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RESEARCH ARTICLE

Entrepreneurs' impatience and digital technologies

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Abstract This paper analyzes the impact of entrepreneurs' preferences (impatience and risk attitudes) on firms' propensity to invest in both general and digital technologies. Using data from the Rilevazione su Imprese e Lavoro (RIL) survey, conducted on a representative sample of Italian firms, we find that impatience significantly reduces the likelihood of adopting digital investments, even when controlling for risk preferences. To address potential endogeneity and simultaneity concerns, we implement an instrumental variable (IV) strategy, exploiting exogenous variation from exposure to earthquakes. The findings remain robust and highlight the crucial role of impatience in shaping investment decisions, particularly in digital technologies.

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Plain English Summary Is impatience holding back digital innovation in Italian firms? This study investigates how entrepreneurs' impatience and risk attitudes affect their investment in digital technologies. Using data from a survey of Italian firms and an innovative approach that leverages earthquakes as a natural experiment, we discovered that impatience significantly reduces the likelihood of investing in digital technologies, even when accounting for risk preferences. This suggests that entrepreneurs' tendency towards impatience can be a major barrier to adopting essential digital innovations. The findings underscore the importance of developing policies that promote long-term investment strategies and help entrepreneurs build patience. Such policies could facilitate greater adoption of digital technologies and boost business competitiveness.

Keywords Time preferences · Risk · Investments · Digital technologies

JEL Classification D22 · D25 · D91

1 Introduction

A growing strand of literature has been focusing on the implications of the personality and demographic

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characteristics of individuals in shaping economic decisions.

Individual preferences—such as risk attitudes and time discounting—have emerged as pivotal factors shaping decisions made under uncertainty, with their outcomes realized in the future. These decisions span various domains including savings versus consumption, asset pricing and portfolio decisions, education, and more (Falk et al., 2023; Della Vigna, 2009; Cadena & Keys, 2015; O'Donoghue & Rabin, 2015; Gollier, 2001).

Understanding these preferences is crucial for comprehending entrepreneurial choices. Entrepreneurial activities, particularly in the accumulation of tangible and intangible assets, inherently involve assessing probabilities of yield and loss and balancing future benefits against present costs. Entrepreneurs are likely to show a different structure of their preferences than non-entrepreneurs. Selection into entrepreneurship might indeed be ascribed to specific attitudes and preferences, in particular, towards risk and impatience in receiving the return on an investment. Andersen et al. (2014), with reference to the Danish population, find that entrepreneurs are more optimistic about the chance of doing well and in general more patient than non-entrepreneurs, while their attitude towards risk seems not to differ compared to the non-entrepreneur peers. Time discounting is hence highlighted as the preference trait mostly characterizing entrepreneurs, rather than risk tolerance.

The relevance of time discounting and risk-taking becomes even more pronounced in the context of modern technologies characterized by increased automation, digitalization, and interconnectivity (Bresnahan & Trajtenberg, 1995; Teece, 2018). Investing in digital technologies can unlock a wide array of production possibilities, necessitating organizational changes and Human Resource Management (hereafter indicated as HRM) practices. Entrepreneurs may face challenges in forming beliefs about the magnitude and time horizon of expected returns, particularly compared to tangible assets or mature technologies (Brynjolfsson & McAfee, 2014). It must be said that time preference could, also, somehow reflect the ability of an entrepreneur. Dohmen et al. (2010) show that risk aversion and time patience are related to cognitive ability. Their results are based on an experiment on 1000 German individuals. Although evidence is heterogeneous, a great deal of studies in psychology show that higher cognitive ability is associated with greater patience while there is less evidence documenting the correlation between cognitive ability and risk. Finding an effect of impatience on entrepreneurial performance could hence be ascribed to a better ability effect, if ability is not observed.

Despite this backdrop, limited attention has been directed towards comprehending the influence of entrepreneurs' preferences on driving innovation and the adoption of new technologies. While some exceptions exist within research examining managers' risk attitudes (Caliendo et al., 2022; Inkinen, 2016), our understanding remains particularly sparse regarding the role of time discounting in the decision-making process. Nonetheless, the time horizon is widely acknowledged to play a significant role in shaping risk-taking attitudes across various economic behaviors (see Boon-Falleur et al., 2021; Charness et al., 2021).

In other words, entrepreneurship entails not only making decisions with varying degrees of risk but also determining whether to invest in new machinery and technologies that may require time for implementation. In this context, the significance of time preferences becomes paramount in understanding an entrepreneur's choices regarding new projects, processes, and technologies.

Another factor that affects entrepreneurial decisions is obviously related to the subjective predictions of future profits. Entrepreneurs enter a market if they see favorable business prospects, which, in turn, optimistic preferences might affect. Entrepreneurial decisions are risky and require an ability to bear the asymmetric timing of revenues with respect to costs, with costs spent at the start of the business and profits only coming in the medium-long run. It is then unlikely to find that entrepreneurs are more risk averse and impatient as well as with pessimistic beliefs, which is in line with the findings by Andersen et al. (2014).

Drawing from these arguments, this paper examines the influence of entrepreneurs' impatience preferences on firms' inclination towards financing both general investments and specific ones in digital technologies, while also considering their risk attitudes.

To achieve this objective, we use data on the risk and time preferences of business owners obtained from the Rilevazione su Imprese e Lavoro (RIL), a survey conducted by INAPP on a representative sample of Italian firms. Employing an econometric approach that addresses simultaneity and endogeneity issues, our analysis yields the following findings: first, time preferences and risk attitudes do not significantly impact the propensity to engage in "general" investments in new machinery and intangible assets. Second, entrepreneurs' impatience regarding time reduces the likelihood of investment in digital technologies, even when considering their risk aversion.

To our knowledge, this study is the first to investigate the relationship between entrepreneurs' time discounting and the adoption of new technologies using a large representative sample of firms. Moreover, our analysis has the potential to shed light on new perspectives for industrial policy by emphasizing the importance of entrepreneurs' psychological traits in navigating ongoing technological changes (Juhász et al., 2023).

Another noteworthy aspect of our contribution is its focus on the Italian context, leveraging an economic environment where the selection process for managerial positions is significantly influenced by family ownership and dynastic ties. In such an environment, time discounting and risk attitudes also reflect the long-term competitive culture and implicit social norms of family-owned businesses (Cardullo et al., 2022). In this regard, we believe our paper advances the understanding of entrepreneurs' preferences beyond existing studies that primarily focus on personal characteristics to explain self-selection into entrepreneurship.

The paper is structured as follows: Section 2 provides a background discussion. Section 3 presents the data and descriptive statistics, while Section 4 outlines the econometric approach and regression results. Section 5 discusses the robustness analysis, and Section 6 concludes the paper.

2 Background discussion

In recent years, an expanding body of research has explored whether the diversity in managerial and entrepreneurial traits influences corporate performance. For example, Bertrand and Schoar (2003) have documented significant and consistent person-specific variations in managerial styles, illustrating that some of these differences are correlated with firm behavior and performance. Other studies have ventured beyond the conventional theory positing that all managerial decisions are guided solely by rational payoff maximization (Guenzel & Malmendier, 2020; Bandera & Passerini, 2020).

Nevertheless, pinpointing the specific managerial and entrepreneurial characteristics—potentially in conjunction with personal attributes and environmental factors—that impact firms' strategies and behaviors remains an ongoing inquiry in economics.

An insightful approach to advance further may involve refining our understanding of the nature of managerial/entrepreneurial diversity and its impact on firm outcomes. In this context, it is plausible to suggest that personal preferences such as time discounting and risk attitudes could embody a wide array of individual variations, while investment decisions regarding digital technologies could serve as a reliable proxy for firms' performance. Indeed, numerous factors may correlate with individual time discounting, risk preferences, and their implications for investment decisions. These factors span from demographic traits to socio-economic factors, as well as the intergenerational transmission of skills and genetics (Becker and Milligan, 1997; Galor & Özak, 2016).[1]

To construct a foundational framework for understanding the relationship between the preferences of those managing firms and the adoption of digital technologies, we briefly explore the role of time discounting and its augmentation of risk attitude within our analytical framework.

Individual time preferences and risk attitude serve as the two parameters in the utility function shaping investment decisions where immediate utility may diverge from delayed utility. Given the inherent uncertainty of the future, risk and time discounting are intricately linked. The individual sensitivity to

[1] Demographic characteristics such as gender, age, and education play a crucial role in shaping time preferences and risk behavior (Falk et al., 2021; Oereopulos and Salvanes, 2011; Perez-Arce, 2017; Laibson, 1997). Additionally, it is important to highlight the influence of social norms, cultural factors, and historical roots on the development of modern corporate governance. The intrinsic connection between entrepreneurial preferences, demography, and innovative behavior is particularly pronounced in productive systems characterized by a prevalence of small, family-owned firms. Disparities in time preferences among countries have been identified in various large-scale studies, such as the INTRA study and the GPS study.

time delay may vary depending on the magnitude of the probabilities of gains and losses. Moreover, the perception of risk associated with expected gains is typically correlated with the relative importance placed on delayed gratification (Anderson & Mellor, 2008; Somasundaram & Eli, 2022).

