Financing Constraints, Radical versus Incremental Innovation, and Aggregate Productivity: Online Appendix

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A Data description

I Description of the sample

The dataset comprises 3 Mediocredito/Capitalia Surveys of manufacturing firms released in 1995, 1998 and 2001. Each survey covers a three-year period, 1992–1994, 1995–1997 and 1998–2000, and analyzes a random sample of approximately 4500 firms with 10 or more employees. For firms with up to 500 employees, the sample is representative of the geographical and sectorial distribution of the population of firms. Moreover, it also includes a random selection of firms larger than 500 employees. Since some firms are retained in the sample for more than one survey, after the selection procedure described below in Subsection III, the main analysis is performed on a sample of 12952 firm-survey observations, of which 9105 are observations of firms appearing in only one survey, 3172 are observations of firms appearing in two surveys, and 675 are observations of firms appearing in all 3 surveys.

I report in Table 1 the size and age distribution of firms in the Italian industry and in the Mediocredito sample. As noted in Caggese and Cunat (2013), in this sample, small firms are underrepresented, and large firms are overrepresented, relative to the population of Italian firms with more than 10 employees.

In addition to the surveys, up to 9 years of balance sheet data are available for each surveyed firm. However, such data might be repeated when a firm is present in more than one survey. For example, suppose that a firm is surveyed in both 1998 and 2001, and the 1998 survey has balance sheet data from 1992 to 1998, while the 2001 survey has data from 1995 to 2000. In this case, the

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Table 1: Size and age distribution of firms in the empirical sample

Size class (n.of employees)	Italian Manufacturing sector	Mediocredito sample
10-49	41%	10.5%
50-99	13%	7.9%
100-199	12%	9.8%
200-499	12%	17.8%
500-999	7%	16.0%
1000 or more	15%	38.0%
Age class (years)	Italian Industry*	Mediocredito sample
0-5 years	14%	4.2%
6-10 years	11%	8.3%
11-15 years	13%	10.2%
16 years or older	62%	77.3%

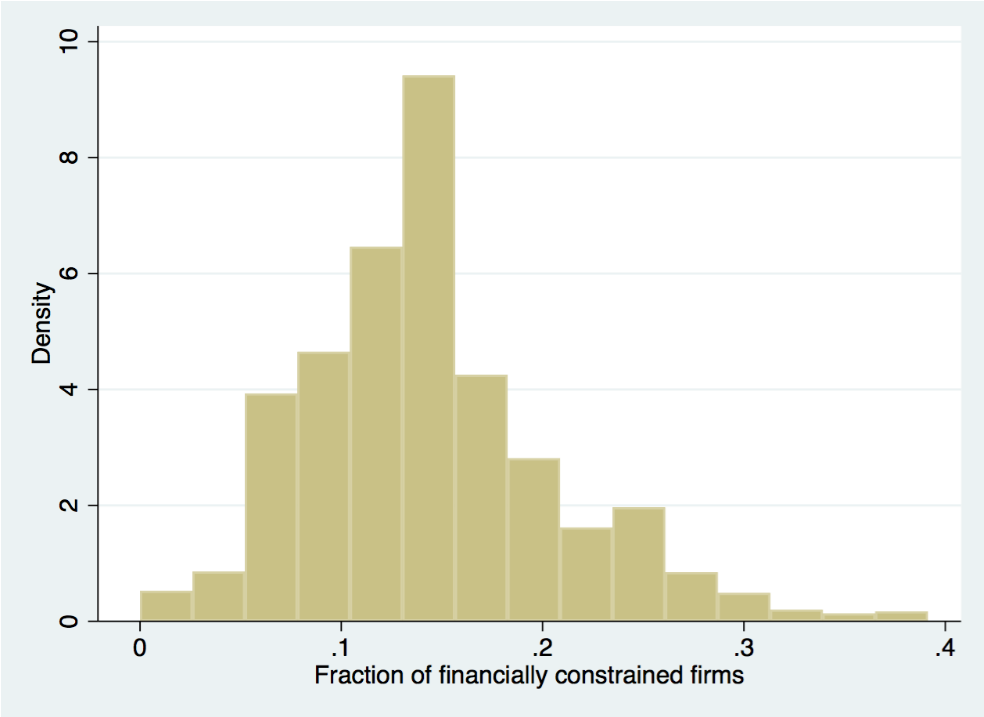
*Age distribution is from the 2011 census of Italian industry. It is for the whole of the Italian industry (mining, manufacturing, and water and electricity supply) except construction, because disaggregated manufacturing data are not available. The size distribution data are also from the same 2011 census.

years 1995–1997 appear twice. I treat these duplicate values as follows: if they coincide perfectly, I eliminate them and consolidate the time series, meaning that the firm in the example would have one series of balance sheet data from 1992 to 2000. However, in some cases, these overlapping data might present some discrepancies. Usually these are small rounding errors, but in some cases they are larger, perhaps reflecting measurement errors or mistakes in the code that identifies the firms. To minimize the likelihood of errors, I decided, for all these discrepancies, to discard the balance sheet data from the oldest survey and retain only those from the most recent survey. This correction eliminates 2.6% of all the firm-year balance sheet data. After this correction, I have a total of 54886 unique firm-year observations with complete balance sheet data that can be used to estimate productivity.

The surveys cover a wide range of firm activity. In the "Technological innovation and R&D" section, firms are asked whether, in the 3 years surveyed, they introduced an innovation in the production process. In the 1995 survey, multiple answers are allowed in the following categories: i) product innovation and ii) process innovation. In the 1998 and 2001 surveys, the additional allowed answers are iii) organizational innovations related to product innovations and iv) organizational innovations related to process innovations.

Furthermore, a separate question asks whether the firm engaged in R&D activity in the previous three years. The firms that answer yes are asked what the amount spent in each of the three years of the survey was, and what percentage of this expenditure was directed toward i) improving existing products; ii) improving existing productive processes; iii) introducing new products; iv) introducing new productive processes; and v) other objectives.

Figure 1: Distribution of the fraction of financially constrained firms across 4-digit sectors



I obtain the information on financing frictions in the section of the surveys on “Finance”. Firms are asked whether, in the last year of each survey, Q1) they desired more credit at the market interest rate; Q2) they were willing to pay a higher interest rate than the market rate to obtain credit; and Q3) they had a loan application rejected. In the 1995 survey, these questions are asked independently, while in the 1998 and 2001 surveys, Q2 and Q3 are only asked to firms that respond in the affirmative to Q1.

II Financial frictions indicators

The benchmark indicator $finprob_{i,s}$ that takes values from 0 (no problem reported) to a maximum of 3 (all problems reported) for firm i in survey s. This indicator is averaged for each 4-digit sector (after excluding the 25% least profitable firms) to obtain the sector-level indicator $finprob_j$. Figure 1 shows the percentage of firms reporting some type of financial problem for each four-digit sector with at least 10 firms. Table 2 shows the list of 2-digit sectors and the fraction of firm-survey observations in the 50% most constrained and the 50% least constrained sectors. Finally, Appendix F lists all four-digit sectors and the financial frictions groups to which they belong.

As a robustness check, I consider 5 alternative financial frictions indicators.

Table 2: Frequency of constrained and unconstrained firms in each 2 digit manufacturing sector

Sector	2 digits Ateco 91 code	Fraction of firms in the group of 50% most constrained 4 digits sectors	Fraction of firms in the group of 50% least constrained 4 digits sectors
Food and Drinks	15	62%	38%
Textiles	17	21%	79%
Shoes and Clothes	18	31%	69%
Leather products	19	40%	60%
Wood Furniture	20	75%	25%
Paper	21	72%	28%
Printing	22	57%	43%
Chemical, Fibers	24	32%	68%
Rubber and Plastic	25	20%	80%
Non-metallic products	26	54%	46%
Metals	27	30%	70%
Metallic products	28	63%	37%
Mechanical Products	29	46%	54%
Electrical Products	31	89%	11%
Television and comm.	32	41%	59%
Precision instruments	33	74%	26%
Other transportation vehicles	35	52%	47%
Other manufacturing	36	81%	18%

Constrained sectors are those with highest frequency of firms declaring some type of financial problem.

Three are directly based on survey responses. The fourth is the Rajan and Zingales (1998) external financial dependence indicator. The fifth is an instrumented version of the survey-based indicator. The three alternative indicators based on survey responses are as follows:

$finprob1_{i,s}$ is equal to one if firm i reports having faced some type of financial problem in survey s, zero otherwise.

$finprob2_{i,s}$ is equal to one if the firm answers question Q1 in the affirmative, zero otherwise.

$finprob3_{i,s}$ considers only the 1998 and 2001 surveys, which have identical structure. It assigns a 50% weight to each follow-up question and therefore takes values of 0 (no problems), 1 (affirmative answer to Q1), 1.5 (affirmative answer to Q1 and to one of the follow-up questions) and 2 (all three problems). It is straightforward that assigning a 100% weight to the two follow-up questions would make $finprob3_{i,s}$ identical to the benchmark indicator $finprob_{i,s}$.

I compute the external financial dependence indicator for firm i in survey s, $EFD_{i,s}$, following Rajan and Zingales, as follows:

$$EFD_{i,s} = \frac{capexp_{i,s} - cashflow_{i,s}}{capexp_{i,s}}$$

I measure $capexp_{i,s}$ from a section of the surveys where firms report their plant and equipment expenditures. I measure $cashflow_{i,s}$ as cash flows from operations (sales - purchases - energy costs - labor cost - taxes) minus the reduction in the net short-term debt position versus customers and suppliers. In both cases, I consider average yearly values for the 3 years of survey s. Then, I compute the value of $EFD_{j,s}$, for the four-digit sector j as the mean of the firm-level value after excluding the 5% tails. Its median value is -.81, and the 10th and 90th percentiles are -1.78 and 0.2, respectively.

The fifth alternative indicator is an instrumented version of the indicator $finprob1_{i,s}$. Guiso, Sapienza and Zingales (2004) show that local financial development is a powerful predictor of the ability of firms and households to access credit in Italy. Differences in financial development across geographical areas are related to different historical developments and are therefore unlikely to be caused by the recent growth opportunities of firms. Pascali (2016) supports this view by showing a causal effect of the presence of Jewish communities in the Middle Ages on current financial development. Jews arrived in Italy during the Roman Empire, and Pascali's (2016) dataset documents the distribution of their communities in 1500. The dataset is collected from historiographical studies, where communities are classified as small (a dozen families), medium (a few dozen families), and large (several dozen families). At the end of the fourteenth century, a sudden change in Catholic doctrine prohibited Catholics from lending for profit but still allowed Jews to do so. Pascali shows that the money-lending businesses of these Jewish communities led to the creation of charitable loan banks, called Monti di Pietà, that were intended to drive the Jews out of the local financial market. The Monti have survived to the present day and gave rise to a significant portion of contemporary Italian banks. Interestingly, Pascali identifies significant differences in

Table 3: First-stage regression

Dependent variable	$finprob1$
Constant	-0.86***
	(0.047)
Small Jewish Community	-0.152**
	(0.068)
Medium Jewish Community	-0.007
	(0.097)
Large Jewish Community	0.183
	(0.125)
Wald test	9.83**
number of observations	3099

Probit regression. Dependent variable is equal to 1 if the firm declares financial problems in the 2001 survey, and zero otherwise. Standard errors, reported in parenthesis, are clustered at the town level. Explanatory variables are dummies equal to 1 if a Jewish community was present in the town in 1500, and zero otherwise. Communities are classified as small (a dozen families), medium (a few dozen families), and large (several dozen families). ***, **, * denote significance at a 1%, 5% and 10% level respectively.

financial development between cities, driven by the presence of Jewish communities in the year 1500, even in narrowly defined geographical areas. I match this dataset with the 2001 Mediocredito/Capitalia Survey, which includes the information on the town where each firm has its headquarters. I am able to match 325 towns in the two datasets. Of these, 163 had no Jewish community, while 162 had some type of community: 95 small, 44 medium, and 24 large. These 325 towns host 2095 firms from the dataset, for a total of 3099 firm-survey observations.

