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

The innovation and technology adoption decisions of firms, during the different phases of their life cycle, are fundamental forces that shape firm dynamics and aggregate productivity growth. 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 dynamics determine large 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? Despite a large literature on finance and growth, it is still an open question whether financial frictions affect the productivity dynamics of firms during the different phases of their life cycle.[1] 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 from 5 up to at least 40 years old. It then develops a firm dynamics model which shows that the interaction between financial frictions and competition, and their effects on the radical innovations of younger firms and the incremental innovations of older firms, 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 qualitative survey information on financial frictions, innovation, market structure and internationalization. I estimate a measure of productivity at the firm level and I show a very consistent empirical pattern: in industries where firms are more likely to be financially constrained, productivity grows less over the firms' life cycle than in the other industries, not only for young firms but also for older firms up to 40 years of age. I perform several tests to rule out a reverse causality interpretation of the results, where lack of growth opportunities cause financial frictions instead of the other way round.

In order to explain these findings, I develop a dynamic 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, firms invest in incremental innovation projects to increase productivity growth over their life cycle. Firm idiosyncratic profitability shocks and financial frictions imply that firms

[1]See the next section for a detailed literature review.

have occasionally binding financing constraints, which might prevent them to invest in innovation, and after a long enough sequence of negative shocks might cause inefficient bankruptcy. I calibrate the model so that the simulated firms 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.

I use the calibrated benchmark model to simulate industries which match the different intensities in financial frictions observed in the industries in the empirical dataset, and I show that financing frictions have two main effects. First, they reduce the frequency of innovation of firms with a binding financing constraints. These are mostly young firms, because older ones can retain earnings and overcame financial frictions relatively early in their life. Therefore, this "binding constraint effect" cannot explain the empirical finding that financial frictions reduce not only the productivity growth of younger firms, but also that of older firms. Second, they increase the bankruptcy probability of young and financially fragile firms, reduce entry and competition, and increase the return of innovation for the firms that manage to survive. This "competition effect" increases the frequency of innovations of unconstrained firms, and further reduces the ability of the benchmark model to match the empirical evidence. In equilibrium these two effects compensate each other, so that the average frequency of innovating firms and the average productivity growth at the firm level change very little as financial constraints become more severe.

Then I consider the "full model", which is identical to the benchmark model except for the fact that firms have both incremental and radical innovation opportunities. By "radical" I mean innovation opportunities with the following three key features: i) they are risky, and fail with positive probability; ii) they are to some degree irreversible. Intuitively, the firm needs 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;[2] iii) if they succeed, they generate a large and persistent increase in firm's productivity. Intuitively, the firm is able to introduce new products of much higher quality that boost their revenues and profitability.

The calibration of the full model requires the identification of radical innovations in the empirical dataset, which I assume to be performed by firms that invest relatively

[2] 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*".

large resources in R&D, which is at least partly directed to develop new products, and that declare to have introduced a product innovation during the last 3-year survey period. Since in the model the main feature of radical innovation is its riskiness, it is plausible to assume that innovations directed to introduce new products are more risky than innovations directed to improve existing ones. Importantly, I provide empirical evidence in support of this identification strategy, showing that, within firms over time, performing radical innovation increases the time series volatility of productivity, while performing incremental innovation does not.

As for the benchmark model, I use the calibrated full model to simulate industries which match the different intensities in financial frictions observed in the industries in the empirical dataset. In all industries 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, the full model generates realistic firm dynamics: young firms are much more likely to invest in radical innovation, and have very volatile growth rates, while older firms are, on average, more productive, more likely to invest in incremental innovation, and have less volatile growth rates.

As in the benchmark model, also in the full model I find that financial constraints reduce entry and lower competition. However the key difference is that lower competition strongly reduces the frequency of radical innovations, because many younger and smaller firms are relatively more profitable at their current productivity level. 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%.

In the last part of the paper, I provide several robustness checks of the key mechanisms that generate the above theoretical findings. In particular, I provide empirical evidence supporting the hypothesis that financial frictions negatively affect innovation and growth indirectly, through the competition effect. I use the information available in the surveys on the location of the main competitors of the firms. If these are outside Italy, then barriers to entry caused by financial frictions in Italy should not affect much their competition, as well as their incentives to innovate. However the location of the competitors of a firm is an endogenous outcome, and it is likely that more productive firms endogenously select to operate in more competitive foreign markets. In order to control for this possibility, I also consider an instrumented measure of foreign competition, using the geographical location of the firms to predict their likelihood to have foreign competitors. Consistently with the hypothesis, I find that the negative relation between financial frictions and innovation is strong for firms that compete against other firms in Italy, and completely absent for firms competing against foreign firms. This result is confirmed also with the instrumented measure of predicted foreign competition. Finally, I validate the competition effect also by selecting sectors according to a measure of competition instead than financial frictions, and I show that in sectors with lower competition, productivity grows slower over the firms life cycle than in sectors with higher competition.

2 Related literature

Despite a large literature on finance and growth (see Levine, 2005, for a review) only a small number of studies examine the relation between financial frictions and productivity growth at the firm level. Among others, see Ferrando and Ruggieri (2015) and Levine and Warusawitharana (2016). With respect to this literature, the main difference of this paper is that its objective is to estimate how financial frictions affect productivity growth not on average, but along the life cycle of firms. In terms of methodology, its main added value is that it uses qualitative surveys on the difficulties of firms in accessing credit, rather than indirect indicators based on balance sheet data, to compute its main financial constraints indicator.[3] Moreover, in order

[3]This paper is not the first to use this dataset to analyse the relation between financial frictions and innovation. Among others, Benfratello, Schiantarelli and Sembenelli (2008) use it to analyse the relation between local banking development and the probability of firms to introduce process and product innovations.

control for the possibility that growth opportunities cause financial frictions, instead of the other way round, it proposes an instrumented version of this indicator using geographical dummies, which are valid instruments because of persistent unequal levels of financial development in Italian regions (see Guiso, Sapienza and Zingales, 2004).

The theoretical section of this paper is related to the literature on financing frictions and firm dynamics, such as, among others, Buera, Kaboski, and Shin (2011), Caggese and Cunat (2013), Midrigan and Xu (2014), and Cole, Greenwood and Sanchez (2015). The main difference is that these papers analyse the effect of financing frictions on entry into entrepreneurship, and on the sector and technology selection of new entrepreneurs, while this paper studies their implications for the ongoing heterogeneous innovations decisions of firms along their life cycle. In Cole, Greenwood 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. Moreover, despite the realistic feature, 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.[4]

The theoretical section of the paper is also closely related to the literature that analyses, in models with firm dynamics and endogenous productivity distribution of firms, the consequences of policy distortions on aggregate productivity, and in particular to Da Rocha et. al. (2016) and Bento and Restuccia (2016). In common with my paper, these authors emphasize how such distortions affect both entry decisions of new entrepreneurs, as well as the productivity enhancing investments of growing firms, lowering aggregate productivity. They focus on tax-like output wedges that can be interpreted as generic types of policy distortions. The main difference in my paper is that I focus on one specific type of distortion (financing frictions), and I analyse its

[4]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.

implications on the heterogeneous types of innovation of continuing firms. On the one hand, my analysis is consistent with their results, because I identify a novel misallocation channel in which the risky innovation decisions of firms amplify the negative effects of imperfect financial markets on aggregate productivity. On the other hand, I derive a set of additional testable predictions of the model, that are verified using micro data, and provide additional support to the empirical importance of such distortions.

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 others, 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. However, I especially focus on the risk component of 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 especially 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 covers the activity of the firms in the three previous years, and it includes detailed information on financing constraints, market structure, internationalization 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.[5] In relation to the objective of this paper, I argue that I provide an added value to the literature in terms of solving this problem, for two main reasons: first, I construct a financing constraints indicator using direct information on financial problems declared by firms in survey answers. I use this indicator directly, but I also compare it with the results obtained using an instrumented version of "predicted financing constraints". Second, this empirical analysis is used to verify the predictions of the structural model I develop in the next section, which allows for both direct and indirect effects of financial frictions. In order to empirically verify the importance of the indirect channel, I do not need to identify precisely which firms are financially constrained at any point in time, but only in which sectors firms face more financial frictions on average.

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.[6] I consider a firm-survey observation "likely financially constrained" if $finprob_{i,s} = 1$, and if the firm has operating profits over added value larger than 0.1. This minimum profitability threshold excludes the 25% least profitable firms, and it reduces the possibility that these survey answers capture financially distressed firms rather than growing firms that face financial imperfections. The 50% four digit sectors with highest frequency of likely financially constrained firm-survey observations is 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.[7] Appendix 2 reports the distri-

[5] For a critical review of this literature see, for example, Farre-Mensa and Ljungqvist (2016).

