Financing Constraints, Radical versus Incremental Innovation, and Aggregate Productivity.*†

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Abstract

I provide new empirical evidence on the negative relation between financial frictions and productivity growth over a firm's 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.

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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 introducing 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 larger than 4 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? This paper shows that they do. It provides new empirical evidence on a strong negative relation between financial frictions and the productivity growth of firms over their life cycle. It then develops a firm dynamics model which shows that the interaction between financial frictions and incremental and radical innovation decisions are essential to explain such evidence.

I analyze a very rich dataset of Italian manufacturing firms with more than 60.000 observations of balance sheet data, as well as direct information on financial frictions and innovation decisions from multiple surveys. I construct two different measures of productivity and 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. I show that these differences are not driven by different trends in productivity for constrained and unconstrained groups, and also that they do not disappear as firms grow older.

These findings are not easily explained by models of firm dynamics that are calibrated to match the level and persistence of firm sales and profits (see, among others, Caggese and Cunat, 2013 and Midrigan and Xu, 2014), because they imply that operating firms accumulate retained earnings and become financially unconstrained very early in their lives. Conversely, I find that in more financially constrained sectors, productivity growth is significantly reduced not only for young firms but also for older firms up to 40 years of age.

In order to explain these findings, I develop an industry model in which 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. I simulate industries which match the different intensities in financial frictions observed in the industries in the empirical dataset, and I show that this model is unable to explain the empirical evidence: financing frictions reduce the frequency of innovation of very young firms, but increase the innovation of older firms, and generate life cycle dynamics inconsistent with the empirical evidence. In part, the intuition for this result is that, as mentioned above, firms with realistic levels of profitability, on average, accumulate retained earnings to become unconstrained relatively early in their life. But I also find an additional indirect "competition effect". Financial frictions, by increasing the bankruptcy probability for young and financially fragile firms, 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. Therefore, older firms that overcame financial frictions are actually more likely to invest in incremental innovation in a more financially constrained industry.

The main theoretical contribution of this paper is to show that the full model, in which firms have both incremental and radical innovation opportunities, is instead able to explain the empirical evidence. I assume that 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 innovation. Newborn firms are, on average, small and far from the frontier technology. 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 their losses by closing down. Firms that succeed in radical innovation become larger and more productive, and find it optimal to engage in incremental innovation. Therefore, in the full model, 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 Akcigit and Kerr (2010), who analyze 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 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.

As for the benchmark model, I use the full model to simulate industries which match the different intensities in financial frictions observed in the industries in the empirical dataset. I find that, in more financially constrained industries, the competition effect strongly reduces the frequency of radical innovation by young firms. This happens because, with lower com-

[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*".

petition, many younger and smaller firms are now relatively more profitable at their current productivity level, and expecting to remain profitable for some time if they do not innovate, they decide to postpone risky radical innovation, because they have more to lose in case of failure. But since fewer young firms do radical innovation, fewer firms become productive enough to invest in incremental innovation. This reduces the number of very large and productive firms, and, as a consequence, competition decreases even more, further discouraging the radical innovation of young firms. The negative interaction between competition and radical and incremental innovation slows down productivity growth over the firm's life cycle for both young and old firms, generating life cycle dynamics consistent with the empirical evidence. Using simulated firm level data, I find that the full model can replicate well the observed negative relation between financial frictions and productivity growth over the firm's life cycle, both qualitatively and quantitatively. The aggregate implications of these effects are also significant. I find that reducing financial frictions in all the most constrained sectors at the median level, and abstracting from general equilibrium effects on wages and interest rates, would increase overall productivity in the Italian manufacturing sector by 6.3%.

Taken together, the results in the full model show that financial frictions have large negative effects on innovation and on the productivity growth of firms, consistent with the empirical evidence, and support the view that financial factors are important in explaining the cross country findings of Hsieh and Klenow (2014).[2] Importantly, these results are obtained in a realistically calibrated model where financial frictions have large aggregate effects despite being binding only for a relatively small fraction of firms, because they matter indirectly, by reducing competition and distorting innovation decisions. In the last part of the paper, I provide several robustness checks of the key mechanisms that generate the above theoretical findings. I find empirical support for the prediction of the model that risky innovation activity is mainly performed by young firms, and for the prediction that financial frictions negatively affect innovation and growth indirectly, because they generate entry barriers that reduce competition.

2 Related literature

My paper is related to the literature on financing frictions and firm dynamics, such as, among others, Buera, Kaboski, and Shin (2011) and Caggese and Cunat (2013), and in particular it is related to Midrigan and Xu (2014) and to Cole, Greenwood and Sanchez (2015). Midrigan and Xu (2014) 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. In Cole, Greenwood

[2] Among other frictions that may contribute to explain this empirical evidence, Akcigit, Alp and Peters (2016) emphasise the difficulty, for entrepreneurs in poor countries, to delegate managerial tasks to outside managers.

and Sanchez (2015), financing frictions prevent new entrepreneurs from adopting the most productive technologies. In their model, new entrepreneurs can select a project type only when they start their firm, and different project types have different productivity ladders. Financial frictions prevent entrepreneurs from selecting riskier projects with steeper productivity ladders, thus reducing growth over the firm's life cycle. In contrast, in my model firms have frequent new innovation opportunities during their lifetime, and financial frictions directly constrain the technology adoption only of the youngest firms in the industry. However, despite the realistic features, common to Midrigan and Xu (2014), that older and larger firms can self finance and are not financially constrained in their technology adoption, my model shows a novel and powerful 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. Because of its emphasis on heterogeneous technological choices, my paper is also related to Bonfiglioli, Crinò and Gancia (2016), who show, in a static multi-sector and multi-country model, that financing frictions distort the type of technologies firms select upon entry and affect both the equilibrium dispersion of sales and the volume of trade. In contrast, I develop a dynamic model which focuses on the dynamic interactions between financial frictions and different types of innovation decisions over the firms life cycle, and on their impact on productivity growth at the firm level and on aggregate productivity.

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 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). I will use this dataset to estimate the relation between financing frictions and the life-cycle dynamics of productivity at the firm level.

Identifying the effect of financial frictions on firm decision is challenging because of an endogeneity problem: do financial imperfections cause the slow growth of firms, or are the lack of growth opportunities that cause financial difficulties? The empirical literature on financing frictions has long recognized how this problem might bias the results of any estimation procedure that relies on financial constraint indicators computed at the firm level using balance sheet data. As an alternative approach, several studies have used time invariant indicators computed at the sector level, which are supposed to capture technological characteristics that make firms more vulnerable to financial frictions. Among these are the External Financial Dependence indicator (Rajan and Zingales, 1998), which measures sector level financial frictions with the fraction of capital expenditures not covered by cash flow, and the Hadlock and Pierce (2010) indicator, which measures them with a linear function of firm size and age. However, none on these indicators directly measure financial frictions, and recently Farre-Mensa and Ljungqvist (2016), after performing several tests based on quasi-natural experiments, reject their validity.

In relation to the objective of this paper, I argue that I can improve on previous studies in identifying the effects of financial frictions on firms growth, because of two key factors: first, I use direct information on financial constraints from survey answers. Second, later in the paper I test a model which predicts that financial frictions matter because of their indirect effect on the innovation decisions of currently unconstrained firms. Therefore, in order to empirically verify the predictions of the model, I do not need to identify which firms are currently more financially constrained, but rather in which sectors firms face more financial frictions on average, and which firms are currently not constrained.

Therefore I proceed as follows: 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 $finprob_{i,s}$, 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.[3] Then, for each 4 digit manufacturing sector I compute the percentage of firms that complain about problems in accessing external finance (the variable $finprob_{i,s}$ is equal to one) and have average operating profits over added value

[3] 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 a 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.

larger than 0.1, thus excluding the 25% least profitable firms.[4]

I identify, as sectors where firms face more financial frictions, the 50% most constrained four digit sectors according to the above methodology, called the "Constrained" group, while the other group is composed of the 50% four digit sectors with the least constrained firms, called the "Unconstrained" group. Furthermore, when testing the predictions of the model, I only focus on currently not financially constrained firms in both groups (those for which the variable $finprob_{i,s}$ is equal to zero). I do so because the model predicts that financial frictions affect productivity growth indirectly, by altering the innovation decisions of unconstrained firms. In other words, it predicts that the effect of financing frictions on productivity growth can be precisely estimated when firms currently financially constrained are excluded from the estimation (and therefore used only to identify which sectors are more constrained on average). The advantage of this approach is that, while among the firms declaring difficulties in obtaining loans there could be many firms that are not currently facing financing imperfections, but are denied financing because of poor performance and lack of growth opportunities, it is much less likely that among the group of firms not declaring financing difficulties there are many facing significant financial frictions.

One residual concern is a selection bias at the sector level, so that the constrained group is composed by sectors with worse growth prospects on average, even after excluding from the analysis the 25% least profitable firms and the firms currently declaring financial problems. In other words, it might be that lower productivity growth at the firm level in the constrained group is driven by the fact that this group is composed by sectors with worse growth opportunities. However, in the next sub-section I estimate the effect of financial frictions on productivity with panel data regressions which include both firm level fixed effects and time*group dummies. Firm fixed effect control for any average difference in productivity across sectors, and time dummies specific to the constrained and unconstrained groups make sure that different group specific shocks do not affect the results.

The outline of the remainder of this section is as follows. First, I compute two alternative measures of firm-level productivity, and I estimate their growth over the firms life cycle for all firms in the constrained and unconstrained groups. Then, in Sections 4-5, I develop and simulate a model which predicts that financial frictions affect innovation indirectly by altering competition and profitability at the industry level. I test this prediction of the model in section 6.

3.1 The relation between age and productivity

Table 1 reports the estimates of productivity growth at the firm level as a function of financial frictions. It considers several regressions where the dependent variables are two different firm

[4] 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 11 in Appendix 2. The table also 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 a few sectors.

level estimates of total factor productivity, $v^1_{i,t}$ and $v^2_{i,t}$. The productivity measure $v^1_{i,t}$ is computed from the following equation:

$$\log \pi_{i,t} = \beta_0 + \beta_1 \log O_{i,t} + v^1_{i,t} \tag{1}$$

Where $\pi_{i,t}$ is operative profits of firm i in period t and $O_{i,t}$ is fixed overhead costs of production measured by the total wages paid to white collars. Appendix 3 derives equation 1 from the first order conditions of the structural model in Section 4, and it shows that $v^1_{i,t}$ is a linear and increasing function of firm's productivity:

$$v^1_{i,t} = b\widetilde{v}_{i,t}, \tag{2}$$

where $\widetilde{v}_{i,t}$ is the deviation of the productivity level ν_t with respect to its firm level average, and b, β_0 and β_1 are industry specific coefficients. A detailed derivation of equation 2 is provided in Appendix 3. Nonetheless, the intuition is simple: in a monopolistic competition model where productivity and size are positively related, a more productive firm has lower variable costs relative to its fixed overhead costs, is able to produce more, and has higher revenues and profits for given overhead costs. Equation 1 is estimated with a panel regression with both firm and time effects. Overhead costs $O_{i,t}$ are estimated using the information in the surveys about the composition of the labour force between blue and white collars. For more details, see Appendix 3.

Since one of the objectives of this paper is to relate its findings to Hsieh and Klenow (2014), I also include a second measure of productivity $v^2_{i,t}$, which follows the procedure adopted by Hsieh and Klenow (2009) and (2014). They consider a monopolistic competition model with a Cobb Douglas production function and derive a measure of physical productivity equal to $\kappa_s \frac{(p_{i,t}y_{i,t})^{\frac{\sigma}{\sigma-1}}}{\left(p^k_{i,t}k_{i,t}\right)^{\alpha} l^{\beta}_{i,t}}$, 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 $l_{i,t}$, I obtain the following relation:

$$(p_{i,t}y_{i,t})^{\frac{\sigma}{\sigma-1}} = e^{v^2_{i,t}} \left(p^k_{i,t}k_{i,t}\right)^{\alpha} (w_{i,t}l_{i,t})^{\beta}, \tag{3}$$

where $v^2_{i,t}$ is physical productivity, $p_{i,t}y_{i,t}$ is added value, $p^k_t k_{i,t}$ is the value of capital, and $w_{i,t}l_{i,t}$ is cost of labour for firm i in period t. I estimate equation 3 using the Levinshon and Petrin (2003) methodology (see the details in Appendix 4), and also in this case, I include in the estimation firm and time effects, which absorb the unobservable sector specific term κ_s.