I estimate a Probit model where the dependent variable is the binary indicator of any type of financial frictions $finprob1$, and the regressors are the binary variables representing the presence of a Jewish community. Table 3 shows the results. Consistent with the hypothesis in Pascali (2016), the presence of a small Jewish community significantly reduces the probability that sample firms report financial frictions. However, the medium and large Jewish community variables are not significant. Possibly, this is because all the larger cities in the sample have had a medium or large Jewish community, and therefore, the only substantial variation in the sample is between smaller towns with or without a community. The regression results have significant power in predicting financing constraints. Among the group of firms with the lowest predicted probability, 15.4% report a financial problem. This probability increases to 24.7% for the group of firms with the highest predicted probability.

I use the predicted probability $P(finprob1)$ as the instrumented measure of financial frictions. The identification assumption is that sectors span a certain geographical area for reasons unrelated to the presence of Jewish communities centuries ago. In other words, some sectors happen to include a smaller fraction of localities with Jewish communities than other sectors for exogenous reasons and are therefore more likely to face financing frictions that affect barriers to entry, reducing the competition faced by the currently unconstrained firms. It is possible that localities with less financial development might attract systematically worse performing firms. However, to the extent that the geographical location of the sectors is at least partly determined by other factors, such as network externalities and distance to main export countries, the results of this instrumental variable estimator should at least partially control for reverse causality problems.

As for the benchmark indicator, I use these 5 alternative indicators to select industries in the groups of the least and most constrained firms. I first compute the average value of each indicator at the four-digit sector level. In the case of the indicators directly based on survey responses ($finprob1_{i,s}$, $finprob2_{i,s}$, and $finprob3_{i,s}$), I first exclude the 25% least profitable firms. Then, I classify the four-digit sectors into the least and most constrained groups according to these average values. Estimation results are shown in the online Appendix B.

III Estimation of productivity

I follow the Wooldridge (2009) extension of Levinsohn and Petrin (2003). I use the code developed by Petrin for Petrin and Levinsohn (2012) and available at "https:// sites.google.com /a/umn.edu/ amil-petrin/ home/Available-Programs". I consider a log linearized version of Eq.1. Following Petrin and Levinsohn (2012), I also add energy consumption and materials as inputs:

(1)
$$\frac{\sigma}{\sigma-1}\log(p_{i,t}y_{i,t}) = \kappa_i + \gamma_t + \beta_1 \log\left(p^k_{i,t}k_{i,t}\right) + \beta_2 \log\left(w_{i,t}l_{i,t}\right) + \beta_3 \log m_{i,t} + \beta_4 \log e_{i,t} + v^1_{i,t},$$

where $\frac{\sigma}{\sigma-1}$ is the term added following Hsieh and Klenow (2009), who infer quantity TFP from revenue data and the assumed elasticity of demand σ (see Eq. (19) in Hsieh and Klenow, 2009). I use the calibrated value of $\sigma = 4$. Apart from this correction and the fact that I have only total wages rather than blue and white collar wages, this specification is identical to that used in the Petrin and Levinsohn (2012) code. κ_i and γ_t are firm and year fixed effects, respectively. The variables, measured at current prices, are as follows: total output py is total sales; capital pk is the book value of fixed capital; labor wl is the total wage cost; m is the cost of materials; and e represents energy costs. The estimation is performed separately for each two-digit manufacturing sector, with the exception of 4 sectors with fewer than 50 observations, which are excluded (these are "Tobacco", "Oil Refineries", "Computerised Systems", and "Recycling Machinery").

Table 4: Estimated elasticities

Sector	N.Obs.	β_1	β_2	β_3	β_4	Returns to scale
Food and Drinks	4621	0.016	0.137	0.354	0.189	0.697
Textiles	5455	0.056	0.198	0.030	0.323	0.606
Shoes and Clothes	2118	0.035	0.195	0.139	0.315	0.684
Leather products	2294	0.056	0.183	0.384	0.229	0.852
Wood Furniture	1588	0.026	0.185	0.452	0.217	0.879
Paper	1817	0.011	0.212	0.663	0.194	1.079*
Printing	1773	0.005	0.274	0.228	0.344	0.850
Chemical Fibers	2891	0.026	0.189	0.091	0.259	0.564
Rubber and Plastic	3057	0.081	0.214	0.150	0.237	0.682
Non-metallic products	3782	0.046	0.252	0.125	0.326	0.749
Metals	2831	0.041	0.200	0.471	0.204	0.916
Metallic products	4904	0.059	0.230	0.303	0.267	0.860
Mechanical Products	8907	0.020	0.253	0.382	0.260	0.916
Electrical products	2045	0.017	0.241	0.426	0.249	0.933
Television and comm.	1279	0.048	0.249	0.220	0.273	0.789
Precision instruments	840	0.005	0.257	0.537	0.269	1.068**
Vehicles (Cars & Trucks)	1241	-0.010	0.240	0.775	0.174	1.179***
Other transportation vehicles	528	0.082	0.274	0.218	0.287	0.861
Other manufacturing	2915	0.027	0.203	0.349	0.250	0.828

*The null hypothesis of constant returns to scale is not rejected ($Prob > \chi^2 = 0.4721$)

**The null hypothesis of constant returns to scale is not rejected ($Prob > \chi^2 = 0.5264$)

***The null hypothesis of constant returns to scale is rejected ($Prob > \chi^2 = 0.0000$)

β_1: Elasticity of output to fixed capital; β_2: Elasticity of output to labour; β_3: Elasticity of output to materials; β_4: Elasticity of output to energy

Table 4 shows the estimated elasticities.[1] The sum of estimated elasticities is below one for all but three sectors. The sectors "Paper" and "Precision instruments" have a sum slightly larger than one, but the hypothesis of constant returns to scale cannot be rejected. By contrast, the "Vehicles" sector has a sum significantly larger than one and a negative elasticity of capital estimate. For these reasons, I decided to eliminate this sector from the sample. Nonetheless, its inclusion does not significantly affect any of the empirical results of the paper. Following Petrin and Levinsohn (2012), I use the estimated elasticities to compute the estimated productivity measure $\widehat{v}_{i,t}$ as a residual. To reduce the incidence of measurement errors in the estimations of firm level productivity growth, I compute the firm-level volatility of $\widehat{v}_{i,t}$ and I exclude from the sample the 1% of observations with highest volatility. For the estimation of Eqs. (2) and (3), I include observations of $\widehat{v}_{i,t}$ for firms between 3 and 45 years old, and with at least 5 years of balance sheet data.

[1] Computed after correcting for the term $\frac{\sigma}{\sigma-1}$ in Eq. (1).

B Additional regressions

I Nonlinear estimation.

For the piecewise linear estimations in Figure 1 in the paper, I estimate the following model:

$$
\begin{aligned}
(2) \qquad \widehat{v}^{j}_{i,s} &= \beta_0 + \sum_{l=1}^{n} \beta^u_l age^l_{i,s} + \sum_{l=1}^{n} \beta^m_l (midconstr_i * age^l_{i,s}) + \\
&+ \sum_{l=1}^{n} \beta^c_l (highconstr_i * age^l_{i,s}) + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s}
\end{aligned}
$$

I construct a set of variables age^l that is equal to the age of the firm if the firm is in group l, zero otherwise. The index $l = 1, 2, 3, 4$ indicates the age intervals, with $l = 1$ indicating firms with ages up to 10 years, and $l = 2, 3, 4$ indicates firms aged 11–20, 21–30 and 31–40 years, respectively. Firms older than 40 years are excluded from the estimation. The coefficients $\beta^u_1 ... \beta^u_4$ measure the differentials between the growth rates in the least and mid constrained groups. The coefficients $\beta^c_1 ... \beta^c_4$ measure the differentials between the growth rates in the least and most constrained groups. The set of control variables includes fixed effects and time dummies. The estimated coefficients are reported in Table 5. The growth rates are significantly lower for the mid and most constrained groups relative to the least constrained group (the omitted category) for all age classes, except for the coefficient of $age_{1-10_i} * mid\ constrained_s$.

Table 6 shows the estimated coefficients used to construct Figure 2 in the paper. $\%constr_i$ is the fraction of financially constrained firms in the four-digit sector to which firm i belongs, and $\%constr^2_i$ is the fraction squared.

II The relationship between age and productivity: alternative indicators

Tables 7 and 8 report regression results for Eqs. (2) and (3) using the alternative financial frictions indicators. In Table 7, columns 1 to 6, the alternative indicators based on the survey responses confirm the main results shown in Table 1 in the paper. In the mid and most constrained sectors, productivity grows more slowly over a firm's life cycle than in the least constrained sectors. However, productivity growth is not always monotonically decreasing, as financial frictions increase from the mid to the most constrained sectors.[2] In the last two columns, the regressions based on the EFD indicator also show similar results. The interaction coefficients are all negative, albeit generally smaller

[2] Nonetheless, replicating Figure 2 in the paper for these indicators confirms the same pattern as observed for the benchmark indicator: productivity growth monotonously declines as financial frictions increase from the 1st up to the 9th decile. These additional results are available upon request.

Table 5: Relationship between age and productivity (piecewise linear estimation)

age_{1-10_i}	0.0147***(0.0033)
age_{11-20_i}	0.0154***(0.0023)
age_{21-30_i}	0.0153***(0.0019)
age_{31-40_i}	0.0149***(0.0018)
age_{1-10_i}*$mid\ constrained_s$	-0.0039 (0.0040)
age_{11-20_i}*$mid\ constrained_s$	-0.0061**(0.0028)
age_{21-30_i}*$mid\ constrained_s$	-0.0053**(0.0024)
age_{31-40_i}*$mid\ constrained_s$	-0.0053**(0.0022)
age_{1-10_i}*$most\ constrained_s$	-0.0085**(0.0040)
age_{11-20_i}*$most\ constrained_s$	-0.0079***(0.0027)
age_{21-30_i}*$most\ constrained_s$	-0.0069***(0.0023)
age_{31-40_i}*$most\ constrained_s$	-0.0074***(0.0022)
N.observations	9940
Firm fixed effects	yes
Time dummies	yes

Panel regression with firm fixed effect. Dependent variable is estimated total factor productivity $\widehat{v}_{i,s}$. Standard errors are clustered at the firm level. The variance-covariance matrix is estimated with a bootstrap procedure with 50000 replications. Standard errors reported in parenthesis. $age_{y-y+1,i}$ is a dummy equal to 1 if the age of firm i is between y and y+t, and zero otherwise. $mid\ constrained_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the median percentage of financially constrained firms, and zero otherwise. $most\ constrained_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10%.