[6] Caggese and Cunat (2008) analyse the reliability of this survey-based indicator of financing frictions. Consistently with the predictions of a broad class of models of firm behaviour with financial frictions, 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.

[7] I use the Ateco 91 classification of the Italian National Statistics Office (Istat). For some firms the reported 4 digit classfication has a final "zero", so that these firms effectively only report their 3 digit classification. I keep these firms in the sample and I treat them as belonging to a residual 4 digit sector. I repeated the empirical analysis after excluding these firms, obtaining very similar results. These additional estimations are available upon request.

bution of constrained firms and shows that they are present in all 2-digit industries, rather than being concentrated in few ones.

The main exercise of this section is to verify whether productivity growth over the life cycle of firms is significantly different across the Constrained and Unconstrained groups. One important concern is the reverse causality problem mentioned above, which might drive the results if weak sector-level growth opportunities increase declared financial frictions. In order to control for this possibility, I proceed as follows: first, 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 effects control for any average difference in productivity across sectors, and time dummies specific to the constrained and unconstrained groups control for group specific shocks and/or trends. Second, I use instruments related to the geographical location of the firms to generate an exogenous measure of predicted financial constraints that is not likely to be influenced by the growth prospects of the sectors the firms belong to.

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 variable $\widehat{v}_{i,t}$ is a firm level estimate of total factor productivity, computed following 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:

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

where $v_{i,t}$ 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 1 using the Levinshon and Petrin (2003) methodology (see the details in Appendix 4). I include in the estimation firm and time effects, which absorb the unobservable sector specific term κ_s. I estimate equation 1 separately for each 2 digit sector, and I use the estimated coefficients to obtain the empirical counterpart of productivity $\widehat{v}_{i,t}$. In order to make sure that the results presented in the remainder of this section are robust to alternative measures of productivity, in Appendix 3 I derive, using the model developed in the next section, a measure of productivity based on a regression of profits on overhead costs of production. Results obtained using this alternative measure are consistent with the results obtained using $\widehat{v}_{i,t}$ (see Appendix 3 for details).

I analyse the relation between age and productivity estimating the following model:

$$\widehat{v}^{j}_{i,s} = \beta_0 + \beta_1 age_{i,s} + \beta_2 age_{i,s} * constrained_i + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \qquad (2)$$

Given that each survey covers a 3-years period, for the estimation of equation 2, I consolidate all the balance sheet variables at the same time interval. Therefore $\widehat{v}_{i,s}$ is the average of $\widehat{v}_{i,t}$ 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 $\widehat{v}_{i,s}$ is 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 likely 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. Column (1) of Table 1 reports the estimated coefficients of age and age interacted with $constrained_i$. The presence of firm fixed-effects implies that β_1 and β_2 are identified only by within-firm changes in productivity. The coefficient of $age_{i,s}$ is positive and significant, indicating that in less constrained sectors, productivity increases on average by 1.03% as a firm becomes one year older. Importantly, the coefficient of $age_{i,s} * constrained_i$ is negative and significant, and indicates that productivity increases only by 1.03%-0.54%=0.49% as firms in most constrained sectors become one year older. 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 decline. In order to control for this alternative explanation, in column (2) I add, among the regressors, time dummies interacted with the constrained group. If productivity in the financially constrained group grows slower as firms age simply because aggregate productivity declines over time for the whole group, the presence of group specific time dummies should make the coefficient of $age_{i,s} * constrained_i$ insignificant. Instead such coefficient remains positive and statistically significant, and with a similar magnitude than in column (1). Furthermore, in column (3), I exclude from the sample all firms declaring financial

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

	(1)	(2)	(3)	(4)	(5)	(6)
$age_{i,s}$	0.0103***	0.0102***	0.0113***	0.0128***	0.0140***	0.0110***
	(6.16)	(5.72)	(5.87)	(5.61)	(5.87)	(5.28)
$age_{i,s}{*}constrained_i$	-0.00547**	-0.00499**	-0.00451*			
	(-2.51)	(-2.10)	(-1.75)			
$age_{i,s}{*}midconstr_i$				-0.00671**	-0.00684**	0.003
				(-2.14)	(-2.05)	(1.07)
$age_{i,s}{*}highconstr_i$				-0.00792**	-0.00757**	-0.0079***
				(-2.74)	(-2.45)	(-2.68)
N.observations	13505	13505	11676	13505	11676	9160
Adj. R-sq.	0.013	0.013	0.017	0.013	0.017	0.0233
Time dummies	yes	no	no	no	no	yes
Time*group dummies	no	yes	yes	yes	yes	no
IV to predict. fin constr.	no	no	no	no	no	yes
fin. constrained excluded	no	no	yes	no	yes	no

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

frictions. In this regression the coefficients of $age_{i,s}{*}constrained_i$ is still positive and statistically significant. Therefore, in sectors where firms are on average more financially constrained, all firms, also those not currently declaring financial problems, have a slower productivity growth as they age.

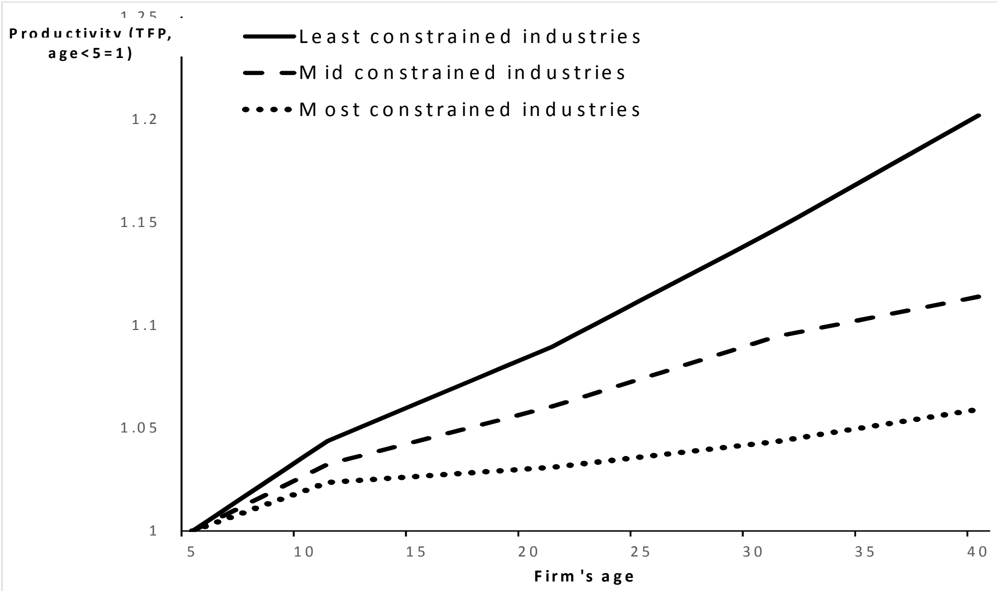
Columns (4) and (5) of Table 1 repeat the estimation in columns (2) and (3) considering a more detailed selection of constrained groups. The estimated equation is:

$$\widehat{v}_{i,s}^{j} = \beta_0 + \beta_1 age_{i,s} + \beta_2 age_{i,s}{*}midconstr_i + \beta_2 age_{i,s}{*}highconstr_i + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \quad (3)$$

where $midconstr_i$ is equal to 1 if firm i is in the 33% of sectors with intermediate constraints, and 0 otherwise, and $highconstr_i$ is equal to 1 if firm i is in the 33% most constrained sectors and zero otherwise. In columns (4) and (5) the coefficient of $age_{i,s}$, which now measures yearly productivity growth in the 33% least constrained sectors, is larger in absolute value than in columns 1-3. Moreover, the effect of age on productivity monotonously decreases with the intensity of financing frictions. Column (5) shows that, even after excluding all firms currently reporting financial problems, yearly productivity growth in the 33% most constrained sectors is 0.76% lower than in the 33% least constrained sectors. Finally, column (6) shows regression results where the variable $constrained_i$ is constructed starting with an instrumented measure of predicted financial constraints, thus controlling for a possible reverse causality bias. I estimate a Probit regression where the dependent variable is equal to 1 if the firm is likely financially constrained, and zero otherwise. The regressors are geographical location variables that have predictive power of the access to credit of the firm, but are unlikely to be correlated to the growth prospects of the industry the firm belongs to. The first is a dummy variable equal to one if the firm's main lender has the main headquarters in the same province than the headquarters of the firm, and is equal to zero otherwise. This variable is informative because is related to conditions that favour relationship lending. I also introduce as regressors a set of geographical dummy variables for the province (55 in total) in which each firm has the main headquarters. Guiso, Sapienza and Zingales (2004) show that local financial development is a powerful predictor of the ability of firms and household to access credit in Italy. Moreover, they argue that differences in financial development across geographical areas are related to different historical developments, and therefore are unlikely to be caused by the recent growth opportunities of firms. The Probit model is able to correctly classify 85% of the observations of the dependent variable. I then construct a predicted "likely financially constrained" variable, which is equal to 1 if the probability estimated in the Probit model is higher than a given threshold, and zero otherwise. The threshold is chosen so that the fraction of predicted financially constrained firms is equal to the fraction of declared financial constraints in the survey. Finally, I use this indicator to construct a group of predicted high constrained and mid constrained sectors. The regression results using the instrumented measure of financial constraints, computed on a smaller number of observations because the instrumental variables are not available for the 1992 survey, are shown in column (6). They are broadly consistent with the results in columns (4) and (5), because they show that firms in the 33% most constrained sectors have a much slower productivity growth than in the 33% least constrained sectors. However, they find no significant differences between the 33% least constrained and the 33% mid constrained sectors.