For both measures of productivity $v^1_{i,t}$ and $v^2_{i,t}$, I estimate equations 1 and 3 separately for each 2 digit sector, and I use the estimated coefficients to obtain their empirical counterparts $\widehat{v}^1_{i,t}$ and $\widehat{v}^2_{i,t}$. I then measure the evolution of productivity over the firm's life cycle by estimating the following model:

$$\widehat{v}_{i,s}^{j} = \beta_0 + \beta_1 age_{i,s} + \beta_2 age_{i,s} * constrained_i + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \quad (4)$$

Given that each survey covers a 3-years period, for the estimation of equation 4, I consolidate all the balance sheet variables at the same time interval. Therefore $\widehat{v}_{i,s}^{j}$ for $j \in \{1,2\}$, is the average of $\widehat{v}_{i,t}^{j}$ for the three years of survey period s. Since balance sheet data for some firms go back to 1989, I have a total of four 3-year survey periods (1989-91, 1992-94, 1995-97 and 1998-2000). The total number of survey-year observations available for the productivity measures $\widehat{v}_{i,s}^{1}$ and $\widehat{v}_{i,s}^{2}$ are respectively, 12776 and 13505. Among the regressors, x_j is the set of m control variables, which include firm fixed effects and time effects. $age_{i,s}$ is the age of firm i in survey s. The financing constraints dummy $constrained_i$ 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. $constrained_i$ is constant over time for each firm and collinear with firm fixed effects. Therefore, I only include it interacted with age, so that 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.

The first two columns of Table 1 report the estimated coefficients of age and age interacted with $constrained_i$. The presence of firm fixed-effects ensures that the estimation of β_1 and β_2 is not affected by a composition bias, since these parameters are identified only by within-firm changes in productivity. Columns 1-2 report the results using $\widehat{v}_{i,s}^{1}$ and $\widehat{v}_{i,s}^{2}$ as dependent variables, respectively. For firms in less constrained sectors, both productivity measures increase with age, even though the increase of $\widehat{v}_{i,s}^{1}$ 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 3 to 4, and also in this case the results are confirmed with minimal differences in the estimated coefficients. The last two columns of Table 1 consider a more detailed selection of constrained groups. The estimated equation is:

$$\widehat{v}_{i,s}^{j} = \beta_0 + \beta_1 age_{i,s} + \beta_2 age_{i,s} * midconstr_i + \beta_2 age_{i,s} * highconstr_i + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \quad (5)$$

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

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

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$\widehat{v}^1_{i,s}$	$\widehat{v}^2_{i,s}$	$\widehat{v}^1_{i,s}$	$\widehat{v}^2_{i,s}$	$\widehat{v}^1_{i,s}$	$\widehat{v}^2_{i,s}$
$age_{i,s}$	0.00390	0.0103***	0.00427	0.0102***	0.0121***	0.0128***
	(1.11)	(6.16)	(1.13)	(5.72)	(2.53)	(5.61)
$age_{i,s}{*}constrained_i$	−0.0117**	−0.00547**	−0.0118**	−0.00499**		
	(−2.55)	(−2.51)	(−2.37)	(−2.10)		
$age_{i,s}{*}midconstr_i$					−0.0185**	−0.00671**
					(−2.88)	(−2.14)
$age_{i,s}{*}highconstr_i$					−0.0208**	−0.00792**
					(−3.41)	(−2.74)
N.observations	12776	13505	12776	13505	12776	13505
Adj. R-sq.	0.002	0.013	0.002	0.013	0.003	0.013
Firm fixed effects	yes	yes	yes	yes	yes	yes
Time dummies	yes	yes				
Time*group dummies			yes	yes	yes	yes

Panel regression with firm fixed effect. Group dummies: one dummy for each financially constrained group of sectors. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $\widehat{v}^1_{i,s}$ is a measure of productivity consistent with the model developed in section 4, and $\widehat{v}^2_{i,s}$ is total factor productivity computed following the procedure of Hsieh and Klenow (2009). $age_{i,s}$ is age in years for firm i in survey s. $constrained_i$, is equal to one if firm i belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. $midconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the median percentage of financially constrained firms, and zero otherwise. $highconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

and zero otherwise. In this case the coefficient of $age_{i,s}$, which measures yearly productivity growth for continuing firms in the 33% least constrained sectors, is positive and significant for both measures $\widehat{v}^1_{i,s}$ and $\widehat{v}^2_{i,s}$. Moreover, 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 of firms 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 4 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 $\widehat{v}^1_{i,s}$ and $\widehat{v}^2_{i,s}$, respectively. 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. Importantly, the differences in productivity between constrained and unconstrained firms also keep growing over time for the older firms in the sample, consistent with the findings of Hsieh and Klenow (2014).[5]

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. 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 in the industry are C.E.S. with elasticity $\sigma > 1$. The C.E.S. price index P_t is equal to:

$$P_t = \left[\int_w p_t(w)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{6}$$

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

[5] Figure 1 shows that the productivity differentials between most constrained and lest constrained 35 years old firms are almost as large as the productivity differentials between US plants and Mexican plants with the same age in Hsieh and Klenow (2014). However comparing productivity between firms of different age in the same sector, figure 1 shows that, in least constrained sectors in Italy, firms have a productivity around 20% higher after 35 years, while Hsieh and Klenow report report an increase by 400% for U.S. establishments. There are several factors that explain this difference: i) the fixed effect estimation only measures within firm variation and firm fixed effects absorb some of the size differences that drive the Hsieh and Klenow measure; ii) my dataset is at the firm level, rather than at the establishment level, and very few firms younger than 5 years old are reported, so tha the average size for age smaller or equal than 5 years old is substantially overestimated; iii) the Italian manufacturing sector has other constraints, beside financial frictions, which limit the growth of firms, such as a labour law that establishes very high firing costs and that applies only to firms larger than 15 employees.

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

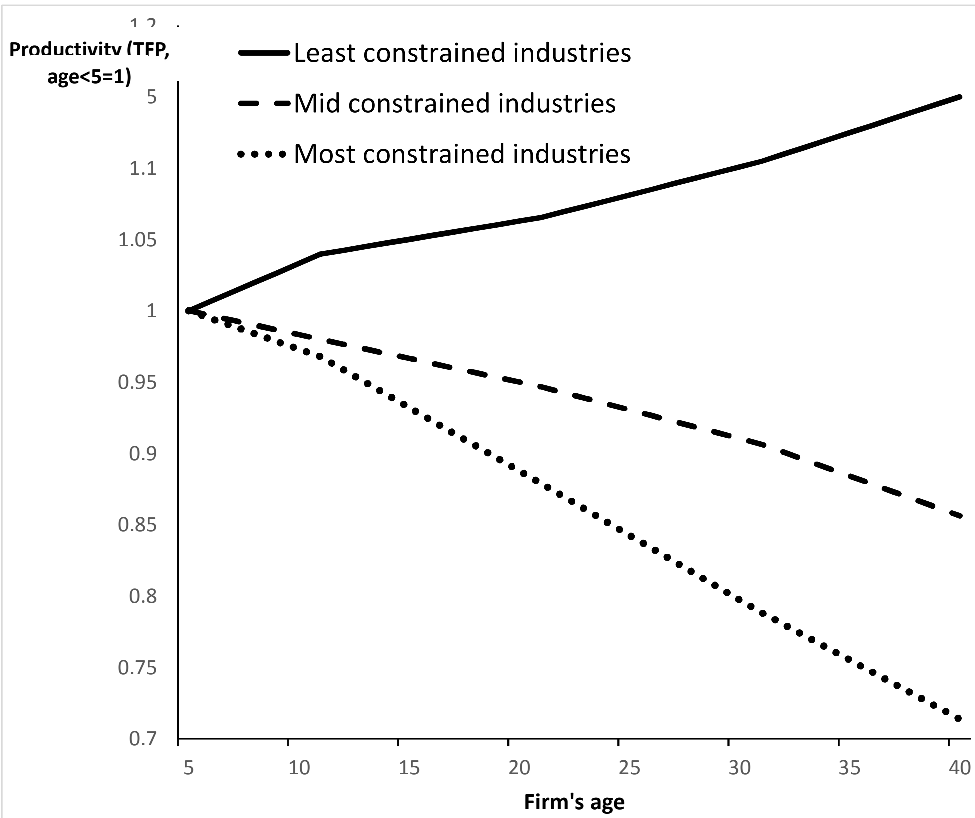
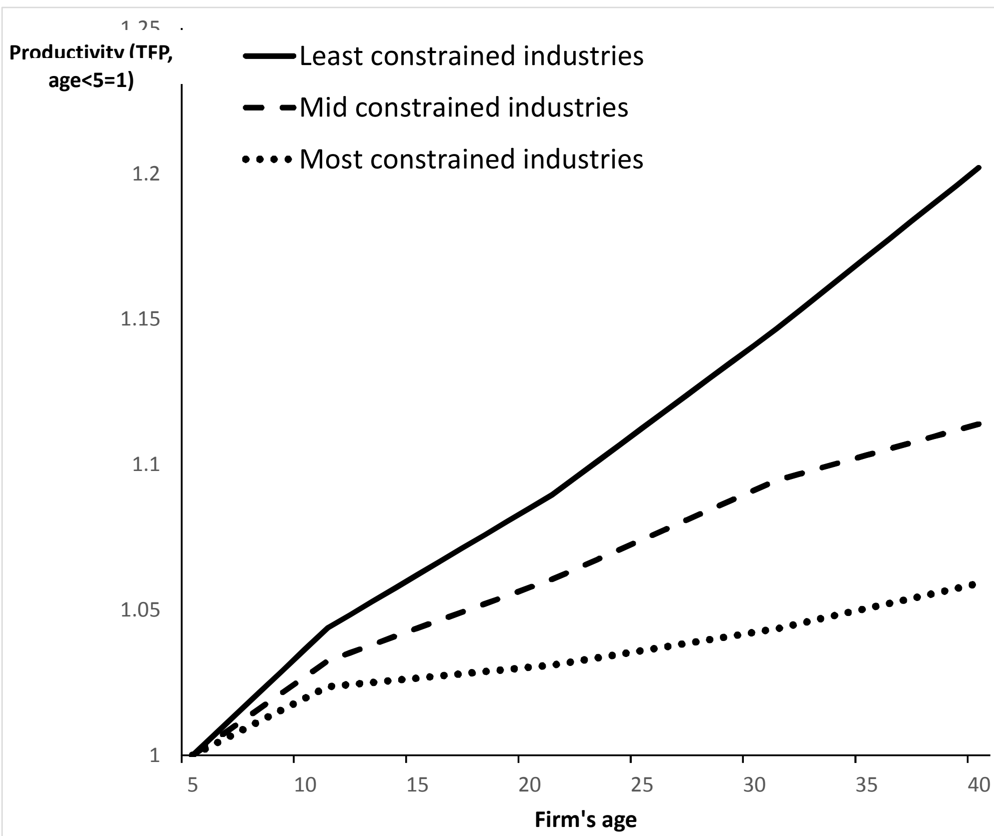


Figure 2: Life cycle of the productivity of firms in the empirical sample, profits based measure v^2



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

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:

$$P_t Q_t = A P_t^{1-\eta} \tag{8}$$

where A is an exogenous demand parameter and $\eta < \sigma$ is the industry price elasticity of demand. From (7) and (8) the demand for an individual variety w is:

$$q_t(w) = A \frac{P_t^{\sigma-\eta}}{p_t(w)^{\sigma}} \tag{9}$$

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:

$$\pi_t(v_t, \varepsilon_t) = p_t(w) q_t(w) - \frac{q_t(w)}{v_t} - F_t \tag{10}$$

Since all of 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:

$$F_t = (1 + \varepsilon_t) F(v_t) \tag{11}$$

where $F'(v_t) > 0$. The fixed cost F_t is proportional to productivity v_t, in order to ensure that the profitability of small and large firms in the simulated model are comparable to those in the empirical sample.[6] 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.[7]

[6] Assuming $F(v_t)$ to be a positive constant $F > 0$ would not change the qualitative results of the model, but would prevent a proper calibration of the profitability dynamics of firms, making its quantitative implications less interesting.