Table 6: Relationship between age and productivity (nonlinear effects of financial frictions)

$age_{i,s}$	0.0214***
	(0.0034)
$age_{i,s}$*$\%constr_i$	-0.121***
	(0.034)
$age_{i,s}$*$\%constr_i^2$	0.266***
	(0.080)
N.observations	10409
Adj. R-sq.	0.081
Firm fixed effects	yes
Time*group dummies	yes

Panel regression with firm fixed effect. Dependent variable is estimated total factor productivity $\widehat{v}_{i,s}$. Standard errors are clustered at the firm level. The variance-covariance matrix is estimated with a bootstrap procedure with 50000 replications. Standard errors reported in parenthesis. $age_{i,s}$ is age in years for firm i in survey s. $\%constr_i$ is the fraction of financially constrained firms in the four digit sector to which firm i belongs, $\%constr_i^2$ is the fraction squared. ***, **, * denote significance at a 1%, 5% and 10%.

and less significant than in columns 1 to 6. This lower significance is likely because the EFD indicator is based on balance sheet data rather than on direct survey information. It captures financing needs but does not capture other sector-specific characteristics, such as the level of informational asymmetries, that affect financial frictions. Consistent with this interpretation, the second row of the table shows that the correlation between the financial problems indicators and EFD is positive and significant, albeit relatively small.

The instrumented results are shown in Table 8. They confirm the negative effect of financial frictions on productivity growth. The constrained group in column 1 and the most constrained group in column 2 have significantly lower productivity growth than the least constrained firms, although the coefficients are generally somewhat smaller and less significant than in the non-instrumented regressions.

III The relationship between age and productivity: weighted regressions

In Table 9, I estimate Eqs. (2) and (3) with weighed regressions. I use probabilistic weights that correct the underrepresentation of smaller firms shown above in Table 1. The weighted results look very similar to the unweighted ones presented in Table 1 in the paper.

Table 7: Relationship between age and productivity. Alternative financial frictions indicators

Indicator:	$finprob1_{i,s}$		$finprob2_{i,s}$		$finprob3_{i,s}$		$EFD_{i,s}$	
Corr. with EFD	0.18**		0.18**		0.15*		1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$age_{i,s}$	0.0132***	0.0143***	0.0120***	0.0141***	0.0127***	0.0160***	0.0114***	0.0128***
	(10.8)	(9.4)	(9.8)	(8.7)	(11.4)	(11.1)	(10.9)	(9.8)
$age_{i,s}*constr_i$	-0.00555***		-0.00359**		-0.00423**		-0.00182	
	(-3.6)		(-2.3)		(-2.7)		(-1.3)	
$age_{i,s}*midc_i$		-0.00649**		-0.00492**		-0.0100***		-0.00251
		(-3.2)		(-2.3)		(-5.2)		(-1.4)
$age_{i,s}*highc_i$		-0.00551**		-0.00557**		-0.00607**		-0.00453**
		(-2.9)		(-2.8)		(-3)		(-2.5)
N.obs.	10380	10380	9649	9649	7963	7963	11094	11094
Adj. R-sq.	0.084	0.084	0.082	0.086	0.096	0.104	0.086	0.087

Panel regression with firm fixed effect. Dependent variable is estimated total factor productivity $\widehat{v}_{i,s}$. Time*constrained group dummies are included as regressors. Standard errors are clustered at the firm level. The variance-covariance matrix is estimated with a bootstrap procedure with 50000 replications. z-statistic reported in parenthesis. $age_{i,s}$ is age in years for firm i in survey s. $constrained_i$, is equal to one if firm i belongs to the 50$\%$ of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. $midconstr_i$, is equal to one if firm i belongs to the 33$\%$ of 4-digit manufacturing sectors with the median percentage of financially constrained firms, and zero otherwise. $highconstr_i$, is equal to one if firm i belongs to the 33$\%$ of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. In columns 1-2 financial frictions are measured with $finprob1_{i,s}$, which is equal to one if firm i declares to face some type of financial problem in survey s, and is equal to zero otherwise; in columns 3-4 by $finprob2_{i,s}$, which is equal to one if the firm answers positively to the question "did the firm desire more credit at the market interest rate?" , and zero otherwise; in columns 5-6 by $finprob3_{i,s}$,which takes values of 0 (no problem), 1 (firms desired more credit at the market rate), 1.5 (firms desired more credit at the market rate, and answers positively also to one of the two follow up questions "was the firm willing to pay a higher interest rate than the market rate to obtain credit?" or "has the firm had a loan application turned down?"), and 2 (all three problems); in columns 7-8 by $EFD_{i,s}$, the value of the external financial dependence indicator EFD constructed following Rajan and Zingales (1998). ***, **, * denote significance at a 1%, 5% and 10% level respectively.

Table 8: Relationship between age and productivity, instrumented financial frictions indicator

Indicator:	$\text{P}(finprob1_{i,s})$	$\text{P}(finprob1_{i,s})$
$age_{i,s}$	0.0123***	0.0107***
	(11.5)	(8.3)
$age_{i,s}$*$constr_i$	-0.00469**	
	(-3.2)	
$age_{i,s}$*$midconstr_i$		0.0006
		(0.4)
$age_{i,s}$*$highconstr_i$		-0.00322*
		(-1.8)
N.obs.	10225	10225
Adj. R-sq.	0.082	0.081
Time dummies	yes	yes

Panel regression with firm fixed effect. Dependent variable is estimated total factor productivity $\widehat{v}_{i,s}$. Standard errors are clustered at the firm level. The variance-covariance matrix is estimated with a bootstrap procedure with 50000 replications. z-statistic reported in parenthesis. $age_{i,s}$ is age in years for firm i in survey s. $constrained_i$, is equal to one if firm i belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. $midconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the median percentage of financially constrained firms, and zero otherwise. $highconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. The indicator of financial friction is $\text{P}(finprob1_{i,s})$, which is the predicted probability that a firm declares some type of financial friction. The predictor is the presence of Jewish communities before the year 1500 in the town where the firm had the headquarters. ***, **, * denote significance at a 1%, 5% and 10% level, respectively.

Table 9: Relationship between age and productivity (weighted regressions)

$age_{i,s}$	.0129***	.0124***	.0133***	.0142***	.0138***	.0149***
	(9.3)	(8.9)	(9)	(7.1)	(6.7)	(6.7)
$age_{i,s}$*$constr_i$	-.00711***	-.00592***	-.00668***			
	(-4)	(-3.4)	(-3.6)			
$age_{i,s}$*$midc_i$				-.00586**	-.00516**	-.00624**
				(-2.4)	(-2.1)	(-2.4)
$age_{i,s}$*$highc_i$				-.00815***	-.00716**	-.00782**
				(-3.4)	(-2.9)	(-3)
N.observations	10401	10401	9901	10401	10401	9901
Adj. R-sq.	0.066	0.068	0.072	0.064	0.068	0.072
Time dummies	yes	no	no	yes	no	no
Time*group dummies	no	yes	yes	no	yes	yes
Constrained excluded	no	no	yes	no	no	yes

Panel regression with firm fixed effect. Dependent variable is estimated total factor productivity $\widehat{v}_{i,s}$. Robust standard errors, and probabilistic weights that correct the underrepresentation of smaller firms shown in Table 1.T-statistic reported in parenthesis. $age_{i,s}$ is age in years for firm i in survey s. $constrained_i$, is equal to one if firm i belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. $midconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the median percentage of financially constrained firms, and zero otherwise. $highconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10%.

Table 10: Relationship between age and productivity (deflated TFP measure)

	(1)	(2)	(3)	(4)	(5)	(6)
$age_{i,s}$	0.0124***	0.0123***	0.0131***	0.0142***	0.0142***	0.0150***
	(11.8)	(11.5)	(11.5)	(9.5)	(9)	(8.8)
$age_{i,s}$*$constrained_i$	-0.00391**	-0.00346**	-0.00423**			
	(-2.9)	(-2.6)	(-2.9)			
$age_{i,s}$*$midconstr_i$				-0.00426**	-0.00430**	-0.00491**
				(-2.3)	(-2.3)	(-2.4)
$age_{i,s}$*$highconstr_i$				-0.00608***	-0.00557**	-0.00629**
				(-3.4)	(-3)	(-3.2)
N.observations	10409	10409	9908	10409	10409	9908
Adj. R-sq.	0.069	0.070	0.074	0.070	0.072	0.075
Time dummies	yes	no	no	yes	no	no
Time*group dummies	no	yes	yes	no	yes	yes
Constrained excluded	no	no	yes	no	no	yes

Panel regression with firm fixed effect. Dependent variable is estimated total factor productivity $\widehat{v}_{i,s}$. Standard errors are clustered at the firm level. The variance-covariance matrix is estimated with a bootstrap procedure with 50000 replications. z-statistic reported in parenthesis. $age_{i,s}$ is age in years for firm i in survey s. $constrained_i$, is equal to one if firm i belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. $midconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the median percentage of financially constrained firms, and zero otherwise. $highconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

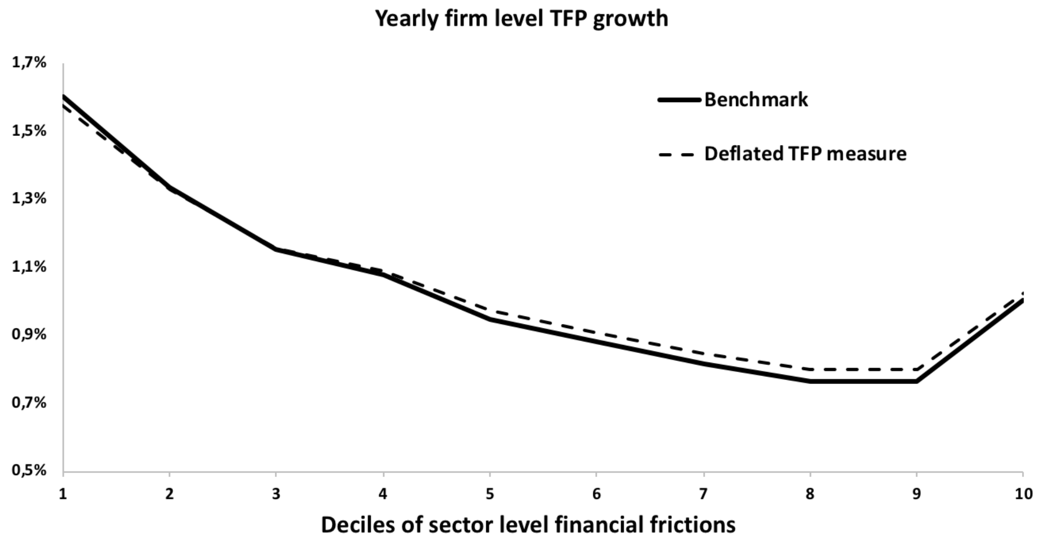
IV The relationship between age and productivity: deflated TFP measure

In Table 10, I estimate Eqs. (2) and (3) using a measure of TFP obtained after deflating output and inputs using the following price indices: for total sales py, the price index of industrial output of the manufacturing sector; for the book value of fixed capital pk, the price index of output in the construction sector; for the wage cost wl, the price index of gross average wages; for the cost of materials m, the price index of industrial output of the manufacturing sector; and for energy costs e, the price index of output in the energy sector. Table 10 and Figure 2 show that the results are very similar to those obtained using the benchmark TFP measure.

