−0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
_wL1	0.53***	0.14*	0.11**	0.10	0.62***	0.09
	(0.15)	(0.09)	(0.05)	(0.07)	(0.18)	(0.08)
_wL0	−0.26***	0.00	−0.21***	−0.13*	−0.38***	−0.01
	(0.10)	(0.07)	(0.08)	(0.08)	(0.13)	(0.07)
_cons	0.14	−0.10	−0.22*	0.04	0.32*	−0.08
	(0.14)	(0.18)	(0.12)	(0.16)	(0.17)	(0.17)
NACE × Year	✓	✓	✓	✓	✓	✓
N	742	480	742	503	742	503

Heckit model estimations. Explanatory variable DT_{t-1}. SE reported in brackets. All the (continuous) control variables are in natural log. Regional (NUTS-2) FE included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We also build an alternative IV using a categorical variable of the survey, reporting the share of the firm's investment in DT on the firm's total investments.[28] We build the dummy variable that takes the value of one if the firm allocates at least 20% of its investment to DT.[29] Finally, a mean is computed in a consistent way with the sampling design and hence grouped by the NUTS-1 region, the NACE 2-digit sector, and the year. For each computation, the firm's observation is left out of the average (i.e., leave-one-out cross-validation). The new variable is then used with the same econometric framework, that is, the Probit-2SLS model for debt quantity, cost, and composition, and the same model augmented with the Heckman correction for the self-reported credit constraints.

The new instrumental variable is then a measure of the firm's exposure to the territorial technological capabilities, as proxied by the average diffusion of digital investments in a NUTS-1 region and in a narrowly defined industry (i.e., the NACE 2-digit sector). In fact, the NUTS-1 aggregation for the Italian regions reflects a quite homogeneous socio-economic and productive structure, while the NACE industry also takes into account the technological specificity of the industry, which ultimately influences firms' choices and technological needs.

At the same time, the average diffusion for the industry–region pair can be considered adequately exogenous since it represents the regional and industrial exposure to the diffusion of investments in DT, while the characteristics of the financing dynamics are at the firm level. Moreover, using the leave-one-out cross-validation, we exclude, from the average computation, the firm's observation, making the instrument more robust.

The alternative instrumental variable is used in the same analytical framework presented in Section 4.2. In Table 12 are reported the coefficients for the main variables of interest (i.e., DT adoption) from the set of regressions.

The robustness confirms, in sign and magnitude, the main results, even though the coefficients are significant only for the results on quantity (leverage and debt cost, Columns 2 and 3). In particular, the adoption in the previous year maintains its signaling effect, reducing the likelihood of being credit rationed, as reported by the first column, even though it has a weak coefficient. Also, the positive effect on

[28] The variable in the survey only assumes five values: no investment; between 0.1 and 5%; between 5.1 and 20%; between 20.1 and 40%; more than 40%.

[29] The distribution of the categorical variable is highly skewed, as expected. The share of firms with no investments in DT is 59.46%, while those investing less than 5% are 21.55% (sampling weights applied).

Table 16
Leverage.

