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Bosses' Impatience and Digital Technologies

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Bosses' Impatience and Digital Technologies[1±]

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Provisional Draft

Abstract

This paper analyses the impact of entrepreneurs' preferences (time impatience and risk attitudes) on firms' propensity to make general investments and also specific investments in digital technologies. To fulfil this aim, we use the responses to the questions intended to measure risk attitude and patience included in the *Rilevazione su Imprese e Lavoro (RIL)* survey conducted by INAPP on a representative sample of Italian firms. The regression estimates show that time impatience has at most a weak effect on firms' 'general' investments, while it reduces the propensity to undertake investments in digital technologies. Risk attitude is positively correlated with digital investment, even though the estimates are weaker in magnitude and statistical significance than those found for impatience. These results are robust to simultaneity and endogeneity issues.

Keywords: Time preferences, Impatience, Investments, Digital technologies

JEL classification: D22, D25, D91

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1. Introduction

A growing strand of literature has been focusing on the implications of the personality and demographic characteristics of the individuals in shaping economic decisions and labour market outcomes (Falk et al., 2018; Della Vigna, 2009; Cadena and Keys 2015; O'Donoghue and Rabin, 2015).

Risk preferences, as well as preference structure overall, are undeniably relevant to understanding economic behaviour, at both firm and consumer levels. For this reason, many surveys, such as the Survey on Household Income and Wealth (SHIW) or the National Longitudinal Survey of Youth (NLSY), have introduced specific questions aimed at measuring risk aversion. Risk attitude is pivotal in determining economic choices such as savings (versus consumption), by generating a smoother consumption trajectory, hence lower savings, than a less risk averse individual (Deaton, 1992). Portfolio decisions, in particular the ratio invested in the stock market, are also shaped by risk aversion parameters (Gollier, 2001), with a higher ratio invested in risky, rather than risk-free, assets for individuals with a lower risk aversion.

Much less attention has been devoted to the role of entrepreneurs' preferences - like time impatience and risk attitude, in the different choices they make under uncertainty, such as investment in human capital and innovation (Inkinen, 2016; Caliendo et al., 2022). Indeed, these activities involve probabilities of yield and loss, and entail weighing future benefits against present costs (Andersen et al., 2014). Furthermore, theoretical and empirical reasons from biology, anthropology and other disciplines lead us to hypothesize that gender, managerial culture and physiological traits interact with each other in shaping the strategic behaviours of economic agents (Guiso et al., 2006) and specifically of entrepreneurs.

When looking at entrepreneurial choices, the literature has rarely focused on the preferences of the entrepreneur herself. It has to be said that the self-selection into entrepreneurship makes the sample of entrepreneurs different from the population overall, with entrepreneurs being less sensitive to risk than their peers. Indeed, there is a positive correlation between the propensity of individuals to take risks and the probability of being self-employed (Van Praag and Cramer, 2001; Cramer et al., 2002; Ekelund et al., 2005; Fossen, 2011; Hvide and Panos, 2014) as well as of being an entrepreneur (Schumpeter, 1911; Gough, 1969). Compared to other workers, entrepreneurs are more exposed to possible failure in operations (Evans and Leighton, 1989; Hamilton, 2000; Hartog et al., 2010; Åstebro, 2012; Hyytinen et al., 2013; Åstebro et al., 2014; De Blasio et al., 2021). Individuals are then more likely to become entrepreneurs if they are more risk tolerant (Knight, 1921; Kihlstrom and Laffont, 1979).

Entrepreneurial activities, especially when it comes to investment decisions, are certainly a domain in which the decisions involve both a risk-taking dimension and an intertemporal one, where an attitude of impatience dominates: investments make the entrepreneur bear high costs in the short term with a stream of (expected) revenue generated in the long run.

What drives investment decisions?

Any investment is understood to be determined by the market conditions (such as the interest rate) and by personal preferences. As previously pointed out, the parameter that has usually been taken into account is risk aversion. Indeed, the degree of risk aversion has a negative impact on the decision to become self-employed (Kan and Tsai, 2006). This means that, as a few studies have pointed out, a less risk averse individual is more likely to become an entrepreneur and to invest more in the stock market (e.g., Marshall, 1890; Knight, 1921; Kanbur, 1979; Kihlstrom and Laffont, 1979; Kan and Tsai, 2006).

When looking at investment decisions, however, the importance of the way in which preferences shape the investment decisions of managers seems to come second to the standard reasoning on the cost–benefit analysis. Abatecola et al. (2013) show that only 11 per cent of studies in personality-based management literature mention risk attitude. In a recent empirical paper, Caliendo et al. (2022) show that risk tolerant and risk averse decision makers have significantly different attitudes to investing in training. Managers who are risk averse offer significantly less general training.

