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Entrepreneurial risk, investment, and innovation ☆

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ABSTRACT

I estimate the effect of uncertainty on risky innovation using a panel of 11,417 manufacturing firms. I find that an increase in uncertainty has a large negative effect on the risky innovation of entrepreneurial firms, while it does not have any significant impact on other firms. This negative effect is stronger for the less diversified entrepreneurial firms in the sample. The estimation results are consistent with the innovation dynamics generated in a model in which entrepreneurs are risk averse and cannot diversify the risk of their business.

1. Introduction

This paper provides new empirical evidence on the effect of uncertainty on innovation. It simulates a model of an entrepreneurial firm and derives testable predictions concerning the relation between financial market frictions, uncertainty, and the decisions to undertake risky productivity-enhancing projects. It then tests these predictions on a data set of 11,417 Italian manufacturing firms. The unique feature of this data set is that it combines a large panel of yearly balance sheet data, for the 1992–2001 period, with three qualitative surveys, conducted in 1995, 1998, and 2001. The surveys include detailed information concerning firms' property structure, their investment in different types of innovation, their financial constraints, and other relevant information that can be used to control the robustness of the results, such as their degree of internationalization and their market structure.

The empirical analysis identifies a significant and large negative effect of uncertainty on the innovation of entrepreneurial firms, of a magnitude comparable to the negative effect found in the calibrated model. Because the level of uncertainty faced by firms varies significantly in the business cycle, this finding could have important consequences for both business cycle fluctuations and growth.

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Entrepreneurial firms are an engine of innovation and technological progress, and they are likely to be responsible for a substantial portion of productivity and employment growth. Despite several recent studies emphasizing the importance of financial factors for the creation and development of new entrepreneurial firms, little is known about the effect of uncertainty on entrepreneurial investment decisions.[1] However, this problem is likely to be important, because entrepreneurial households appear not to be able to diversify the risk of their business. Moskowitz and Vissing-Jørgensen (2002) analyze US data and show that 48% of all private equity is owned by households for whom it constitutes at least 75% of their total net worth. Furthermore, Bitler, Moskowitz, and Vissing-Jørgensen (2005) provide evidence that agency considerations play a key role in explaining why entrepreneurs on average hold large ownership stakes, indicating that their lack of diversification is driven by market imperfections, not by risk-loving preferences.[2]

Does uncertainty prevent entrepreneurs from investing in risky and innovative projects? In this paper I answer this question by testing the following hypothesis: In an industry in which innovation is risky, uncertainty should negatively affect the innovation of entrepreneurial firms far more than that of publicly owned firms. Because of capital market imperfections, entrepreneurial households have most of their wealth invested in their own businesses. Therefore, in response to an increase in uncertainty, their main instrument to rebalance the risk-return profile of their assets is the choice of the riskiness of their investment projects. The same effect does not operate in publicly owned firms, in which the firm's manager is exposed only to a fraction of the firm's risk and can more easily diversify it.

In the paper I first conduct a simulation exercise as a preliminary step before the actual estimation with the empirical firm-level data. In the model an entrepreneurial firm maximizes the intertemporal consumption of its owner-manager. It can invest in its own production and borrow or lend at the risk-free rate. The production function is linear in technology and concave in capital, and it is also subject to exogenous profit shocks. Moreover, the firm can improve its technology by investing in innovative projects that are risky and yield an uncertain return. The only instrument available to partially insure against profits and innovation shocks is to save in the risk-free asset.

I use the model to simulate many identical firms that differ only in the realization of their shocks. In the benchmark case, the firms can borrow up-front the net present value of future earnings. Because this collateral constraint is almost never binding, they can almost always implement their optimal risk-adjusted investment decisions. The parameters are calibrated so that the volatility of profits matches that observed for the Italian firms in the empirical sample.

These simulations show a substantial negative effect of uncertainty on risky innovation, especially for the firms with lower levels of financial assets. I then simulate several firms with debt limited by a tighter exogenous borrowing limit, and I show that lowering such limit reduces both the frequency of innovation and its sensitivity to changes in uncertainty. This occurs because the innovation decision of an undiversified entrepreneurial firm that also faces a binding borrowing constraint is determined by the current availability of credit, not by uncertainty concerning future profits. These results indicate that to verify the uncertainty–innovation hypothesis, it is necessary to properly identify the presence of borrowing constraints.

After conducting this preliminary simulation exercise, the main section of this paper verifies empirically the following predictions.

Prediction i. An increase in the volatility of the exogenous profits shocks reduces the risky innovation of entrepreneurial firms. This reduction is stronger the less diversified firms are.

Prediction ii. The negative effect of uncertainty on the innovation of entrepreneurial firms is dampened by the presence of firms facing binding borrowing constraints.

Prediction iii. A change in exogenous uncertainty does not affect the investment in innovation for all firms when the innovation risk is very low.

The first part of the empirical section of the paper illustrates and checks the validity of the assumptions adopted to select the group of entrepreneurial firms and to identify the risky innovation decisions. Then Prediction i is verified with a panel data estimation in which the innovation decisions of the firms are regressed on the level on uncertainty, lagged one period, as well as on other control variables, on time dummies, and on two-digit sector dummies.

As a measure of uncertainty I consider the volatility of the profits/assets ratio, computed for every period across firms for every three-digit sector. The use of a sector-specific measure of the volatility of profits avoids possible reverse causality problems. Nonetheless, estimation results could still be biased by unobservable factors affecting both the dispersion of profits across firms and their innovation decisions. However, the test predicts a negative uncertainty–innovation relation for entrepreneurial firms only. Therefore, any unobserved factor that affects this relation in the same direction for all firms is likely to bias the test toward rejecting, not accepting, the hypothesis. Moreover, several robustness checks are performed in the paper to ensure that the results are not driven by an endogeneity problem. First, I consider a panel regression in which I introduce fixed effects at the three-digit level, so that the uncertainty coefficient is identified only by changes in uncertainty within sectors instead of by differences across sectors. Second, I verify that both the pooled and the fixed effect regressions are also consistent with Predictions ii and

[1] Among the studies on financial factors and entrepreneurship, see Evans and Jovanovic (1989), Holtz-Eakin, Joulfaian, and Rosen (1994), Gentry and Hubbard (2004), and Hurst and Lusardi (2004).

[2] Supporting this conclusion, experimental studies generally find entrepreneurs to be as risk averse as—and some studies find them to be even more risk averse than—nonentrepreneurs (Sarasvathy, Simon, and Lave, 1998; Miner and Raju, 2004; Hongwei and Ruef, 2004).

iii. Third, I correct for the endogeneity of the measure of uncertainty using an instrumental variable estimation technique, in which the instrument is the cross-sectional dispersion of the profits/assets ratio for US manufacturing firms in the same sectors and periods as the Italian sample.

Both the pooled and the fixed effect regressions find a significant and negative effect of uncertainty on the risky innovation of entrepreneurial firms, and they confirm that the effect is stronger for firms that do not face borrowing constraints. Moreover, the regressions find no significant effect of uncertainty on the risky innovation of nonentrepreneurial firms, as well as on the nonrisky innovation of all firms. Importantly, the estimation results are quantitatively consistent with the model's predictions. Using the most reliable measure of risky innovation available from the empirical data, the percentage change in the frequency of risky innovation after a 1% increase in uncertainty is equal to -0.69% for all entrepreneurial firms (compared with a value of -0.63% in the simulations) and equal to -0.92% for the group of less diversified ones (compared with a value of -0.99% in the simulations).

This paper is related to the recent literature that emphasizes the importance of financial factors for entrepreneurship and innovation. Among these, Herrera and Minetti (2007) and Benfratello, Schiantarelli, and Sembenelli (2008) provide empirical evidence on the importance of bank finance for entrepreneurial innovation. Czarnitzki and Kraft (2004) study the innovation of owner-led firms versus managerial firms. The paper is also related to some recent studies on undiversifiable entrepreneurial risk and investment. In particular, Heaton and Lucas (2000) study the implications of entrepreneurial undiversifiable risk for portfolio choices and asset prices of entrepreneurial households. Miao and Wang (2007) and Chen, Miao, and Wang (2010) extend the standard real option approach to investment to an incomplete market environment and analyze the effect of market incompleteness on consumption, investment, and exit decisions.[3]

The outline of this paper is as follows. Section 2 illustrates the model. Section 3 shows the results of the simulations of the entrepreneurial firms. Section 4 shows the empirical analysis of the Italian manufacturing firms. Section 5 summarizes the conclusions.

2. The model

I consider a simple model of a firm owned and managed by an entrepreneur who cannot completely diversify the risk of her business. The model does not analyze the factors that affect entry into entrepreneurship, and it does not endogenize the reasons that the entrepreneur cannot hold a diversified portfolio of other businesses.[4] This simplification does not significantly limit the analysis because the model does not aim to explain the factors that influence entry into entrepreneurship. Instead, it aims to analyze the uncertainty–innovation relation for levels of risk analogous to those observed in the empirical data.

2.1. Technology

The entrepreneurial firm has access to a technology that produces output using capital and is subject to exogenous idiosyncratic shocks to its revenues.[5] As in Abel and Eberly (2005), I assume that by paying a fixed cost the firm can upgrade its technology to the frontier. If the firm does not innovate, its technology becomes less productive than the frontier technology, due to obsolescence. More formally, at time t the firm produces output y_t using the production function

$$y_t = A_t k_t^{\alpha} + \varepsilon_t, \quad 0 < \alpha < 1, \tag{1}$$

where k_t is the capital, A_t is the technology level, and ε_t is a stationary and persistent revenue shock, which follows an AR(1) process, $\varepsilon_t = \rho^{\varepsilon}\varepsilon_{t-1} + v_t$ with $0 < \rho^{\varepsilon} < 1$, where v_t is an independent and identically distributed shock with mean zero and standard deviation σ_{ε}^2. I introduce exogenous uncertainty as an additive shock to simplify the analysis, because such shock does not affect the marginal productivity of capital for the firm. In Section 3.1, I relax this assumption and show that the main predictions of the model are robust to considering a multiplicative shock in the production function.

In the model I introduce an indicator function I_t to denote the innovation decision. If the firm does not innovate, then $I_t = 0$ and the technology depreciates at the rate δ_A, with $A_{t+1} = (1-\delta_A)A_t$. If the firm invests in innovation, then $I_t = 1$ and the technology is upgraded in the next period at the cost F_{t+1}, so that $A_{t+1} = \overline{A}$, where $\overline{A}$ is the technology frontier. I assume that such frontier is constant, to preserve the stationarity property of the maximization problem. The upgrading cost F_{t+1} is stochastic:

$$F_{t+1} = F + \xi \quad \text{with probability 0.5,}$$

$$F_{t+1} = F - \xi \quad \text{with probability 0.5.} \tag{2}$$

Therefore, the term F measures the fixed costs of innovating in period t, and the term ξ measures the uncertainty in revenues and profits that such innovation will generate in the future. It follows that if ξ is relatively small, then the $I_t = 1$ decision can be interpreted as technology adoption. The firm pays a fixed cost to adopt a new technology,

[3] The theoretical section of the paper is related to Rampini (2004), Cagetti and De Nardi (2006), Castro, Clementi, and MacDonald (2004), Meh and Quadrini (2006), Angeletos (2007), and Covas (2006), who develop general equilibrium models in which financing imperfections and undiversifiable risk affect the decision to become an entrepreneur or to invest in risky projects. Moreover, Castro, Clementi, and MacDonald (2009) and Michelacci and Schivardi (forthcoming) analyze how idiosyncratic risk affects investment and growth in different sectors in a cross section of countries.

[4] Other authors who follow the same strategy are Angeletos and Calvet (2006), Angeletos (2007), and Covas (2006). Alternatively, one could model an economy with heterogenous entrepreneurs in which the market incompleteness arises endogenously due to financing frictions, as, for example, do Meh and Quadrini (2006).

[5] Henceforth, I refer to the "entrepreneurial firm" simply as "firm".

which will allow it to produce more efficiently. Instead, if ξ is relatively large, then the $I_t=1$ decision can be interpreted as risky innovation. The firm develops or adopts a new product, which, if successful, will greatly increase profits and, if unsuccessful, will generate a substantial loss.

The timing of the model is the following: At the beginning of time t the firm produces y_t; repays b_t, the debt contracted in the previous period; and pays the innovation cost F_t, if it innovated in period $t-1$. Net worth w_t is

$$w_t=\pi_t+(1-\delta)k_t-b_t, \tag{3}$$

where δ is the depreciation rate of fixed capital and π_t is total revenues in period t:

$$\pi_t=y_t-F_tI_{t-1} \tag{4}$$

Eqs. (2) and (4) imply that the larger is the innovation risk ξ, the more volatile revenues π_t are for the innovating firm. After producing, the firm decides the consumption of the entrepreneur c_t, the level of fixed capital that will be productive in the next period k_{t+1}, the amount to be borrowed or lent b_{t+1}, and whether or not to innovate and upgrade the technology. The budget constraint is

$$k_{t+1}+c_t=w_t+\frac{b_{t+1}}{R}, \tag{5}$$

where $R\equiv 1+r$ and b_{t+1} is the face value of debt to be repaid in the next period. In the benchmark case, I assume that the firm is subject to the following collateral constraint: It cannot borrow more than the amount that guarantees non-negative consumption with certainty in the next period.

