Financing Constraints, Radical versus Incremental Innovation, and Aggregate Productivity

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This version: November 2015
(May 2013)

Barcelona GSE Working Paper Series

Working Paper nº 865

Financing Constraints, Radical versus Incremental Innovation, and Aggregate productivity.[*][†]

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First Version: May 2013
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Abstract

I provide new empirical evidence on a negative relation between financial frictions and productivity growth over firms' life cycle. I show that a model of firm dynamics with incremental innovation cannot explain such evidence. However also including radical innovation, which is very risky but potentially very productive, allows for joint replication of several stylized facts about the dynamics of young and old firms and of the differences in productivity growth in industries with different degrees of financing frictions. These frictions matter because they act as a barrier to entry that reduces competition and the risk taking of young firms.

1   Introduction

Innovation and technology adoption are fundamental forces that shape firm dynamics and aggregate productivity growth. New firms bring new ideas and are better suited

to introduce radical innovations that generate permanent improvements in aggregate productivity. However new firms are also more likely to face financing frictions, which may distort their investment and innovation decisions. Hsieh and Klenow (2014) show that US manufacturing plants on average increase their productivity by a factor of 9.3 from their birth until they are 35 years of age, suggesting an important role for learning and innovation in building firm specific intangible capital. The same authors also show that for similar plants in India and Mexico productivity increases only by a factor of 1.7 and 1.5, respectively. These different life cycle dynamics shape cross country productivity and income differences, and it is therefore important to understand their causes. Do financial imperfections play an important role in explaining them?

The two main contributions of this paper are to provide new empirical evidence on the relation between financial factors and the life cycle dynamics of firms, and to show that the interaction between financial factors and heterogeneous innovation decisions are essential to explain such evidence. First, I analyse a very rich dataset of Italian manufacturing firms for which more than 60.000 observations of balance sheet data as well as direct information on financial frictions from multiple surveys are available. I construct alternative measures of productivity and I show a very consistent empirical pattern: in industries where firms are more likely to be financially constrained productivity grows less over the firms' life cycle than in the other industries. Importantly, these growth differentials do not disappear as firms grow older. Second, motivated by this evidence, I develop an industry model with financing frictions, firm dynamics, and innovation decision. I show that if innovation is modelled as a standard incremental process, financing frictions reduce the innovation of very young firms and aggregate TFP, but have a very limited effect on the innovation decisions and the life cycle dynamics of all the other firms, contradicting the empirical evidence. In continuation, I calibrate a version of the model with both incremental and radical innovation, where the latter is a very risky experimentation process that can reduce the competitiveness of the firm if it fails, but is also potentially able to generate a very large increase in productivity if it succeeds. I show that in equilibrium this model matches several stylised facts about the innovation dynamics of young and old firms, and at the same time generates a relation between financial frictions and productivity dynamics consistent with the empirical evidence. The empirical and theoretical findings of this paper mutually reinforce each other. The model provides an explanation of the empirical evidence and at the same time generates a series of additional testable predictions that both confirm its implications as well as the validity of the empirical methodology followed to construct the indicator of financial frictions used in the paper.

The results support the view that financial factors are important in explaining the cross country findings of Hsieh and Klenow (2014).

In the model, monopolistically competitive firms are subject to financing frictions and every period receive innovation opportunities with some probability. In the benchmark model only incremental innovation is available, which increases productivity growth after paying a fixed cost. In a calibrated version of this model, innovation is optimal for all firms except the very unproductive ones. Moreover since firms can retain earnings to increase their self financing, all firms except the very young ones are able to innovate, and life cycle dynamics are largely unaffected by financial factors.

I then consider a model with both incremental and radical innovation opportunities. Radical innovation is risky, but potentially able to generate a very large increase in productivity. It is risky both because it fails with positive probability, and because such failure reduces the firm's productivity below the level it had before innovating. The intuition for this assumption is that radical innovation, because of its disruptive nature, is not complementary to the existing tangible and intangible capital of the firm. Furthermore, such innovation is irreversible and requires the firm to replace the physical capital, knowledge and organizational capital which were used to operate the old technology. Therefore in case of failure the firm cannot easily revert back to the old technology, and its efficiency will be lower with respect to the situation before innovating.[1] I calibrate a financially unconstrained industry with both types of innovations, and show that it generates realistic life-cycle dynamics whereby young firms are much more likely to invest in radical innovation, while older firms are on average more productive, more likely to invest in incremental innovation, and have less volatile growth rates. These dynamics are consistent with the observation that innovation is a risky experimentation process, whereby entrepreneurs do not know in advance "*whether a particular technology or product or business model will be successful, until one has actually invested in it*" (Kerr, Nanda and Rhodes-Kropf, 2014). They are also consistent with Akcigit and Kerr (2010), who analyse US patents data and show that small firms do relatively more exploration R&D and have a relatively higher rate of major inventions than large firms, and with Haltiwanger et al (2014), who analyse US data and find that many young firms fail in their first few years, so that the higher mean net employment growth of small versus large firms is driven by a small fraction of surviving very fast growing firms.

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[1] This type of innovation is similar to the concept of radical innovation as it is defined in management studies. For example Utterback (1996) defines radical innovation as a "*change that sweeps away much of a firm's existing investment in technical skill and knowledge, designs, production technique, plant and equipment*".

I use the model with both radical and incremental innovation to simulate industries with different degrees of financial frictions. These frictions increase bankruptcy probability for young and financially fragile firms, and reduce entry and competition. Lower competition increases the profitability of firms that manage to survive, and also raises the expected value of a successful innovation. This "Shumpeterian effect" makes incremental innovation more desirable. However, lower competition also discourages the radical innovation of young firms with relatively low productivity. This happens because with more competition these young firms are less profitable. On the one hand, radical innovation is their best chance to rapidly grow in productivity and size. On the other hand, its cost is limited by the exit option: in case of failure these firms can cut the losses by closing down. Instead, with lower competition these firms are more profitable at current productivity levels, have more to lose from a failed radical innovation, and have a lower propensity to attempt it. A realistically calibrated model predicts that radical innovation among young firms is up to 48% lower in a financially constrained industry relative to an unconstrained one. This implies that fewer firms become large and profitable enough to invest in incremental innovation, slowing down productivity growth over the life cycle for both young and old firms, and generating life cycle dynamics consistent with the empirical evidence. Lower radical innovation caused by financial frictions reduces industry level TFP by up to 18.1%.

In the last part of the paper I provide further empirical evidence supporting the predictions of the model. I confirm the prediction that differences in productivity growth across sectors are related to both R&D intensity and to differences in competition. Moreover I construct approximate empirical measures of radical and incremental innovation and find support for the prediction of the model that firms in more financially constrained industries do relatively less of both types of innovation, and that incremental innovation, which increases with firm's age, is lower in these industries especially among older firms. Furthermore I combine the simulation results and the empirical data to estimate the aggregate importance of the distortions in innovation caused by financial frictions. I find that lowering financial frictions in the 50% most constrained sectors to the average level, and abstracting from general equilibrium effects on wages and interest rates, would increase the overall productivity of the Italian manufacturing sector by 6.3%.

2   Related literature

My paper is related to the literature on financing frictions and firm dynamics, such as Buera, Kaboski, and Shin (2011) and Caggese and Cunat (2013), among others. In particular, the paper is related to Midrigan and Xu (2014), who show that financing frictions delay firm entry in technologically advanced sectors. In their model this "delay effect" substantially reduces aggregate productivity, but once firms enter into the advanced sector, they accumulate retained earnings and financial frictions become almost irrelevant for the efficient allocation of resources. My model shares this self financing feature, and also shows a novel indirect channel of financial frictions on innovation decisions and productivity, which affects the growth dynamics of both young and old firms, with significant aggregate consequences.

Many authors have recently emphasized the importance of innovation to understand firm dynamics and productivity growth in models with heterogeneous firms and heterogeneous innovations (among other recent papers, see Klette and Kortum, 2004, Akcigit and Kerr, 2010 and Acemoglu, Akcigit and Celik, 2014). In common with these papers, in my paper radical innovation is an investment that has the potential to greatly increase firm's productivity and profitability. Moreover I emphasize the importance of the risk of such innovation, and thus my paper relates to Dorastzelsky and Jaumandreu (2013) and Castro, Clementi and Lee (2015), who notice that innovation related activities increase the volatility of productivity growth, to Caggese (2012), who estimates a negative effect of uncertainty on the riskier innovation decisions of entrepreneurial firms, and to Gabler and Poschke (2013), who also consider the importance of innovation risk for selection, reallocation, and productivity growth. Finally, the paper is also related to the literature on competition and innovation, because it provides a novel (to the best of my knowledge) explanation for the positive relation between competition and innovation often found in empirical studies, which is complementary to the "Escape Competition effect" of Aghion *et al.* (2001).

3   Empirical evidence

In this section I provide empirical evidence on the relation between financing frictions and the life-cycle dynamics of productivity at the firm level. I study a sample of 11429 firms, drawn from the Mediocredito/Capitalia surveys of Italian manufacturing firms. It is based on an unbalanced panel of firms with balance-sheet data from 1989 to 2000, as well as additional qualitative information from three surveys conducted in 1995,

1998 and 2001. Each survey reports information about the activity of the firms in the three previous years, and it includes detailed information on financing constraints and innovation (see Appendix 2 for details).

In each Mediocredito/Capitalia survey firms report whether, in the last year of the survey, they had a loan application turned down recently; whether they desired more credit at the market interest rate; and whether they would be willing to pay a higher interest rate than the market rate to obtain credit. Following Caggese and Cunat (2008) I aggregate these three variables into a single variable $constrained_{i,s}$, which is equal to one if firm i declares to face some type of financial problem in survey s (14% of all firm-year observations), and is equal to zero otherwise.[2]

A firm-level indicator of financial constraints should satisfy two properties. First, it should be positively related to the probability that the firm faces problems in accessing external finance because of informational or enforceability problems with lenders. Second, it should be unrelated to growth opportunities or other unobserved variables that directly affect the dependent variable of interest. The variable $constrained_{i,s}$ is likely to satisfy the first property. However it may not satisfy the second one, because less productive and profitable firms are at the same time more likely to claim difficulties in accessing loans and have worse investment and innovation opportunities. Indeed in the dataset firms that declare financing frictions are less profitable than the other firms in the same sector. The difficulty in formulating a reliable indicator of financing frictions is well known in the corporate finance literature (e.g. see, among others, Farre-Mensa and Ljungqvist, 2015). In order to control for these problems, I proceed as follows: first, I consider as constrained only firms that complain about problems in accessing external finance while at the same time have average operative profits over added value larger than 0.1. This threshold excludes the 25% least profitable firms. Second, I calculate the frequency of financially constrained firms in each 4 digit manufacturing sector, and I select sectors in 2 different groups.[3] One group is composed by the 50% four digit sectors with most constrained firms, called the "Constrained" group, and the other group is composed of the 50% four digit sectors with least constrained firms, called the "Unconstrained" group. Thus the constrained group includes all firms more likely to face financing problems because of sector specific factors. Third, the model

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[2]Caggese and Cunat (2008) analyse the reliability of this survey-based indicator of financing frictions, and find that it is consistent with alternative indicators based on balance sheet data. In particular they find that firms with higher coverage ratio, higher net liquid assets, more financial development in their region and those with headquarters in the same region as the headquarters of their main bank are less likely to declare to be financially constrained.

