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

Andrea Caggese‡
UPF, CREI, and Barcelona GSE.

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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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†Keywords: Firm Dynamics, Financing Frictions, Radical innovation, Incremental Innovation.

‡Pompeu Fambra University, Economics Department, Room 20.222, Carrer Ramon Trias Fargas 25, 08005, Barcelona, Spain. Email: andrea.caggese@upf.edu
1 Introduction

Innovation and technology adoption are fundamental forces that shape firm dynamics and aggregate productivity growth. New firms bring new ideas and are better suited to introducing radical innovations that generate permanent improvements in aggregate productivity. However, new firms are also more likely to face financing frictions, which may distort their investment and innovation decisions. Hsieh and Klenow (2014) show that US manufacturing plants, on average, increase their productivity by a factor of 9.3 from their birth until they are 35 years of age, suggesting an important role for learning and innovation in building firm specific intangible capital. The same authors also show that for similar plants in India and Mexico productivity increases only by a factor of 1.7 and 1.5, respectively.

These different life cycle dynamics shape cross country productivity and income differences, and it is, therefore, important to understand their causes. Do financial imperfections play an important role in explaining them? This paper shows that they do. It provides new empirical evidence on a strong negative relation between financial frictions and the productivity growth of firms over their life cycle. It then develops a firm dynamics model which shows that the interaction between financial frictions and incremental and radical innovation decisions are essential to explain such evidence.

I analyse a very rich dataset of Italian manufacturing firms with more than 60,000 observations of balance sheet data, as well as direct information on financial frictions and innovation decisions from multiple surveys. I construct two different measures of productivity and show a very consistent empirical pattern: in industries where firms are more likely to be financially constrained, productivity grows less over the firms’ life cycle than in the other industries. I show that these differences are not driven by different trends in productivity for constrained and unconstrained groups, and also that they do not disappear as firms grow older.

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

In order to explain these findings, I develop an industry model in which monopolistically competitive firms are subject to financing frictions and every period receive innovation opportunities with some probability. In the benchmark model, only incremental innovation is available, which increases productivity growth after paying a fixed cost. I simulate industries with different degrees of financial frictions, and I show that this model is unable to explain the empirical evidence: financing frictions reduce the frequency of innovation of very young firms, but increase the innovation of older firms, and generate life cycle dynamics inconsistent with the empirical evidence. In part, the intuition for this result is that, as mentioned
above, firms with realistic levels of profitability, on average, accumulate retained earnings to become unconstrained relatively early in their life. But I also find an additional indirect "competition effect". Financial frictions, by increasing the bankruptcy probability for young and financially fragile firms, reduce entry and competition. Lower competition increases the profitability of firms that manage to survive, and also raises the expected value of a successful innovation. Therefore, older firms that overcame financial frictions are actually more likely to invest in incremental innovation in a more financially constrained industry.

The main theoretical contribution of this paper is to show that the full model, in which firms have both incremental and radical innovation opportunities, is instead able to explain the empirical evidence. I assume that radical innovation is risky but potentially able to generate a very large increase in productivity. It is risky both because it fails with positive probability, and because such failure reduces the firm’s productivity below the level it had before innovating. The intuition for this assumption is that radical innovation, because of its disruptive nature, is not complementary to the existing tangible and intangible capital of the firm. Furthermore, such innovation is irreversible and requires the firm to replace the physical capital, knowledge and organizational capital which were used to operate the old technology. Therefore, in case of failure, the firm cannot easily revert back to the old technology, and its efficiency will be lower with respect to the situation before innovating.¹

I calibrate a financially unconstrained industry with both types of innovation. Newborn firms are, on average, small and far from the frontier technology. On the one hand, radical innovation is their best chance to rapidly grow in productivity and size. On the other hand, its cost is limited by the exit option: in case of failure these firms can cut their losses by closing down. Firms that succeed in radical innovation become larger and more productive, and find it optimal to engage in incremental innovation. Therefore, in the full model, young firms are much more likely to invest in radical innovation, while older firms are, on average, more productive, more likely to invest in incremental innovation, and have less volatile growth rates. These dynamics are consistent with Akcigit and Kerr (2010), who analyse US patents data and show that small firms do relatively more exploration R&D and have a relatively higher rate of major inventions than large firms, and with Haltiwanger et al (2014), who find that many young firms fail in their first few years, so that the higher mean net employment growth of small versus large firms is driven by a small fraction of surviving very fast growing firms.

I use the full model to simulate industries with different degrees of financial frictions. I find that, in more financially constrained industries, the competition effect, while it still has a positive impact on incremental innovation, strongly reduces the frequency of radical innovation by young firms. This happens because, with lower competition, many younger and smaller firms are now relatively more profitable at their current productivity level, and

¹This 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".
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 lowering financial frictions in the 50% most constrained sectors to the average level, and abstracting from general equilibrium effects on wages and interest rates, would increase the overall productivity of the Italian manufacturing sector by 6.3%.

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

2 Related literature

My paper is related to the literature on financing frictions and firm dynamics, such as, among others, Buera, Kaboski, and Shin (2011) and Caggese and Cunat (2013), and in particular it is related to Midrigan and Xu (2014) and to Cole, Greenwood and Sanchez (2015). Midrigan and Xu (2014) show that financing frictions delay firm entry in technologically advanced sectors. In their model, this delay effect substantially reduces aggregate productivity, but once firms enter into the advanced sector, they accumulate retained earnings and financial frictions become almost irrelevant for the efficient allocation of resources. In Cole, Greenwood and Sanchez (2015), financing frictions prevent new entrepreneurs from adopting the most

\(^2\) Among other frictions that may contribute to explain this empirical evidence, Akeigit, Alp and Peters (2016) emphasise the difficulty, for entrepreneurs in poor countries, to delegate managerial tasks to outside managers.
productive technologies. In their model, new entrepreneurs can select a project type only when they start their firm, and different project types have different productivity ladders. Financial frictions prevent entrepreneurs from selecting riskier projects with steeper productivity ladders, thus reducing growth over the firm’s life cycle. In contrast, in my model firms have frequent new innovation opportunities during their lifetime, and financial frictions directly constrain the technology adoption only of the youngest firms in the industry. However, despite the realistic features, common to Midrigan and Xu (2014), that older and larger firms can self finance and are not financially constrained in their technology adoption, my model shows a novel and powerful indirect channel of financial frictions on innovation decisions and productivity, which affects the growth dynamics of both young and old firms, with significant aggregate consequences. Because of its emphasis on heterogeneous technological choices, my paper is also related to Bonfiglioli, Crinò and Gancia (2016), who show, in a static multi-sector and multi-country model, that financing frictions distort the type of technologies firms select upon entry and affect both the equilibrium dispersion of sales and the volume of trade. In contrast, I develop a dynamic model which focuses on the dynamic interactions between financial frictions and different types of innovation decisions over the firms life cycle, and on their impact on productivity growth at the firm level and on aggregate productivity.

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

3 Empirical evidence

In this section, I provide empirical evidence on the relation between financing frictions and the life-cycle dynamics of productivity at the firm level. I study a sample of 11429 firms, drawn from the Mediocredito/Capitalia surveys of Italian manufacturing firms. It is based on an unbalanced panel of firms with balance-sheet data from 1989 to 2000, as well as additional qualitative information from three surveys conducted in 1995, 1998 and 2001. Each survey
reports information about the activity of the firms in the three previous years, and it includes detailed information on financing constraints and innovation (see Appendix 2 for details).

In each Mediocredito/Capitalia survey, firms report whether, in the last year of the survey, they had a loan application turned down recently; whether they desired more credit at the market interest rate; and whether they would be willing to pay a higher interest rate than the market rate to obtain credit. Following Caggese and Cunat (2008), I aggregate these three variables into a single variable constrained\textsubscript{i,s}, which is equal to one if firm \textit{i} declares to face some type of financial problem in survey \textit{s} (14% of all firm-year observations), and is equal to zero otherwise.\footnote{Caggese and Cunat (2008) analyse the reliability of this survey-based indicator of financing frictions, and find that it is consistent with alternative indicators based on balance sheet data. In particular, they find that firms with a higher coverage ratio, higher net liquid assets, more financial development in their region and those with headquarters in the same region as the headquarters of their main bank are less likely to declare to be financially constrained.}

A firm-level indicator of financial constraints should satisfy two properties. First, it should be positively related to the probability that the firm faces problems in accessing external finance because of informational or enforceability problems with lenders. Second, it should be unrelated to growth opportunities or other unobserved variables that directly affect the dependent variable of interest. The variable constrained\textsubscript{i,s} is likely to satisfy the first property. However, it may not satisfy the second one, because less productive and profitable firms are at the same time more likely to claim difficulties in accessing loans and have worse investment and innovation opportunities. Indeed, in the dataset, firms that declare financing frictions are less profitable than the other firms in the same sector. The difficulty in formulating a reliable indicator of financing frictions is well known in the corporate finance literature (e.g. see, among others, Farre-Mensa and Ljungqvist, 2015).

In order to ensure that capital market imperfections, rather than growth opportunities, determine the selection of constrained firms, I proceed as follows: first, I consider as constrained only firms that complain about problems in accessing external finance while at the same time have average operating profits over added value larger than 0.1. This threshold excludes the 25\% least profitable firms. Second, I calculate the frequency of financially constrained firms in each 4 digit manufacturing sector, and I select sectors in 2 different groups.\footnote{I use the Ateco 91 classification of the Italian National Statistics Office (Istat). The 2-digit Ateco 91 sectors included in the sample are listed in Table 11 in Appendix 2.} One group is composed by the 50\% four digit sectors with the most constrained firms, called the "Constrained" group, and the other group is composed of the 50\% four digit sectors with the least constrained firms, called the "Unconstrained" group. Thus, the constrained group includes all firms more likely to face financing problems because of sector specific factors. Third, and most importantly, the model developed and simulated in Sections 4-5 predicts that financial frictions affect innovation indirectly by altering competition and profitability at the industry level. In other words, it predicts that the effect of financing frictions on productivity growth can be precisely estimated also if firms currently financially constrained...
are excluded from the estimation. In addition to being a testable implication, which I will empirically verify in Section 6, this is a very useful property, because eliminating from the analysis firms declaring financial problems substantially reduces the above mentioned selection problems. Table 11 in Appendix 2 reports the distribution of firms in the two groups for each two digit manufacturing sector. It shows that financial frictions are present in all industries and not concentrated in only a few sectors.