[7] 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,

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:

$$\pi_t(v_t, \varepsilon_t) = \frac{(\sigma - 1)^{\sigma-1}}{\sigma^{\sigma}} A P^{\sigma-\eta} v_t^{\sigma-1} - F_t \tag{13}$$

Equation 13 clarifies that profits depend on firm specific productivity v_t and shock ε_t, as well as on market competition which affects the aggregate price index P. 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 of 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:

$$a_t = R[a_{t-1} - K(I_{t-1}) - d_{t-1}] + \pi_t(v_t, \varepsilon_t) \tag{14}$$

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 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:

$$a_t - \pi_t(v_t, \varepsilon_t) \geq F_t, \tag{15}$$

If constraint (15) is not satisfied, then the firm cannot continue its activity and is forced to liquidate. Constraint (15) 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).

Conditional on continuation, innovation of type I_t is feasible only if:

$$a_t \geq K(I_t). \tag{16}$$

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

thus making the solution of the model more complicated.

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.

Here, I define innovation as an investment directed to increase production efficiency. This approach is consistent with Hsieh and Klenow (2014) who also focus explicitly on the growth of process efficiency along the life cycle of plants. However, 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 under certain assumptions, their efficiency 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. The 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.[8]

A firm which selects $I_t = 0$ with $K(0) = 0$, either because has no innovation opportunities or because it 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:

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

where 1 is the normalized value of the frontier technology.

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

4.2 Full model with radical and incremental innovation

In the full model, I assume 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.[9] Implementing the incremental idea ($I_t = 1$) 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 τ^R measures both the downside and upside risk of radical innovation. This symmetric structure in the change in productivity conditional on success and failure is convenient to simplify the calibration, but is not essential for the results, and is relaxed in Appendix 5.

I call this alternative innovation "radical" because, in calibrating the model, τ^R matches the frequency of large changes in productivity at the firm level, and is an order of magnitude larger than τ, while ξ^R, which matches the frequency of radical innovation, is relatively small. It follows that in the calibrated model radical innovation is very risky, but potentially able to generate a large increase in firm´s productivity and profitability. Therefore, it 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 productivity becomes:

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

4.3 Value functions

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

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

[9] 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 chosen by old/large firms.

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

$$V_t^2(a_t, \varepsilon_t, v_t) = -K(2) + \frac{1-\delta}{R} \left\{ \begin{array}{c} \xi^R E_t \left\{ \begin{array}{c} \pi_{t+1} \left\{ \varepsilon_{t+1}, \min\left[v_t (1+g)^{\tau^R}, 1 \right] \right\} + \\ V_{t+1} \left\{ a_{t+1}, \varepsilon_{t+1}, \min\left[v_t (1+g)^{\tau^R}, 1 \right] \right\} \end{array} \right\} \\ + \left(1-\xi^R\right) E_t \left\{ \pi_{t+1} \left(\varepsilon_{t+1}, \frac{v_t}{(1+g)^{\tau^R}} \right) + V_{t+1} \left[a_{t+1}, \varepsilon_{t+1}, \frac{v_t}{(1+g)^R} \right] \right\}, \end{array} \right\} \tag{18}$$

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

$$V_t^0(a_t, \varepsilon_t, v_t) = \frac{1-\delta}{R} \left\{ \begin{array}{c} \xi E_t \left\{ \pi_{t+1}(\varepsilon_{t+1}, v_t) + V_{t+1}(a_{t+1}, \varepsilon_{t+1}, v_t) \right\} \\ + (1-\xi) E_t \left\{ \pi_{t+1} \left(\varepsilon_{t+1}, \frac{v_t}{1+g} \right) + V_{t+1} \left[a_{t+1}, \varepsilon_{t+1}, \frac{v_t}{1+g} \right] \right\} \end{array} \right\} \tag{19}$$

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

$$V_t^*(a_t, \varepsilon_t, v_t) = \gamma \max_{I_t \in \{0,1\}} \left\{ V_t^0(a_t, \varepsilon_t, v_t), V_t^1(a_t, \varepsilon_t, v_t) \right\} + (1-\gamma) V_t^0(a_t, \varepsilon_t, v_t) \tag{20}$$

While in the full model is equal to:

$$V_t^*(a_t, \varepsilon_t, v_t) = \gamma \max_{I_t \in \{0,1,2\}} \left\{ V_t^0(a_t, \varepsilon_t, v_t), V_t^1(a_t, \varepsilon_t, v_t), V_t^2(a_t, \varepsilon_t, v_t) \right\} + (1-\gamma) V_t^0(a_t, \varepsilon_t, v_t) \tag{21}$$

such that equation (16) is satisfied. Given the optimal continuation value $V_t^*(a_t, \varepsilon_t, v_t)$, the value of the firm at the beginning of time t, $V_t(a_t, \varepsilon_t, v_t)$, is:

$$V_t(a_t, \varepsilon_t, v_t) = 1\left(a_t - \pi_t(v_t, \varepsilon_t) \geq F_t\right) \left\{ \max\left[V_t^*(a_t, \varepsilon_t, v_t), 0 \right] \right\} \tag{22}$$

Equation (22) implies that the value of the firm is equal to zero in two cases. First, when the indicator function $1(a_t \geq F_t)$ is equal to zero because the liquidity constraint (15) is not satisfied. Second, when the value in the curly brackets is equal to zero, which indicates that since $V_t^*(a_t, \varepsilon_t, v_t) < 0$, 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:

$$\int_{\underline{v}}^{\overline{v}} \max\left\{E^{\varepsilon_0}\left[V_0\left(a_0, \varepsilon_0, v_0\right)\right], 0\right\} f(v_0) dv_0 - S^C = 0 \tag{23}$$

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 (23) is satisfied. The number of firms in equilibrium ensures that P_t also satisfies the aggregate price equation (6). Aggregation is very simple because all operating firms with productivity v choose the same price $p(v)$, as determined by equation (12).

4.6 Financing frictions and innovation decisions

Even though the model does not have an analytical solution, it is useful to analyze the above equations to get an intuition of the effects of financial frictions on firm dynamics and innovation decisions. By "financially constrained", I mean firms with low financial wealth a_t, for which constraints (15) and (16) might be binding today or in the future. First, constraint (16) implies that firms with low financial wealth a_t are unable to finance innovation. I call this the "*binding constraint effect*". Second, equation (22) implies that the larger the probability of bankruptcy $prob(a_t \geq F_t)$, the lower is the expected value of the firm. Therefore, higher expected probability of bankruptcy for new firms reduces the value of the term $E^{\varepsilon_0}\left[V_0\left(a_0, \varepsilon_0, v_0\right)\right]$ in the entry condition (23) for a given aggregate price P. It follows that the term on the left hand side of (23) becomes negative: $\int_{\underline{v}}^{\overline{v}} \max\left\{E^{\varepsilon_0}\left[V_0\left(a_0, \varepsilon_0, v_0\right)\right], 0\right\} f(v_0) dv_0 - S^C < 0$, and entry must fall until lower competition increases P, increases expected profits and the value of a new firm, and ensures the equilibrium in the free entry condition. In other words, 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.[10]

4.7 Calibration

[10] To be precise, there is also a "*selection effect*": less productive firms generate less profits, suffer larger losses when the realization of the shock ε_t is negative, and are likely to go bankrupt if their wealth is low. Since the defaulting firms are replaced by new firms on average more productive, this effect improves selection towards more productive firms. However this effect is of marginal importance in driving the results illustrated in the next sections.

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

4.7.1 Benchmark model

The parameters are illustrated in Table 2. 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.[11] The following six parameters determine the dynamics of innovation and productivity: the mean $\widehat{v}_0$ and variance $\sigma^2_{\nu_0}$ of the distribution of productivity of new firms v_0.[12] 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 of 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 and 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 $F(v_{it})$ is:

$$F_{it} = \lambda \frac{v_{it}}{\widehat{v}_0} \tag{24}$$

where $\lambda > 0$ and $\widehat{v}_0$ is average productivity of new firms. λ 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 innovation opportunity γ matches the percentage of innovating firms. In the sample, there are 37% firm-survey observations reporting R&D activity. However, for many firms R&D spending is very small relative to output. 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 large impact on a 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. Therefore, I classify as

[11] 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.

[12] 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.

Table 2: Calibration of the benchmark model with only incremental innovation

Parameter	Value	Empirical moment	Data	Model
λ	0.5	Fraction of firms with negative profits	0.40	0.35
θ	0.15	Avg. of time series st.dev. of profits/sales	0.117[1]	0.106
$K(1)$	3	Average R&D expenditures /profits	67%[2]	66%
γ	0.45	Percentage of innovating firms	22%[2]	21%
$\widehat{v}$	0.53	Median TFP relative to the 99th percentile	0.78	0.84
σ_v^2	0.03	Average cross sectional standard deviation of TFP	0.34[3]	0.25
g	0.009	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	6.9
ξ^{NI}	0.25	Percentage of firms with age >60 years	4.8%	8.5%
δ	0.01	Average age	24	21
a_0	12	Percentage of firms going bankrupt every period	1.3%	1.02%

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 the cost of R&D over sales is greater than 0.5%.

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

"innovating" all firms in the empirical sample with R&D expenditure higher than 0.5% of sales (22% of all firms). 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 $a_0 = 8$, which in equilibrium corresponds to 30% of average firm sales in the industry, and which matches the average share of firms going bankrupt every period.[13] Although the model is relatively stylized, Table 2 shows that, apart from some difficulty in replicating the empirical size distribution of firms, it matches these empirical moments reasonably well. 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.

4.7.2 Full model with incremental and radical innovation

The full model requires choosing three additional parameters: the probability of success ξ^R, the change in productivity after innovating τ^R, and the cost $K(2)$ of radical innovation. Unfortunately, in the dataset I do not have information on patents, which could help identify how risky and radical innovation is. Therefore I proceed as follows: out of the 22% of firms classified as innovating in the previous section, I consider as radical all firms that declare R&D spending on projects related to developing and producing new products (see Appendix 2 for details), and I consider as incremental all the other innovation projects, which are directed

[13] A 2003 study by Istat (available online at: http://www.bnk209.it/sezioni/files/105/33_2001-istat-fallimenti-in-italia.pdf) shows that in 2001 in the whole Italian economy 1.35% of limited liability companies went bankrupt, and around 0.32%-0.39% of other types of companies. In the sample analyzed in this paper 92% of all the firms are limited liability companies.

to improve current products and productive processes. The idea is that in the model the difference between incremental and radical innovation is that the latter has a very uncertain outcome, and it is reasonable to assume that R&D directed to high-risk and high-reward projects often includes spending at least partly directed to new products. The drawback is that this classification might be noisy, because in some cases product innovation might relate to new products that embody small incremental improvements on existing products. Conversely, projects that improve current products and/or productive processes might include a substantial risk component. On the one hand, in section 6 I provide some evidence in support of the chosen indicator of radical innovation, showing that it is positively related to increases in the time series volatility of productivity at the firm level. On the other hand in section 5.3 I show that the main qualitative results of the model do not require a precise identification of radical innovation, because they hold for a large range of radical innovation parameter values.

I choose ξ^R and τ^R to jointly match the fraction of firms doing radical innovation in the empirical sample, as measured above (11.5%), and the 90th percentile, across all firms in the sample, of the firm level time series standard deviation of productivity. This statistic ranges from 18.4% for the $\widehat{v}^2$ measure to 38.3% for $\widehat{v}^1$. Since these volatility measures are likely biased upwards because of measurement errors, I calibrate the parameters so that the model counterpart is closer to the lower bound. This corresponds to $\tau^R = 30$, which implies that after a successful radical innovation productivity v 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. The calibrated value of ξ^R , the success probability of radical innovation, is 4.5%. Finally, the cost of radical innovation $K(2)$ is set equal to the cost of incremental innovation in expected terms, so that $K(2) = \xi^R\ K(1)$.