Risk attitudes serve as dependable indicators of time preferences and vice versa, despite not always aligning perfectly.[2] The risk-taking inherent in an employer's decision involves anticipating the expected returns on investment and is contingent upon the significance of the future within her time horizon. Individuals with short time horizons or who are impatient may assign less importance to the potential degradation or obsolescence of their investment—whether embodied in tangible and intangible assets, skills, or organizational capabilities—which may occur over an extended period following the risky decision. In essence, risk aversion may hold less relevance for more patient individuals, while risk-taking may be less significant for impatient ones (Boon-Falleur et al., 2022).[3]

As previously mentioned, these arguments hold significant importance, particularly in the context of digital technologies. It is well established that digitalization is often regarded as a general-purpose technology that catalyzes profound transformations within firms, bolstering new HRM practices and organizational capabilities and expanding the capacity to absorb future innovation. Consequently, the anticipated returns from these enabling technologies may span a long-time horizon, corresponding to varying levels of risk tolerance among entrepreneurs. Similarly, we anticipate a negative correlation between the adoption of digital technologies and employers' risk aversion across different levels of time discounting.

It is widely acknowledged that time discounting and risk attitudes are not only individual traits but also reflect the cultural and social norms and institutional characteristics of the environment in which entrepreneurs or managers operate (Galor & Özak, 2016). This phenomenon is particularly prevalent in economies where the dominance of family ownership and dynastic ties tends to influence or diminish the self-selection process for managerial roles and entrepreneurship.

These considerations underscore the fact that our analysis does not delve into the decisions surrounding entrepreneurship itself, such as the factors influencing the choice to become an entrepreneur. This aspect is crucial given that the preferences of entrepreneurs can diverge significantly from those of the general population due to the self-selection process (e.g., De Blasio et al., 2021). However, it is worth noting that our sample primarily comprises individuals who make investment decisions not only as CEOs and/or managers but also as direct representatives of ownership, selected through dynastic mechanisms by the owning family.[4]

In essence, risk and time preferences may embody both the entrepreneurial self-selection process and the framework of family governance. It is recognized that corporate governance preferences and objectives are shaped by implicit social and cultural norms, as well as deep historical roots, particularly in countries with heterogeneous and fragmented production systems like Italy. Consequently, we hypothesize that individuals within family-owned enterprises exhibit a greater inclination towards long-term objectives and a lower risk aversion compared to professional managers and/or founders.

[2] For instance, Anderson and Mellor (2008) discovered that decision-makers exhibit insensitivity to time delays when faced with small probabilities of gains. Similarly, Charness et al. (2021) observed a negative correlation between subjects' level of risk aversion and their implicit discount factors.

[3] Time preferences are quantified through the discount function, where a higher time preference corresponds to a greater discount applied to future returns. Frederik et al. (2002) provide a comprehensive review of empirical research on intertemporal choices, while Wang et al. (2016) present findings from a large-scale international survey on time discounting. The literature examines various factors that influence subjective time discounting and their implications for economic behavior, encompassing socio-demographic and cultural factors, income disparities, intergenerational transmission of skills, and genetic influences (Becker and Mulligan, 1997; Frederik et al., 2002; Laibson, 1997).

[4] Specifically, our focus is on individuals who bear direct responsibility for business decisions, typically representing the owning family in approximately 95% of cases. These individuals are often selected through dynastic mechanisms within the ownership structure. They assume the dual roles of owners and managers, making investment decisions. Hence, we refer to them as entrepreneurs rather than CEOs, as this distinction attenuates some aspects of agency theory.

As previously mentioned, the literature on entrepreneurial decision-making has seldom delved into the preferences of the entrepreneurs themselves. It is noteworthy that the self-selection process into entrepreneurship results in a distinct sample of entrepreneurs, characterized by a lower sensitivity to risk compared to the general population. Indeed, there exists a positive correlation between individuals' propensity to take risks and the likelihood of being self-employed (Cramer et al., 2002; Ekelund et al., 2005; Fossen, 2011; Hvide & Panos, 2014; Van Praag & Cramer, 2001), as well as becoming an entrepreneur (Gough, 1969; Schumpeter, 1911). Entrepreneurs, relative to other workers, face heightened exposure to potential operational failures (Åstebro, 2012; Åstebro et al., 2014; De Blasio et al., 2021; Evans & Leighton, 1989; Hamilton, 2000; Hartog et al., 2010; Hyytinen et al., 2013). This constant uncertainty, ranging from market volatility to financial challenges, requires entrepreneurs to make decisions under conditions of substantial risk. Consequently, individuals are more inclined to pursue entrepreneurship if they exhibit higher levels of risk tolerance (Kihlstrom & Laffont, 1979; Knight, 1921). However, the role of risk preferences extends beyond the decision to become an entrepreneur; they also play a crucial part in the key decisions entrepreneurs make after entering business. Risk tolerance influences critical aspects such as hiring employees, making investments, and expanding operations. Entrepreneurs who are more risk-tolerant should be more likely to invest aggressively in new technologies and markets, whereas risk-averse individuals may hesitate, potentially stifling growth and innovation (Ruhnka & Young, 1991).

In addition to risk preferences, time preferences—specifically impatience or future orientation—also shape entrepreneurial decisions. Entrepreneurs with a stronger present bias may prefer short-term gains over long-term strategic investments, which can influence decisions on capital expenditures, digital investment, and business expansion. Those with a higher degree of patience, on the other hand, could be more likely to engage in forward-looking decisions, such as investing in technologies with delayed returns, building human capital, or entering long-term strategic partnerships (De Blasio et al., 2021). Both risk and time preferences therefore play pivotal roles in shaping how entrepreneurs allocate resources, balance risk, and plan for future growth. Understanding the joint effect of these behavioral traits is key to analyzing how entrepreneurs navigate uncertainty and make decisions that determine the trajectory of their businesses.

3 Data

The empirical analysis is based on an original database drawn from the RIL conducted in 2018 by the National Institute for the Analysis of Public Policies (INAPP) on a representative sample of partnerships and limited liability firms.[5]Each wave of the survey covers over 30,000 firms operating in the non-agricultural private sector.

The RIL-INAPP survey collects a rich set of information about characteristics of the management and corporate governance, employment composition and other workplace characteristics, and the firm's productive specialization and competitive strategies.

Further, the V wave of the RIL survey collected information on the adoption of digital technologies—hereafter I4.0 technologies. A specific question asked whether, in the period 2015–2017 (or in the near future), the firm had invested (or intended to invest) in new technologies. The respondent was presented with the following options: internet of things (IoT), robotics, big data analytics, augmented reality, cybersecurity, and others. It was possible to give multiple answers, as firms may pursue different strategies and decide to invest in one specific I4.0 technology or in more than one I4.0 technology.[6]

It is useful for our purposes that the RIL data allow us to link the information about a firm's adoption of new technologies to the data on entrepreneurial/

[5] The RIL survey sample is stratified by size, sector, geographical area, and legal form of the firm. Inclusion depends on firm size, measured by the total number of employees. This choice has required the construction of a "direct estimator" to consider the different probabilities of firms belonging to specific strata being included. For more details on the RIL questionnaire, sample design and methodological issues, see: http://www.inapp.org/it/ril.

[6] The data were collected after the implementation of the "National Enterprise Plan 4.0," an incentive scheme that was specifically designed by the Italian government to lower the financial constraints to investment and accelerate the diffusion of I4.0 technologies. All firms were eligible to join the scheme, and all received the incentive if they invested.

managerial psychology in terms of time preferences and risk attitudes. The wording used in the questionnaire reflects the standard method by which preferences are elicited within surveys (see, for instance, Falk et al., 2018).

The wording of the questions related to risk and impatience proposed in the RIL questionnaire appears to be in line with the well-known questions used in the German Socio-Economic Panel (SOEP), a longitudinal survey of German private households in the Federal Republic of Germany undertaken by the Deutsches Institut für Wirtschaftsforschung (DIW) and the Survey on Household Income and Wealth (SHIW), a longitudinal survey of Italian private households provided by the Bank of Italy. They play a fundamental role in scientific literature as they allow researchers to delve into the socio-economic and behavioral dynamics of families and individuals (Deole & Rieger, 2023; Dohmen et al., 2010). The inclusion of such questions provides a unique opportunity to analyze how people manage financial risk, make long-term economic decisions, and address challenges related to economic security (Sutter, 2013; Gallo et al., 2018). The accurate and appropriate wording of these questions is essential to ensure the validity and consistency of responses, thereby contributing to the robustness of the collected data. The careful formulation of questions on risk and impatience in these survey panels reflects the meticulous attention paid by researchers to ensure that respondents clearly understand the context of the questions, facilitating the collection of accurate and meaningful information (see Falk et al., 2023). The use of such questions is therefore crucial to enrich the understanding of economists, enabling them to study phenomena such as time preferences, financial decisions, and the overall economic behavior of families, thus making a significant contribution to academic research and the analysis of economic policies (Albanese et al., 2016).

In particular, the questions relating to impatience and risk-taking are, respectively:

Impatience Suppose you were given the choice between a payment (say €x, equal to your current annual income) today and a higher payment (€x + a given percentage, as clarified below) in 12 months. We will now present to you six situations. The payment today is the same in every situation. The payment in 12 months is different in every situation. For each of these situations, we would like to know which one you would choose. Please assume there is no inflation, i.e., future prices are the same as today's prices. Would you rather receive €x today or €x + the following premia in 12 months: (1) 1%, (2) 5%, (3) 10%, (4) 50%, (5) 100%, (6) 300%, (7) none of the previous?

Risk-taking Please imagine the following situation. You have a lottery ticket that gives you a 50 percent chance of receiving an amount equal to your current annual income and the same 50 percent of receiving nothing. Would you give away your lottery ticket in exchange for a percentage of your current annual income? What percentage would it be: (1) 5%, (2) 10%, (3) 25%, (4) 50%,(5) 80%, (6) none of the previous?