V The relationship between age and productivity: Implied TFPQ

In Table 11, I estimate Eqs. (2) and (3) with a measure of TFP computed following the approach of De Loecker and Warzynski (2012) as implemented by Fons-Rosen et al. (2017). Total factor productivity $TFPQ_{it}$ can be written

Figure 2: Nonlinear relationship between intensity of financial frictions and productivity growth: benchmark versus deflated TFP.



as:

$$TFPQ_{it} = \frac{TFPR_{it}}{P_{it}}$$

where $TFPR_{it}$ is revenue total factor productivity and the price P_{it} is equal to the product of markup μ_{it} and marginal costs MC_{it}. I estimate μ_{it} as the elasticity of output to the flexible input divided by the expenditure share of this input. Following Fons-Rosen et al. (2017), I consider labor cost as the flexible input, and I proxy the marginal cost MC_{it} with the sum of material, labor and other variable costs divided by revenues. The results in Table 11 are very similar to those obtained for the benchmark TFP measure.

VI The relationship between age and productivity: alternative performance measures

Table 12 considers alternative measures of performance instead of TFP. These are employment growth, labor productivity growth, and fixed capital growth. Employment is total employees. Labor productivity is total sales divided by labor costs. Fixed capital is the total stock of capital. All variables are transformed into logs, and only firm-year observations with a yearly growth rate of less than 50% in absolute value are included.[3] The results broadly confirm that financial frictions reduce the growth of firms, although they are

[3] These three variables are considerably more noisy than TFP computed following the procedure outlined previously. For the estimated TFP, the maximum yearly deviation is 40%.

Table 11: Relationship between age and productivity (implied TFPQ measure)

	(1)	(2)	(3)	(4)	(5)	(6)
$age_{i,s}$	0.0114***	0.0109***	0.0114***	0.0135***	0.0134***	0.0140***
	(12.5)	(12)	(11.8)	(10.7)	(10.2)	(10)
$age_{i,s}*constrained_i$	-0.00427***	-0.00356**	-0.00490***			
	(-3.6)	(-3)	(-3.8)			
$age_{i,s}*midconstr_i$				-0.00593***	-0.00587***	-0.00684***
				(-3.8)	(-3.6)	(-3.9)
$age_{i,s}*highconstr_i$				-0.00614***	-0.00571***	-0.00723***
				(-3.9)	(-3.6)	(-4.2)
N.observations	10340	10340	9843	10340	10340	9843
Adj. R-sq.	0.069	0.07	0.066	0.071	0.072	0.068
Time dummies	yes	no	no	yes	no	no
Time*group dummies	no	yes	yes	no	yes	yes
Constrained excluded	no	no	yes	no	no	yes

Panel regression with firm fixed effect. Dependent variable is estimated total factor productivity $\widehat{v}_{i,s}$. Standard errors are clustered at the firm level. The variance-covariance matrix is estimated with a bootstrap procedure with 50000 replications. z-statistic reported in parenthesis. $age_{i,s}$ is age in years for firm i in survey s. $constrained_i$, is equal to one if firm i belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. $midconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the median percentage of financially constrained firms, and zero otherwise. $highconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

generally more noisy and less significant than the results obtained using TFP. For labor productivity, this is expected, as it is a much noisier measure of productivity than TFP. For capital and labor, a plausible reason is that firms in Italy have institutional constraints on their growth in size, and therefore, some improvements in measured TFP might measure quality improvements in products for firms that, because of these constraints, are reluctant to expand in size.

C Model solution

To obtain a numerical solution for the value functions $V_t^0(a_t, \varepsilon_t, v_t)$, $V_t^1(a_t, \varepsilon_t, v_t)$, $V_t^2(a_t, \varepsilon_t, v_t)$, $V_t^*(a_t, \varepsilon_t, v_t)$ and $V_t(a_t, \varepsilon_t, v_t)$, I consider values of a_t in the interval between 0 and $\overline{a}$, where $\overline{a}$ is a sufficiently high level of assets that the firm never risks bankruptcy now or in the future. I then discretize this interval in a grid of 100 points. The grid is unequally spaced, with higher density for low values of a_t. The shock ε_t is modeled as a two-state symmetric Markov process. The productivity state v_t is a grid of N points, where $v_n = \frac{1}{(1+g)^{n-1}}$ for $n = 1, ..., N$. N is set at 150, which is a value large enough that, conditional on the other parameter values, no firm remains in operation when $v = \frac{1}{(1+g)^{N-1}}$.

To solve the dynamic problem, I first make an initial guess about the equilibrium aggregate price P. Based on this guess, I calculate the value functions $V_t^0(a_t, \varepsilon_t, v_t)$, $V_t^1(a_t, \varepsilon_t, v_t)$, $V_t^2(a_t, \varepsilon_t, v_t)$, the optimal innovation and exit policy functions, and then compute the value function $V_t(a_t, \varepsilon_t, v_t)$, using an iterative procedure. I then apply the zero-profit condition, as defined by Eq. (19) in the paper, and update the guess of P accordingly. I repeat this procedure until the solution converges to the equilibrium. I then simulate an artificial industry in which, every period, the total number of new entrants ensures that condition (4) in the paper is satisfied.

D Calibration

I Auxiliary calculations for the main calibration

For the calibration of θ, the matched frequency of bankruptcies of 1.3% is computed as follows. A 2003 study by ISTAT (available online at: http://www.bnk209.it/sezioni/ files/105/ 33_2001-istat-fallimenti-in-italia.pdf) shows that, in 2001, in the whole Italian economy, 1.35% of limited liability companies went bankrupt, and approximately 0.32%-0.39% of other types of companies did so. In the sample analyzed in this paper, 92% of all firms are limited liability companies.

For the calibration of the mean $\widehat{v}_0$ and variance $\sigma_{\nu_0}^2$ of the distribution of the productivity of new firms, in the empirical data, the technological frontier is approximated by the 99th percentile of estimated productivity $\widehat{v}_{i,t}$. In the simulations, I approximate a log-normal distribution of productivity of new

Table 12: Relationship between age and other measures of performance

	log(Employment)		log(Fixed Capital)		log(sales/labour cost)	
	Panel A: all firms					
$age_{i,s}$	.00305*	.00389**	.0839***	.0872***	.0115***	.00776***
	(1.96)	(2)	(20.1)	(14.7)	(6.6)	(3.4)
$age_{i,s}$*$constr_i$	-.00310**		-.0128**		-.00484**	
	(-2.4)		(-2.4)		(-2)	
$age_{i,s}$*$midc_i$		-.00249		-.007		.00263
		(-1.4)		(-0.9)		(0.8)
$age_{i,s}$*$highc_i$		-.00410**		-.0204**		-.00032
		(-2.6)		(-2.8)		(-0.1)
N.obs.	10739	10739	8648	8648	8867	8867
Adj. R-sq.	0.079	0.080	0.262	0.264	0.063	0.062
	Panel B: financially constrained firms excluded					
$age_{i,s}$	.00346*	.00398*	.0866***	.0923***	.0111***	.00798**
	(1.8)	(1.7)	(20.4)	(15.5)	(6.1)	(3.3)
$age_{i,s}$*$constr_i$	-.00277*		-.0162**		-.00467*	
	(-1.9)		(-2.9)		(-1.8)	
$age_{i,s}$*$midc_i$		-.00166		-.0122*		.00179
		(-.8)		(-1.7)		(0.5)
$age_{i,s}$*$highc_i$		-.00343*		-.0260***		-.00055
		(-1.9)		(-3.5)		(-0.2)
N.obs.	9169	9169	8032	8032	8245	8245
Adj. R-sq.	0.077	0.079	0.267	0.268	0.064	0.064
Time*group dummies	yes	yes	yes	yes	yes	yes

Panel regression with firm fixed effect. Dependent variable is estimated total factor productivity $\widehat{v}_{i,s}$. Standard errors are clustered at the firm level. The variance-covariance matrix is estimated with a bootstrap procedure with 50000 replications. z-statistic reported in parenthesis. $age_{i,s}$ is age in years for firm i in survey s. $constrained_i$, is equal to one if firm i belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. $midconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the median percentage of financially constrained firms, and zero otherwise. $highconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

firms v_0, with a bounded distribution with support $[v_L, v_H]$ by cutting the 1% tails off the distribution. The censored probability distribution is re-scaled to ensure that its integral over the support $[v_L, v_H]$ is equal to 1.

II Simulation methodology

I compute the statistics for the simulated industries as follows. I simulate each industry starting with an exogenous initial number of firms and an exogenous initial distribution of productivity. I simulate this industry for 500 periods, such that it reaches the steady-state number of firms and the steady-state equilibrium distribution of firms over productivity and financial wealth. Then, I simulate 300 additional periods; I compute the aggregate statistics for every period, and at the end of the simulation, I compute the average statistics across the 300 periods.

For the regressions on simulated data in Table 5 in the paper, I simulate each industry for 500 periods, such that it reaches the steady state. Then, I simulate a panel of firm-level data for 10 additional periods. I randomly sample from this panel a number of firms and a number of consecutive observations for each firm to obtain a final panel comparable to the empirical one in both dimensions.

III Evidence supporting the identification assumption of radical innovation

Here, I provide supporting evidence for the assumption that radical innovation attempts, identified as R&D to introduce new products, are riskier than incremental innovations. Caggese (2012), using the same dataset analyzed in this paper, provides cross-sectional evidence. He shows a positive correlation between the dispersion of profits across firms for each sector and the ratio of the frequency of product innovation to the frequency of innovation directed toward improving current production.

Here, I provide time-series evidence. Specifically, I verify, at the firm level, the correlation between radical innovation and changes in the volatility of productivity. To control for firm-specific factors, I consider $\sigma_{\widehat{v},i,s}$, the standard deviation of productivity $\widehat{v}_{i,t}$ computed over the three years of survey s. Since R&D information is available for multiple surveys, I can check weather the volatility of productivity changes relative to a change in the type of R&D, while controlling for firm fixed effects that absorb any other sector- or firm-level factor that is constant over time. Therefore, I estimate the following regression:

$$\sigma^2_{\widehat{v},i,s} = \beta_0 + \beta_1 innovation\_type_{i,s} + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s}, \tag{3}$$

where $innovation\_type_{i,s}$ is equal to one if firm i performs innovation of $type = radical, incremental$, zero otherwise. Since, by construction, the innovation types are mutually exclusive, they are introduced separately in each regression. The control variables x_j include time dummies. Errors are clustered at the firm level. I estimate Eq. (3) with firm fixed effects, meaning that the coefficient β_1 is positive if, over time and within firms, innovation increases the volatility of productivity. The model predicts that β_1 should be positive for radical innovation and zero or negative for incremental innovation. I consider the full sample and the sample of firms that perform R&D. For the full sample, the coefficient β_1 is identified both by firms changing between innovation and non-innovation status and between types of innovation. For the sample of R&D firms, it is only identified by R&D-performing firms changing innovation types, which permits a cleaner interpretation. Table 13 reports the results for the full sample and for younger firms only.[4] Comparing the constant term with the coefficients of radical innovation, it follows that changing to radical innovation increases the volatility of productivity from a minimum of 3.4% to a maximum of 82%, the coefficients being significant in 2 out of the 3 specifications when considering R&D-performing firms only. Conversely, changing to incremental innovation has a negative effect both in the full sample and in the sample of R&D-performing firms (by construction, in this subsample, the coefficient is the inverse of the coefficient of radical innovation).