Table 1 reports the estimates of productivity growth at the firm level as a function of financial frictions. It considers several regressions where the dependent variables are two different firm level estimates of total factor productivity, \( v_{i,t}^1 \) and \( v_{i,t}^2 \). The productivity measure \( v_{i,t}^1 \) is computed from the following equation:

\[
\log \pi_{i,t} = \beta_0 + \beta_1 \log O_{i,t} + v_{i,t}^1
\]  

(1)

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

\[
v_{i,t}^1 = b\bar{v}_{i,t},
\]  

(2)

where \( \bar{v}_{i,t} \) is the deviation of the productivity level \( \nu_t \) with respect to its firm level average, and \( b, \beta_0 \) and \( \beta_1 \) are industry specific coefficients. A detailed derivation of equation 2 is provided in Appendix 3. Nonetheless, the intuition is simple: in a monopolistic competition model where productivity and size are positively related, a more productive firm has lower variable costs relative to its fixed overhead costs, is able to produce more, and has higher revenues and profits for given overhead costs. Equation 1 is estimated with a panel regression with both firm and time effects. Overhead costs \( O_{i,t} \) are estimated using the information in the surveys about the composition of the labour force between blue and white collars. For more details, see Appendix 3.

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

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

(3)

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

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

\[
\hat{v}_{i,s}^j = \beta_0 + \beta_1 \text{age}_{i,s} + \beta_2 \text{age}_{i,s} \ast \text{constrained}_i + \sum_{j=1}^m \beta_j x_{j,i,s} + \varepsilon_{i,s} \tag{4}
\]

Given that each survey covers a 3-years period, for the estimation of equation 4, I consolidate all the balance sheet variables at the same time interval. Therefore \( \hat{v}_{i,s}^j \) for \( j \in \{1, 2\} \), is the average of \( \hat{v}_{i,t}^j \) for the three years of survey period \( s \). Since balance sheet data for some firms go back to 1989, I have a total of four 3-year survey periods (1989-91, 1992-94, 1995-97 and 1998-2000). The total number of survey-year observations available for the productivity measures \( \hat{v}_{i,s}^1 \) and \( \hat{v}_{i,s}^2 \) are respectively, 12776 and 13505. Among the regressors, \( x_j \) is the set of \( m \) control variables, which include firm fixed effects and time effects. \( \text{age}_{i,s} \) is the age of firm \( i \) in survey \( s \). The financing constraints dummy \( \text{constrained}_i \) 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. \( \text{constrained}_i \) is constant over time for each firm and collinear with firm fixed effects. Therefore, I only include it interacted with age, so that \( \beta_1 \) measures the effect of age on productivity for the unconstrained group of firms, and \( \beta_2 \) measures the differential effect of age for the constrained group.

The first two columns of Table 1 report the estimated coefficients of age and age interacted with \( \text{constrained}_i \). The presence of firm fixed-effects ensures that the estimation of \( \beta_1 \) and \( \beta_2 \) is not affected by a composition bias, since these parameters are identified only by within-firm changes in productivity. Columns 1-2 report the results using \( \hat{v}_{i,s}^1 \) and \( \hat{v}_{i,s}^2 \) as dependent variables, respectively. For firms in less constrained sectors, both productivity measures increase with age, even though the increase of \( \hat{v}_{i,s}^1 \) is not statistically significant. Importantly, the coefficient of \( \text{age}_{i,s} \ast \text{constrained}_i \) is always negative and significant, meaning that the relation between age and productivity is significantly more negative for the firms in the more financially constrained sectors. While this evidence supports the hypothesis that financing frictions reduce productivity growth, one possible alternative explanation of the findings is that more financially constrained sectors happen to be sectors in relative decline, with a progressive reduction in productivity over time. This possibility can be controlled for by introducing time dummies interacted with the constrained group among the regressors. This is done in columns 3 to 4, and also in this case the results are confirmed with minimal differences in the estimated coefficients. The last two columns of Table 1 consider a more detailed selection of constrained groups. The estimated equation is:
### Table 1: Relation between age and productivity (empirical sample)

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

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. $\tilde{v}_{1,s}^1$ is a measure of productivity consistent with the model developed in section 4, and $\tilde{v}_{1,s}^2$ is total factor productivity computed following the procedure of Hsieh and Klenow (2009). $age_{i,s}$ is age in years for firm $i$ in survey $s$. constrained$_i$, is equal to one if firm $i$ belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. midconstr$_i$, is equal to one if firm $i$ belongs to the 33% of 4-digit manufacturing sectors with the median percentage of financially constrained firms, and zero otherwise. highconstr$_i$, is equal to one if firm $i$ belongs to the 33% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10% level respectively.
\[ \hat{v}_{i,s} = \beta_0 + \beta_1 \text{age}_{i,s} + \beta_2 \text{age}_{i,s} \times \text{midconstr}_i + \beta_3 \text{age}_{i,s} \times \text{highconstr}_i + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \] (5)

where \( \text{midconstr}_i \) is equal to 1 if firm \( i \) is in the 33% of sectors with intermediate constraints, and 0 otherwise, and \( \text{highconstr}_i \) is equal to 1 if firm \( i \) is in the 33% most constrained sectors and zero otherwise. In this case the coefficient of \( \text{age}_{i,s} \), which measures yearly productivity growth for continuing firms in the 33% least constrained sectors, is positive and significant for both measures \( \hat{v}_{i,s}^1 \) and \( \hat{v}_{i,s}^2 \). Moreover, the effect of age on productivity monotonously decreases with the intensity of financing frictions, in all the different regressions.

I represent graphically the relation between age and productivity for the different groups of firms in Figures 1 and 2. The curves are computed from the estimated coefficients of a piecewise linear regression in which the \( \beta \) coefficient is allowed to vary for four different age groups: up to 10 years, 11-20 years, 21-30 years and 31-40 years (see Appendix 4 for details). Firm fixed effects and time dummies interacted with the constrained group are included as control variables in the regression. Figures 1 and 2 show the age profile of \( \hat{v}_{i,s}^1 \) and \( \hat{v}_{i,s}^2 \), respectively. The lines are normalized to a value of 1 for firms younger than 5 years old. Both figures show that in the less constrained sectors, productivity grows faster as firms become older, relative to the more constrained sectors. Importantly, the differences in productivity between constrained and unconstrained firms also keep growing over time for the older firms in the sample, consistent with the findings of Hsieh and Klenow (2014).\(^5\)

4 Model

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

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\(^5\)Figure 1 shows that the productivity differentials between most constrained and least constrained 35 years old firms are almost as large as the productivity differentials between US plants and Mexican plants with the same age in Hsieh and Klenow (2014). However comparing productivity between firms of different age in the same sector, figure 1 shows that, in least constrained sectors in Italy, firms have a productivity around 20% higher after 35 years, while Hsieh and Klenow report report an increase by 400% for U.S. establishments. There are several factors that explain this difference: i) the fixed effect estimation only measures within firm variation and firm fixed effects absorb some of the size differences that drive the Hsieh and Klenow measure; ii) my dataset is at the firm level, rather than at the establishment level, and very few firms younger than 5 years old are reported, so 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.
Figure 1: Life cycle of the productivity of firms in the empirical sample, productivity measure $v^1$. 

![Graph showing the life cycle of productivity for firms in the empirical sample.](image)

- **Least constrained industries**
- **Mid constrained industries**
- **Most constrained industries**

Productivity (TFP, age<5=1) vs. Firm's age.
Figure 2: Life cycle of the productivity of firms in the empirical sample, profits based measure $v^2$. 

![Graph showing productivity of firms across different constraints.](Image)
$\sigma > 1$. The C.E.S. price index $P_t$ is equal to:

$$P_t = \left[ \int \! \frac{p_t(w)^{1-\sigma}}{w} \, dw \right] \frac{1}{1-\sigma}$$

(6)

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

$$Q_t = \left[ \int \! \frac{q_t(w)^{\frac{\sigma}{\sigma-1}}}{w} \, dw \right] \frac{\sigma-1}{\sigma}$$

(7)

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

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

(8)

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

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

(9)

Each variety is produced by a firm using labour. I assume that the marginal productivity of labour for the frontier technology is equal to $\bar{v}^F_t$, 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 $\bar{v}^F_t$. I define $v^n_t$ as the marginal productivity of labour for the firm and as $v_t = v^n_t/\bar{v}^F_t$ 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:

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

(10)

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

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

(11)

where $F'(v_t) > 0$. The fixed cost $F_t$ is proportional to productivity $v_t$, in order to ensure that the profitability of small and large firms in the simulated model are comparable to those in the empirical sample.\(^6\) $\varepsilon_t$ is a mean zero i.i.d. shock which introduces uncertainty in

\(^6\)Assuming $F(v_t)$ to be 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
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.\footnote{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.}

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:

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

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

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

Equation 13 clarifies that profits depend on firm specific productivity $v_t$ and shock $\varepsilon_t$, as well as on market competition which affects the aggregate price index $P$. The timing of the model for a firm which was already in operation in period $t - 1$ is the following. At the beginning of period $t$ with probability $\delta$ 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 $\varepsilon_t$ and receives profits $\pi_t$, and its financial wealth $a_t$ is:

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

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

$$a_t \geq F_t,$$

If constraint (15) is not satisfied, then the firm cannot continue its activity and is forced to liquidate. Constraint (15) is a simple way to introduce financing frictions in the model, and it generates a realistic downward sloping hazard rate for firms. It can be interpreted as a shortcut for more realistic models of firm dynamics with financing frictions such as, for instance, Clementi and Hopenhayn (2006).
Conditional on continuation, innovation of type $I_t$ is feasible only if:

$$a_t \geq F_t + K(I_t).$$  \hfill (16)

The presence of financing frictions and the fact that the firm discounts future profits at the constant interest rate $R$ implies that it is never optimal to distribute dividends while in operation, since accumulating wealth reduces future expected financing constraints. Hence, dividends $d_t$ are always equal to zero. Profits increase wealth $a_t$, which is distributed as dividends only when the firm is liquidated. After observing $\varepsilon_t$ and realizing profits $\pi_t$, 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 $\gamma$. The arrival of ideas is independent across firms and over time for each firm. A firm with a new idea in period $t$ on how to improve productivity has the opportunity to select $I_t = 1$, pay an innovation cost $K(1) > 0$ to implement the idea, and increase its relative productivity $v_{t+1}$ up to the maximum between $v_t(1 + g)^\tau$ and the frontier technology, where $\tau > 0$ measures how productive the innovation is.\footnote{$\gamma$ can also be interpreted as the probability that a better technology is available and $K(1)$ as a cost of technology adoption.}