The impatience variable then shows the subjective discount rate: the higher the discount rate, the higher the value of the money today versus tomorrow, corresponding to a higher premium for postponing. As for the risk-taking variable, the lottery example in the questionnaire implies a price of the lottery for a risk-neutral agent equal to 50% of her income. The higher the amount of money that a person would turn down to enroll in the lottery, the higher the willingness to take risks (Andersen et al., 2014; Falk et al., 2018; Guiso & Paiella, 2008).[7]

It is worth underlining that the questions relating to preferences are only submitted to the sub-group of survey respondents who run a firm—about 6000 individuals; the great majority of these (90%) are the owners of the firm; that is, entrepreneurs, while around 10%, are managers. Therefore, we focus on this sample of firms, where the separation between ownership and control is expected not to influence the relationships between the preferences and the investment in digital technologies. Moreover, we have already argued that in the Italian environment, the phenomenon of self-selection into entrepreneurial/managerial activities is expected to be limited compared to what emerges in other countries; this supports the hypothesis that the profile of the individual preferences in our sample is

[7] We acknowledge that eliciting time discounting within a fixed time horizon (e.g., 1 year) may have certain limitations. Cross-country evidence indicates that discount rates over short time horizons tend to be higher and more heterogeneous compared to those over longer time horizons.

not so different from what we might have found for the rest of the Italian workforce.[8]

The data on preferences are enriched by information on the characteristics of the individual who runs the firm (age, education, gender), the ownership structure, and the occurrence of external recruitment of managers. This offers the great advantage of controlling for important sources of heterogeneity in management practices (as discussed by Bloom and Van Reenen (2011) and Lazear and Oyer (2012)). Finally, we take advantage of a wide set of variables describing the composition of the workforce (education, age, professional status, gender, contractual arrangements, citizenship, hiring), the firm's productive and competitive characteristics (size, sales per employee, foreign trade, whether multinational, age in years), and other economic activities (see Table 18 in Appendix 3). In addition to that, the preference effect could also be confounded with financial constraints if not considered. Entrepreneurs who need cash for an investment might be likely to answer for an immediate money payment irrespective of their subjective discount rate. So, we include as additional control a variable which addresses whether a bank loan has been requested to address cash flow needs or liquidity issues to capture the presence of liquidity constraints.

As for sample selection, we consider only those firms for which the respondent is an entrepreneur/manager and the firm employs at least one worker, to avoid phenomena related to self-employment. After also excluding firms with missing information for the key variables, the cross-sectional sample (RIL 2018) includes more than 4400 firms while the longitudinal sample has about 2200 firms observed in both 2018 and 2015.

3.1 Descriptive statistics

Looking at the distribution of impatience, Table 1 shows that the time preferences are roughly constant across the different values, with a peak at the average value, which could indeed show an "easy answer," as well as the last option, which set at 300% the discount rate associated with one year's wait.

Table 1 Descriptive statistics on impatient—continuous index

	N	Percent	Cum
0.01	508	11.01	11.01
0.05	535	12.39	23.4
0.1	821	17.46	40.86
0.5	1246	23.76	64.62
1	599	15.53	80.15
3	710	19.85	100
Total	4419	100	

Source: Our calculations are based on RIL 2018 data. Note: Sampling weights applied

Table 2 Descriptive risk tolerance—continuous index

	N	Percent	Cumul
0.05	674	15.44	15.44
0.1	372	7.04	22.48
0.25	549	12.04	34.53
0.5	1260	30.58	65.11
0.8	937	17.74	82.84
1	627	17.16	100
Total	4419	100	

Source: Our calculations are based on RIL 2018 data. Note: Sampling weights applied

The risk measure in the survey is like that in Barsky et al. (1997), by eliciting risk in intervals rather than point values. People are asked in ascending order how much they would pay for that lottery (or, equivalently, how much income they would give up) without asking them the exact percentage. Also, the amount at stake is relevant, given that is proportional to their income, by making the lottery more credible and of a substantial amount compared to their current resources (Rabin, 2000).

Table 2 illustrates that our measure of risk tolerance has more uneven values, with a peak at 0.5, which corresponds to the risk-neutral individual who would pay the exact amount of the lottery value. The distribution shows that 34% of individuals are risk averse, with different intensities, and 18% are risk tolerant; note that 17% of the individuals do not express any value at which they would take the risk, possibly indicating that they would not undertake the lottery game at all.

Both variables show a larger distribution mass at the central value, coherent with the preference usually stated for the "easiest" value (see Basiglio et al., 2023).

[8] On the other hand, there are studies that show that entrepreneurs are not more likely to have a higher tolerance for risk than non-entrepreneurs, i.e., that it is not risk preferences per se but preferences for competition that drive entrepreneurial choice (Holm et al., 2013). See also Cadena and Keys (2015).

Table 3 Descriptive statistics on number of digital techs

	Effective		Future	
	Freq	Percent	Freq	Percent
0	2909	74.75	4169	97.08
1	1068	20.04	188	2.25
2	312	3.62	39	0.46
3	106	1.33	16	0.12
4	18	0.09	3	0.02
5	6	0.17	4	0.07
Total	4419	100	4419	100

Source: Our calculations are based on RIL 2018 data. Note: Sampling weights applied

Turning to the outcome variables, Table 3 reports the weighted statistics for the number of digital technologies in which firms have invested or intend to invest in the future. Note that about 25% of the firms financed "at least one" digital technology over the period 2015–2017, a percentage that reduces to 3% if we consider the subgroup of firms that said they would invest in the future.

Note that fewer than 6% (1%) of the firms invested (or said they would invest) in more than two digital technologies, confirming that the Industry 4.0 paradigm in Italy is generally limited to the adoption of a "single technology" rather than being a "multi-technology" strategy based on simultaneous investments in complementary technologies. Moreover, the average number of new enabling technologies is less than one (0.32), a figure that decreases to 0.1 if cybersecurity is not included (for a detailed discussion, see Cirillo et al., 2020).[9]

As for digital heterogeneity, Table 10 distinguishes between different types of I4.0 investments. Not surprisingly, we observe that the majority of firms invested or will invest in cybersecurity (22%), whereas the Internet of Things (5%), big data analytics (3%), robotics (1,5%), and augmented reality (1,2%) cover a marginal share of adopters. This is coherent with the picture provided by Istat (2020) according to which Italian firms tend to give priority to infrastructure technologies investments (e.g., cloud solutions, management software, and cybersecurity) thus leaving the adoption of application digital ones such as IoT, automation, robotics, and big data analysis to a later stage (see also Cirillo et al., 2020, 2023).

Table 4 displays the summary statistics of the main control variables. As for the characteristics of the management, we observe that 23% of the firms are run by individuals with tertiary education and 58% by individuals with upper secondary education, while females lead only 27% of the businesses.

The strong prevalence of family-owned firms (96.2%) makes evident one of the main drivers behind the dynastic selection of managers; in other words, the intergenerational transmission of control that typifies family-owned firms is a pervasive characteristic that leads to a substantial overlap—on average—between the individual profile of entrepreneurs and that of managers in the Italian economy. On the other hand, the incidence of external management, selected from outside the family, amounts to 0.4% in our sample (see also Cardullo et al., 2022).

Concerning the workforce composition, the shares of workers with tertiary and upper secondary education are 15% and 54%, respectively, while the share of women is 50% and that of fixed-term workers is 21%. Table 4 also indicates that, on average, 42% of the firms had hired workers in the past year (a proxy for the business cycle), 1% had experienced a merger or acquisition event in the past year, and the firms were relatively concentrated in the northwestern regions.

4 Econometric analysis

To investigate the role of the entrepreneurs' impatience (and risk attitude) in their firms' investment behavior, we formalize the following regression equation:

$$y_i = a_0 + a_1 impatient_{it} + a_2 risk_{it} + a_3 female_{it} + \beta M_{it} + \delta W_{it} + \mu F_{it} + \varepsilon_{it} \quad (1)$$

where i indexes the firms, and y_i represents alternatively: (i) the probability of investing in tangible and intangible assets, (ii) the probability of adopting at least one digital technology over the period

[9] In a previous study, Cirillo et al. (2020) show that the percentage that financed "at least one" digital technology falls to 8.4% when one excludes firms that invested exclusively in cybersecurity. To put it differently, information security is the most frequent choice of Italian firms while a smaller share is concerned with augmented reality, robotics, the "IoT," and big data analytics.

2015–2017, (iii) the number of digital technologies adopted in the same period.[10]

As for the key explanatory variables, the entrepreneurs' impatience and risk tolerance are measured using a cardinal scale derived from the RIL questions as discussed in the previous section. As for the other controls, the vector M_{it} stands for managerial and corporate governance characteristics, and W_{it} includes the workforce composition, while F_{it} formalizes a rich set of the firms' productive characteristics, geographical location, and sectorial specialization. The complete set of the explanatory variables included in the analysis is reported in Table 18 (see Appendix 3). Finally, the parameter ε_i is the idiosyncratic error term with zero mean and finite variance.

Our identification strategy is initially based on linear probability models, cross-sectional data ($t=2018$), and selection of the observables. Then we verify whether using a different specification of Eq. (1) and adding an increasing number of explanatory variables means that the coefficient a_1 remains relatively stable in magnitude and statistical significance. In this regard, changes in the estimated coefficient a_1 reflecting the introduction of additional covariates—that is, risk tolerance and other individual characteristics of the entrepreneurs—may be used to assess the possible unobserved selection biases in the effect of impatience on digital technologies (Oster, 2019; Wooldridge, 2010).[11]

[10] As pointed out in the previous section, we could differentiate between effective and future intended investments in digital technologies. On the other hand, descriptive statistics show that the number of firms indicating their intention to invest in digital technologies in the future is quite small. This is the reason why we decided to report results only for effective investments, as they are more representative and robust for our analysis. For the sake of clarity, we ran some tests using only the sample of future investments, and we also tried an ordered model differentiating between firms that have not invested in digital technologies, those that intend to do so, and those that have already made this type of investment. However, these analyses did not substantially add to the overall narrative, which is why we opted not to include the results in the manuscript (results available upon request).