Dependent variable: (ln) Leverage	At least 1 DT		Operational DT		Information DT	
	Full samp. (1)	Manufact. (2)	Full samp. (3)	Manufact. (4)	Full samp. (5)	Manufact. (6)
DT adoption	4.19***	3.50***	1.38***	2.32***	6.12**	5.07**
	(1.35)	(1.09)	(0.52)	(0.80)	(2.70)	(2.05)
investments_L1	−0.03	−0.08	−0.00	−0.06	−0.05	−0.10
	(0.05)	(0.06)	(0.03)	(0.05)	(0.08)	(0.09)
investments_L2	0.07	0.03	0.06	0.03	0.09	0.03
	(0.06)	(0.07)	(0.04)	(0.05)	(0.09)	(0.09)
investments_L3	0.01	0.03	−0.04	−0.05	0.00	0.01
	(0.06)	(0.06)	(0.04)	(0.05)	(0.07)	(0.08)
marketshare_L1	−0.08	0.39	0.72***	0.82**	−0.53	0.06
	(0.50)	(0.47)	(0.26)	(0.40)	(0.80)	(0.68)
marketshare_L2	0.10	−0.41	−0.46	−0.70	0.20	−0.45
	(0.56)	(0.48)	(0.34)	(0.53)	(0.78)	(0.64)
marketshare_L3	−0.21	−0.22	−0.34	−0.29	0.10	0.10
	(0.38)	(0.37)	(0.23)	(0.36)	(0.56)	(0.51)
rating_L1	0.16**	0.22***	0.24***	0.25***	0.12	0.21**
	(0.06)	(0.06)	(0.03)	(0.05)	(0.09)	(0.09)
rating_L2	0.06	0.01	0.04	0.06	0.03	−0.04
	(0.08)	(0.08)	(0.04)	(0.06)	(0.11)	(0.11)
rating_L3	0.16***	0.19***	0.15***	0.15***	0.19**	0.23**
	(0.06)	(0.06)	(0.03)	(0.05)	(0.09)	(0.09)
export_L1	−0.74	−0.52	−0.34	−0.20	−1.03	−0.86
	(0.61)	(0.65)	(0.33)	(0.47)	(0.90)	(0.94)
export_L2	0.75	0.49	0.04	−0.09	1.08	0.70
	(0.73)	(0.73)	(0.39)	(0.50)	(1.06)	(1.03)
export_L3	−0.79	−0.88*	−0.64*	−0.65*	−0.57	−0.67
	(0.56)	(0.52)	(0.33)	(0.37)	(0.75)	(0.71)
labprod_L1	0.03	−0.32	−0.85***	−0.71*	0.55	0.07
	(0.51)	(0.47)	(0.26)	(0.39)	(0.84)	(0.70)
labprod_L2	−0.27	0.05	0.36	0.34	−0.51	−0.08
	(0.53)	(0.44)	(0.33)	(0.50)	(0.76)	(0.59)
labprod_L3	0.33	0.36	0.51**	0.43	0.09	0.14
	(0.36)	(0.34)	(0.23)	(0.36)	(0.52)	(0.47)
_ws_ident	−0.00***	−0.00**	−0.00**	−0.00	−0.00*	−0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
_cons	−2.22*	−0.03	1.09**	1.86***	−3.58	−0.12
	(1.31)	(0.94)	(0.44)	(0.72)	(2.29)	(1.31)
NACE × Year	✓	✓	✓	✓	✓	✓
N	2200	1529	2180	1522	2200	1529

Probit-2SLS model estimations. Explanatory variable DT_{t-1}. SE reported in brackets. All the (continuous) control variables are in natural log. Regional (NUTS-2) FE included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the expansion of leverage (of about 1.4% for at least 1 DT) and the reduction of the debt cost (of about 1.1% for at least 1 DT) are confirmed. In both cases, the results seem to be driven by the effect of information DT.

Finally, the composition effect appears to be substantially unchanged after the adoption of DT. The coefficients for the adoption of at least 1 DT show a zero effect on the log of the debt shares, due to a differentiated impact from the different technologies considered. Overall, the use of an alternative instrumental variable confirms the consistency of the overall results on the debt quantity and cost.

6. Conclusions

The results provided highlight that the adoption of DT affects firms' financial and credit conditions by signaling a transformation in the firm's technological capabilities. The empirical analysis makes use of an IV strategy, and the findings are supported by a set of robustness checks.

Three results arise. Due to the signaling effect exerted by the technology, the adoption of DT decreases the likelihood of being credit-constrained. Moreover, the resulting enhanced access to credit leads to a higher level of leverage, which is at the same time associated with a lower debt cost. Here, a composition effect is found: the adoption of DT and the corresponding increase in the firm's debt are associated with a larger share of bank debt compared to financial debt.