A firm which selects $I_t = 0$ with $K(0) = 0$, either because has no innovation opportunities or because it decides not to implement the innovation, is nonetheless able with probability $\xi$ 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:
if \( I_t = 0 \):
\[
\begin{align*}
& v_{t+1} = v_t \text{ with probability } \xi \\
& v_{t+1} = \frac{v_t}{1 + g} \text{ with probability } 1 - \xi
\end{align*}
\]

if \( I_t = 1 \), \( v_{t+1} = \max \left[ v_t (1 + g)^\tau, 1 \right] \)

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 \( \gamma \) the firm receives both an "incremental" idea and a "radical" idea. The firm can choose to implement one of the two, or neither, but it cannot implement both.\(^9\) Implementing the incremental idea (\( I_t = 1 \)) is similar to before. If the firm chooses to implement the radical idea (\( I_t = 2 \)), it invests an amount equal to \( K(2) > 0 \) and is successful with probability \( \xi^R \). In case of success \( v_{t+1} \) increases by \( (1 + g)^\tau^R \), or up to the frontier technology. However, with probability \( 1 - \xi^R \) the innovation fails and \( v_{t+1} \) decreases to \( \frac{v_t}{(1 + g)^\tau^R} \). Therefore, the term \( \tau^R \) 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 Section 5.3. Radical innovation is interpreted as a decision to radically change the firm’s organizational structure and/or to invest in new technologies, products and production processes. The intuition for the downside risk is that such change is irreversible, and requires the firm to replace the capital and expertise which was used to operate the old technology. Therefore, in case of failure, the firm cannot easily revert back to the old technology, and its efficiency will be lower with respect to the situation before innovating. The law of motion of productivity becomes:

\[
\begin{align*}
\text{if } I_t &= 0 : \\
& \left\{ \begin{array}{l}
  v_{t+1} = v_t \text{ with probability } \xi \\
  v_{t+1} = \frac{v_t}{1 + g} \text{ with probability } 1 - \xi
\end{array} \right.
\end{align*}
\]

\[
\begin{align*}
\text{if } I_t &= 1, v_{t+1} = \max \left[ v_t (1 + g)^\tau, 1 \right]
\end{align*}
\]

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

\(^9\)The assumption that innovation probabilities are not independent simplifies the analysis but is not essential for the results. Allowing firms to have independent radical and incremental ideas and to potentially implement both in the same period would not significantly 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 $\pi_t$ and conditional on doing incremental innovation in period $t$:

$$V_t^1 (a_t, \varepsilon_t, v_t) = -K(1) + \frac{1 - \delta}{R} E_t \left\{ \frac{\pi_{t+1} (\varepsilon_{t+1}, \max [v_t(1+g)^T, 1])}{1 + V_{t+1} (a_{t+1}, \varepsilon_{t+1}, \max [v_t(1+g)^T, 1])} \right\}. \tag{17}$$

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 $t$:

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

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

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

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

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

While in the full model is equal to:

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

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

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

Equation (22) implies that the value of the firm is equal to zero in two cases. First, when the indicator function $1 (a_t \geq F_t)$ is equal to zero because the liquidity constraint (15) is not satisfied. Second, when the value in the curly brackets is equal to zero, which indicates that since $V_t^* (a_t, \varepsilon_t, v_t) < 0$, the firm is no longer profitable and exits from production.
4.4 Entry decision

Every period there is free entry, and there is a large amount of new potential entrants with a constant endowment of wealth $a_0$. They draw their relative productivity $v_0$ from an initial distribution with support $[\underline{v}, \overline{v}]$, after having paid an initial cost $S^C$. Once they learn their type, they decide whether or not to start activity. The free entry condition requires that ex ante the expected value of paying $S^C$ conditional on the expectation of the initial values $v_0$ and $\varepsilon_0$ is equal to zero:

$$
\pi \int \max \{E^{\varepsilon_0} [V_0 (a_0, \varepsilon_0, v_0)], 0\} f(v_0)dv_0 - S^C = 0
$$

(23)

4.5 Aggregate equilibrium

In the steady state, the aggregate price $P_t$, the aggregate quantity $Q_t$, and the distribution of firms over the values of $v_t$, $\varepsilon_t$ and $a_t$ are constant over time. The presence of technological obsolescence implies that the age of firms is finite and that the distribution of wealth across firms is non-degenerate. Aggregate price $P_t$ is set to ensure that the free entry condition (23) is satisfied. The number of firms in equilibrium ensures that $P_t$ also satisfies the aggregate price equation (6). Aggregation is very simple because all operating firms with productivity $v$ choose the same price $p(v)$, as determined by equation (12).

4.6 Financing frictions and innovation decisions

Even though the model does not have an analytical solution, it is useful to analyse the above equations to get an intuition of the effects of financial frictions on firm dynamics and innovation decisions. By "financially constrained", I mean firms with low financial wealth $a_t$, for which constraints (15) and (16) might be binding today or in the future. First, constraint (16) implies that firms with low financial wealth $a_t$ are unable to finance innovation. I call this the "binding constraint effect". Second, there is a "selection effect": less productive firms generate less profits, suffer larger losses when the realization of the shock $\varepsilon_t$ 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. Third, equation (22) implies that the larger the probability of bankruptcy $prob(a_t \geq F_t)$, the lower is the expected value of the firm. Therefore, higher expected probability of bankruptcy for new firms reduces the value of the term $E^{\varepsilon_0} [V_0 (a_0, \varepsilon_0, v_0)]$ in the entry condition (23) for a given aggregate price $P$. It follows that the term on the left hand side of (23) becomes negative: $
\pi \int \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 reestablishes 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. By increasing profits, the competition effect generates negative selection. Some unconstrained, unproductive firms that would exit with higher competition, are instead sufficiently productive to remain in operation. More importantly, less competition also increases expected innovation rents from incremental innovation. The intuition is that the cost of innovation $K(I_1)$ is fixed, while the gains from improving productivity increase when expected profits are higher. Conversely, the relation between the competition effect and radical innovation is ambiguous. From equation (18), it is clear that higher expected profits increase the gains from succeeding but also increase the loss, in case of failure. Furthermore, the relation between expected profits and radical innovation is complicated by the asymmetry induced by the exit option available when the value of the firm becomes negative (see equation 22). In other words, the cost of failing radical innovation is bounded below at zero, and because of this asymmetry an increase in expected profitability may have very different effects on radical innovation than on incremental innovation. In Section 5.2, I show that when radical innovation is sufficiently risky, the downside risk implies that less competition induced by higher financial frictions significantly discourages radical innovation.

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 $S^C$, $\sigma$, $\eta$ 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. The following six parameters determine the dynamics of innovation and productivity: the mean $\hat{v}_0$ and variance $\sigma^2_{v_0}$ of the distribution of productivity of new firms $v_0$. The depreciation rate of technology $g$; the parameter which

---

10This effect of competition on innovation is well known in Endogenous Growth Theory, see for example Aghion and Howitt (1992).

11The 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 $\sigma$, 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 $\eta$, the industry price elasticity of demand, is set equal to 1.5, following Constantini and Melitz (2008). The difference between the values of $\eta$ and $\sigma$ 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.

12I 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 $\text{prob}(v < v_L) = \text{prob}(v > v_H) = 1\%$. The censored probability
determines the increase in productivity after innovating \( \tau \); the probability that productivity depreciates for non-innovating firms \( 1 - \xi \); the exogenous exit probability \( \delta \). 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 \( \varepsilon \) is modeled as a two state i.i.d. process where \( \varepsilon \) takes the values of \( \theta \) and \( -\theta \) with equal probability, where \( \theta \) is a positive constant. The fixed per period cost of operation \( F(v_{it}) \) is:

\[
F_{it} = \lambda \frac{v_{it}}{\hat{v}_0}
\]

where \( \lambda > 0 \) and \( \hat{v}_0 \) is average productivity of new firms. \( \lambda \) and \( \theta \) 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 \( \gamma \) matches the percentage of innovating firms. In the sample, there are 37% firm-survey observations reporting R&D activity. However, for many firms R&D spending is very small relative to output. Firms with very low R&D spending are likely to have only marginal innovation projects which do not substantially affect their productivity. Since in the model, innovation has a large impact on a firm’s sales and profits, I calibrate it on the fraction of firms in the data which have R&D spending above a minimum threshold. Therefore, I classify as "innovating" all firms in the empirical sample with R&D expenditure higher than 0.5% of sales (22% of all firms). Finally, the parameter \( a_0 \), the initial endowment of wealth of new firms, affects the intensity of financing frictions and the probability of bankruptcy. I chose a value of \( a_0 = 12 \), which in equilibrium corresponds to 40% of average firm sales in the industry, and which matches an average share of firms going bankrupt every period equal to 0.5%.

\[13\] Although the model is relatively stylized, Table 2 shows that it matches these empirical moments reasonably well. The scale parameter \( A \) does not affect the results of the analysis and its value ensures that the number of firms in the calibrated industry is sufficiently large, and allows to compute reliable aggregate statistics.