[11] Linear probability models allow us to easily interpret the coefficients and avoid some complications associated with non-linear ones. Following Angrist and Pischke (2009), we argue that linear probability models may be used if the predicted value for the probability of investing or adopting digital technologies is in the [0–1] range. We will see that this is the case in our framework. However, we also apply Logit and Poisson regression models at the sake of completeness (results not reported but available upon request).

Table 4 Descriptive statistics—control variables

	Mean	Std Dev	Min	Max
Management characteristics				
Tertiary education	0.234	0.423	0	1
Upper secondary education	0.577	0.494	0	1
Female	0.267	0.443	0	1
Share of age > 54	0.353	0.478	0	1
Family ownership	0.963	0.190	0	1
External managers	0.004	0.064	0	1
Workforce characteristics				
Share of tertiary education	0.156	0.305	0	1
Share of upper-second education	0.541	0.404	0	1
Share of lower education	0.303	0.385	0	1
Share of executives	0.036	0.148	0	1
Share of white collar	0.429	0.426	0	1
Share of blue collar	0.534	0.431	0	1
Share of female	0.506	0.412	0	1
Share of fixed-term contract	0.211	0.337	0	1
Share of age > 54	0.254	0.340	0	1
Firms' characteristics				
Credit constraint for cash flow	0.015	0.122	0	1
Hirings	0.422	0.494	0	1
Investment	0.356	0.479	0	1
ln (sales per employee)	11.539	1.183	3.218	15.047
ln (n of employees)	1.081	0.920	0	8.665
Firms age (in years)	19.152	13.271	0	113
Northwest	0.304	0.460	0	1
Northeast	0.232	0.422	0	1
Center	0.205	0.404	0	1
South	0.259	0.438	0	1
N of Obs		4419		

Source: Our calculations on RIL 2018 data. Note: Sampling weights applied

In general, as this is a standard regression model there may be concerns about the causal interpretation of the estimated effect of impatience on a firm's investment, even though a large set of observed controls has contributed to minimizing the potential omitted variable biases. First, the RIL survey data on time preferences are associated with individuals who have already chosen to be entrepreneurs. This raises reverse causality concerns, as a specific attitude towards risk and a specific type of patience might be developed endogenously by individuals in the exercise of the entrepreneurial profession and/or after having undertaken investment.[12]

Second, even when the measurement of preferences does not precede entrepreneurial choice (see Caliendo et al., 2009), it is not simple to establish a causal relationship in Eq. (1), since other unobservable characteristics might be correlated to both preferences and a firm's adoption of digital technologies. For instance, individuals with a favorable socio-economic background—as is typically the case in countries like Italy where around 90% of firms are family-owned and managed with dynastic ties—may be more patient (and risk-tolerant) and more prone to invest in digital technologies, as they have implicit financial security based on their family resources. Moreover, there could be measurement errors, since the proxies for risk attitude and impatience may correspond poorly with the type of risk attitude and impatience that matter in practices for investment decisions: this may create an attenuation bias.

In order to control for these endogeneity issues, we perform an instrumental variable strategy.[13] We exploit data from the catalogue of Italian earthquakes held by the National Institute of Geophysics and Volcanology (INGV) for the year 1000 onwards (Rovida et al., 2016). The data provide information on the date, latitude, longitude, depth, and magnitude (measured on the Moment Magnitude scale, Mw) of the seismic event. We focus our attention on "very strong" seismic events[14][15] that occurred in the last 50 years, as these may therefore have had an impact on an entrepreneur when she was at the head of the firm.

The use of an instrumental variable, such as having experienced an earthquake during adolescence, emerges as a compelling strategy to explore how such an experience can go beyond merely modifying the risk propensity rate, significantly influencing individual impatience rates as well. The vivid perception of uncertainty and precariousness triggered by an earthquake at a young age may shape a mind-set characterized by increased impatience in seeking immediate gratifications. This shift in temporal perspective could, in turn, steer the individual towards a tendency to avoid long-term investments. The preference for immediate gains, heightened by the earthquake experience, could impact the ability to resist immediate temptations, leading to financial choices that reflect a greater inclination towards short-term investments rather than those more future-oriented. The analysis of this instrumental variable thus provides a comprehensive and articulated interpretative key to understanding how the experience of traumatic events in adolescence can shape not only risk perception but also impatience propensity and the attitude towards long-term investments.

Table 17 in Appendix 2 reports the list of seismic episodes used in our analysis. It shows that seismic events are concentrated in the northern regions, such as Friuli-Venezia Giulia, and the central-southern areas of Italy (e.g., Calabria and Sicily). In addition to that, in Fig. 1, we provide a map that displays the seismic risk issued by the Italian Civil Protection Department (2019)[16] and the seismic episodes examined (identified with red circles).

The RIL dataset and the seismic events are merged by exploiting the information on the municipality in which each firm is located. We then build

[12] This concern is resolved by observing that the demographical aspects of the RIL entrepreneurs are similar to those of the entire sample of respondents.

[13] For a similar approach on entrepreneurship decisions, see De Blasio et al. (2021).

[14] According to the United States Geological Survey (USGS), the classification of an earthquake should also depend on the intensity experienced by those who actually felt the event. The Modified Mercalli Intensity therefore assigns a specific value to the seismic episode on a scale that goes from weak (I, not felt; II, weak…) to strong (VII, very strong; ….; XII, extreme). Source: https://www.usgs.gov/natural-hazards/earthquake-hazards/science/modified-mercalli-intensity-scale?qt-science_center_objects=0#qt-science_center_objects

[15] On the Modified Mercalli Intensity scale, an earthquake is classified as "very strong" if the event has a magnitude equal to or greater than 5.7 Mw. The standard classification requires a threshold of 6.0 Mw; however, following Rovida et al. (2016) who suggested assuming a measurement error of 0.25 Mw, we choose 5.7 Mw as the limit.

[16] The data on seismic risk is an indicator that allows the classification of Italian municipalities in terms of seismic risk. The scale goes from 1 to 4, where 1 identifies the areas in which earthquakes are less frequent and therefore classified as less dangerous areas, while 4 indicates the areas where earthquakes can be much more frequent and therefore more dangerous in terms of seismic risk.

Source: http://www.protezionecivile.gov.it/attivita-rischi/rischio-sismico/attivita/classificazionesismica.

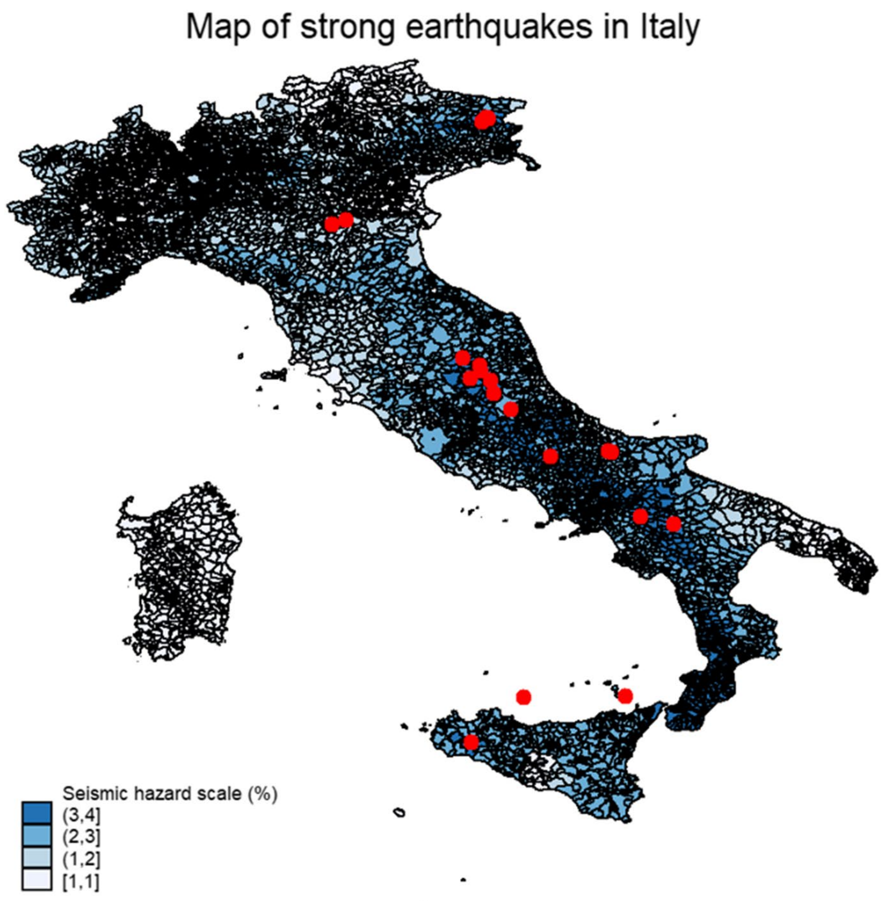

Fig. 1 Map of strong earthquakes in Italy (1968–2017). Note: own elaboration on INGV data and Italian Civil Protection Department (2019) data. Seismic hazard scale from 1 (seismically low-risk area) to 4 (seismically very risky area). Red circles identify the strong earthquake episodes presented in Table 17

a dummy variable that takes the value one if there has been a strong earthquake near the place in which the firm is located (i.e., the firm lies within 50 km from the epicenter of the earthquake) and zero otherwise.