As a final robustness check I allow the relation between age and productivity to be non linear, and I represent it graphically in figure 1. The curves are computed from the

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



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. Figure 1 shows the age profile of $\widehat{v}_{i,s}$. 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.[8]

Taken together, the results of this section indicate that financial frictions at the sector level are related to slower productivity growth of younger firms, as well as older ones until at least 40 years of age. The results are strongly significant also for currently un-

[8] Figure 1 shows that the relative productivity differentials between most constrained and lest constrained 40 years old firms are large. 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 40 years, while Hsieh and Klenow 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 that 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.

constrained firms. The fact that they survive the introduction of time*sector dummies, and the use of an instrumented "predicted financial constraints" measure, support a causal interpretation, where sector level financial frictions have indirect effects on the productivity growth of currently unconstrained firms.

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:

$$P_t = \left[\int_w p_t(w)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{4}$$

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

$$Q_t = \left[\int_w q_t(w)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{5}$$

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:

$$P_t Q_t = A P_t^{1-\eta} \tag{6}$$

where A is an exogenous demand parameter and $\eta < \sigma$ is the industry price elasticity of demand. From (5) and (6) the demand for an individual variety w is:

$$q_t(w) = A \frac{P_t^{\sigma-\eta}}{p_t(w)^{\sigma}} \tag{7}$$

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:

$$\pi_t(v_t, \varepsilon_t) = p_t(w)q_t(w) - \frac{q_t(w)}{v_t} - F_t \tag{8}$$

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:

$$F_t = (1 + \varepsilon_t)F(v_t) \tag{9}$$

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.[9] 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.[10]

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:

$$p_t = \frac{\sigma}{\sigma - 1}\frac{1}{v_t} \tag{10}$$

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

$$\pi_t(v_t, \varepsilon_t) = \frac{(\sigma - 1)^{\sigma-1}}{\sigma^\sigma} A P^{\sigma-\eta} v_t^{\sigma-1} - F_t \tag{11}$$

Equation 11 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 fol-

[9] 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.

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

lowing. 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:

$$a_t = R\left[a_{t-1} - K\left(I_{t-1}\right) - d_{t-1}\right] + \pi_t\left(v_t, \varepsilon_t\right) \tag{12}$$

where $R = 1 + r$ and r is the real interest rate. d_t are dividends. $K\left(I_{t-1}\right)$ 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 assuming that the firm cannot borrow, and has to finance its investments with internally generated earnings:

$$a_t \geq 0 \tag{13}$$

Equation 12 implies that constraint 13 is not satisfied when current profits $\pi_t\left(v_t, \varepsilon_t\right)$ are negative, and larger than savings $R\left[a_{t-1} - K\left(I_{t-1}\right) - d_{t-1}\right]$. In this case the firm cannot continue its activity and is forced to liquidate. Constraint 13 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:

$$a_t \geq K(I_t). \tag{14}$$

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

4.1 Benchmark model with incremental innovation.

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 minimum between $v_t(1+g)^\tau$ and the frontier technology, where $\tau > 0$ measures how productive the innovation is.[11]

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.

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

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

neither, but it cannot implement both.[12] 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 technology, and/or to introduce very innovative projects. 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 and/or produce the old products. 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:

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

[12] 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.

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:

$$V_t^1(a_t, \varepsilon_t, v_t) = -K(1) + \frac{1-\delta}{R} E_t \left\{ \begin{array}{c} \pi_{t+1}\left(\varepsilon_{t+1}, \min\left[v_t(1+g)^\tau, 1\right]\right) \\ +V_{t+1}\left(a_{t+1}, \varepsilon_{t+1}, \min\left[v_t(1+g)^\tau, 1\right]\right) \end{array} \right\}. \tag{15}$$

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:

$$V_t^2(a_t, \varepsilon_t, v_t) = -K(2) + \frac{1-\delta}{R} \left\{ \begin{array}{c} \xi^R E_t \left\{ \begin{array}{c} \pi_{t+1}\left\{\varepsilon_{t+1}, \min\left[v_t(1+g)^{\tau^R}, 1\right]\right\} + \\ V_{t+1}\left\{a_{t+1}, \varepsilon_{t+1}, \min\left[v_t(1+g)^{\tau^R}, 1\right]\right\} \end{array} \right\} \\ +\left(1-\xi^R\right) E_t \left\{\pi_{t+1}\left(\varepsilon_{t+1}, \frac{v_t}{(1+g)^{\tau^R}}\right) + V_{t+1}\left[a_{t+1}, \varepsilon_{t+1}, \frac{v_t}{(1+g)^R}\right]\right\}, \end{array} \right\} \tag{16}$$

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

$$V_t^0(a_t, \varepsilon_t, v_t) = \frac{1-\delta}{R} \left\{ \begin{array}{c} \xi E_t\left\{\pi_{t+1}(\varepsilon_{t+1}, v_t) + V_{t+1}(a_{t+1}, \varepsilon_{t+1}, v_t)\right\} \\ +(1-\xi) E_t \left\{\pi_{t+1}\left(\varepsilon_{t+1}, \frac{v_t}{1+g}\right) + V_{t+1}\left[a_{t+1}, \varepsilon_{t+1}, \frac{v_t}{1+g}\right]\right\} \end{array} \right\} \tag{17}$$

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

$$V_t^*(a_t, \varepsilon_t, v_t) = \gamma \max_{I_t \in \{0,1\}} \left\{V_t^0(a_t, \varepsilon_t, v_t), V_t^1(a_t, \varepsilon_t, v_t)\right\} + (1-\gamma) V_t^0(a_t, \varepsilon_t, v_t) \tag{18}$$

While in the full model is equal to:

$$V_t^*(a_t, \varepsilon_t, v_t) = \gamma \max_{I_t \in \{0,1,2\}} \left\{V_t^0(a_t, \varepsilon_t, v_t), V_t^1(a_t, \varepsilon_t, v_t), V_t^2(a_t, \varepsilon_t, v_t)\right\} + (1-\gamma) V_t^0(a_t, \varepsilon_t, v_t) \tag{19}$$

such that equation (14) 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:

$$V_t(a_t, \varepsilon_t, v_t) = 1(a_t \geq 0)\left\{\max\left[V_t^*(a_t, \varepsilon_t, v_t), 0\right]\right\} \tag{20}$$

Equation (20) implies that the value of the firm is equal to zero in two cases. First, when the indicator function $1(a_t \geq 0)$ is equal to zero because the liquidity constraint (13) 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:

$$\int_{\underline{v}}^{\overline{v}} \max\left\{E^{\varepsilon_0}\left[V_0(a_0, \varepsilon_0, v_0)\right], 0\right\} f(v_0) dv_0 - S^C = 0 \tag{21}$$

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 (21) is satisfied. The number of firms in equilibrium ensures that P_t also satisfies the aggregate price equation (4). Aggregation is very simple because all operating firms with productivity v choose the same price $p(v)$, as determined by equation (10).

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 (13) and (14) might be binding today or in the future. First, constraint (14) implies that firms with low financial wealth a_t are unable to finance innovation. I call this the "*binding constraint effect*". Second, equation (20) implies that the larger the probability of bankruptcy $prob(a_t < 0)$, the lower is the expected value of the firm. Therefore, higher expected probability of bankruptcy for new firms reduces the value of the term $E^{\varepsilon_0}[V_0(a_0, \varepsilon_0, v_0)]$ in the entry condition (21) for a given aggregate price P. It follows that the term on the left hand side of (21) becomes negative: $\int_{\underline{v}}^{\overline{v}} \max\{E^{\varepsilon_0}[V_0(a_0, \varepsilon_0, v_0)], 0\} f(v_0) dv_0 - S^C < 0$, 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.[13]

4.7 Calibration

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

4.7.1 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.[14] 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.[15] The depreciation

[13]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.

[14]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.

[15]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.

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:

$$F_{it} = \lambda \frac{v_{it}}{\widehat{v}_0} \tag{22}$$

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, which are identified using two sets of information present in the survey: whether the firm introduced an innovation during the sample period, and whether the firm does R&D (see appendix 2 for details).