[3]I use the Ateco 91 classification of the Italian National Statistics Office (Istat). The 2-digit Ateco 91 sectors included in the sample are listed in Table 12 in Appendix 2.

developed and simulated in sections 4-5 predicts that financial frictions mainly affect innovation indirectly by altering competition and profitability at the industry level. In other words, it predicts that the effect of financing frictions on productivity growth can be precisely estimated also if firms currently financially constrained are excluded from the estimation. Beside being a testable implication, which I will empirically verify in section 6, this is a very useful property, because eliminating from the analysis firms declaring financial problems further reduces the above mentioned selection problems. Table 12 in Appendix 2 reports the distribution of firms in the two groups for each two digit manufacturing sector. It shows that financial frictions are present in all industries and not concentrated in only few sectors. Tables 1 and 2 analyse the age profile of productivity. They report the results of several regressions where the dependent variable is a firm level estimate of total factor productivity. The first measure is $\widehat{v}_{i,t}^{1}$, revenue total factor productivity. I estimate the following production function at the two digit level using the Levinshon and Petrin (2003) methodology (see the details in Appendix 1):

$$p_{i,t}y_{i,t} = e^{v_{i,t}^{1}} \left(p_{i,t}^{k}k_{i,t}\right)^{\alpha} (w_{i,t}l_{i,t})^{\beta} \tag{1}$$

Where $p_{i,t}y_{i,t}$ is added value, $p_{t}^{k}k_{i,t}$ is the value if capital, and $w_{i,t}l_{i,t}$ is cost of labour for firm i in period t. Years and firms fixed effects are also included in the estimation. I use the parameters $\widehat{\alpha}$ and $\widehat{\beta}$, estimated separately for each 2 digits sector, to obtain an empirical counterpart $\widehat{v}_{i,t}^{1}$ of $v_{i,t}^{1}$. A possible limitation of this approach is that revenue productivity may not capture differences in efficiency levels if these are passed to consumers in the form of price reductions.[4] Therefore I also compute two alternative measures. $v_{i,t}^{2}$ is computed following Hsieh and Klenow (2009), who derive a monopolistic competition model with a Cobb Douglas production function similar to equation (1). They and notice that while revenue productivity is equal to $\frac{p_{i,t}y_{i,t}}{\left(p_{i,t}^{k}k_{i,t}\right)^{\alpha}(w_{i,t}l_{i,t})^{\beta}}$, physical productivity is equal to $\kappa_{s}\frac{(p_{i,t}y_{i,t})^{\frac{\sigma}{\sigma-1}}}{\left(p_{i,t}^{k}k_{i,t}\right)^{\alpha}l_{i,t}^{\beta}}$, where κ_{s} is a sector level coefficient and $\sigma > 1$ is the elasticity of substitution between firms. Following Hsieh and Klenow (2009) in using labour cost to measure labour input $l_{i,t}$, and assuming that the unobservable κ_{s} is absorbed by firm and time fixed effects, I estimate the following function:

$$(p_{i,t}y_{i,t})^{\frac{\sigma}{\sigma-1}} = e^{v_{i,t}^{2}} \left(p_{i,t}^{k}k_{i,t}\right)^{\alpha} (w_{i,t}l_{i,t})^{\beta}, \tag{2}$$

where $v_{i,t}^{2}$ is the proxy for physical productivity analogous to the one computed in Hsieh

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[4]For example in the model considered in the previous section an increase in marginal productivity of labour v does not affect revenue total factor productivity because the fall in prices completely offsets the productivity gain.

and Klenow (2009) and (2014).[5] A third measure $v_{i,t}^3$ is based on the profitability of firms. I consider the ratio between profits and labour cost for each firm-year observation, $\frac{\pi_{i,t}}{w_{i,t}l_{i,t}}$. This ratio is monotonously increasing in the productivity of the firm as long as the firm has some competitive power (or is a price taker but has a decreasing returns to scale production function), also when improvements in productivity are passed to consumers in the form of price reductions.[6] I regress this measure over a set of fixed effects:

$$\frac{\pi_{i,t}}{w_{i,t}l_{i,t}} = \beta_0 + \sum_{s=1}^{N_s} \beta_s D_s + \sum_{s=1}^{N_y} \beta_y D_y + v_{i,t}^3 \tag{4}$$

Where D_s are 3 digit sector dummies and D_y are year dummies. $\widehat{v}_{i,t}^3$ is the estimated residual of this regression. Changes over time in $\widehat{v}_{i,t}^3$ are orthogonal to aggregate demand and industry factors, and thus are likely to capture changes in the productivity of the firm.

I measure the evolution of productivity over the firm's life cycle by estimating the following model:

$$\widehat{v}_{i,s}^j = \beta_0 + \beta_1 age_{i,s} + \beta_2 age_{i,s} * constrained_i + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \tag{5}$$

Given that each survey covers a 3-years period, for the following regressions I consolidate all the balance sheet variables at the same time interval. The productivity measure $j \in \{1, 2, 3\}$ of firm i in survey s $\widehat{v}_{i,s}^j$ is the dependent variable, and is the average of $\widehat{v}_{i,t}^j$ for the three years of survey s. Among the regressors, the age of the firm $age_{i,s}$ is included individually and interacted with the financing constraints dummy $constrained_i$, which is equal to one if the firm belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. Thus β_1 measures the effect of age on productivity for the unconstrained group of firms, and β_2 measures the differential effect of age for the constrained group. x_j is the set of m control variables, which include firm fixed effects and time effects.

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[5]I set $\sigma = 3$, as in Hsieh and Klenow (2009). The idea is that quantity $y_{i,t}$ is inferred using revenues $p_{i,t}y_{i,t}$ and the assumed elasticity of demand σ.

[6]For the case of the calibrated model analyzed in the next section, it is possible to show that

$$\frac{\pi_{i,t}}{w_{i,t}l_{i,t}} = a - \frac{b}{(v_t)^2} \tag{3}$$

Where a and b are positive constants which only depend on sector level variables. By linearising equation (3) around the sector average value of v_t, and redefining it as v_t^3, it is possible to derive equation (4).

Table 1: Relation between age and productivity (empirical sample)

Dependent variable	$\widehat{v}_{i,s}^1$	$\widehat{v}_{i,s}^2$	$\widehat{v}_{i,s}^3$	Time dummies interacted with the constrained group are included $\widehat{v}_{i,s}^1$	$\widehat{v}_{i,s}^2$	$\widehat{v}_{i,s}^2$
$age_{i,s}$	0.00616***	0.00926***	0.00067	0.00590***	0.00885***	0.000235
	(5.83)	(5.84)	(1.35)	(5.22)	(5.22)	(0.43)
$age_{i,s}*constrained_i$	−0.00360**	−0.00541**	−0.00207***	−0.00290*	−0.0043*	−0.00138*
	(−2.59)	(−2.6)	(−3.3)	(−1.91)	(−1.9)	(−1.95)
N.observations	12390	12390	12672	12390	12390	12672
Adj. R-sq.	0.011	0.011	0.006	0.012	0.012	0.007

Panel regression with firm fixed effect. Time effects are also included. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $\widehat{v}_{i,s}^1$ is revenue total factor productivity, $\widehat{v}_{i,s}^2$ is total factor productivity computed following the procedure of Hsieh and Klenow (2009), and $\widehat{v}_{i,s}^3$ is profits based productivity for firm i in survey s. $age_{i,s}$ 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. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

In Table 1 the estimated coefficients of age and age interacted with $constrained_i$ are reported. The presence of firm fixed-effects ensures that the estimation of β_1 and β_2 is not affected by a selection bias (the most productive firms are more likely to survive), since these parameters are identified only by within-firm changes in productivity. Columns 1-3 report the results using $\widehat{v}_{i,s}^1$, $\widehat{v}_{i,s}^2$ and $\widehat{v}_{i,s}^3$ as dependent variables, respectively. For firms in less constrained sectors all three productivity measures increase with age, even though the increase of $\widehat{v}_{i,s}^3$ is not statistically significant. Importantly, the coefficient of $age_{i,s}*constrained_i$ is always negative and significant, meaning that the relation between age and productivity is significantly more negative for the firms in the more financially constrained sectors. While this evidence supports the hypothesis that financing frictions reduce productivity growth, one possible alternative explanation of the findings is that more financially constrained sectors happen to be sectors in relative decline, with a progressive reduction in productivity over time. This possibility can be controlled for by introducing time dummies interacted with the constrained group among the regressors. This is done in columns 4 to 6, and also in this case the results are confirmed, even though they are slightly less significant.

Table 2 replicates the analysis of table 1 with a different selection of constrained groups. The estimated equation is:

Table 2: Relation between age and productivity, different classification of constrained groups (empirical sample)

| Dependent variable | $\widehat{v}_{i,s}^1$ | $\widehat{v}_{i,s}^2$ | $\widehat{v}_{i,s}^3$ | Time dummies interacted with the constrained groups are included | | |
				$\widehat{v}_{i,s}^1$	$\widehat{v}_{i,s}^2$	$\widehat{v}_{i,s}^3$
$age_{i,s}$	0.00755***	0.0113***	0.000722	0.00752***	0.011***	0.000127
	(5.79)	(5.8)	(1.18)	(5.33)	(5.34)	(0.18)
$age_{i,s}*midconstr_i$	−0.00387**	−0.00582**	−0.000528	−0.00373*	−0.00557*	−0.000174
	(−2.19)	(−2.19)	(−0.66)	(−1.89)	(−1.88)	(−0.19)
$age_{i,s}*highconstr_i$	−0.00529**	−0.00794**	−0.0026***	−0.00503**	−0.00755**	−0.00158*
	(−3.16)	(−3.16)	(−3.42)	(−2.75)	(−2.75)	(−1.79)
N.observations	12390	12390	12672	12390	12390	12672
Adj. R-sq.	0.011	0.011	0.006	0.013	0.013	0.007

Panel regression with firm fixed effect. Time effects are also included. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $\widehat{v}_{i,s}^1$ is revenue total factor productivity, $\widehat{v}_{i,s}^2$ is total factor productivity computed following the procedure of Hsieh and Klenow (2009), and $\widehat{v}_{i,s}^3$ is profits based productivity for firm i in survey s. $age_{i,s}$ is age in years for firm i in survey s. $midconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the medium 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.

$$\widehat{v}_{i,s}^j = \beta_0 + \beta_1 age_{i,s} + \beta_2 age_{i,s}*midconstr_i + \beta_2 age_{i,s}*highconstr_i + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \quad (6)$$

where $midconstr_i$ is equal to 1 if firm i is in the 33% of sectors with intermediate constraints, and 0 otherwise, and $highconstr_i$ is equal to 1 if firm i is in the 33% most constrained sectors and zero otherwise. The results show that the effect of age on productivity monotonously decreases with the intensity of financing frictions, in all the different regressions.

I represent graphically the relation between age and productivity for the different groups in figures 1 and 2. The curves are computed from the estimated coefficients of a piecewise linear regression in which the β coefficient is allowed to vary for four different age groups: up to 10 years, 11-20 years, 21-30 years and 31-40 years (see appendix 2 for details). Firm fixed effects and time dummies interacted with the constrained group are included as control variables in the regression. Figures 1 and 2 show the age profile of $\widehat{v}_{i,s}^2$ and $\widehat{v}_{i,s}^3$, respectively. I omit the figure constructed using

Figure 1: Life cycle of the productivity of firms in the empirical sample, TFP measure v^2
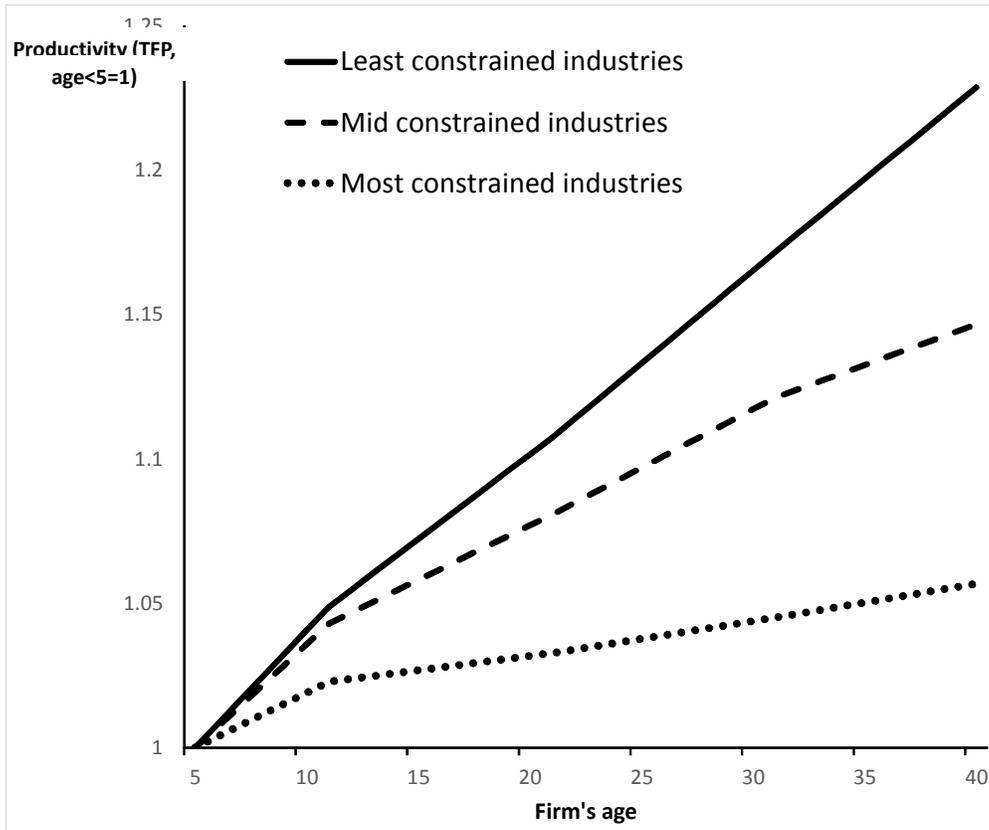

$\widehat{v}^1_{i,s}$ because it looks qualitatively similar to figure 1. The lines are normalized to a value of 1 for firms younger than 5 years old. Both figures show that in the less constrained sectors productivity grows faster as firms become older, relative to the more constrained sectors. Moreover the differences in growth rates do not disappear for older firms, consistently with the findings of Hsieh and Klenow (2014).