In addition to risk aversion, virtually nothing is known about how impatience enters the decision making process. However, as shown in a recent paper by Boon-Falleur and colleagues (2021), the time horizon of an individual also plays an important role in shaping risk taking behaviours such as not wearing a seat belt.

The novelty of our work is that it sheds light on the roles of risk aversion as well as impatience as the two parameters in the utility function shaping investment decisions. Time discount, for example, is one of the drivers leading to long investments with risky returns, which are less volatile over the long-term horizon. Moreover, risk aversion matters in different ways depending on the domain in which risk is considered.[2] To the best of our knowledge, this work is the first to look at the impact of impatience, as well risk aversion, on investment decisions.

As mentioned above, being an entrepreneur involves not only making more or less risky decisions but also deciding whether or not to invest in projects that may take time to be implemented. Along

[2] For example, women tend to risk more if the investment is in relation to their child's health. Time discount is more objectively related to the patience to wait until the events start to produce a return. If women are more impatient than men to see the rewards of their investment, we can expect that controlling for time discount will dilute the gender gap in credit. Part of the gender gap might indeed be associated with different levels of patience.

these lines, in order to therefore increase the firm's turnover, it can often become essential to invest in new projects, processes and technologies.

From this perspective, it seems relevant to investigate the implications of entrepreneurs' preferences on the diffusion and implementation of digital and automation technologies in modern economies (Brynjolfsson and McAfee, 2014). These technologies have been associated with those disruptive process innovation technologies that are referred to as enabling technologies (Teece, 2018); however, they also display some of the characteristics of general purpose technologies (Bresnahan and Trajtenberg, 1995). New digital technologies encompass a complex set of devices whose joint use identifies a broad continuum of production possibilities conditional on the infrastructural characteristics of production (or service provision), firms' organizational choices, and the composition of value chains. It is important to stress that a cluster of 'enabling technologies' may or may not lead to a new and fundamentally different 'techno-economic paradigm' (Freeman and Perez, 1988). The ability of entrepreneurs to invest in these sources of competitive advantage is, therefore, likely to be a determinant of growth, because of the performance-enhancing attributes of these enabling technologies.

Based on these arguments, this paper documents the impact of entrepreneurs' preferences (their time impatience and risk attitudes) on their firms' propensity to invest in digital technologies. To fulfil this aim, we use the responses to the questions intended to measure risk attitude and patience that were included in the *Rilevazione su Imprese e Lavoro (RIL)* survey conducted by INAPP in 2018 on a representative sample of Italian firms. Anticipating our results, which also control for the endogeneity of the utility parameters, we find the following. First, entrepreneurs' preferences – in particular, their time impatience – exert no significant effect on their firms' 'general' investments, that is, investments without specific digital content. Second, entrepreneurs' impatience has a negative impact on their investment in digital technologies, and this is also true when the propensity to take risks is taken into account.

In sum, we believe that our contribution to the literature is twofold. As already argued, to the best of our knowledge this is the first study that investigates the impact of entrepreneurs' time discounting on investment and new technologies. Further, by focusing on the Italian experience we take advantage of an interesting case study. As Italy is characterized by a predominance of small firms run under dynastic management, our results refer to an economic environment in which there is a close link between the personal profile of the individuals who run the firm and the investment choices. In other words, we analyse a situation in which the selection of the sample for managerial activities is somewhat limited by the large incidence of family ownership and culture, or socio-emotional wealth. This is expected to make our results relatively robust to the problem of self-selectivity into managerial/entrepreneurial activities, as compared to the position in other countries. Moreover, in such an environment the personal traits of those who take the investment decisions become even more important when digitalization is concerned, as the general purpose nature of these technologies limits the ability to enforce contractual terms about their expected returns.

The paper is organized as follows. Section 2 presents the data and descriptive statistics while Section 3 illustrates the econometric strategy and the regression results. Section 4 illustrates the robustness analysis. Section 5 concludes the paper.

2. 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.[3] 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.[4]

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/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).

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

[3] 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 take into account 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.

[4] 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.

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 per cent chance of receiving an amount equal to your current annual income and the same 50 per cent 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 in order to enrol in the lottery, the higher the willingness to take risks (Guiso and Paiella, 2008; Andersen et al., 2014; Falk et al., 2018).

It is worth underlining that the questions relating to preferences are only submitted to the sub-group of survey respondents who actually run a firm – about 6,000 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 not so different from what we might have found for the rest of the Italian workforce.[5]

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 of 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

[5] 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).

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 A.1 in the Appendix).

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, in order 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 4,400 firms while the longitudinal sample has about 2,200 firms observed in both 2018 and 2015.