Consistently with the literature on innovative activities and market signals (Hottenrott et al., 2016), the results of the analyses confirm that the adoption of DT exerts a signaling effect that provides a "sorting mechanism" to the lenders, in line with the first research hypothesis. Banks face the demand for loans from firms and rank the applications according to their creditworthiness and projects' reliability. Since the firms involved in the digital transformation present more favorable perspectives in terms of profitability, this lowers their probability of being credit-rationed. This result stems from the second research hypothesis: a better evaluation of the firm's creditworthiness, along with the increased profitability perspective, allows the bank to apply more favorable credit conditions, resulting in a lower debt cost. These two results are also in line with Ren et al. (2023), where the digital transformation positively affects (with a reduction) the cost of equity capital through the mediation of improved information disclosure.

On the other side, the evaluation of the firm's technology as a signal can be favored by the proximity between banks and firms in an environment where "relationship lending" is prevailing, such as in the case of Italy[30] (Banerjee et al., 2021; Barboni and Rossi, 2019). Here is the third contribution of the paper: the banks exert a better evaluation

[30] Even if the survey excludes firms with less than 20 employees, the bank channel remains one of the most important sources of financing. In the sample, large firms present, on average, a bank-debt share of 67%, against the 33% of

Table 17
Debt cost.

Dependent variable: (ln) Debt cost	At least 1 DT		Operational DT		Information DT	
	Full samp. (1)	Manufact. (2)	Full samp. (3)	Manufact. (4)	Full samp. (5)	Manufact. (6)
DT adoption	−3.56***	−2.38***	−1.45***	−1.51**	−5.14**	−3.43**
	(1.17)	(0.84)	(0.47)	(0.62)	(2.23)	(1.46)
investments_L1	0.01	0.07	−0.01	0.05	0.03	0.08
	(0.05)	(0.05)	(0.03)	(0.04)	(0.07)	(0.06)
investments_L2	−0.05	−0.02	−0.04	−0.02	−0.06	−0.02
	(0.06)	(0.05)	(0.04)	(0.04)	(0.08)	(0.07)
investments_L3	−0.04	−0.03	0.01	0.02	−0.03	−0.02
	(0.05)	(0.05)	(0.04)	(0.04)	(0.07)	(0.06)
marketshare_L1	0.46	−0.07	−0.20	−0.35	0.85	0.16
	(0.47)	(0.40)	(0.26)	(0.33)	(0.71)	(0.53)
marketshare_L2	−0.19	0.33	0.31	0.54	−0.28	0.35
	(0.53)	(0.41)	(0.33)	(0.37)	(0.70)	(0.50)
marketshare_L3	−0.03	−0.03	0.05	−0.00	−0.30	−0.24
	(0.34)	(0.29)	(0.23)	(0.28)	(0.48)	(0.38)
rating_L1	0.11**	0.09*	0.04	0.07*	0.14*	0.09
	(0.06)	(0.05)	(0.03)	(0.04)	(0.08)	(0.06)
rating_L2	0.06	0.07	0.08*	0.04	0.08	0.11
	(0.07)	(0.07)	(0.04)	(0.05)	(0.09)	(0.09)
rating_L3	−0.04	−0.06	−0.03	−0.04	−0.06	−0.08
	(0.06)	(0.05)	(0.03)	(0.04)	(0.08)	(0.07)
export_L1	0.40	0.43	0.12	0.21	0.64	0.64
	(0.58)	(0.57)	(0.35)	(0.44)	(0.81)	(0.73)
export_L2	−0.34	−0.19	0.26	0.19	−0.61	−0.33
	(0.72)	(0.67)	(0.44)	(0.52)	(0.96)	(0.84)
export_L3	0.42	0.45	0.33	0.30	0.20	0.29
	(0.52)	(0.46)	(0.37)	(0.41)	(0.65)	(0.55)
labprod_L1	−0.41	0.04	0.31	0.32	−0.86	−0.24
	(0.47)	(0.39)	(0.26)	(0.33)	(0.74)	(0.54)
labprod_L2	0.29	−0.10	−0.24	−0.32	0.50	−0.01
	(0.50)	(0.37)	(0.31)	(0.33)	(0.68)	(0.46)
labprod_L3	−0.03	−0.09	−0.16	−0.12	0.20	0.07
	(0.33)	(0.28)	(0.24)	(0.28)	(0.45)	(0.35)
_ws_ident	0.00	0.00	0.00	−0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
_cons	−0.54	−2.30***	−2.80***	−3.54***	0.36	−2.26**
	(1.11)	(0.83)	(0.38)	(0.60)	(1.79)	(1.08)
NACE × Year	✓	✓	✓	✓	✓	✓
N	2171	1512	2152	1505	2171	1512