4 Model

Motivated by the empirical evidence in the previous section, in this section I develop a model to study the relation between financial frictions, innovation decisions, and the growth of firms. I consider an industry with firm dynamics and monopolistic competition as in Melitz (2003). To this framework I add financial frictions and different types of innovation. Each firm in the industry produces a variety w of a consumption good. There is a continuum of varieties $w \in \Omega$. Consumers preferences for the varieties

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Figure 2: Life cycle of the productivity of firms in the empirical sample, profits based measure v^3
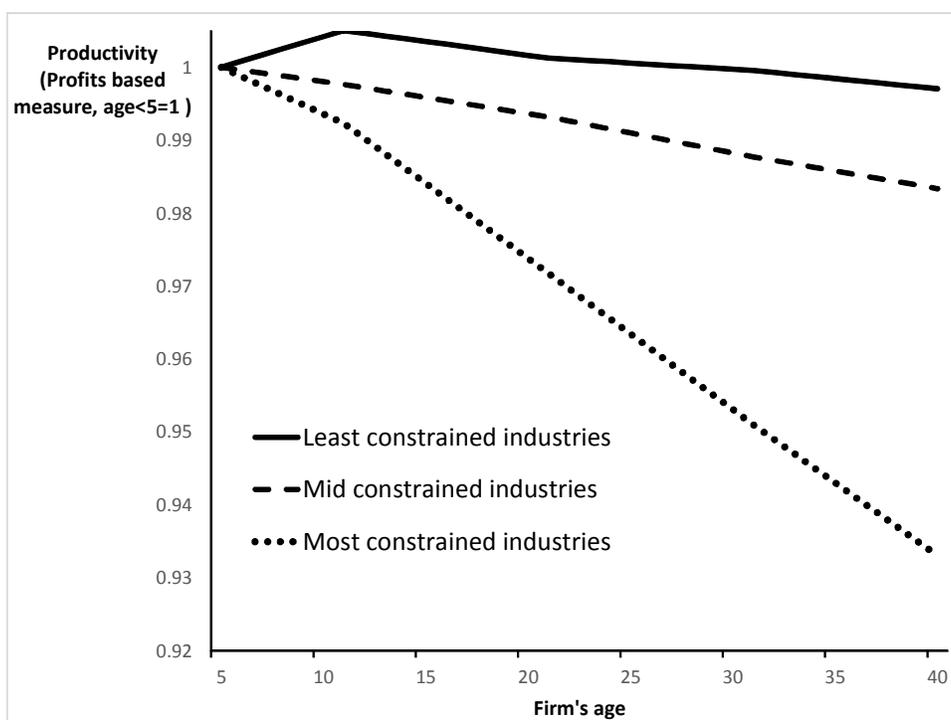
in the industry are C.E.S. with elasticity $\sigma > 1$. The C.E.S. price index P_t is equal to:

$$P_t = \left[\int_w p_t(w)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{7}$$

And the associated quantity of the aggregated differentiated good Q_t is:

$$Q_t = \left[\int_w q_t(w)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{8}$$

where $p_t(w)$ and $q_t(w)$ are the price and quantity consumed of the individual varieties w, respectively. The overall demand for the differentiated good Q_t is generated by:

$$Q_t = AP_t^{1-\eta} \tag{9}$$

where A is an exogenous demand parameter and $\eta < \sigma$ is the industry price elasticity of demand. From (8) and (9) the demand for an individual variety w is:

$$q_t(w) = A \frac{P_t^{\sigma-\eta}}{p_t(w)^{\sigma}} \tag{10}$$

Each variety is produced by a firm using labour. I assume that the marginal productivity of labour for the frontier technology is equal to $\overline{v_t^n}$, and it grows every period at the rate $g > 0$. To normalize the model, I assume that labour cost also grows at the same rate and is also equal to $\overline{v_t^n}$. I define v_t^n as the marginal productivity of labour for the firm and as $v_t = v^n / \overline{v^n}$ the productivity relative to the frontier. It follows that $v_t = 1$ at the frontier, that marginal labour cost is $\frac{1}{v_t}$, and that total labour cost is $\frac{q_t(w)}{v_t}$. The profits for a firm with productivity v_t and variety w are given by:

$$\pi_t (v_t, \varepsilon_t) = p_t(w)q_t(w) - \frac{q_t(w)}{v_t} - F_t \tag{11}$$

Since all the formulas are identical for all varieties, I drop the indicator w from now on. Firms are heterogeneous in terms of productivity v_t and fixed costs $F_t > 0$. These are the overhead costs of production that have to be paid every period. I assume that they are subject to an idiosyncratic shock ε_t which is uncorrelated across firms:

$$F_t = (1 + \varepsilon_t)F(v_t)$$

where $F'(v_t) > 0$.[7] ε_t is a mean zero i.i.d. shock which introduces uncertainty in profits and affects the accumulation of wealth and the probability of default. $\varepsilon_t F(v_t)$ enters additively in $\pi_t(v_t, \varepsilon_t)$ so that it does not affect the firm decision on the optimal price p_t and quantity produced q_t. This makes the model both easier to solve and more comparable to the basic model without financing frictions.[8]

The firm is risk neutral and chooses p_t in order to maximize $\pi_t(v_t, \varepsilon_t)$. The first order condition yields the standard pricing function:

$$p_t = \frac{\sigma}{\sigma - 1} \frac{1}{v_t} \tag{12}$$

where $\frac{\sigma}{\sigma-1}$ is the mark-up over the marginal cost $\frac{1}{v_t}$. It then follows that:

$$\pi_t(v_t, \varepsilon_t) = \frac{(\sigma - 1)^{\sigma-1}}{\sigma^\sigma} AP^{\sigma-\eta} v_t^{\sigma-1} - F_t$$

The timing of the model for a firm which was already in operation in period $t-1$ is the following. At the beginning of period t with probability δ its technology becomes useless forever, and the firm liquidates all its assets and stops activity. With probability $1-\delta$ the firm is able to continue. It observes the realization of the shock ε_t and receives profits π_t, and its financial wealth a_t is:

$$a_t = R[a_{t-1} - K(I_{t-1}) - d_{t-1}] + \pi_t(v_t, \varepsilon_t) \tag{13}$$

where $R = 1 + r$ and r is the real interest rate. d_t are dividends. $K(I_{t-1})$ is the cost of innovation and I_{t-1} is an indicator function which defines the innovation decision in period $t-1$. Financing frictions are introduced by following Caggese and Cuñat (2013) and assuming that the firm cannot borrow to finance the fixed cost of its operations. While it can pay workers with the stream of revenues generated by their labour input, it has to pay in advance the other costs of production. Therefore continuation is feasible only if:[9]

$$a_t \geq F_t, \tag{14}$$

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[7]The fixed cost F is proportional to productivity v to ensure that the profitability of small and large firms in the simulated model are comparable to those in the empirical sample.

[8]A multiplicative shock of the type $\varepsilon_t p_t q_t$ would not change the qualitative results of the model, but it would imply that the optimal quantity produced q_t would be a function of the intensity of financing frictions, thus making the solution of the model more complicated.

[9]Constraint (14) is a simple way to introduce financing frictions in the model, and it generates a realistic downward sloping hazard rate for firms. It can be interpreted as a shortcut for more realistic models of firm dynamics with financing frictions such as, for instance, Clementi and Hopenhayn (2006).

If the constraint (14) is not satisfied, then the firm cannot continue its activity and is forced to liquidate. Conditional on continuation, innovation of type I_t is feasible only if:

$$a_t \geq F_t + K(I_t). \tag{15}$$

The presence of financing frictions and the fact that the firm discounts future profits at the constant interest rate R implies that it is never optimal to distribute dividends while in operation, since accumulating wealth reduces future expected financing constraints. Hence dividends d_t are always equal to zero. Profits increase wealth a_t, which is distributed as dividends only when the firm is liquidated. After observing ε_t and realizing profits π_t, the firm decides whether or not to continue activity the next period. It may decide to exit if it is not profitable enough to cover the fixed cost F_t. In this case the firm liquidates and ceases to operate forever.

4.1 Benchmark model with incremental innovation.

Below I define how innovation affects firm's productivity. The empirical analysis in section 3 estimates productivity measures that are based on revenues and profits, and are therefore driven both by changes in demand and in production efficiency. Indeed many authors (e.g. see, among others, Foster Haltiwanger and Syverson, 2015) argue that gradual increases in plants' idiosyncratic demand levels are important to explain the growth of plants in the US. Regarding this, Hsieh and Klenow (2014) notice that while they focus explicitly on the growth of process efficiency along the plants life cycle, under certain assumptions their measure is equivalent to a composite of process efficiency and idiosyncratic demand coming from quality and variety improvements. Similarly, in my model for simplicity I define an innovation process that affects production efficiency, but an alternative model with quality and/or variety innovations that affect firm idiosyncratic demand would have very similar qualitative and quantitative implications.

In the model I assume that every period a firm receives a new idea with probability γ. Arrival of ideas is independent across firms and over time for each firm. A firm with a new idea in period t on how to improve productivity has the opportunity to select $I_t = 1$, pay an innovation cost $K(1) > 0$ to implement the idea, and increase its relative productivity v_{t+1} up to the maximum between $v_t(1 + g)^\tau$ and the frontier technology, where $\tau > 0$ measures how productive the innovation is.[10]

---

[10]γ can also be interpreted as the probability that a better technology is available and $K(1)$ as a cost of technology adoption.

A firm which selects $I_t = 0$ with $K(0) = 0$, either because has no innovation opportunities or because decides not to implement the innovation, is nonetheless able with probability ξ to marginally improve its productivity to keep pace with the technology frontier. Therefore its relative productivity v remains constant. With probability $1 - \xi$ its relative productivity decreases by $1 + g$. Therefore the law of motion of v_t is:

$$
\begin{aligned}
\text{if } I_t &= 0 : \left\{ \begin{array}{l} v_{t+1} = v_t \text{ with probability } \xi \\ v_{t+1} = \frac{v_t}{1+g} \text{ with probability } 1 - \xi \end{array} \right\} \\
\text{if } I_t &= 1, \ v_{t+1} = \max\left[v_t(1+g)^\tau, 1 \right]
\end{aligned}
$$

4.2 Full model with radical and incremental innovation

I modify the previous model by assuming that with probability γ the firm receives both an "incremental" idea and a "radical" idea. The firm can choose to implement one of the two, or neither, but it cannot implement both.[11] Implementing the incremental ideal ($I_t = 1$) is similar to before. If the firm chooses to implement the radical idea ($I_t = 2$), it invests an amount equal to $K(2) > 0$ and is successful with probability ξ^R. In case of success v_{t+1} increases by $(1 + g)^{\tau^R}$, or up to the frontier technology. However with probability $1 - \xi^R$ the innovation fails and v_{t+1} decreases to $\frac{v_t}{(1+g)^{\tau^R}}$. Therefore the term $\tau^R >> \tau > 0$ measures both the downside and upside risk of radical innovation. This symmetric structure is not essential for the results, but is convenient to simplify the calibration. The qualitative and quantitative results of the model are confirmed under alternative hypotheses regarding radical innovation, as long as the drop in productivity conditional on failure is not negligible. Radical innovation can be interpreted as a decision to radically change the firm's organizational structure and/or to invest in new technologies, products and production processes. The intuition for the downside risk is that such change is irreversible, and requires the firm to replace the capital and expertise which was used to operate the old technology. Therefore in case of failure the firm cannot easily revert back to the old technology, and its efficiency will be lower with respect to the situation before innovating. The law of motion of

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[11]The assumption that innovation probabilities are not independent simplifies the analysis but is not essential for the results. Allowing firms to have independent radical and incremental ideas and to potentially implement both in the same period would not significanly change the quantitative and qualitative results of the model, because in equilibrium, for the calibrated parameters, radical innovation is chosen almost exclusively by young/small firms, and incremental innovation is chosed by old/large firms.

productivity becomes:

$$
\begin{aligned}
\text{if } I_t &= 0 : \left\{ \begin{array}{l} v_{t+1} = v_t \text{ with probability } \xi \\ v_{t+1} = \frac{v_t}{1+g} \text{ with probability } 1 - \xi \end{array} \right\} \\
\text{if } I_t &= 1, \ v_{t+1} = \max\left[v_t(1+g)^\tau, 1 \right] \\
\text{if } I_t &= 2 : \left\{ \begin{array}{l} v_{t+1} = \max\left[v_t(1+g)^{\tau^R}, 1 \right] \text{ with probability } \xi^R \\ v_{t+1} = \frac{v_t}{(1+g)^{\tau^R}} \text{ with probability } 1 - \xi^R \end{array} \right\}
\end{aligned}
$$

4.3   Value functions

I define the value function $V_t^1\left(a_t, \varepsilon_t, v_t\right)$ as the net present value of future profits after receiving π_t and conditional on doing incremental innovation in period t:[12]

$$
V_t^1\left(a_t, \varepsilon_t, v_t\right) = -K(1) + \frac{1-\delta}{R} E_t \left\{ \pi_{t+1}\left(\varepsilon_{t+1}, \max\left[v_t(1+g)^\tau, 1\right]\right) + V_{t+1}\left(a_{t+1}, \varepsilon_{t+1}, \max\left[v_t(1+g)^\tau, 1\right]\right) \right\}.
\tag{16}
$$