2.1 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 impatient - continuous index

	N	Percent	Cum.
0,01	518	11.01	11.01
0,05	550	12.45	23.47
0,1	837	17.38	40.85
0,5	1,266	23.92	64.76
1	606	15.53	80.29
3	719	19.71	100.00
Total	4,496	100	

Source: our calculations on RIL 2018 data. Note: sampling weights applied.

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., 2022).

Table 2: Descriptive risk tolerance - continuous index

	N	Percent	Cumul
0,05	687	15.54	15.54
0,1	381	7.00	22.54
0,25	563	12.12	34.66

0,5	1,276	30.48	65.14
0,8	948	17.78	82.92
1	641	17.08	100.00
N of Obs	4,496	100	

Source: our calculations on RIL 2018 data. Note: sampling weights applied.

Turning to the outcome variables, Table 3 reports the weighted statistics for our different measures of the firms' investments. Note that about 25% of the firms financed 'at least one' digital technology over the period 2015-2017, a percentage that increases to 28% if we add in those firms that said they would invest in the near future.

Note that fewer than 6% (7%) 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 (see Cirillo et al., 2020). Moreover, the average number of new enabling technologies is less than one (0.32), a figure that decreases to 0.1 if cyber security is not included.[6]

Table 3: Descriptive Incidence and number of Digital Tech Investment

	effective 2015-2017		effective and future*	
	N	Freq	N	Freq
0	2,962	74.59	2,812	72.64
1	1,085	20.14	1,137	21.10
2	317	3.70	344	4.02
3	108	1.31	147	1.60
4	18	0.09	37	0.35
5	6	0.17	19	0.29
N of Obs	4,496	100.00	4,496	100.00

Source: our calculations on RIL 2018 data. Note: sampling weights applied. *indicates that also investment in digital technologies that will be done in the next future are computed.

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

[6] 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 cyber security. 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.

– 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) and 1% had experienced a merger or acquisition event in the past year, and that the firms were relatively concentrated in the north western regions.

Table 4: Descriptive statistics - control variables

	mean	std dev	Min	Max
	management characteristics			
tertiary education	0.231	0.422	0	1
upper secondary education	0.577	0.494	0	1
female	0.270	0.444	0	1
family ownership	0.963	0.189	0	1
external managers	0.004	0.064	0	1
	workforce characteristics			
share of tertiary education	0.157	0.305	0	1
share of upper second education	0.540	0.403	0	1
share of lower education	0.304	0.385	0	1
share of executives	0.036	0.147	0	1
share of white collar	0.429	0.426	0	1
share of blue collar	0.536	0.430	0	1
share of female	0.505	0.412	0	1
share of fixed term contract	0.211	0.336	0	1
share of age>54	0.254	0.339	0	1
	Firms' characteristics			
hirings	0.422	0.494	0	1
ln (sales per employee)	11.54	1.188	3,22	15,05
mergers & acquisitions	0.011	0.106	0	1
ln (n of employees)	1.085	0.920	1	8.667
firms age (in years)	19.16	13.26	0	113
Northwest	0.305	0.461	0	1
Northeast	0.229	0.420	0	1
Centre	0.204	0.403	0	1
South	0.260	0.439	0	1
N of Obs		4490		

Source: our calculations on RIL 2018 data. Note: sampling weights applied.

3. Econometric Analysis

To investigate the role of the entrepreneurs' impatience (and risk attitude) in their firms' investment behaviour, 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) investment in at least one digital technology over the period 2015-2017 or the intention to undertake such investment in the near future, and iii) the number of digital technologies in which the firm invested or will invest in the near future.

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 A.1 (see the Appendix). Finally, the parameter ε_i is the idiosyncratic error term with zero mean and finite variance.

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

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 have 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.[7]

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 equation [1], since other unobservable characteristics might be correlated to both preferences and a firm's adoption of digital technologies. For instance, individuals with a favourable 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

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

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.[8] 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[9][10] that occurred in the last fifty years, as these may therefore have had an impact on an entrepreneur when she was at the head of the firm.

Table B.1 in Appendix B 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 Figure B.1, we provide a map that displays the seismic risk issued by the Italian Civil Protection Department (2019)[11] 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 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 epicentre 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.

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

[9] 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

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

[11] 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/classificazione sismica

3.1 Main Estimates

Table 5 reports the OLS estimates of equation [1] with the different dependent variables.

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 female and an older entrepreneur is negatively associated with the likelihood of investing, while tertiary education favours it (+11%).

As for digital technologies, the estimates in columns [3] and [4] make it clear that impatience leads to a reduction in the effective adoption of 'at least one digital technology' over the period 2015-2017, while risk tolerance is confirmed to be 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.