A restrictive assumption of this calibration, the symmetry in the innovation risk τ^R, is relaxed in Appendix 5. 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 $K(2)$. Finally, I recalibrate the parameters $K(1), \tau$, γ, δ and a_0 in order 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 of the other parameters unchanged. Table 3 illustrates the parameters of the full model.

5 Simulation results

In this section, I use the calibrated models to generate firm level data for simulated sectors with different degrees of financial frictions. More precisely, I generate 3 simulated industries, each of them with the same intensity of financing frictions of the "33% most constrained", "33% mid constrained" and "33% most constrained" empirical sectors, respectively, which are analyzed in figures 1 and 2. I generate these sectors for both the benchmark model and the full model, and in both cases I analyze these artificial firm level datasets with the

Table 3: Calibration of the full model with radical and incremental innovation

Parameter	Value	Empirical moment	Data	Model
λ	0.5	Fraction of firms with negative profits	0.40	0.35
θ	0.15	Avg. of time series st.dev. of profits/sales	0.117[1]	0.094
$K(1)$	6	Average R&D expenditures /profits	67%[2]	58%
γ	0.85	Percentage of innovating firms	22%[2]	22%
$\widehat{v}$	0.53	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]	0.31
g	0.009	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	11.0
ξ^{NI}	0.25	Percentage of firms with age >60 years	4.8%	13.4%
δ	0.015	Average age	24	25
a_0	4.5	Percentage of firms going bankrupt every period	1.3%	1.17%
ξ^R	0.045	Percentage of firms doing radical innovation	11.5%	10.4%
τ^R	30	90% percentile of volatility of productivity	18.4%	20.1%

Other parameters: S^C=4; r=2%; η=1.5; σ=4; $K(2) = 0.01$; 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.

identical procedure used in section 3 on the empirical data. The results are used to evaluate the capacity of the benchmark model and the full model to replicate the relation between financial frictions and life cycle dynamics of productivity observed in the empirical dataset.

For this exercise to be informative, it is necessary to quantitatively pin down an industry's financial frictions in the model and the data, in a comparable manner. I do so by focusing on an indicator of the intensity of financial frictions widely used in the firm dynamics literature, the wedge ϕ between the value of cash inside and outside the firm. Virtually all microfounded models of firm financial frictions predict a positive relation between their intensity and ϕ. Thus I make the following identifying assumption: in the empirical data, there is an unobservable common threshold $\overline{\phi}$, such that firm i in period t declares financial difficulties if $\phi_{it} > \overline{\phi}$. Conditional on this assumption, I proceed as follows:

First, I measure $\phi_{i,t}$ in the simulated data as the expected return of retained earnings in excess of the real interest rate r. Since the value of the firm $V_{it}(a_{it}, \varepsilon_{it}, v_{it})$, as defined in eq. 22, is the present value of future profits net of current wealth a_t, it follows that, for a simulated firm, ϕ_{it} is the derivative of $V_{it}(a_{it}, \varepsilon_{it}, v_{it})$ with respect to financial wealth:

$$\phi_{it} = \frac{\partial V_{it}(a_{it}, \varepsilon_{it}, v_{it})}{\partial a_{it}} \geq 0 \tag{25}$$

In other word, ϕ_{it} is strictly positive for a financially constrained firm because it measures the extra return 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

Table 4: Financial constraints in empirical and simulated sectors

	10% least constrained sectors	33% least constrained sectors	33% mid constrained sectors	33% most constrained sectors	10% most constrained sectors
average % of firms declaring financial problems	5.6%	8.4%	13.6%	20.7%	26.8%
			Calibrated value of a_0		
Model with only incremental Innovation,	12	10	8	3.5	1.75
Model with both incremental and radical Innovation,	8	7	4	2	0.75

zero for values of a_{it} high enough so that the firm is unconstrained today or in the future.

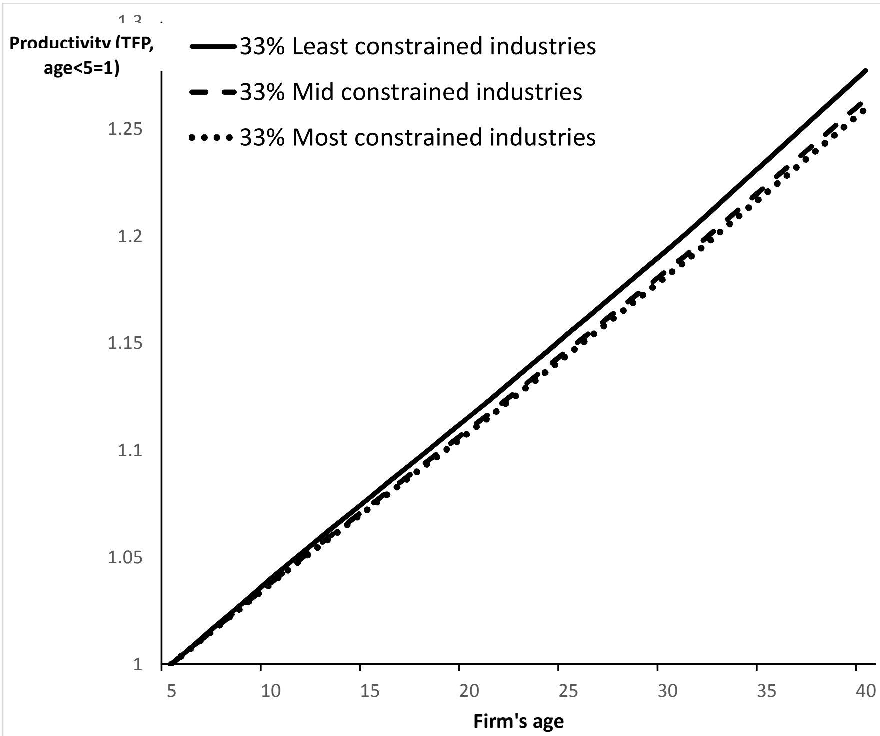
Second, given the value of ϕ_{it}, I measure the threshold $\overline{\phi}$ so that the percentage of simulated firms with $\phi_{it} > \overline{\phi}$ is the same as in the whole empirical sample (14% of all firm-year observations).

Third, given the value of $\overline{\phi}$, 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 financing frictions, the mean value of ϕ_{it} across firms, and also the fraction of "financially constrained" firms with $\phi_{it} > \overline{\phi}$. Thus I select values of a_0 in order to have three groups of simulated industries with the same intensity of financial frictions than the 3 groups of 33% most constrained, 33% mid constrained and 33% least constrained sectors analyzed in section 3. I also simulate more extreme values of a_0 to match financial frictions in the 10% least constrained and 10% most constrained sectors. Table 4 below summarizes the values of a_0 in the simulated industries in the two models. The wedge threshold $\overline{\phi}$ is equal to 2% in the model with only incremental innovation and 4% in the model with both innovation types. The value of $\overline{\phi}$, can also be interpreted as the premium in the opportunity cost of external finance caused by financing frictions. In the empirical sample the average difference between the interest rate paid on debt and the risk free interest rate (on 1 year treasury bills) is 3.6%.

5.1 Productivity over the firms life cycle

The calibration procedure illustrated above ensures that the simulated firms in both models match the empirical firms in terms of average age, profitability and innovation intensity, in terms of cross sectional dispersion of size, age and productivity, and in terms of the time series volatility of profits. Therefore the two models are evaluated for their ability to replicate the average productivity growth over the firms life cycle, and especially the relation between productivity growth and financial frictions.

Figure 3: Life cycle of the productivity of firms in the benchmark model with only incremental innovation.

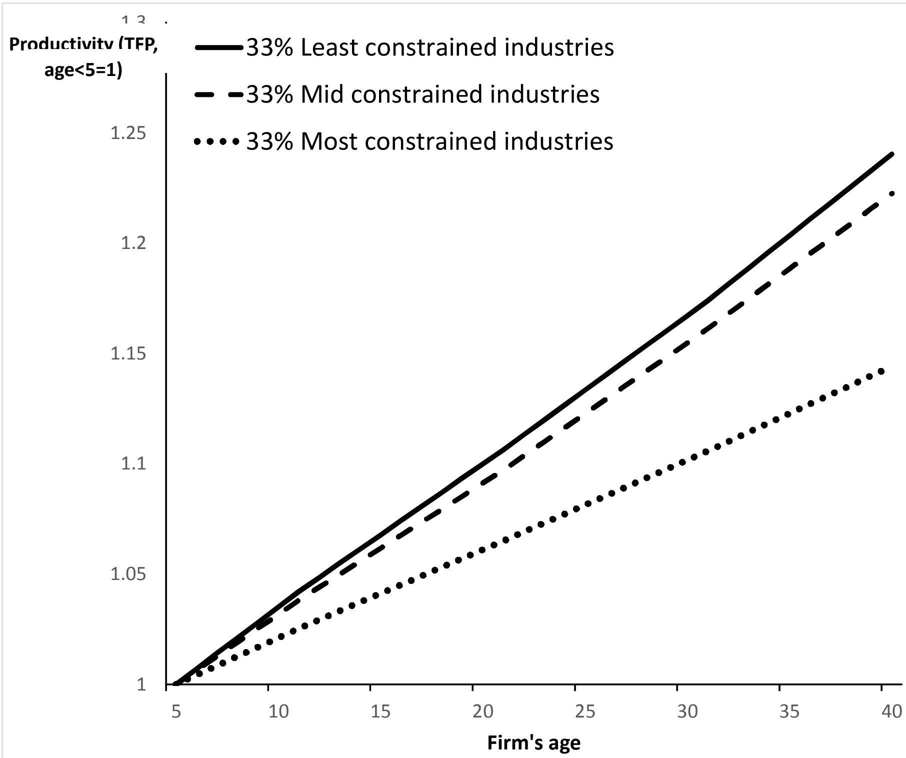


Figures 3 and 4 show the productivity over the life cycle of firms using the benchmark model with only incremental innovation and the full model with also radical innovation, respectively. They are the simulated counterparts of figures 1 and 2. More precisely, I consider an equal number of firms from the 3 simulated "33% most constrained", "33% mid constrained", and "33% least constrained" industries. I pool firms together to generate a simulated panel of N firms observed for T periods, where N and T are equal to the average number of firms and periods in the empirical dataset. Finally, I measure the relation between age and productivity with the same fixed effect regression used to estimate figures 1 and 2 (see Appendix 4 for details).