The firm chooses b_{t+1}, k_{t+1}, and I_t to maximize the value function equation (6) subject to the budget constraint equation (5) and the collateral constraint equation (9):

$$V(w_t,A_t)=\max_{I_t,}\{V^{up}(w_t,A_{t+1}),V^{noup}(w_t,A_{t+1})\}, \tag{6}$$

where

$$V^{up}(w_t,A_t)=\left\{\max_{k_{t+1},b_{t+1}} u(c_t)+\beta[E_tV(w_{t+1},A_{t+1})|I_t=1]\right\}, \tag{7}$$

$$V^{noup}(w_t,A_t)=\left\{\max_{k_{t+1},b_{t+1}} u(c_t)+\beta[E_tV(w_{t+1},A_{t+1})|I_t=0]\right\}, \tag{8}$$

and

$$b_{t+1}\le\overline{b}(w_t,A_t). \tag{9}$$

The utility function $u(c_t)$ is a constant elasticity of substitution function:

$$u(c_t)=\frac{c_t^{1-\eta}}{1-\eta} \tag{10}$$

and

$\eta>0$.

The borrowing limit $\overline{b}(w_t,A_t)$ is endogenous because it depends on the stream of profits generated by the business and is, therefore, a function of the state variables w_t and A_t. Results of simulations show that, for reasonable parameter values, constraint Eq. (9) is almost never binding. In Section 3.1, I analyze how the results are affected if constraint equation (9) is substituted by an exogenous borrowing limit that is binding with a positive probability.

The risk of innovation is reflected in the term $E_t[V(w_{t+1},A_{t+1})|I_t=1]$ in Eq. (7). The higher the ξ is, the higher the variance of future consumption conditional on innovating is, the lower the expected utility from consumption and the value of $E_t[V(w_{t+1},A_{t+1})|I_t=1]$ are. This effect reduces the firm's incentive to innovate.

3. Numerical solution

I solve the model numerically using a value function iteration method (see the Appendix for details) and simulate several identical entrepreneurial firms, which differ only for the realization of their technology and innovation shocks. For calibration purposes, I also simulate the behavior of risk-neutral firms, which are identical to the entrepreneurial firms, except that they maximize the net present value of profits instead of utility from consumption. Table 1 illustrates the choice of benchmark parameters. Whenever possible, the parameters are calibrated by matching one-to-one a set of empirical moments of the sample of Italian entrepreneurial firms analyzed in Section 4.

The parameter α determines the curvature of the production function and can be interpreted as the firm's degree of market power. Because net profits are monotonously decreasing in α, I calibrate it to match the average of the net profits/sales ratio for the entrepreneurial firms in the Italian sample.

The parameter σ_ε^2 matches the variability of profits observed in the empirical data set. Because a higher value of σ_ε^2 increases the dispersion of profits both over time and across firms, it could be matched using either a cross-sectional or a time series measure of volatility.[6] However, the time dimension in the empirical data set is too short to allow an estimation of this moment using time series data, because only 10% of the firms have at least nine years of balance sheet data. Therefore, I calibrate σ_ε^2 to match the cross-sectional standard deviation of the net income/sales ratio for the Italian sample.

The frontier technology $\overline{A}$ is normalized to one. The depreciation rate of technology δ_A directly affects the size of the technological upgrade (the difference $\overline{A}-A_t$) for an innovating firm and the size of the associated fixed capital investment $k_{t+1}-k_t$, because in the production function technology and fixed capital are complementary. Even though in the empirical sample I do not observe $\overline{A}-A_t$, the surveys provide information about the amount of fixed

[6] To verify the equivalence of these two different measures of uncertainty, I simulate several groups of firms with different values of σ_ε^2. For each group I compute the volatility of profits for each firm over time and average it across firms. I also compute the cross-sectional dispersion of profits for each period and then average it over time. The two alternative measures are almost identical, with a correlation coefficient of 0.98 across the different groups.

Table 1
Calibrated parameters.
For the standard deviation, I compute the cross-sectional standard deviation for each three-digit sector and then compute the average across sectors. I exclude as outliers the observations greater than one in absolute value. Average frequency of innovation is the fraction of entrepreneurial firms that declare to perform research and development in order to introduce new products. F and ξ are measured as a fraction of the net present value of the total profits expected from the innovation.

Parameter	Value	Matched moment	Data	Simulations
α	0.939	Average (operating income/sales)	0.057	0.056
δ	0.145	Average depreciation of capital	14.5%	14.5%
σ_ε	1.12	Standard deviation (operating income/sales)	0.054	0.054
r	0.02	Real interest rate	2%	2%
β	0.94	Percentage of private equity from entrepreneurial households with concentration $\geq 75\%$	48%	48%
F	3%	Average frequency of innovation	31%	31%
ξ	17%	Difference in average frequency of innovation between risk-neutral firms versus entrepreneurial firms	5%	4.5%
δ_A	0.0005	Fixed investment related to innovation as a percentage of sales	10%	11%
Noncalibrated parameters (sensitivity analysis)				
ρ^ε	0.8–0.95			
η	0.8–2			

capital investment related to innovation. Therefore, I calibrate δ_A so that the average fixed capital investment related to innovation in the empirical data matches the same moment in the simulations.

Regarding the innovation cost shock F_t, its fixed component F determines the frequency of innovation, because with a higher F the firm waits longer before upgrading its technology. Therefore, I calibrate it to match the average frequency of innovation in the empirical sample. Conversely, the uncertainty component ξ increases the volatility of profits for firms that innovate. In the model, this additional risk reduces the frequency of innovation for the entrepreneurial firm, while it is by construction irrelevant for profit-maximizing firms, because condition Eq. (2) implies that $E_t(F_{t+1}) = F$. Therefore, I calibrate ξ so that the difference in the frequency of innovation between simulated entrepreneurial firms and profit-maximizing firms matches the difference observed in the Italian sample between entrepreneurial and nonentrepreneurial firms.

Among the remaining parameters, the depreciation rate of capital δ is set equal to 14.5%, following Gomes (2001). The gross real interest rate R is 1.02, which is consistent with the average short-term real interest rates in Italy in the sample period. The parameters η and ρ^ε cannot be identified by one specific empirical moment. For the base calibration I assign them values of 2 and 0.95, respectively. In Section 3.1, I verify that the results are not sensitive to changing such values.

Finally, the discount factor of the entrepreneurial households β plays a key role because it affects the accumulation of financial wealth w_t as a precautionary motive. The stock of wealth w_t yields a constant gross return of R and is the only alternative available to the risky investment in capital and innovation. If βR is equal to one, then the firm postpones consumption until w_t becomes very large and the innovation and technology shocks become irrelevant for innovation decisions. Therefore, for the model to generate realistic levels of wealth, βR needs to be sufficiently smaller than one, so that the firm is impatient and accumulates financial wealth w_t up to the point that the desire to save to smooth consumption against the volatility of profits is balanced by the desire to anticipate consumption.

Given these considerations, I calibrate β by first constructing the ratio $R^w = MV_t/(w_t+MV_t)$ where MV_t is the net present value of the future expected profits. The term (w_t+MV_t) can be interpreted as the net worth of the firm; R^w, as the ratio of equity over total net worth. Therefore, the higher R^w is, the less diversified the firm is, because less financial assets are available to smooth consumption.

I calibrate β so that the value of R^w is on average equal to 0.75. On the one hand, this value is consistent with Moskowitz and Vissing-Jørgensen (2002), who estimate that 48% of all private equity is owned by households for whom it constitutes at least 75% of their total net worth. On the other hand, it implies that the average ratio of financial assets relative to the value of the firm, w_t/MV_t, is equal to 0.33. This value is consistent with the financial assets holding of the Italian firms in the empirical sample. The closest proxy of w_t/MV_t for the firms in the sample, almost all of which are not quoted on the stock market, is the ratio between liquid assets and total assets, which is on average equal to 0.38.

Fig. 1 shows the relation between uncertainty and innovation. It displays three lines, corresponding to simulations of entrepreneurial firms with different values of σ_ε^2, and a fourth line corresponding to the simulations of risk-neutral firms for the benchmark value of σ_ε^2. Each point on any of the lines represents the average frequency of innovation calculated on a simulated sample of one thousand ex ante identical firms, for 50 years each, for a total of 50 thousand firm-year observations. Along each line all parameters are constant, except the innovation shock ξ, which increases along the x-axis, and the discount factor β, which is recalibrated to ensure that the average holdings of liquid assets R^w are consistent with the empirical data. The high uncertainty line refers to

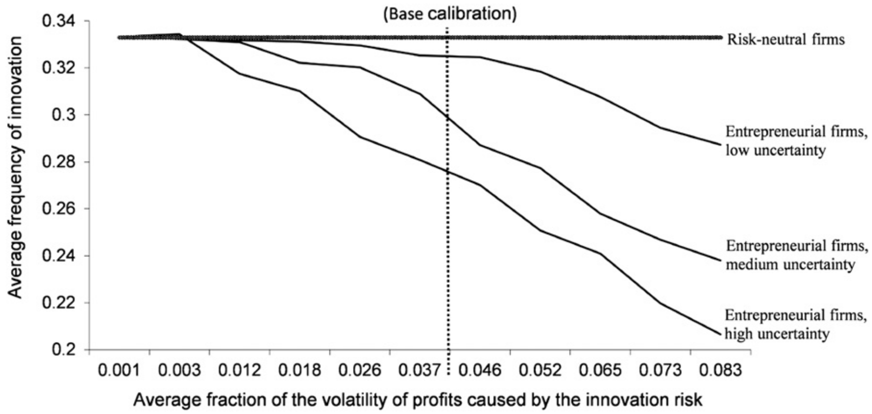

Fig. 1. Average frequency of innovation of the simulated firms conditional on exogenous uncertainty.

a 20% increase in σ_ε^2 relative to the benchmark; the low uncertainty line, to a 20% reduction in σ_ε^2. The relative contribution of the ξ shock to the total volatility of profits is reported on the x-axis. A value close to zero corresponds to riskless technology adoption, where it is possible to innovate by paying a fixed cost F without increasing the uncertainty in revenues. Higher values correspond to risky innovation, which has an uncertain outcome and even though it is on average profitable, it increases the volatility of profits.

The figure shows that innovation risk ξ does not affect the risk-neutral firms.[7] Importantly, it shows that the higher such risk is, the stronger the negative uncertainty–innovation relation is for the entrepreneurial firms, measured as the vertical distance between the high uncertainty and the low uncertainty line. The intuition is as follows: When innovation is risky, the choice to innovate increases the volatility of revenues. An entrepreneurial firm that already faces a highly volatile productivity shock prefers to reduce the frequency of innovation, at the cost of producing less efficiently, to avoid the additional fluctuations in profits and consumption caused by the innovation shock.

3.1. Regression analysis on simulated data

In this subsection I perform several regressions on the simulated data to estimate the effect of uncertainty on innovation and determine a set of predictions to be tested on the empirical sample.

I simulate 30 artificial sectors, each composed of two hundred firms for 50 years, for a total of 300,000 observations. Firms in a given sector are all identical except for the realization of their shocks. Sectors differ only for the volatility of the productivity shock σ_ε^2, which is uniformly increasing from sector 1 to sector 30. The values are chosen so that the range of variation in the volatility of profits across simulated sectors is comparable to the same range for the three-digit sectors in the empirical sample of Italian firms.

Table 2 shows the estimation results. The dependent variable $INN_{i,s,t+1}$ is equal to one if firm i innovates in period t and produces with the new technology in period $t+1$, and it is zero otherwise. The main explanatory variable is the measure of profit uncertainty. As argued in the previous subsection, because only the cross-sectional measure of uncertainty is available in the empirical data set, for consistency I use a similar measure for the simulated data. $sdroa_{s,t}$ is the cross-sectional standard deviation of roa for each sector s and year t. To control for profitability, I also include the average of roa for each sector and year, called $avgroa_{s,t}$. $roa_{s,t}$ is computed as profits over assets:

$$roa_{s,t} = \frac{y_t - (r+\delta)k_t - F_t I_{t-1}}{k_t}. \tag{11}$$

Panel A in Table 2 considers the risky innovation case, with the benchmark value of ξ. The first column refers to the full sample and shows that the coefficient of $sdroa_{s,t}$ is negative and significant, indicating that sectors with greater uncertainty innovate less. The coefficient of $avgroa_{s,t}$ is positive and significant because individual shocks do not completely wash out at the sector level. When firms in some sectors accumulate more wealth thanks to a higher frequency of positive shocks, then they are able to innovate more. In Column 2, I select for each sector only those firms that, because of positive revenue shocks, have higher than average financial wealth. Column 3 refers to the other firms, with less than average financial wealth. Even though the borrowing constraint is not binding for almost any of these firms, financial wealth is important because it measures how diversified firms are. The estimation results show that the coefficient of $sdroa_{s,t}$ is much larger for less diversified firms, because the uncertainty in profits has a greater effect on their consumption decisions. Panel B repeats the same exercise as Panel A, the only difference being that innovation is not risky ($\xi = 0$). In this case uncertainty is irrelevant for the innovation decision, and none of the estimated coefficients

[7] Because the innovation shock enters additively in Eq. (4), it does not affect expected profits and, hence, is irrelevant for the optimal decisions of the risk-neutral firm. This linearity assumption simplifies the model and the interpretation of the results. Nevertheless, in Section 3.1, I relax it and introduce a more standard multiplicative shock in the production function.

Table 2
Relation between risk and innovation, simulated data.