Moreover, impatience is found to weaken the digitalization process if the dependent variable includes the intention to undertake investment in new technology in the near future. In this regard, columns [5] and [6] show that, in line with previous results, an entrepreneur with a 100% discount rate has almost an 11 percentage point lower probability of investing in digital technologies than one with a zero discount.

As discussed above, considering both past and future investment allows us to control for potential biases derived from simultaneity concerns, and provides initial support for the robustness of our results.

Further, Table 5 shows that some personal characteristics affect the adoption of new technologies: this is the case for having tertiary education – between +8% and +9% according to the different specifications – and for being a female – between -7.5% and -8.5%.[12]

Table 5: Linear probability estimates. Dep Var.: investment and digital tech investments

	all investment		effective		effective and future	
	[1]	[2]	[3]	[4]	[5]	[6]
impatience	-0.003	-0.003	-0.012**	-0.015*	-0.011**	-0.011*
	(0.004)	(0.005)	(0.003)	(0.006)	(0.003)	(0.004)
risk tolerance		0.002		0.021		0.004
		(0.006)		(0.016)		(0.008)
female	-0.106***	-0.106***	-0.074***	-0.075***	-0.085***	-0.085***
	(0.017)	(0.017)	(0.010)	(0.010)	(0.012)	(0.012)
graduate	0.109**	0.110**	0.080*	0.080*	0.090*	0.090*
	(0.025)	(0.024)	(0.033)	(0.034)	(0.036)	(0.037)
years>54	-0.076***	-0.076***	-0.004	-0.004	-0.014	-0.014
	(0.007)	(0.007)	(0.005)	(0.005)	(0.008)	(0.008)

[12] Since cyber security is not necessarily a general purpose technology and is also less of a frontier technology than others in Industry 4.0, as a robustness check we performed the same analysis excluding cyber security. The results are not reported, for brevity, and are available upon request.

other controls	Yes	Yes	Yes	Yes	Yes	Yes
constant	-0.106	-0.107	-0.296***	-0.302***	-0.302***	-0.303***
	(0.071)	(0.073)	(0.017)	(0.014)	(0.018)	(0.016)
Obs	4419	4419	4419	4419	4419	4419
R2	0.196	0.196	0.182	0.182	0.191	0.191

Source: our elaborations on RIL 2018 data. Note: the other controls include the composition of employment in terms of professions, education, age classes, contractual arrangement, gender; firms' characteristics such as the (log of) sales per employee, hiring, firms age in years, sector of activities, (log of) number of the employees and nuts 2 regions. Standard errors (in parentheses) are clustered at firms' size classes. *** statistical significance at 1%, ** at 5%, * at 10%.

To go a step further, Table 6 reports the OLS estimates when the dependent variable is the number of I4.0 technologies adopted. Here, we confirm that impatience reduces the probability of having adopted multiple types of I4.0 technology (column [1]), even if we control for risk attitude and a wide set of other explanatory variables (column [2]). Analogously, OLS regressions support the hypothesis that the bias towards the present of the entrepreneurs compresses the intensity of digitalization when we account for the intention to undertake investment in technology in the near future (see columns [3] and [4]).

Table 6: Linear probability estimates. Dep Var.: Number of digital tech

	effective		effective and future	
	[1]	[2]	[3]	[4]
impatience	-0.020**	-0.024*	-0.014*	-0.016
	(0.005)	(0.009)	(0.008)	(0.011)
risk tolerance		0.029		0.017
		(0.027)		(0.025)
female	-0.094**	-0.095**	-0.115**	-0.116**
	(0.021)	(0.021)	(0.026)	(0.026)
graduate	0.148**	0.149**	0.169**	0.169**
	(0.031)	(0.032)	(0.031)	(0.032)
years>54	0.002	0.002	-0.021	-0.021
	(0.008)	(0.008)	(0.015)	(0.015)
other controls	Yes	Yes	Yes	Yes
constant	-0.426*	-0.434*	-0.393*	-0.398**
	(0.146)	(0.141)	(0.128)	(0.123)
Obs	4419	4419	4419	4419
R2	0.161	0.161	0.163	0.163

Source: our elaborations on RIL 2018 data. Note: the other controls include the composition of employment in terms of professions, education, age classes, contractual arrangements, gender; firms' characteristics such as the (log of) sales per employee, hiring, firms age in years, sector of activities, log of number of employees and nuts 2 regions. Standard errors (in parentheses) are clustered at 4 firms' size classes. *** statistical significance at 1%, ** at 5%, * at 10%.

