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

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Abstract

This paper develops the model of an industry with heterogeneous firms, and studies the effect of financing frictions on the trade-off between radical innovations, risky but potentially able to generate huge improvements in productivity, and incremental innovations. The model shows that financing friction increase bankruptcy probability for young and financially fragile firms, and reduce entry and competition. Therefore firms that survive, and accumulate enough financial wealth to become financially unconstrained, operate in a less competitive environment, are profitable also at relatively low productivity levels, and are less willing to engage in risky innovation activity. Simulation results show that, for realistic parameter values, lower radical innovation slows down productivity growth along the firms’ life-cycle, reducing aggregate productivity by up to 21%. I test and confirm the main predictions of the model on a sample of 11429 Italian manufacturing firms with direct survey information on financing frictions an on innovation decisions.

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1 Introduction

Innovation and technology adoption are fundamental forces that shape firm dynamics and aggregate productivity growth. New firms bring new ideas and are better suited to introduce radical innovations that generate permanent improvements in aggregate productivity. However new firms are also more likely to face financing frictions, which may distort their investment and innovation decisions. Hsieh and Klenow (2014) show that US manufacturing plants on average increase their productivity 9 times 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 1.7 times and 2 times, respectively, along the plants life-cycle. Financial imperfections related to lower financial development in these countries could play an important role in explaining these differences.

In this paper I develop an industry model to study how financial factors affect entry, exit, and different types of innovation decisions of firms. I calibrate and solve the model and simulate several industries with varying degree of financial frictions. I show that the different life cycle dynamics between financially constrained and unconstrained simulated industries are consistent with the empirical evidence of Hsieh and Klenow (2014). Moreover I also directly test and confirm the main predictions of the model using a dataset of Italian Manufacturing firms with both balance sheet and qualitative survey information on innovation and on financial frictions.

In the model firms are monopolistically competitive, and draw their productivity from an initial distribution after they pay a fixed cost to enter production. Their productivity depreciates at a constant rate every period, because of technological obsolescence, unless they choose to invest in one of two types of innovation, "radical" innovation or "incremental" innovation.

Radical innovation is risky but potentially able to generate a large increase in productivity relative to the competitors. It is risky both because it fails with positive probability, and because conditional on failing the firms' productivity is reduced 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 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. This type of innovation is similar to the concept of radical innovation as it is defined in management studies. For example Utterback (1996) defines radical innovation as a "change that sweeps away much of a firm's existing investment in technical skill and knowledge, designs, production technique, plant and equipment".

Incremental innovation, is less risky than radical innovation, both because is more likely to succeed, and because in case of failure the firms can keep operating with its current technology. However if it succeeds it only increases productivity by "one step", thus maintaining its position relative to the competitors and avoiding obsolescence.

In the absence of financial frictions, the interplay between these different innovation types generates lifecycle dynamics of firms whereby young firms are more likely to invest in radical innovation, have more volatile growth rates, and grow faster in terms of both size and productivity, while older firms are on average more productive, more likely to invest in incremental innovation to maintain their position, and have less volatile growth rates. The implied behaviour of firms is therefore consistent with several stylized facts on firms dynamics as well as with the empirical evidence by Hsieh and Klenow (2014) on US manufacturing plants.

To this framework I add financial frictions, by assuming that firms face borrowing constraints and are hit by idiosyncratic revenue shocks. Their profits are volatile and in the absence of sufficient internal finance they are forced to liquidate after a negative shock, even if they are still productive. I solve the model and show that financing frictions have both direct and indirect effects on innovation. First, they directly negatively affect both types of innovation, for firms that cannot innovate because they lack internal funds. Second, financing friction increase bankruptcy probability for young and financially fragile firms, and reduce entry and competition. Lower competition increases the expected profits from a successful innovation and this "Shumpeterian effect" makes incremental innovation more desirable. However lower competition also increases current profits for firms that do not innovate, and raises the cost of failing in radical innovation, thus discouraging it. In other words, financing frictions increase the chances that firms go bankrupt in the early stages of their life. Firms that survive this
phase and accumulate enough financial wealth to become financially unconstrained, operate in a less competitive environment, are profitable also at relatively low productivity levels, and have a lower propensity to attempt a risky innovation process. Lower radical innovation among young firms in the financially constrained industry implies that fewer firms become large and profitable enough to invest in incremental innovation. This reduces the rate of productivity growth at the firm level and aggregate productivity. I calibrate the model with realistic parameter values and show that financing frictions, because of their negative effect on radical innovation, reduce aggregate TFP by up to 21%.

Finally, I test several predictions of the model on a panel of 11429 Italian manufacturing firms, for which I have direct survey information on both financing frictions and on the innovation decisions of firms, as well as balance sheet data, and I find that: i) the life cycle and innovation decisions of firms significantly differ across groups of sectors selected according to the intensity of financing frictions; ii) these different dynamics are consistent with the predictions of the model, and are significantly related to both R&D intensity and to differences in competition across sectors.

This paper is related to several strands of literature. Many authors have recently emphasized the importance of innovation to understand firm dynamics and productivity growth in models with heterogeneous firms (among others, see Klette and Kortum, 2004, Akcigit and Kerr, 2010 and Acemoglu, Akcigit and Celik, 2014). In common with these papers, in my paper radical innovation is modeled as an innovation decision 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), who notice that R&D increases 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.

My paper is also closely related to the literature on financing frictions and firm dynamics, such as Buera, Kaboski, and Shin (2011) and Caggese and Cunat (2013). In particular, the paper is related to Midrigan and Xu (2014), who show that financing frictions may 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 firms accumulate financial wealth and financial frictions become almost irrelevant for the efficient allocation of resources. My model shares this self financing feature, and yet shows a novel indirect channel of financial frictions on innovation decisions, with significant aggregate consequences.