The coefficients are estimated using maximum likelihood probit estimation on a sample of 30 artificial sectors, each one composed of two hundred firms for 50 years. Because the regressors are lagged and one observation is dropped for every firm, 294,000 firm-year observations are included in the estimation. A Huber and White estimator of the variance–covariance matrix is used to correct for heteroskedasticity. Standard errors are clustered at the sector level. The z statistic is added in parenthesis. *** denotes significance at the 99% confidence level. The dependent variable $INN_{i,s,t+1}$ is a binary variable equal to one if firm i in sector s innovates in year $t+1$ and equal to zero otherwise. F_{t+1} is innovation cost. $sdroa_{s,t}$ is the standard deviation of the cross section of the profits/assets ratio for the simulated firms in sector s and year t. $avgroa_{s,t}$ is the cross-sectional mean of the profits/assets ratio for the simulated firms in sector s and year t. In the columns labeled "All," all observations are included. In the other columns, firms are selected according to $w_{i,s}/MV_{i,s}$, which is the average of financial wealth w over value of the firm MV, for firm i in sector s.

	Panel A: Risky innovation ($F_{t+1}=F\pm\xi$)			*Panel B: nonrisky innovation* ($F_{t+1}=F$)		
Variable	All	$\frac{w_{i,s}}{MV_{i,s}}\geq 0.33$	$\frac{w_{i,s}}{MV_{i,s}}<0.33$	All	$\frac{w_{i,s}}{MV_{i,s}}\geq 0.33$	$\frac{w_{i,s}}{MV_{i,s}}<0.33$
Constant	−0.04	−0.14***	0.05	−0.43***	−0.44***	−0.42***
	(−1.38)	(−4.82)	(1.22)	(−514.3)	(−46.2)	(−42.1)
$sdroa_{s,t}$	−62.6***	−37.1***	−84.8***	0.003	0.20	−0.19
	(−28.7)	(−18.7)	(−30.6)	(0.41)	(0.90)	(−0.79)
$avgroa_{s,t}$	8.75***	2.54	12.78***	−0.01	0.53	−0.56
	(5.04)	(1.03)	(3.58)	(−0.11)	(0.67)	(−0.67)
Number of observations	294,000	149,450	144,550	294,000	148,274	145,726

is significant. Uncertainty is also irrelevant for the risk-neutral firms, as shown in Fig. 1. Therefore, this regression is omitted from Table 2.

The negative effect of uncertainty on innovation is not driven by financing constraints, because in the simulations the collateral constraint equation (9) is almost never binding. However, in reality, entrepreneurs could be both unable to diversify their business risk and unable to borrow to finance their investments. Therefore, Table 3 shows the results when a fraction of firms face a tighter borrowing limit:

$$b_t \leq \overline{b}. \tag{12}$$

I assume that in each simulated sector 15% of the firms face constraint equation (12). This percentage corresponds to the percentage of firms in the Italian sample declaring difficulties in obtaining external finance. The value of $\overline{b}$ is 20, which corresponds to around 30% of the optimal capital for an innovating firm. The first column estimates the uncertainty–innovation relation for all firms, and Columns 2 and 3 consider unconstrained and constrained firms, respectively. The results show that the coefficient of $sdroa_{s,t}$ is negative for all firms. However, it is much larger in absolute value for the unconstrained firms than for the constrained ones. Borrowing constraints dampen the uncertainty–innovation relation because they make uncertainty less important for investment decisions. If the borrowing constraint is not binding, an entrepreneurial firm allocates resources between consumption, investment, and innovation according to an internal solution of its optimization problem. This internal solution implies that uncertainty reduces the net present value of the expected utility of consumption, conditional on innovating. Conversely, if constraint equation (12) is binding, the current availability of funds matters more than the future expected volatility of profits in determining investment and innovation decisions. This intuition is confirmed by the last row in Table 3, which reports the average percentage of innovating firms. For the firms that face the borrowing limit, the average frequency of entrepreneurial innovation is much lower.[8] Table 4 presents

Table 3
Relation between risk and innovation, simulated data with financing frictions.

The coefficients are estimated using maximum likelihood probit estimation on a sample of 30 artificial sectors, each one composed of two hundred firms for 50 years. In each sector, 15% of firms are assumed to be financially constrained and their borrowing b cannot be larger than $\overline{b}=20$. The other firms are financially unconstrained and able to borrow upfront future expected revenues. Because the regressors are lagged and one observation is dropped for every firm, 294,000 firm-year observations are included in the estimation. A Huber and White estimator of the variance–covariance matrix is used to correct for heteroskedasticity. Standard errors are clustered at the sector level. The z statistic is added in parenthesis. * denotes significance at the 90% confidence level; ** significance at the 95% confidence level; *** significance at the 99% confidence level. The dependent variable $INN_{i,s,t+1}$ is a binary variable equal to one if firm i in sector s innovates in year $t+1$ and equal to zero otherwise. $sdroa_{s,t}$ is the standard deviation of the cross section of the profits/assets ratio for the simulated firms in sector s and year t. $avgroa_{s,t}$ is the cross-sectional mean of the profits/assets ratio for the simulated firms in sector s and year t. In the column labeled " All," all observations are included in the estimation. In the second and third columns only financially unconstrained and constrained firms are included, respectively.

Variable	All	Unconstrained firms	Constrained firms
Constant	−0.18**	−0.16**	−0.29**
	(−2.37)	(0.079)	(−2.53)
$sdroa_{s,t}$	−41.3***	−43.7***	−28.3***
	(−10.32)	(4.4)	(−4.14)
$avgroa_{s,t}$	2.16	6.05	−23.7***
	(0.54)	(4.20)	(−3.31)
Number of observations	294,000	250,429	43,571
Percentage of innovating firms	28.2	29.4	21.0

[8] This happens for two reasons. First, a negative innovation shock implies that the firm could face a binding constraint in financing both consumption and capital, and this discourages innovation ex ante. Second, innovation is only profitable if after innovating the firm can also increase its fixed capital investment, but this is not possible if the financing constraint is binding.

Table 4

Relation between risk and innovation on simulated data, and robustness checks.

The coefficients are estimated using maximum likelihood probit estimation. A Huber and White estimator of the variance–covariance matrix is used to correct for heteroskedasticity. Standard errors are clustered at the sector level. The z statistic is added in parenthesis. *** denotes significance at the 99% confidence level. The dependent variable $INN_{i,s,t+1}$ is a binary variable equal to one if firm i in sector s innovates and equal to zero otherwise. $sdroa_{s,t}$ is the standard deviation of the cross section of the profits/assets ratio for the simulated firms in sector s and year t. $avgroa_{s,t}$ is the cross-sectional mean of the profits/assets ratio for the simulated firms in sector s and year t. Panel A presents estimations on a single sector of one hundred firms for five hundred years. In the column labeled "All," all observations are included. In the other columns, firms are selected according to $w_{i,s}/MV_{i,s}$, which is the average of financial wealth w over value of the firm MV for firm i in sector s. Panel B presents estimations on a sample of 30 artificial sectors, each one composed of two hundred firms for 50 years. Because the regressors are lagged and one observation is dropped for every firm, 294,000 firm-year observations are included in the estimation. Column 1, calibration with $\eta = 0.8$; column 2, calibration with $\rho^{\varepsilon} = 0.8$; column 3, a multiplicative shock is added to the production function.

	Panel A: Time varying volatility			*Panel B: Other robustness checks*		
Variable	All	$\frac{w}{MV} \geq 0.33$	$\frac{w}{MV} < 0.33$	(1)	(2)	(3)
Constant	−0.53***	−0.49***	−0.56***	−0.025	0.012	−0.20
	(−6.10)	(−3.58)	(−4.96)	(−0.29)	(0.24)	(−0.82)
$sdroa\_1_{s,t}$	−15.0***	−11.30	−17.5***	−62.9***	−53.39***	−68.0***
	(−3.20)	(−1.53)	(−2.89)	(−8.00)	(−9.99)	(−2.92)
$avgroa\_1_{s,t}$	10.72	6.60	13.52	11.69***	0.49	31.34***
	(1.41)	(0.55)	(1.38)	(6.76)	(0.25)	(6.34)
Number of observations	49,900	20,202	29,698	294,000	294,000	294,000

some robustness checks of the results. In all the simulations presented so far, uncertainty faced by firms varies across sectors but not over time. This assumption is relaxed in Panel A of Table 4. Here I simulate a single sector of one hundred firms for five hundred years, and I allow the volatility of profits to change over time according to the regime $S_t \in \{H,L\}$, with $\sigma^2_{\varepsilon}(H) > \sigma^2_{\varepsilon}(L)$, $prob(S_t = S_{t-1}) = \rho^s$, and $prob(S_t \neq S_{t-1}) = 1-\rho^s$. The persistence parameter ρ^s is equal to 0.95. The values of $\sigma^2_{\varepsilon}(H)$ and $\sigma^2_{\varepsilon}(L)$ correspond to the values chosen in the previous simulations for the sectors at the 90th and the 10th percentile of the volatility of profits, respectively. In this single sector simulation, all firms have a constant discount factor β and are allowed to vary their amount of precautionary saving over time as uncertainty changes. Simulation results show that the negative uncertainty–innovation relation is confirmed, even though the coefficient of $sdroa\_1_{s,t}$ is smaller in absolute value. Panel B of Table 4 shows that the negative uncertainty–innovation relation is robust to lowering the risk-aversion coefficient η (Column 1), to lowering the persistence ρ^{ε} of the productivity shock (Column 2), and to adding a multiplicative productivity shock (Column 3). In this last case, the production function becomes

$$y_t = e^{\tau\varepsilon_t} A_t k_t^{\alpha} + \varepsilon_t, \quad 0 < \alpha < 1; \ \tau \geq 0, \tag{13}$$

so that ε_t also enters multiplicatively in the production function. The magnitude of τ determines the relative importance of the multiplicative component of the shock. In Column 3, I consider simulated sectors in which I progressively increase τ, starting from a value of $\tau = 0$, which corresponds to the linear shock case. Because the profits function is convex in $e^{\tau\varepsilon_t}$, the higher τ is , the more uncertainty also increases average expected profits. This profitability effect increases risky innovation. Another implication of the multiplicative shock is that the outcome of innovation is now positively correlated to the exogenous profits shock, through the term $e^{\tau\varepsilon_t}$. This effect further increases innovation risk for the least diversified entrepreneurs. These two counteracting effects help to explain the regression results. Sectors with higher values of τ are more profitable and innovate more. Hence, the coefficient of *avgroa* is now larger than in the previous regressions. However, conditional on *avgroa*, the uncertainty–innovation relation is still negative and significant. These findings suggest that, to empirically estimate the importance of undiversifiable risk for the negative effect of uncertainty on entrepreneurial innovation, it could be important to control for average firm profitability.

4. Empirical analysis

The simulations illustrated in the previous section determine the following testable predictions:

Prediction 1. An increase in uncertainty, as measured by the volatility of profits, on average negatively affects the risky innovation of entrepreneurial firms, whereas it does not affect the risky innovation of nonentrepreneurial firms. The reduction in entrepreneurial innovation is stronger the less diversified firms are.

Prediction 2. The negative effect of uncertainty on the innovation of entrepreneurial firms is dampened by the presence of firms facing binding borrowing constraints.

Prediction 3. An increase in uncertainty does not affect the technological adoption of both entrepreneurial and nonentrepreneurial firms.

I test these predictions on a panel of small and medium-size Italian manufacturing firms based on the 1995, 1998, and 2001 Mediocredito Centrale Surveys. Each survey covers the activity of a sample of more than 4,400 firms in the three previous years. Mediocredito Centrale selected these samples balancing the criteria of randomness and continuity. Each survey contains three consecutive years of data. After the third year, most of the sample is replaced and the new sample is then kept for the three following years. The surveys provide detailed qualitative information on property structure, employment, research and development (R&D) and innovation, internationalization, and financial structure. In addition to this qualitative information, Mediocredito Centrale provides, for most of the surveyed firms, an unbalanced panel with balance sheet data items going back as far as 1989.

The sample analyzed in this paper contains the 11,417 firms with both balance sheet and survey data. This data set has several useful features. First, it includes qualitative information not only on the amount spent by each firm on R&D, but also on the type of fixed investment and R&D expenditure.[9] This information can be used to identify which firms are investing in projects that involve risky innovation. Second, it includes information concerning the property structure of the firms, which allows identifying which firms are entrepreneurial, in the sense that they are owned and managed by the same individual. Third, it includes additional information that can be used to control for the effect of other factors that are potentially important for innovation, such as borrowing constraints, market structure, and internationalization.

4.1. Construction of the data set

In this subsection, I discuss the set of assumptions adopted to derive the empirical test of Predictions 1, 2, and 3. Such assumptions concern the identification of entrepreneurial firms, the measurement of the riskiness of their innovation, the measurement of exogenous uncertainty, and the inability of firms to diversify the innovation risk.

4.1.1. Selection of entrepreneurial firms

I select the sample of entrepreneurial firms using the following property structure information from the surveys. Firms are asked if their three largest shareholders are individuals, financial companies, or industrial companies and if they have direct control of the firm. For each of these shareholders their share of ownership in the firm is also specified.

Using this information, I select as entrepreneurial those firms that (a) have one individual who owns at least 50% of the shares of the firm and (b) are actively managed by this individual.

In the model, the entrepreneur owns 100% of the shares of the firm. Therefore, criterion (a) could seem too inclusive. However, I argue that this is not the case and that this selection criterion is the most efficient in identifying firms that are effectively fully owned and managed by a single entrepreneurial household. This claim can be verified using the information provided by the 1995 survey, in which firms also indicate, in the event more than one shareholder is an individual, whether there are family ties among them (unfortunately this information is not included in the 1998 and 2001 surveys). I consider the firms classified as entrepreneurial firms in the 1995 survey, according to criteria (a) and (b). Among all the entrepreneurial firms that have more than one shareholder, 94% have other individuals as shareholders and 71% have family ties among all the shareholders.