3.2 IV-2SLS Estimates

In this section, we report the IV-2SLS estimates by exploiting the exogenous variation caused by the occurrence of exposure to a natural disaster, that is, an earthquake during last five decades.[13]

In particular, columns [1] and [2] in Table 7 confirm that impatience significantly reduces the probability of adopting at least one type of technology – both when we control for risk taking and when we do not. Including the intention to invest in the dependent variables does not alter the empirical picture of the IV estimates – as one can see in the coefficient estimates of columns [3] and [4].

Further, the first stage statistics in Table 7 indicate that our instrument has a positive and significant impact (the coefficient is significant at the 1% level) on the outcome variables we are considering. Moreover, in line with the empirical literature, the F-statistic is greater than 10, indicating that the instrument is not weak (Cragg and Donald, 1993; Stock and 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. 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). In this case, the time dimension plays a fundamental role for new technologies, since these are general purpose investments, so it is difficult to understand the real rate of obsolescence.

Table 7 IV 2SLS estimates. Dep Var.: digital tech (0/1)

	effective		effective and future	
	[1]	[2]	[3]	[4]
impatience	-0.059**	-0.080**	-0.065***	-0.086***
	(0.014)	(0.022)	(0.009)	(0.012)
risk tolerance		0.106*		0.103**
		(0.043)		(0.024)
female	-0.077***	-0.076***	-0.089***	-0.089***
	(0.012)	(0.011)	(0.014)	(0.013)
other controls	Yes	Yes	Yes	Yes
N of Obs	4484	4484	4484	4484
R2	0.062	0.055	0.071	0.063
	first stage statistics			
earthquake 30 years	0.352***	0.256***	0.352***	0.256***
	[0.000]	[0.000]	[0.000]	[0.000]
Kleibergen-Paap F	168.40	159.44	168.40	159.44
Prob > F	[0.000]	[0.001]	[0.000]	[0.001]

[13] 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, for instance, De Blasio et al. (2021)). On the other hand, digital technologies are a relatively recent phenomenon.

Source: our elaborations on RIL 2018 data. Note: the other controls include the composition of employment in terms of professions, education, age classes, contractual arrangements, gender; firms' characteristics such as the (log of) sales per employee, hiring, mergers& acquisitions. firms age in years, 2-digit sector of activities, log of number of employees, nuts regions. Standard errors (in parentheses) are clustered at 1904 municipalities and 4 firms' size classes. *** statistical significance at 1%, ** at 5%, * at 10%.

Table 8 shows the IV second stage estimates if the dependent variable in equation [1] is the number of investments in digital technology. The results confirm the trend found up to this point. The effect related to impatience appears to be negative and statistically significant, underlining the fact that being impatient tends to decrease the number of investments in digital technology.

Table 8: IV 2SLS estimates. Dep Var.: Number of digital tech

	effective		effective and future	
	[1]	[2]	[3]	[4]
impatience	-0.111***	-0.152**	-0.083*	-0.114
	(0.018)	(0.031)	(0.037)	(0.055)
risk tolerance		0.198*		0.149
		(0.065)		(0.092)
female	-0.088**	-0.087**	-0.120**	-0.119**
	(0.024)	(0.023)	(0.026)	(0.024)
other controls	Yes	Yes	Yes	Yes
Obs	4484	4484	4484	4484
R2	0.044	0.031	0.061	0.056
	first stage statistics			
earthquake 30 years	0.352***	0.256***	0.352***	0.256***
	[0.000]	[0.000]	[0.000]	[0.000]
Kleibergen-Paap F	168.40	159.44	168.40	159.44
Prob > F	[0.000]	[0.001]	[0.000]	[0.001]

Source: our elaborations on RIL 2018 data. Note: the other controls include the composition of employment in terms of professions, education, age classes, contractual arrangements, gender; firms' characteristics as the (log of) sales per employee, hiring, mergers& acquisitions, firms age in years, 2-digit sector of activities, log of number of employees and nuts 2 regions. Standard errors (in parentheses) are clustered at 1904 municipalities and 4 firms' size classes. *** statistical significance at 1%, ** at 5%, * at 10%.

4. Robustness

4.1 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.[14]

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 9).

Table 9: Linear probability estimates

	Digital Tech		N of digital Tech	
	[1]	[2]	[3]	[4]
impatience (0/1)	-0.103**	-0.106**	-0.076*	-0.077*
	(0.027)	(0.030)	(0.027)	(0.031)
risk tolerance		0.015		0.004
		(0.015)		(0.020)
female	-0.085***	-0.086***	-0.110**	-0.110**
	(0.013)	(0.013)	(0.026)	(0.027)
other controls	Yes	Yes	Yes	Yes
constant	-0.315***	-0.319***	-0.469**	-0.470**
	(0.012)	(0.015)	(0.112)	(0.108)
Obs	4490	4490	4490	4490
R2	0.164	0.164	0.151	0.150

Source: our elaborations on RIL 2015-2018 data. Note: the other controls include the composition of employment in terms of professions, education, age classes, contractual arrangements, gender; firms' characteristics such as the (log of) sales per employee, hiring, mergers& acquisitions, firms age in years, 2-digit sector of activities, log of number of employees and nuts 2 regions. Standard errors (in parentheses) are clustered at 1904 municipalities and 4 firms' size classes. *** statistical significance at 1%, ** at 5%, * at 10%.