Finally, the paper is also related to the literature on competition and innovation (among others, see Aghion et al., 2005). In my model financing frictions affects innovation decisions mainly indirectly, by affecting entry, competition and profitability. Thus I provide a novel explanation to 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).

2 Model

I consider an industry with firm dynamics and monopolistic competition as in Melitz (2003). To this framework I introduce financial frictions and different types of innovation. Each firm in the industry produces a variety \( w \) of a consumption good. There is a continuum of varieties \( w \in \Omega \). Consumers preferences for the varieties in the industry are C.E.S. with elasticity \( \sigma > 1 \). The C.E.S. price index \( P_t \) is then equal to:

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

And the associated quantity of the aggregated differentiated good \( Q_t \) is:

\[
Q_t = \left[ \int_{w} q_t(w)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{2}
\]

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

\[
Q_t = AP_t^{1-\eta} \tag{3}
\]

where \( A \) is an exogenous demand parameter and \( \eta < \sigma \) is the industry price elasticity of demand. From (2) and (3) the demand for an individual variety \( w \) is:

\[
q_t(w) = A \frac{P_t^{\sigma-\eta}}{p_t(w)^{\eta}} \tag{4}
\]
Each variety is produced by a firm using labour. I assume that the marginal productivity of labour for the frontier technology is equal to \( \bar{v}_t \), and it grows every period at the gross rate \( g > 1 \). To normalize the model, I assume that labour cost also grows at the same rate and is also equal to \( \bar{v}_t \). I define \( v_t^\alpha \) as the marginal productivity of labour for the firm and as \( v_t = v^\alpha / \bar{v}_t \) its relative productivity. Therefore marginal labour cost for a firm with relative productivity \( v_t \) and variety \( w \) are given by:

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

(5)

Since all the formulas are identical for all varieties, I drop the indicator \( w \) from now on. Firms are heterogeneous in terms of productivity \( v_t \) and fixed costs \( F > 0 \). 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:

\[
F_t = F + \varepsilon_t
\]

where \( F \) is a positive constant. The shock \( \varepsilon_t \) introduces uncertainty in profits and affects the accumulation of wealth and the the probability of default. It 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.\(^1\) 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:

\[
p_t = \frac{\sigma}{\sigma - 1} \frac{1}{v_t}
\]

(6)

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

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

The timing of the model for a firm which was already in operation in period \( t - 1 \) is the following. At the beginning of period \( t \) with probability \( \delta \) its technology becomes

\(^1\)A multiplicative shock of the type \( \varepsilon_t p_t q_t \) would not change the qualitative results of the model, but it would have two main consequences. First, 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 problem more complicated. Second, it would imply that expected profits are a function of the volatility of the shock \( \varepsilon_t \).
useless forever, and the firm liquidates all its assets and stops activity. With probability $1 - \delta$ the firm is able to continue with the current technology. It observes the realization of the shock $\varepsilon_t$ and receives profits $\pi_t$, and its financial wealth $a_t$ is:

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

(7)

where $d_t$ are dividends and $I_{t-1} \in \{0, 1, 2\}$ is an indicator function that is equal to 1,2 if the firm decided to invest in type 1 or type 2 innovation, respectively, in period $t - 1$. It is equal to 0 if the firm did not innovate in period $t - 1$. $K(I_{t-1})$ is the cost of innovation. Financing frictions are introduced by following Caggese and Cúñat (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:

$$a_t \geq F_t,$$

(8)

and innovation of type $I_t$ is feasible only if:

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

(9)

If the constraint (8) is not satisfied, then the firm cannot continue its activity and is forced to liquidate. Conditional on continuation, Given the presence of financing frictions, and the fact that the firm discounts future profits at the constant interest rate $R$, it is trivial to show that it is never optimal for the firm 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 voluntarily exit if it is not profitable enough to cover the fixed per period cost $F$. In this case the firm voluntarily liquidates and ceases to operate forever.

Conditional on continuation, with probability $\gamma$ the firm has the opportunity to implement a radical innovation project, and it has to choose between three alternatives, with $I_t \in \{0, 1, 2\}$, as illustrated in figure 1:

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2 Constraint (8) is a simple way to introduce financing frictions in the model. Nonetheless it generates realistic firm dynamics, and can be interpreted as a shortcut for more realistic models of firm dynamics with financing frictions, such as, for instance, Clementi and Hopenhayn (2006).
Figure 1: Productivity dynamics conditional on the innovation decision

i) If the firm does not innovate \((I_t = 0)\), it does not pay any innovation cost \((K(0) = 0)\), but its technology depreciates at the rate \(g > 0\).

ii) If the firm chooses type 1 \((I_t = 1)\) or "incremental" innovation, it invests an amount equal to \(K(1) > 0\) to marginally improve its technology with probability \(\xi^{INC}\). If successful, the firms’ productivity \(v^n\) increases by \(g\) and its relative productivity \(v\) remains constant, otherwise with probability \(1 - \xi^{INC}\) \(v\) depreciates at the rate \(g\). Incremental innovation is a type of innovation that tries to improve on the current technology without radical changes to the products and production processes. If innovation is not successful it means that the innovation process generated new ideas and knowledge which were not useful in increasing productivity, and therefore were not applied to the firm production process.

iii) If the firm chooses type 2 \((I_t = 2)\) or "radical" innovation, it will invests an amount equal to \(K(2) > 0\) and will be successful with probability \(\xi^{rad}(v)\). Otherwise will fail with probability \(1 - \xi^{rad}(v)\). I assume that success probability \(\xi^{rad}(v)\) is a monotonous function of productivity \(v\). In case of success \(v_{t+1}\) jumps up relative to \(v_t\), and it becomes equal to the maximum between \((1 + g)^\tau v_t\) and 1 (the frontier technology). In case of failure \(v_t\) jumps down to \(\frac{v_t}{(1+g)^\tau}\). Therefore the term \(\tau > 1\) measures both the downside and upside risk of radical innovation, which represents a decision to radically change the firm’s organizational structure and/or to invest in...
new technologies, products and production processes.\(^3\) 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.