Finally, we check whether simultaneity concerns may be at play in inducing further reverse causality issues. To fulfil this aim, we exploit the longitudinal component of the IV and V RIL surveys, using the data on managerial preferences and other control variables measured in the sample year 2015: this allows us to infer the effect of preferences on the future adoption of digital technologies.

4.1 Main estimates

Table 5 reports the OLS estimates of Eq. (1) with the different outcomes. To begin with, the results in columns [1] and [2] indicate that neither time preferences nor risk attitude significantly affect the propensity to invest *tout court*, that is, in machinery, material, and intangible assets. Further, we notice that being a woman is negatively associated with the likelihood of investing (around − 4.6 percentage points for one standard deviation increase), while tertiary education favors it (around + 5.3 percentage points for one standard deviation increase).

As for digital technologies, the estimates in columns [3] and [4] show that impatience leads to a reduction in the effective adoption of "at least one digital technology," while risk tolerance is not significant: a person with a 100% discount rate has almost a 15-percentage point lower probability of investing in digital technologies than a person with a zero discount. Additionally, our analysis reveals that certain individual characteristics of entrepreneurs play

Table 5 Effective investment choices—overall and digital technologies

	Overall investment		Digital techs		*N* of digital techs	
	[1]	[2]	[3]	[4]	[5]	[6]
Impatience	0.000	0.000	−0.012**	−0.015*	−0.021**	−0.025*
	[0.005]	[0.005]	[0.003]	[0.006]	[0.006]	[0.009]
Risk tolerance		0.005		0.021		0.028
		[0.005]		[0.016]		[0.026]
Female	−0.103***	−0.104***	−0.074***	−0.075***	−0.096**	−0.097**
	[0.016]	[0.016]	[0.010]	[0.010]	[0.022]	[0.023]
Graduated	0.126**	0.127**	0.079*	0.080*	0.146**	0.147**
	[0.026]	[0.025]	[0.033]	[0.033]	[0.030]	[0.031]
Credit constraints	−0.033***	−0.034***	0.008	0.007	0.103	0.101
	[0.003]	[0.003]	[0.010]	[0.009]	[0.063]	[0.061]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.135	−0.137	−0.296***	−0.303***	−0.430*	−0.438*
	[0.063]	[0.065]	[0.017]	[0.014]	[0.144]	[0.139]
N of Obs	4419	4419	4419	4419	4419	4419
R^2	0.192	0.192	0.182	0.182	0.161	0.161

Source: Authors' calculations on RIL data. OLS estimates. Note: Other controls include dummy indicators for family ownership and dynastic management, employment composition by professional status, education, age classes, gender, and contractual arrangements; the (log of) sales per employee, dummy for hiring firm, firms' age in years, the (log of) number of the employees, 2-digit sector of activities, nuts 2 regions. Standard errors (in parentheses) are clustered at 4 firm size classes. Statistical significance: ***1%, **5%, *10%. Regressions used sampling weights

a significant role in influencing their likelihood of investing in digital technologies. Having a tertiary education is associated with a greater propensity to adopt digital tools, suggesting that higher levels of education may equip entrepreneurs with the knowledge and confidence needed to navigate complex technological investments. On the other hand, being female is linked to a lower likelihood of investing in these technologies, which aligns with existing research indicating that women may approach investment decisions with more caution.

Columns [5] and [6] refer to the number of digital technologies adopted. Here, we confirm that impatience negatively correlates with the choice of investing in multiple digital technologies even if risk attitude is added to the set of explanatory variables. Again, being female (having a tertiary education) predicts negatively (positively) the number of digital technologies adopted.

Overall, Table 5 supports the hypothesis that the bias towards the present of who runs the firm compresses the digitalization process at the workplace. Note that these findings hold when we introduce step by step an increased number of covariates in the Eq. (1) in coherence with a strategy based on the selection of observables[17].[18]

[17] To illustrate better this issue, Tables 13 and 14 present five different specifications of Eq. (1) for both digital outcomes under study. Firstly, we consider impatience without additional controls (column 1); subsequently, we add personal characteristics of the entrepreneurs and corporate governance (column 2), workforce composition (column 3), firms' characteristics and productive specialization (column 4), and, finally, risk tolerance (column 5). Then Tables 13 and 14 make it evident that the estimates for impatience remain negative and statistically significant in each specification, even though their magnitudes are reduced in columns 4 and 5. Indeed, changes in the magnitude of the coefficients (and in R^2) detected in more complete specification suggest the possible unobserved selection as suggested by Oster (2019). At the same time, the wide set of controls in columns 4 and 5 seems to work well to capture additional firm hidden heterogeneity—they can pick up part of the impact of preferences on our outcomes.

[18] However, for the OLS estimation reported above, many predictions for dependent variables falls in the unitary range (only for 72 out of 4419 observations, the predictions are out of the [0–1] range). This encourages us to rely on linear probability models that help set IV regressions and interpret coefficients. Non-linear estimates and results from this test are not reported but available upon request.

Table 6 Effective investments in digital techs—no cybersecurity

	Digital techs		*N* of digital techs	
	[1]	[2]	[3]	[4]
Impatience	−0.007***	−0.009***	−0.009***	−0.010***
	[0.000]	[0.000]	[0.001]	[0.001]
Risk tolerance		0.015***		0.006**
		[0.001]		[0.001]
Female	−0.019**	−0.019**	−0.026**	−0.026**
	[0.004]	[0.004]	[0.004]	[0.004]
Graduated	0.001	0.002	0.045**	0.045**
	[0.004]	[0.004]	[0.006]	[0.006]
Credit constraints	−0.049***	−0.050***	0.005**	0.004**
	[0.001]	[0.001]	[0.001]	[0.001]
Other controls	Yes	Yes	Yes	Yes
Constant	−0.054*	−0.058*	−0.104*	−0.106*
	[0.015]	[0.014]	[0.028]	[0.028]
N of Obs	4419	4419	4419	4419
R^2	0.093	0.093	0.109	0.109

Source: Authors' calculations on RIL data. OLS estimates. Note: Other controls include dummy indicators for family ownership and dynastic management, employment composition by professional status, education, age classes, gender, and contractual arrangements; the (log of) sales per employee, dummy for hiring firm, firms' age in years, the (log of) number of the employees, 2-digit sector of activities, nuts 2 regions. Standard errors (in parentheses) are clustered at 4 firm size classes and 1885 municipalities. Statistical significance: ***1%, **5%, *10%

4.2 Focus on cybersecurity technology

So far, we have not differentiated between types of digital technologies, despite noting that most firms adopting at least one technology have invested in cybersecurity (see Table 10).

Cybersecurity is typically classified as a non-machine-based digital technology, whereas IoT, robotics, augmented reality, and big data are machine-based, due to their complexity and broader impact on production processes (see Balsmeier & Woerter, 2019; Istat, 2018). To better assess the role of time and risk preferences, we re-estimate the main specification excluding cybersecurity (Table 6). OLS estimates in columns [1] and [2] confirm the negative correlation between impatience and the likelihood of adopting digital technologies, except for cybersecurity. The statistical significance is stronger, though the magnitude is slightly weaker than in Table 5. Excluding cybersecurity, risk tolerance has a significantly positive effect on investments in IoT, robotics, big data, and augmented reality, with impatience playing a lesser role. This suggests risk tolerance becomes the key factor for less standard, high-risk investments. The previously insignificant risk tolerance coefficient might be due to competing effects when cybersecurity is included; its negative association with cybersecurity investments could offset the positive effects seen in other digital technologies. Columns [3] and [4] further clarify the distinct effects of impatience and risk tolerance, reinforcing their relative importance in digital technology investments. Ultimately, the results in Table 6 support the idea that impatience reduces the adoption of Industry 4.0 technologies that combine data, automation, and communication, while cybersecurity functions more as infrastructure to protect systems (Istat, 2020; MiSE, 2018).

4.3 IV-2SLS estimates

In this section, we control for the potential endogeneity of the preference parameter focusing on investments overall. Despite recognizing the potential endogeneity of both parameters, we concentrate on impatience, which is the novelty of our analysis, and since it is the main actor of overall investments, including the more standard cyber investments. We report the IV-2SLS estimates by exploiting the exogenous variation caused

Table 7 Effective investments in digital techs—IV 2SLS approach

	Digital techs		*N* of digital techs	
	[1]	[2]	[3]	[4]
Impatience	−0.055**	−0.074**	−0.064*	−0.085*
	[0.013]	[0.021]	[0.020]	[0.032]
Risk tolerance		0.105*		0.113
		[0.038]		[0.058]
Female	−0.065***	−0.065***	−0.086**	−0.087**
	[0.009]	[0.009]	[0.022]	[0.021]
Other controls	Yes	Yes	Yes	Yes
N of Obs	4414	4414	4414	4414
First-stage statistics				
Earthquake 30 years	0.400***	0.301***	0.400***	0.301***
	[0.000]	[0.000]	[0.000]	[0.000]
Kleibergen-Paap *F*	99.458	156.663	99.458	156.663
Prob > *F*	[0.002]	[0.001]	[0.002]	[0.001]

Source: Authors' calculations on RIL data. IV-2SLS estimates. Note: Other controls include dummy indicators for family ownership and dynastic management, employment composition by professional status, education, age classes, gender, and contractual arrangements; the (log of) sales per employee, dummy for hiring, dummy for credit constraints, firms' age in years, the (log of) number of the employees, 2-digit sector of activities, nuts 2 regions. Standard errors (in parentheses) are clustered at 4 firm size classes and 1885 municipalities. Statistical significance: ***1%, **5%, *10%. Regressions used sampling weights

by the occurrence of exposure to a natural disaster, that is, an earthquake during the last five decades.[19]

Columns [1] and [2] in Table 7 confirm that impatience significantly reduces the probability of adopting at least one type of technology, both when controlling for risk tolerance and when not. Coefficient estimates of columns [3] and [4] show the IV second stage estimates when the dependent variable is the number of investments in digital technologies. These results reinforce the observed trend: impatience appears to have a negative and statistically significant impact on the number of investments in digital technologies.