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 "innovating" all firm-survey observations in the empirical sample such that: i) the firm declared to have implemented a product and/or process innovation in the survey period. On average it has R&D expenditure higher than 0.5% of sales (20.5% of all firms satisfy both criteria). 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 $a_0 = 6.4$, which in equilibrium corresponds to 28% of average firm sales in the industry, and which matches the average share of firms going bankrupt every period.[16]

[16] 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

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	0.37
θ	0.15	Avg. of time series st.dev. of profits/sales	0.117[1]	0.11
$K(1)$	3	Average R&D expenditures /profits for firms doing R&D	62%[2]	71%
γ	0.45	Percentage of innovating firms	20.5%[2]	20%
$\widehat{v}$	0.53	Median TFP relative to the 99th percentile	0.78	0.87
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]	0.3%
τ	3	Ratio between 90th pctile and 10th pctile of size distrib.	13.2	5.8
ξ^{NI}	0.25	Percentage of firms with age >60 years	4.8%	7.0%
δ	0.03	Average age	24	19
a_0	6.4	Percentage of firms going bankrupt every period	1.3%	1.6%

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.

Although the model is relatively stylized, Table 2 shows that it matches these empirical moments reasonably well, with the exception of the cross sectional dispersion of size across firms. 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 the three additional parameters related to radical innovation: the probability of success ξ^R, the change in productivity after innovating τ^R, and the cost $K(2)$ of radical innovation. Out of the 20.5% of empirical firm-survey observations classified as innovating in the previous section, I consider radical those that satisfy the two following properties: i) they declare to have implemented a product innovation in the survey period, and ii) on average they declare R&D expenditures partly or fully directed to develop new products. All the other innovating firm-year observations that do not satisfy the two above criteria, because they relate to improving current product or productive processes, are classified as incremental. 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 innovations related to the development and introduction of new products is riskier than innovations

analyzed in this paper 92% of all the firms are limited liability companies.

related to improving current 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 I provide, in section 6, empirical 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 calibrate ξ^R and τ^R to jointly match: i) the fraction of firms doing radical innovation in the empirical sample, as measured above (11.4%); ii) 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. The calibrated value of $\tau^R = 30$ 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%. The cost of radical innovation $K(2)$ is calibrated to match the weighted average of the ratio between innovation cost and profits for firms performing radical innovation. A restrictive assumption of this calibration, the symmetry in the innovation risk τ^R, is relaxed in the next section. Finally, I recalibrate the parameters $K(1)$, τ, 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% least constrained", "33% mid constrained" and "33% most constrained" empirical sectors, respectively, which are analyzed in figure 1. I generate these sectors for both the benchmark model and the full model, and in both cases I analyze them with

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	0.36
θ	0.15	Avg. of time series st.dev. of profits/sales	0.117[1]	0.096
$K(1)$	6	Average R&D expenditures /profits for all firms doing R&D	62%[2]	57%
$K(2)$	0.16	Average R&D expenditures /profits for radical innovations	72%[2]	70%
γ	0.85	Percentage of innovating firms	20.5%[2]	20.9%
$\widehat{v}$	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]	0.3%
τ	2	Ratio between 90th pctile and 10th pctile of size distrib.	13.2	10.5
ξ^{NI}	0.25	Percentage of firms with age >60 years	4.8%	12.8%
δ	0.015	Average age	24	24
a_0	3.4	Percentage of firms going bankrupt every period	1.3%	1.5%
ξ^R	0.045	Percentage of firms doing radical innovation	11.4%	10%
τ^R	30	90% percentile of volatility of productivity	18.4%	19.3%

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.

the identical procedure used in section 3 on the empirical data. The results are used to analyse weather the benchmark model and the full model can 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. 20, 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:

$$\phi_{it} = \frac{\partial V_{it}(a_{it}, \varepsilon_{it}, v_{it})}{\partial a_{it}} \geq 0 \tag{23}$$

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 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 of financial wealth of new firms 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 $\phi_{it} > \overline{\phi}$. It is important to note that, in the context of this partial equilibrium industry model, assuming that the intensity of financial frictions across industries is determined by different borrowing limits of firms, would yield identical results than assuming different initial endowments of financial wealth.

I select values of a_0 in order to have three groups of simulated industries with the

Table 4: Financial constraints in empirical and simulated sectors

	10% least constr.	33% least constr.	33% mid constr.	33% most constr.	10% most constr.
Average % of constrained firms	5.6%	8.4%	13.6%	20.7%	26.8%
Calibrated value of a_0					
Only incremental Innovation	9.4	7.9	6.4	1.1	0.1
Both incremental and radical Inn.	7.9	7.15	2.9	1.4	0.1

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 3% in the model with only incremental innovation and 3.5% 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 short-term debt and the risk free interest rate (on 1 year treasury bills) is 3.6%.

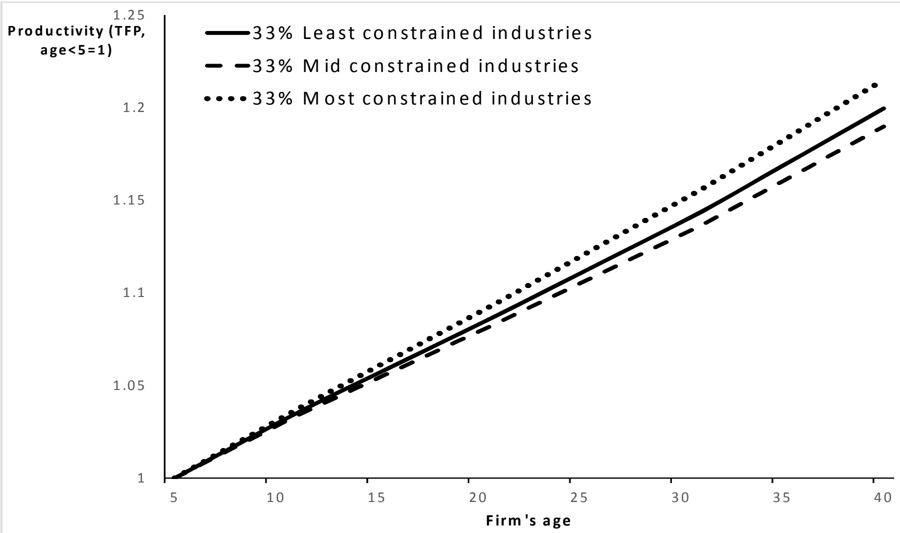
5.1 Productivity over the firms' life cycle

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.

Figures 2 and 3 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 figure 1. 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 figure 1, where I multiply relative productivity $v_t = v_t^n / \overline{v_t^n}$ by the frontier productivity $\overline{v_t^n}$ in order to recover actual productivity v_t^n.

Figure 2 shows that the model with only incremental innovation is able to replicate

Figure 2: Life cycle of the productivity of firms in the benchmark model with only incremental innovation.

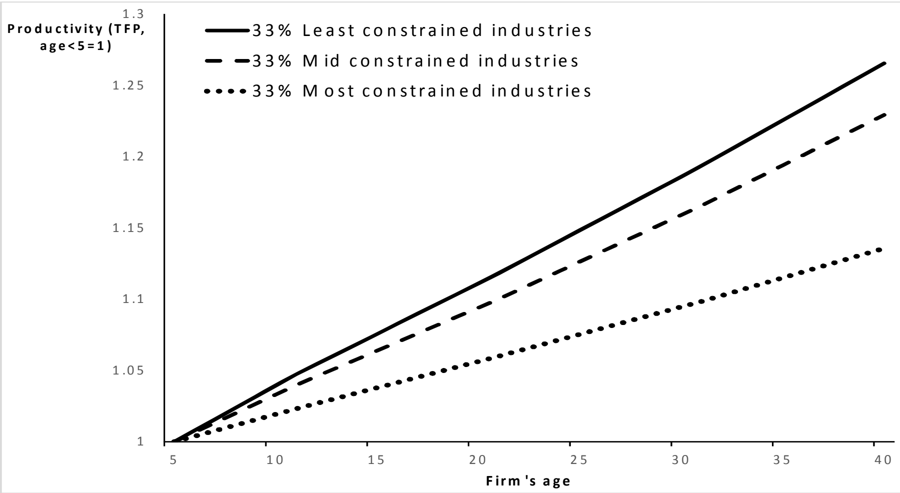


a steady productivity growth of firms over their life cycle. In the 33% least constrained industries productivity increases by approximately 20% between 5 and 40 years of age, the same increase observed in the empirical sample for the same industries (see figure 1). However, this model fails to generate 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 the 33% most constrained ones actually have a faster growth of productivity, contradicting the empirical evidence.