In the full sample composed of the three surveys, 33.2% of the firms are classified as entrepreneurial. The sorting criterion is fairly stable over time, so that if I exclude from the entrepreneurial group those firms that are present in more than one survey, and are not selected as entrepreneurial firms in all the surveys, the ratio falls very little, from 33.2% to 30.2%. Table 5 illustrates some summary statistics regarding the firms in the data set. Entrepreneurial firms are on average younger, smaller, and have a marginally higher return on capital.

Table 5
Summary statistics.
Data set of 11,417 manufacturing firms, for the 1992–2001 period, based on the 1995, 1998 and 2001 Mediocredito Centrale Surveys, for a total of 13,589 firm-survey observations.

Variable	Entrepreneurial firms	Other firms
Mean number of employees	45	183
Median number of employees	25	41
Mean age	23	27
Median age	19	21
Mean operative income/total assets	7.4%	6.8%
Percentage of exporting firms	66	71
Number of firm-survey observations	4,505	9,084

4.1.2. Identification of risky innovation

I identify the investment in risky innovation using the direct questions in the Mediocredito Surveys. In the section under the heading “Technological innovation and R&D,” firms are asked whether they engaged, in the previous three years, in R&D expenditure. The firms that answer yes (37% of the total) are asked what percentage of this expenditure was directed toward improving existing products, improving existing productive processes, introducing new products, introducing new productive processes, or other objectives.

Furthermore, in the section of the survey under the heading “Investment,” firms are asked if they undertook new investment in plant or equipment in the three previous years. The firms that answer yes (89% of the total) are asked to specify to what extent the fixed investment had the following objectives: to improve existing products, to increase the production of existing products, to produce new products, to reduce pollution, to reduce the cost of materials, to reduce labor costs, or other objectives. For each chosen answer, the firm indicates three possible degrees of intensity: low, medium, or high.

I use the above questions to construct indicators of risky innovation activity. In the model, risky innovation increases productivity on average, but it also increases the volatility of revenues and profits. I identify risky innovation in the data by considering that on average the innovation related to the introduction of new products is more risky than the

[9] Other authors have analyzed the innovation data of the Mediocredito Surveys. Hall, Lotti, and Mairesse (2008) study the relation between employment, innovation, and productivity. Parisi, Schiantarelli, and Sembenelli (2006) study the relation between productivity, innovation, and R&D. Herrera and Minetti (2007) and Benfratello, Schiantarelli, and Sembenelli (2008) analyze the effect of banking development on firm innovation.

innovation directed toward improving the existing production. This assumption is plausible because on average an innovation that introduces new products generates a higher demand and profit uncertainty than an innovation that improves the current production. At the end of this subsection, I demonstrate that the data are consistent with this identification assumption.

I summarize the information concerning innovation and technology adoption in the following four dichotomous variables. The variable that identifies risky innovation is $r\&d\_inn_{i,p}$, which is equal to one if more than 50% of R&D spending of firm i in survey p is directed toward developing new products and zero otherwise. $r\&d\_t.a._{i,p}$, the variable that identifies technology adoption (less risky innovation) is equal to one if firm i did R&D activity in survey p but $r\&d\_inn_{i,p}=0$, and it is zero otherwise. An alternative indicator of risky innovation is $fix\_inn_{i,p}$, which is equal to one if fixed investment spending of firm i is partly or fully directed toward the introduction of new products and is equal to zero otherwise.[10] Finally, $fix\_t.a._{i,p}$ is equal to one if firm i undertook a new fixed investment project but $fix\_inn_{i,p}=0$, and it is zero otherwise. Table 6 reports the percentage of firms selected according to the four criteria above. It shows that entrepreneurial firms on average engage less in R&D than nonentrepreneurial firms. Moreover around 60% of both entrepreneurial and nonentrepreneurial firms invest in fixed capital to improve existing products or to introduce new productive processes, while entrepreneurial firms on average are less likely to introduce new products.

Below I present some empirical evidence confirming the claim that product innovation is on average more risky than the innovation directed toward improving the current production. Figs. 2 and 3 pool the data for each three-digit sector for the entire sample period (1992–2000). They show the correlation between the dispersion of profits across firms for each sector, as well as the ratio of the frequency of product innovation relative to the frequency of innovation directed toward improving the current production. The figures show that the dispersion of returns is significantly increasing in such ratio.

Furthermore, I provide firm-level evidence on the correlation between innovation and the volatility of profits. I first estimate the following profits function[11]

$$\log prof_{i,t} = a_i + d_t + h_p + \alpha \log k_{i,t-1} + \beta \log w_{i,t} + \gamma \log l_{i,t} + \eta \log y_{i,t} + \varepsilon^{prof}_{i,t}, \tag{14}$$

Table 6
Share of firms that invest in innovation.
Data set of 11,417 manufacturing firms, for the 1992–2001 period, based on the 1995, 1998 and 2001 Mediocredito Centrale Surveys, for a total of 13,589 firm-survey observations.

Variable	Entrepreneurial firms	Other firms
Research and development		
No *r&d*	69%	59%
r&d_innov = 1	15%	20%
r&d_t.a = 1	16%	21%
New fixed investment		
No new fixed investment	15%	9%
fix_innov	26%	31%
fix_t.a.	59%	60%

where the dependent variable is the logarithm of operating profits at the end of period t, $\log prof_{i,t}$, and the regressors are the logarithm of revenues at the end of period t, $\log y_{i,t}$, of fixed capital at the end of period $t-1$, $\log k_{i,t-1}$, and of variable capital and labor cost, $\log w_{i,t}$ and $\log l_{i,t}$, respectively. Fixed effects, time dummies, and survey dummies, a_i, d_t, and h_p, respectively, are also included in the regression, which explains 63% of the total variation in $\log prof_{i,t}$. The residual $\varepsilon^{prof}_{i,t}$ represents a profits shock. In a second stage, I test the prediction of the model that the volatility of such shock is positively correlated with the decisions of firms to engage in risky innovation. The dependent variable of the second-stage regression is the absolute value of the estimated residual $\widehat{\varepsilon}^{prof}_{i,t}$, while the regressors are fixed effects, time dummies, and survey dummies, the indicators of risky innovation $r\&d\_inn_{i,p}$, and $fix\_inn_{i,p}$, plus an additional set of control variables described below . I also repeat the same procedure using as dependent variable the volatility of the residual from the following standard production function:

$$\log y_{i,t} = a_i + d_t + h_p + \alpha \log k_{i,t-1} + \beta \log w_{i,t} + \gamma \log l_{i,t} + \varepsilon^{rev}_{i,t}. \tag{15}$$

Regression equation (15) explains 92% of the total variation in $\log y_{i,t}$.[12] The reason that I use both a profits shock and a revenues shock is that, in the model, risky innovation raises the volatility of both. Table 7 verifies the relation between the absolute values $abs(\widehat{\varepsilon}^{prof}_{i,t})$ and $abs(\widehat{\varepsilon}^{rev}_{i,t})$ and the risky innovation indicator $r\&d\_inn_{i,p}$, for all firm-year observations with positive R&D spending. Because I am adding firm fixed effect, the coefficient of $r\&d\_inn_{i,p}$ is identified by variations in $abs(\widehat{\varepsilon}^{prof}_{i,t})$ and $abs(\widehat{\varepsilon}^{rev}_{i,t})$ across surveys for firms that are present in more than one survey and have different risky innovation decisions in the different surveys. As control variables I include *R&D expenditure*$_{i,p}$, which is the log of total R&D expenditure for firm i in survey p, and three further dichotomous variables that indicate the use of R&D expenditure for other objectives. $r\&d\_inn^{low}_{i,p}$ is equal to one if firm i in survey p spends between 1% and 49% of its R&D budget on

[10] An alternative strategy is to construct risky innovation indicators that use the full variation of the data. For example, it is possible to construct an indicator *r&d_inn_full*, that is equal to zero when *r&d_inn* is equal to zero and is equal to the percentage of R&D expenditure for new products when *r&d_inn* is equal to one. However, the percentages indicated in the surveys are not precise, because they are frequently rounded at the 5%, 10%, 20%, and especially at the 50% level. This approximation makes it difficult to interpret the observed percentage as a continuous variable representing the amount of R&D expenditure on new products. Nonetheless I perform all the regressions presented in this paper using *r&d_inn_full* instead of *r&d_inn*. Furthermore, I proceed similarly with respect to the other indicator *fix_inn*, and in both cases I find no substantial differences in the results. These additional regression results are available upon request.

[11] I use a fixed effect estimator. A Huber and White estimator of the variance–covariance matrix is used to correct for heteroskedasticity.

[12] In Eqs. (14) and (15) the regressors are potentially correlated with the error term, and adding fixed effect corrects this problem only partially. However, I do not expect that this factor would significantly bias the second step estimation of the effect of innovation on the volatility of the residuals.

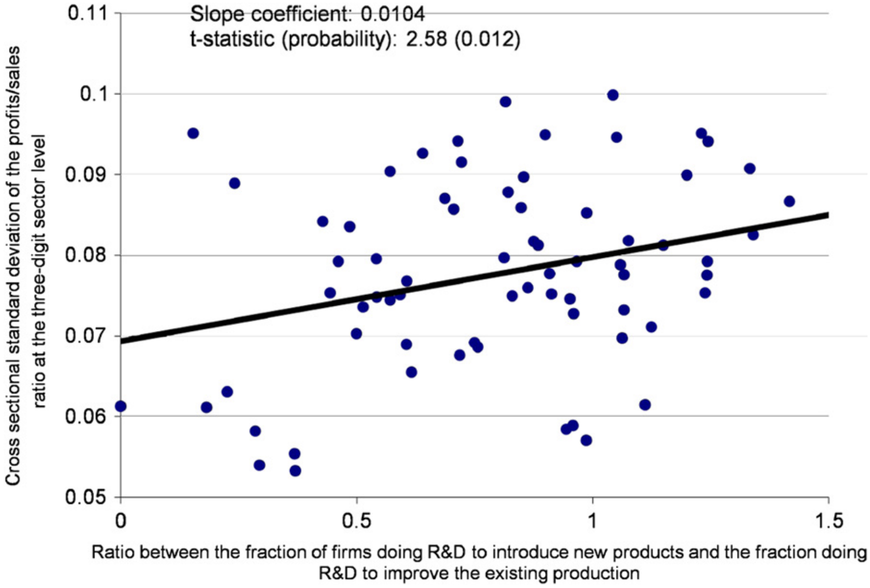

Fig. 2. Cross-sectional dispersion of the profits/sales ratio (three-digit manufacturing sectors) as a function of research and development (R&D) composition.

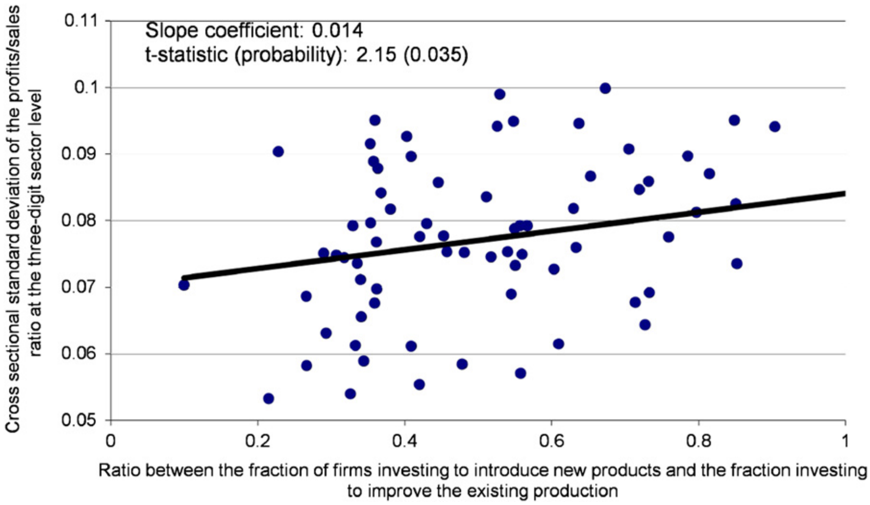

Fig. 3. Cross-sectional dispersion of the profits/sales ratio (three-digit manufacturing sectors) as a function of fixed investment composition.

introducing new products. $r\&d\_improve^1_{i,p}$ is equal to one if firm i in survey p spends more 50% of its R&D budget on introducing new productive processes and zero otherwise. $r\&d\_improve^2_{i,p}$ is equal to one if firm i in survey p spends more than 50% of its R&D budget on improving its existing products and zero otherwise. $r\&d\_improve^3_{i,p}$ is equal to one if firm i in survey p spends more 50% of its R&D budget to improve its productive processes and zero otherwise.

If $r\&d\_inn_{i,p}$ is a good indicator of risky innovation, its coefficient should be positive and significant. Table 7 confirms this. Furthermore, the coefficient of $r\&d\_inn_{i,p}$ is always larger than the coefficient of $r\&d\_inn^{low}_{i,p}$ and the coefficients of the other R&D indicators. The model predicts that this happens because product innovation increases the volatility of profits. One possible alternative explanation of this result is that when a firm is hit by a positive productivity shock, it simultaneously implements more innovation and generates higher than average profits. This alternative explanation is ruled out by the results shown at the bottom of Table 7, where the coefficient of $r\&d\_inn_{i,p}$ is reported for the regressions in which the dependent variables are $\widehat{\varepsilon}^{prof}_{i,t}$ and $\widehat{\varepsilon}^{rev}_{i,t}$ instead of their absolute values. If the alternative explanation was correct, these coefficients should also be positive and significant, because more innovation should be correlated with higher than expected profits. Instead, the coefficients are negative, very small, and not significant.