Further, the first stage statistics, presented in Table 7, indicate that our instrument, derived from exposure to natural disasters, has a positive and significant impact on the outcome variables, with the coefficient being significant at the 1% level. Consistent with the empirical literature, the *F*-statistic exceeds the threshold of 10, indicating that the instrument is robust and is not weak (Cragg & Donald, 1993; Stock & Yogo, 2005).

The results confirm those obtained with the linear probability model. The magnitude appears to be greater, and the role of risk also assumes significance. Focusing on the gender effect, we find that being a woman significantly decreases the probability of investing in digital technologies (an increase of one standard deviation—0.443—in females corresponds to a decrease of around 2.88 percentage points in investments in digital technologies). This finding is consistent with the broader literature, which suggests that women generally tend to adopt a more cautious or risk-averse approach towards investment decisions. Such prudence may reflect underlying differences in risk tolerance, as various studies have documented that women often exhibit greater concern for potential losses compared to their male counterparts, particularly in contexts involving financial uncertainty or long-term investments.

Notably, by isolating the effects of impatience and risk tolerance, the results indicate that impatience has a more pronounced effect on investment decisions. This approach underscores the importance of impatience as a critical behavioral trait influencing investment choices in digital technologies. Risk tolerance, while also significant, is controlled in line with established literature to

[19] As discussed above, this idea is in line with the literature, which states that there is a relationship between risk preferences and the negative shocks related to a natural disaster (see,

Footnote 19 (continued)
for instance, De Blasio et al., 2021). On the other hand, digital technologies are a relatively recent phenomenon.

ensure that the focus remains on impatience. As pointed out in previous paragraphs, there are reasons why, in investment decisions (the temporal dimension of which is essential), the role of impatience is decisive for risk attitude (Boon-Falleur et al., 2021). This distinction is crucial as impatience directly impacts investment decisions, particularly in the context of new technologies where the temporal dimension is significant. These technologies are general-purpose investments with uncertain obsolescence rates, making the role of impatience particularly relevant in understanding investment behavior. Our analysis highlights the nuanced interplay between impatience and risk tolerance, with impatience emerging as a key determinant of investment in digital technologies. This refined focus provides clearer insights into the relative importance of these factors, offering a deeper understanding of how impatience and risk tolerance influence digital technology investments.

5 Robustness

5.1 Dichotomous preferences

One possible concern is linked to the nature of the measurement of impatience. For this reason, we created an indicator variable which takes the value one when the individual is impatient and zero otherwise.[20]

By focusing our attention on the columns regarding investments in new technologies, for example, it is possible to say that being impatient decreases the probability of investing in new technologies by about 10 percentage points (see Table 8).

5.2 Simultaneity issues

As a final robustness check, we investigate whether the previous estimates are exposed to potential simultaneity biases. This concern emerges because the dependent variable is formalized by the effective investment in digital technologies undertaken over the period 2015–2017.

The empirical picture discussed so far could be misleading if a simultaneity bias is at play affecting the cross-sectional OLS estimates. To go more in-depth into this issue, we take advantage of the longitudinal component of the RIL data from 2015 and 2017.

In Table 12 in Appendix 1, we report the summary statistics of the subsample panel of the main control variables. The sample appears to be very similar to the cross-sectional one. Indeed, 20% of the firms are run by individuals with tertiary education, while females lead only 20% of them. Again, there is a strong prevalence of family-owned firms (the share is 96%). As for the workforce composition, the shares of workers with tertiary and upper secondary education are 7% and 58% respectively. Finally, on average, 24% of the firms hired workers (a significantly lower percentage than in the cross-sectional sample), and the firms are relatively concentrated in the northern regions.

We then perform a linear regression of a panel version of Eq. (1) where the dependent variable, that is, the different measures of the firms' investment, is calculated for 2018, while the explanatory ones, that is, impatience, managerial characteristics, and workforce

Table 8 Effective investments in digital techs—dichotomous preferences

	Digital techs		*N* of digital techs	
	[1]	[2]	[3]	[4]
Impatience (0/1)	−0.075**	−0.078**	−0.055*	−0.056*
	[0.022]	[0.024]	[0.023]	[0.026]
Risk tolerance		0.015		0.004
		[0.012]		[0.017]
Female	−0.073***	−0.074***	−0.098**	−0.098**
	[0.010]	[0.010]	[0.023]	[0.023]
Other controls	Yes	Yes	Yes	Yes
Constant	−0.261***	−0.265***	−0.411*	−0.412*
	[0.025]	[0.023]	[0.153]	[0.149]
N of Obs	4419	4419	4419	4419
R^2	0.184	0.184	0.161	0.161

Source: Authors' calculations on RIL data. OLS estimates. Note: Other controls include dummy indicators for family ownership and dynastic management, employment composition by professional status, education, age classes, gender, and contractual arrangements; the (log of) sales per employee, dummy for hiring, dummy for credit constraints, firms' age in years, the (log of) number of the employees, 2-digit sector of activities, nuts 2 regions. Standard errors (in parentheses) are clustered at 4 firm size classes and 1885 municipalities. Statistical significance: ***1%, **5%, *10%

[20] The variable therefore assumes the value one when the individual never moves from the option of taking everything immediately, whatever the premium; a zero value identifies individuals who say yes to procrastination (or who say yes to some premium).

composition, refer to the previous sample period of 2015. Of course, in doing so, we lose a lot of observations, and this could lead to potential problems in the statistical significance of the point estimates.

The estimates, reported in Table 9, confirm the previous results, showing that impatience tends to weaken the digitalization process.

5.3 Evidence on specific sub-samples

A further check focuses on the subsample of firms with no employees and, conversely, on those firms that did not recruit external managers (Tables 15 and 16 in Appendix 1). These analyses address two specific concerns: first, the potential influence of entrepreneurs' preferences on investment decisions in firms without employees, and second, the robustness of results when excluding hired managers who may not have the same ownership stakes or decision-making influence as entrepreneurs themselves. We examined firms without employees as they may represent a particularly interesting group where the influence of the entrepreneur's personal characteristics, including impatience and risk tolerance, could play an even larger role in shaping investment decisions (Table 15). In micro-firms, where the entrepreneur's behavior directly determines the firm's strategy, the demographic characteristics and personal preferences of the entrepreneur become critically important. In such cases, the overlap between self-declared risk and time preferences and investment choices may be stronger (Parker, 2004). However, selecting firms with no employees leads to a significant reduction in the sample size, which limits the comparability with other results and may affect the statistical power of the estimates.

Regarding the exclusion of hired managers, we have also performed robustness checks by limiting the sample to firms where the entrepreneur is solely responsible for decision-making without the involvement of external managers (Table 16). This additional analysis ensures that our results are not driven by managerial decision-making processes that could differ from those of owner-entrepreneurs. By excluding firms with hired managers, we strengthen the interpretation of our findings, as the digital investment decisions are more directly influenced by the entrepreneur's personal characteristics. As expected, impatience remains a limiting factor in digital adoption, consistent with the findings from the broader sample.

Therefore, these additional analyses provide more nuanced insights into the impact of impatience and risk tolerance on digital investment. They demonstrate that even in the absence of employees or external managers, the entrepreneur's behavioral traits, particularly impatience, continue to play a crucial role in determining investment choices. This underscores

Table 9 Effective investments in digital techs—longitudinal component 2015–2018

	Digital Techs		N of Digital techs	
	[1]	[2]	[3]	[4]
Impatience (0/1)	−0.039***	−0.027***	−0.044***	−0.025***
	[0.006]	[0.001]	[0.005]	[0.003]
Risk tolerance		−0.093		−0.145
		[0.045]		[0.064]
Female	0.016	0.018	−0.046***	−0.044**
	[0.012]	[0.013]	[0.006]	[0.008]
Other controls	Yes	Yes	Yes	Yes
Constant	−0.150	−0.135	−0.128	−0.105
	[0.129	[0.122]	[0.197]	[0.187]
N of Obs	2048	2048	2048	2048
R^2	0.144	0.147	0.144	0.147

Source: Authors' calculations on RIL longitudinal data. OLS estimates. Note: Other lagged controls include dummy indicators for family ownership and dynastic management, employment composition by professional status, education, age classes, gender, and contractual arrangements; the (log of) sales per employee, dummy for hiring, dummy for credit constraints, firms' age in years, the (log of) number of the employees, 2-digit sector of activities, nuts 2 regions. Standard errors (in parentheses) are clustered at 4 firm size classes and 1885 municipalities. Statistical significance: ***1%, **5%, *10%

the importance of understanding how personal preferences influence key strategic decisions, especially in small, owner-operated firms.