The results for the full model are shown in Figure 3. In this case the model is able to generate a much larger negative effect of financial frictions on productivity growth, especially between the 33% least constrained and the 33% most constrained sectors, and much closer to the empirical evidence shown in figure 1.

Do these results 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, because it controls 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 4 and 5 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 report firm level productivity relative to average industry productivity, and show two additional industries with an intensity of financing frictions matching the 10% least constrained and 10% most

Figure 3: Life cycle of the productivity of firms in the full model with both radical and incremental innovation



constrained empirical sectors. They confirm and reinforce the results related to the effects of financial frictions. In particular, in the benchmark model with only incremental innovation (figure 4), financial frictions have only a very small negative effect on productivity growth when moving from the 33% mid constrained to the 33% most constrained firms. Moreover this negative effect vanishes when increasing financing frictions further to the 10% most constrained industries. Conversely figure 5 confirms that, in the full model, productivity growth is strongly negatively affected by financial frictions. As firms increase in age from 5 to 40 year old, their productivity on average increases by 46% in the 10% least constrained industries, and only by 6% in the 10% most 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 subsections, I analyze in details the mechanism that generates this result.

Figure 4: Life cycle of the productivity of firms in the benchmark model with only incremental innovation - exact measure for a cohort of continuing firms

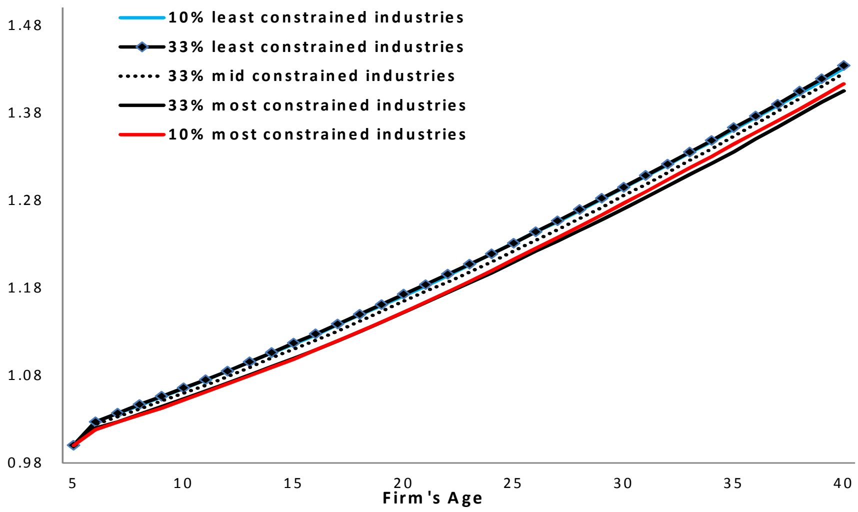
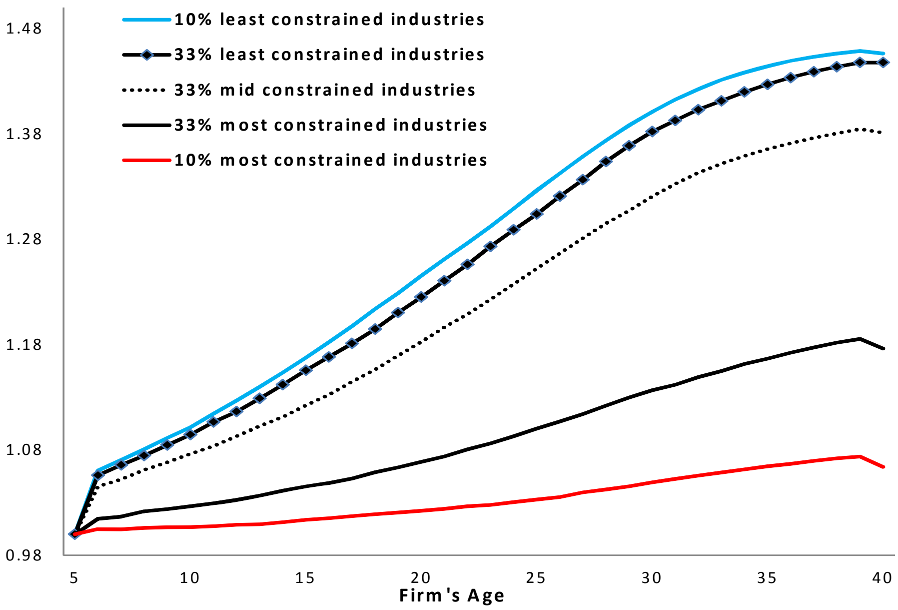


Figure 5: Life cycle of the productivity of firms in the full model with both radical and incremental innovation - exact measure for a cohort of continuing firms



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 2 and 4). The overall small 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 25% 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 14.7% larger in column 5 than in column 1. Higher profits also increase expected innovation rents, and make incremental innovation more profitable.[17] 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 3) the binding constraint effect dominates, and innovation and TFP slightly decline. But for higher levels (from column 3 to columns 4 and 5) the competition effect dominates, and innovation and TFP slightly increase.

To further illustrate these counteracting effects, Figure 6 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 the frontier technology) find it optimal to innovate. In the constrained industry, there are two main differences. The minimum productivity to innovate is lower (0.51), because the competition effect increases the return of innovation. 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 (14), and cannot take

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

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

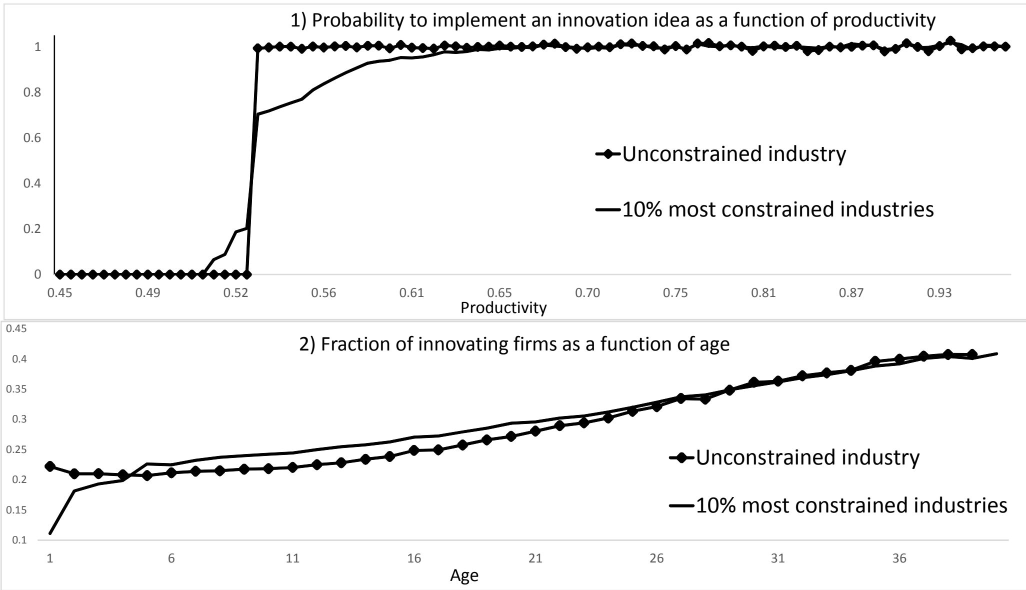
	(1)	(2)	(3)	(4)	(5)
	10% least constrained industries	33% least constrained industries	33% mid constrained industries	33% most constrained industries	10% most constrained industries
% going bankrupt every period	0.8%	1.1%	1.6%	7.4%	9.2%
% not innovating for lack of funds[1]	2.2%	3.1%	4.6%	19.4%	25.2%
Price index P rel. to 10% least constr.	100%	100.05%	100.1%	103.1%	103.6%
avg$(\pi^{unconstr} \mid v)$ rel. to 10% least c.	100%	100.19%	100.69%	112.74%	114.71%
Average % of innovating firms	22.4%	21.6%	19.8%	22.5%	22.9%
Avg. TFP relative to 10% least constr.	100%	98.3%	97.2%	98.4%	98.2%

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.

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.[18] As a consequence, the lower panel 2 of Figure 6 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 6 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 get closer to 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

[18] 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 6: Productivity and propensity to innovate in the benchmark model with only incremental innovation



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 over time surviving firms are on average able to self finance themselves out of financial frictions relatively quickly.