### 4.7.2 Full model with incremental and radical innovation

Out of the 22% of firms classified as innovating in the previous section, I consider two additional criteria to measure the fraction of radical innovations for calibration purposes: first, since this innovation represents a radical change to the current production, it needs to involve

distribution is re-scaled to make sure that its integral over the support \([v_L, v_H]\) is equal to 1.

\[13\] A 2003 study by Istat shows that in 2001 in the whole Italian economy 0.25% of firms went bankrupt, while the share was equal to 0.4% in the manufacturing sector. The same study also shows an average share of bankruptcies of 0.3% for the whole economy in the 1997-2001 period. I apply the same proportion to estimate a share of bankruptcies in manufacturing equal to 0.5% for the sample period.
Table 2: Calibration of the benchmark model with only incremental innovation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Empirical moment</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda$</td>
<td>0.5</td>
<td>Fraction of firms with negative profits</td>
<td>0.40</td>
<td>0.33</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.15</td>
<td>Avg. of time series st.dev. of profits/sales</td>
<td>0.117(^1)</td>
<td>0.102</td>
</tr>
<tr>
<td>$K(1)$</td>
<td>3</td>
<td>Average R&amp;D expenditures /profits</td>
<td>67(^2)%</td>
<td>66%</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.45</td>
<td>Percentage of innovating firms</td>
<td>22(^2)%</td>
<td>24%</td>
</tr>
<tr>
<td>$\bar{v}$</td>
<td>0.45</td>
<td>Median TFP relative to the 99th percentile</td>
<td>0.78</td>
<td>0.79</td>
</tr>
<tr>
<td>$\sigma_v^2$</td>
<td>0.03</td>
<td>Average cross sectional standard deviation of TFP</td>
<td>0.34(^3)</td>
<td>0.25</td>
</tr>
<tr>
<td>$g$</td>
<td>1.009</td>
<td>Average yearly decline in TFP for firms not doing R&amp;D</td>
<td>0.4(^3)%</td>
<td>0.23%</td>
</tr>
<tr>
<td>$\tau$</td>
<td>3</td>
<td>Ratio between 90th petile and 10th petile of size distrib.</td>
<td>13.2</td>
<td>7.29</td>
</tr>
<tr>
<td>$\zeta_{NI}$</td>
<td>0.25</td>
<td>Percentage of firms with age &gt;60 years</td>
<td>4.8%</td>
<td>8.9%</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.01</td>
<td>Average age</td>
<td>24</td>
<td>22</td>
</tr>
<tr>
<td>$a_0$</td>
<td>12</td>
<td>Percentage of firms going bankrupt every period</td>
<td>0.5%</td>
<td>0.5%</td>
</tr>
</tbody>
</table>

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

R&D spending at least partly directed to develop and produce new products (see Appendix 2 for details). Second, it has to be related to large changes in productivity. Therefore, I measure the fraction of firm-survey observations doing radical innovation in the empirical sample as those that satisfy the first criterion, and the volatility of their estimated productivity $\hat{\tau}_1$ is larger than the 75th percentile. While this approximate estimate is only for the purpose of calibrating the average fraction of innovation that is radical, in Section 6 I will test the specific prediction of the model on the relation between radical innovation and the time series volatility of productivity at the firm level.

The full model with radical innovation requires choosing three additional parameters: the probability of success $\xi^R$, the change in productivity after innovating $\tau^R$, and the cost of radical innovation $K(2)$. I choose $\xi^R$ and $\tau^R$ to jointly match the fraction of firms doing radical innovation in the empirical sample, as measured above, 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 $\hat{\tau}_2$ measure to 38.3\% for $\hat{\tau}_1$. Since these volatility measures are likely biased upwards because of measurement errors, I calibrate the parameters so that the model counterpart is closer to the lower bound. This corresponds to $\tau^R = 30$, which implies that after a successful radical innovation productivity $v$ increases by $[(1 + g)\tau^R - 1] \% = 31\%$, while it decreases by $[1 - \frac{1}{(1+g)\tau^R}] \% = 24\%$ in case of failure. The calibrated value of $\xi^R$, the success probability of radical innovation, is 4.5\%. Finally, the cost of radical innovation $K(2)$ is set equal to the cost of incremental innovation in expected terms, so that $K(2) = \xi^R K(1)$.

A restrictive assumption of this calibration, the symmetry in the innovation risk $\tau^R$, is
### Table 3: Calibration of the full model with radical and incremental innovation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Empirical moment</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\eta$</td>
<td>0.5</td>
<td>Fraction of firms with negative profits</td>
<td>0.40</td>
<td>0.34</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.15</td>
<td>Avg. of time series st.dev. of profits/sales</td>
<td>0.117$^1$</td>
<td>0.087</td>
</tr>
<tr>
<td>$K(1)$</td>
<td>6</td>
<td>Average R&amp;D expenditures /profits</td>
<td>67%$^2$</td>
<td>58%</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.85</td>
<td>Percentage of innovating firms</td>
<td>22.4%$^2$</td>
<td>23.3%</td>
</tr>
<tr>
<td>$\tilde{\nu}$</td>
<td>0.45</td>
<td>Median TFP relative to the 99th percentile</td>
<td>0.78</td>
<td>0.62</td>
</tr>
<tr>
<td>$\sigma_v^2$</td>
<td>0.03</td>
<td>Average cross sectional standard deviation of TFP</td>
<td>0.34$^3$</td>
<td>0.32</td>
</tr>
<tr>
<td>$g$</td>
<td>1.009</td>
<td>Average yearly decline in TFP for firms not doing R&amp;D</td>
<td>0.4%$^3$</td>
<td>0.4%</td>
</tr>
<tr>
<td>$\tau$</td>
<td>2</td>
<td>Ratio between 90th pctile and 10th pctile of size distrib.</td>
<td>13.2</td>
<td>12.2</td>
</tr>
<tr>
<td>$\xi^{NI}$</td>
<td>0.25</td>
<td>Percentage of firms with age &gt;60 years</td>
<td>4.8%</td>
<td>14.4%</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.015</td>
<td>Average age</td>
<td>24</td>
<td>26</td>
</tr>
<tr>
<td>$a_0$</td>
<td>4.5</td>
<td>Percentage of firms going bankrupt every period</td>
<td>0.5%</td>
<td>0.06%</td>
</tr>
<tr>
<td>$\xi^R$</td>
<td>0.045</td>
<td>Percentage of firms doing radical innovation</td>
<td>7%</td>
<td>10%</td>
</tr>
<tr>
<td>$\tau^R$</td>
<td>30</td>
<td>90% percentile of volatility of productivity</td>
<td>18.4%</td>
<td>16.3%</td>
</tr>
</tbody>
</table>

Other parameters: $S^C = 4; r = 2\%; \eta = 1.5; \sigma = 4; K(2) = 0.01; A = 25010$. 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.

later relaxed in section 5.3. Moreover, the radical innovation decisions are mainly determined by the values of $\tau^R$ and $\xi^R$, and are not very sensitive to variations in $K(2)$. Finally, I recalibrate the parameters $K(1), \tau, \gamma, \delta$ and $a_0$ to match the distribution of productivity, the overall percentage of innovating firms, the cost of innovation, the average age of firms, and the percentage of bankruptcies, while leaving all of the other parameters unchanged. Table 3 illustrates the parameters of the full model.

### 5 Simulation results

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

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

5.1 Simulation results, benchmark model

In order to explain innovation and productivity dynamics in the benchmark model, it is useful to refer to the “selection”, “competition”, and “binding constraint” effects defined in Section 4.6. To better illustrate these effects, Figure 3 focuses on the comparison between the extreme cases of the unconstrained industry and the severely constrained industry. The upper panel A) of Figure 3 shows the probability to implement an innovation idea. The variable on the X-axis 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, we notice two main differences. The minimum productivity to innovate is lower (51%), because of the competition effect: more financial frictions reduce entry and competition, increase expected profits for firms that do not go bankrupt, and increases innovation rents. Furthermore, in the region of \( v \) between 0.51 and 0.65, the probability to implement the innovation is positive but smaller than one. Innovation is profitable, but some firms have insufficient funds and a binding constraint (16), and cannot take advantage of it. The middle panel B) of Figure 3 shows the productivity distribution of firms. In the unconstrained industry, there is a large mass of firms in the region with \( v < 0.53 \), where innovation is not profitable, which make up 35% of all the active firms. In the constrained industry, even though the minimum productivity of active firms is lower, fewer firms are in this no-innovation region because the selection effect accelerates the exit of unproductive firms. In summary, while the binding constraint effect reduces innovation (relative to the unconstrained industry), the other two effects increase it. The competition effect does so because it makes the innovation region larger and the selection effect because it reduces the density of firms in the no innovation region. I find that the binding constraint effect is rather limited, because firms that do not default are able to quickly accumulate retained earnings and become unconstrained. As a consequence, the lower panel C of Figure 3 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. 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 3: Innovation and Growth in the benchmark model

Table 4: Simulated industries, benchmark model with only incremental innovation: descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Financially unconstr. industry (a₀=30)</th>
<th>Benchmark industry (a₀=12)</th>
<th>Moderately Financially Constrained industry (a₀=4)</th>
<th>Financially Constrained industry (a₀=2)</th>
<th>Severely Financially Constr. industry (a₀=1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>% going bankrupt every period</td>
<td>0%</td>
<td>0.5%</td>
<td>3.1%</td>
<td>5.7%</td>
<td>7.7%</td>
</tr>
<tr>
<td>% not innovating for lack of funds¹</td>
<td>0%</td>
<td>1.9%</td>
<td>11%</td>
<td>18%</td>
<td>25%</td>
</tr>
<tr>
<td>Price index $P$ relative to benchmark</td>
<td>99.9%</td>
<td>100%</td>
<td>100.7%</td>
<td>102.3%</td>
<td>103.5%</td>
</tr>
<tr>
<td>$E(\pi</td>
<td>\nu)$ relative to benchmark</td>
<td>99.6%</td>
<td>100%</td>
<td>102.1%</td>
<td>109.6%</td>
</tr>
<tr>
<td>Average % of innovating firms</td>
<td>25.7%</td>
<td>23.8%</td>
<td>16.7%</td>
<td>21.3%</td>
<td>23.3%</td>
</tr>
<tr>
<td>Avg. TFP relative to benchmark</td>
<td>102.2%</td>
<td>100%</td>
<td>92.9%</td>
<td>96.4%</td>
<td>97.4%</td>
</tr>
</tbody>
</table>

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.
Table 4 shows summary statistics for all of the different simulated industries in the benchmark model. The first two rows of Table 4 show that the more constrained the industry is, the larger is the fraction of firms which go bankrupt and which cannot invest in innovation. The next two rows quantify the strength of the competition effect. Average profits are 14% higher in the severely constrained industry with respect to the benchmark. The fifth row shows that 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 is relatively large while the competition and the selection effects are small. Therefore, both innovation and TFP decline. But for higher levels (from column 3 to column 5) the competition and selection effects dominate, and innovation and TFP increase. Taken together, Figure 3 and Table 4 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.

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

In the previous section, the simulation of the benchmark model generates two main insights: first, financial constraints prevent some young firms from investing in productivity enhancing innovation and reduce aggregate TFP, even though the overall negative effect is compensated by the fact that financial frictions also act as barriers to entry and increase profits and innovation rents for financially unconstrained firms. Second, the model is unable to generate large differences in the life cycle dynamics of firms between industries with different degrees of financing frictions. This contradicts the empirical evidence shown in Section 3.