6 Conclusions

The preferences of investors have been investigated theoretically and empirically. The features of household investment have been investigated widely with respect to risk attitude and impatience. As for the determinants of investment by firms, little is known about how the preferences of managers and employers affect firms' investment and innovation choices. There are few studies that focus on. The few relevant studies mainly focus on risk attitude, while no evidence is available about the effect of the entrepreneur's impatience on a firm's investment in digital technologies (O'Donoghue & Rabin, 2015; DellaVigna, 2009).

Filling this gap has been the main motivation of the paper. Employers' decisions involving risk have a temporal dimension, and this dimension plays a key role in the decision to finance the adoption of new technologies (see Boon-Falleur et al., 2021).[21]

Using an innovative dataset of Italian firms, we detect that impatience significantly reduces the propensity to undertake investment in digital technologies even if one accounts for preferences regarding risk. Further, we show that risk aversion is positively correlated with Industry 4.0 technologies, even though the estimates are weaker and not always statistically significant than those found for impatience.

If we consider that new technologies increase productivity and competitiveness, and given that we have found that entrepreneurs' impatience leads to less digital adoption, we would suggest that, on average, those who run Italian firms have trouble undertaking the investments that best serve their long-term interests.

This in turn opens the door to policies to encourage more long-term strategies which would allow entrepreneurs to enjoy the expected payoffs from higher present investment in digitalization. For instance, policies designed to favor the adoption of digital technologies or to increase the average human capital of those who run firms may create an economic environment that, by reducing the discount rate for investment choices, encourages digitalization and economic competitiveness. This argument is supported by those studies that suggest that personality traits, patience, and other non-cognitive skills (like risk attitude and risk consciousness) can be learned and are not entirely innate (Oreopoulos & Salvanes, 2011; Perez-Arce, 2017).

Another crucial aspect that is left for the research agenda is to detect the role of entrepreneurial capability, which could be correlated with risk aversion and impatience. If cognitive ability, not revealed to the researcher, is correlated with impatience, the preference structure could be actually signaling a better ability to be an entrepreneur, rather than having a higher discount rate. Future research could hence further explore the interaction between impatience, cognitive ability, and digital investment decisions. Impatience may be negatively correlated with cognitive ability, as suggested by Dohmen et al. (2010), indicating that the negative effect of impatience on digital investment might be partially driven by the positive impact of higher cognitive skills. Entrepreneurs with greater cognitive ability may be better positioned to assess the long-term benefits of digital technologies, reducing present bias and enhancing the likelihood of digital adoption. Understanding how cognitive ability moderates the relationship between impatience and investment behavior would provide valuable insights for policy interventions.

Such insights could lead to more effective policy design, targeting both cognitive skills development and fostering patience, thereby promoting more forward-looking strategies among entrepreneurs. By addressing both the cognitive and non-cognitive factors influencing investment decisions, future policies could better support digital transformation and strengthen firms' competitiveness in the global economy. Exploring these dynamics in greater depth would provide a more comprehensive understanding of the factors shaping entrepreneurial investment behavior.

[21] In this environment, one may argue that taking risks to finance the initial costs depends on the amount and time horizon of the expected returns on the investment. For each given amount and time horizon of the expected returns from new technologies, we expect that impatience shapes the risk attitude because the expected returns on the investment will be discounted at a higher rate.

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Declarations

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.

Appendix 1. Additional tables

Table 10, 11, 12, 13, 14, 15, 16, 17 and 18.

Table 10 Descriptive statistics on typologies of digital techs

	Effective		Future	
	Mean	std dev	Mean	std dev
Internet of Things	0.050	0.219	0.010	0.098
Robotics	0.015	0.121	0.004	0.065
Big data	0.030	0.169	0.004	0.064
Augmented reality	0.012	0.108	0.006	0.078
Cyber-security	0.218	0.413	0.015	0.123
N of Obs	4419			

Source: Our calculations are based on RIL 2018 data. Note: Sampling weights applied

Table 11 Descriptive statistics on preferences 2015–2018

	N	Percent	Cum
Impatience			
0.01	342	12.47	12.47
0.05	265	12.87	25.34
0.1	402	20.04	45.39
0.5	554	26.76	72.14
1	217	14.69	86.83
3	281	13.17	100.00
Risk tolerance			
0.05	407	15.06	15.06
0.1	191	8.77	23.83
0.25	251	13.87	37.70
0.5	591	27.65	65.36
0.8	373	18.97	84.33
1	248	15.67	100.00
N of Obs	2061	100.00	

Source: Our calculations on RIL 2015–2018 longitudinal data. Note: Sampling weights applied

Table 12 Descriptive statistics: control variables 2015–2018

	Mean	std dev	Min	Max
Management characteristics				
Tertiary ed	0.205	0.404	0	1
Upper secondary ed	0.582	0.493	0	1
Female	0.204	0.403	0	1
Family ownership	0.960	0.195	0	1
External managers	0.008	0.089	0	1
Workforce characteristics				
Share of tertiary ed	0.072	0.198	0	1
Share of upper second ed	0.585	0.399	0	1
Share of lower ed	0.342	0.395	0	1
Share of executives	0.019	0.080	0	1
Share of white collar	0.481	0.437	0	1
Share of blue collar	0.500	0.439	0	1
Share of female	0.484	0.406	0	1
Share of ft. contract	0.083	0.207	0	1
Share of age > 54	0.231	0.331	0	1
Firms' characteristics				
Hirings	0.245	0.430	0	1
ln(sales per employee)	11.837	1.109	3.68	15.04
Mergers and acquisitions	0.008	0.092	0	1
Firms age (in years)	22.94	16.24	0	821
ln (*n* of employees)	1.099	0.992	0	7.57
Northwest	0.320	0.468	0	1
Northeast	0.318	0.466	0	1
Center	0.224	0.417	0	1
South	0.137	0.344	0	1
N of Obs	2061			

Source: Our calculations on RIL 2015–2018 longitudinal data. Note: Sampling weights applied

Table 13 Effective investments in digital techs—full set of controls

	[1]	[2]	[3]	[4]	[5]
Impatience	−0.031***	−0.021***	−0.029**	−0.012**	−0.015*
	[0.005]	[0.003]	[0.005]	[0.003]	[0.006]
Risk tolerance					0.0210
					[0.016]
Female (0/1)		−0.116***	−0.103***	−0.074***	−0.074***
		[0.007]	[0.017]	[0.010]	[0.010]
Tertiary (0/1)		0.137***	0.115***	0.080*	0.081*
		[0.003]	[0.014]	[0.033]	[0.034]
Upper secondary educ (0/1)		0.130***	0.098**	0.067*	0.068*
		[0.017]	[0.023]	[0.028]	[0.028]
Aged > 54 years (0/1)		0.025***	0.042***	−0.004	−0.004
		[0.003]	[0.005]	[0.006]	[0.005]
Family firms (0/1)		0.050	0.137	0.119	0.117
		[0.074]	[0.072]	[0.062]	[0.060]
External managers (0/1)		0.256***	0.184**	0.086	0.084
		[0.036]	[0.044]	[0.060]	[0.060]
Share of tertiary educ			−0.048	−0.025***	−0.026**
			[0.032]	[0.004]	[0.005]
Share of upper secondary educ			0.112***	0.102***	0.102***
			[0.010]	[0.001]	[0.001]
Share of executives			0.159**	0.152***	0.150***
			[0.035]	[0.021]	[0.022]
Share of white collar			0.122**	0.049**	0.049**
			[0.032]	[0.012]	[0.013]
Share of female			−0.024**	0.019*	0.020*
			[0.006]	[0.007]	[0.008]
Share of FT contracts			−0.002	0.001	0.000
			[0.009]	[0.003]	[0.004]
Share of aged			−0.107***	−0.147***	−0.147***
			[0.017	[0.010]	[0.010]
ln (*n* of employees)			0.086***	0.092***	0.091***
			[0.001]	[0.001]	[0.001]
Credit constraints				0.011	0.010
				[0.011]	[0.010]
ln (sales per empl)				0.020*	0.020*
				[0.008]	[0.008]
Firms age (in years)				0.001***	0.001***
				[0.000]	[0.000]
Sectors and nuts regions	Yes	Yes	Yes	Yes	Yes
Constant	0.280***	0.138	−0.09	−0.294***	−0.300***
	[0.018	[0.097]	[0.075]	[0.015]	[0.012]
N of Obs	4419	4419	4419	4419	4419
R^2	0.006	0.032	0.096	0.182	0.182

Source: Authors' calculations on RIL data. OLS estimates. Note: Standard errors (in parentheses) are clustered at 4 firm size classes. Statistical significance: *** 1%, ** 5%, * 10%. Regressions used sampling weights