IV Matching entry and exit rates in the data and model

Turnover rates are not included in the Mediocredito dataset. Therefore, I obtain them from the Italian National Statistics Office (ISTAT). The available data have several limitations. First, entry and exit rates are available only from the year 2000 onward. Second, they are not available at the 4-digit ATECO level, which is the level of disaggregation used in the paper to select sectors according to financing constraints. They are available at a level slightly more aggregated than the 2-digit sector classification, as shown in Figure 3. The first column presents the fraction of firms reporting financing constraints in the 2001 survey. Entry and exit rates are averages for the 2000–2003 period, from ISTAT. The number of employees is from the first year with available data from ISTAT, which is 2002.

Using these data, Figure 4 shows a positive correlation between turnover rates and the intensity of financial frictions, validating the mechanism of the model.

For calibration purposes, I should compute exit rates for the 33% most constrained, 33% mid constrained and 33% least constrained groups of 4-digit sectors analyzed in the paper. Unfortunately, as explained above, exit rates are available only for the 11 macro sectors shown in Figure 3. Therefore, I compute the weighted average of the exit rates in the 33% most constrained, 33% mid constrained and 33% least constrained firms in the 11 macro sectors, and I interpret them as proxies for the corresponding values of the groups in

[4]Given the presence of firm fixed effects, the identification of the coefficient β_1 requires at least 6 years of data (to calculate the volatility of productivity for two consecutive surveys), and therefore, I cannot include the category of firms ≤ 5 years old.

Table 13: Innovation and volatility of productivity

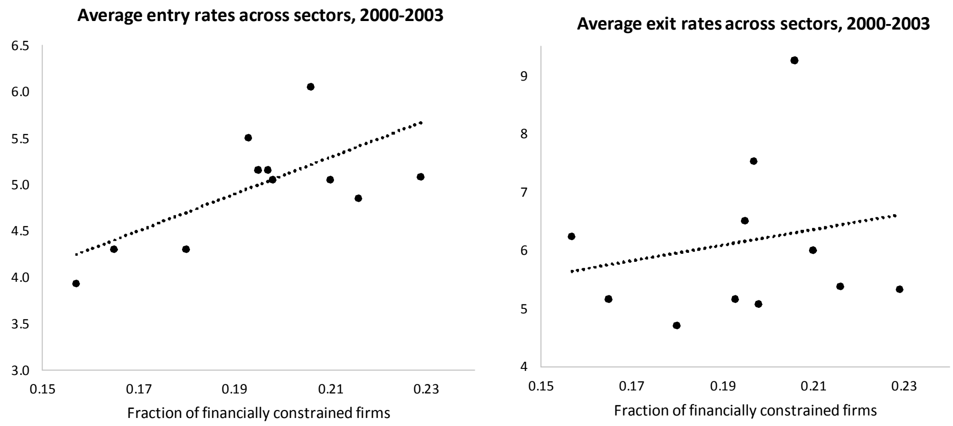
Dependent variable: volatility of productivity of firm i in Survey s, $\sigma_{\widehat{v},i,s}$						
	Panel A: all firms					
	All ages		$Age \leq 10$		$Age \leq 20$	
$type_{i,s} = radical$	0.0029		0.0144		0.0049	
	(0.6)		(0.6)		(0.5)	
$type_{i,s} = incremental$		-0.0043		-0.0336**		-0.0049
		(-1.2)		(-2)		(-0.7)
Constant	0.084***	0.085***	0.087***	0.095***	0.088***	0.0899***
	(104.1)	(125.6)	(21.8)	(34.3)	(51.9)	(77)
N.observations	9180	9180	1543	1543	4401	4401
	Panel B: only firms doing R&D					
$type_{i,s} = radical$	0.0120**		0.0483*		0.013	
	(2.1)		(1.7)		(1.1)	
$type_{i,s} = incremental$		-0.0120**		-0.0483*		-0.0131
		(-2.13)		(-1.7)		(-1.1)
Constant	0.076***	0.088***	0.0588***	0.107***	0.0781***	0.0912***
	(27.4)	(30.4)	(4)	(7.7)	(13.2)	(14.7)
N.observations	3425	3425	537	537	1530	1530

Robust standard errors, reported in parenthesis, are clustered at the firm level. $R\&D\_radical_{i,s}$ is equal to one for firm i in survey s if the firm has performed R&D to develop and produce new products, and zero otherwise. $R\&D\_incremental_{i,s}$ is equal to one for firm i in survey s if the firm has performed R&D to improve current products of productive processes. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

Figure 3: Financial frictions and turnover rates, data

Sector	% Financially constrained	Exit rates	Entry rates	Number of Employees	Cumulative share of employment
Wood Furniture	15.70%	6.2	3.9	449162	0.10
Rubber & Plastic	16.50%	5.2	4.3	207455	0.15
Chemical & Fibers	18%	4.7	4.3	207647	0.19
Mechanical products	19.30%	5.2	5.5	593227	0.33
Electrical Products	19.50%	6.5	5.2	450958	0.43
Leather Products	19.70%	7.5	5.2	197311	0.47
Metals +metallic products	19.80%	5.1	5.1	821520	0.66
Textiles + Shoes & Clothes	20.60%	9.3	6.1	580654	0.79
Paper	21%	6.0	5.1	252420	0.84
Non-metallic products	21.60%	5.4	4.9	249616	0.90
Food & Drinks	22.90%	5.3	5.1	449162	1.00

Figure 4: Financial frictions and turnover rates, 2 digit ISTAT sectors.



the paper. The weights are total employment in each sector. I obtain values of 6.9, 5.8, and 5.4, respectively.[5][6]

After obtaining the target empirical exit rates, I simulate several industries for different values of the initial endowment. As shown in Figure 5, in the simulated industries, there is also a clear mapping from low initial endowments to a high percentage of firms with binding financing constraints and high exit rates. As the endowment increases, the percentage of firms unable to invest in innovation because of a binding financing constraint falls from 17% to 5%.[7] I obtain the target exit rates of 6.9, 5.8, and 5.4 for values of the initial endowment of 0.09, 1.15 and 1.6, respectively.

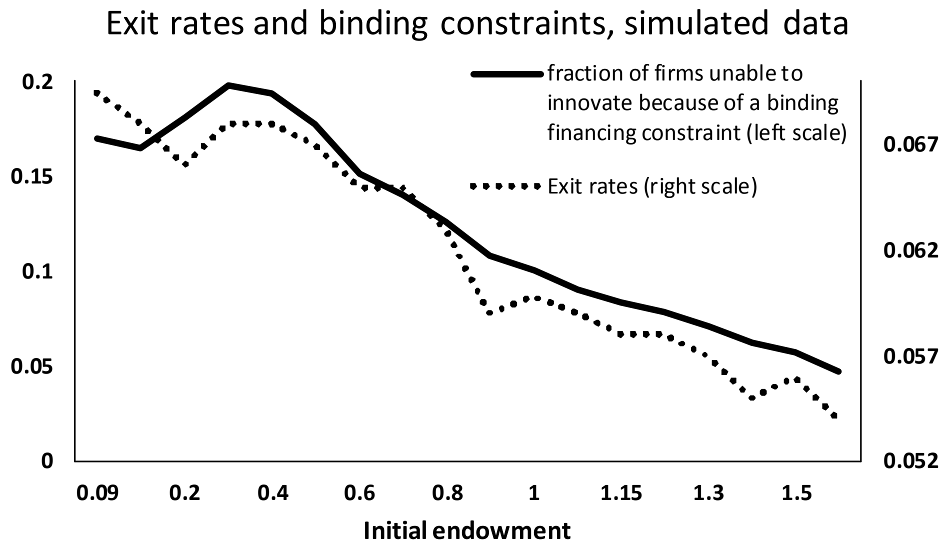
Finally, in Section V, where I analyze differences in patenting activity, I compare the empirical 50% least and 50% most constrained sectors. For the simulated 50% most constrained sectors, I average the sectors with endow-

[5] I target exit rather than entry rates because variations in financial frictions in the sample period that vary bankruptcy rates immediately affect exit rates, while their effects on entry rates might be delayed. Nonetheless, Figure 4 implies that the differences in entry rates, between the least and most most financially constrained sectors, are quantitatively similar to the difference in exit rates, suggesting that using entry rates (or an average between entry and exit rates) would not significantly affect the results.

[6] Note that this matching exercise is based on the 2001 survey only. Therefore, I measure financial frictions in the data using the binary financial friction indicator $finprob1$, which ensures more consistency across surveys that the benchmark indicator $finprob$ (see Appendix A). For the same reason, I use $finprob1$ also for the comparison between least, mid, and most constrained empirical and simulated sectors in Table 3 in the paper. However using the benchmark indicator $finprob$ does not significantly change these results.

[7] Note that the relationship between endowment and the percentage of firms unable to innovate is monotonously decreasing except for the lowest values of endowment between 0.09 and 0.3. When the initial endowment is very low and bankruptcy risk is very high, the indirect competition effect raises profits for surviving firms and helps them to more rapidly accumulate wealth, thus reducing in equilibrium the fraction of firms unable to innovate because of a lack of funds.

Figure 5: Financial frictions and turnover rates, model



ments between 0.9 and 1.15 (the value of the median sector) shown in Figure 5. For the simulated 50% least constrained sectors, I consider the sectors with endowments between 1.15 and 1.6. An alternative strategy of calibrating these sectors with their exit rates yields similar results.

V Matching the deciles of sector level financial frictions

To determine the simulated sectors corresponding to the deciles of financial frictions in Figure 4 in the paper, I proceed as follows. I interpolate the initial endowments for the 33% least, mid and most constrained groups and obtain an estimated endowment for the first decile of financial frictions, obtaining 1.61, and for the 10th decile, obtaining a negative value. I approximate the latter with a value that is very close to zero but positive (0.02), and then, I simulate the 10 deciles assuming that the endowment decreases linearly between these two extremes.

Moreover, in Figure 4 in the paper, the empirical growth rates are computed from a regression analysis with firm fixed effects, in which only firms with at least two survey observations (i.e., with a minimum of 5–6 years of age) are included. Therefore, to make the simulations comparable with the empirical data, I compute the simulated growth rates as the weighted average of the yearly growth rates for firms 5 years old or older, using as weights the fraction of firms with that age.

VI Counterfactual simulations with only one innovation type.