Table 8 shows the results obtained using $fix\_inn_{i,p}$, the binary variable indicating new fixed investment at least partially directed toward introducing new products, as the dependent variable. The $fix\_inn_{i,p}$ coefficient is generally

Table 7
Research and development (R&D) innovation and revenues risk.

All regressions are estimated with a fixed effect estimator. A Huber and White estimator of the variance-covariance matrix is used to correct for heteroskedasticity. Standard errors, reported in parenthesis, are clustered at the firm level. * denotes significance at the 90% confidence level; ** significance at the 95% confidence level; *** significance at the 99% confidence level. $abs(\hat{\varepsilon}_{i,t}^{prof})$ is the absolute value of the estimated error in a profits forecasting equation for firm i in period t. $abs(\hat{\varepsilon}_{i,t}^{rev})$ is the absolute value of the estimated error in a revenues forecasting equation for firm i in period t. $r\&d\_inn_{i,p}$ is equal to one if firm i in survey p spends more 50% of its R&D budget for the development of new products and equal to zero otherwise. $r\&d\_inn_{i,p}^{low}$ is equal to one if firm i in survey p spends between 1% and 50% of its R&D budget for the development of new products and equal to zero otherwise. $r\&d\_improve_{i,p}^{1}$ is equal to one if firm i in survey p spends more 50% of its R&D budget to introduce new productive processes and equal to zero otherwise. $r\&d\_improve_{i,p}^{2}$ is equal to one if firm i in survey p spends more 50% of its R&D budget to improve its existing products and equal to zero otherwise. $r\&d\_improve_{i,p}^{3}$ is equal to one if firm i in survey p spends more 50% of its R&D budget to improve its productive processes and equal to zero otherwise. $R\&D\ expenditure_{i,p}$ is the log of R&D expenditure for firm i in survey p.

	Dependent variable: $abs(\hat{\varepsilon}_{i,t}^{prof})$			Dependent variable: $abs(\hat{\varepsilon}_{i,t}^{rev})$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.31***	0.34***	0.33***	0.079***	0.080***	0.077***
	(0.013)	(0.039)	(0.039)	(0.003)	(0.003)	(0.008)
$r\&d\_inn_{i,p}$	0.023*	0.024*	0.027*	0.008**	0.008**	0.009***
	(0.014)	(0.014)	(0.014)	(0.003)	(0.003)	(0.003)
$r\&d\_inn_{i,p}^{low}$	0.014	0.015	0.013	0.007***	0.007***	0.005**
	(0.011)	(0.011)	(0.012)	(0.002)	(0.002)	(0.002)
$R\&D\ expenditure_{i,p}$		−0.004	−0.004		−0.00002	−0.00006
		(0.006)	(0.006)		(0.001)	(0.001)
$r\&d\_improve_{i,p}^{1}$			−0.009			0.003
			(0.015)			(0.003)
$r\&d\_improve_{i,p}^{2}$			0.009			0.005*
			(0.012)			(0.003)
$r\&d\_improve_{i,p}^{3}$			0.008			0.004*
			(0.011)			(0.002)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Survey dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	14,288	14,288	14,288	15,882	15,882	15,882
	Dependent variable: $\hat{\varepsilon}_{i,t}^{prof}$			Dependent variable: $\hat{\varepsilon}_{i,t}^{rev}$		
$r\&d\_inn_{i,p}$	−0.004	−0.005	−0.005	−0.003	−0.004	−0.004
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)

positive and significant, but it is also positive and significant in the alternative regressions shown at the bottom of the table. Therefore, the regression results are not conclusive for the validity of $fix\_inn_{i,p}$ as an indicator of risky innovation. However, because the indirect evidence from Fig. 3 is instead supporting it, for the following empirical analysis I keep both $fix\_inn_{i,p}$ and $r\&d\_inn_{i,p}$ as risky innovation indicators.

4.1.3. Measurement of profit uncertainty

To test the predictions of the model, I choose a measure of profit uncertainty analogous to the one used in the simulations. $sdroa\_1_{s,p}$ is the cross-sectional standard deviation of the return on assets (operating profits divided by total assets) for the firms in the three-digit sector s in the most recent year of survey p (e.g., year 1994 for the 1995 survey).[13] $sdroa\_1_{s,p}$ has 191 observations in total.

The advantage of using a sectorial measure of uncertainty is that it is exogenous from the point of view of the single firm, thereby reducing possible biases caused by the reverse causality problem in which innovation positively affects the volatility of profits. Moreover, the test is based on finding a negative relation between uncertainty and innovation only for entrepreneurial firms. Therefore, it is unlikely to be affected by any endogeneity problem that biases the relation between risk and innovation in the same direction for both entrepreneurial and nonentrepreneurial firms.

Nevertheless, the coefficient of $sdroa\_1_{s,p}$ could still be biased by the presence of sector-specific omitted variables that affect the innovation decision of entrepreneurial and nonentrepreneurial firms in different ways. In Section 4.3.2, I address this problem by showing that the empirical results are robust to using sector fixed effects, which take care of all time-invariant characteristics, and instrumental variables, which control for the possibility of other omitted variables affecting the results.

4.1.4. The financing of innovation

In this subsection, I verify that the empirical data are consistent with the assumption that the entrepreneurs cannot issue risky debt to diversify the innovation risk. Table 9 analyzes the composition of liabilities for the surveyed firms. The main source of debt financing is

[13] I consider the most recent year of each survey because it includes a higher number of observations. This is because not all firms have balance sheet data for all three years in the survey. Nonetheless, the results do not differ substantially if I instead consider a cross-sectional measure of risk that covers all three years in the survey.

Table 8
Fixed investment innovation and revenues risk.

All regressions are estimated with a fixed effect estimator. A Huber and White estimator of the variance-covariance matrix is used to correct for heteroskedasticity. Standard errors, reported in parenthesis, are clustered at the firm level. * denotes significance at the 90% confidence level; ** significance at the 95% confidence level; *** significance at the 99% confidence level. $abs(\widehat{\varepsilon}_{i,t}^{prof})$ is the absolute value of the estimated error in a profits forecasting equation for firm i in period t. $abs(\widehat{\varepsilon}_{i,t}^{rev})$ is the absolute value of the estimated error in a revenues forecasting equation for firm i in period t. $fix\_inn_{i,p}$ is equal to one if firm i in survey p installed new capital with the objective to produce new products, and zero otherwise. $K\ expenditure_{i,p}$ is the log of capital expenditure for firm i in survey p. $fix\_improve_{i,p}^{1}$ is equal to one if firm i in survey p installed new capital with the objective to increase the production of its existing products and equal to zero otherwise. $r\&d\_improve_{i,p}^{2}$ is equal to one if firm i in survey p installed new capital with the objective to increase the quality of its existing products and equal to zero otherwise. $r\&d\_improve_{i,p}^{3}$ is equal to one if firm i in survey p installed new capital with the objective to reduce costs and equal to zero otherwise.

	Dependent variable: $abs(\widehat{\varepsilon}_{i,t}^{prof})$			Dependent variable: $abs(\widehat{\varepsilon}_{i,t}^{rev})$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
constant	0.326***	0.0334***	0.328***	0.084***	0.084***	0.081***
	(0.007)	(0.011)	(0.012)	(0.002)	(0.002)	(0.002)
$fix\_inn_{i,p}$	0.020***	0.021***	0.016**	0.004***	0.004***	0.002
	(0.006)	(0.006)	(0.007)	(0.001)	(0.001)	(0.001)
$K\ expenditure_{i,p}$		−0.001	−0.001		0.000003	−0.0002
		(0.001)	(0.001)		(0.0003)	(0.0003)
$fix\_improve_{i,p}^{1}$			−0.010			0.003*
			(0.008)			(0.002)
$fix\_improve_{i,p}^{2}$			0.010			0.004**
			(0.009)			(0.002)
$fix\_improve_{i,p}^{3}$			0.014**			−0.001
			(0.007)			(0.001)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Survey dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	39,752	39,752	39,752	44,180	44,180	44,180
	Dependent variable: $abs(\widehat{\varepsilon}_{i,t}^{prof})$			Dependent variable: $abs(\widehat{\varepsilon}_{i,t}^{rev})$		
$fix\_inn_{i,p}$	0.007***	0.007**	0.005*	0.007***	0.007**	0.005*
	(0.002)	(0.003)	(.003)	(0.003)	(0.003)	(0.003)

short-term banking debt, which accounts for around 13% of total assets.[14] Unfortunately, no additional information is provided on the characteristics of these loans, whether they are backed by collateral or by other types of guarantees. However, short-term banking debt to small and medium Italian firms is usually provided as credit lines, as confirmed by Detragiache, Garella, and Guiso (2000), who study a subset of 1,849 firms from the 1995 Mediocredito Centrale Survey. For these firms the authors have additional detailed information of the loans characteristics, and they report that all firms in their sample have at least one credit line. Because banks often ask entrepreneurs for a personal guarantee when they open a credit line, this source of financing usually provides few risk-sharing opportunities. Long-term banking loans are relatively less important, averaging around 5%. Importantly, the table shows that the composition of debt financing is similar across entrepreneurial and nonentrepreneurial firms, as well as across the different types of innovation.

Finally, in the surveys, firms are also asked to specify what sources of financing are used to finance innovation between equity, self-finance, medium–long-term debt, and fiscal deductions. The responses show that most of the investment in innovation is self-financed. For example, the data from the 1998–2000 survey show that among the entrepreneurial firms that invest in risky innovation 80% finance at least 50% of R&D with self-finance, and 61% finance 100% of R&D with self-finance. Among the other sources, equity finance is irrelevant, because only 0.8% of the entrepreneurial firms finance at least 50% of R&D with new equity. Debt finance is slightly larger, with 8% of the entrepreneurial firms financing at least 50% of R&D with medium–long-term debt finance. Similarly, the fixed investment section of the surveys shows that retained earnings are also the main funding source for fixed investment directed toward introducing new products.

Overall this information is consistent with the hypothesis that Italian entrepreneurial firms have few opportunities to use external finance to diversify their business risk.

[14] Trade debt is also widely used by the firms in the sample, averaging 22% of total assets. However, this debt is standardized, because typically firms delay the payment of suppliers to match the delay in payment asked by their customers. Therefore, usually the total amount of trade debt matches the total amount of trade credit, and it depends on the volume of activity of the firm, not on investment decisions.

Table 9
Financing sources.
Data set of 11,417 manufacturing firms, for the 1992–2001 period, based on the 1995, 1998 and 2001 Mediocredito Centrale Surveys, for a total of 13,589 firm-survey observations.

Variable	All firms	All firms doing research and development (R&D)	Entrepreneurial firms doing R&D	Entrepreneurial firms doing risky R&D
Short-term banking debt	12.4%	13.9%	13.3%	13%
Other types of short-term borrowing	1.3%	1.6%	1%	1%
Bonds	0.5%	0.6%	0.5%	0.6%
Long-term banking debt	4.1%	5.0%	4.3%	5.1%
Other types of long-term borrowing	1.4%	1.6%	1.2%	1.3%

4.2. Estimation

I test Predictions 1, 2, and 3 by regressing the innovation decision on the measure of uncertainty $sdroa\_1_{s,p}$ and on several control variables:

$$y_{i,p} = \alpha_0 + \alpha_1 sdroa\_1_{s,p} + \alpha_2 export_{i,p} + \alpha_3 supply_{i,p} + \alpha_4 constrained_{i,p} + \alpha_5 avgroa\_1_{s,p} + \alpha_6 \ln(size_{i,p}) + \alpha_7 age_{i,p} + \alpha_8 age^2_{i,p} + d^{2digits}_{i,p} + d^{survey}_{i,p} + u_{i,p}. \quad (16)$$

The dependent variable $y_{i,p}$ is one of the innovation indicators, namely the risky innovation indicators $r\&d\_inn$ and fix_inn, and the two technology adoption indicators $r\&d\_t.a$ and $fix\_t.a$. Among the control variables, I include the average profitability of firms, $avgroa\_1_{s,p}$, which is the cross-sectional mean of the return on assets for sector s in survey p. This explanatory variable is important because it controls for the possibility that higher uncertainty could affect innovation indirectly by increasing expected returns. $export_{i,p}$ is equal to one (69% of total) if firm i exports part of its production outside Italy, and it is equal to zero otherwise. The variable capturing market structure is $supply_{i,p}$, which is equal to one (44% of total) if firm i produces 100% of its output based on the order placed by downstream firms, and it is equal to zero otherwise. The variable capturing financing constraints is $constrained_{i,p}$, which is equal to one if firm i declares financing constraints (14% of total) and zero otherwise.[15] The other control variables are $size_{i,p}$, which is the number of employees of firm i, and $age_{i,p}$, which is the age of firm i (relative to the year of the survey) measured in years. $age^2_{i,p}$ is $age_{i,p}$ squared. Finally, $d^{2digits}_{i,p}$ is a series of two-digit sector dummy variables, and $d^{survey}_{i,p}$ is a series of survey dummy variables.