Table 14 Effective number of investments in digital techs—full set of controls

	[1]	[2]	[3]	[4]	[5]
Impatience	−0.040***	−0.028**	−0.038**	−0.021**	−0.024*
	[0.006]	[0.005]	[0.007]	[0.006]	[0.009]
Risk tolerance					0.028
					[0.026]
Female (0/1)		−0.148***	−0.125**	−0.096**	−0.096**
		[0.010]	[0.026]	[0.023]	[0.023]
Tertiary (0/1)		0.223***	0.192***	0.147**	0.148**
		[0.016]	[0.010]	[0.030]	[0.031]
Upper secondary educ (0/1)		0.173***	0.133***	0.091**	0.092*
		[0.008]	[0.022]	[0.028]	[0.029]
Aged > 54 years (0/1)		0.025***	0.050***	0.001	0.001
		[0.003]	[0.002]	[0.008]	[0.008]
Family firms (0/1)		−0.02	0.117	0.130*	0.127*
		[0.078	[0.059	[0.05	[0.048
External managers (0/1)		0.318**	0.208**	0.090	0.088
		[0.059]	[0.053]	[0.068]	[0.067]
Share of tertiary educ			−0.041	−0.028	−0.030
			[0.038]	[0.021]	[0.022]
Share of upper secondary educ			0.145***	0.129***	0.129***
			[0.006]	[0.007]	[0.008]
Share of executives			0.261*	0.257*	0.255*
			[0.095]	[0.093]	[0.095]
Share of white collar			0.170*	0.059	0.059
			[0.061]	[0.032]	[0.033]
Share of female			−0.050***	0.044***	0.045***
			[0.002]	[0.005]	[0.004]
Share of FT contracts			0.002	0.022***	0.019***
			[0.023]	[0.002]	[0.002]
Share of aged			−0.159***	−0.218***	−0.218***
			[0.006]	[0.002]	[0.002]
ln (*n* of employees)			0.138***	0.141***	0.140***
			[0.011]	[0.012]	[0.012]
Credit constraints				0.105	0.103
				[0.059]	[0.057]
ln (sales per empl)				0.031	0.031
				[0.014]	[0.015]
firm age (in years)				0.000	0.000
				[0.000]	[0.000]
Sectors and nuts regions	Yes	Yes	Yes	Yes	Yes
Constant	0.361***	0.246*	−0.098*	−0.428*	−0.436**
	[0.035]	[0.104]	[0.036]	[0.139]	[0.134]
N of Obs	4419	4419	4419	4419	4419
R^2	0.005	0.027	0.091	0.161	0.161

Source: Authors' calculations on RIL data. OLS estimates. Note: Standard errors (in parentheses) are clustered at 4 firm size classes. Statistical significance: *** 1%, ** 5%, * 10%. Regressions used sampling weights

Table 15 Effective investments in digital techs in firms without employees

	[1]	[2]	[3]	[4]
Impatience	−0.012*	−0.018**	−0.016*	−0.015
	[0.007]	[0.009]	[0.009]	[0.010]
Risk tolerance		0.038	0.037	0.032
		[0.029]	[0.029]	[0.030]
Female (0/1)			0.018	0.028
			[0.021]	[0.024]
Tertiary (0/1)			0.150***	0.081***
			[0.027]	[0.029]
Upper secondary educ (0/1)			0.099***	0.071***
			[0.016]	[0.017]
Aged > 54 years (0/1)			−0.011	−0.01
			[0.017]	[0.017]
Family firms (0/1)			−0.002	−0.032
			[0.090]	[0.082]
External managers (0/1)			0.075	0.136
			[0.142]	[0.129]
Sectors and nuts regions	No	No	No	Yes
Constant	0.137***	0.124***	0.049	0.104
	[0.011]	[0.014]	[0.090]	[0.083]
N of Obs	1599	1599	1580	1573
R^2	0.001	0.001	0.026	0.089

Source: Authors' calculations on RIL data. OLS estimates. Dependent variable: investments in digital technologies. Note: Standard errors (in parentheses) are clustered at 4 firm size classes. Statistical significance: *** 1%, ** 5%, * 10%. Regressions used sampling weights

Table 16 Effective investments in digital techs excluding external managers

	Overall investment		Digital techs		*N* of digital techs	
	[1]	[2]	[3]	[4]	[5]	[6]
Impatience	0.002	0.002	−0.011**	−0.015**	−0.020**	0.006
	[0.005]	[0.006]	[0.002]	[0.004]	[0.004]	[0.004]
Risk tolerance		0.004		0.028		−0.015***
		[0.005]		[0.017]		[0.002]
Female	−0.097***	−0.097***	−0.076***	−0.077***	−0.102**	−0.019**
	[0.014]	[0.014]	[0.010]	[0.011]	[0.022]	[0.004]
Graduated	0.136**	0.137**	0.087*	0.089*	0.157***	0.021**
	[0.027]	[0.027]	[0.030]	[0.031]	[0.023]	[0.005]
Age > 54 years	0.013	0.013	−0.002	−0.002	0.001	−0.017
	[0.006]	[0.006]	[0.006]	[0.006]	[0.009]	[0.007]
Credit constraints	−0.022**	−0.023**	−0.027	−0.030*	0.085	−0.062***
	[0.005]	[0.006]	[0.014]	[0.011]	[0.070]	[0.003]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.062	−0.064	−0.282***	−0.291***	−0.440***	0.039
	[0.084]	[0.086]	[0.020]	[0.024]	[0.062]	[0.040]
N of Obs	4223	4223	4223	4223	4223	4223
R^2	0.196	0.196	0.181	0.181	0.168	0.021

Source: Authors' calculations on RIL data. OLS estimates. Note: Other controls include dummy indicators for family ownership and dynastic management, employment composition by professional status, education, age classes, gender, and contractual arrangements; the (log of) sales per employee, dummy for hiring, firms' age in years, the (log of) number of the employees, 2-digit sector of activities, nuts 2 regions. Standard errors (in parentheses) are clustered at 4 firm size classes. Statistical significance: *** 1%, ** 5%, * 10%. Regressions used sampling weights

Appendix 2. Data on earthquakes

Table 17 List of strong earthquakes in Italy (1968–2017)

Year	Epicentral area	Magnitude (Mw)	Region
1968	Valle del Belice	6.41	Sicily
1976	Friuli	6.45	Friuli-Venezia Giulia
1976	Friuli	5.93	Friuli-Venezia Giulia
1976	Friuli	5.95	Friuli-Venezia Giulia
1978	Golfo di Patti	6.03	Sicily
1979	Valnerina	5.83	Umbria
1980	Irpinia-Basilicata	6.81	Campania/Basilicata
1984	Monti della Meta	5.86	Lazio
1990	Potentino	5.77	Basilicata
1997	Appennino umbro-marchigiano	5.97	Umbria/Marche
2002	Tirreno meridionale	5.92	Sicily
2002	Molise	5.74	Molise
2002	Molise	5.72	Molise
2009	Aquilano	6.29	Abruzzo
2012	Pianura emiliana	6.09	Emilia-Romagna
2012	Pianura emiliana	5.90	Emilia-Romagna
2016	Monti della Laga	6.18	Abruzzo/Lazio/Marche
2016	Valnerina	6.07	Umbria
2016	Valnerina	6.61	Umbria
2017	Aquilano	5.70	Abruzzo

Source: Own elaboration on INGV data. Note: Seismic events of magnitude greater or equal than 5.7 Mw and depth of the epicentral area below 50 km

Appendix 3. Description of variables

Table 18 Definition of variables

Labels	Description
Main variables	
Investment	Dummy variable that equals 1 if firms financed any investment in tangible and/or intangible assets, 0 otherwise
Effective digital technologies	Dummy variable that equals 1 if firms adopted "at least one" digital technology (internet of things, robotics, big data analytics, augmented reality, cybersecurity) over the period 2015–2017, 0 otherwise
N of digital technologies (effective)	Categorical variable—ranging from 1 to 5—that equals the total number of I4.0 technologies adopted over the period 2015–2017
Management and corporate governance	
Entrepreneurs' education	Three dummy variables that equal to 1 whether the educational level of the entrepreneurs/managers who run the firm is (i) tertiary, (ii) upper secondary, (iii) lower secondary or elementary, 0 otherwise
Entrepreneurs' age	Dummy variable that equals 1 whether the age of the entrepreneurs/ who run the firm is higher than 49 years, 0 otherwise
Entrepreneurs' gender	Dummy variable that equals 1 whether the entrepreneurs/managers who run the firm are female, 0 otherwise
Family ownership	Dummy variable that equals 1 if the ownership of the firm is held by a single family, 0 otherwise
External managers	Dummy variable that equals 1 if the firm recruited their managers in the outside market rather than selecting them on the basis of dynastic ties with the family ownership, 0 otherwise
Workforce characteristics	
Education	Three variables indicating the share of employees (on the firms' total number of employees) with (i) tertiary education, (ii) upper secondary education, (iii) lower secondary or elementary
Age	Three variables indicating the share of workers (on the firms' total number of employees) with: i) less than 35 years old; ii) between 35 and 49 years old; iii) more than 49 years old
Professional status	Three variables indicating the share (on the firms' total number of employees) of (i) executives, (ii) white collars, and (iii) blue collars
Contractual arrangements	Share of workers with a fixed-term contract on the firms' total number of employees
Female share	Share of female workers on the firms' total number of employees
Firms' characteristics	
Credit Constraint	Dummy variable that equals 1 if the firms requested a bank loan to address cash flow needs or liquidity issues to capture the presence of liquidity constraints, 0 otherwise
Hiring	Dummy variable that equals 1 if the firms hired some worker in the current year, 0 otherwise
Profitability	(Log of) the total sales (in Euros) per employee. The amount of sales is deflated
Firm's size	(Log of) total number of employees
Firms' age	Number of years since the firm has been funded
Geographical localization	20 dummies variables indicating the Italian Nuts 2 regions
Sector of activities	14 dummies variables indicating: 1, electricity, gas, and water distribution (public utilities); 2, food, tobacco, etc.; 3, textile, woods, papers, etc.; 4, chemistry and metallurgy; 5, mechanics; 6, other manufacturing; 7, construction; 8, retail and wholesale; 9, tourism, hotels, and restaurants; 10, transportation; 11, insurance and financial intermediation; 12, information and communication; 13, other business services; 14, healthcare, educational, and social services; others

Source: RIL Data. Note: To deflate the sales we relied on sectoral deflators (NACE 2 digit) provided by the National Statistical Institute (ISTAT) based on industrial production prices (the base year is 2010). The deflators are available at: http://dati.istat.it/#

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