In this section, I demonstrate that a model with both radical and incremental innovation is, instead, consistent with the empirical evidence. Figures 4-7 analyse innovation dynamics in the full model. I first illustrate the trade-off between radical and incremental innovation in the unconstrained industry only (Figure 4). I then discuss the implications of financial frictions (Figures 5-7). The upper panel of Figure 4 is analogous with panel A in Figure 3, and shows the probability to implement an innovation idea. As in the benchmark model, here incremental innovation is also performed only by the larger/more productive firms. The minimum productivity threshold for radical innovation is higher than in Figure 3 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.
Figure 4: Innovation decisions in the unconstrained industry, full model with both radical and incremental innovation.
The lower panel of Figure 4 shows innovation as a function of firm age. Very young firms, on average, perform most of the radical innovation in the industry. These firms then either exit after failure, or grow fast after success, and once they become large they start investing in incremental innovation. Therefore, the fraction of firm doing incremental innovation rises gradually with age. It is important to note that the innovation dynamics of young and old firms in Figure 4 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. This is not only with the well know fact that small firms grow faster than larger firms and have more volatile growth rate, but also with the observation that innovation is a risky experimentation process (Kerr, Nanda and Rhodes-Kropf, 2014), as well as with the findings of Akcigit and Kerr (2010), who analyse US patents data and show that small firms do relatively more exploration R&D and have a relatively higher rate of major inventions than large firms. Finally, it is also consistent with the high positive skewness in the growth of young firms observed by Haltiwanger et al (2014) : "...median net employment growth for young firms is about zero. As such, the higher mean reflects the substantial positive skewness with a small fraction of very fast growing firms driving the higher mean net employment growth."

Figures 5-7 describe the relation between financing frictions, 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 3, on the comparison between the extreme cases of the unconstrained industry and the severely constrained industry. Figure 5 shows the probability to innovate as a function of productivity. The range of productivity values in which firms radically innovate in the constrained industry is much smaller than in the unconstrained industry. The difference is highlighted by the gray area, and is not caused by current binding financing constraints, because the cost of radical innovation $K(2)$ is calibrated to be relatively low. 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. Table 6 below show that in the full model, very few surviving firms have a binding financing constraint. 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. In this case, there is also 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.\textsuperscript{14} This effect explains the shaded area for values of $v$ around 0.52, where firms perform radical innovation only in the unconstrained industry. Since the distribution of firms, consistent with the empirical evidence, is heavily skewed with many young and small firms, the shaded area determines a large difference in radical innovation across industries. Conversely, the binding constraint effect explains why, for certain values of productivity $v$, the percentage of firms undertaking an innovation opportunity is positive in the constrained industry but lower than one. This happens especially in the intermediate region of $v$ between 0.65 and 0.75. However, very few firms are in this region, and, therefore, this effect is going to be negligible at the aggregate level.\textsuperscript{15}

Figure 6 compares the life cycle profile of innovation in the unconstrained industry and in

\textsuperscript{14}The empirical competition literature often estimates a positive relation between competition and innovation (e.g. Blundell \textit{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 \textit{et al.} (2001).

\textsuperscript{15}To be precise, there is also a "gambling for resurrection" effect: bankruptcy risk implies that the value of a firm $V_t(a_t, \varepsilon_t, v_t)$ is convex around the value of $a_t = F$. Intuitively, $V_t(a_t, \varepsilon_t, v_t)$ as defined in equation (22) is strictly concave for $a_t \geq F$, because higher wealth reduces bankruptcy risk, and is equal to zero for $a_t < F$. Such local convexity encourages firms close to the bankruptcy region to take more risk, and explains a positive radical innovation probability in the constrained industry in the bottom left part of the shaded area. However, the aggregate impact of this effect is negligible.
the severely constrained industry. In the latter, young firms perform less radical innovation, so that at any given age fewer firms reach a level of productivity high enough to find it optimal to invest in incremental innovation. This explains why the fraction of firms doing incremental innovation increases more slowly in this industry than in the unconstrained industry.

Finally, Figure 7 shows the implications of different innovation dynamics for the lifecycle profile of size and productivity in the two industries. Average productivity steeply increases with age in the unconstrained industry. The difference in lifecycle dynamics of productivity between unconstrained and constrained industries are qualitatively and quantitatively comparable to the empirical results in Section 3. The previous discussion clarifies that financial factors matter in the full model not because the lack of internal finance prevents firms from investing optimally, but because the competition effect reduces the incentives to innovate for many young firms. Likewise, in the severely constrained industry shown in Figure 7 average size and productivity grow slowly for older firms not because these are financially constrained, but because many of them have not reached a level of productivity sufficiently high to invest in incremental innovation.

For a more direct evaluation of the model’s consistency with the empirical evidence presented in Section 3, I perform the estimation of the equation 5 on artificial firm level data obtained from both the benchmark model and the full model. I simulate a set of firm-year observations from the five industries considered above, then I define as mid-constrained (midconstr; = 1) firms in the "moderately financially constrained industry" and in the "financially constrained industry", and as high-constrained firms in the "severely financially
Figure 7: Size and productivity over the firm’s life-cycle (new firms = 1; simulated industries, full model with both radical and incremental innovation).

![Graph showing size](image1)

![Graph showing productivity](image2)

constrained industry\(^n\) \((high\text{str}_i = 1)\). Table 5 compares the results obtained using the empirical sample, shown in columns 1 and 2, with those using the simulated data, shown in the third and fourth column. The specification is identical in all regressions, including firm fixed effects and time dummies. For the regression on the simulated data, the age coefficient indicates that unconstrained firms, on average, increase their productivity by 1.1% every year, both in the benchmark and in the full model. This value is very similar to the values estimated for the empirical measures of productivity \(v_{1,s}^i\) and \(v_{2,s}^i\). This result is remarkable considering that the models are calibrated only to match the profitability of firms and the cost and frequency of innovation, not their productivity growth. Furthermore, the other estimated coefficients clearly show that only the full model with radical innovation is able to replicate the empirical finding of the strongly negative effect of financial frictions on productivity growth. By adding the coefficients of \(age_{i,s} \times \text{mid}\text{str}_i\) and \(age_{i,s} \times \text{high}\text{str}_i\) to the \(age_{i,s}\) coefficient in column 3, it follows that in the benchmark model firms in the mid constrained industries grow at 1.04% every year, while firms in the most constrained industry grow at 1.29% every year, and thus at a higher rate than the unconstrained firms. This non-monotonicity reflects the U shaped relation shown in Table 4, and contradicts the empirical evidence. Conversely, column 4 of Table 5 shows that the full model with radical and incremental innovation replicates very well the negative relation between financial frictions and productivity growth over the firm’s life cycle. Not only is such growth progressively lower as constraints increase, but also the implied productivity growth in the different constrained
groups in the empirical sample, using the $\tilde{w}_{i,s}$ productivity measure, is quantitatively very close to the simulated values for the full model, as shown in the bottom part of Table 5. Finally, Panel A of table 6 shows the summary statistics for the simulated industries in the full model. Radical innovation in the severely constrained industry is more than 50% lower than in the benchmark industry, despite the fact that less than 1% of firms cannot innovate because of a binding financing constraint. As a consequence, average TFP is 18.1% lower in this industry than in the benchmark one.

How much does the reduction in radical innovation caused by financial frictions matter for the whole Italian manufacturing sector? By combining the above simulation results and the data from the empirical dataset, I can estimate its aggregate effects for the Italian manufacturing industry. First, I define a mapping between the declared financing frictions in the surveys and the intensity of financial frictions in the model. The latter can be measured by the expected return of retained earnings in excess of the real interest rate $r$. Since the value of the firm $V_{it}(a_{it},\varepsilon_{it},v_{it})$ is the present value of future profits net of current wealth $a_{it}$, I define the excess expected return of firm $i$ in period $t$ $\phi_{it}$ as:

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

(25)

where $\phi_{it}$ measures the extra return for firm $i$ in period $t$ of accumulating cash reserves and reducing current and future expected financial problems. It is straightforward to show that $\phi_{it}$ is negatively related to $a_{it}$ and it is equal to zero for values of $a_{it}$ high enough so that the firm is unconstrained today or in the future. I assume that in the empirical sample firms declare financial difficulties if $\phi_{it}$ is higher or equal than an unobserved common threshold $\phi$. I then fix the value of $\phi$ in the simulations so that for the benchmark calibration, the percentage of simulated firms "declaring financial frictions" is the same as in the whole empirical sample (14% of all firm-year observations). Finally, I simulate a continuum of industries with identical parameters except for the value of the initial endowment $a_0$. A lower value of $a_0$ increases the mean value of $\phi_{it}$ across firms in equilibrium. I use the fraction of firms declaring financial difficulties (the fraction of firms with $\phi_{it} > \phi$) to match the simulated industries with the empirical 4 digit sectors of the Italian sample, and I compute the weighted average of the reduction in productivity caused by financial frictions across these sectors. I find that reducing financial frictions in the 50% most constrained sectors at the benchmark level, and abstracting from general equilibrium effects on wages and interest rates, would increase overall productivity in the Italian manufacturing sector by 6.3%.