With probability \(1 - \gamma\) the firm does not have the option to invest in radical innovation, then it can only choose \(I_t \in \{0, 1\}\). The assumptions about the innovation technology are summarized below:

**Technology assumption 1:** both innovation technologies are costly: \(K(1) > 0, K(2) > K(0) = 0\).

**Technology assumption 2:** Both innovation types are risky: \(1 > \xi^{INC} > 0; 1 > \xi^{RAD}(v) > 0\). Moreover radical innovation probability is a monotonous function of productivity \(v\).

**Technology assumption 3:** The outcome of radical innovation implies a larger change in productivity than the outcome of incremental innovation: \(\tau > 1\)

Even though ex ante I do not impose any restriction on the sign of \(\frac{\partial \xi^{rad}(v)}{\partial v}\), from the calibration it follows that necessary conditions for the model to match the empirical moments about innovation are \(\frac{\partial \xi^{rad}(v)}{\partial v} > 0\) and \(\xi^{INC} > \xi^{rad}(v)\) for all values of \(v\). These conditions are realistic, they imply that radical innovation is less likely to succeed than incremental innovation and that more productive firms are more likely to succeed in radical innovation than less productive ones.

I define \(V^{I}_t(a_t, \varepsilon_t, v_t)\) as the value function after receiving \(\pi_t\) and conditional on doing incremental innovation:\(^4\)

\[
V^{I}_t(a_t, \varepsilon_t, v_t) = -K(1) + \frac{1 - \delta}{R}\left\{\xi^{INC} E_t\left[\pi_{t+1}(\varepsilon_{t+1}, v_t) + V^{I}_{t+1}(a_{t+1}, \varepsilon_{t+1}, v_t)\right] + (1 - \xi^{INC}) E_t\left[\pi_{t+1}(\varepsilon_{t+1}, \frac{v_t}{1+g}) + V^{I}_{t+1}(a_{t+1}, \varepsilon_{t+1}, \frac{v_t}{1+g})\right]\right\}
\]

Then I define \(V^{2}_t(a_t, \varepsilon_t, v_t)\) as the value function today conditional on doing radical innovation:

\(^3\)This symmetric structure is not essential for the results, but is convenient to simplify the calibration. The qualitative and quantitative results of the model are confirmed under alternative hypotheses regarding radical innovation, as long as the drop in productivity conditional on failure is not negligible.

\(^4\)I define the value of the firm as the net present value of future profits. Since the discount factor of the firm is \(1/R\), and the firm is risk neutral, this value coincides with the net present value of expected dividends.
\[ V_t^2(a_t, \varepsilon_t, v_t) = -K(2) + \frac{1 - \delta}{R} \left\{ \xi^{RAD}(v_t) E_t \left\{ \pi_{t+1}^\varepsilon \left[ \varepsilon_{t+1}, v_t \right] \right\} + \left[ 1 - \xi^{RAD}(v_t) \right] E_t \left[ \pi_{t+1}^\varepsilon \left( \frac{v_t}{1+g} \right) \right] + V_{t+1} \left( a_{t+1}, \varepsilon_{t+1}, \frac{v_t}{1+g} \right) \right\} \]

And finally, the value function conditional on not innovating is:

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

The firm then makes the innovation decision \( I_t \) which maximizes its value:

\[ V_t^* = \gamma \max_{I_t \in \{0,1,2\}} \{ V_t^0 (a_t, \varepsilon_t, v_t), V_t^1 (a_t, \varepsilon_t, v_t), V_t^2 (a_t, \varepsilon_t, v_t) \} \]

\[ + (1 - \gamma) \max_{I_t \in \{0,1,2\}} \{ V_t^0 (a_t, \varepsilon_t, v_t), V_t^1 (a_t, \varepsilon_t, v_t) \} \] (10)

such that equation (9) is satisfied. Given the optimal innovation decision conditional on continuation, the value of the firm at the beginning of time \( t \), \( V_t (a_t, \varepsilon_t, v_t) \), is:

\[ V_t (a_t, \varepsilon_t, v_t) = 1(a_t \geq F_t) \left\{ \max [V_t^* (a_t, \varepsilon_t, v_t), 0] \right\} \] (11)

Equation 11 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 (8) is not satisfied. Second, when value in the curly brackets is equal to zero, which indicates that the firm is not profitable enough and exits from production.

### 2.1 Entry decision

Every period there is free entry. 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, after having paid an initial cost \( S^C \). Once they learn their type they decide whether or not to start activity. If they start, then draw \( \varepsilon_0 \) from an initial uniform distribution. The free entry condition requires that ex ante the expected value of paying \( S^C \) conditional on the expectation of the initial value of the shock \( \varepsilon_0 \) is zero:

\[ \int_{\varepsilon_0}^{1} \max \{ E^{\varepsilon_0} [V_0 (a_0, v_0, \varepsilon_0)], 0 \} f(v_0)dv_0 - S^C = 0 \] (12)
2.2 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 (12) is satisfied. The number of firms in equilibrium ensures that $P_t$ also satisfies the aggregate price equation (1). Aggregation is very simple because all operating firms with productivity $v$ choose the same price $p(v)$, as determined by (6).