Figure 3 shows that the model with only incremental innovation is able to replicate a steady productivity growth of firms over their life cycle, even though at a faster rate than in the empirical sample. In the 33% least constrained industries productivity increases by approximately 28% after 40 years, versus an increase by 15% and 21% in figures 1 and 2, respectively. More importantly, this model fails to generate any significant relation between financial frictions and productivity growth. The 33% mid constrained industries have a slightly slower growth than the 33% least constrained ones, but there is no difference between them and the 33% most constrained ones, contradicting both figures 1 and 2

The results for the full model are shown in Figure 4. In this case the model is able to

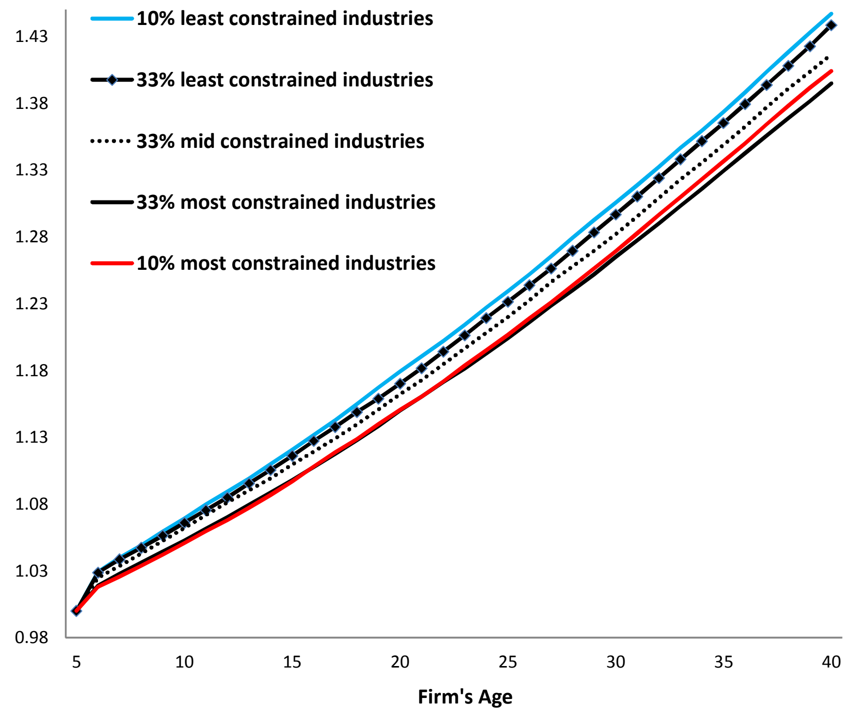
Figure 4: Life cycle of the productivity of firms in the full model with both radical and incremental innovation



generate a much larger negative effect of financial frictions on productivity growth, especially moving from the 33% mid constrained to the 33% most constrained sectors

Do these result depend on the specific estimation method employed? The firm fixed effects estimation method used above is very useful in the context of the empirical sample, to control for firm specific factors which might affect growth opportunities. However they do not capture productivity improvements that are reflected in average differences across firms of different age. Therefore figures 5 and 6 make full use of the simulated data and report the life cycle profile of productivity measured directly, for cohorts of firms that survive for at least 40 years, thus eliminating possible confounding selection effects. These figures add two further industries with an intensity of financing frictions matching the 10% least constrained and 10% most constrained empirical sectors. In other words, while figures 3 and 4 are the most appropriate counterparts of the empirical estimates in section 3, figures 5 and 6 are more precise measures of the average productivity of firms over their lifecycle. These figures confirm and reinforce the results related to the effects of financial frictions. In particular, in the benchmark model with only incremental innovation (figure 5), not only financial frictions have very small negative effects on productivity growth when moving from the 33% mid constrained to the 33% most constrained firms, but this negative effect vanishes

Figure 5: Life cycle of the productivity of firms in the benchmark model with only incremental innovation - exact measure for a cohort of continuing firms



when increasing financing frictions further to the 10% most constrained industries.

Conversely figure 6 confirms that, in the full model, productivity growth is strongly negatively affected by financial frictions, and the negative effect becomes monotonously stronger with the intensity of frictions. The increase in productivity of firms between ages 5 to 40 is 6.7 times lower in the 10% most constrained industries than in the 10% least constrained ones. Regarding the implications for aggregate productivity, I find that reducing financial frictions in all the most constrained sectors at the median level, and abstracting from general equilibrium effects on wages and interest rates, would increase overall productivity in the Italian manufacturing sector by 6.3%.

The above results show that the full model with both types of innovation is the only one able to explain, qualitatively and quantitatively, the relation between financial frictions and life cycle productivity growth estimated in section 3. In the next subsection I analyze in details the mechanism that generates this result.

5.2 Benchmark model, inspecting the mechanism

I first discuss the finding that, in the model with only incremental innovation, financing frictions do not significantly affect productivity growth (figures 3 and 5). The overall small

Figure 6: Life cycle of the productivity of firms in the full model with both radical and incremental innovation - exact measure for a cohort of continuing firms

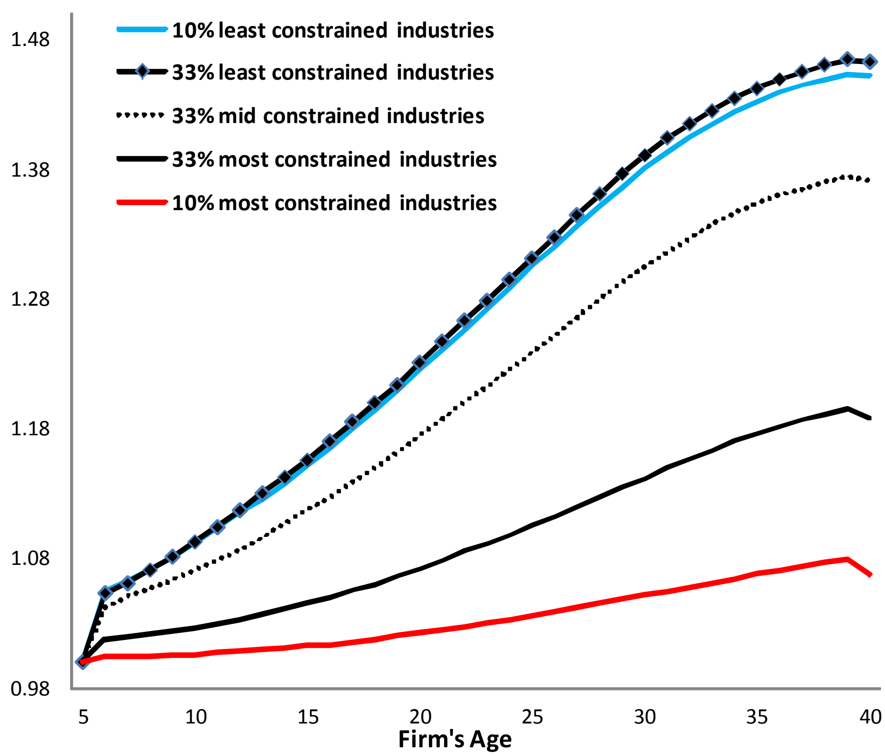


Table 5: Simulated industries, benchmark model with only incremental innovation: descriptive statistics

	(1)	(2)	(3)	(4)	(5)
	10% least constrained industries	33% least constrained industries	33% mid constrained industries	33% most constrained industries	10% most constrained industries
% going bankrupt every period	0.4%	0.7%	1.02%	3.2%	6.6%
% not innovating for lack of funds[1]	1.97%	2.66%	4.4%	13.9%	20.1%
Price index P rel. to 10% least constr.	100%	100.03%	100.1%	101.03%	102.9%
$\text{avg}\left(\pi^{unconstr} \mid v\right)$ rel. to 10% least c.	100%	100%	100.17%	102.6%	107.4%
Average % of innovating firms	23.6%	22.5%	21.02%	18.4%	22.6%
Avg. TFP relative to 10% least constr.	100%	99%	97.9%	94.5%	97.1%

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.

effect of financial frictions is the result of the two competing forces which are individually large but which offset each other, the "competition" and "binding constraint" effects. Table 5 reports summary statistics for all the different simulated industries in the benchmark model. An increase in financial frictions (moving from column 1 to column 5) causes a large increase in the fraction of firms unable to innovate because of a binding financing constraint, from 2% in column 1 to 20% in column 5. However, the other main effect of financial frictions is to increase entry barriers, reduce competition, and increase the profits of the unconstrained firms. Row 4 shows that expected profits conditional on productivity, for unconstrained firms, are 7% larger in column 5 than in column 1. Higher profits also increase expected innovation rents, and make incremental innovation more profitable.[14] Therefore, in industries with more financial frictions, financially unconstrained firms innovate more on average, compensating the lower innovation from financially constrained firms. These counteracting forces explain why the relation between financing frictions and innovation is U shaped. For moderate increases of financing frictions (from column 1 to column 4) the binding constraint effect dominates, and innovation and TFP decline. But for higher levels (from column 4 to column 5) the competition effect dominates, and innovation and TFP increase.

To further illustrate these counteracting effects, Figure 7 shows innovation as a function of productivity (panel 1) and age (panel 2) for an "unconstrained industry" (where a_0 is sufficiently high so that no firm is constrained), and for the 10% most constrained industries. The variable on the X-axis of panel 1 is productivity v relative to the frontier, which also determines the relative size of the firm. In the unconstrained industry, productivity is a sufficient statistic for the innovation decisions. All firms with v larger than 0.53 (or 53% than

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

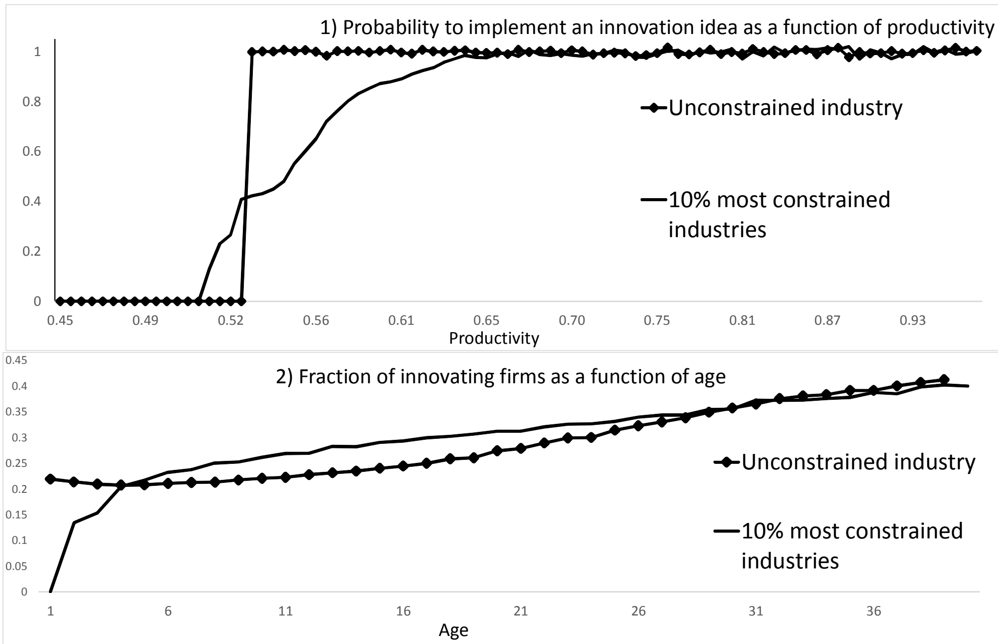
the frontier technology) find it optimal to innovate. In the constrained industry, there are two main differences. The minimum productivity to innovate is lower (51%), because of the competition effect: more financial frictions reduce entry and competition, increase expected profits for firms that do not go bankrupt, and increases innovation rents. Furthermore, in the region of v between 0.51 and 0.65, the probability to implement the innovation is positive but smaller than one. Innovation is profitable, but some firms have insufficient funds and a binding constraint (16), and cannot take advantage of it. This happens especially for very young firms, because firms are profitable on average and most firms able to self finance innovation after some periods.[15] As a consequence, the lower panel 2 of Figure 7 shows that the fraction of innovating firms is significantly lower in the constrained industry for very young firms, but the difference is already reversed for firms older than 4 years: young financially constrained firms either exit after negative shocks and are replaced by new firms, or accumulate profits and quickly become unconstrained. At this point, they are more likely to invest in innovation than in the unconstrained industry, because of the competition effect. Taken together, Figure 7 and Table 5 demonstrate that the benchmark model with only incremental innovation is unable to generate the negative relation between financial frictions on productivity growth found in the empirical data in Section 3. How general is this result? In other words, what changes in parameters could generate, in the model with only incremental innovation, a negative relation between financial frictions and productivity growth along the firms life cycle? One way to obtain this result would be to increase the return of innovation, and reduce the distribution of productivity of new entrants, so that all unconstrained firms find it optimal to implement innovation opportunities. This would eliminate the "competition effect" and the binding constraint effect alone would have stronger negative overall impact on productivity growth. However such calibration would have two counterfactual features, too low cross sectional dispersion in productivity across operating firms, and too little heterogeneity in innovation behavior across firms. More importantly, it would still not generate the significant differences in productivity growth for older firms found in the empirical data, because as firms age they are on average able to self finance themselves out of financial frictions.