5.3 Full model, robustness checks

The main results shown in the previous section are based on the assumption that radical innovation risk $\tau^R$ is symmetric: the percentage drop in productivity in case of failure is equal to its increase in case of success. In this section, I show that the results are confirmed.
Table 5: Relation between age and productivity, comparison between empirical and simulated data

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Empirical data</th>
<th>Simulated data, benchmark model</th>
<th>Simulated data, full model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$v_{i,s}$</td>
<td>0.0121**</td>
<td>0.0128**</td>
<td>0.0119***</td>
</tr>
<tr>
<td>$v_{i,s}$</td>
<td>0.0121**</td>
<td>0.0128**</td>
<td>0.0119***</td>
</tr>
<tr>
<td>$v_{i,t}$</td>
<td>0.0119***</td>
<td>0.0114***</td>
<td>0.0114***</td>
</tr>
<tr>
<td>$v_{i,s}$</td>
<td>0.00671**</td>
<td>0.00792**</td>
<td>0.00101**</td>
</tr>
<tr>
<td>$v_{i,s}$</td>
<td>0.00671**</td>
<td>0.00792**</td>
<td>0.00101**</td>
</tr>
<tr>
<td>$v_{i,t}$</td>
<td>0.00383***</td>
<td>0.00542***</td>
<td>0.00542***</td>
</tr>
<tr>
<td>$v_{i,s}$</td>
<td>0.00101**</td>
<td>0.00542***</td>
<td>0.00542***</td>
</tr>
<tr>
<td>$v_{i,t}$</td>
<td>0.00101**</td>
<td>0.00542***</td>
<td>0.00542***</td>
</tr>
<tr>
<td>N. observations</td>
<td>12776</td>
<td>13505</td>
<td>13757</td>
</tr>
<tr>
<td>Adj. R-sq.</td>
<td>0.003</td>
<td>0.013</td>
<td>0.436</td>
</tr>
<tr>
<td>Firm fixed effects</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Time*group dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Yearly average productivity growth for continuing firms

<table>
<thead>
<tr>
<th></th>
<th>Empirical data, using $\tilde{v}_{i,s}^2$</th>
<th>Simulated data, using $v$ from the full model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unconstrained industries</td>
<td>1.28%</td>
<td>1.14%</td>
</tr>
<tr>
<td>Mid constrained industries</td>
<td>0.61%</td>
<td>0.76%</td>
</tr>
<tr>
<td>Highly constrained industries</td>
<td>0.49%</td>
<td>0.59%</td>
</tr>
</tbody>
</table>

Panel regression with firm fixed effect. Group dummies: one dummy for each financially constrained group of firms. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $\tilde{v}_{i,s}^2$ is a measure of productivity consistent with the model developed in section 4, and $\tilde{v}_{i,s}^2$ is total factor productivity computed following the procedure of Hsieh and Klenow (2009); $v_{i,t}$ is productivity of simulated firm $i$ in period $t$. $age_{i,s}$ is age in years for firm $i$ in survey $s$. $midconstr_i$, is equal to one if firm $i$ belongs to the 33% of 4-digit manufacturing sectors with the medium percentage of financially constrained firms, and zero otherwise. $highconstr_i$, is equal to one if firm $i$ belongs to the 33% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10% level respectively.
even if the symmetry assumption on $\tau^R$ is relaxed in favour of a much lower productivity drop in case of failure. I define $\tau^H$ and $\tau^L$, such that in case of success of radical innovation $v_{t+1} = (1+g)^{\tau^H} v_t$, while in case of failure $v_{t+1} = \frac{v_t}{(1+g)^{\tau^L}}$. Once I do not restrict $\tau^L$ and $\tau^H$ to be equal, it is easy to show that a necessary condition for the results of the previous section is that radical innovation has a high return and low success probability. That is, a high value of $\tau^H$ associated with a low value of $\xi^R$. If these two conditions are satisfied, then the results hold also conditional to a relatively low value of the "downside risk" $\tau^L$. Intuitively, if innovation is very risky, then even a low value of $\tau^L$ is sufficient to ensure that radical innovation is mainly performed by young and small firms, and that increases in competition encourage these firms to take on more risk. This is shown in Panel B, where I keep $\tau^H = 30$ and reduce $\tau^L$ to 5, which corresponds to productivity falling by 4.4% if radical innovation fails, while at the same time lowering the parameter $\xi$ 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 Panel A, with financing frictions reducing both types of innovation and aggregate productivity.

In the previous section, I also argued that in the full model currently binding or future expected binding financial frictions do not matter, in terms of the results. Financial constraints affect innovation and growth dynamics almost exclusively indirectly, via the competition effect. I support this claim with additional simulation evidence in this section and additional empirical evidence in Section 6. Here I precisely identify the importance of the competition effect in Panel C, which repeats the same exercise of Panel A, but varying the entry cost $S^C$ across industries, while keeping $a_0$ fixed at the benchmark level. I choose the values of $S^C$ to match the equilibrium prices in the four industries analyzed in Panel A. In other words, in Panel C entry costs replicate the competition effect generated by financing frictions in Panel A. The results show that the higher the barriers to entry, the lower is the radical innovation, which also implies less incremental innovation and average TFP. In the industry with very high entry barriers, average TFP is 15.1% lower than in the benchmark industry.

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. The model in the previous section matches well the empirical findings both qualitatively and quantitatively, and is based on three key mechanisms: First, radical innovation is risky and is mainly performed by young firms. Second, financial frictions negatively affect growth because of their impact on innovation activity. Third, financial frictions affect innovation and growth indirectly because they generate entry barriers that reduce competition and distort the incentives to innovate.

In this section, I will provide empirical support for each of these mechanisms. I verify the first mechanism by estimating the relation between firms’ age and the likelihood that
Table 6: Simulated industries: descriptive statistics, full model with both incremental and radical innovation

<table>
<thead>
<tr>
<th></th>
<th>Financially unconstr. industry</th>
<th>Benchmark industry</th>
<th>Moderately Financially Constrained industry</th>
<th>Financially Constrained industry</th>
<th>Severely Financially Constr. industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average P relative to benchmark</td>
<td>99.4%</td>
<td>100%</td>
<td>100.1%</td>
<td>102.1%</td>
<td>103.0%</td>
</tr>
<tr>
<td>$E (\pi</td>
<td>v)$ relative to benchmark</td>
<td>97.7%</td>
<td>100%</td>
<td>100.2%</td>
<td>107.0%</td>
</tr>
<tr>
<td>Average percentage of innovating firms</td>
<td>20.4%</td>
<td>20.8%</td>
<td>21.9%</td>
<td>10.7%</td>
<td>8.6%</td>
</tr>
<tr>
<td>Percentage doing Radical Innovation</td>
<td>9.3%</td>
<td>9.9%</td>
<td>10.5%</td>
<td>5.4%</td>
<td>4.5%</td>
</tr>
<tr>
<td>Not doing R.I. because of lack of funds</td>
<td>0%</td>
<td>0%</td>
<td>0.02%</td>
<td>0.2%</td>
<td>0.06%</td>
</tr>
<tr>
<td>Percentage doing Incremental Innovation</td>
<td>11.1%</td>
<td>10.9%</td>
<td>11.4%</td>
<td>5.3%</td>
<td>4.2%</td>
</tr>
<tr>
<td>Not doing I.I. because of lack of funds</td>
<td>0%</td>
<td>1.7%</td>
<td>1.6%</td>
<td>0.5%</td>
<td>0.4%</td>
</tr>
<tr>
<td>Weighted Avg. TFP relative to benchmark</td>
<td>98.0%</td>
<td>100%</td>
<td>98.3%</td>
<td>85.6%</td>
<td>81.9%</td>
</tr>
</tbody>
</table>

|                        | 21.7%                          | 21.8%              | 21.4%                                         | 12.3%                           | 10.6%                                |
| Percentage doing Radical Innovation | 14.3%                          | 14.5%              | 14.2%                                         | 8.1%                            | 7.0%                                 |
| Percentage doing Incremental Innovation | 7.4%                           | 7.3%               | 7.2%                                          | 4.2%                            | 3.6%                                 |
| Weighted Avg. TFP relative to benchmark | 101%                           | 100%               | 100%                                          | 91.0%                           | 87.5%                                |

|                        | 99.9%                          | 100%               | 100.6%                                        | 102.6%                          | 103.6%                               |
| Entry cost F relative to benchmark | 99.4%                          | 100%               | 115%                                         | 177%                            | 212%                                 |
| Average percentage of innovating firms | 20.9%                          | 23.38%             | 18.0%                                         | 11.3%                           | 8.0%                                 |
| Percentage doing Radical Innovation | 9.8%                           | 11.0                | 8.4%                                          | 5.1%                            | 3.6%                                 |
| Percentage doing Incremental Innovation | 11.1%                          | 12.3%              | 9.6%                                          | 6.2%                            | 4.4%                                 |
| Weighted Avg. TFP relative to benchmark | 100.1%                         | 100%               | 97.4%                                         | 90.5%                           | 84.9%                                |

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

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innovation is related to an increase in volatility of productivity:

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

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

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

Finally, the third mechanism implies these two testable predictions:

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

**Prediction 4**: The difference in the life cycle dynamics between financially constrained and financially unconstrained industries is similar to the difference between industries selected according to competition.

### 6.1 Innovation and volatility of productivity

In this section, I explain the mapping from the theoretical prediction of the model (young firms do most of the radical innovation) into the testable Prediction 1.

First, I consider an empirical measure of innovation as close as possible to the radical innovation in the model. In the calibration Section 4.7 I consider, as necessary conditions for radical innovation in the empirical sample, the presence of non negligible amounts of R&D spending directed to introduce new products. Accordingly, I define the variable $R&D_{\text{prodinn},i,s}$ which is equal to one if firm $i$ in survey $s$ does R&D spending larger than 0.5% of sales, and at least part of this spending is directed to develop and produce new products (see Appendix 2 for details). I also define $R&D_{\text{other},i,s}$, which is equal to one if firm $i$ in survey $s$ does R&D spending larger than 0.5% of sales but all R&D spending is directed to improve current products or productive processes.

The identifying assumption is that $R&D_{\text{prodinn},i,s}$ is more likely to capture radical innovation than $R&D_{\text{other},i,s}$. Given this assumption, and given that radical innovation in the model is mostly performed by younger firms, the model predicts that the relation between $R&D_{\text{prodinn},i,s}$ and time series changes in the volatility of productivity should be stronger for young than for old firms. Conversely, the same relation should be significantly weaker for the $R&D_{\text{other},i,s}$ innovation indicator.

Therefore, I estimate the following regression:

$$
\sigma_{v,i,s}^2 = \beta_0 + \beta_1 R&D_{\text{prodinn},i,s} + \beta_2 R&D_{\text{other},i,s} + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s} \quad (26)
$$

$\sigma_{\tilde{v},i,s}$ is the standard deviation of productivity measure $\tilde{v}_{1,t}^i$ computed over the three years of survey $s$. The two main regressors are $R&D_{\text{prodinn},i,s}$ and $R&D_{\text{other},i,s}$, and the control
variables $x_j$ include time dummies. Errors are clustered at the firm level. I test prediction 1 by estimating equation 26 with firm fixed effect, so that the coefficient $\beta_1$ is positive if, over time within firms, the innovation related to introduce new products is associated with higher volatility of productivity. $\beta_2$ has a similar interpretation for the innovation related to improve current products and productive processes. Prediction 1 is verified if $\beta_1$ is significantly larger when estimating equation 26 on younger firms. The first three columns of Table 7 show estimation results for all firms, for firms $\leq$ 10 years old, and for firms $\leq$ 7 year old, respectively. The results show that the $R\&D_{prodinn_i,s}$ coefficient significantly increases for younger firms, indicating that when younger firms invest in product innovation, they experience larger increases in the volatility of productivity than older firms, thus confirming Prediction 1. As a further confirmation, the increase in the coefficient of $R\&D_{other_i,s}$ for younger firms is much smaller and less statistically significant. For comparison, the last three columns of Table 7 repeat the same procedure on simulated data from the full model, and obtain very similar qualitative results.