Table 10 reports the estimation of Eq. (16). Consistently with Prediction 1, an increase in uncertainty, as measured by the $sdroa\_1_{s,p}$ variable, has a significant and negative effect on the investment in risky innovation of the entrepreneurial firms, while it does not affect the investment in risky innovation of the other firms. Importantly, while entrepreneurial and nonentrepreneurial firms differ with respect to the correlation between risk and innovation, they do not differ much with respect to the significance of the other control variables. With respect to the regressions that use the product innovation variables $r\&d\_inn_{i,p}$ and $fix\_inn_{i,p}$ as dependent variables, I find that firms that export more and larger firms innovate more. Conversely, firms that produce based on orders of downstream firms instead of for the market innovate less. These findings could be explained by the fact that large firms that produce for the market and that export abroad are under greater pressure to innovate by their competitors.

Conversely, the regressions that use $fix\_t.a_{i,p}$ as the dependent variable show that uncertainty does not affect the less risky innovation of both entrepreneurial and nonentrepreneurial firms, thus confirming Prediction 3. They also show that firms that install new fixed capital to improve the existing production have opposite characteristics from the firms that introduce new products. They export less and they produce more upon orders and less for the market.

4.3. Robustness checks

In this subsection I perform several robustness checks of the consistency between the predictions of the model and the empirical evidence.

4.3.1. Financing constraints and diversification

The first robustness check is related to the prediction of the model that the presence of financing constraints reduces the negative effect of uncertainty on the risky innovation of entrepreneurial firms. Table 11 replicates the analysis in Table 10 after excluding the 14% of firms that declare financing problems in any of the three surveys. The results are consistent with the predictions of the model. The comparison between Tables 10 and 11 shows that excluding

[15] Firms are asked the three following questions about financing problems: (1) "During the last year, did the firm desire to borrow more at the interest rate prevailing in the market?" (2) "If the previous answer was yes: Was the firm willing to pay a higher interest rate in order to get additional credit?" (3) "During the last year, did the firm ask for more credit without obtaining it?" The variable $constrained_{i,p}$ is equal to one if the answer to any of the three questions is positive. Caggese and Cuñat (2008) employ the same data set to study the effect of financing constraints on firms' employment decisions and show that this variable is a very reliable indicator of the presence of financing constraints for the surveyed firms. I also tried an alternative measure $constrained2_{i,p}$, which is equal to one if the answer to at least two of the three questions is positive (5.4% of all firms), obtaining results similar than those with $constrained_{i,p}$.

Table 10
Relation between risk and innovation, empirical data.

All regressions are estimated with a maximum likelihood probit estimator. A Huber and White estimator of the variance–covariance matrix is used to correct for heteroskedasticity. Standard errors are clustered at the three digit sector level. The z statistic is reported in parenthesis. * denotes significance at the 90% confidence level; ** significance at the 95% confidence level; *** significance at the 99% confidence level. $r\&d\_inn_{i,p}$ is equal to one if more than 50% of research and development (R&D) spending of firm i in survey p is directed to develop new products and equal to zero otherwise. $r\&d\_t.a._{i,p}$ is equal to one if firm i did R&D activity in survey p but $r\&d\_inn_{i,p}=0$ and equal to zero otherwise. $fix\_inn_{i,p}$ is equal to one if fixed investment spending of firm i is partly or fully directed to the introduction of new products and equal to zero otherwise. $fix\_t.a_{i,p}$ is equal to one if firm i undertook a new fixed investment project but $fix\_inn_{i,p}=0$ and equal to zero otherwise. The dependent variable is innovation decision $y_{i,p}$. $sdroa\_1_{i,s}$ is the standard deviation of the cross section of the gross income/assets ratio for the firms in the three-digit sector s in the most recent year of each survey. $export_{i,p}$ is equal to one if firm i exports part of its production outside Italy and equal to zero otherwise. $supply_{i,p}$ is equal to one if firm i produces 100% of its output based on the order placed by downstream firms and equal to zero otherwise. $constrained_{i,p}$ is equal to one if the firm declares financing constraints and equal to zero otherwise. $avgroa\_1_{i,s}$ is the cross-sectional mean of the return on assets for sector s in the most recent year of the survey. $size_{i,p}$ is the number of employees of firm i. $age_{i,p}$ is the age of the firm (relative to the year of the survey) in years. Two-digit sector dummy variables and survey dummy variables are also included. In columns labeled "Entr." only entrepreneurial firms are included in the estimation. In columns labeled "Other" all firms except the entrepreneurial firms are included in the estimation.

	$y_{i,p}=r\&d\_inn_{i,p}$		$y_{i,p}=r\&d\_t.a_{i,p}$		$y_{i,p}=fix\_inn_{i,p}$		$y_{i,p}=fix\_t.a._{i,p}$	
Variable	Entr.	Other	Entr.	Other	Entr.	Other	Entr.	Other
$sdroa\_1_{s,p}$	−5.04**	−1.87	3.31	1.16	−4.62**	−1.01	2.16	−0.22
	(−2.3)	(−1.3)	(1.5)	(0.9)	(−2.5)	(−0.8)	(1.2)	(−0.2)
$export_{i,p}$	0.37***	0.52***	0.26***	0.32***	0.19***	0.24***	−0.07	−0.11***
	(5.4)	(10.4)	(4.4)	(7.6)	(3.4)	(6.1)	(−1.3)	(−3.0)
$supply_{i,p}$	−0.24***	−0.15***	0.07	−0.03	−0.10**	−0.15	0.14***	0.17***
	(−4.0)	(−4.0)	(1.3)	(−0.8)	(−2.0)	(−4.4)	(2.9)	(5.5)
$constrained_{i,p}$	0.06	0.18***	0.042	0.013	0.09	0.18***	−0.04	−0.12***
	(0.9)	(3.6)	(0.6)	(0.3)	(1.5)	(4.0)	(−1.5)	(−2.6)
$avgroa\_1_{s,p}$	−1.62	−0.78	−2.98	−0.09	4.36**	2.40*	−2.13	−0.04
	(−0.7)	(−0.5)	(−1.4)	(−0.1)	(2.2)	(1.8)	(−1.2)	(−0.1)
$\ln(size_{i,p})$	0.25***	0.24***	0.18***	0.13***	0.27***	0.18***	−0.05	−0.05***
	(7.0)	(15.4)	(5.4)	(8.8)	(8.4)	(12.8)	(−1.5)	(−3.3)
$age_{i,p}$	0.003	0.006*	−0.002	−0.002	0.007**	0.006**	−0.01***	−0.004*
	(0.8)	(1.7)	(−0.5)	(−1.0)	(2.0)	(2.2)	(−2.8)	(−1.8)
$age^2_{i,p}$	−0.0001	−0.0001***	0.0004	0.0001***	−0.0001**	−0.0001***	0.0001***	0.00001***
	(−1.1)	(−3.2)	(0.6)	(3.2)	(−2.5)	(−3.7)	(3.2)	(3.1)
Number of observations	3,627	7,703	3,631	7,708	3,638	7,710	3,636	7,710
Pseudo R^2	0.11	0.13	0.04	0.06	0.06	0.05	0.04	0.03

financially constrained firms increases the negative effect of uncertainty on risky innovation. Importantly, the bottom part of Table 11 shows that such negative effect disappears when the model is estimated for financially constrained firms only.

The second robustness check is related to the prediction of the model that the negative relation between uncertainty and innovation holds only for undiversified entrepreneurial households. More precisely, simulation results predict that the entrepreneurial households that hold a relatively large amount of financial assets with respect to the size of their business are less affected by changes in uncertainty. To verify this prediction, I construct the measure of financial wealth $fin\_a_{i,t}$, which is equal to the ratio between the net financial assets of firm i (financial investment + liquidity + short term financial credit − short term financial debt) divided by the total assets of firm i in period t. I eliminate the largest 1% and smallest 1% values as outliers. The measure of diversification I consider is $divers_{i,p}$, which is the average of $fin\_a_{i,t}$ across the three years of survey p. The mean of $divers_{i,p}$ is equal to 0.38, and its standard deviation is equal to 0.21. I verify prediction 2 in Table 12, where I estimate Eq. (16) using the risky innovation indicators $r\&d\_inn_{i,p}$ and $fix\_inn_{i,p}$ as dependent variables and separating firms according to whether the value of the variable $divers_{i,p}$ is below or above the 0.5 cutoff point.[16] Panel A includes all firms and confirms the prediction that the negative effect of risk on innovation is driven by the undiversified entrepreneurial firms, because the coefficient of $sdroa\_1_{s,p}$ is significant only for the firms with a low value of $divers_{i,p}$. Importantly, also in this case, few substantial variations exist in the coefficients of the other main determinants of innovation across the different regressions. Furthermore, these results are unlikely to be driven by the fact that low $divers_{i,p}$ firms are financially constrained firms, because both the model and the regression results show that financing constraints reduce rather than increase the negative effect of risk on the entrepreneurial innovation decisions. This is confirmed by Panel B of Table 12, which not only splits the sample in the same

[16] Simulation results shown in Table 2 would suggest a cutoff point around 0.3. I choose the empirical cutoff point to be larger because in the simulated data the measure of diversification is computed using the value of the firm's future profits at the denominator, while in the empirical data the denominator is the book value of the assets, which is likely to underestimate the real value of the firm.

Table 11
Relation between risk and innovation, empirical data, financially constrained firms excluded.

All regressions are estimated with a maximum likelihood probit estimator. A Huber and White estimator of the variance–covariance matrix is used to correct for heteroskedasticity. Standard errors are clustered at the three digit sector level. The z statistic is reported in parenthesis. * denotes significance at the 90% confidence level; ** significance at the 95% confidence level; *** significance at the 99% confidence level. $r\&d\_inn_{i,p}$ is equal to one if more than 50% of research and development (R&D) spending of firm i in survey p is directed to develop new products and equal to zero otherwise. $r\&d\_t.a._{i,p}$ is equal to one if firm i did R&D activity in survey p but $r\&d\_inn_{i,p}=0$ and equal to zero otherwise. $fix\_inn_{i,p}$ is equal to one if fixed investment spending of firm i is partly or fully directed to the introduction of new products and equal to zero otherwise. $fix\_t.a_{i,p}$ is equal to one if firm i undertook a new fixed investment project but $fix\_inn_{i,p}=0$ and equal to zero otherwise. The dependent variable is innovation decision $y_{i,p}$. $sdroa\_1_{i,s}$ is the standard deviation of the cross section of the gross income/assets ratio for the firms in the three-digit sector s in the most recent year of each survey. $export_{i,p}$ is equal to one if firm i exports part of its production outside Italy and equal to zero otherwise. $supply_{i,p}$ is equal to one if firm i produces 100% of its output based on the order placed by downstream firms and equal to zero otherwise. $avgroa\_1_{i,s}$ is the cross-sectional mean of the return on assets for sector s in the most recent year of the survey. $size_{i,p}$ is the number of employees of firm i. $age_{i,p}$ is the age of the firm (relative to the year of the survey) in years. Two-digit sector dummy variables and survey dummy variables are also included. In columns labeled "Entr." only entrepreneurial firms are included in the estimation. In columns labeled "Other" all firms except the entrepreneurial firms are included in the estimation.

	$y_{i,p}=r\&d\_inn_{i,p}$		$y_{i,p}=r\&d\_t.a_{i,p}$		$y_{i,p}=fix\_inn_{i,p}$		$y_{i,p}=fix\_t.a._{i,p}$	
Variable	Entr.	Other	Entr.	Other	Entr.	Other	Entr.	Other
$sdroa\_1_{s,p}$	−7.36***	−1.77	4.44**	0.78	−5.21**	−0.94	2.89	−0.19
	(−3.0)	(−1.1)	(1.9)	(0.6)	(2.5)	(−0.7)	(1.5)	(−0.2)
$export_{i,p}$	0.40***	0.51***	0.30***	0.35***	0.16***	0.25***	−0.05	−0.13***
	(5.2)	(9.3)	(4.4)	(7.5)	(2.6)	(−2.9)	(−1.0)	(−3.2)
$supply_{i,p}$	−0.20***	−0.16***	0.08	−0.04	−0.10*	−0.13***	0.15***	0.16***
	(−3.2)	(−3.7)	(1.4)	(−1.1)	(−1.8)	(−3.6)	(2.8)	(4.6)
$avgroa\_1_{s,p}$	−0.49	−2.01	−4.16*	0.80	5.56***	1.39	−2.75	0.80
	(−0.2)	(−1.2)	(−1.8)	(0.5)	(2.6)	(1.0)	(−1.4)	(0.6)
$\ln(size_{i,p})$	0.25***	0.25***	0.19***	0.13***	0.27***	0.18***	−0.04	−0.04***
	(6.5)	(14.6)	(5.2)	(8.2)	(7.9)	(12.0)	(−1.1)	(−2.7)
$age_{i,p}$	0.001	0.006	−0.0002	−0.002	0.006*	0.004	−0.009**	−0.002
	(0.2)	(1.6)	(−0.1)	(−0.8)	(1.6)	(1.4)	(−2.4)	(−1.0)
$age^2_{i,p}$	−0.00003	−0.0001***	0.00003	0.0001***	−0.0001**	−0.0001***	0.0001***	0.0001**
	(−0.6)	(−3.0)	(0.7)	(2.8)	(−2.1)	(−2.9)	(2.6)	(2.4)
Number of observations	3,014	6,698	3,006	6,703	3,024	6,705	3,022	6,705
Pseudo R^2	0.12	0.14	0.04	0.06	0.06	0.05	0.04	0.03
Financially constrained firms only								
$sdroa\_1_{s,p}$	4.93	−1.36	−1.74	4.66	−2.26	−0.23	−3.06	−0.81
	(1.0)	(−0.3)	(−0.4)	(1.3)	(−0.5)	(−0.1)	(−0.7)	(−0.2)
Number of observations	599	1,002	613	997	590	1,002	590	1,002
Pseudo R^2	0.12	0.13	0.13	0.07	0.07	0.10	0.05	0.06

way as Panel A but it also excludes financially constrained firms from the sample. In this case, the coefficient of $sdroa\_1_{s,p}$ becomes more significant and larger in absolute value for low $divers_{i,p}$ firms.