5.3 Full model, inspecting the mechanism

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. Financial frictions increase the fraction of firms that go bankrupt (row 1) and generate an increase in expected profits, conditional on productivity, thanks to the competition effect (rows 4 and 5). However very few firms have a binding financing constraint that prevents them from innovating, because the cost of radical innovation, calibrated to match the empirical dataset, is relatively low. Moreover once firms become productive enough to invest in incremental innovation, they often already accumulated sufficient wealth to invest. Nonetheless 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). This happens because in the full model the indirect competition effect reduces rather than increases radical innovation. Moreover if fewer firms radically innovate, fewer firms become large enough to perform incremental innovation, with

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

	10% least constr. sectors	33% least constr. sectors	33% mid constr. sectors	33% most constr. sectors	10% most constr. sectors
1)% going bankrupt every period	0.007%	0.1%	1.47%	5.1%	6.5%
2)% not innov. (increm.) for lack of funds[1]	1.1%	1.3%	1.5%	0.6%	0.4%
3)% not innov. (radical) for lack of funds[1]	0%	0%	0.02%	0.1%	0.6%
4)Average P relative to 10% least. constr.	100%	100.04%	100.8%	102.6%	103.7%
5)$E(\pi \mid v)$ relative to 10% least. constr.	100%	100.02%	103.5%	110.4%	114.16%
6)Average percentage of innovating firms	22.8%	23.2%	20.9%	11.4%	8.7%
7)Percentage doing Radical Innovation	10.9%	10.9%	10.1%	5.9%	4.5%
8)Percentage doing Incremental Innovation	11.9%	12.3%	10.8%	5.5%	4.2%
9)Weighted TFP relative to 10% least. constr.	100%	99.2%	98.1%	86.4%	82.8%

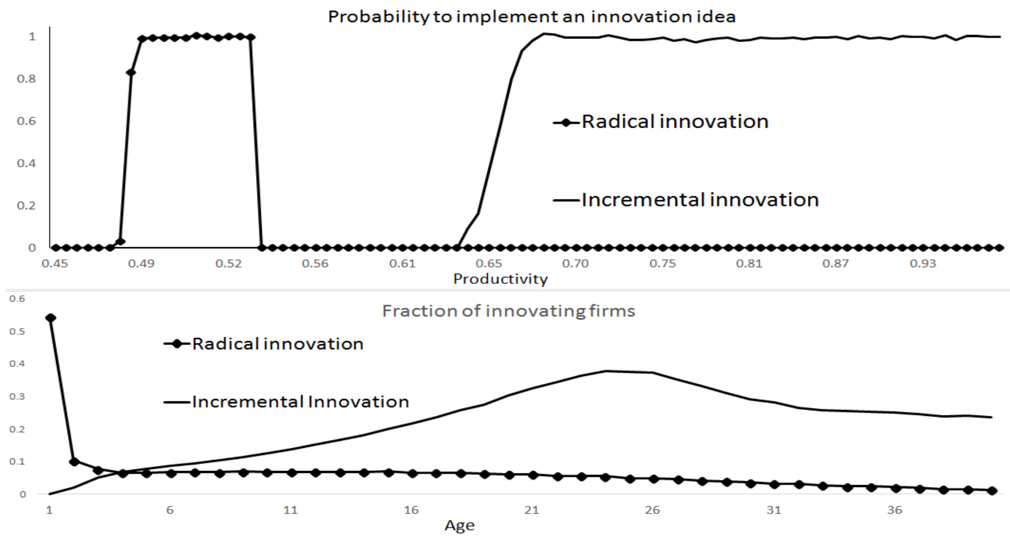
For all industries, I simulate 3000 periods then discard the first 300 and use the remaining ones to compute aggregate statistics.

substantial negative effects on aggregate productivity, as shown in row 9.

In order to explain this key finding of the paper more in details, figures 7-9 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 7). I then discuss the implications of financial frictions (Figures 8-9). The upper panel of Figure 7 is analogous to panel 1 of Figure 6, 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 6, 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 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 7 shows innovation as a function of firm's age. Very young firms, on average, perform most of the radical innovation in the industry. These

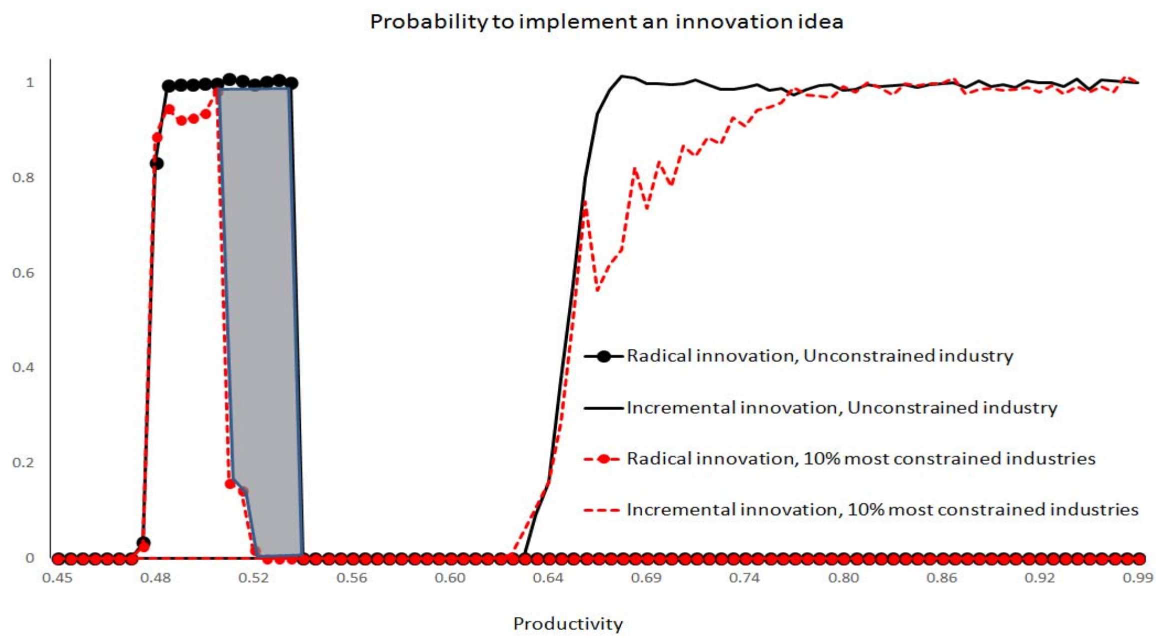
Figure 7: Innovation decisions in the unconstrained industry, full model with both radical and incremental innovation.



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 7 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.*"

Figure 8: Probability to innovate, comparison of industries, full model with both radical and incremental innovation.



Figures 8 and 9 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 6, on the comparison between the extreme cases of the unconstrained industry and the 10% most constrained industries. Figure 8 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, which are almost never binding, as shown in table Table 6. 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 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.[19] Since the distribution of firms, consistently 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.[20]

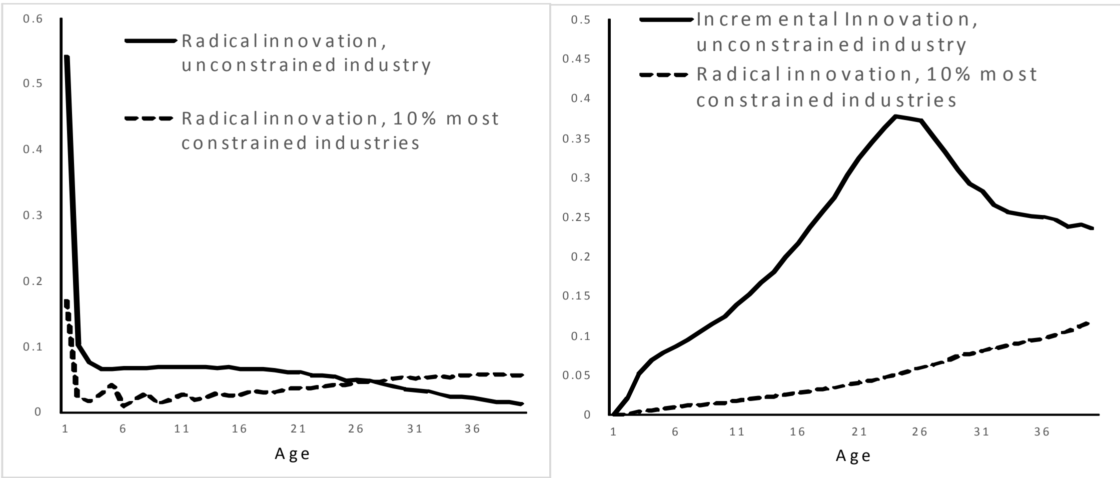
Figure 9 compares the life cycle profile of innovation in the unconstrained industry and in the group of 10% most constrained industries. In the latter, young firms perform less radical innovation, so that at any given age fewer firms reach a level of productivity high enough to find it optimal to invest 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 order for the model to generate the results. Below, in Panel A of Table 7, I relax the assumption that the downside and upside risks of radical innovation are

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

[20] To be precise, there is also a "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 (20) is strictly concave for values of a_t around constraint 13 binding with equality, because higher wealth reduces bankruptcy risk, and $V_t(a_t, \varepsilon_t, v_t)$ is equal to zero if constraint 13 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 9: Fraction of innovating firms in the full model, different industries



symmetric. More specifically, 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 $v_{t+1} = \frac{v_t}{(1+g)^{\tau^L}}$. I keep τ^H equal to the benchmark value of $\tau^R = 30$, and I reduce the downside risk from 30 to τ^L=5 , which corresponds to productivity falling only 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. 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.