4.2 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 deeply into this issue, we take advantage of the longitudinal component of the RIL data from 2015 and 2017.

[14] 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).

In Table A.3 in the Appendix, 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 equation [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, workforce composition and so on, 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 10, confirm the previous results, showing that impatience tends to weaken the digitalization process.

Table 10: Linear probability estimates - 2018-2015

	Digital Tech		N of digital Tech	
	[1]	[2]	[3]	[4]
impatience	-0.042**	-0.029***	-0.048***	-0.064***
	(0.008)	(0.002)	(0.005)	(0.003)
risk tolerance		-0.096		0.046
		(0.045)		(0.135)
female	0.019	0.021	-0.046***	0.067***
	(0.011)	(0.013)	(0.006)	(0.004)
other controls	Yes	Yes	Yes	Yes
constant	-0.177	-0.159	-0.195	0.462
	(0.123)	(0.113)	(0.189)	(0.257)
Obs	2055	2055	2055	697
R2	0.136	0.140	0.148	0.167

Source: our elaborations on RIL 2015-2018 data. Note: the other controls include the composition of employment in terms of professions, education, age classes, contractual arrangements, gender; firms' characteristics such as the (log of) sales per employee, hiring, mergers & acquisitions, firms age in years, 2-digit sector of activities, log of number of employees and nuts 2 regions. Standard errors (in parentheses) are clustered at 1904 municipalities and 4 firms' size classes. *** statistical significance at 1%, ** at 5%, * at 10%.

5. 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. The few studies that there are 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 and 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).[15]

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 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 in 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 pay-offs 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 and Salvanes, 2011; Perez-Arce, 2017).

[15] 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.

References

Abatecola, G., Mandarelli, G., & Poggesi, S. (2013). The personality factor: How top management teams make decisions. A literature review. *Journal of Management & Governance, 17*(4), 1073-1100.

Andersen, S., Di Girolamo, A., Harrison, G. W., & Lau, M. I. (2014). Risk and time preferences of entrepreneurs: Evidence from a Danish field experiment. *Theory and Decision*, *77*(3), 341-357.

Åstebro, T. (2012). Returns to entrepreneurship. In D. Cummins (Ed.), *Handbook of entrepreneurial finance* (pp. 45-108). Oxford University Press.

Åstebro, T., Herz, H., Nanda, R., & Weber, R. A. (2014). The behavioral economics of entrepreneurship. *Journal of Economic Perspectives*, *28*(3), 49-70.

Basiglio, S., Rossi, M. C., & van Soest, A. (2022). Subjective inheritance expectations and economic outcomes. *Review of Income and Wealth*. https://doi.org/10.1111/roiw.12621

Bloom, N., & Van Reenen, J. (2011). Human resource management and productivity. In *Handbook of Labor Economics*, *4*, 1697-1767. Elsevier.

Boon-Falleur, M., Baumard, N., & André, J-B. (2021). Risk-seeking or impatient? Disentangling variance and time in hazardous behaviors. *Evolution and Human Behavior*, *42*(5), 453-460.

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth'? *Journal of Econometrics*, *65*(1), 83-108.

Brynjolfsson, E. & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Cadena, B. C., & Keys, B. J. (2015). Human capital and the lifetime costs of impatience. *American Economic Journal: Economic Policy*, *7*(3), 126-153.

Caliendo, M., Cobb-Clark, D. A., Pfeifer, H., Uhlendorff, A., & Wehner, C. (2022). Managers' risk preferences and firm training investments. IZA Discussion Paper 15043, Institute of Labor Economics (IZA).

Caliendo, M., Fossen, F. M., & Kritikos, A. S. (2009). Risk attitudes of nascent entrepreneurs – New evidence from an experimentally validated survey. *Small Business Economics*, *32*(2), 153-167.

Cardullo, G., Conti, M., Damiani, M., Ricci, A., Scicchitano, S., & Sulis, G. (2022), Dynastic management and historical origins. The Italian experience. INAPP WP 94, Roma.

Cirillo, V., Fanti, L., Mina, A., & Ricci, A. (2020). Digitizing firms: Skills, work organization and the adoption of new enabling technologies. *INAPP Working Paper 53*.

Cragg, J. G., & Donald, S. G. (1993). Testing identifiability and specification in instrumental variable models. *Econometric Theory*, *9*, 222-240.