Probit-2SLS model estimations. Explanatory variable DT_{t-1}. SE reported in brackets. All the (continuous) control variables are in natural log. Regional (NUTS-2) FE included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of the firm's production process (i.e., the technology adopted) since the latter is a "soft information", simpler and cheaper for SMEs to produce, and for relational banks to evaluate (Liberti and Petersen, 2019; Gropp and Guettler, 2018).

From a technological point of view, the mechanism at work brings us to two conclusive arguments. At a more aggregate level, the adoption of DT may shape the markets' composition through the consolidation of adopting firms. The larger amount of financial resources at their disposal positively affects the opportunities for growth and survival, intensifying the heterogeneity in the productivity distribution. On the other hand, having productive and technologically advanced firms is a desirable objective for modern and competitive economies, and the adoption of digital technologies can play a pivotal role[31].

To be ready to adopt advanced digital technologies firms are required to have the proper capabilities, such as enabling infrastructures like high-speed broadband internet and managerial quality (Nicoletti et al., 2020), but also workforce training (upskilling and on-the-job training) and the proper organizational arrangements (e.g., decentralized bargaining) (Cirillo et al., 2023). Therefore public policies should aim at supporting complementary investments in terms of infrastructures, skills upgrading, and organizational change which enable the adoption of DT. Then, the signaling mechanism shall play a role in providing the needed financial resources to the adopting—and then closer to the frontier—firms.

Finally, from a firm-level perspective, the results on the composition (and dynamics) of the firm's debts show that the adoption should be supported by external financial resources, even when a fiscal incentive is at play. In this respect, a firm-level comprehensive assessment of the impact of the fiscal incentive is currently lacking due to the limited availability of data and needs to be addressed.[32]

financial-debt. The value is also higher for SMEs, where the average bank-debt share is 84%.

[31] Building on the Regional Innovation Systems approach, Zhou et al. (2024) provide evidence of the mediation role of the digital economy (i.e., "digital industrialization" and "industrial digitalization") in improving local and regional innovation outcomes

[32] Very few studies have been conducted on the impact of hyper-depreciation included in the Italian *National Plan Industry 4.0*. To the best of our knowledge, only two studies have analyzed the impact of this fiscal incentive plan so far: Bratta et al. (2022) for impacts on employment and growth of digital investment, and Calabrese et al. (2024) on corporate finance in the automotive sector.

Table 18
Bank debt.