Another key element of the model is that financial constraints affect innovation and growth dynamics almost exclusively indirectly, via the competition effect. I precisely identify the importance of the competition effect in Panel B of Table 7, 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

Table 7: Simulated industries: descriptive statistics, full model with both incremental and radical innovation

PANEL A: Lower downside risk	10% least constr. sectors	33% least constr. sectors	33% mid constr. sectors	33% most constr. sectors	10% most constr. sectors
Average percentage of innovating firms	25.3%	25.6%	22.2%	14.1%	11.9%
Percentage doing Radical Innovation	17.6%	17.6%	15.5%	9.8%	8.5%
Percentage doing Incremental Innovation	7.7%	7.9%	6.6%	4.3%	3.5%
Weighted Avg. TFP rel. to 10% least. constr.	100%	100.6%	96.0%	88.3%	86.3%

PANEL B: Barriers to entry	Very Low Barriers	Low Barriers	mid level Barriers	High Entry Barriers	Very high Entry Barriers
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.

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 15.3% lower than in the benchmark industry. This finding implies 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, verified in the next section.[21]

[21] Another reason why the negative effect of competition on radical innovation has such a large impact in the simulated industries, is because the calibrated radical innovation cost $K(2)$ is relatively low. An higher value of $K(2)$ would imply that, in more constrained industries, firms do less radical innovation because of binding financial constraints rather than because of the indirect competition effect. However, the value of $K(2)$ is not arbitrarily chosen, but rather calibrated to match the magnitude of radical R&D costs (relative to profits) observed in the empirical data. Moreover, the fact that the negative relation between financial frictions and innovation, shown in section 3 for the empirical sample, is strong also for firms not currently financially constrained, is consistent with the view that the direct binding constraint effect is not important for the empirical findings.

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 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 likelihood that innovation is related to an increase in volatility of productivity:

Prediction 1: Radical innovation is related to an increase in the time-series volatility of productivity.

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 difference in the life cycle dynamics between financially constrained and financially unconstrained industries is stronger for firms whose main competitor is in Italy.

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 Prediction 1: Innovation and volatility of productivity

Following the criteria used in sections 4.7.1 and 4.7.2 to identify innovating firms, here I define the variable $R\&D\_radical_{i,s}$, which is equal to one for firm i in survey s if: i) firm i has average R&D spending larger than 0.5% of sales; ii) at least part of this spending is directed to develop and produce new products; iii) in survey s firm i introduced a product innovation (see Appendix 2 for details). I also define $R\&D\_incremental_{i,s}$,which is equal to one for firm i in survey s if: i) firm i has average R&D spending larger than 0.5% of sales; ii) in survey s firm i introduced an innovation to improve current products of productive processes.

While some product innovations might not be radical, 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 $R\&D\_incremental$. Conditional on this assumption, the model predicts that $R\&D\_radical_{i,s}$ should be related, over time at the firm level, with increases in the volatility of productivity.[22] Moreover it predicts that this positive relation should be stronger for younger firms, for which the variable $R\&D\_radical_{i,s}$ is more likely to capture riskier innovations.

Therefore, I estimate the following regression:

$$\sigma^2_{\widehat{v}^1,i,s} = \beta_0 + \beta_1 R\&D\_radical_{i,s} + \beta_2 R\&D\_incremental_{i,s} + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \quad (24)$$

$\sigma_{\widehat{v}^1,i,s}$ 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 24 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 positive, significant, and larger than β_2, and that β_1 increases when focusing on a sample of younger firms. The first column shows the regression for all firms, and the other columns for firms 11 year old or older, 10 year old or younger, and 7 year old or younger, respectively.[23] The results show that 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 firms experience increases in the volatility of productivity when introducing radical innovations, and not when introducing incremental innovations. Moreover the coefficient of $R\&D\_radical_{i,s}$ is larger for younger firms, consistently with the

[22] As argued at the beginning of section 4.1, the estimated efficiency measure $\widehat{v}$ can be interpreted as a composite of process efficiency and idiosyncratic demand coming from quality and variety improvements.

[23] 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 $R\&D\_radical_{i,s}$ and $R\&D\_incremental_{i,s}$ 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 8: Relation between age and innovation

Dependent variable: volatility of productivity of firm i in period s, $\sigma_{\hat{v}^1,i,s}$				
	All firms	$Age > 10$	$Age \leq 10$	$Age \leq 7$
$R\&D\_radical_{i,s}$	0.034**	0.032**	0.118*	0.289***
	(0.015)	(0.013)	(0.065)	(0.099)
$R\&D\_incremental_{i,s}$	0.006	0.009	0.006	0.078
	(0.012)	(0.012)	(0.059)	(0.074)
constant	0.165***	0.166***	0.149***	0.094**
	(0.005)	(0.005)	(0.023)	(0.037)
Firm fixed effects	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes
N.observations	10678	8642	2036	1110

Standard Errors, reported in parenthesis, are clustered at the firm level. $R\&D\_radical_{i,s}$ is equal to one for firm i in survey s if: i) firm i has average R&D spending larger than 0.5% of sales; ii) at least part of this spending is directed to develop and produce new products; iii) in survey s firm i introduced a product innovation. $R\&D\_incremental_{i,s}$ is equal to one for firm i in survey s if: i) firm i has average R&D spending larger than 0.5% of sales; ii) in survey s firm i introduced an innovation to improve current products of productive processes. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

hypothesis that product innovation is more radical for younger firms. Taken together, the results in table 8 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 Prediction 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, 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 9, columns 1 and 2 replicate the results obtained for the whole sample. Columns 3 and 4 repeat the analysis 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, thus confirming Prediction 2.

Table 9: Relation between age and productivity - firms doing research and development excluded (empirical sample)

	All observations		Firms with positive R&D excluded	
$age_{i,s}$	0.0102^{***}	0.0128^{***}	0.0064^{**}	0.0090^{**}
	(5.72)	(5.61)	(2.29)	(2.58)
$age_{i,s}{*}constrained_i$	-0.00499^{**}		-0.0010	
	(-2.10)		(-0.28)	
$age_{i,s}{*}midconstr_i$		-0.00671^{**}		-0.0054
		(-2.14)		(-1.12)
$age_{i,s}{*}highconstr_i$		-0.00792^{**}		-0.0035
		(-2.74)		(-0.85)
N.observations	13505	13505	6664	6664
Adj. R-sq.	0.013	0.014	0.11	0.011
Firm fixed effects	yes	yes	yes	yes
Time*group dummies	yes	yes	yes	yes

Panel regression with firm fixed effect. Dependent variable: $\widehat{v}_{i,s}$. Group dummies: one dummy for each financially constrained group of sectors. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $age_{i,s}$ is age in years for firm i in survey s. $constrained_i$, is equal to one if firm i belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. $midconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the median percentage of financially constrained firms, and zero otherwise. $highconstr_i$, is equal to one if firm i belongs to the 33% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

6.3 Predictions 3 and 4: Financial frictions and barriers to entry

In Table 1, the negative relation between financial frictions and productivity growth is confirmed after excluding firms which are currently declaring financing problems. This finding is important both because it is consistent with the prediction of the model that financial frictions matter indirectly, and because it validates the strategy used to identify more financially constrained sectors. Prediction 3 provides a more direct test of the hypothesis that financial frictions matter because of the indirect competition effect. The idea is that if the firm's main competitors are outside Italy, then barriers to entry caused by financial frictions in Italy should not affect much the competitiveness of their market and their incentives to innovate. To test this hypothesis I use the information provided in the surveys, where a question specifically asks where the main competitors of the firm are located, whether in the same county or region, or inside or outside Italy. I use the answers to this question to create the dummy variable f_comp_i, which is equal to 1 if the main competitors of firm i are outside Italy, and zero otherwise. Since f_comp_i is an endogenous variable, it is possible that more productive firms endogenously select to sell their products in more competitive foreign markets. In order to control for this possibility, I also consider an instrumented measure of foreign competition, where f_comp_i is regressed over province dummy variables in a Probit regression, and the outcome of the regression is used to estimate a predicted version $P(f\_comp_i)$, which is equal to one if the probability that firm i faces foreign competition, because its geographical location, is larger than a threshold, and equal to zero otherwise. The threshold is chosen so to get roughly the same frequency of zeros and ones. In the first two columns of Table 10, the relation between age and productivity is estimated separately for $f\_comp_i = 0$ and $f\_comp_i = 1$ firms. Consistently with the hypothesis, the negative relation between financial frictions and innovation is strong for firms that compete mainly against other firms in Italy, and completely absent for firms competing mainly with foreign firms. The next two columns repeat the analysis for firms separated according to the predicted measures of foreign competition, $P(f\_comp_i) = 0$ and $P(f\_comp_i) = 1$, and yield very similar results.