3 Model’s solution and simulations.

In the next subsections I illustrate the calibration of the model and the firm dynamics in the simulated industries.

3.1 Calibration

The parameters are illustrated in Table 1, and are calibrated to match a set of simulated moments with the moments estimated from the panel of Italian manufacturing firms analyzed in section 4. The only exceptions are the values of $S^C, \sigma, \eta$ and $r$, for which I choose values consistent with related studies.

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 $F$ and the size of the profits shock $\theta$ affect the cross sectional distribution and the variability of profits. They jointly match the fraction of firms reporting negative profits and the time series volatility of firm’s profits over sales. The distribution of productivity of new firms relative to the frontier is assumed to be

\footnote{The initial entry cost $S^C$ is set equal to 4. This is 1.3 times the average annual firm profits in the simulated industry. I experimented with larger and smaller values without obtaining a significant change in the results. The average real interest rate $r$ is equal to two percent, which is consistent with the average short-term real interest rates in Italy in the sample period. The value of $\sigma$, 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.}
lognormally distributed. Its mean value $\bar{\pi}$ is calibrated to match the ratio between the size of the firms at the 90th and 10th decile of the size distribution, where size is measured as total labour cost. Its variance $\sigma^2_\pi$ matches the average cross sectional standard deviation of TFP. The depreciation rate of technology $g$ is set to 1.009, which is the estimated yearly decline in TFP for firms which do not innovate, where innovation is measure as positive R&D expenditures in the data.

The calibration of the innovation parameters requires first to specify a functional form for the success probability of radical innovation $\xi^{RAD}(v)$. I assume the following:

$$\xi^{RAD}(v) = \kappa^1 - \kappa^2(1 - v)$$

Where $\kappa^1$ measures the success probability of radical innovation for a firm at the frontier ($v = 1$), and $\kappa^2$ is the marginal reduction in such probability for a marginal increase in the distance from the frontier. In order to calibrate the innovation parameters $\gamma$, $\kappa^1, \kappa^2, K(I = 1), K(I = 2)$ and $\xi^{INC}$ I need to specify a criterion to map the radical and incremental innovation types in the model with analogous types in the data. Unfortunately in the empirical data there is no direct measure of how radical innovation is. The surveys distinguish between R&D directed to improve existing products and R&D to introduce new products, but there is no measure of how "radical" these new products are. However, the third survey on the Italian Manufacturing firms covering the 1998-2000 period includes additional information on the percentage of income due to new products introduced during the survey period. Radical innovation in the model can be interpreted as introducing new products that greatly increase income if successful or reduce it if unsuccessful. Since matching innovation moments in the data always requires $\kappa^1$ and $\kappa^2$ to be both positive and of similar magnitude, I assume for simplicity that $\kappa^1 = \kappa^2$ and I calibrated them follows: the probability $\gamma$ to have the option to invest in radical innovation and the value of $\kappa^1 = \kappa^2$ jointly match the percentage of firms with more than 15% of income from new product in each period, and the percentage of firms doing R&D. The innovation costs $K(I = 1)$ and $K(I = 2)$ jointly match the average cost of R&D expenditure over value added, and the fraction of firms exiting every period. The incremental innovation probability $\xi^{INC}$ matches the average age of firms.

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6The empirical value of 6% is calculated from Audretsch, Santarelli, and Vivarelli (1999), who analyse a dataset similar to mine.
### Table 1: Calibration

<table>
<thead>
<tr>
<th>Matched parameters</th>
<th>Value</th>
<th>Moment to match</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F$</td>
<td>0.5</td>
<td>Fraction of firms with negative profits</td>
<td>0.31</td>
<td>0.35</td>
</tr>
<tr>
<td>$\tau$</td>
<td>1</td>
<td>Ratio between 90th percentile and 10th percentile of size distr.</td>
<td>13.2</td>
<td>10.55</td>
</tr>
<tr>
<td>$\sigma^2_v$</td>
<td>0.969</td>
<td>avg. cross sect. std. of TFP</td>
<td>0.341</td>
<td>0.34</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.15</td>
<td>average of time series st.dev. of profits/sales at the firm level</td>
<td>0.0582</td>
<td>0.079</td>
</tr>
<tr>
<td>$g$</td>
<td>1.009</td>
<td>average yearly decline in TFP for non innovating firms.</td>
<td>0.9%</td>
<td>0.9%</td>
</tr>
<tr>
<td>$K(I = 1)$</td>
<td>0.6</td>
<td>average r&amp;d/value added</td>
<td>6.21</td>
<td>4.3</td>
</tr>
<tr>
<td>$K(I = 2)$</td>
<td>3</td>
<td>Fraction of exiting firms</td>
<td>6%</td>
<td>8.8%</td>
</tr>
<tr>
<td>$\xi^{inc}$</td>
<td>0.8</td>
<td>average age of firms</td>
<td>24.4</td>
<td>29.2</td>
</tr>
<tr>
<td>$\tau$</td>
<td>10</td>
<td>Sensitivity analysis</td>
<td>n.a.</td>
<td>n.a.</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.28</td>
<td>% of firms with more than 15% of income from new products.</td>
<td>19.2%</td>
<td>22.4%</td>
</tr>
<tr>
<td>$\kappa^1$</td>
<td>0.88</td>
<td>% of firms doing R&amp;D</td>
<td>34%</td>
<td>32.9%</td>
</tr>
<tr>
<td>$\kappa^2$</td>
<td>$\kappa^1$</td>
<td>n.a.</td>
<td>n.a</td>
<td>n.a</td>
</tr>
<tr>
<td>$a_0$</td>
<td>0.55</td>
<td>% of firms going bankrupt every period</td>
<td>0.5%</td>
<td>0.5%</td>
</tr>
<tr>
<td>$A$</td>
<td>25010</td>
<td>Number of firms</td>
<td>3500</td>
<td>3500</td>
</tr>
<tr>
<td>Other parameters:</td>
<td></td>
<td>$S_C = 4; r = 2%; \eta = 1.5; \sigma = 4$.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Profits denote operative profits.