Dependent variable: (ln) Bank debt, share						
	At least 1 DT		Operational DT		Information DT	
	Full samp. (1)	Manufact. (2)	Full samp. (3)	Manufact. (4)	Full samp. (5)	Manufact. (6)
DT adoption	2.75*	2.45**	−0.08	0.14	6.04	6.01
	(1.46)	(1.08)	(0.46)	(0.56)	(5.22)	(3.68)
investments_L1	−0.08**	−0.12**	−0.05**	−0.07***	−0.13	−0.20
	(0.04)	(0.05)	(0.02)	(0.02)	(0.10)	(0.13)
investments_L2	−0.06	−0.07	−0.06***	−0.07***	−0.05	−0.06
	(0.04)	(0.05)	(0.02)	(0.02)	(0.08)	(0.10)
investments_L3	−0.01	−0.08*	−0.05*	−0.11***	−0.01	−0.10
	(0.04)	(0.05)	(0.02)	(0.03)	(0.08)	(0.09)
marketshare_L1	−0.27	−0.36	0.30	0.10	−1.01	−1.22
	(0.48)	(0.47)	(0.27)	(0.35)	(1.24)	(1.07)
marketshare_L2	0.42	0.41	0.05	0.13	0.65	0.62
	(0.58)	(0.60)	(0.42)	(0.52)	(0.94)	(0.91)
marketshare_L3	−0.30	−0.22	−0.42	−0.31	0.10	0.27
	(0.38)	(0.39)	(0.26)	(0.31)	(0.75)	(0.72)
rating_L1	−0.01	0.02	0.01	0.01	−0.05	0.04
	(0.05)	(0.05)	(0.03)	(0.03)	(0.10)	(0.11)
rating_L2	−0.02	−0.03	−0.03	0.01	−0.05	−0.13
	(0.06)	(0.07)	(0.04)	(0.04)	(0.11)	(0.16)
rating_L3	−0.04	−0.03	−0.03	−0.05	−0.01	0.02
	(0.05)	(0.05)	(0.03)	(0.04)	(0.09)	(0.11)
export_L1	−0.86	−0.93	−0.30	−0.32	−1.49	−1.87
	(0.53)	(0.63)	(0.35)	(0.45)	(1.30)	(1.44)
export_L2	0.59	0.47	0.15	0.11	0.93	0.66
	(0.68)	(0.79)	(0.51)	(0.64)	(1.24)	(1.37)
export_L3	0.09	0.05	0.14	0.09	0.59	0.65
	(0.59)	(0.70)	(0.48)	(0.61)	(0.95)	(1.12)
labprod_L1	0.42	0.60	−0.20	0.06	1.28	1.62
	(0.51)	(0.51)	(0.29)	(0.39)	(1.38)	(1.18)
labprod_L2	−0.35	−0.31	0.10	0.04	−0.81	−0.80
	(0.54)	(0.53)	(0.38)	(0.47)	(1.01)	(0.86)
labprod_L3	0.07	−0.01	0.17	0.11	−0.25	−0.45
	(0.36)	(0.37)	(0.24)	(0.30)	(0.68)	(0.68)
_ws_ident	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
_cons	−1.77	0.24	0.29	0.45	−4.05	−0.23
	(1.25)	(0.80)	(0.40)	(0.75)	(3.90)	(1.69)
NACE × Year	✓	✓	✓	✓	✓	✓
N	2003	1397	1985	1390	2003	1397

Probit-2SLS model estimations. Explanatory variable DT_{t-1}. SE reported in brackets. All the (continuous) control variables are in natural log. Regional (NUTS-2) FE included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Focusing on the technological-finance nexus, the possibilities for future research are many. On the one hand, digital technologies represent a unique opportunity for firms to upgrade their technological capabilities. This should promote the firms' confidence in taking risks, eventually influencing their willingness to take risks, as well as apply for credit. In other words, leveraging on the potentialities given by DT, this may also positively affect the so-called "discouraged borrowers". Finally, what is left for future research is the assessment of how long the competitive advantage due to DT is sustained over time. The diffusion of DT has a very high pace, and it is pervasive in all industries. The technology-finance nexus may also contribute to exacerbate the heterogeneity in adoption, eventually widening all the gaps relating to innovation, productivity, and market performance.

CRediT authorship contribution statement

Raffaello Bronzini: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Anna Giunta:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Eleonora Pierucci:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marco Sforza:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We would like to thank the editor and two anonymous referees for their helpful comments. We wish also thank Giovanni Cerulli, Elena Lazzaro, the participants to the Eu-SPRI Annual Conference (June 2023, University of Sussex), to the Italian Economic Association Annual Meeting (October 2023, Gran Sasso Science Institute), and to the Eu-SPRI Early Career Conference (March 2023, CNR-IRCrES) for the very helpful comments and suggestions received on earlier versions of the paper. The usual disclaimers apply.

Appendix

See Tables 13–20.

Data availability

The authors do not have permission to share data.

Table 19
Financial debt.