Table 13 compares the magnitude of the uncertainty–innovation relation estimated in the empirical data with the one estimated in the simulated data analyzed in Section 3. In the simulations, the percentage change in the frequency of risky innovation after a 1% increase in the cross-sectional standard deviation of roa is equal to −0.69% for all entrepreneurial firms and equal to −0.99% for the group of less diversified ones. When using $r\&d\_inn_{i,p}$ as an indicator of risky innovation, I find remarkably similar values in the empirical data, with elasticities equal to −0.63% for all entrepreneurial firms and equal to −0.92% for the group of less diversified ones. The same elasticities are also negative but smaller in absolute value when using $fix\_inn_{i,p}$ as the dependent variable. These results confirm that $r\&d\_inn_{i,p}$ is a more precise indicator of risky innovation, as the evidence shown in Tables 7 and 8 indicates.

4.3.2. Endogeneity problems

In the previous subsections I argued that the measure of profit uncertainty $sdroa\_1_{s,p}$ is exogenous from the point of view of the single firm, while it could still be correlated to sectorial characteristics that could matter for firms' innovation decisions and, thus, bias the estimation results.

This subsection verifies that the observed negative relation between uncertainty and entrepreneurial innovation is not driven by such unobserved characteristics. If unobservable sector characteristics do affect the cross-sectional volatility of profits and the firms' innovation decisions, then they are likely to bias the coefficient of $sdroa\_1_{s,p}$ upward rather than downward, thus making Prediction 1 more likely to be rejected. This could happen, for example, if firms that belong to more dynamic sectors

Table 12
The relationship between risk and innovation, empirical data. Entrepreneurial firms selected according to the degree of diversification.

All regressions are estimated with a maximum likelihood probit estimator. A Huber and White estimator of the variance–covariance matrix is used to correct for heteroskedasticity. Standard errors are clustered at the three digit sector level. The z statistic is reported in parenthesis. * denotes significance at the 90% confidence level; ** significance at the 95% confidence level; *** significance at the 99% confidence level. $r\&d\_inn_{i,p}$ is equal to one if more than 50% of research and development (R&D) spending of firm i in survey p is directed to develop new products and equal to zero otherwise. $fix\_inn_{i,p}$ is equal to one if fixed investment spending of firm i is partly or fully directed to the introduction of new products and equal to zero otherwise. The dependent variable is innovation decision $y_{i,p}$. $divers_{i,p}$ is the average of the ratio between the net financial assets and total assets for firm i in survey p. $sdroa\_1_{i,s}$ is the standard deviation of the cross section of the gross income/assets ratio for the firms in the three-digit sector s in the most recent year of each survey. $export_{i,p}$ is equal to one if firm i exports part of its production outside Italy and equal to zero otherwise. $supply_{i,p}$ is equal to one if firm i produces 100% of its output based on the order placed by downstream firms and equal to zero otherwise. $constrained_{i,p}$ is equal to one if the firm declares financing constraints and equal to zero otherwise. $avgroa\_1_{i,s}$ is the cross-sectional mean of the return on assets for sector s in the most recent year of the survey. $size_{i,p}$ is the number of employees of firm i. $age_{i,p}$ is the age of the firm (relative to the year of the survey) in years. Two-digit sector dummy variables and survey dummy variables are also included.

	Panel A: Financially constrained included				*Panel B: Financially constrained excluded*			
	$y_{i,p}=r\&d\_inn_{i,p}$		$y_{i,p}=fix\_inn_{i,p}$		$y_{i,p}=r\&d\_inn_{i,p}$		$y_{i,p}=fix\_inn_{i,p}$	
Variable	$divers_{i,p} \leq 0.5$	$divers_{i,p} > 0.5$	$divers_{i,p} \leq 0.5$	$divers_{i,p} > 0.5$	$divers_{i,p} \leq 0.5$	$divers_{i,p} > 0.5$	$divers_{i,p} \leq 0.5$	$divers_{i,p} > 0.5$
$sdroa\_1_{s,p}$	−7.88***	−1.77	−5.10**	−3.97	−12.6***	−1.98	−6.32**	−3.78
	(−2.7)	(−0.5)	(−2.1)	(−1.3)	(−3.8)	(−0.6)	(−2.3)	(−1.2)
$export_{i,p}$	0.40***	0.33***	0.26***	0.10	0.47***	0.33***	0.27***	0.03
	(4.3)	(3.2)	(3.5)	(1.2)	(4.3)	(3.0)	(3.2)	(0.4)
$supply_{i,p}$	−0.25***	−0.22**	−0.12*	−0.08	−0.24***	−0.18*	−0.09	−0.11
	(−3.3)	(−2.3)	(−1.8)	(−1.0)	(−2.8)	(−1.8)	(−1.3)	(-1.3)
$constrained_{i,p}$	0.16*	−0.14	0.07	0.12				
	(1.7)	(−1.1)	(0.9)	(1.2)				
$avgroa\_1_{s,p}$	−0.39	−2.55	2.88	6.88**	2.15	−3.09	4.35	7.90**
	(−0.14)	(−0.7)	(1.1)	(2.2)	(0.7)	(−0.9)	(1.5)	(2.4)
$\ln(size_{i,p})$	0.24***	0.23***	0.22***	0.30***	0.25**	0.22***	0.22***	0.29***
	(5.3)	(3.6)	(5.3)	(5.4)	(4.9)	(3.3)	(4.8)	(4.9)
$age_{i,p}$	0.002	0.003	0.01**	0.002	−0.0008	0.002	0.01*	0.002
	(0.3)	(0.6)	(2.2)	(0.4)	(−0.1)	(0.3)	(1.7)	(0.4)
$age^2_{i,p}$	−0.00004	−0.00005	−0.0001**	−0.00006	−0.00002	−0.00003	−0.0001*	−0.00005
	(−0.7)	(−0.8)	(−2.4)	(−1.1)	(−0.27)	(−0.5)	(−1.9)	(-1.0)
Number of observations	1,958	1,669	1,954	1,679	1581	1397	1,578	1,439
Pseudo R^2	0.11	0.12	0.06	0.05	0.13	0.12	0.06	0.06

Table 13
Uncertainty and innovation. Comparison between simulated and empirical data.

Percentage change in the frequency of risky entrepreneurial innovation after a one percent increase in the standard deviation of return on assets.

	Simulated data	Empirical data: Using $r\&d\_inn_{i,p}$	Empirical data: Using $fix\_inn_{i,p}$
All firms	−0.698%	−0.632%	−0.448%
Less diversified firms only	−0.999%	−0.924%	−0.456%

implement more innovation on average and also have a higher volatility and cross-sectional dispersion of profits. In this case the exclusion of sector fixed effects should bias the coefficient of $sdroa\_1_{s,p}$ upward. This claim is confirmed by Table 14, which estimates the effect of uncertainty with and without including the set of control variables. The first five columns estimate the model with $r\&d\_inn_{i,p}$ as the dependent variable. In Column 1, no control variable is included. In Column 2, I include only the sector and survey dummies. In Column 3, I include the control variables representing internationalization and market structure; in Column 4, the variable that controls for the average profitability of the firms in the sectors; and, in Column 5, the full specification. The coefficient of $sdroa\_1_{s,p}$ is negative and significant in all specifications except the first one. In this case, the coefficient of $sdroa\_1_{s,p}$ becomes positive, because the volatility of profits and the frequency of innovation are positively correlated across two-digit sectors and across surveys and, therefore, if these dummies are omitted the coefficient of $sdroa\_1_{s,p}$ is biased upward, for both entrepreneurial and nonentrepreneurial firms (see the last row of Table 14). Similar results are found when I use $fix\_inn_{i,p}$ as the dependent variable, in the second part of the table, in columns 6 to 10.

Therefore, for the results presented above to be explained by an endogeneity problem, some other factor, which varies across three-digit sectors, would at the same time be negatively correlated with the risky innovation of entrepreneurial firms and positively correlated with the volatility of profits in the sector.

Table 14
Relation between risk and innovation: equation selection (financially constrained firms excluded).

All regressions are estimated with a maximum likelihood probit estimator. A Huber and White estimator of the variance–covariance matrix is used to correct for heteroskedasticity. Standard errors are clustered at the three digit sector level. The z statistic is reported in parenthesis. * denotes significance at the 90% confidence level; ** significance at the 95% confidence level; *** significance at the 99% confidence level. $r\&d\_inn_{i,p}$ is equal to one if more than 50% of research and development (R&D) spending of firm i in survey p is directed to develop new products and equal to zero otherwise. $fix\_inn_{i,p}$ is equal to one if fixed investment spending of firm i is partly or fully directed to the introduction of new products and equal to zero otherwise. The dependent variable is innovation decision $y_{i,p}$. $sdroa\_1_{i,s}$ is the standard deviation of the cross section of the gross income/assets ratio for the firms in the three-digit sector s in the most recent year of each survey. $export_{i,p}$ is equal to one if firm i exports part of its production outside Italy and equal to zero otherwise. $supply_{i,p}$ is equal to one if firm i produces 100% of its output based on the order placed by downstream firms and equal to zero otherwise. $constrained_{i,p}$ is equal to one if the firm declares financing constraints and equal to zero otherwise. $avgroa\_1_{i,s}$ is the cross-sectional mean of the return on assets for sector s in the most recent year of the survey. $size_{i,p}$ is the number of employees of firm i. $age_{i,p}$ is the age of the firm (relative to the year of the survey) in years. *Dummies* are two-digit sector dummy variables and survey dummy variables.

	$y_{i,p}=r\&d\_inn_{i,p}$ (entrepreneurial firms)					$y_{i,p}=fix\_inn_{i,p}$ (entrepreneurial firms)				
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$sdroa\_1_{s,p}$	5.01***	−7.58***	−7.62***	−7.38***	−7.36***	2.79*	−3.21*	−3.19*	−5.18**	−5.21**
	(3.0)	(−3.4)	(−3.4)	(−3.1)	(−3.0)	(1.8)	(−1.7)	(−1.7)	(-2.5)	(2.5)
$export_{i,p}$			0.49***	0.49***	0.40***			0.27***	0.26***	0.16***
			(6.5)	(6.6)	(5.2)			(4.6)	(4.4)	(2.6)
$supply_{i,p}$			−0.22***	−0.22***	−0.20***			−0.11**	−0.12**	−0.10*
			(−3.4)	(−3.4)	(−3.2)			(−2.0)	(−2.1)	(−1.8)
$avgroa\_1_{s,p}$				−0.62	−0.49				4.99**	5.56***
				(−0.3)	(−0.2)				(2.4)	(2.6)
ln $(size_{i,p})$					0.25***					0.27***
					(6.5)					(7.9)
$age_{i,p}$					0.001					0.006*
					(0.2)					(1.6)
$age^2_{i,p}$					−0.00003					−0.0001**
					(−0.6)					(−2.1)
dummies	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Number of observations	3,063	3,023	3,022	3,022	3,014	3,063	3,023	3,033	3,033	3,024
Pseudo R^2	0.003	0.08	0.10	0.10	0.12	0.001	0.03	0.03	0.04	0.06
	$y_{i,p}=r\&d\_inn_{i,p}$ (nonentrepreneurial firms)					$y_{i,p}=fix\_inn_{i,p}$ (nonentrepreneurial firms)				
$sdroa\_1_{s,p}$	6.12***	−0.90	−1.69	−0.92	−1.77	4.06***	0.25	−0.07	−0.48	−0.95
	(5.9)	(−0.7)	(−1.2)	(−0.6)	(−1.1)	(4.2)	(0.2)	(−0.1)	(-0.4)	(−0.7)

In Tables 15 and 16, I provide two further robustness checks that rule out this hypothesis. In Table 15, I include three-digit sector dummies in the estimation. This implies that the coefficient of $sdroa\_1_{s,p}$ is identified only by variations in uncertainty in each sector over time, not by changes across sectors. The combined presence of three-digit sector fixed effects and survey fixed effects controls for the impact of any sector-specific unobserved variable and for any survey-specific effect.[17] Moreover, I substitute the control variables $supply_{i,p}$, $constrained_{i,p}$, $avgroa\_1_{i,p}$, $\ln(size_{i,p})$, $age_{i,p}$, and $age^2_{i,p}$ with sector-specific variables. For example, I substitute $constrained_{i,p}$ with $constrained_{s,p}$, the latter being the fraction of constrained firms in sector s and survey p. This change takes into account the fact that such variables at firm level are also possibly endogenous. Table 15 shows that the coefficient of $sdroa\_1_{s,p}$ is very similar, across the different groups, to the coefficient estimated in the regressions that included only two-digit sector dummies (see Table 10). At the bottom of Table 15, I report the estimated coefficient of $sdroa\_1_{s,p}$ for the groups of firms selected according to diversification and to financing constraints. When using the R&D indicator $r\&d\_inn_{i,p}$ as a measure of financing frictions, these results also confirm the prediction that undiversified entrepreneurial firms are those with the highest sensitivity of risky innovation to uncertainty.