5.3 Full model, inspecting the mechanism

I now discuss the findings, in figures 4 and 6, that in the model with both incremental and radical innovation financing frictions significantly reduce firms productivity growth. Table 6 shows the summary statistics for the simulated industries in the full model, from the least constrained in column 1 to the most constrained in column 5. Rows 6-8 show that the frequency of both types of innovation sharply declines once financial frictions increase above the median level (from column 3 to column 5). In this model the competition effect is still

[15] The finding that self financing limits the importance of the binding constraint effect on technology adoption is common to other calibrated firm dynamics models with realistic dynamics of profits at the firm level, such as Midrigan and Xu (2014).

Figure 7: Productivity, age and propensity to innovate in the benchmark model with only incremental innovation



operational, as shown in rows 4 and 5, but it reduces rather than increases innovation. The intuition of this result is that radical innovation is very risky, and more attractive for young firms the more competitive the industry is. If financial frictions lower competition, many young firms are more profitable and less inclined to invest in very risky projects. Moreover less radical innovation implies that fewer firms become large and profitable enough to invest in incremental innovation.

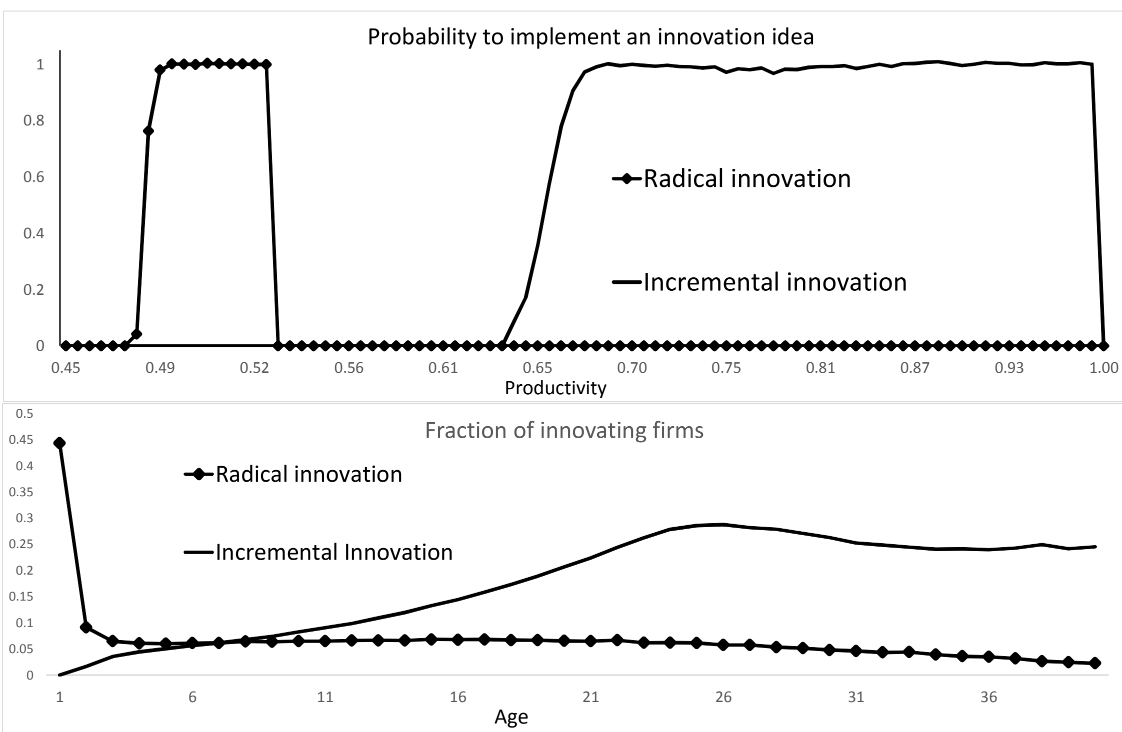
In order to explain this key finding of the paper more in details, figures 8-10 illustrate the innovation dynamics in the full model. I first illustrate the trade-off between radical and incremental innovation in the unconstrained industry only (Figure 8). I then discuss the implications of financial frictions (Figures 9-10). The upper panel of Figure 8 is analogous with panel 1 in Figure 7, and shows the probability to implement an innovation idea. As in the benchmark model, also here incremental innovation is performed only by the larger/more productive firms. The minimum productivity threshold for incremental innovation is higher than in Figure 7, because the model is calibrated to have the same total innovation as in benchmark model, but a smaller fraction of incremental innovation, given the presence of radical innovation. Conversely, radical innovation is performed by smaller/less productive firms. The key feature that generates this result is that radical innovation is a high risk investment, with low probability of success but a very high reward if it succeeds. It is not so attractive for medium and large firms, because they already have a profitable business which

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

	10% least constrained sectors	33% least constrained sectors	33% mid constrained sectors	33% most constrained sectors	10% most constrained sectors
1)% going bankrupt every period	0.009%	0.014%	1.17%	5.03%	6.06%
2)% not innov. (increm.) for lack of funds[1]	1.3	1.4	1.7%	0.5%	0.3%
3)% not innov. (radical) for lack of funds[1]	0%	0%	0.02%	0.2%	1.05%
4)Average P relative to 10% least. constr.	100%	100.07%	100.5%	102.5%	103.6%
5)$E(\pi \mid v)$ relative to 10% least. constr.	100%	100%	100.4%	103.8%	105.6%
6)Average percentage of innovating firms	20.4%	20.8%	21.9%	10.7%	8.6%
7)Percentage doing Radical Innovation	10.5%	10.4%	10.4%	5.4%	3.3%
8)Percentage doing Incremental Innovation	11.6%	12.05%	11.4%	5.6%	4.0%
9)Weighted TFP relative to 10% least. constr.	100%	101.3%	99%	88.1%	83.2%

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

Figure 8: Innovation decisions in the unconstrained industry, full model with both radical and incremental innovation.



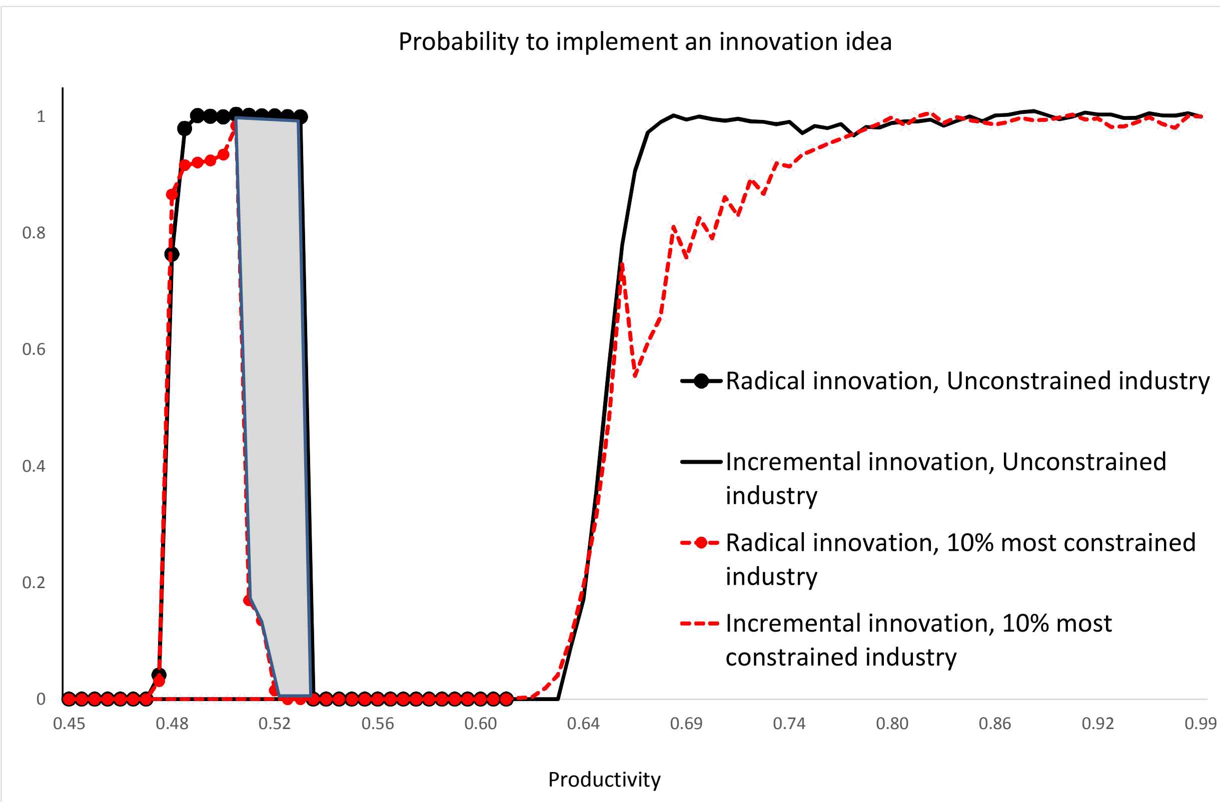
generates substantial profits. However, it is very attractive for smaller firms. The reason is that they do not value the upside potential and the downside risk symmetrically, because the value function is bounded below at zero, since they can always cut losses by exiting from production.

The lower panel of Figure 8 shows innovation as a function of firm age. 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 they become large they start investing in incremental innovation. Therefore, the fraction of firm doing incremental innovation rises gradually with age. It is important to note that the innovation dynamics of young and old firms in Figure 8 are interrelated. On the one hand, the experimentation of young firms is essential to generate a steady flow of firms which become large and productive enough to start investing in incremental innovation. On the other hand, more incremental innovation means a higher density of very large and productive firms, which raises competitive pressures and generates even stronger incentives for smaller firms to try radical innovation.

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 analyze 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 9-10 describe the relation between financing frictions, innovation and growth dynamics in the full model. In order to better illustrate the different effects at play, I focus, as I did in Figure 7, on the comparison between the extreme cases of the unconstrained industry and the 10% most constrained industries. Figure 9 shows the probability to innovate as a function of productivity. The range of productivity values in which firms radically innovate in the constrained industry is much smaller than in the unconstrained industry. The difference, highlighted by the gray area, is not caused by current binding financing constraints, because the cost of radical innovation $K(2)$ is calibrated to be relatively low. Indeed Table 6 above shows that in the full model, very few operating firms have a binding financing constraint. It is also not caused by future expected financing constraints, because conditional on failure, most firm exit immediately, while conditional on success, the firms become very profitable and financially unconstrained. Instead, the higher probability to do radical innovation in the unconstrained industry is explained almost entirely by the competition effect. In the constrained industry, competition is lower and profits are higher for all firms. Many younger and smaller firms are now relatively more profitable at their current productivity level, and

Figure 9: Probability to innovate, comparison of industries, full model with both radical and incremental innovation.



expecting to be profitable for some time if they do not innovate, they decide to postpone risky radical innovation, because they have more to lose in case of failure. Also in this case, there is a feedback effect. If fewer young firms do radical innovation, fewer firms become large and productive, and overall competition decreases, discouraging radical innovation even further. 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.[16] This effect explains the gray area for values of v around 0.52, where firms perform radical innovation only in the unconstrained industry. Since the distribution of firms, consistent with the empirical evidence, is heavily skewed with many young and small firms, the gray 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.[17]

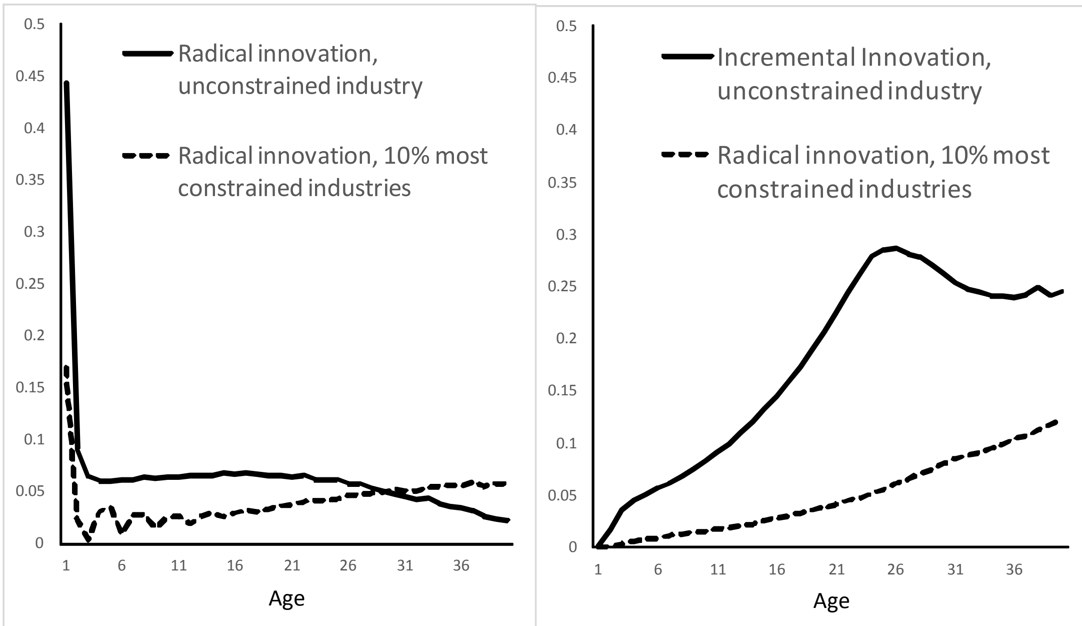
Figure 10 compares the life cycle profile of innovation in the unconstrained industry and in the 10% most constrained industries. In the latter, young firms perform less radical innovation, so that at any given age fewer firms reach a level of productivity high enough to find it optimal to invest in incremental innovation. This explains why the fraction of firms doing incremental innovation increases more slowly, with age, in this industry than in the unconstrained industry.