Finally, In order to verify Prediction 4, as an empirical measure of competition I consider the Price-cost margin (PCM):

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

Where $r_{i,t}$ is total revenues and m_{it} are variable costs for firm i in survey s. I calculate

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

Dependent variable: $\widehat{v}_{i,s}$					
	Separate estimates according to foreign competition				Using $lowcomp_i$
	$f\_comp_i = 0$	$f\_comp_i = 1$	$P(f\_comp_i) = 0$	$P(f\_comp_i) = 1$	
$age_{i,s}$	0.0096^{***}	0.0113^{***}	0.0132^{***}	0.0142^{***}	0.0103^{***}
	(4.20)	(3.96)	(4.38)	(4.52)	(5.75)
$age_{i,s}{*}constrained_i$	-0.0060^{**}	-0.0021	-0.0086^{**}	-0.0047	
	(-2.04)	(-0.53)	(-2.14)	(-1.14)	
$age_{i,s}{*}lowcomp_i$					-0.00603^{**}
					(-2.54)
N.observations	9055	4450	3318	3043	13505
Adj. R-sq.	0.0114	0.0285	0.0187	0.0365	0.014
Firm fixed effects	yes	yes	yes	yes	yes
Time*group dummies	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. $age_{i,s}$ 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.

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. the last column of 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 7 and confirm Prediction 4.[24]

[24] 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 B of Table 7, 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 (for online publication)

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 (21) and update the guess of P accordingly. I repeat this procedure until the solution converges to the equilibrium. I then simulate an artificial industry in which, every period, the total number of new entrants ensures that condition (4) is satisfied.

9 Appendix 2 (for online publication)

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. 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 Surveys on "Technological innovation and R&D". One question asks whether the firm, in the 3 years surveyed, has introduced an innovation in the production process. In the 1994 survey, multiple answers are allowed in the following categories: i) product innovation; ii) process innovation. In the 1997 and 2000 surveys, the additional allowed answers are: iii) organizational innovations related to product innovations; iv) organizational innovations related to process innovations.

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

I obtain the information on the location of competitors in the section of the surveys on "Market". A question in this section asks "where are located the main competitors of the firm". Multiple answers are allowed in the following categories: i) same province of the firm; ii) same region of the firm; iii) other Italian regions; iv) EU countries; v) other industrialized countries; vi) developing countries.

I obtain the information on financing frictions in the section of the surveys on "Finance": One question asks whether the headquarters of the bank are in the same province of the firm. The questions on financial frictions ask whether, in the last year of the survey period, the firm: i) would have liked to borrow more at the interest rate prevailing in the market; ii) would have been willing to pay an higher interest rate in order to obtain more credit; iii) the firm demanded more credit without obtaining it.

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 identified following the procedure outlined in section 3.

10 Appendix 3 (for online publication)

In this section, I compute an alternative productivity measure $v_{i,t}^2$, directly derived from the model in section 4. the intuition is that 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. From equation (8), I substitute q_t using equation (7) and p_t using equation (10) and I obtain:

$$\pi_t(\nu_t, \varepsilon_t) = \frac{(\sigma - 1)^{\sigma - 1}}{\sigma^\sigma} AP^{\sigma - \eta} v_t^{\sigma - 1} - F_t \tag{25}$$

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%

I divide both sides by F_t and take logs:

$$\log\left(\frac{\pi_t(\nu_t,\varepsilon_t)}{F_t}\right)=\log\left(\frac{\frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma}AP^{\sigma-\eta}\upsilon_t^{\sigma-1}}{F_t}-1\right) \tag{26}$$

The left hand side of equation 26 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 26 directly implies that $\log\left(\frac{\pi_t(\nu_t,\varepsilon_t)}{F_t}\right)$ is monotonously increasing in productivity υ. 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 (22) I obtain:

$$\log\left(\frac{\pi_t(\nu_t,\varepsilon_t)}{F_t}\right)=\log\left(\frac{\frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma}AP^{\sigma-\eta}\widehat{\upsilon}_0\upsilon_t^{\sigma-2}}{\lambda}-1\right) \tag{27}$$

Therefore, $\log\left(\frac{\pi_t(\nu_t,\varepsilon_t)}{F_t}\right)$ is monotonously increasing in productivity υ 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 (27) around average firm-level productivity $\overline{\upsilon}$:

$$\log\left(\frac{\frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma}AP^{\sigma-\eta}\widehat{\upsilon}_0\upsilon_t^{\sigma-2}}{\lambda}-1\right)\approx\log\frac{\overline{\pi}}{\overline{F}}+\frac{\overline{F}}{\overline{\pi}}\Psi\widetilde{\upsilon}_t$$

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

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 26 becomes:

$$\log\pi_{i,t}=a+\log F_{i,t}+\upsilon_{i,t}^2 \tag{28}$$

where $\upsilon_{i,t}^2=b\widetilde{\upsilon}_{i,t}$, $a=\log\frac{\overline{\pi}}{\overline{F}}$, $b=\frac{\overline{F}}{\overline{\pi}}\Psi$. $\widetilde{\upsilon}_{i,t}$ 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. In order to estimate equation (28) 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 Manasse, 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 $O_{i,t}$:

$$O_{i,t} = \left(\frac{w^{WC}}{w^{TOT}}\right)_{i} w_{i,t}^{TOT} \tag{29}$$

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 $F_{i,t}$:

$$F_{i,t} = cO_{i,t}^{d} \tag{30}$$

where c and d are positive constants which I allow to vary at the two digit sector level. Taking logs of equation (30) and substituting it into (28), I obtain:

$$\log \pi_{i,t} = \beta_0 + \beta_1 \log O_{i,t} + v_{i,t}^2 \tag{31}$$

Equation (31) is estimated separately for each 2 digit sector. Firm and time fixed effects are included in the estimation. I use the estimated coefficients to obtain the empirical counterpart $\widehat{v}_{i,t}^2$. Table 12 reports the estimation of equations (2) and (3) for this alternative measure, and it confirms the negative effect of financial frictions on the lifecycle profile of firm-level productivity.

11 Appendix 4 (for online publication)

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

$$\frac{\sigma}{\sigma-1}\log(p_{i,t}y_{i,t}) = \kappa_i + \gamma_t + \alpha \log\left(p_{i,t}^{k}k_{i,t}\right) + \beta \log\left(w_{i,t}l_{i,t}\right) + v_{i,t}^{1} \tag{32}$$

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

Table 12: Relation between age and productivity (empirical sample, alternative measure of productivity)

	(1)	(2)	(3)	(4)	(5)
Dependent variable	$\widehat{v}_{i,s}^2$	$\widehat{v}_{i,s}^2$	$\widehat{v}_{i,s}^2$	$\widehat{v}_{i,s}^2$	$\widehat{v}_{i,s}^2$
$age_{i,s}$	0.00390	0.00427	0.0121***	0.00431	0.0113**
	(1.11)	(1.13)	(2.53)	(1.05)	(2.20)
$age_{i,s}{*}constrained_i$	−0.0117**	−0.0118**		−0.0105*	
	(−2.55)	(−2.37)		(−1.94)	
$age_{i,s}{*}midconstr_i$			−0.0185**		−0.0172**
			(−2.88)		(−2.47)
$age_{i,s}{*}highconstr_i$			−0.0208**		−0.0181**
			(−3.41)		(−2.74)
N.observations	12776	12776	12776	11049	11049
Adj. R-sq.	0.002	0.002	0.003	0.001	0.003
Firm fixed effects	yes	yes	yes	yes	yes
Time dummies	yes				
Time*group dummies		yes	yes	yes	yes
Fin. constr. excluded	no	no	no	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. $\widehat{v}_{i,s}^2$ is a measure of productivity consistent with the model developed in section 4. $age_{i,s}$ 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.

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 Figure 1, I estimate the following model:

$$\begin{aligned} \widehat{v}^{j}_{i,s} &= \beta_0 + \sum_{l=1}^{n} \beta^{u}_{l}(unconstr_i * age^{l}_{i,s}) + \sum_{l=1}^{n} \beta^{m}_{l}(midconstr_i * age^{l}_{i,s}) + \\ &\quad + \sum_{l=1}^{n} \beta^{c}_{l}(highconstr_i * age^{l}_{i,s}) + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \end{aligned} \tag{33}$$

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 $\beta^{u}_{1}...\beta^{u}_{4}$, $\beta^{m}_{1}...\beta^{m}_{4}$ and $\beta^{c}_{1}...\beta^{c}_{4}$ 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.