### 6.2 Innovation and firm level productivity growth

Prediction 2 verifies the importance of innovation in driving the empirical relation between financing frictions and productivity growth. The model predicts that more radical innovation among young firms generates more incremental innovation among older firms, thus increasing productivity growth over the firm’s life cycle in less financially constrained sectors (see Figures 6 and 7). 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 8, columns 1 and 2 replicate the results obtained in the second part of Table 1. Columns 3 and 4 repeat the analysis after eliminating the firm-survey observations that reported doing R&D, and columns 5 and 6 repeat it after eliminating all the observations of firms that did R&D in at least one survey. The results show that the life-cycle profiles of productivity for firms in constrained and unconstrained groups are no longer significantly different, once innovating firms are excluded from the analysis, thus confirming Prediction 2.

### 6.3 Financial frictions and barriers to entry

Predictions 3 and 4 verify that financial frictions matter for productivity growth because they act as barriers to entry, not because borrowing constraints limit the ability of firms to invest in innovation. In order to verify Prediction 3, I repeat the estimation of equations 4

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16 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 $\beta_1$ and $\beta_2$ coefficients for an even lower age threshold. For the regressions in Section 3, the dependent variables $v_1^{i,s}$ and $v_2^{i,s}$ are constructed starting from more than 60000 firm-year observations of balance sheet data available in the sample (see Appendix 2 for details). Unfortunately, the innovation variables $R\&D_{prodinn_i,s}$ and $\beta_2R\&D_{other_i,s}$ only have one observation for each three-year survey, and they have little within-firm variation, both because few firms are present in more than one survey and because R&D is persistent over time for each firm.
Table 7: Relation between age and innovation

<table>
<thead>
<tr>
<th>In period s, $\sigma_{v_i,s}$</th>
<th>Empirical Data</th>
<th>Simulated data, full model</th>
</tr>
</thead>
<tbody>
<tr>
<td>All firms</td>
<td>Age $\leq$ 10</td>
<td>Age $\leq$ 7</td>
</tr>
<tr>
<td>$R&amp;D_{prodinn_i,s}$</td>
<td>0.052**</td>
<td>0.225***</td>
</tr>
<tr>
<td>(2.00)</td>
<td>(2.70)</td>
<td>(3.87)</td>
</tr>
<tr>
<td>$R&amp;D_{other_i,s}$</td>
<td>0.050**</td>
<td>0.114**</td>
</tr>
<tr>
<td>(2.36)</td>
<td>(1.97)</td>
<td>(1.46)</td>
</tr>
<tr>
<td>constant</td>
<td>0.395***</td>
<td>0.247***</td>
</tr>
<tr>
<td>(4.79)</td>
<td>(4.23)</td>
<td>(2.43)</td>
</tr>
<tr>
<td>Firm fixed effects</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Time dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>N. observations</td>
<td>9352</td>
<td>1754</td>
</tr>
</tbody>
</table>

Probit regression. Standard Errors, reported in parenthesis, are clustered at the firm level. $R&D_{prodinn_i,s}$ is equal to one if firm $i$ in survey $s$ does R&D spending larger than 0.5% of sales, and at least part of this spending is directed to develop and produce new products. $R&D_{other_i,s}$ is equal to one if firm $i$ in survey $s$ does R&D spending larger than 0.5% of sales but all R&D spending is directed to improve current products or productive processes. $Dage_{i,s}$ is equal to 1 if firm $i$ in survey $s$ belongs to age group $l \in \{1, 2, 3, 4\}$, and is equal to zero otherwise. $l = 1$ indicates firms with age up to 10 years, and $l = 2, 3, 4$ indicates firms aged 11-20, 21-30 and 31-40 years, respectively. Control variables include 2 digit sector dummies and time dummies. $\text{constrained}_i$ is equal to one if firm $i$ belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

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

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>All observations</th>
<th>Firm-survey obs. with positive R&amp;D excluded</th>
<th>Firms with some positive R&amp;D excluded</th>
</tr>
</thead>
<tbody>
<tr>
<td>$age_{i,s}$</td>
<td>0.00427</td>
<td>0.0102***</td>
<td>0.0145</td>
</tr>
<tr>
<td>(1.13)</td>
<td>(5.72)</td>
<td>(0.80)</td>
<td>(17.54)</td>
</tr>
<tr>
<td>$age_{i,s} \times \text{constrained}_i$</td>
<td>-0.0118**</td>
<td>-0.00499**</td>
<td>-0.0108*</td>
</tr>
<tr>
<td>(-2.37)</td>
<td>(-2.10)</td>
<td>(-1.67)</td>
<td>(-0.53)</td>
</tr>
<tr>
<td>N. observations</td>
<td>12776</td>
<td>13505</td>
<td>10608</td>
</tr>
<tr>
<td>Adj. R-sq.</td>
<td>0.002</td>
<td>0.013</td>
<td>0.002</td>
</tr>
<tr>
<td>Firm fixed effects</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Time dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Panel regression with firm fixed effect. Time effects are also included. Standard errors clustered at the firm level. T-statistic reported in parenthesis. $\overline{v}_{i,s}^2$ is a measure of productivity consistent with the model developed in section 4, and $\overline{v}_{i,s}^2$ is total factor productivity computed following the procedure of Hsieh and Klenow (2009). $age_{i,s}$ is age in years for firm $i$ in survey $s$. $\text{constrained}_i$ is equal to one if firm $i$ belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10% level respectively.
Table 9: Relation between age and productivity (excluding currently constrained firms)

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>All observations</th>
<th>Currently constrained firms excluded</th>
<th>Currently constrained firms excluded</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\vec{v}_{1,i,s}^{*})</td>
<td>0.00427</td>
<td>0.0102***</td>
<td>0.00393</td>
</tr>
<tr>
<td>(\vec{v}_{2,i,s}^{*})</td>
<td>(1.13)</td>
<td>(5.72)</td>
<td>(0.98)</td>
</tr>
<tr>
<td>(\vec{v}_{1,i,s}^{*})</td>
<td>0.00393</td>
<td>0.0110**</td>
<td>0.0115**</td>
</tr>
<tr>
<td>(\vec{v}_{2,i,s}^{*})</td>
<td>(0.98)</td>
<td>(5.80)</td>
<td>(2.3)</td>
</tr>
<tr>
<td>age (i,s)</td>
<td>0.0115**</td>
<td>0.0133**</td>
<td></td>
</tr>
<tr>
<td>(\vec{v}_{1,i,s}^{*})</td>
<td>(2.3)</td>
<td>(5.57)</td>
<td></td>
</tr>
<tr>
<td>(\vec{v}_{2,i,s}^{*})</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>age (i,s) * constrained (i)</td>
<td>-0.0118**</td>
<td>-0.00499**</td>
<td>-0.00969*</td>
</tr>
<tr>
<td>(\vec{v}_{1,i,s}^{*})</td>
<td>(-2.37)</td>
<td>(-2.10)</td>
<td>(-1.82)</td>
</tr>
<tr>
<td>(\vec{v}_{2,i,s}^{*})</td>
<td></td>
<td></td>
<td>(-1.67)</td>
</tr>
<tr>
<td>age (i,s) * midconstr (i)</td>
<td>-0.0185**</td>
<td>-0.00605*</td>
<td></td>
</tr>
<tr>
<td>(\vec{v}_{1,i,s}^{*})</td>
<td>(-2.74)</td>
<td>(-1.83)</td>
<td></td>
</tr>
<tr>
<td>(\vec{v}_{2,i,s}^{*})</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>age (i,s) * highconstr (i)</td>
<td>-0.0173**</td>
<td>-0.00693**</td>
<td></td>
</tr>
<tr>
<td>(\vec{v}_{1,i,s}^{*})</td>
<td>(-2.68)</td>
<td>(-2.25)</td>
<td></td>
</tr>
<tr>
<td>(\vec{v}_{2,i,s}^{*})</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N. observations</td>
<td>12776</td>
<td>13505</td>
<td>11362</td>
</tr>
<tr>
<td>Adj. R-sq.</td>
<td>0.002</td>
<td>0.013</td>
<td>0.001</td>
</tr>
<tr>
<td>Firm fixed effects</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Time*group dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

Panel regression with firm fixed effect. Time effects are also included. Standard errors clustered at the firm level. T-statistic reported in parenthesis. \(\vec{v}_{1,i,s}^{*}\) is a measure of productivity consistent with the model developed in section 4, and \(\vec{v}_{2,i,s}^{*}\) is total factor productivity computed following the procedure of Hsieh and Klenow (2009). age \(i,s\) is age in years for firm \(i\) in survey \(s\). constrained \(i\) is equal to one if firm \(i\) belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. ***, **, * denote significance at a 1%, 5% and 10% level respectively.

and 5 after excluding firms which are currently declaring financing problems. Table 9 shows that the coefficient of constrained \(i\) interacted with age is still negative and significant in all specifications, thus confirming Prediction 1. This finding is important because it validates ex post the strategy used to identify more financially constrained sectors. As argued in Section 3, the approach of using firms declaring financing constraints to measure the intensity of financing frictions at the sector level, but then excluding them from the analysis of the age-productivity relation, ensures that the main results of the analysis are robust to a reverse causality problem where poor growth opportunities cause lack of access to credit.