Cramer, S., Hartog, J., Jonker, N., & Van Praag, C. (2002). Low risk aversion encourages the choice for entrepreneurship: An empirical test of a truism. *Journal of Economic Behavior & Organization*, *48*(1), 29-36.

Deaton, A. (1992). *Understanding consumption*. Clarendon Press.

De Blasio, G., De Paola, M., Poy, S., & Scoppa, V. (2021). Massive earthquakes, risk aversion, and entrepreneurship. *Small Business Economics*, *57*(1), 295-322.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic literature*, *47*(2), 315-372.

Ekelund, J., Johansson, E., Jarvelin, M., & Lichtermann, D. (2005). Self-employment and risk aversion: Evidence from psychological test data. *Labour Economics*, *12*(5), 649-659.

Evans D., & Leighton, L. S. (1989). Some empirical aspects of entrepreneurship. *American Economic Review*, *79*(3), 519-535.

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., & Sunde, U. (2018). Global evidence on economic preferences. *The Quarterly Journal of Economics*, *133*, 1645-1692.

Fossen, F. (2011). The private equity premium puzzle revisited: New evidence on the role of heterogeneous risk attitudes. *Economica*, *78*(313), 656-675.

Freeman, C., & Perez, C. (1988). Structural crises of adjustment: Business cycles and investment behaviour. In G. Dosi, C. Freeman, R. Nelson, G. Silverberg, and L. Soete (Eds.), *Technical change and economic theory*, 39-66. Pinter Publisher.

Gollier, C. (2001). *The economics of risk and time* The MIT Press.

Gough, J. W. (1969). *The rise of the entrepreneur*. Schocken Books.

Guiso, L., & Paiella, M. (2008). Risk aversion, wealth, and background risk. *Journal of the European Economic Association*, *6*(6), 1109-1150.

Guiso, L., Sapienza, P., & Zingales, L. (2006). Does culture affect economic outcomes? *Journal of Economic Perspectives*, *20*(2), 23-48.

Hamilton B. H. (2000). Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy*, *108*(3), 604-631.

Hartog, J., van Praag, C. M., & van der Sluis, J. (2010). If you are so smart, why aren't you an entrepreneur? Returns to cognitive and social ability: Entrepreneurs versus employees. *Journal of Economics & Management Strategy*, *19*, 947-989.

Holm, H. J., Opper, S., & Nee, V. (2013). Entrepreneurs under uncertainty: An economic experiment in China. *Management Science*, *59*(7), 1671-1687.

Hvide, H., & Panos, G. A. (2014). Risk tolerance and entrepreneurship. *Journal of Financial Economics*, *111*(1), 200-223.

Hyytinen, A., Ilmakunnas, P., & Toivanen, O. (2013). The return-to-entrepreneurship puzzle. *Labour Economics*, *20*, 57-67.

Inkinen, H. (2016). Review of empirical research on knowledge management practices and firm performance. *Journal of Knowledge Management*, *20*(2), 230-257.

Kan, K., & Tsai, W. D. (2006). Entrepreneurship and risk aversion. *Small Business Economics*, *26*(5), 465-474.

Kanbur, S. M. (1979). Of risk taking and the personal distribution of income. *Journal of Political Economy*, *87*, 760-797.

Kihlstrom, R. R., & Laffont, J. J. (1979). A general equilibrium entrepreneurial theory of new firm formation based on risk aversion. *Journal of Political Economy*, *87*, 304-316.

Knight, F. (1921). *Risk, uncertainty, and profit*. University of Chicago Press.

Lazear, E., & Oyer, P. (2012). Personnel economics. In R. Gibbons & J. Roberts (Eds.), *Handbook of Organizational Economics*. Princeton University Press.

Marshall, A. (1890). *Principles of economics*. Macmillan.

O'Donoghue, T., & Rabin, M. (2015). Present bias: Lessons learned and to be learned. *American Economic Review*, *105*(5), 273-279.

Oreopoulos, P., & Salvanes, K. G. (2011). Priceless: The nonpecuniary benefits of schooling. *Journal of Economic Perspectives*, *25*(1), 159-184.

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, *37*(2), 187-204.

Perez-Arce, F. (2017). The effect of education on time preferences. *Economics of Education Review*, *56*, 52-64.

Rovida, A. N., Locati, M., Camassi, R. D., Lolli, B., & Gasperini, P. (2016). *CPTI15, the 2015 version of the Parametric Catalogue of Italian Earthquakes*. Istituto Nazionale di Geofisica e Vulcanologia.

Schumpeter, J. A. (1911). *The theory of economic development*. Harvard University Press.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In D. W. K. Andrews & J. H. Stock (Eds.), *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg* (pp. 80-108). Cambridge University Press.