The above analysis clarifies that the negative effect of competition on radical innovation is key to allow the full model to explain the relation between financial frictions and lifecycle dynamics of firms. How robust is this result to changes in parameter values? Necessary conditions for this result are that: i) at least part of growth opportunities for firms come in the form of projects with a lot of upside risk and a non negligible downside risk; ii) the ability to implement these risky projects is not perfectly correlated with the profitability of current projects. Condition (i) means that these projects need to be at least partly irreversible, in the sense that if they fail, productivity falls compared to the previous status quo. This downside risk needs not to be very large. In appendix 5 I relax the assumption that the downside and upside risks of radical innovation are symmetric, and show that a downside risk which corresponds to productivity falling by 4.4%, if radical innovation fails, is sufficient

[16] 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).

[17] To be precise, there is also a "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 (22) is strictly concave for values of a_t around constraint 15 binding with equality, because higher wealth reduces bankruptcy risk, and $V_t(a_t, \varepsilon_t, v_t)$ is equal to zero if constraint 15 is violated. 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 10: Fraction of innovating firms in the full model, different industries



to generate similar results to those illustrated above. Intuitively, as long as radical innovation is sufficiently risky (a low probability of success but a large gain in productivity if it succeeds), then even a low value of τ^L is sufficient to ensure that radical innovation is mainly performed by less profitable firms, and that increases in competition encourage these firms to take on more risk. Condition ii) means that the results would be eliminated if only very large and productive firms have the necessary ability to implement radical innovation projects. However, as long as some small and/or very young firms have to some extent the ability to radically innovate, the qualitative results of the paper hold.

Finally, Appendix 5 also shows that in the full model not only financial frictions, but any other factor that raises entry costs and reduces competition has similar negative effects on productivity growth. This property is another testable prediction of the model, analyzed below.

6 Empirical evidence, robustness checks

In the empirical Section 3, I have shown that financial frictions are related to lower productivity growth over the firm's life cycle. Section 5 shows that the full model matches well the empirical findings both qualitatively and quantitatively, because of three key mechanisms: First, radical innovation is risky and is mainly performed by young firms. Second, financial frictions negatively affect growth because of their impact on innovation activity. Third, financial frictions affect innovation and growth indirectly because they generate entry barriers that reduce competition and distort the incentives to innovate.

In this section, I will provide empirical support for each of these mechanisms. I verify the first mechanism by estimating the relation between firms' age and the likelihood that innovation is related to an increase in volatility of productivity:

Prediction 1: The frequency of innovation related to an increase in the time-series volatility of productivity is higher among very young firms and declines rapidly with firm's age

In order to verify the second mechanism, I show that innovation is essential to generate the negative effect of financial frictions on productivity growth:

Prediction 2: The difference in the life cycle dynamics between financially constrained and financially unconstrained industries disappears if I only include in the analysis firms not performing R&D.

Finally, the third mechanism implies these two testable predictions:

Prediction 3: the result that a firm's productivity growth is lower in financially constrained industries should hold after excluding firms declaring financial difficulties.

Prediction 4: 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.

6.1 Innovation and volatility of productivity

In section 4.7 I identify radical innovation in the data, for calibration purposes, with firms that declare R&D spending on projects related to developing and producing new products (see Appendix 2 for details). Accordingly, here I define the variable $R\&D\_radical_{i,s}$, which is equal to one if firm i in survey s does R&D spending larger than 0.5% of sales, and at least part of this spending is directed to develop and produce new products (see Appendix 2 for details). I also define $R\&D\_incremental_{i,s}$,which is equal to one if firm i in survey s does R&D spending larger than 0.5% of sales but all R&D spending is directed to improve current products or productive processes.

The identifying assumption is that $R\&D\_radical_{i,s}$ is more likely to capture R&D directed to high-risk and high-reward projects than $R\&D\_other_{i,s}$. Given this assumption, the model predicts that $R\&D\_radical_{i,s}$ should be a less noisy indicator of radical innovation for younger firms, and therefore that the relation between $R\&D\_radical_{i,s}$ and time series changes in the volatility of productivity is stronger for young than for old firms in the empirical sample. Conversely, the same relation should be significantly weaker for the $R\&D\_incremental_{i,s}$ innovation indicator. This can be interpreted as a joint test of the predictions of the model that i) radical innovation is mostly performed by younger firms, and ii) radical innovation is related to higher volatility of productivity over time. In other words this test, even though it does not directly measure how radical innovation is, verifies whether the firm level relation between innovation and volatility of profits in the empirical sample is consistent with the main element of the model, that younger firms perform riskier innovation activity. Therefore, I estimate the following regression:

$$\sigma^2_{\widehat{v}^1,i,s} = \beta_0 + \beta_1 R\&D\_radical_{i,s} + \beta_2 R\&D\_incremental_{i,s} + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \qquad (26)$$

$\sigma_{\widehat{v}^1,i,s}$ is the standard deviation of the productivity measure $\widehat{v}^1_{i,t}$ computed over the three years of survey s. The two main regressors are $R\&D\_radical_{i,s}$ and $R\&D\_incremental_{i,s}$, and the control variables x_j include time dummies. Errors are clustered at the firm level. I estimate equation 26 with firm fixed effect, so that the coefficient β_1 is positive if, over time within firms, the innovation related to introduce new products is associated with higher volatility of productivity. β_2 has a a similar interpretation for the innovation related to improve current products and productive processes. The model predicts that β_1 is larger than β_2, and that β_1 increases when focusing on a sample of younger firms. I perform the regression for all firms and for independent firms only, because for firms belonging to an industrial group the innovation variable $R\&D\_radical_{i,s}$ cannot capture changes in productivity caused by innovation generated by other firms in the group. Columns 1-3 focus on the regressions on all firms, on firms younger than 11 years, and on firms younger than 8 years, respectively.[18] The results show that, when estimating the model on younger firms, the coefficient of $R\&D\_radical_{i,s}$ is positive and significant while the coefficient of $R\&D\_incremental_{i,s}$ is not significant, indicating that younger firms experience increases in the volatility of productivity only when performing innovation classified as radical. However the coefficient of $R\&D\_radical_{i,s}$ is not significant when estimated for the whole sample (column 1). Columns 4 to 6 estimate the model on independent firms, for which the innovation indicators should be more precise. In this case the coefficient of $R\&D\_radical_{i,s}$ is positive and significant in all specifications, and larger for younger firms, while the coefficient of $R\&D\_incremental_{i,s}$ is only significant in column 4. Taken together, the results in table 7 support the interpretation of $R\&D\_radical_{i,s}$ as an indicator positively related to the riskiness of innovation, more so than $R\&D\_incremental_{i,s}$.

6.2 Innovation and firm level productivity growth

Prediction 2 verifies the importance of innovation in driving the empirical relation between financing frictions and productivity growth. The model predicts that more radical innovation among young firms generates more incremental innovation among older firms, thus increasing productivity growth over the firm's life cycle in less financially constrained sectors. Therefore,

[18] The model actually predicts that radical innovation is concentrated among even younger firms, but because there are few very young firms in the sample, and because few firms are present in more than one survey, it is not possible to identify the β_1 and β_2 coefficients for an even lower age threshold. For the regressions in Section 3, the dependent variables $\widehat{v}^1_{i,s}$ and $\widehat{v}^2_{i,s}$ are constructed starting from more than 60000 firm-year observations of balance sheet data available in the sample (see Appendix 2 for details). Unfortunately, the innovation variables $R\&D\_prodinn_{i,s}$ and $\beta_2 R\&D\_other_{i,s}$ 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.

Table 7: Relation between age and innovation

Dependent variable: volatility of productivity of firm i in period s, $\sigma_{\widehat{v}^1,i,s}$						
	All firms			Only independent firms		
	All ages	$Age \leq 10$	$Age \leq 7$	All ages	$Age \leq 10$	$Age \leq 7$
	1	2	3	4	5	6
$R\&D\_radical_{i,s}$	0.034	0.172**	0.429***	0.084***	0.248***	0.443***
	(1.4)	(2.27)	(3.44)	(2.6)	(3.3)	(3.1)
$R\&D\_incremental_{i,s}$	0.044	0.086	0.145	0.065*	0.023	0.128
	(1.4)	(1.39)	(1.31)	(1.9)	(0.24)	(0.89)
constant	0.38***	0.19***	0.21**	0.45*	0.27**	0.23*
	(4.98)	(3.86)	(2.28)	(1.93)	(4.81)	(1.91)
Firm fixed effects	yes	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes	yes
N.observations	9352	1754	944	6840	1283	678

Standard Errors, reported in parenthesis, are clustered at the firm level. $R\&D\_radical_{i,s}$ is equal to one if firm i in survey s does R&D spending larger than 0.5% of sales, and at least part of this spending is directed to develop and produce new products. $R\&D\_incremental_{i,s}$ is equal to one if firm i in survey s does R&D spending larger than 0.5% of sales but all R&D spending is directed to improve current products or productive processes. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

if the model is correct, eliminating innovating firms should both reduce average productivity growth and the difference between less and more financially constrained sectors. In Table 8, columns 1 and 2 replicate the results obtained in the second part of Table 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 analysis, thus confirming Prediction 2.

6.3 Financial frictions and barriers to entry

Predictions 3 and 4 verify that financial frictions matter for productivity growth because they act as barriers to entry, not because borrowing constraints limit the ability of firms to invest in innovation. In order to verify Prediction 3, I repeat the estimation of equations 4 and 5 after excluding firms which are currently declaring financing problems. Table 9 shows 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 validates ex post the strategy used to identify more financially constrained sectors. As argued in Section 3, the approach of using firms declaring financing constraints to measure the intensity of financing frictions at the sector level, but then excluding them from the analysis of the age-productivity relation, ensures that the main results of the analysis are robust to a reverse causality problem where poor growth opportunities cause lack of access to credit.

In order to verify Prediction 4, as an empirical measure of competition I consider the

Table 8: Relation between age and productivity - firms doing research and development excluded (empirical sample)

	All observations		Firm-survey obs. with positive R&D excluded		Firms with some positive R&D excluded	
Dependent variable	$\widehat{v}^1_{i,s}$	$\widehat{v}^2_{i,s}$	$\widehat{v}^1_{i,s}$	$\widehat{v}^2_{i,s}$	$\widehat{v}^1_{i,s}$	$\widehat{v}^2_{i,s}$
$age_{i,s}$	0.00427	0.0102***	0.0415	0.00902***	0.00016	0.00636**
	(1.13)	(5.72)	(0.80)	(−0.00314)	(0.03)	(2.29)
$age_{i,s}$*$constrained_i$	−0.0118**	−0.00499**	−0.0108*	−0.00477	−0.00691	−0.00098
	(−2.37)	(−2.10)	(−1.67)	(−0.53)	(−0.95)	(−0.28)
N.observations	12776	13505	10608	11204	6306	6664
Adj. R-sq.	0.002	0.013	0.002	0.015	0.002	0.011
Firm fixed effects	yes	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes	yes

Panel regression with firm fixed effect. Time effects are also included. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $\widehat{v}^1_{i,s}$ is a measure of productivity consistent with the model developed in section 4, and $\widehat{v}^2_{i,s}$ is total factor productivity computed following the procedure of Hsieh and Klenow (2009). $age_{i,s}$ 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.