Furthermore, I define $V_t^2\left(a_t, \varepsilon_t, v_t\right)$ as the value function today conditional on doing radical innovation in period t:

$$
V_t^2\left(a_t, \varepsilon_t, v_t\right) = -K(2) + \frac{1-\delta}{R} \left\{ \begin{array}{l} \xi^R E_t \left\{ \begin{array}{l} \pi_{t+1}\left\{ \varepsilon_{t+1}, \max\left[v_t(1+g)^{\tau^R}, 1\right]\right\} + \\ V_{t+1}\left\{ a_{t+1}, \varepsilon_{t+1}, \max\left[v_t(1+g)^{\tau^R}, 1\right]\right\} \end{array} \right\} \\ + \left(1 - \xi^R\right) E_t \left\{ \pi_{t+1}\left(\varepsilon_{t+1}, \frac{v_t}{(1+g)^{\tau^R}}\right) + V_{t+1}\left[a_{t+1}, \varepsilon_{t+1}, \frac{v_t}{(1+g)^R}\right]\right\} \end{array} \right\},
\tag{17}
$$

And $V_t^0\left(a_t, \varepsilon_t, v_t\right)$ as the value function conditional on not innovating in period t:

$$
V_t^0\left(a_t, \varepsilon_t, v_t\right) = \frac{1-\delta}{R} \left\{ \begin{array}{l} \xi E_t \left\{ \pi_{t+1}\left(\varepsilon_{t+1}, v_t\right) + V_{t+1}\left(a_{t+1}, \varepsilon_{t+1}, v_t\right)\right\} \\ + \left(1 - \xi\right) E_t \left\{ \pi_{t+1}\left(\varepsilon_{t+1}, \frac{v_t}{1+g}\right) + V_{t+1}\left[a_{t+1}, \varepsilon_{t+1}, \frac{v_t}{1+g}\right]\right\} \end{array} \right\}
\tag{18}
$$

Conditional on continuation the firm's innovation decision I_t maximizes its value. In the benchmark model it is equal to:

$$
V_t^*\left(a_t, \varepsilon_t, v_t\right) = \gamma \arg\max_{I_t \in \{0,1\}} \left\{ V_t^0\left(a_t, \varepsilon_t, v_t\right), V_t^1\left(a_t, \varepsilon_t, v_t\right) \right\} + \left(1 - \gamma\right) V_t^0\left(a_t, \varepsilon_t, v_t\right)
\tag{19}
$$

---

[12]Since the discount factor of the firm is $1/R$, and the firm is risk neutral, this value coincides with the present value of expected dividends net of current wealth a_t.

While in the full model is equal to

$$V_t^* \left(a_t, \varepsilon_t, v_t\right) = \gamma \arg \max_{I_t \in \{0,1,2\}} \left\{V_t^0 \left(a_t, \varepsilon_t, v_t\right), V_t^1 \left(a_t, \varepsilon_t, v_t\right), V_t^2 \left(a_t, \varepsilon_t, v_t\right)\right\} + \left(1 - \gamma\right) V_t^0 \left(a_t, \varepsilon_t, v_t\right)$$

(20)

such that equation (15) is satisfied. Given the optimal continuation value $V_t^* \left(a_t, \varepsilon_t, v_t\right)$, the value of the firm at the beginning of time t, $V_t \left(a_t, \varepsilon_t, v_t\right)$, is:

$$V_t \left(a_t, \varepsilon_t, v_t\right) = 1 \left(a_t \geq F_t\right) \left\{\max \left[V_t^* \left(a_t, \varepsilon_t, v_t\right), 0\right]\right\}$$

(21)

Equation (21) implies that the value of the firm is equal to zero in two cases. First, when the indicator function $1 \left(a_t \geq F\right)$ is equal to zero because the liquidity constraint (14) is not satisfied. Second, when value in the curly brackets is equal to zero, which indicates that since $V_t^* \left(a_t, \varepsilon_t, v_t\right) < 0$, the firm is no longer profitable and exits from production.

4.4   Entry decision

Every period there is free entry, and there is a large amount of new potential entrants with a constant endowment of wealth a_0. They draw their relative productivity v_0 from an initial distribution with support $[\underline{v}, \overline{v}]$, after having paid an initial cost S^C. Once they learn their type they decide whether or not to start activity. The free entry condition requires that ex ante the expected value of paying S^C conditional on the expectation of the initial values v_0 and ε_0 is equal to zero:

$$\int_{\underline{v}}^{\overline{v}} \max \left\{E^{\varepsilon_0} \left[V_0 \left(a_0, \varepsilon_0, v_0\right)\right], 0\right\} f(v_0) dv_0 - S^C = 0$$

(22)

4.5   Aggregate equilibrium

In the steady state the aggregate price P_t, the aggregate quantity Q_t, and the distribution of firms over the values of v_t, ε_t and a_t are constant over time. The presence of technological obsolescence implies that the age of firms is finite and that the distribution of wealth across firms is non-degenerate. Aggregate price P_t is set to ensure that the free entry condition (22) is satisfied. The number of firms in equilibrium ensures that P_t also satisfies the aggregate price equation (7). Aggregation is very simple because all operating firms with productivity v choose the same price $p \left(v\right)$, as determined by equation (12).

4.6   Calibration

I first illustrate the calibration of the benchmark model, then I discuss how I select the parameters for radical innovation in the full model.

4.6.1   Benchmark model

The parameters are illustrated in Table 3. With the exception of S^C, σ, η and r, all parameters are calibrated to match a set of simulated moments with the moments estimated from the empirical sample analyzed in section 3.[13] The following six parameters determine the dynamics of innovation and productivity: the mean $\widehat{v}$ and variance σ_ν^2 of the distribution of productivity of new firms v.[14] The depreciation rate of technology g; the parameter which determines the increase in productivity after innovating τ; The probability that productivity depreciates for non innovating firms $1 - \xi$; the exogenous exit probability δ. Since all these parameters jointly determine the size, age and productivity distribution of firms, I identify them with 6 moments of these distributions: 1) the ratio median productivity/99th percentile of productivity; 2) the average cross sectional standard deviation of TFP; 3) the yearly decline in TFP for non innovating firms; 4) the ratio between the 90th and 10th percentile of the size distribution; 5) the percentage of firms older than 60 years; 6) the average age of firms.

The profits shock ε is modeled as a two state i.i.d. process where ε takes the values of θ and $-\theta$ with equal probability, where θ is a positive constant. The fixed per period cost of operation $F_{it}(v_{it})$ is $F_{it} = F\frac{v_{it}}{v_L}$, with $F > 0$.[15] F and θ affect the variability of profits, and jointly match the fraction of firms reporting negative profits and the time series volatility of profits over sales. The cost of innovation $K(1)$ matches the average value of R&D expenditures over profits; the probability to have an

---

[13]The initial entry cost S^C is set equal to 4. This is 1.3 times the average annual firm profits in the simulated industry. I experimented with larger and smaller values without obtaining a significant change in the results. The average real interest rate r is equal to two percent, which is consistent with the average short-term real interest rates in Italy in the sample period. The value of σ, the elasticity of substitution between varieties, is equal to 4, in line with Bernard, Eaton, Jensen and Kortum (2003), who calculate a value of 3.79 using plant level data. The value of η, the industry price elasticity of demand, is set equal to 1.5, following Constantini and Melitz (2008). The difference between the values of η and σ is consistent with Broda and Weinstein (2006), who estimate that the elasticity of substitution falls between 33% to 67% moving from the highest to the lowest level of disaggregation in industry data.

[14]I approximate a log-normal distribution of v_0 to a bounded distribution with support $[v_L, v_H]$ by cutting the 1% tails of the distribution. So that $prob(v < v_L) = prob(v > v_H) = 1\%$. The censored probability distribution is re-scaled to make sure that its integral over the support $[v_L, v_H]$ is equal to 1.

[15]v_L is the lower bound of the productivity distribution of new firms, see fn.14.

Table 3: Calibration of the benchmark model with only incremental innovation

Parameter	Value	Empirical moment	Data	Model
F	0.5	Fraction of firms with negative profits	0.40	0.33
θ	0.15	Avg. of time series st.dev. of profits/sales	0.117[1]	0.102
$K(1)$	3	Average R&D expenditures /profits	67%[2]	66%
γ	0.45	Percentage of innovating firms	22.4%[2]	24%
$\widehat{v}$	0.45	Median TFP relative to the 99th percentile	0.78	0.79
σ_v^2	0.03	Average cross sectional standard deviation of TFP	0.34[3]	0.25
g	1.009	Average yearly decline in TFP for firms not doing R&D	0.4%[3]	0.23%
τ	3	Ratio between 90th pctile and 10th pctile of size distrib.	13.2	7.29
ξ^{NI}	0.25	Percentage of firms with age >60 years	4.8%	8.9%
δ	0.01	Average age	24	22
a_0	12	Percentage of firms going bankrupt every period	0.5%	0.5%

Other parameters: $S^C = 4; r = 2\%; \eta = 1.5; \sigma = 4; A = 25010$.

Profits denote operative profits.

1. I use net income over value added, eliminating 1% outliers on both tails, compute its standard deviation for each firm with at least 6 yearly observations and then compute the average across firms.

2. Including only R&D where cost of R&D over sales is greater than 0.5%.

3. These statistics are calculated after excluding the 1% outliers on both tails.

innovation opportunity γ matches the percentage of innovating firms, where I classify as "innovating" all firms in the empirical sample with R&D expenditure higher than 0.5% of sales.[16] Despite the model is relatively stylized, table 3 shows that it matches these empirical moments reasonably well.

Finally, the parameter a_0, the initial endowment of wealth of new firms, affects the intensity of financing frictions and the probability of bankruptcy. I chose a value of $a_0 = 12$, which in equilibrium corresponds to 40% of average firm sales in the industry, and which matches an average share of firms going bankrupt every period equal to 0.5%.[17] The scale parameter A does not affect the results of the analysis and its value ensures that the number of firms in the calibrated industry is sufficiently large, and allows to compute reliable aggregate statistics.

---

[16]Firms with very low R&D spending are likely to have only marginal innovation projects which do not substantially affect their productivity. Since in the model innovation has a lage impact on firm's sales and profits, I calibrate it on the fraction of firms in the data which have R&D spending above a minimum threshold.

[17]A 2003 study by Istat shows that in 2001 in the whole Italian economy 0.25% of firms went bankrupt, while the share was equal to 0.4% in the Manufacturing sector. The same study also shows an average share of bankruptcies of 0.3% for the whole economy in the 1997-2001 period. I apply the same proportion to estimate a share of bankruptcies in manufacturing equal to 0.5% for the sample period.

4.6.2 Full model with incremental and radical innovation

Adding radical innovation to the model requires choosing three additional parameters: the probability of success ξ^R, the change in productivity after innovating τ^R, and the cost of radical innovation $K(2)$. Since it is very difficult to identify R&D directed to radical innovations in the data, I use the following strategy: first, I set a value of $\tau^R = 30$, which implies that after a successful radical innovation productivity increases by $\left[(1+g)^{\tau^R} - 1 \right] \% = 31\%$, while it decreases by $\left[1 - \frac{1}{(1+g)^{\tau^R}} \right] \% = 24\%$ in case of failure. Second, given the value of τ^R, the probability of success of radical innovation ξ^R is chosen to ensure that at least 40% of all innovation is performed by firms attempting to produce a new radical innovation, while the cost of this experimentation process is set equal to the cost of incremental innovation in expected terms, so that $K(2) = \xi^R K(1)$. These assumptions generate a value of $\xi^R = 4.5\%$, so that every period 1.8% of firms in the industry are successful radical innovators and increase their size on average by 224%. The values of τ^R, ξ^R and $K(2)$ do not match a specific moment of the empirical sample, and a sensitivity analysis of the results to changing these parameters is provided in section 5.2. The qualitative results of the model are consistent with a large range of values of τ^R, as long as ξ^R is sufficiently low and productivity decreases by a non negligible amount when radical innovation fails. Moreover the radical innovation decisions are mainly determined by the values of τ^R and ξ^R, and are not very sensitive to variations in $K(2)$. Third, I recalibrate the parameters $K(1), \tau, \gamma, \delta$ and a_0 to match the distribution of productivity, the overall percentage of innovating firms, the cost of innovation, the average age of firms, and the percentage of bankruptcies, while leaving all the other parameters unchanged. Table 4 illustrates the parameters of the full model.

5   Simulation results

In the following sub-sections I simulate several industries in which different values of the initial endowment a_0 generate different degrees of financial frictions. The lower a_0 is, the higher is the fraction of young firms that go bankrupt evert period, or that have insufficient funds to invest in innovation. This assumption is a simple way to introduce industry level differences in the intensity of financing frictions, and has similar implications to assuming that the endowment is identical in all industries but the borrowing capacity of firms is higher in less constrained industries, as it is frequently assumed in the firm dynamics literature (e.g. see Buera, Kaboski, and Shin, 2011, and Midrigan and Xu, 2014).