Tables 14 and 15 show the calibrated parameters for the counterfactual simulations with only incremental innovation and only radical innovation, respectively. The calibration strategy and the moments matched are the same as for the benchmark model, except that in the first case, I assume that all the innovations in the data are incremental innovations, and in the second case, I assume that they are all radical innovations. Moreover, for the case of the counterfactual with only radical innovation, I cannot follow the same procedure as in the benchmark calibration to identify the success probability ξ^2. Therefore, I calibrate it to match the fraction of innovating firms, while I keep τ^2_{fail} at the same value as in the benchmark calibration. For each counterfactual model, I simulate three groups with different endowments such that, in equilibrium, they have the same fraction of financially constrained firms as the most constrained, mid constrained and least constrained groups analyzed above.

The statistics are presented in Table 16. As in the benchmark model, in these counterfactual models, the most constrained group of firms has a higher frequency of binding constraints, higher bankruptcy and entry rates, a lower total number of firms, less competition and higher profitability (conditional on productivity). The productivity dynamics of these models are shown in Figure 6, which complements Table 5 in the paper. The model with only radical innovation, shown in Panel A, generates substantial differences in productivity growth between the most and least constrained groups, albeit quantitatively smaller differences than in the benchmark model. On the one hand, the indirect competition effect reduces risk taking and the frequency of radical innovation among younger firms. On the other hand, this model is unable to generate the gradual productivity growth observed empirically for firms 20 to 40 years old. Older and more productive firms do not wish to risk radical innovation, and in this model, they cannot improve their productivity using incremental innovation. Conversely, the model with only incremental innovation in Panel B is able to generate constant productivity growth but only very small differences between groups. Over 40 years, productivity growth is 45% slower in the most constrained group than the least constrained group in the benchmark model in Figure 3 in the paper. In Panel A, it is 33% slower, and in Panel B, it is 12% slower. Therefore, these two counterfactual simulations imply that radical innovation generates approximately three-quarters of the differences in productivity growth between the least and most constrained groups, while incremental innovation is responsible for only approximately one-quarter of these differences. Finally, in Panel C of Figure 6, I consider the simulation with only incremental innovation, in which, for each group, I match not only financial frictions but also the frequency of innovation. I do so by setting a higher value for the probability of having an innovation opportunity γ for the least constrained sectors. Panel C shows that in this case, the model with only incremental innovation is able to generate larger differences in productivity growth, but these are still relatively small, only approximately half the size of the differences in productivity growth generated in the benchmark model with both innovations.

Figure 6: Productivity over the firms' life cycle - counterfactual calibrations with only one innovation type.

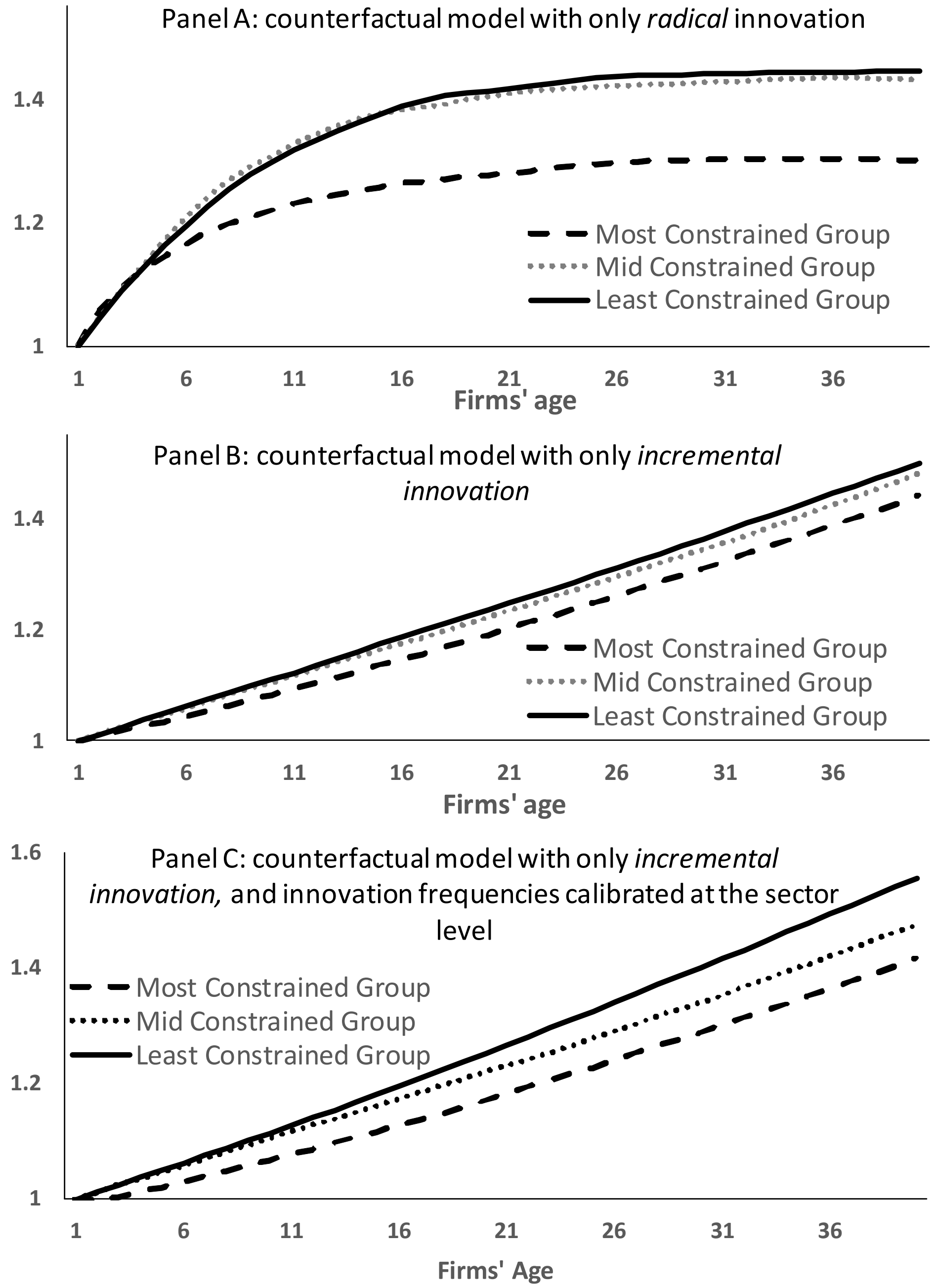


Table 14: Calibration of the counterfactual model with only incremental innovation

Parameter	Value	Empirical moment	Data	Model
S^C	2.4	Profits sales ratio for the 50% percentile	0.02	0.02
κ	2.45	Profits sales ratio for the 95% percentile	0.11	0.11
θ	0.3	Fraction of firms going bankrupt	1.3%	1.3%
$K(1)$	0.2	Average R&D expenditures /sales	2%	2%
γ	371	Percentage of innovating firms	33.8%	33.1%
τ^1_{succ}	3	Ratio between 90th pctile and 10th pctile of size distrib.	13.2%	12.6%
$\widehat{v}$	0.37	Avg. prod. of new firms relative to the frontier	0.37[1]	0.37
σ^2_v	0.1	Cross sectional dispersion of productivity	0.34[2]	0.33
g	0.01	Average aggregate TFP growth	1%[3]	1%
ξ^0	0.75	Average yearly decline in TFP for firms not doing R&D	0.4%[2]	0.4%
δ	0.0219	Average age	24[2]	26
a_0	2	Average entry/exit rate	5.8%	5.9%

Other parameters: r=2%; η=1.5; σ=4; A=50010. Profits denote operative profits. 1. For the empirical data the frontier is proxied with the 99th percentile of the distribution of productivity. 2. These statistics are calculated after excluding the 1% outliers on both tails. 3. Data for the whole of Italy's industrial sector, 1990-2000 period. For the simulated moments, I simulate the industry for 500 periods, so that it reaches the steady state number of firms and the steady state equilibrium distribution of firms over productivity and financial wealth. Then I simulate 300 additional periods, I compute the aggregate statistics for every period, and at the end of the simulation I compute the average statistics across the 300 periods.

Table 15: Calibration of the counterfactual model with only radical innovation

Parameter	Value	Empirical moment	Data	Model
S^C	5.9	Profits sales ratio for the 50% percentile	0.02	0.012
κ	2.45	Profits sales ratio for the 95% percentile	0.11	0.11
θ	0.3	Fraction of firms going bankrupt	1.3%	1.3%
$K(2)$	0.1	Average R&D expenditures /sales	2%	1.9%
ξ^2	0.1175	Percentage of innovating firms	33.8%	34.6%
γ	39	Ratio between 90th pctile and 10th pctile of size distrib.	13.2	13.1
τ^2_{succ}	30	Right tail of firm level productivity changes	0.125	0.193
τ^2_{fail}	4	Same value as in the benchmark calibration		
$\widehat{v}$	0.37	Avg. prod. of new firms relative to the frontier	0.37[1]	0.37
σ^2_v	0.1	Cross sectional dispersion of productivity	0.34[2]	0.38
g	0.01	Average aggregate TFP growth	1%[3]	1%
ξ^0	0.75	Average yearly decline in TFP for firms not doing R&D	0.4%[2]	0.4%
δ	0.01725	Average age	24[2]	26
a_0	1.2	Average entry/exit rate.	5.8%	5.6%

Other parameters: r=2%; η=1.5; σ=4; A=50010. Profits denote operative profits. 1. For the empirical data the frontier is proxied with the 99th percentile of the distribution of productivity. 2. These statistics are calculated after excluding the 1% outliers on both tails. 3. Data for the whole of Italy's industrial sector, 1990-2000 period. For the simulated moments, I simulate the industry for 500 periods, so that it reaches the steady state number of firms and the steady state equilibrium distribution of firms over productivity and financial wealth. Then I simulate 300 additional periods, I compute the aggregate statistics for every period, and at the end of the simulation I compute the average statistics across the 300 periods.

Table 16: Counterfactual simulated industries with only one innovation type: descriptive statistics

	Only radical innovation			Only incremental innov.			Only incremental innovation, matched at sector level		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Initial endowment a_0	1.5	1.2	0.3	4	2	0.4	10	2	0.18
Probability to innovate γ	0.39	0.39	0.39	0.371	0.371	0.371	0.391	0.371	0.37
% bankrupt every period	0.9%	1.3%	4.0%	0.8%	1.3%	3.9%	0.3%	1.3%	4.7%
% not inn. for lack of funds[1]	3.7%	5.0%	12.6%	2.2%	4.2%	13.3%	0.8%	4.2%	15%
% innovating firms	34.6%	34.6%	32.8%	33.8%	33.1%	31.6%	36%	33.1%	28.5%
Entry=exit rates	5.4%	5.6%	6.9%	5.4%	5.8%	6.9%	5.4%	5.8%	5.4%
Number of firms	11962	11214	10670	8682	7541	6410	10766	7842	6630
Avg. P wrt 33% least constr.	100%	100.5%	103.3%	100%	102.3%	105.8%	100%	106.9%	111.1%
$E\left(\frac{\pi}{y} \mid v\right)$ wrt 33% l.c.	100%	100.9%	112.5%	100%	113.9%	131.9%	100%	155%	184%

(1) Least constrained group; (2) Mid constrained group; (3) Most constrained group. For each group, I simulate 500 periods, so that it reaches the steady state number of firms and the steady state equilibrium distribution of firms over productivity and financial wealth. Then I simulate 300 additional periods, I compute the aggregate statistics for every period, and at the end of the simulation I compute the average statistics across the 300 periods.