1. The 1% outliers on both tails are excluded.
2. Standard deviation computed for each firm with at least 6 observations and then average across firms.

The parameter $\tau$, which measures the symmetric downside and upside risk of radical innovation, is the only technology parameter not explicitly matched to a specific empirical moment. I choose a benchmark value of $\tau = 10$, which implies that firms doing radical innovation increase their sales and profits between 10% and 40% (depending on their current productivity) if successful, and reduce it by a similar amount if unsuccessful. Finally, The parameter $a_0$, the initial wealth of new firms, affects the intensity of financing frictions and the probability of bankruptcy. I set a benchmark value such that 0.5% of firms go bankrupt every period. This corresponds to a reasonable average value for the Italian industry.\(^7\) Later on I compare simulation results across industries with different values of $a_0$. The scale parameter $A$ does not affect the results of the analysis and is calibrated to match the average number of firms in the sample.

---

\(^7\)As a comparison, business bankruptcies in Italy in the recent deep 2009-2012 recession have been around 2-3% per year.
3.2 Simulation results

In this section I simulate the benchmark industry as well as several industries with different degrees of financial frictions. I assume that all industries are identical, except that they have different values of the initial endowment $a_0$. The lower $a_0$, the higher the fraction of young firms that go bankrupt every period, or that have insufficient funds to invest in innovation.

Figures 2-4 compare 4 industries:

i) The benchmark industry, with $a_0 = 5.5$, which corresponds to 29% of $\bar{\sigma}$, where $\bar{\sigma}$ is average of firm income in the industry. In this industry 0.5% of firms go bankrupt every year and 0.2% of firms are prevented from innovating because of insufficient funds.

ii) An "unconstrained industry", with $a_0 = 30$, or 155% of $\bar{\sigma}$. In this industry no firm goes bankrupt and no firm is every financially constrained.

iii) A "moderately financially constrained industry", with $a_0 = 3$, or 22% of $\bar{\sigma}$. In this industry 1.8% of firms go bankrupt every year and 1.1% of firms are prevented from innovating because of insufficient funds.

iv) A "severely financially constrained industry", with $a_0 = 2$ or 16% of $\bar{\sigma}$. In this industry 3.4% of firms go bankrupt every year and 1.9% of firms are prevented from innovating because of insufficient funds.

In all industries firms that survive the first periods of operation retain sufficient earnings to self finance all expenditures, and therefore the liquidity constraint (9) is binding for a small fraction of firms.

I simulate each industry for 300 periods, and I use the last 150 periods to compute firm level and aggregate statistics. Figures 2-4 show the life cycle dynamics of innovation and productivity. I display the interval between 5 to 40 years of age, for which I can compute the empirical counterpart in the next section. Following Hsieh and Klenow (2014) I calculate the life cycle of firms, and therefore each figure represents average values for a cohort of firms that stay in operation during the whole period, thus excluding selection effects.

---

8 This assumption is a simple way to introduce industry level differences in the intensity of financing frictions, and has similar implication than 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).

9 This result is consistent with Midrigan and Xu (2014), who notice that binding financing constraints for operating firms have very little importance for aggregate investment and output, because in equilibrium firms avoid such constraints by accumulating financial wealth.

10 The first 150 observations are discarded because the industry has not yet converged to its time invariant distribution.
Figure 2 shows the probability that a firm innovates over its life cycle, in each industry, which is the sum of the fraction of firms with radical and incremental innovation. The benchmark industry and the unconstrained industry behave similarly, with a probability to innovate constantly increasing as firm’s become older. In the moderately constrained industry innovation increases less over the firms’ life cycle and is also lower on average, and it diminishes further in the severely financially constrained industry.

Figure 3 shows the productivity dynamics over the firms life cycle. Average productivity steeply increases with age in the unconstrained industry, while the increase is much smaller the higher are financing frictions. Comparing this figure with the empirical results of Hsieh and Klenow (2014) suggests that the steeper growth in size and productivity in US manufacturing firms versus Indian and Mexican firms could be at least partially explained by the better access to external finance of US firms.

Figures 4 and 5 show the dynamics of radical and incremental innovation, respectively. Figure 4 shows that radical innovation is on average higher for young firms, and it declines gradually over the life cycle of firms. Older firms do less radical innovation because as firms age they become more likely to have successfully innovated in the past and to be currently doing incremental innovation to maintain their high levels of
productivity.\footnote{ Nonetheless old firms still have a substantial probability to do radical innovation. These are mostly firms which were very successful in the past, but their products have become obsolete, and they need to try new risky ventures to become competitive again. Also note that the assumption that the productivity distribution of new firm does not include very high levels, so that no new firm does incremental innovation, is useful for calibration purposes, but is not essential for the qualitative results of the paper. In alternative calibrations I assumed that the initial distribution of productivity is more dispersed so that some new firms are created very productive and start incremental innovation immediately. These calibrations do not imply substantial changes in the main results of the paper.} This property of the model is consistent with the empirical evidence of Akcigit and Kerr (2010), who analyse US patents data and show that small and young firms do relatively more exploration R&D and have a relatively higher rate of major inventions than large and old firms. Importantly, figure 4 shows that radical innovation is larger in the unconstrained industry at all age levels, and especially for younger firms. Figure 5 shows that incremental innovation increases gradually over time. Since more firms do radical innovation in the unconstrained industry, more firms reach an high level of productivity at every age. This explains why incremental innovation probability and average productivity increase faster in this industry than in the financially constrained industries.