Table 4: Calibration of the full model with radical and incremental innovation

Parameter	Value	Empirical moment	Data	Model
F	0.5	Fraction of firms with negative profits	0.40	0.34
θ	0.15	Avg. of time series st.dev. of profits/sales	0.117[1]	0.087
$K(1)$	6	Average R&D expenditures /profits	67%[2]	58%
γ	0.85	Percentage of innovating firms	22.4%[2]	23.3%
$\widehat{v}$	0.45	Median TFP relative to the 99th percentile	0.78	0.62
σ_v^2	0.03	Average cross sectional standard deviation of TFP	0.34[3]	0.32
g	1.009	Average yearly decline in TFP for firms not doing R&D	0.4%[3]	0.4%
τ	2	Ratio between 90th pctile and 10th pctile of size distrib.	13.2	12.2
ξ^{NI}	0.25	Percentage of firms with age >60 years	4.8%	14.4%
δ	0.015	Average age	24	26
a_0	4.5	Percentage of firms going bankrupt every period	0.5%	0.06%

Additional radical innovation parameters: $K(2) = 0.01$; $\xi^R = 0.045$; $\tau^R = 30$

Other parameters: S^C=4; r=2%; η=1.5; σ=4; A=25010. Profits denote operative profits.

1. I use net income over value added, eliminating 1% outliers on both tails, compute its standard deviation for each firm and then compute the average across firms. Standard deviation computed only for firms with at least 6 yearly observations and then averaged across firms.

2. including only R&D where cost of R&D over sales is greater than 0.5%.

3. These statistics are calculated after excluding the 1% outliers on both tails.

For both the benchmark and the full model I compare 4 industries: i) A "*financially unconstrained industry*", with $a_0 = 30$, or 100% of $\overline{y}$, .where $\overline{y}$ is the average of firm sales in the industry. For this industry the value of a_0 is sufficiently high so that no firm is financially constrained in equilibrium. ii) *The benchmark industry*; iii) A "*moderately financially constrained industry*", with $a_0 = 4$; iv) A "*financially constrained industry*", with $a_0 = 2$; v) A "*severely financially constrained industry*", with $a_0 = 1$.

5.1   Benchmark model

Table 5 shows summary statistics for the benchmark model. In order to illustrate the results it is useful to first distinguish two channels trough which financial frictions can potentially affect innovation: first, there is a "competition effect". Financing frictions increase bankruptcy risk, and fewer firms enter so that in equilibrium expected bankruptcy costs are compensated by lower competition and higher profitability. Second, there is a "binding constraint effect", when constraint (15) is binding with equality and firms are not able to innovate.

The first column of table 5 reports the statistics for the unconstrained industry. Despite no firm is ever financially constrained, only 25.6% of the firms innovate on average,

Table 5: Simulated industries, benchmark model with only incremental innovation: descriptive statistics

	Financially unconstr. industry ($a_0=30$)	Benchmark industry ($a_0=12$)	Moderately Financially Constrained industry ($a_0=4$)	Financially Constrained industry ($a_0=2$)	Severely Financially Constr. industry ($a_0=1$)
% going bankrupt every period	0%	0.5%	3.1%	5.7%	7.7%
% not innovating because of fin. frictions[1]	0%	1.9%	11%	18%	25%
Price index P relative to benchmark	99.9%	100%	100.7%	102.3%	103.5%
$E\left(\pi \mid v\right)$ relative to benchmark	99.6%	100%	102.1%	109.6%	114.0%
Average percentage of innovating firms	25.7%	23.8%	16.7%	21.3%	23.3%
Weighted Avg. TFP relative to benchmark	102.2%	100%	92.9%	96.4%	97.4%

1. Defined as firms that would like to innovate but have insufficient financial wealth to invest in innovation.

For all industries I simulate 3000 periods then discard the first 300 and use the remaining ones to compute aggregate statistics.

much less than the probability to get an innovation opportunity $\gamma = 45\%$, because incremental innovation is performed only by larger and more productive firms. Some unproductive and small firms do not innovate because the cost of innovation $K(1)$, which is constant, is larger than the gains from innovation, which are proportional to the firm's current productivity.

Comparing the different industries, The first two rows of table 5 show that the more constrained the industry is, the larger is the fraction of firms which go bankrupt and which cannot invest in innovation. The finding that financing frictions reduce the investment and technology adoption of young and financially constrained firms is common to other models of firm dynamics with financial imperfection (e.g. Buera Kaboski and Shin, 2011, and Midrigan and Xu, 2014, among others). The next two rows show that financing frictions act as a barrier to entry which reduces competition, and increases prices and expected profits for firms that do not go bankrupt, also increasing the expected return from incremental innovation.[18] Because of the competition effect, average profits are 14% higher in the severely constrained industry with respect to the benchmark. This is why the relation between financing frictions and innovation in the fifth row of the table is U shaped. For moderate increases of financing frictions (from column 1 to column 3) the binding constraint effect dominates and innovation and TFP decline, but for higher levels (from column 3 to column 5) the indirect competition effect dominates, and innovation and TFP increase.

---

[18] This effect of competition on innovation is well known in Endogenous Growth Theory, see for example Aghion and Howitt (1992).

Figure 3: Size and productivity over the firm's life-cycle (new firms=1; simulated industries, benchmark model with only incremental innovation).
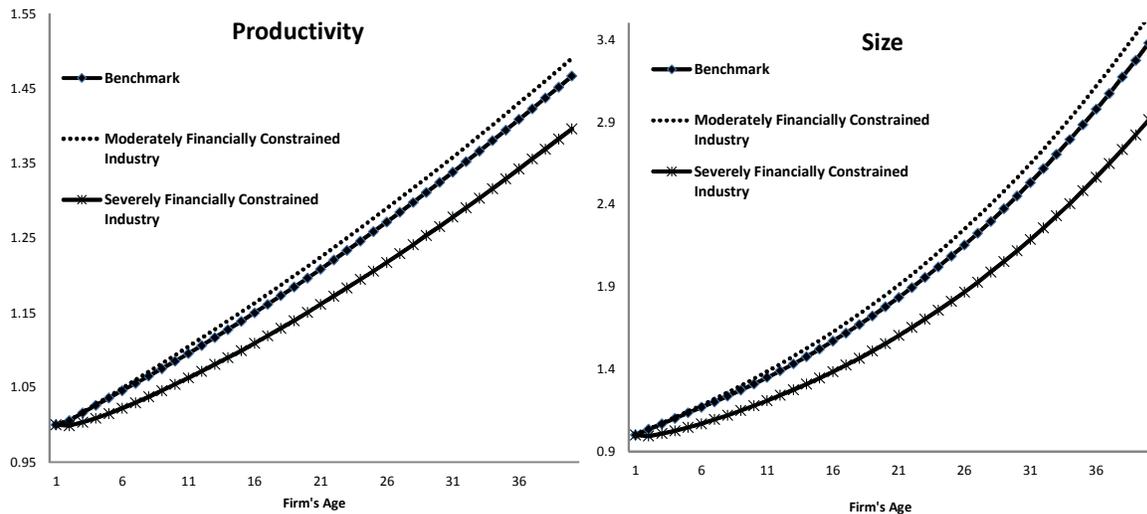

Figure 3 shows the life cycle dynamics of size and productivity for industries with different degrees of financing frictions. To make the graph more readable I include only three industries. Following Hsieh and Klenow (2014) the values are relative to the value for new firms, which is normalized to 1, and each line represents average values for a cohort of firms that stay in operation during the whole period, thus excluding selection effects. Figure 3 shows that financial frictions have an ambiguous effect on the growth dynamics of firms as they grow older, with a moderate amount of financial frictions generating a slightly faster growth. Surprisingly, despite 25% of firms cannot innovate in the severely financially constrained industry, firms growth is not very different from the benchmark industry. The intuition for this result is that firms use retained earnings to overcame financial frictions very early on in their life.

5.2 Simulation results, full model with incremental e radical innovation.

In the previous section the simulation of the benchmark model generates two main insights: first, financial constraints prevent some young firms to invest in productivity enhancing innovation and reduce aggregate TFP, even though the overall negative effect is mitigated by the fact that financial frictions also act as barriers to entry and increase profits and innovation rents for financially unconstrained firms. Second, the model is unable to generate large differences in the life cycle dynamics of firms between

Figure 4: Innovation decisions in the unconstrained industry, full model with both radical and incremental innovation.
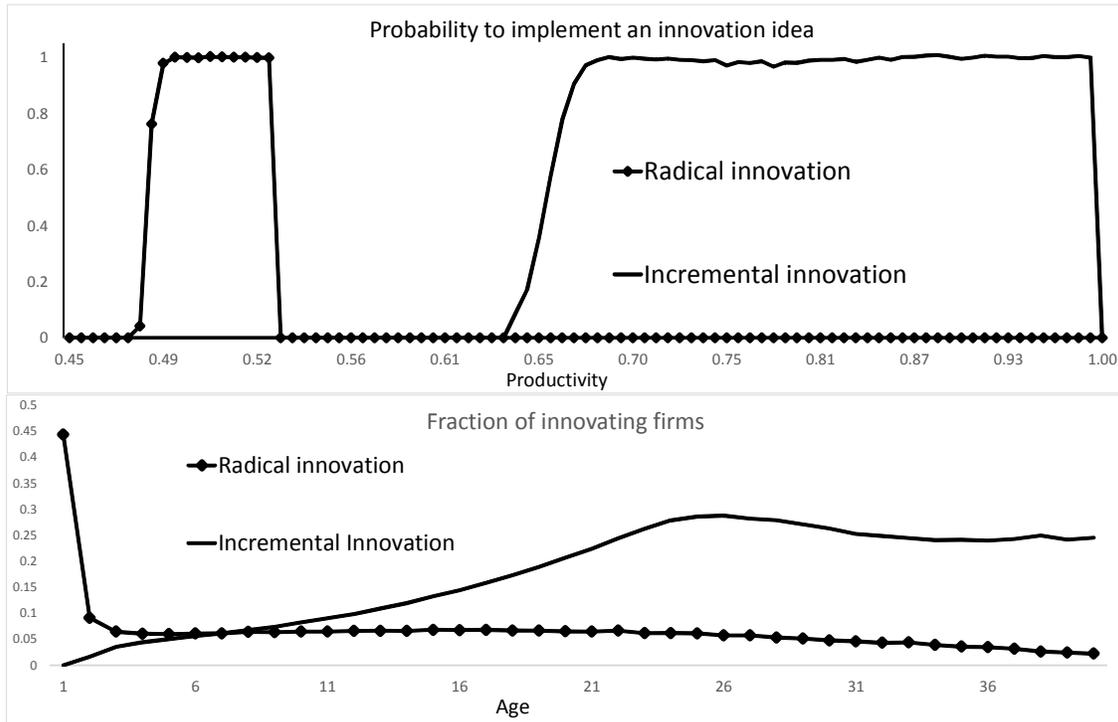
industries with different degrees of financing frictions. Contradicting both the empirical evidence shown in section 3, and the intuition that financial factors should play a role in explaining the life cycle dynamics of plants estimated by Hsieh and Klenow (2014).

In this section I demonstrate that a model with both radical and incremental innovation is instead consistent with the empirical evidence. Figure 4 shows innovation dynamics in the unconstrained industry for the full model. The upper panel shows the probability to implement an innovation idea. The variable on the X-axis is relative productivity v, which also uniquely determines the relative size of the firm. As in the benchmark model, also here incremental innovation is performed only by the larger/more productive firms. Conversely radical innovation is performed only by smaller/less productive firms. The high risk of failure of this innovation, with the associated drop in productivity, makes it not very attractive for large firms. Conversely smaller firms do not value the upside potential and the downside risk symmetrically, because the value function is bounded below at zero, since they can always cut losses by exiting from production. The lower panel shows innovation dynamics along the firms life cycle. Very young firms on average perform most of the radical innovation in the industry. These firms then either exit after failure, or grow fast after success, and once