E Additional robustness checks

I Radical innovation as a function of productivity and size

The stylized model in this paper implies that age, size, and productivity are all strongly positively correlated, and any of the three could be used to test the model's predictions about radical innovation dynamics. However, in the paper, I focus on age rather than size or productivity. As shown in Figure 5 in the paper, the different innovation decisions of younger versus older firms are the key property that allows the model to explain the life-cycle dynamics of productivity. Moreover, age is directly observed, while productivity is not and must be estimated. Finally, in the data, the correlation between age, productivity and size is likely to be weaker than in the model. In the model, all firms find it optimal to become large, while in reality, some small firms that innovated and improved the quality of their products and their measured productivity might be reluctant to increase their size. They might want to remain small, either to avoid more stringent labor regulations, or because they are owned and managed by a small number of close family members.

Nonetheless, Tables 17 and 18 show that using size and productivity broadly confirms the results in the paper using age. Specifically, in Table 17, I show the data on patenting probability for firms sorted into 5 size classes. Each class has the same number of firms, with size being measured as number of employees. It is plausible, when comparing firms of different sizes, that smaller firms, even when they innovate more intensely than larger ones, might have a smaller number of patents simply due to a scale effect. Therefore, the table reports the yearly probability of having a new patent per 100 employees. The table shows that the probability is generally higher for the smaller quintiles, especially for the group of unconstrained firms. Table 18 shows the number of patents for firms sorted into 5 equally sized productivity classes, where productivity is measured by estimated TFP. Although in this case the relationship is not always monotonous, it broadly shows that, consistent with the model's predictions, firms with lower measured productivity tend to have a larger number of innovations.

II Relationship between barriers to entry and concentration

Figure 7 shows values of the normalized Herfindahl index:

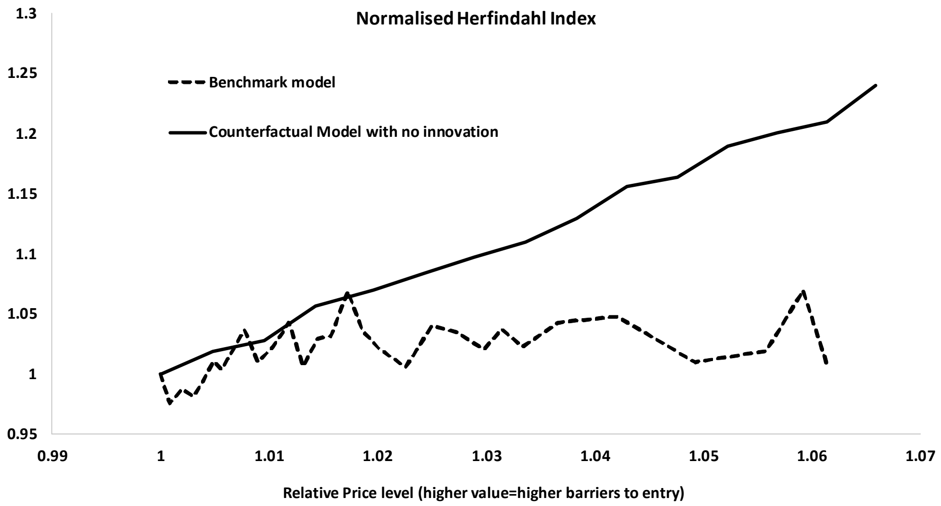
$$H = \frac{\left(\sum_{i=1}^{N} s_i^2 - \frac{1}{N}\right)}{1 - 1/N}$$

where s_i is the market share of firm i, and N is the total number of firms. H ranges from 0 to 1, and a higher value indicates more concentration. I consider the benchmark model and a counterfactual model with the same parameters as the benchmark model but without innovation by incumbents. The black line in the figure represents the value of H (normalized such that it starts at 1) for a sequence of simulations of the counterfactual model in which I hold all parameters constant, except that I increase entry barriers by increasing the fixed entry cost S^C. The x-axis shows that higher entry barriers reduce competition and increase the price level by up to 6% relative to the initial simulation with the lowest entry barriers. The black line measures the effect of higher entry barriers on concentration. The Herfindahl index increases by up to 25%, confirming that higher entry barriers reduce competition from new entrants and increase concentration.

The discontinuous line shows the sequence of values for the benchmark model. In this case, higher barriers to entry on the x-axis are generated by progressively reducing the initial endowment a_0. The line for the benchmark model is approximately flat, which means that for an increase in barriers to entry and a reduction in competition comparable to those in the counterfactual model, there is no significant increase in concentration. As explained in the paper, In the benchmark model, an additional force is at play: higher barriers to entry reduce the incentive to pursue radical innovation, which reduces the mass of very large and productive firms in equilibrium and thus reduces concentration. The figure implies that the two opposite effects cancel one another out.

III Regressions eliminating innovating firms

Figure 7: Concentration and competition



The model predicts that the different innovation decisions across sectors drive differences in productivity growth. Table 19 confirms this by showing that eliminating innovating firms reduces average productivity growth and the difference between less and more financially constrained sectors. In Table 19, columns 1 and 3 replicate the results obtained for the full sample. Columns 2 and 4 repeat the analysis after eliminating all the observations of R&D-performing firms and all patenting firms. The results show that the life-cycle profiles of productivity for firms in the constrained and unconstrained groups are no longer significantly different.

Table 17: Relationship between size and innovation

	Probability of having a patent awarded, per year per 100 employees					
	Italian Patents Office		European Patents Office (EPO)		Top 10% patents (EPO)	
Size quintile (average number of employees)	Constrained group	Unconstr. group	Constrained group	Unconstr. group	Constrained group	Unconstr. group
Q1 (13.5)	0.0520	0.0873	0.0790	0.0998	0.0104	0
Q2 (18.4)	0.0542	0.0713	0.0651	0.0978	0.0046	0.0079
Q3 (24.5)	0.0390	0.0451	0.0544	0.0654	0.0062	0.0068
Q4 (40.2)	0.0374	0.0369	0.0449	0.0579	0.0061	0.0025
Q5 (310)	0.0066	0.0055	0.0167	0.0127	0.0017	0.0029

The constrained and unconstrained simulated groups pool together the 50% least constrained and 50% most constrained simulated sectors. For each sector, I simulate 500 periods, so that it reaches the steady state number of firms and the steady state equilibrium distribution of firms over productivity and financial wealth. Then I simulate 300 additional periods, I compute the aggregate statistics for every period, and at the end of the simulation I compute the average statistics across the 300 periods.

Table 18: Relationship between estimated TFP and innovation

	Probability of having a patent awarded per year					
	Italian Patents Office		European Patents Office (EPO)		Top 10% patents (EPO)	
Productivity quintile	Constrained group	Unconstr. group	Constrained group	Unconstr. group	Constrained group	Unconstr. group
Q1	0.0155	0.0175	0.0239	0.0282	0.0034	0.0056
Q2	0.0149	0.0159	0.0230	0.0309	0.0024	0.0026
Q3	0.0125	0.0156	0.0163	0.0249	0.0003	0
Q4	0.0056	0.0157	0.0079	0.0167	0.0013	0.0010
Q5	0.0080	0.0086	0.0251	0.0204	0.0024	0.0031

The constrained and unconstrained simulated groups pool together the 50% least constrained and 50% most constrained simulated sectors, respectively. For each sector, I simulate 500 periods, so that it reaches the steady state number of firms and the steady state equilibrium distribution of firms over productivity and financial wealth. Then I simulate 300 additional periods, I compute the aggregate statistics for every period, and at the end of the simulation I compute the average statistics across the 300 periods.

Table 19: Relationship between age and productivity - effect of expenditures on research and development

	(1)	(2)	(3)	(4)
$age_{i,s}$	0.0133***	0.00913**	0.0148***	0.0112***
	(11)	(5.1)	(8.4)	(4.7)
$age_{i,s}$*$constrained_i$	-0.00546***	-0.00219		
	(-3.6)	(-1)		
$age_{i,s}$*$midconstr_i$			-0.00533**	-0.00447
			(-2.5)	(-1.5)
$age_{i,s}$*$highconstr_i$			-0.00633**	-0.00411
			(-3)	(-1.4)
N.observations	10409	5478	10409	5478
Adj. R-sq.	0.085	0.056	0.085	0.057
Time*group dummies	yes	yes	yes	yes
R&d performing excluded	no	yes	no	yes

Panel regression with firm fixed effect. Dependent variable is estimated total factor productivity $\widehat{v}_{i,s}$. Standard errors are clustered at the firm level. The variance-covariance matrix is estimated with a bootstrap procedure with 50000 replications. z-statistic reported in parenthesis. $age_{i,s}$ is age in years for firm i in survey s. $constrained_i$, is equal to one if firm i belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. $midconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the median percentage of financially constrained firms, and zero otherwise. $highconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