Finally, Table 16 proposes an instrumental variable estimation. I instrument the variable $sdroa\_1_{s,p}$ with $sdroaUS\_1_{s,p}$, which is the cross-sectional standard deviation computed for US manufacturing firms in sector s and in the last year of survey p. From Compustat, I obtain an unbalanced panel of 4,189 manufacturing firms for the 1992–2000 period. I then compare the four-digit North American Industry Classification System (NAICS) code of these firms with the three-digit Industry Classification System code of the Italian sample (ATECO). Because of several differences in the two classification schemes, I could obtain a good match for just 57 of the 136 ATECO sectors.

[17] For example, it could be that the sectors in which the frequency of innovation and the volatility of profits is higher are also those where human capital and know-how are more important for innovation. Then it could be that entrepreneurial firms invest less in those sectors not because they suffer more from risk but because they do not have the human capital or the know-how necessary to innovate. This alternative explanation would imply that by adding fixed effect to the regression the negative effect of uncertainty on entrepreneurial innovation should be eliminated.

Table 15
Relation between risk and innovation, empirical data, fixed effects at the three-digit sector level included.

All regressions are estimated with a maximum likelihood probit estimator. A Huber and White estimator of the variance–covariance matrix is used to correct for heteroskedasticity. Standard errors are clustered at the three digit sector level. The z statistic is reported in parenthesis. * denotes significance at the 90% confidence level; ** significance at the 95% confidence level; *** significance at the 99% confidence level. $r\&d\_inn_{i,p}$ is equal to one if more than 50% of research and development (R&D) spending of firm i in survey p is directed to develop new products and equal to zero otherwise. $r\&d\_t.a._{i,p}$ is equal to one if firm i did R&D activity in survey p but $r\&d\_inn_{i,p}=0$ and equal to zero otherwise. $fix\_inn_{i,p}$ is equal to one if fixed investment spending of firm i is partly or fully directed to the introduction of new products and equal to zero otherwise. $fix\_t.a_{i,p}$ is equal to one if firm i undertook a new fixed investment project but $fix\_inn_{i,p}=0$ and equal to zero otherwise. The dependent variable is innovation decision $y_{i,p}$. $sdroa\_1_{i,s}$ is the standard deviation of the cross section of the gross income/assets ratio for the firms in the three-digit sector s in the most recent year of each survey. $export_{i,p}$ is equal to one if firm i exports part of its production outside Italy and equal to zero otherwise. $supply_{i,p}$ is equal to one if firm i produces 100% of its output based on the order placed by downstream firms and equal to zero otherwise. $constrained_{i,p}$ is equal to one if the firm declares financing constraints and equal to zero otherwise. $avgroa\_1_{i,s}$ is the cross-sectional mean of the return on assets for sector s in the most recent year of the survey. $size_{i,p}$ is the number of employees of firm i. $age_{i,p}$ is the age of the firm (relative to the year of the survey) in years. Three-digit sector dummy variables and survey dummy variables are also included. In columns labeled "Entr." only entrepreneurial firms are included in the estimation. In columns labeled "Other" all firms except the entrepreneurial firms are included in the estimation.

	$y_{i,p}=r\&d\_inn_{i,p}$		$y_{i,p}=r\&d\_t.a_{i,p}$		$y_{i,p}=fix\_inn_{i,p}$		$y_{i,p}=fix\_t.a._{i,p}$	
Variable	Entr.	Other	Entr.	Other	Entr.	Other	Entr.	Other
$sdroa\_1_{s,p}$	−5.19**	−1.42	5.04	1.07	−5.13**	−0.26	2.69	−0.19
	(−2.1)	(−0.9)	(1.5)	(0.6)	(−2.3)	(−0.1)	(1.4)	(−0.1)
$export_{s,p}$	0.71	0.74	0.51	0.52**	0.26	0.35	0.15	0.03
	(1.5)	(2.5)	(1.2)	(2.0)	(0.6)	(1.4)	(0.4)	(0.1)
$supply_{s,p}$	−0.45	0.20	−0.35	0.12	0.09	0.25	0.27	−0.33
	(−0.9)	(0.7)	(−1.0)	(0.5)	(0.2)	(1.0)	(0.8)	(−1.3)
$constrained_{s,p}$	−1.04	0.40	0.85	−0.50	0.37	0.63	−0.07	−0.38
	(−1.3)	(0.8)	(1.0)	(−1.1)	(0.4)	(1.3)	(−0.1)	(−0.9)
$avgroa\_1_{s,p}$	1.00	−0.67	−2.92	−1.60	3.74	3.86**	−0.64	−1.86
	(0.3)	(−0.4)	(−1.1)	(−0.9)	(1.3)	(2.1)	(−0.3)	(−1.2)
$\ln(size_{s,p})$	0.06	−0.03	0.12	0.21	0.40**	0.08	−0.26	−0.15
	(0.6)	(−0.2)	(0.6)	(1.4)	(2.2)	(0.7)	(−1.4)	(−1.3)
$age_{s,p}$	0.025	0.063**	−0.12*	−0.09***	0.12**	0.03	−0.17	−0.02
	(0.5)	(2.1)	(−1.7)	(−3.5)	(2.3)	(1.1)	(−3.2)	(−0.6)
$age^2_{s,p}$	−0.0001	−0.001**	0.002	0.001***	−0.002	−0.0005	0.003	0.0003
	(−0.1)	(−2.3)	(1.7)	(4.0)	(−2.0)	(−1.2)	(3.1)	(0.7)
Number of observations	3,507	7,703	3,601	7,753	3,591	7,759	3,620	7,759
Pseudo R^2	0.095	0.080	0.048	0.040	0.044	0.033	0.047	0.03
Coefficient of $sdroa\_1_{s,p}$ for firms selected according to diversification and financing constraints								
$divers_{i,p} \leq 0.5$	−7.06**	−2.10	3.73	1.96	−4.08*	−2.18	−1.90	0.39
	(−2.1)	(−1.2)	(1.1)	(0.9)	(−1.7)	(−1.0)	(−0.8)	(0.25)
$divers_{i,p} \leq 0.5$ and not constrained	−14.01***	−4.09**	3.06	2.81	−5.12	−3.24	−1.05	1.41
	(−3.2)	(−2.2)	(1.0)	(1.1)	(−1.5)	(−1.4)	(−0.3)	(0.8)

I then used the US data to compute the cross-sectional standard deviation of return on assets for all the matched sectors with at least 15 firms, obtaining the values of the instrument for 43 sectors for three survey periods. Using the instrument comes at the cost of dropping around two-thirds of the sample. However, it has the advantage of being orthogonal to any unobservable factor that is specific to the Italian firms and that could drive the observed correlation between uncertainty and entrepreneurial innovation.[18] Table 16 shows the estimation results and it reports, for the sake of brevity, only the estimates of the coefficient of $sdroa\_1_{s,p}$ for all the different regressions. When using $r\&d\_inn_{i,p}$, which the previous analysis in Section 4.1.2 has shown to be the most reliable measure of risky innovation, the estimated sensitivity of innovation to uncertainty confirms the previous results: Greater uncertainty reduces risky innovation for entrepreneurial firms, especially undiversified ones, while it does not reduce the risky innovation of the other firms. Conversely, risky innovation as measured by $y_{i,p}=fix\_inn_{i,p}$ is not affected by uncertainty for all firms.

5. Conclusions

I develop a model in which undiversifiable risk matters for the investment decisions of an entrepreneurial firm, and I analyze the consequences for the relation between uncertainty and risky innovation. The predictions of the model are confirmed by the empirical analysis of a sample of small and medium-size Italian manufacturing firms.

The main message of this paper is that the effect of uncertainty on entrepreneurial innovation is quantitatively significant. The results of the estimation imply that a 1% increase in the cross-sectional standard deviation of

[18] The validity of the instrument is confirmed by the results of the first-stage regression. $sdroaUS\_1_{s,p}$ is significantly correlated to $sdroa\_1_{s,p}$, and such correlation also holds separately for the sectors with higher and lower frequency of entrepreneurial firms.

Table 16
The relation between risk and innovation, empirical data, fixed effects at the three digits level and instrumental variable estimation.

All regressions are estimated with an instrumental variable probit using Newey's (1987) efficient two-step estimator. The endogenous regressor $sdroa\_1_{s,p}$ is instrumented using $sdroaUS\_1_{s,p}$, which is the cross-sectional standard deviation computed for US manufacturing firms in sector s and in the last year of survey p. The z statistic is reported in parenthesis. * denotes significance at the 90% confidence level; ** significance at the 95% confidence level; *** significance at the 99% confidence level. $r\&d\_inn_{i,p}$ is equal to one if more than 50% of research and development (R&D) spending of firm i in survey p is directed to develop new products and equal to zero otherwise. $r\&d\_t.a._{i,p}$ is equal to one if firm i did R&D activity in survey p but $r\&d\_inn_{i,p}=0$ and equal to zero otherwise. $fix\_inn_{i,p}$ is equal to one if fixed investment spending of firm i is partly or fully directed to the introduction of new products and equal to zero otherwise. $fix\_t.a_{i,p}$ is equal to one if firm i undertook a new fixed investment project but $fix\_inn_{i,p}=0$ and equal to zero otherwise. The dependent variable is innovation decision $y_{i,p}$. The independent variables are as follows: $sdroa\_1_{i,s}$ is the standard deviation of the cross section of the gross income/assets ratio for the firms in the three-digit sector s in the most recent year of each survey. $export_{i,p}$ is equal to one if firm i exports part of its production outside Italy and equal to zero otherwise. $supply_{i,p}$ is equal to one if firm i produces 100% of its output based on the order placed by downstream firms and equal to zero otherwise. $constrained_{i,p}$ is equal to one if the firm declares financing constraints and equal to zero otherwise. $avgroa\_1_{i,s}$ is the cross-sectional mean of the return on assets for sector s in the most recent year of the survey. $size_{i,p}$ is the number of employees of firm i. $age_{i,p}$ is the age of the firm (relative to the year of the survey) in years. $d^{survey}_{i,p}$ is a series of dummy variables that are equal to one if firm i is surveyed in survey p and equal to zero otherwise. In columns labeled "Entr." only entrepreneurial firms are included in the estimation. In columns labeled "Other" all firms except the entrepreneurial firms are included in the estimation. $divers_{i,p}$ is the average of the ratio between the net financial assets and total assets for firm i in survey p.

	$y_{i,p}=r\&d\_inn_{i,p}$		$y_{i,p}=r\&d\_t.a_{i,p}$		$y_{i,p}=fix\_inn_{i,p}$		$y_{i,p}=fix\_t.a._{i,p}$	
Variable	Entr.	Other	Entr.	Other	Entr.	Other	Entr.	Other
Panel A: Coefficient $sdroa\_1_{s,p}$, two-digit fixed effects included								
All firms	−15.5*	−6.86	−9.21	−6.12	3.09	−4.0	−7.8	1.97
	(−1.61)	(−1.12)	(−0.96)	(−1.03)	(0.36)	(−0.71)	(−0.93)	(0.36)
Number of observations	1,108	2,610	1,108	2,630	1,108	2,630	1,112	2,630
$divers_{i,p} \leq 0.5$	−28.8**	0.54	8.19	−12.52	0.45	1.27	−5.83	−9.78
constrained excluded	(−2.01)	(0.07)	(0.58)	(−1.55)	(0.04)	(0.17)	(−0.47)	(−1.31)
Number of observations	465	1,370	465	1,386	475	1,384	480	1,384
Panel B: Coefficient $sdroa\_1_{s,p}$, three-digit fixed effects included								
All firms	−46.8*	−0.31	8.7	−9.30	3.59	−1.5	−9.04	2.05
	(−1.84)	(−0.02)	(0.43)	(−0.70)	(0.19)	(−0.12)	(−0.49)	(0.17)
Number of observations	1,033	2,606	1,095	2,617	1,091	2,626	1,106	2,626
$divers_{i,p} \leq 0.5$ &	−82.5**	5.36	51.8	−25.7	5.2	12.8	−16.9	−24.8
constrained excluded	(−1.96)	(0.29)	(1.39)	(−1.36)	(0.17)	(0.73)	(−0.56)	(−1.44)
Number of observations	426	1,367	446	1,376	449	1,381	459	1,381

profits reduces the frequency of risky innovation of entrepreneurial firms by -0.69%. Moreover, the drop in risky innovation for the less diversified entrepreneurial firms is estimated as being as much as -0.92%. If one believes that the level of uncertainty faced by firms varies significantly in the business cycle, and that entrepreneurial innovation is a source of growth and positive externalities for the economy, then this finding implies that the uncertainty–innovation relation has an important impact on both business cycle fluctuations and growth.

Appendix

The dynamic investment problem of the entrepreneurial firm is solved with a numerical method. First, I discretize the state space of the state variables w_t and A_t in grids of 600 points and 10 points, respectively. Then I formulate an initial guess of $E_t[V(w_{t+1},A_{t+1})]$, and I use it to compute the value functions $V_t^{up}(w_t,A_t)$ and $V_t^{noup}(w_t,A_t)$. Then I compare the two function and determine the new guess of $V(w_t,A_t)$. I iterate this process until the value function converges. The final outcome is the optimal policy functions of consumption $c_t(w_t,A_t)$, capital $k_{t+1}(w_t,A_t)$, borrowing $b_{t+1}(w_t,A_t)$, and innovation decision $I_t(w_t,A_t)$.

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