25

Figure 5: Probability to innovate, comparison of industries, full model with both radical and incremental innovation.
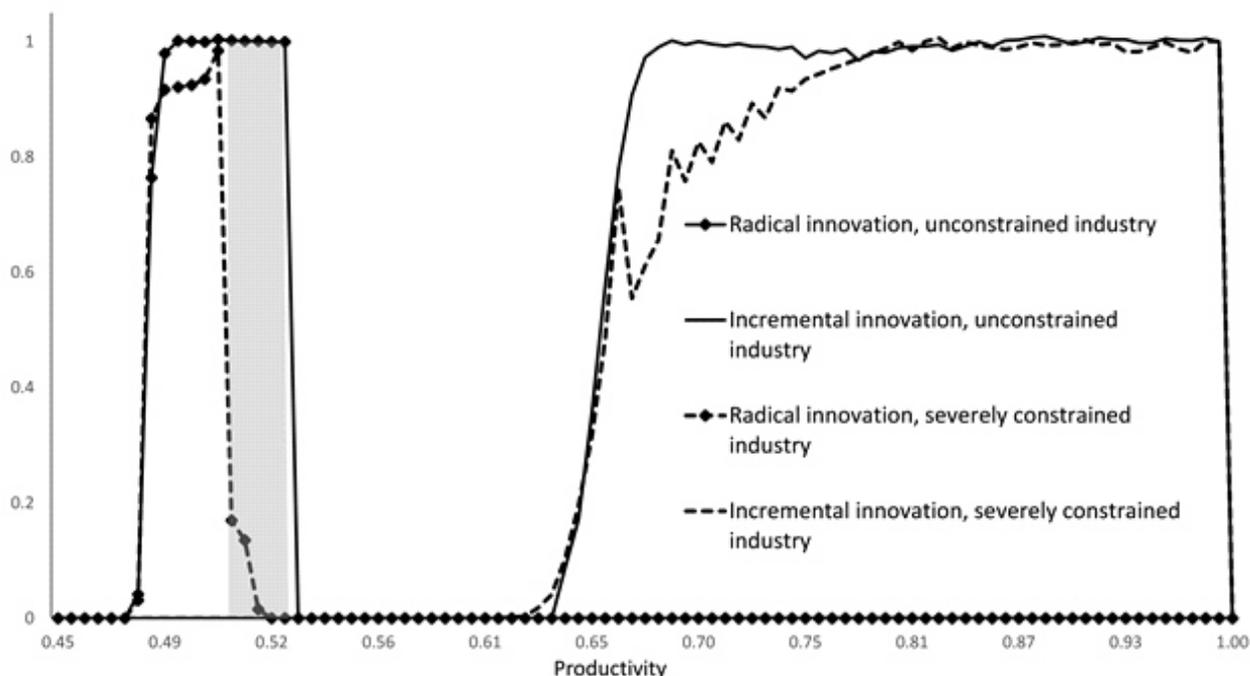
they become large they start investing in incremental innovation. Therefore the fraction of firm doing incremental innovation rises gradually with age. Thus the full model with both radical and incremental innovation generates firm dynamics consistent with the empirical evidence. Not only with the well know fact that small firms grow faster than larger firms and have more volatile growth rate, but also with the observation that innovation is a risky experimentation process (Kerr, Nanda and Rhodes-Kropf, 2014), as well as with the findings of Akcigit and Kerr (2010), who analyse US patents data and show that small firms do relatively more exploration R&D and have a relatively higher rate of major inventions than large firms. Finally it is also consistent with the high positive skewness in the growth of young firms observed by Haltiwanger et al (2014) : "...*median net employment growth for young firms is about zero. As such, the higher mean reflects the substantial positive skewness with a small fraction of very fast growing firms driving the higher mean net employment growth.*"

Figures 5-7 describe the relation between financing frictions and innovation and growth dynamics in the full model. In order to better illustrate the different effects at play, I focus on the comparison between the extreme cases of the unconstrained industry and the severely constrained industry. Figure 5 shows the probability to innovate as

a function of productivity. The differences in radical innovation across industries are driven almost entirely by the competition effect. The lower is competition, the higher are the profits of the younger and smaller firms, so that many of them decide to postpone risky radical innovation. If financing frictions are reduced and competition increases, the same firms have a much lower profitability and much less to lose if they fail to innovate, thanks to the exit option, and they find it optimal to innovate much sooner.[19] This effect explains the shaded area for values of v around 0.52, where firms perform radical innovation only in the unconstrained industry. Since the distribution of firms, consistently with the empirical evidence, is heavily skewed with a lot of young and small firms, the shaded area determines a large difference in radical innovation across industries. Conversely the binding constraint effect explains why, for certain values of productivity v, the percentage of firms undertaking an innovation opportunity is positive in the constrained industry but lower than one. This happens especially in the intermediate region of v between 0.65 and 0.75. However very few firms are in this region, and therefore this effect is going to be negligible at the aggregate level.[20]

Figure 6 compares the life cycle profile of innovation in the unconstrained industry and in the severely constrained industry. In the latter young firms perform less radical innovation, so that at any given age fewer firms reach a level of productivity high enough to find optimal to invest in incremental innovation. This explains why the fraction of firms doing incremental innovation increases more slowly in this industry than in the unconstrained industry. Figure 7 shows the implications of different innovation dynamics for the lifecycle profile of size and productivity in the two industries. Average productivity steeply increases with age in the unconstrained industry. As a consequence firm's size over the life-cycle grows by 500%, while it grows only by 50% in the severely constrained industry. Figure 7 contrasts sharply with the analogous figure 3, which showed little effect of financing frictions on size and productivity growth in the model with only incremental innovation. Financial factors matter in the full model not because the lack of internal finance prevents firms to invest optimally, but because the competition effect reduces the incentives to innovate for many young firms. Likewise in

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[19]The empirical competition literature often estimates a positive relation between competition and innovation (e.g. Blundell *et al.* 1995, and Nickell, 1996). To the best of my knowledge this paper proposes a novel theoretical mechanism consistent with this evidence, different from and complementary to the well known "Escape Competition effect" of Aghion *et al.* (2001).

[20]To be precise, there is also a third "gambling for resurrection" effect: bankruptcy risk implies that the value of a firm $V_t(a_t, \varepsilon_t, v_t)$ is convex around the value of $a_t = F$. Intuitively, $V_t(a_t, \varepsilon_t, v_t)$ as defined in equation (21) is strictly concave for $a_t \geq F$, because higher wealth reduces bankruptcy risk, and is equal to zero for $a_t < F$. Such local convexity encourages firms close to the bankruptcy region to take more risk, and explains a positive radical innovation probability in the constrained industry in the bottom left part of the shaded area. However the aggregate impact of this effect is negligible.

Figure 6: Fraction of innovating firms, different industries
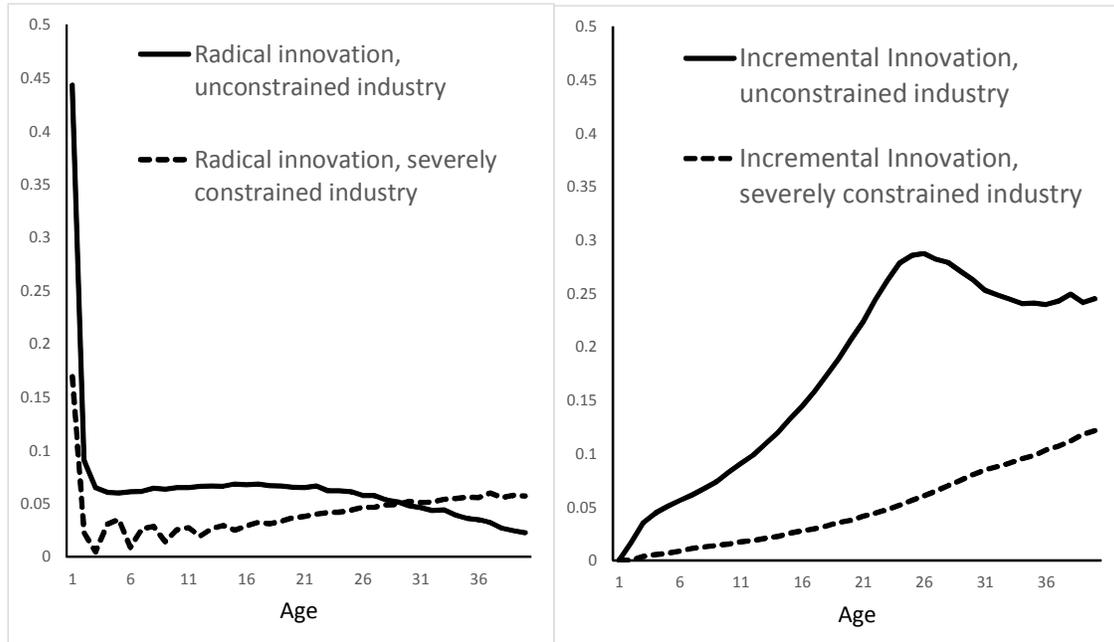
the severely constrained industry shown in figure 7 average size and productivity grow slowly for older firms not because these are financially constrained, but because many of them have not reached a level of productivity sufficiently high to invest in radical innovation.

Table 6 shows the summary statistics for the simulated industries. Radical innovation in the severely constrained industry is more than 50% lower than in the benchmark industry, despite less than 1% of firms cannot innovate because of a binding financing constraint.[21] This confirms that the indirect competition effect is the main reason why financing frictions reduce innovation. As a consequence average TFP is 18.1% lower in this industry than in the benchmark one.

How much does the reduction in radical innovation caused by financial frictions matter for the whole economy? By combining the above simulation results and the data from the empirical dataset I can estimate its aggregate effects for the Italian manufacturing industry. First, I define a mapping between the declared financing frictions in the surveys and the intensity of financial frictions in the model. The latter

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[21]In equilibrium innovation is constrained by internal finance only for a very small fraction of firms, even in the most constrained industry, because the cost of radical innovation $K(2)$ is relatively small, and by the time firms become large enough to invest in incremental innovation, they are also wealthier and not financially constrained.

Figure 7: Size and productivity over the firm's life-cycle (new firms=1; simulated industries, full model with both radical and incremental innovation).
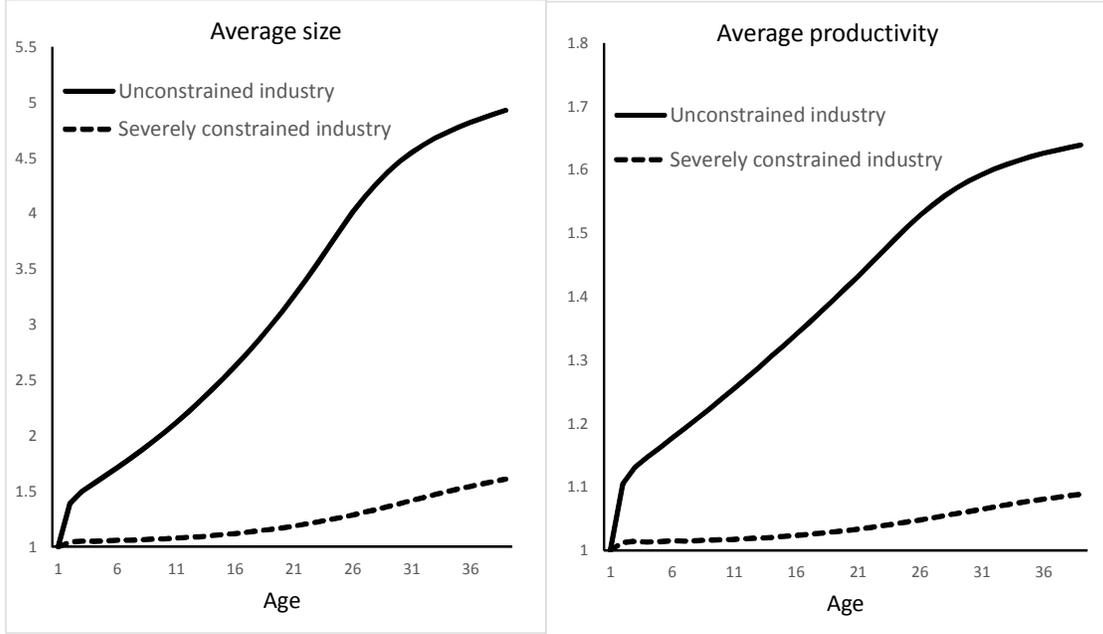
can be measured by the expected return of retained earnings in excess of the real interest rate r. Since the value of the firm $V_{it}\left(a_{it}, \varepsilon_{it}, v_{it}\right)$ is the present value of future profits net of current wealth a_t, I define the excess expected return of firm i in period t ϕ_{it} as:

$$\phi_{it} = \frac{\partial V_{it}\left(a_{it}, \varepsilon_{it}, v_{it}\right)}{\partial a_{it}}, \tag{23}$$

where ϕ_{it} measures the extra return for firm i in period t of accumulating cash reserves and reducing current and future expected financial problems. It is straightforward to show that ϕ_{it} is negatively related to a_{it} and it is equal to zero for values of a_{it} high enough so that the firm is unconstrained today or in the future. I assume that in the empirical sample firms declare financial difficulties if ϕ_{it} is higher or equal than an unobserved common threshold $\overline{\phi}$. Then I fix the value of $\overline{\phi}$ in the simulations so that for the benchmark calibration the percentage of simulated firms "declaring financial frictions" is the same as in the whole empirical sample (14% of all firm-year observations). Finally, I simulate a continuum of industries with identical parameters except for the value of the initial endowment a_0. A lower value of a_0 increases the mean value of ϕ_{it} across firms in equilibrium. I use the fraction of firms declaring financial difficulties (the fraction of firms with $\phi_{it} > \overline{\phi}$) to match the simulated industries with the

empirical 4 digit sectors of the Italian sample, and I compute the weighted average of the reduction in productivity caused by financial frictions across these sectors. I find that reducing financial frictions in the 50% most constrained sectors at the benchmark level, and abstracting from general equilibrium effects on wages and interest rates, would increase overall productivity in the Italian manufacturing sector by 6.3%

Since the risk of radical innovation τ^R is not calibrated, it is important to describe how the results depend on its value. Therefore I relax the symmetry assumption, so that in case of success of radical innovation $v_{t+1} = (1+g)^{\tau^H} v_t$, while in case of failure $v_{t+1} = \frac{v_t}{(1+g)^{\tau^L}}$. Once I do not restrict τ^L and τ^H to be equal, it is easy to show that a necessary condition for the results is that radical innovation has a high return and low success probability. That is, a high value of τ^H associated with a low value of ξ^R. If these two conditions are satisfied, then the results hold also conditional to a relatively low value of the "downside risk" τ^L. Intuitively, if innovation is very risky then even a low value of τ^L is sufficient to ensure that radical innovation is mainly performed by young and small firms, and that increases in competition encourage these firms to take on more risk. This is shown in Panel B, where I keep $\tau^H = 30$ and reduce τ^L to 5, while lowering the parameter ξ to ensure that average radical and incremental innovation remain roughly constant in the "benchmark" column. The results of this panel are qualitatively similar to Panel A, with financing frictions reducing both types of innovation and aggregate productivity.