The previous figures show that financing frictions reduce both innovation and productivity growth. Productivity differences across the industries are primarily caused
Figure 4: Probability that a firm does radical innovation along its life cycle.

Figure 5: Probability that a firm does incremental innovation along its life cycle.
by differences in radical innovation by young firms, and are amplified by the ability of older and successful firms to maintain their position using incremental innovation. Why do financing frictions reduce radical innovation? This outcome is a net result of several effects:

i) First, there is a "competition effect". Financing frictions increase bankruptcy risk, and fewer firms enter so that in equilibrium expected bankruptcy costs are compensated by lower competition. Since profits are higher at any productivity level, the expected return on innovation is also higher. Therefore in this model competition is negatively related to any type of innovation that can improve current productivity with some probability without any risk of reducing it. However radical innovation has also a "downside risk", which is the risk of facing a reduction in productivity if innovation fails. The firm does not value the upside potential and the downside risk symmetrically, because the value function is bounded below at zero, since the firm can always limit losses by exiting from production. New firms that did not yet succeed in radical innovation have relatively low productivity. Many of these have sufficient profitability when competition is low so to decide to postpone radical innovation. If financing frictions are reduced and competition increases, the same firms have a much lower profitability and much less to lose if they fail to innovate, thanks to the exit option, and they find it optimal to innovate much sooner. Therefore the "downside risk" generates a positive relation between competition and innovation. For realistic parameter values the downside risk is the prevailing effect, and therefore a reduction in competition caused by financing frictions reduces aggregate radical innovation.13

ii) Second, there is a "binding constraint" effect when constraint (9) is binding with equality and firms are not able to innovate, generating a negative relation between financing frictions and radical innovation. However this effect is small at the aggregate level, since few firms have a binding constraint at any point in time.

iii) Third, there is a "gambling for resurrection" effect. Bankruptcy risk implies that the value of a firm \( V_t(a_t, \varepsilon_t, v_t) \), as defined in equation (11), goes to zero when its wealth \( a_t \) goes below \( F \). As \( a_t \) increases, \( V_t(a_t, \varepsilon_t, v_t) \) increases rapidly. Therefore

---

12 This Schumpeterian effect is well known in endogenous growth theory, see for example Aghion and Howitt, 1992.
13 The empirical competition literature often estimates a positive relation between competition and innovation (e.g. Nickell, 1996, and Blundell et al. 1995). To the best of my knowledge this paper proposes a novel theoretical mechanism consistent with this evidence, different from and complementary to the well known "escape competition effect" of Aghion et al. (2001).
$V_t(a_t, \varepsilon_t, v_t)$ is strictly concave for $a_t \geq F$, is equal to zero for $a_t < F$, and is convex in an interval around the value of $a_t = F$. Such local convexity encourages firms close to the bankruptcy region to take more risk, including engaging in risky innovation. In more financially constrained industries firms’ wealth is on average lower and more firms are in this region, and this tends to increase radical innovation. However this effect is also small, since all surviving firms rapidly accumulate wealth and increase $a_t$.

In summary, while effects (i) and (ii) predict a negative relation between financial frictions and radical innovation, the effect (iii) predicts a positive relation. However effects (ii) and (iii) only affect a small percentage of firms, and tends to cancel out each other, while effect (i) affects all firms, and dominates in equilibrium on the other two. Regarding Incremental innovation, effects (ii) and (iii) are not affecting it because only relatively old and wealthy firms perform this type of innovation. Effect (i) predicts a positive relation between financing frictions and incremental innovation for a given productivity level. However such frictions also imply that few firms manage to become so productive to find it optimal to engage in incremental innovation, thus explaining the evidence shown in figures 2-4.

Table 2 reports detailed statistics about the different industries, which quantify the importance of each effect. PANEL A compares the four industries illustrated above. Financing frictions act as barriers to entry that reduce competition, so that in the severely constrained industry profits are on average 11% higher than in the benchmark case. Radical innovation in the severely constrained industry is 30% lower than in the benchmark industry, and only one third of this difference is due to binding financing constraints. In other words, most of the reduction in radical innovation is driven by firms choosing not to innovate in the constrained industry, rather than forced to do so by lack of financing. This confirms that the competition effect is the main reason why firms in more constrained industry do less radical innovation. As a consequence, total innovation is 43.2% lower, and average TFP is 21.5% lower in the severely constrained industry than in the benchmark industry.

In order to further identify the importance of the competition effect, Panel B 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 $S^C$ so to match the equilibrium prices in the four industries analyzed in panel A. In other words, in PANEL B entry costs replicate the competition effect generated by financing frictions in PANEL
A. The results show that the higher are the barriers to entry, the lower is radical innovation, which also implies less incremental innovation and average TFP. In the industry with very high entry barriers average TFP is 30% lower than in the benchmark industry.14

In Panels C and D I reduce the downside risk of radical innovation by assuming that $\tau$ is asymmetric. In case of success of radical innovation $v_{t+1} = (1 + g)^{\tau^H} v_t$, while in case of failure $v_{t+1} = \frac{\kappa \tau}{(1+g)^{\tau^L}}$. In the benchmark case $\tau^H = \tau^L = 10$. In these panels I reduce $\tau^L$ and I recalibrate the parameter $\kappa^1$ to ensure that average TFP remains the same as in the "benchmark" column. In Panel C the downside risk is halved by reducing $\tau^L$ to 5.15 The results of this panel are qualitatively similar to Panel A, with financing frictions reducing both types of innovation and aggregate productivity, and quantitatively smaller, thus confirming the importance of the downside risk in driving the results. In Panel D I set $\tau^L = 1$, so that a failed radical innovation has similar consequences than a failed incremental innovation. In this exercise the "downside risk" effect is absent, and the other effects roughly compensate each other, therefore the percentage of firms doing innovation does not change significantly across the different industries.