Appendix F

Ateco code	Name	Constrained	Unconstrained	Most Constrained	Mid Constrained	Least Constrained
1510	Animal Slaughtering and Processing	0	1	0	0	1
1511	Production, processing and preservation of meat, excluding poultry	1	0	1	0	0
1513	Production of meat products	1	0	1	0	0
1520	Seafood Product Preparation and Packaging	1	0	0	1	0
1530	Fruit and Vegetable Preserving and Specialty Food Manufacturing	1	0	1	0	0
1533	Processing and preservation of fruits and vegetables	1	0	1	0	0
1541	Manufacture of raw oils and fats	0	1	0	1	0
1542	Manufacture of refined oils and greases	1	0	1	0	0
1551	Hygienic treatment, preservation and milk processing	1	0	0	1	0
1560	Sugar and Confectionery Product Manufacturing	0	1	0	0	1
1561	Processing of grains	1	0	1	0	0
1570	Animal Food Manufacturing	1	0	1	0	0
1580	Other Food Manufacturing	0	1	0	0	1
1581	Manufacture of bakery and fresh bakery products	1	0	1	0	0
1582	Production of preserved pastries	1	0	1	0	0
1585	Manufacture of macaroni, noodles, couscous and similar farinaceous products	1	0	1	0	0
1586	Coffee and tea processing	0	1	0	0	1
1589	Manufacture of other food products	1	0	1	0	0
1590	Beverage Manufacturing	0	1	0	0	1
1591	Manufacture of spirits distilled	0	1	0	0	1
1593	Manufacture of grape wine (not of own production)	0	1	0	0	1
1598	Production of mineral waters and of non-alcoholic beverages	1	0	1	0	0
1710	Fiber, Yarn, and Thread Mills	0	1	0	1	0
1712	Preparation and spinning of carded wool	0	1	0	0	1
1713	Preparation and spinning of worsted wool	0	1	0	0	1
1715	Silk twisting and preparation (including waste) of synthetic or artificial yarns	1	0	1	0	0
1720	Fabric Mills	0	1	0	0	1
1721	Weaving of cotton yarns	0	1	0	0	1
1722	Weaving of carded wool	1	0	1	0	0
1724	Weaving of silk	0	1	0	0	1
1725	Weaving of other textile materials	1	0	0	1	0
1730	Textile and Fabric Finishing and Fabric Coating Mills	0	1	0	0	1
1740	Textile Furnishings Mills	1	0	0	1	0
1753	Manufacture of non-wovens, excluding articles of clothing	0	1	0	0	1
1760	Apparel Knitting Mills	1	0	1	0	0
1770	Cut and Sew Apparel Manufacturing	0	1	0	1	0
1771	Manufacture of knitwear articles	1	0	1	0	0
1772	Manufacture of jerseys, cardigans and other knitted or crocheted articles	0	1	0	0	1
1773	Manufacture of other outerwear	1	0	0	1	0
1810	Production of leather clothing	0	1	0	0	1
1820	Production of other articles of clothing and accessories	0	1	0	0	1
1822	Production of other outer garments	1	0	1	0	0
1823	Prodction of Underwear Clothing	0	1	0	0	1
1824	Production of other clothing items and accesories	0	1	0	0	1
1910	Other Leather and Allied Product Manufacturing	1	0	1	0	0
1920	Production of luggage, handbags, saddlery	1	0	0	1	0
1930	Footwear Manufacturing	0	1	0	1	0
2010	Sawmills and Wood Preservation	1	0	0	1	0
2020	Veneer, Plywood, and Engineered Wood Product Manufacturing	0	1	0	0	1
2030	Production of carpentry elements in wood and carpentry for building	1	0	1	0	0
2040	Production of packagings in wood	1	0	1	0	0
2051	Manufacture of other wood products	1	0	1	0	0
2052	Manufacture of articles of cork, straw and plaiting materials	0	1	0	1	0
2110	Pulp, Paper, and Paperboard Mills	1	0	1	0	0
2112	Manufacture of paper and paperboard	1	0	1	0	0
2120	Converted Paper Product Manufacturing	0	1	0	0	1
2121	Manufacture of paper and corrugated cardboard (also for packaging)	1	0	0	1	0
2122	Manufacture of paper and board products for domestic and sanitary purposes	1	0	1	0	0
2123	Manufacture of paper products	1	0	1	0	0
2125	Manufacture of other articles of paper and paperboard	1	0	0	1	0
2210	Printing and Related Support Activities	1	0	1	0	0
2211	Edition of books, brochures, music books and other publications	1	0	1	0	0

Ateco code	Name	Constrained	Unconstrained	Most Constrained	Mid Constrained	Least Constrained
2213	Edition of magazines and periodicals	1	0	1	0	0
2220	Printing and Press Activities	0	1	0	0	1
2222	Other graphic arts prints	1	0	1	0	0
2224	Composition and photo engraving	0	1	0	0	1
2225	Other printing services	1	0	1	0	0
2410	Resin, Synthetic Rubber, and Artif. and Synthetic Fibers and Filaments Manuf.	0	1	0	0	1
2411	Manufacture of industrial gases	0	1	0	0	1
2412	Manufacture of dyes and pigments	0	1	0	0	1
2413	Manufacture of other inorganic base chemicals	0	1	0	0	1
2416	Manufacture of plastic materials in primary forms	1	0	0	1	0
2430	Paint, Coating, and Adhesive Manufacturing	0	1	0	0	1
2440	Pharmaceutical and Medicine Manufacturing	0	1	0	1	0
2441	Manufacture of basic pharmaceutical products	1	0	0	1	0
2442	Manufacture of pharmaceuticals and pharmaceutical preparations	1	0	1	0	0
2450	Soap, Cleaning Compound, and Toilet Preparation Manufacturing	0	1	0	0	1
2451	Manufacture of soaps and detergents	0	1	0	0	1
2452	Manufacture of perfumes and toilet products	1	0	0	1	0
2466	Manufacture of other chemical products	1	0	1	0	0
2510	Rubber Product Manufacturing	0	1	0	0	1
2513	Manufacture of other rubber products	0	1	0	0	1
2520	Plastics Product Manufacturing	0	1	0	1	0
2521	Manufacture of plates, sheets, tubes and profiles in plastic materials	1	0	1	0	0
2522	Manufacture of plastic packaging materials	1	0	0	1	0
2523	Manufacture of plastic articles for building	1	0	0	1	0
2524	Manufacture of other articles in plastic materials	0	1	0	1	0
2610	Glass and Glass Product Manufacturing	0	1	0	0	1
2612	Processing and transformation of flat glass	1	0	1	0	0
2615	Manuf. of other glass (incl. glass for technical uses)	0	1	0	0	1
2621	Manufacture of ceramic products for domestic and ornamental purposes	0	1	0	0	1
2622	Manufacture of ceramic sanitary ware	0	1	0	1	0
2630	Manufacture of tiles and ceramic slabs for floors and cladding	1	0	0	1	0
2640	Manufacture of bricks, tile and other products for building in terracotta	0	1	0	1	0
2650	Cement and Concrete Product Manufacturing	0	1	0	0	1
2651	Production of cement	1	0	1	0	0
2652	Production of lime	1	0	1	0	0
2660	Lime and Gypsum Product Manufacturing	0	1	0	1	0
2661	Manufacture of concrete products for building	1	0	1	0	0
2663	Manufacture of ready-to-use concrete	1	0	1	0	0
2670	Cutting, molding and finishing of stone	1	0	1	0	0
2681	Manufacture of abrasive products	0	1	0	1	0
2710	Steel Product Manufacturing from Purchased Steel	1	0	1	0	0
2720	Manufacturing of tubes	1	0	0	1	0
2722	Manufacture of steel tubes	1	0	1	0	0
2730	Forging and Stamping	0	1	0	1	0
2732	Cold rolling of tapes	1	0	1	0	0
2733	Profiling by forming, bending and cold forming	1	0	1	0	0
2734	Drawing	1	0	0	1	0
2735	Other first-processing iron and steel processing; production of non-ECSC ferroalloys	1	0	1	0	0
2742	Production of aluminum and semi-manufactures	0	1	0	0	1
2750	Foundries	0	1	0	0	1
2751	Iron casting	0	1	0	0	1
2752	Steel casting	1	0	1	0	0
2753	Light metal casting	0	1	0	0	1
2810	Architectural and Structural Metals Manufacturing	1	0	1	0	0
2811	Manufacture of metal structures and parts of structures	1	0	1	0	0
2812	Manufacture of doors and windows in metal	1	0	1	0	0
2820	Boiler, Tank, and Shipping Container Manufacturing	1	0	0	1	0
2821	Manufacture of tanks, reservoirs and containers of metal	0	1	0	0	1
2822	Manufactures of radiators and boilers for central heating	1	0	1	0	0
2840	Forging, stamping, stamping and profiling of metals; powder metallurgy	0	1	0	0	1
2850	Coating, Engraving, Heat Treating, and Allied Activities	0	1	0	1	0
2851	Treatment and coating of metals	1	0	1	0	0
2852	Works of general mechanics for third parties	1	0	1	0	0
2862	Manufacture of utensils	1	0	1	0	0

Ateco code	Name	Constrained	Unconstrained	Most Constrained	Mid Constrained	Least Constrained
2863	Manufacture of locks and hinges	1	0	0	1	0
2870	Hardware Manufacturing	0	1	0	0	1
2872	Manufacture of light metal packaging	1	0	1	0	0
2874	Manufacture of screws, bolts, chains and springs	0	1	0	0	1
2875	Manufacture of other metal products	1	0	1	0	0
2910	Industrial Machinery Manufacturing	0	1	0	0	1
2911	Manufacture of engines and turbines, except engines for aircraft and vehicles	0	1	0	0	1
2912	Manufacture of pumps and compressors	0	1	0	1	0
2913	Manufacture of taps and valves	1	0	1	0	0
2914	Manufacture of bearings, gears and transmission parts	1	0	1	0	0
2920	Commercial and Service Industry Machinery Manufacturing	1	0	1	0	0
2921	Manufacture of furnaces and burners	0	1	0	0	1
2922	Manufacture of lifting and handling machines and apparatus	1	0	0	1	0
2923	Manufacture of equipment, non-domestic use, for refrigeration and air cond.	1	0	1	0	0
2924	Manufacture of other general-purpose machines	1	0	1	0	0
2930	Agriculture, Construction, and Mining Machinery Manufacturing	1	0	0	1	0
2932	Manufacture of other machinery for agriculture and forestry	1	0	1	0	0
2940	Manufacturing of machine tools (including parts and accessories)	0	1	0	0	0
2950	Manufacture of other special purpose machines	0	1	0	0	1
2951	accessories,installation, maintenance and repair)	1	0	1	0	0
2952	parts and accessories, installation, maintenance and repair)	1	0	1	0	0
2953	(including parts and accessories, installation, maintenance and repair)	0	1	0	1	0
2954	Manufacture of machinery for the textile, clothing and leather industries	1	0	0	1	0
2955	and accessories, installation, maintenance and repair)	0	1	0	0	1
2956	Manufacture of other special purpose machines	1	0	0	1	0
2970	Household Appliance Manufacturing	0	1	0	0	1
2971	Manufacture of household appliances	0	1	0	1	0
3110	Electrical Equipment Manufacturing	1	0	1	0	0
3120	Manufacturing of equipments for the distribution and the control of electricity	1	0	0	1	0
3130	Manufacture of wires and isolated cables	1	0	1	0	0
3150	Electric Lighting Equipment Manufacturing	0	1	0	0	1
3160	Other Electrical Equipment and Component Manufacturing	1	0	0	1	0
3161	Manufacture of electric appliances for engines and vehicles	1	0	1	0	0
3162	Manufacture of other electrical appliances	1	0	1	0	0
3210	Manufacturing of electronic tubes and valves and other electronic components	0	1	0	0	1
3220	Communications Equipment Manufacturing	1	0	0	1	0
3230	Audio and Video Equipment Manufacturing	0	1	0	0	1
3310	Manufacture of medical, surgical and orthopedic appliances	0	1	0	0	1
3320	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	1	0	0	1	0
3330	Production of equipment for the control of industrial processes	1	0	1	0	0
3340	Manufacturing and Reproducing Magnetic and Optical Media	1	0	0	1	0
3511	Shipbuilding and repair of ships	1	0	1	0	0
3520	Railroad Rolling Stock Manufacturing	1	0	1	0	0
3530	Aerospace Product and Parts Manufacturing	0	1	0	0	1
3540	Production of motorcycles and bicycles	0	1	0	0	1
3610	Production of Furniture	1	0	1	0	0
3611	Manufacture of chairs and seats	1	0	1	0	0
3612	Manufacture of office and shop furniture	1	0	0	1	0
3613	Manufacture of kitchen furniture	1	0	1	0	0
3614	Manufacture of other furniture	0	1	0	1	0
3615	Manufacture of mattresses	1	0	1	0	0
3620	Jewelery and goldsmiths	0	1	0	0	1
3622	Manufacture of jewelery items and attached articles	1	0	1	0	0
3650	Production of games and toys	1	0	1	0	0
3663	Other manufacturing industries	1	0	0	1	0