In order to further identify the importance of the competition effect, Panel C repeats the same exercise of Panel A, but varying the entry cost S^C across industries, while keeping a_0 fixed at the benchmark level. I choose the values of S^C to match the equilibrium prices in the four industries analyzed in panel A. In other words, in Panel C entry costs replicate the competition effect generated by financing frictions in Panel A. The results show that the higher are the barriers to entry, the lower is radical innovation, which also implies less incremental innovation and average TFP. In the industry with very high entry barriers average TFP is 15.1% lower than in the benchmark industry.

6 Robustness checks

The simulation results in the previous section provide an explanation of the empirical evidence shown in section 3: financial frictions negatively affect growth because they reduce risky innovation activity. They do so by generating entry barriers that reduce

Table 6: Simulated industries: descriptive statistics, full model with both incremental and radical innovation

	PANEL A: Main analysis				
	Financially unconstr. industry	Benchmark industry	Moderately Financially Constrained industry	Financially Constrained industry	Severely Financially Constr. industry
Average P relative to benchmark	99.4%	100%	100.1%	102.1%	103.0%
$E\left(\pi \mid v\right)$ relative to benchmark	97.7%	100%	100.2%	107.0%	110.0%
Average percentage of innovating firms	20.4%	23.3%	21.9%	10.7%	8.6%
Percentage doing Radical Innovation	9.3%	11.0%	10.5%	5.4%	4.5%
Not doing R.I.. because of fin. frictions	0%	0%	0.02%	0.2%	0.06%
Percentage doing Incremental Innovation	11.1%	12.3%	11.4%	5.3%	4.2%
Not doing I.I. because of fin. frictions	0%	1.7%	1.6%	0.5%	0.4%
Weighted Avg. TFP relative to benchmark	98.0%	100%	98.3%	85.6%	81.9%
	PANEL B: Lower downside risk				
Average percentage of innovating firms	21.7%	21.8%	21.4%	12.3%	10.6%
Percentage doing Radical innovation	14.3%	14.5%	14.2%	8.1%	7.%
Percentage doing Incremental innovation	7.4%	7.3%	7.2%	4.2%	3.6%
Weighted Avg. TFP relative to benchmark	101%	100%	100%	91.0%	87.5%
	PANEL C: Barriers to entry				
	Moderately Lower Barriers	Benchmark industry	Moderately High Barriers	High Entry Barriers	Very high Entry Barriers
Average P relative to benchmark	99.9%	100%	100.6%	102.6%	103.6%
Entry cost F relative to benchmark	99.4%	100%	115%	177%	212%
Average percentage of innovating firms	20.9%	23.38%	18.0%	11.3%	8.0%
Percentage doing Radical innovation	9.8%	11.0	8.4%	5.1%	3.6%
Percentage doing Incremental innovation	11.1%	12.3%	9.6%	6.2%	4.4%
Weighted Avg. TFP relative to benchmark	100.1%	100%	97.4%	90.5%	84.9%

For all industries I simulate 3000 periods then discard the first 300 and use the remaining ones to compute aggregate statistics. In Panels A and B only the value of a_0 varies across industries. In panel B the value of τ conditional on failing radical innovation is $\tau^L = 5$, and ξ^R is recalibrated to match the average number of innovating firms in the benchmark column. In Panel C the industries with barriers to entry have identical parameters than in the benchmark industry except for S^C.

Table 7: Relation between age and productivity (empirical sample)

	All observations			Currently constrained firms excluded		
Dependent variable	$\widehat{v}_{i,s}^1$	$\widehat{v}_{i,s}^2$	$\widehat{v}_{i,s}^3$	$\widehat{v}_{i,s}^1$	$\widehat{v}_{i,s}^2$	$\widehat{v}_{i,s}^3$
$age_{i,s}$	0.00616***	0.00926***	0.00067	0.0686***	0.0103***	0.00078
	(5.83)	(5.84)	(1.35)	(6.17)	(6.18)	(1.49)
$age_{i,s}*constrained_i$	−0.00360***	−0.00541**	−0.00207***	−0.00351**	−0.00528**	−0.00208**
	(−2.59)	(−2.60)	(−3.3)	(−2.37)	(−2.37)	(−3.11)
N.observations	12390	12390	12672	11065	11065	11299
Adj. R-sq.	0.011	0.011	0.006	0.013	0.013	0.005

Panel regression with firm fixed effect. Time effects are also included. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $\widehat{v}_{i,s}^1$ is revenue total factor productivity, $\widehat{v}_{i,s}^2$ is total factor productivity computed following the procedure of Hsieh and Klenow (2009), and $\widehat{v}_{i,s}^3$ is profits based productivity for firm i in survey s. $age_{i,s}$ 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. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

competition and distort the incentives to innovate. These implications of the model can be tested on the empirical sample. More specifically, the indirect competition effect implies the two following predictions:

Prediction 1: the result that firm's productivity growth is lower in financially constrained industries should hold after excluding firms declaring financial difficulties.

Prediction 2: The difference in the life cycle dynamics between financially constrained and financially unconstrained industries is similar to the difference between industries selected according to competition.

Moreover, I can use the information on R&D spending in the empirical sample to perform a robustness check related to the importance of innovation:

Prediction 3: The difference in the life cycle dynamics between financially constrained and financially unconstrained industries should disappear if I only include in the analysis firms not performing R&D.

Finally, I estimate empirical proxies of radical and incremental innovation to provide empirical evidence related to innovation dynamics:

Prediction 4: Firms in more financially constrained industries do relatively less innovation. Radical innovation decreases with firm's age, and is lower in financially constrained industries especially among younger firms. Incremental innovation increases with firm's age, and is lower in financially constrained industries especially among older firms.

In order to test prediction 1, I repeat the estimation of equations 5 and 6 after ex-

Table 8: Relation between age and productivity, different classification of constrained groups (empirical sample)

Dependent variable	All observations			Currently constrained firms excluded		
	$\widehat{v}_{i,s}^{1}$	$\widehat{v}_{i,s}^{2}$	$\widehat{v}_{i,s}^{3}$	$\widehat{v}_{i,s}^{1}$	$\widehat{v}_{i,s}^{2}$	$\widehat{v}_{i,s}^{3}$
$age_{i,s}$	0.00755***	0.00113***	0.000722	0.00818***	0.0123***	0.000647
	(5.79)	(−0.00582)	(1.18)	(6.02)	(6.03)	(1.02)
$age_{i,s}*midconstr_{i}$	−0.00387**	−0.00582**	−0.000528	−0.00359*	−0.00541*	−0.000209
	(−2.19)	(−2.19)	(−0.66)	(−1.94)	(−1.94)	(−0.25)
$age_{i,s}*highconstr_{i}$	−0.00529***	−0.00794***	−0.0026***	−0.00529**	−0.00794**	−0.00246**
	(−3.16)	(−3.16)	(−3.42)	(−2.96)	(−2.97)	(−3.05)
N.observations	12390	12390	12672	11065	11065	11299
Adj. R-sq.	0.011	0.011	0.006	0.013	0.013	0.005

Panel regression with firm fixed effect. Time effects are also included. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $\widehat{v}_{i,s}^{1}$ is revenue total factor productivity, $\widehat{v}_{i,s}^{2}$ is total factor productivity computed following the procedure of Hsieh and Klenow (2009), and $\widehat{v}_{i,s}^{3}$ is profits based productivity for firm i in survey s. $age_{i,s}$ is age in years for firm i in survey s. $midconstr_{i}$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the medium 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.

cluding firms which are currently declaring financing problems. Tables 7 and 8 confirm that the coefficient of $constrained_{i}$ interacted with age is still negative and significant in all specifications, thus confirming prediction 1. This finding is important because it confirms that the empirical relation between financing frictions and productivity growth estimated in section 3 is not driven by firms declaring financial difficulties because of their poor performance. In order to verify prediction 2, as an empirical measure of competition I consider the Price-cost margin (PCM):

$$PCM_{i,t} = \frac{r_{i,t} - m_{i,t}}{r_{it}}$$

Where $r_{i,t}$ is total revenues and m_{it} are variable costs for firm i in survey s. I calculate the average of $PCM_{i,s}$ for each 4 digit sector and generate a dummy which is equal to one if firm i belongs to one of the 50% of sectors with highest Price-cost margin, and zero otherwise, called $lowcomp_{i}$. I interact this dummy variable with age in a regression similar to the one performed in table 1. Table 9 shows the regression results. The estimated difference in the relation between age and productivity among different groups is remarkably similar to the one estimated in table 1, for all productivity measures. In other words, the low competition sectors behave very similarly to the

Table 9: Relation between age and productivity - sectors selected according to competition (empirical sample)

Dependent variable	Baseline			Time dummies interacted with the low competition group are included		
	$\widehat{v}_{i,s}^1$	$\widehat{v}_{i,s}^2$	$\widehat{v}_{i,s}^3$	$\widehat{v}_{i,s}^1$	$\widehat{v}_{i,s}^2$	$\widehat{v}_{i,s}^3$
$age_{i,s}$	0.00622***	0.00935***	0.000293	0.00613***	0.00919***	0.000288
	(5.8)	(5.81)	(0.63)	(5.31)	(5.31)	(0.58)
$age_{i,s}*lowcomp_i$	-0.00404**	-0.00607**	-0.00153**	-0.00379**	-0.00566**	-0.00155**
	(-2.91)	(-2.91)	(-2.48)	(-2.47)	(-2.46)	(-2.26)
N.observations	12390	12390	12672	12390	12390	12672
Adj. R-sq.	0.011	0.011	0.005	0.011	0.011	0.005

Panel regression with firm fixed effect. Time effects are also included. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $\widehat{v}_{i,s}^1$ is revenue total factor productivity, $\widehat{v}_{i,s}^2$ is total factor productivity computed following the procedure of Hsieh and Klenow (2009), and $\widehat{v}_{i,s}^3$ is profits based productivity for firm i in survey s. $age_{i,s}$ is age in years for firm i in survey s. $lowcomp_i$, is equal to one if firm i belongs to the 50% of 4-digit manufacturing sectors with highest average Price-cost margin, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

high financing frictions sectors with respect to productivity dynamics along the firms life-cycle. These results are consistent with the simulation results shown in panel C of table 6 and confirm Prediction 2.[22]

The third robustness check verifies the importance of innovation in driving the empirical relation between financing frictions and productivity growth. In table 10 columns 1 and 2 replicate the results obtained in the second part of table 1. To save space I do not report the results using $\widehat{v}_{i,s}^2$, which are qualitatively very similar to using $\widehat{v}_{i,s}^1$. Columns 3 and 4 repeat the analysis after eliminating the firm-survey observations that reported doing R&D, and columns 5 and 6 repeat it after eliminating all the observations of firms that did R&D in at least one survey. The results show that the life-cycle profiles of productivity for firms in constrained and unconstrained groups are no longer significantly different once innovating firms are excluded from the

[22]Note that the correlation between the average of the price cost margin PCM_s and the fraction of constrained firms $constrained_s$ across four-digit sectors is nearly zero in the empirical data, being equal to -0.0379. This low correlation is consistent with the model, where variations in financing frictions affect total profits of the firms but do not significantly affect the relation between profits and sales, which mainly depends on the elasticity of substitution σ. In other words, changes in financing frictions are similar to variations in competition driven by differences in entry barriers, while the empirical price-cost margin is related to variations in competition generated by variations in the elasticity of substitutions σ. In Panel C of Table 6 I have shown simulation results where competition varies because of different entry costs. Simulations where changes in competition are caused by variations in σ yield very similar results.