4 Empirical evidence

The simulations illustrated in the previous section yield several predictions on the relation between sectorial level intensity of financing friction, innovation and productivity, both along the firm life cycle and at the aggregate level. To the extent that the simulated industries with different level of financing frictions are representative of differences in financial development across countries, the results are consistent with the evidence by Hsieh and Klenow (2014). In this section I use a sample of Italian Manufacturing firms to directly test the main predictions of the model. This panel is drawn from the

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14 So TFP is 11% lower than in the industry with severe financial constraints, despite these two industries have by construction the same competition effect. The difference is mainly caused by selection effects. In the industry with high $F$, higher profitability implies that firms with low productivity stay longer in operation. This negative selection effect, which reduces average TFP, is mitigated when entry barriers are due to financing frictions, because low productivity firms are also likely be low wealth firms that go bankrupt.

15 Here a failed radical innovation reduces profits by 15-20%, depending on the productivity state, less than half than the reduction in the benchmark calibration.
Table 2: Aggregate productivity differences

### PANEL A: Financing frictions

<table>
<thead>
<tr>
<th></th>
<th>Benchmark industry</th>
<th>Unconstr. industry</th>
<th>Moderately Constrained industry</th>
<th>Severely Constrained industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average P relative to Benchmark</td>
<td>100%</td>
<td>99.88%</td>
<td>100.57%</td>
<td>101.2%</td>
</tr>
<tr>
<td>Average π relative to benchmark</td>
<td>100%</td>
<td>98.82%</td>
<td>105.27%</td>
<td>111.13%</td>
</tr>
<tr>
<td>Average percentage of innovating firms</td>
<td>32.9%</td>
<td>34.1%</td>
<td>23.6%</td>
<td>18.7%</td>
</tr>
<tr>
<td>Doing Radical Innovation</td>
<td>22.8%</td>
<td>23.4%</td>
<td>18.7%</td>
<td>16.0%</td>
</tr>
<tr>
<td>Not doing R.I. because of fin. frictions</td>
<td>0.2%</td>
<td>0%</td>
<td>1.1%</td>
<td>1.9%</td>
</tr>
<tr>
<td>Incremental Innovation</td>
<td>10.1%</td>
<td>10.7%</td>
<td>4.9%</td>
<td>2.7%</td>
</tr>
<tr>
<td>Not doing I.I. because of fin. frictions</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Weighted Average TFP</td>
<td>0.863</td>
<td>0.874</td>
<td>0.753</td>
<td>0.677</td>
</tr>
<tr>
<td>Number of firms</td>
<td>8900</td>
<td>8645</td>
<td>11764</td>
<td>13601</td>
</tr>
</tbody>
</table>

### PANEL B: Barriers to entry

<table>
<thead>
<tr>
<th></th>
<th>Benchmark industry</th>
<th>Low Entry Barriers</th>
<th>High Entry Barriers</th>
<th>Very high Entry Barriers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average P relative to Benchmark</td>
<td>100%</td>
<td>99.4%</td>
<td>100.57%</td>
<td>101.2%</td>
</tr>
<tr>
<td>Average percentage of innovating firms</td>
<td>32.9%</td>
<td>36%</td>
<td>23.7%</td>
<td>17.4%</td>
</tr>
<tr>
<td>Doing Radical innovation</td>
<td>22.8%</td>
<td>22.9%</td>
<td>19.5%</td>
<td>16.2%</td>
</tr>
<tr>
<td>Doing Incremental innovation</td>
<td>10.1%</td>
<td>13.1%</td>
<td>4.2%</td>
<td>1.2%</td>
</tr>
<tr>
<td>Weighted Average TFP</td>
<td>0.863</td>
<td>0.916</td>
<td>0.732</td>
<td>0.603</td>
</tr>
<tr>
<td>Number of firms</td>
<td>8900</td>
<td>7816</td>
<td>12375</td>
<td>15665</td>
</tr>
</tbody>
</table>

### PANEL C: Reduced downside risk

<table>
<thead>
<tr>
<th></th>
<th>Benchmark industry</th>
<th>Unconstr. industry</th>
<th>Moderately Constrained industry</th>
<th>Severely Constrained industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>Doing Radical innovation</td>
<td>16.5%</td>
<td>20%</td>
<td>13.4%</td>
<td>11.9%</td>
</tr>
<tr>
<td>Doing Incremental innovation</td>
<td>10.5%</td>
<td>12.7%</td>
<td>8.4%</td>
<td>7.5%</td>
</tr>
<tr>
<td>Weighted Average TFP</td>
<td>0.883</td>
<td>0.916</td>
<td>0.850</td>
<td>0.836</td>
</tr>
</tbody>
</table>

### PANEL D: No downside risk

<table>
<thead>
<tr>
<th></th>
<th>Benchmark industry</th>
<th>Unconstr. industry</th>
<th>Moderately Constrained industry</th>
<th>Severely Constrained industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>Doing Radical innovation</td>
<td>18.3%</td>
<td>18.5%</td>
<td>16.7%</td>
<td>17.3%</td>
</tr>
<tr>
<td>Doing Incremental innovation</td>
<td>8.4%</td>
<td>8.5%</td>
<td>7.9%</td>
<td>8.7%</td>
</tr>
<tr>
<td>Weighted Average TFP</td>
<td>0.877</td>
<td>0.880</td>
<td>0.858</td>
<td>0.879</td>
</tr>
</tbody>
</table>
Mediocredito/Capitalia surveys of small and medium manufacturing firms. It is an unbalanced panel of more than 10,000 firms with annual balance-sheet data and profit and loss statements from 1989 to 2000, as well as 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, in particular, it includes detailed information on financing constraints and innovation (see Appendix 2 for details).