Table 9: Relation between age and productivity (excluding currently constrained firms)

	All observations		Currently constrained firms excluded		Currently constrained firms excluded	
Dependent variable	$\widehat{v}^1_{i,s}$	$\widehat{v}^2_{i,s}$	$\widehat{v}^1_{i,s}$	$\widehat{v}^2_{i,s}$	$\widehat{v}^1_{i,s}$	$\widehat{v}^2_{i,s}$
$age_{i,s}$	0.00427	0.0102***	0.00393	0.0110**	0.0115**	0.0133**
	(1.13)	(5.72)	(0.98)	(5.80)	(2.3)	(5.57)
$age_{i,s}$*$constrained_i$	−0.0118**	−0.00499**	−0.00969*	−0.00426*		
	(−2.37)	(−2.10)	(−1.82)	(−1.67)		
$age_{i,s}$*$midconstr_i$					−0.0185**	−0.00605*
					(−2.74)	(−1.83)
$age_{i,s}$*$highconstr_i$					−0.0173**	−0.00693**
					(−2.68)	(−2.25)
N.observations	12776	13505	11362	12065	11362	12065
Adj. R-sq.	0.002	0.013	0.001	0.016	0.003	0.016
Firm fixed effects	yes	yes	yes	yes	yes	yes
Time*group dummies	yes	yes	yes	yes	yes	yes

Panel regression with firm fixed effect. Time effects are also included. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $\widehat{v}^1_{i,s}$ is a measure of productivity consistent with the model developed in section 4, and $\widehat{v}^2_{i,s}$ is total factor productivity computed following the procedure of Hsieh and Klenow (2009). $age_{i,s}$ 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.

Table 10: Relation between age and productivity - sectors selected according to competition (empirical sample)

Dependent variable	$\widehat{v}^1_{i,s}$	$\widehat{v}^2_{i,s}$	$\widehat{v}^1_{i,s}$	$\widehat{v}^2_{i,s}$
$age_{i,s}$	0.00299	0.0109**	0.0204	0.0103**
	(0.83)	(6.55)	(0.53)	(5.75)
$age_{i,s}$*$lowcomp_i$	−0.0110**	−0.00721***	−0.00954*	−0.00603**
	(−2.41)	(−3.33)	(−1.92)	(−2.54)
N.observations	12776	13505	12776	13505
Adj. R-sq.	0.001	0.013	0.001	0.014
Firm fixed effects	yes	yes	yes	yes
Time dummies	yes	yes		
Time*group dummies			yes	yes

Panel regression with firm fixed effect. Time effects are also included. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $\widehat{v}^1_{i,s}$ is a measure of productivity consistent with the model developed in section 4, and $\widehat{v}^2_{i,s}$ is total factor productivity computed following the procedure of Hsieh and Klenow (2009). $age_{i,s}$ 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.

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 10 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. In other words, the low competition sectors are similar to the high financing frictions sectors with respect to productivity dynamics along the firm's life-cycle. These results are consistent with the simulation results shown in Panel B of Table 12 and confirm Prediction 4.[19]

[19] 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 12, 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.

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 having a binding financing constraint 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 (23) and update the guess of P accordingly. I repeat this procedure until the solution converges to the equilibrium. I then simulate an artificial industry in which, every period, the total number of new entrants ensures that condition (6) 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) analyze 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 11 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 firm-year observations of balance sheet data.

I obtain the information on innovation in the section of the Survey on "Technological innovation and R&D", where firms are asked whether they engaged, in the previous three years, in R&D expenditure. The firms that answer yes are asked what percentage of this expenditure was directed towards: i) improving existing products; ii) improving existing

Table 11: 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%

productive processes; iii) introducing new products; iv) introducing new productive processes; v) other objectives.

10 Appendix 3

Derivation of productivity measure $v_{i,t}^1$.

From equation (10), I substitute q_t using equation (9) and p_t using equation (12) and I obtain:

$$\pi_t(\nu_t, \varepsilon_t) = \frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma} A P^{\sigma-\eta} v_t^{\sigma-1} - F_t \tag{27}$$

I divide both sides by F_t and take logs:

$$\log\left(\frac{\pi_t(\nu_t, \varepsilon_t)}{F_t}\right) = \log\left(\frac{\frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma} A P^{\sigma-\eta} v_t^{\sigma-1}}{F_t} - 1\right) \tag{28}$$

The left hand side of equation 28 is a quantity measurable using the empirical dataset. Since σ, A and P are industry specific coefficients, if F_t is constant across firms with different productivity, then equation 28 directly implies that $\log\left(\frac{\pi_t(\nu_t,\varepsilon_t)}{F_t}\right)$ is monotonously increasing in productivity v. However, for a realistically calibrated version of the model a constant F_t is too restrictive, because it implies that large firms have disproportionately larger profits relative to assets and sales than small firms. Therefore, substituting F_t using equation (24) I obtain:

$$\log\left(\frac{\pi_t(\nu_t, \varepsilon_t)}{F_t}\right) = \log\left(\frac{\frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma} A P^{\sigma-\eta} \widehat{v}_0 v_t^{\sigma-2}}{\lambda} - 1\right) \tag{29}$$

Therefore, $\log\left(\frac{\pi_t(\nu_t,\varepsilon_t)}{F_t}\right)$ is monotonously increasing in productivity v if $\sigma > 2$. Broda and Weinstein (2006) estimate a value of σ larger than 2 for nearly 90% of all 3 digit SITC sectors in the 1990-2001 period. I log linearize the right hand side of equation (29) around average firm-level productivity $\overline{v}$:

$$\log\left(\frac{\frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma} A P^{\sigma-\eta} \widehat{v}_0 v_t^{\sigma-2}}{\lambda} - 1\right) \approx \log\frac{\overline{\pi}}{\overline{F}} + \frac{\overline{F}}{\overline{\pi}} \Psi \widetilde{v}_t$$

$$\Psi \equiv (\sigma-2)\frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma} A P^{\sigma-\eta} \frac{\widehat{v}_0}{\lambda} \overline{v}^{\sigma-3}$$

Where $\overline{\pi}$ and $\overline{F}$ are average firm-level profits and overhead costs, respectively, A and P are sector specific parameters, and Ψ is a positive constant. Therefore, adding the subscript i to denote an individual firm, equation 28 becomes:

$$\log \pi_{i,t} = a + \log F_{i,t} + v_{i,t}^1 \tag{30}$$

where $v_{i,t}^1 = b\widetilde{v}_{i,t}$, $a = \log\frac{\overline{\pi}}{\overline{F}}$, $b = \frac{\overline{F}}{\overline{\pi}}\Psi$. In order to estimate equation (30) with empirical data, I estimate overhead costs F_t using the information presented in the Mediocredito Capitalia Surveys. Each 3 year survey reports total employment as well as the number of white and blue collars. Moreover, the yearly balance sheet data reports the information on total wage costs. Since separate wage costs for different types of workers are not available, I follow Manase, Stanca and Turrini (2004), who study a sample of Italian manufacturing firms and report an average wage premium of 20% in 1997 for skilled vs. non skilled workers. Given that I have the same disaggregation of worker types that Manase et. al. do, I can use this wage premium to calculate an estimate of the wage of white collar workers in my sample for each of the three Mediocredito surveys. Given total wage costs $w_{i,s}^{TOT}$ and white collar wage costs $w_{i,s}^{WC}$ for firm i in survey s, respectively, I compute the ratio $\left(\frac{w^{WC}}{w^{TOT}}\right)_{i,s}$ for each firm-survey observation and then I compute its firm level average $\left(\frac{w^{WC}}{w^{TOT}}\right)_{i}$. I multiply this ratio by total wage costs at the firm-year level, and I obtain an estimate of overhead costs $O_{i,t}$:

$$O_{i,t} = \left(\frac{w^{WC}}{w^{TOT}}\right)_{i} w_{i,t}^{TOT} \tag{31}$$

Since white collar costs are not the only component of fixed overhead costs, I allow some flexibility in the relation between estimated overhead costs $O_{i,t}$ and the theoretical counterpart $F_{i,t}$:

$$F_{i,t} = cO_{i,t}^{d} \tag{32}$$

where c and d are positive constants which I allow to vary at the two digit sector level. Taking logs of equation (32) and substituting it into (30), I obtain equation (1) in the paper, where $\beta_0 = a + \log(c)$ and $\beta_1 = d$.

11 Appendix 4

For the estimation of the production function (3), by taking logs and adding fixed effects I obtain:

$$\frac{\sigma}{\sigma - 1}\log(p_{i,t}y_{i,t}) = \kappa_i + \gamma_t + \alpha \log\left(p_{i,t}^{k}k_{i,t}\right) + \beta \log\left(w_{i,t}l_{i,t}\right) + v_{i,t}^{1} \tag{33}$$

where κ_i and γ_t are firm and year fixed effects, respectively, and $\sigma = 4$. 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 the 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.

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 sub-indices refer to firm i and year t.

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

$$\begin{aligned} \widehat{v}_{i,s}^{j} &= \beta_0 + \sum_{l=1}^{n} \beta_l^u (unconstr_i * age_{i,s}^l) + \sum_{l=1}^{n} \beta_l^m (midconstr_i * age_{i,s}^l) + \\ &+ \sum_{l=1}^{n} \beta_l^c (highconstr_i * age_{i,s}^l) + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \end{aligned} \tag{34}$$

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.

12 Appendix 5

In this appendix, I relax the assumption that the change in productivity conditional on success and failure of innovation is driven by the same parameter τ^R. I define τ^H and τ^L, such 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 shown in section 5 for the full model 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 also hold with a relatively low value of the "downside risk" τ^L .

In Panel A of Table 12 I keep τ^H equal to $\tau^R = 30$, and I set τ^L equal to 5 , which corresponds to productivity falling by 4.4% if radical innovation fails. At the same time I lower the parameter ξ to ensure that average radical and incremental innovation remain roughly the same as in the benchmark calibration. The results of this panel are qualitatively similar to Table 6, with financing frictions reducing both types of innovation and aggregate productivity.

In section 5 I also argued that in the full model currently binding or future expected financial frictions do not matter, in terms of the results. Financial constraints affect innovation and growth dynamics almost exclusively indirectly, via the competition effect. I support this claim with additional simulation evidence in this section and additional empirical evidence

Table 12: Simulated industries: descriptive statistics, full model with both incremental and radical innovation

PANEL A: Lower downside risk	10% least constrained sectors	33% least constrained sectors	33% mid constrained sectors	33% most constrained sectors	10% most constrained sectors
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 rel. to 10% least. constr.	100%	100.5%	99.5%	91.0%	87.5%
PANEL B: Barriers to entry	very Low Barriers	Low Barriers	mid level Barriers	High Entry Barriers	Very high Entry Barriers
Average P relative to v.low barriers	100%	100.1%	100.7%	102.7%	103.7%
Entry cost F relative to v.low barriers	100%	100.6%	116%	180%	220%
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 v. low barriers	100%	99.9%	97.3%	90.4%	84.7%

For all industries, I simulate 3000 periods then discard the first 300 and use the remaining ones to compute aggregate statistics. In Panel A, 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 B, the industries with barriers to entry have identical parameters than in the benchmark industry except for S^C.

in Section 6. Here I precisely identify the importance of the competition effect in Panel B of 12, which repeats the same exercise of Table 6, 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 five industries analyzed in Table 6. In other words, in Panel B entry costs replicate the competition effect generated by financing frictions in Table 6. The results show that the higher the barriers to entry, the lower is the 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.