Dependent variable: (ln) Financial debt, share						
	At least 1 DT		Operational DT		Information DT	
	Full samp. (1)	Manufact. (2)	Full samp. (3)	Manufact. (4)	Full samp. (5)	Manufact. (6)
DT adoption	−6.64***	−4.03***	−1.94***	−3.33***	−8.90**	−6.12***
	(2.23)	(1.31)	(0.71)	(1.14)	(3.93)	(2.29)
investments_L1	0.21*	0.25**	0.15**	0.26***	0.25*	0.30**
	(0.11)	(0.10)	(0.06)	(0.10)	(0.14)	(0.14)
investments_L2	0.03	0.13	0.07	0.15	0.03	0.18
	(0.12)	(0.12)	(0.08)	(0.12)	(0.16)	(0.16)
investments_L3	−0.13	−0.09	−0.00	0.01	−0.15	−0.13
	(0.11)	(0.11)	(0.07)	(0.10)	(0.15)	(0.14)
marketshare_L1	−1.17	−1.13	−1.92**	−1.35	−0.83	−1.07
	(0.91)	(0.94)	(0.77)	(1.13)	(1.19)	(1.14)
marketshare_L2	0.49	1.02	1.28	1.28	0.48	1.28
	(1.19)	(1.31)	(1.27)	(1.73)	(1.41)	(1.50)
marketshare_L3	0.95	0.34	0.72	0.23	0.65	0.03
	(0.85)	(0.80)	(0.78)	(1.03)	(1.01)	(0.95)
rating_L1	0.07	0.03	−0.00	−0.06	0.12	0.04
	(0.12)	(0.11)	(0.08)	(0.12)	(0.15)	(0.14)
rating_L2	0.11	0.05	−0.01	−0.09	0.20	0.17
	(0.16)	(0.15)	(0.10)	(0.14)	(0.21)	(0.20)
rating_L3	−0.16	−0.13	−0.09	−0.04	−0.24	−0.20
	(0.12)	(0.12)	(0.08)	(0.12)	(0.16)	(0.15)
export_L1	1.26	1.63	1.21*	1.67*	1.57	2.01
	(0.98)	(1.05)	(0.64)	(0.92)	(1.29)	(1.33)
export_L2	−1.11	−0.48	−0.04	0.22	−1.70	−0.92
	(1.25)	(1.17)	(0.77)	(1.05)	(1.64)	(1.47)
export_L3	0.24	−0.17	−0.52	−0.81	0.19	−0.12
	(0.96)	(0.86)	(0.57)	(0.72)	(1.20)	(1.10)
labprod_L1	0.55	0.60	1.80**	1.01	0.03	0.31
	(0.96)	(0.98)	(0.77)	(1.15)	(1.32)	(1.20)
labprod_L2	0.20	−0.72	−0.97	−1.09	0.49	−0.65
	(1.17)	(1.28)	(1.25)	(1.70)	(1.43)	(1.46)
labprod_L3	−0.77	−0.30	−0.90	−0.43	−0.56	−0.08
	(0.82)	(0.78)	(0.78)	(1.01)	(0.97)	(0.91)
_ws_ident	0.00*	0.00	−0.00	−0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
_cons	1.66	0.48	−1.73**	−0.93	3.27	1.34
	(2.26)	(2.17)	(0.87)	(1.64)	(3.43)	(2.96)
NACE × Year	✓	✓	✓	✓	✓	✓
N	1460	979	1449	984	1460	979

Probit-2SLS model estimations. Explanatory variable DT_{t-1}. SE reported in brackets. All the (continuous) control variables are in natural log. Regional (NUTS-2) FE included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 20
Descriptive statistics for firms' heterogeneity (by size and size-age).

	N		Mean		SD		Min		Max	
	Age	Size	Age	Size	Age	Size	Age	Size	Age	Size
SME		1357	37.37	54.83	15.75	38.64	3.00	5.00	103.00	244.92
Large		853	37.79	660.58	19.17	3639.14	3.00	12.92	117.00	141,579.80
SME#Young		729	24.32	57.08	7.48	40.87	3.00	5.33	33.00	244.92
SME#Old		618	48.65	52.88	11.82	36.52	34.00	5.00	103.00	244.58
Large#Young		416	22.62	806.01	7.50	5048.93	3.00	12.92	33.00	141,579.80
Large#Old		437	51.99	524.36	15.54	1328.17	34.00	30.42	117.00	44,075.58
Total		2200	37.43	144.83	16.30	1419.18	3.00	5.00	117.00	141,579.80

Summary statistics for variables "Size" (Eurostat classification) and Size-Age (the latter defined over the sample median) used for the heterogeneity analyses (sampling weights applied).

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