Teece, D. J. (2018). Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Research Policy*, *47*(8),1367-1387.

Van Praag, C., & Cramer, S. (2001). The roots of entrepreneurship and labour demand: Individual ability and low risk aversion. *Economica*, *68*(269), 45-62.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT Press.

Appendix A – Additional tables

Table A.1: Descriptive preferences - continuous indexes 2015-2018

	N	Percent	Cum.
	impatient		
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	2,061	100.00	

Source: our calculations on RIL 2015-2018 data. Note: sampling weights applied.

Table A.3: 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	.4030322	0	1
family ownership	0.960	.1948813	0	1
external managers	0.008	.0896678	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 & acquisitions	0.008	.0916	0	1
firms age (in years)	22.94	16.24	0	821
ln (n of employees)	1.099	.992	0	7.57
North West	0.320	.468	0	1
North East	0.318	.466	0	1
Centre	0.224	.417	0	1
South	0.137	.344	0	1
N of Obs		2,061		

Source: our calculations on RIL 2015-2018 data. Note: sampling weights applied.

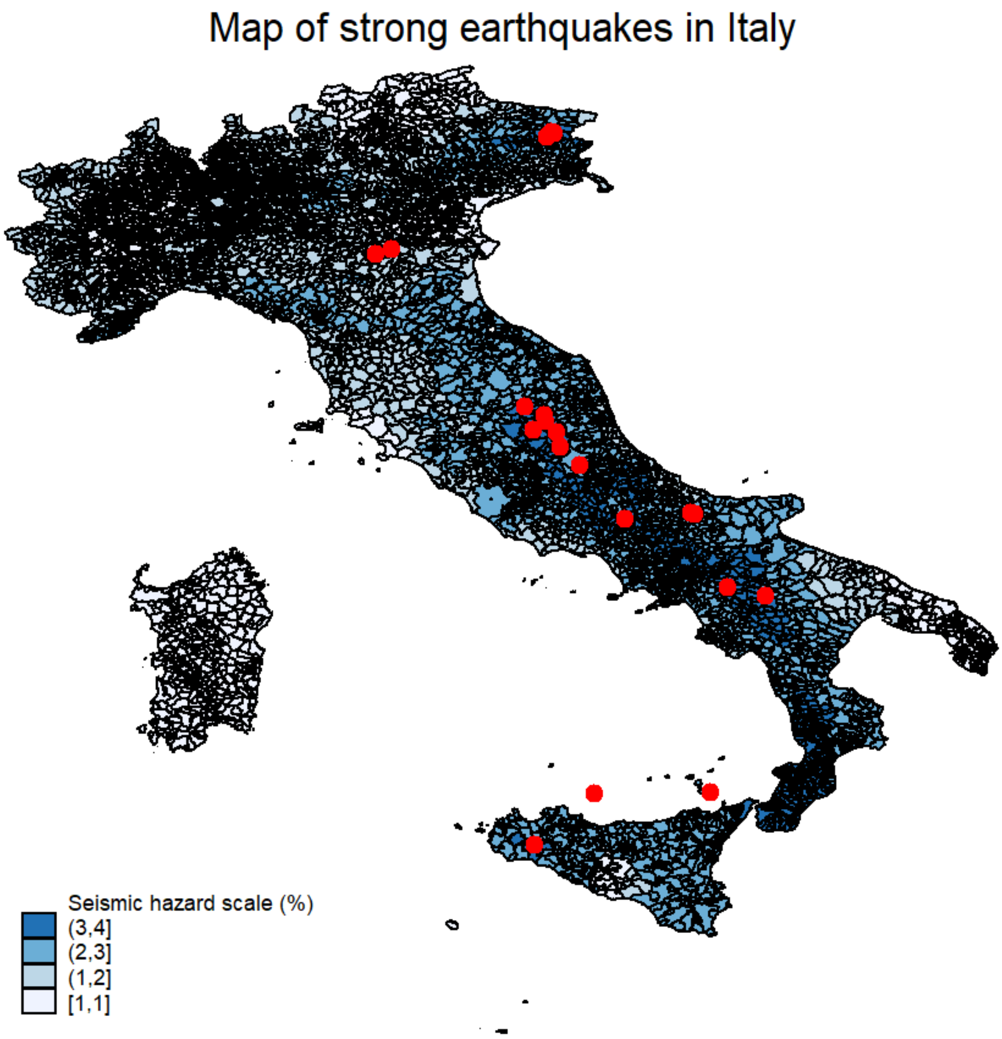
Appendix B - Data on earthquakes

Table B.1 - 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

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

Figure B.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 earthquakes episodes presented in Table B.1.