Table 10: Relation between age and productivity - firms doing research and development excluded (empirical sample)

Dependent variable	Baseline		Firm-survey obs. with positive R&D excluded		Firms with some positive R&D excluded	
	$\widehat{v}_{i,s}^{1}$	$\widehat{v}_{i,s}^{3}$	$\widehat{v}_{i,s}^{1}$	$\widehat{v}_{i,s}^{3}$	$\widehat{v}_{i,s}^{1}$	$\widehat{v}_{i,s}^{3}$
$age_{i,s}$	0.00590***	0.000235	0.0575***	−0.000832	0.00429*	−0.00147*
	(5.22)	(0.43)	(3.73)	(−1.16)	(2.46)	(−1.94)
$age_{i,s}*constrained_{i}$	−0.00290*	−0.00138*	−0.00222	−0.000307	−0.00109	−0.0001
	(−1.91)	(−1.95)	(−1.12)	(−0.34)	(−0.49)	(−0.09)
N.observations	12390	12672	10287	10505	6156	6273
Adj. R-sq.	0.012	0.007	0.014	0.010	0.010	0.012

Panel regression with firm fixed effect. Time effects are included individually as well as interacted with the "constrained" group. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $\widehat{v}_{i,s}^{1}$ is revenue total factor productivity and $\widehat{v}_{i,s}^{3}$ is profits based productivity for firm i in survey s. $age_{i,s}$ 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. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

analysis, thus confirming Prediction 3.

The last robustness check is related to Prediction 4. As a very rough proxy I classify as doing radical innovation all firms investing in R&D and having very volatile productivity. I first calculate sd_{i}^{v}, the standard deviation for firm i of the estimated measure of productivity $\widehat{v}_{i,t}^{1}$ (see section 3 for details). The Radical Innovation indicator $Rad\_inn_{i,s}$ is equal to 1 if firm i in survey s has a ratio of R&D spending over sales larger than 0.5% and if the volatility of the estimated productivity is larger than the 75th percentile, and is equal to zero otherwise ($Rad\_inn_{i,s} = 1$ for 9.5% of all firms). The complementary indicator of Incremental Innovation $Incr\_inn_{i.s}$ is equal to 1 if firm i in survey s has a ratio of R&D spending over sales larger than 0.5% and if the volatility of its productivity is smaller than the 75th percentile, and is equal to zero otherwise ($Incr\_inn_{i.s} = 1$ for 13.5% of all firms). The joint indicator is $Tot\_inn_{is} = Rad\_inn_{is} + Incr\_inn_{is}$. I verify Prediction 4 by estimating a Logit

model on the relation between age and the probability to innovate:[23]

$$Inn_{i,s} = \beta_0 + \sum_{l=2}^{n} \beta_l Dage_{i,s}^l + \sum_{l=1}^{n} \beta_l^c (constrained_i * Dage_{i,s}^l) + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \quad (24)$$

where $Inn_{i,s}$ is equal to the innovation indicators $Rad\_inn_{i,s}$, $Incr\_inn_{i,s}$ and $Tot\_inn_{i,s}$ in three separate regressions, and $Dage_{i,s}^l$ is equal to 1 if firm i in survey s belongs to age group $l \in \{1, 2, 3, 4\}$, and is equal to zero otherwise. $l = 1$ indicates firms with age 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 control variables x_j include 2 digit sector dummies and time dummies, and errors are clustered at the firm level. The coefficients β_l for $l = 2, 3, 4$, in equation (24) measure the difference in frequency of innovation for these age groups relative to the omitted group of youngest firms ($l = 1$). If innovation increases over firm's age, these coefficients should be positive and with an increasing value as l increases. The coefficients $\beta_1^c, ..., \beta_4^c$ measure the difference in innovation probability between firms of similar age in the constrained group relative to the unconstrained one. As shown in figure 6, the model predicts that they should be negative and that their magnitude should increase in age for incremental innovation, while they should decrease in age for radical innovation.

Regression results are shown in table 11. Consistently with Prediction 4 the probability to innovate increases with age for Tot_inn_{is}, and to a greater extent for $Incr\_inn_{is}$, while it decreases with age for Rad_inn_{is}. Even though for the latter variable the relation is not monotonous, the group of oldest firms (age 31-40) are significantly less likely to do radical innovation than the omitted group of youngest firms (less than 10 years old). Regarding financing frictions, their effect is generally negative but not always significant, especially for radical innovation. This is probably caused by the absence of very young firms in the empirical sample, because the model predicts that most differences in radical innovation activity across industries happen for firms between 1 and 4 years old (see figure 6). Nonetheless, for incremental innovation the

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[23]For the regressions in section 3 the dependent variables $\widehat{v}_{i,s}^1$, $\widehat{v}_{i,s}^2$ and $\widehat{v}_{i,s}^3$ are constructed starting from more than 60000 firm-year observations of balance sheet data available in the sample (see appendix 2 for details). This large sample size makes it possible to perform a panel estimation with firm fixed effects. Unfortunately the innovation variables $Rad\_inn_{i,s}$ and $Incr\_inn_{i,s}$ only have one observation for each three-year survey, and they have little within-firm variation, both because few firms are present in more than one survey and because R&D is persistent over time for each firm. For example, the variable $Incr\_inn_{i,s}$ is equal to 1 for 1538 out of 13601 valid firm-survey observations, but only 363 firms report a change in the value of such variable over time. Therefore instead of estimating a fixed effect model I estimate equation 24 with sector specific fixed effects.

Table 11: Relation between age and innovation (empirical sample)

Dependent variable	$Tot\_inn_{i,s}$	$Incr\_inn_{i,s}$	$Rad\_inn_{i,s}$
$Dage_{i,s}^2$	0.0556 (0.1100)	0.2520 (0.1437)*	-0.1818 (0.1458)
$Dage_{i,s}^3$	0.1060 (0.1182)	0.2793 (0.1529)*	-0.1177 (0.1581)
$Dage_{i,s}^4$	0.2530 (0.1304)*	0.6269 (0.1621)***	-0.3324 (0.1904)*
$constrained_i * Dage_{i,s}^1$	0.0044 (0.0167)	0.0172 (0.0212)	-0.0102 (0.0227)
$constrained_i * Dage_{i,s}^2$	-0.0141 (0.0062)**	-0.0103 (0.0077)	-0.0159 (0.0088)*
$constrained_i * Dage_{i,s}^3$	-0.0060 (0.0044)	-0.0093 (0.0055)*	-0.0004 (0.0061)
$constrained_i * Dage_{i,s}^4$	-0.0078 (0.0042)*	-0.0093 (0.0049)*	-0.0028 (0.0065)
Time dummies	yes	yes	yes
2 digit sector dummies	yes	yes	yes
N.observations	8844	8844	8844
Adj. R-sq.	0.08	0.07	0.06

Probit regression. Standard Errors, reported in parenthesis, are clustered at the firm level. $Tot\_inn_{i,s}, Incr\_inn_{i,s}$ and $Rad\_inn_{i,s}$ are equal to one if firm i in survey s performs any innovation, incremental innovation and radical innovation, respectively, and equal to zero otherwise. $Dage_{i,s}^l$ is equal to 1 if firm i in survey s belongs to age group $l \in \{1, 2, 3, 4\}$, and is equal to zero otherwise. $l = 1$ indicates firms with age up to 10 years, and $l = 2, 3, 4$ indicates firms aged 11-20, 21-30 and 31-40 years, respectively. Control variables include 2 digit sector dummies and time dummies. $constrained_i$, 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. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

effect of financing frictions is significantly negative for the groups of oldest firms (age 21-40) consistently with the simulations results in figure 6. Overall these results are noisy but broadly in line with the predictions of the model.

7 Concluding remarks

This paper analyses a dataset of Italian manufacturing firms with both survey and balance sheet information and documents a significantly negative relation between financing frictions and the productivity growth of firms along their life cycle. It explains this finding with the model of an industry with both radical and incremental innovation, where the indirect effects of financing frictions are much more important for innovation decisions than the direct effects. For realistic parameter values, despite relatively few firms have a binding financing constraints in equilibrium, financing frictions act as barriers to entry which reduce competition and negatively affect radical innovation, productivity growth at the firm level, and aggregate productivity. The empirical and theoretical findings of this paper mutually reinforce each other. The model provides

an explanation of the empirical evidence and at the same time generates a series of additional testable predictions that both confirm its implications as well as the validity of the empirical methodology followed to construct the indicator of financial frictions used in the paper. Finally, the predictions of the model regarding the relation between competition and radical innovation apply not only to financial frictions but also to any other factor which could raise barriers to entry into an industry. Therefore the results have potentially wider implications and applicability than the specific financial channel which is the focus of this paper.

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8   Appendix 1

In order 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 such that the firm never risks bankruptcy now or in the future. I then discretize this interval in a grid of 300 points. 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 chosen to be equal to 120, which is a value large enough so that, conditional on the other parameter values, no firm remains in operation when $v = \frac{1}{(1+g)^{N-1}}$.

In order to solve the dynamic problem I first make an initial guess of the equilibrium aggregate price P. Based on this guess I calculate the optimal value of $V_t(a_t, \varepsilon_t, v_t)$ using an iterative procedure. I then apply the zero profits condition (22) and I update the guess of P accordingly. I repeat this procedure until the solution converges to the equilibrium. Then I simulate an artificial industry in which every period the total number of new entrants ensures that condition (7) is satisfied.

9   Appendix 2

Each Mediocredito survey covers 3 years, therefore the 1995, 1998 and 2001 surveys cover the 1992-1994, 1995-1997 and 1998-2000 periods respectively. Each survey covers around 4500 firms, including a representative sample of the population of firms below 500 employees as well as a random sample of larger firms. Caggese and Cunat (2013) analyse the same dataset and find that, relative to the population of Italian firms, small firms are underrepresented and large firms are overrepresented. Nonetheless Caggese and Cunat (2013) verify that results obtained after using population weights for firms larger than 10 employees are very similar to the results obtained using the original sample.

Since some firms are kept in the sample for more than one survey, I have a total of 13601 firm-survey observations, of which 9502 are observations of firms appearing in only one survey, 3364 are observations of firms appearing in two surveys, and 735 are observations of firms appearing in all 3 surveys. Table 12 shows the list of 2 digit sectors included in the final sample (5 sectors with less than 50 firms are excluded) and the fraction of firms in the constrained and unconstrained groups.

Moreover for each firm surveyed Mediocredito/Capitalia makes available several years of balance sheet data in the 1989-2000 period. In total I have available 67519

Table 12: Frequency of constrained and unconstrained firms in each 2 digit manufacturing sector

Sector	2 digits Ateco 91 code	n. observations	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	1037	75%	25%
Textiles	17	1224	30%	70%
Shoes and Clothes	18	571	38%	62%
Leather products	19	564	87%	13%
Wood Furniture	20	357	65%	35%
Paper	21	408	72%	28%
Printing	22	500	51%	49%
Chemical, Fibers	24	650	43%	57%
Rubber and Plastic	25	755	44%	56%
Non metallic products	26	886	76%	24%
Metals	27	665	49%	51%
Metallic products	28	1264	69%	31%
Mechanical Products	29	2187	42%	58%
Electrical Products	31	550	90%	10%
Television and comm.	32	320	45%	55%
Precision instruments	33	199	75%	25%
Vehicles	34	285	75%	25%
other manufacturing	36	696	62%	38%

firm-year observations of balance sheet data.

For the estimation of the production function (1), by taking logs and adding fixed effects I obtain:

$$\log(p_{i,t}y_{i,t}) = \kappa_i + \gamma_t + \alpha \log\left(p_{i,t}^k k_{i,t}\right) + \beta \log\left(w_{i,t}l_{i,t}\right) + v_{i,t}^1 \qquad (25)$$

where κ_i and γ_t are firm and year fixed effects, respectively. I use the following variables: added value py is sales minus cost of variable inputs used during the period plus capitalized costs minus cost of services; capital pk is the book value of fixed capital; labour wl is total wage cost; I follow the methodology of Levinshon and Petrin (2003) and I use the cost of variable inputs to control for unobservable productivity shocks. I also include yearly dummies. In order to eliminate outliers I exclude from the estimation all firm-year observations with values of $\frac{y}{k}$ and $\frac{y}{l}$ larger than the 99% percentile and smaller than the 1% percentile. I estimate the production function separately for each 2 digit sector for which I have at least 50 firms in the dataset. I follow the same procedure also for the estimation of equation (2).

For the estimation of the price-cost margin $PCM_{i,t}$: $r_{i,t}$ is total revenues and $m_{i,t}$ is total cost of variable inputs used in the period plus total wage costs. The subindexes refer to firm i and year t.

For the piecewise linear estimations in figures 1 and 2 I estimate the following model:

$$\begin{aligned}
\widehat{v}_{i,s}^j &= \beta_0 + \sum_{l=1}^{n} \beta_l^u (unconstr_i * age_{i,s}^l) + \sum_{l=1}^{n} \beta_l^m (midconstr_i * age_{i,s}^l) + \qquad (26) \\
&\quad + \sum_{l=1}^{n} \beta_l^c (highconstr_i * age_{i,s}^l) + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s}
\end{aligned}$$

I construct a set of variables age^l which is equal to the age of the firm if the firm is in group l, and zero otherwise. The index $l = 1, 2, 3, 4$ indicates the age intervals, with $l = 1$ indicating firms with age 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 dummy "unconstr" is the complementary of "midconstr+highconstr", so that the coefficients $\beta_1^u...\beta_4^u$, $\beta_1^m...\beta_4^m$ and $\beta_1^c...\beta_4^c$ measure the effect of age on productivity for the unconstrained, mid constrained and most constrained industries, respectively. The set of control variables includes fixed effects, time dummies, and time dummies interacted with the constrained groups.