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

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

Where \(r_{i,t}\) is total revenues and \(m_{i,t}\) are variable costs for firm \(i\) in survey \(s\). I calculate the average of \(PCM_{i,s}\) for each 4-digit sector and generate a dummy which is equal to one if firm \(i\) belongs to one of the 50% of sectors with highest price-cost margin, and zero otherwise, called lowcomp. I interact this dummy variable with age in a regression similar to the one performed in Table 1. Table 10 shows the regression results. The estimated difference in the relation between age and productivity among different groups is remarkably similar to the one estimated in table 1, for all productivity measures. In other words, the low competition
Table 10: Relation between age and productivity - sectors selected according to competition (empirical sample)

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>$\hat{v}_{i,s}^1$</th>
<th>$\hat{v}_{i,s}^2$</th>
<th>$\hat{v}_{i,s}^3$</th>
<th>$\hat{v}_{i,s}^4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>age$_{i,s}$</td>
<td>0.00299</td>
<td>0.0109**</td>
<td>0.0204</td>
<td>0.0103**</td>
</tr>
<tr>
<td></td>
<td>(0.83)</td>
<td>(6.55)</td>
<td>(0.53)</td>
<td>(5.75)</td>
</tr>
<tr>
<td>age$<em>{i,s}$*lowcomp$</em>{i}$</td>
<td>$-0.0110^{**}$</td>
<td>$-0.00721^{***}$</td>
<td>$-0.00954^{**}$</td>
<td>$-0.00603^{**}$</td>
</tr>
<tr>
<td></td>
<td>($-2.41$)</td>
<td>($-3.33$)</td>
<td>($-1.92$)</td>
<td>($-2.54$)</td>
</tr>
<tr>
<td>N. observations</td>
<td>12776</td>
<td>13505</td>
<td>12776</td>
<td>13505</td>
</tr>
<tr>
<td>Adj. R-sq.</td>
<td>0.001</td>
<td>0.013</td>
<td>0.001</td>
<td>0.014</td>
</tr>
<tr>
<td>Firm fixed effects</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Time dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Time*group dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

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

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 C of Table 6 and confirm Prediction 4.17

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

17Note that the correlation between the average of the price cost margin $PCM_s$ and the fraction of constrained firms $\text{constrained}_s$ 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 $\sigma$. 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 $\sigma$. In Panel C of Table 6, I have shown simulation results where competition varies because of different entry costs. Simulations where changes in competition are caused by variations in $\sigma$ yield very similar results.
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.

References


8 Appendix 1

In order to obtain a numerical solution for the value functions $V^0_t(a_t, \varepsilon_t, v_t)$, $V^1_t(a_t, \varepsilon_t, v_t)$, $V^2_t(a_t, \varepsilon_t, v_t)$, $V^*_t(a_t, \varepsilon_t, v_t)$ and $V_t(a_t, \varepsilon_t, v_t)$ I consider values of $a_t$ in the interval between 0 and $\pi$, where $\pi$ 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 $\varepsilon_t$ is modeled as a two-state symmetric Markov process. The productivity state $v_t$ is a grid of $N$ points, where $v_n = \frac{1}{(1+g)^{n-1}}$ for $n = 1, ..., N$. $N$ is chosen to be equal to 120, which is a value large enough so that, conditional on the other parameter values, no firm remains in operation when $v = \frac{1}{(1+g)^{N-1}}$.

In order to solve the dynamic problem, I first make an initial guess of the equilibrium aggregate price $P$. Based on this guess, I calculate the optimal value of $V_t(a_t, \varepsilon_t, v_t)$ using an iterative procedure. I then apply the zero profits condition (23) and update the guess of $P$ accordingly. I repeat this procedure until the solution converges to the equilibrium. I then simulate an artificial industry in which, every period, the total number of new entrants ensures that condition (6) is satisfied.

9 Appendix 2

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

Since some firms are kept in the sample for more than one survey, I have a total of 13601 firm-survey observations, of which 9502 are observations of firms appearing in only one survey, 3364 are observations of firms appearing in two surveys, and 735 are observations of firms appearing in all 3 surveys. Table 11 shows the list of 2 digit sectors included in the final sample (5 sectors with less than 50 firms are excluded) and the fraction of firms in the constrained and unconstrained groups.

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

I obtain the information on innovation in the section of the Survey on “Technological innovation and R&D”, where firms are asked whether they engaged, in the previous three years, in R&D expenditure. The firms that answer yes are asked what percentage of this expenditure was directed towards: i) improving existing products; ii) improving existing
Table 11: Frequency of constrained and unconstrained firms in each 2 digit manufacturing sector

<table>
<thead>
<tr>
<th>Sector</th>
<th>2 digits Ateco 91 code</th>
<th>n. observations</th>
<th>Fraction of firms in the group of 50% most constrained 4 digits sectors</th>
<th>Fraction of firms in the group of 50% least constrained 4 digits sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food and Drinks</td>
<td>15</td>
<td>1037</td>
<td>75%</td>
<td>25%</td>
</tr>
<tr>
<td>Textiles</td>
<td>17</td>
<td>1224</td>
<td>30%</td>
<td>70%</td>
</tr>
<tr>
<td>Shoes and Clothes</td>
<td>18</td>
<td>571</td>
<td>38%</td>
<td>62%</td>
</tr>
<tr>
<td>Leather products</td>
<td>19</td>
<td>564</td>
<td>87%</td>
<td>13%</td>
</tr>
<tr>
<td>Wood Furniture</td>
<td>20</td>
<td>357</td>
<td>65%</td>
<td>35%</td>
</tr>
<tr>
<td>Paper</td>
<td>21</td>
<td>408</td>
<td>72%</td>
<td>28%</td>
</tr>
<tr>
<td>Printing</td>
<td>22</td>
<td>500</td>
<td>51%</td>
<td>49%</td>
</tr>
<tr>
<td>Chemical, Fibers</td>
<td>24</td>
<td>650</td>
<td>43%</td>
<td>57%</td>
</tr>
<tr>
<td>Rubber and Plastic</td>
<td>25</td>
<td>755</td>
<td>44%</td>
<td>56%</td>
</tr>
<tr>
<td>Non-metallic products</td>
<td>26</td>
<td>886</td>
<td>76%</td>
<td>24%</td>
</tr>
<tr>
<td>Metals</td>
<td>27</td>
<td>665</td>
<td>49%</td>
<td>51%</td>
</tr>
<tr>
<td>Metallic products</td>
<td>28</td>
<td>1264</td>
<td>69%</td>
<td>31%</td>
</tr>
<tr>
<td>Mechanical Products</td>
<td>29</td>
<td>2187</td>
<td>42%</td>
<td>58%</td>
</tr>
<tr>
<td>Electrical Products</td>
<td>31</td>
<td>550</td>
<td>90%</td>
<td>10%</td>
</tr>
<tr>
<td>Television and comm.</td>
<td>32</td>
<td>320</td>
<td>45%</td>
<td>55%</td>
</tr>
<tr>
<td>Precision instruments</td>
<td>33</td>
<td>199</td>
<td>75%</td>
<td>25%</td>
</tr>
<tr>
<td>Vehicles</td>
<td>34</td>
<td>285</td>
<td>75%</td>
<td>25%</td>
</tr>
<tr>
<td>other manufacturing</td>
<td>36</td>
<td>696</td>
<td>62%</td>
<td>38%</td>
</tr>
</tbody>
</table>
productive processes; iii) introducing new products; iv) introducing new productive processes; v) other objectives.

10 Appendix 3

Derivation of productivity measure \( v_{i,t} \).

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

\[
\pi_t (\nu_t, \varepsilon_t) = \frac{(\sigma - 1)^{\sigma - 1}}{\sigma} \frac{\eta}{\sigma - 1} - F_t
\]

I divide both sides by \( F_t \) and take logs:

\[
\log \left( \frac{\pi_t (\nu_t, \varepsilon_t)}{F_t} \right) = \log \left( \frac{\frac{(\sigma - 1)^{\sigma - 1}}{\sigma} \frac{\eta}{\sigma - 1} - F_t}{F_t} - 1 \right)
\]

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

\[
\log \left( \frac{\pi_t (\nu_t, \varepsilon_t)}{F_t} \right) = \log \left( \frac{\frac{(\sigma - 1)^{\sigma - 1}}{\sigma} \frac{\eta}{\sigma - 1} - F_t}{\frac{\eta}{\sigma} - \lambda} - 1 \right)
\]

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

\[
\log \left( \frac{\frac{(\sigma - 1)^{\sigma - 1}}{\sigma} \frac{\eta}{\sigma - 1} - F_t}{\frac{\eta}{\sigma} - \lambda} - 1 \right) \approx \log \frac{\pi}{F} + \frac{\bar{\nu}}{\Psi} \bar{\nu}
\]

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

\[
\log \pi_{i,t} = a + \log F_{i,t} + v_{i,t}^1
\]

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

$$O_{i,t} = \left(\frac{w_{i,s}^{WC}}{w_{i,s}^{TOT}}\right) w_{i,t}^{TOT} \quad (31)$$

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

$$F_{i,t} = cO_{i,t}^d \quad (32)$$

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

11 Appendix 4

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

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

where $\kappa_i$ and $\gamma_t$ are firm and year fixed effects, respectively, and $\sigma = 4$. I use the following
variables: added value $py$ is sales minus cost of variable inputs used during the period plus
capitalized costs minus cost of services; capital $pk$ is the book value of fixed capital; labour
$wl$ is the total wage cost; I follow the methodology of Levinshon and Petrin (2003) and I
use the cost of variable inputs to control for unobservable productivity shocks. I also include
yearly dummies. In order to eliminate outliers, I exclude from the estimation all firm-year
observations with values of $\frac{y}{k}$ and $\frac{y}{l}$ larger than the 99% percentile and smaller than the 1%
percentile. I estimate the production function separately for each 2 digit sector for which I
have at least 50 firms in the dataset.

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

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

\[
\hat{v}_{i,s} = \beta_0 + \sum_{l=1}^{n} \beta_u^l (unconstr_i \ast age_{i,s}^l) + \sum_{l=1}^{n} \beta_m^l (midconstr_i \ast age_{i,s}^l) + \\
\sum_{l=1}^{n} \beta_h^l (highconstr_i \ast age_{i,s}^l) + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \epsilon_{i,s} 
\]  

(34)

I construct a set of variables age\(^l\) which is equal to the age of the firm if the firm is in 
group l, and zero otherwise. The index \(l = 1, 2, 3, 4\) indicates the age intervals, with \(l = 1\) 
indicates firms with age up to 10 years, and \(l = 2, 3, 4\) indicates firms aged 11-20, 21-30 and 
31-40 years, respectively. Firms older than 40 years are excluded from the estimation. The 
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 \(\beta_h^1,...,\beta_h^4\) 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.