Even though this dataset does not contain direct information on how radical or risky innovation is, I can test several key predictions of the model regarding the life cycle dynamics of firms. First of all, the main prediction regarding the relation between financial frictions and productivity:

Prediction 1: Firms in less financially constrained industries have a growing productivity over the life cycle, more so than firms in more financially constrained industries.

Furthermore, I can test several related predictions, which serve as robustness checks of the main mechanism of the paper. The most important robustness check is to verify that prediction 1 is driven by the indirect competition effect:

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

Finally, assuming that R&D spending is related to both radical and incremental innovation, I perform two additional robustness checks:

Prediction 3: The differences in productivity growth of prediction 1 should diminish if I only include in the analysis firms not performing R&D.

Prediction 4: Firms in less financially constrained industries do less R&D on average, and R&D grows faster over the firms life cycle, than in more financially constrained industries.

4.1 Identification of financially constrained firms.

In each Mediocredito/Capitalia survey firms report whether, in the last year of the survey, they had a loan application turned down recently; whether they desired more credit at the market interest rate; and whether they would be willing to pay a higher interest rate than the market rate to obtain credit. Following Caggese and Cunat (2008) I aggregate these three variables into a single variable "$constrained_{i,s}$", which is equal
to one if firm $i$ declares to face some type of financial problem in survey $s$, and is equal to zero otherwise. $\text{constrained}_{i,s}$ is equal to one for 17% percent of observations.\footnote{Caggese and Cunat (2008) analyse extensively the reliability of this survey based indicator of financing frictions, and find that it is consistent with alternative indicators based on balance sheet data. In particular they find that firms with higher coverage ratio, higher net liquid assets, more financial development in their region and those with headquarters in the same region as the headquarters of their main bank are less likely to declare to be financially constrained.}

In general a firm-level indicator of financial constraints is useful to estimate the effects of financial factors on firms decision if it satisfies 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 survey answers used in this paper are likely to satisfy the first property, more so than indirect measures of financing frictions based on balance sheet data. However, they may not satisfy the second criterion, 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 sample firms that declare financing frictions are less profitable than the other firms in their sector. However I argue that a simple solution to this problem is available for the empirical analysis of this paper, because the main predictions of the model refer to different dynamics of firms in industries with different intensity of financing frictions, regardless on whether or not the constraints are currently binding for these firms. Therefore I proceed as follows: first, I consider as constrained only firms that complain about problems in accessing external finance while at the same have average operative profits over added value larger than 0.1. This threshold excludes the 25% least profitable firms. I then use the firm-level variable "$\text{constrained}_{i,s}$" to calculate the frequency of financially constrained firms in each 4 digit manufacturing sector, and I select sectors in 2 different groups. One group is composed by the 50% four digit sectors with most constrained firms, called the "Constrained" group, and the other group is composed of the 50% four digit sectors with least constrained firms, called the "Unconstrained" group. Thus the constrained group includes all firms more likely to face financing problems because of sector specific factors. Finally, when analyzing the results I exclude all firms declaring financing frictions, thus reducing selection problems. In other words, I perform the
Table 3: Frequency of constrained and unconstrained firms in each 2 digit manufacturing sector

<table>
<thead>
<tr>
<th>Sector</th>
<th>Class.</th>
<th>n. observations</th>
<th>% of firms in the &quot;Constrained&quot; group</th>
<th>% of firms in the &quot;Unconstrained&quot; group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food and Drinks</td>
<td>15</td>
<td>960</td>
<td>25%</td>
<td>75%</td>
</tr>
<tr>
<td>Textiles</td>
<td>17</td>
<td>1150</td>
<td>30%</td>
<td>70%</td>
</tr>
<tr>
<td>Shoes and Clothes</td>
<td>18</td>
<td>551</td>
<td>38%</td>
<td>62%</td>
</tr>
<tr>
<td>Wood Furniture</td>
<td>20</td>
<td>343</td>
<td>65%</td>
<td>35%</td>
</tr>
<tr>
<td>Paper</td>
<td>21</td>
<td>379</td>
<td>72%</td>
<td>28%</td>
</tr>
<tr>
<td>Printing</td>
<td>22</td>
<td>457</td>
<td>51%</td>
<td>49%</td>
</tr>
<tr>
<td>Chemical, Fibers</td>
<td>24</td>
<td>614</td>
<td>43%</td>
<td>57%</td>
</tr>
<tr>
<td>Rubber and Plastic</td>
<td>25</td>
<td>717</td>
<td>44%</td>
<td>56%</td>
</tr>
<tr>
<td>Non metallic products</td>
<td>26</td>
<td>823</td>
<td>76%</td>
<td>24%</td>
</tr>
<tr>
<td>Metals</td>
<td>27</td>
<td>614</td>
<td>49%</td>
<td>51%</td>
</tr>
<tr>
<td>Metallic products</td>
<td>28</td>
<td>1183</td>
<td>69%</td>
<td>31%</td>
</tr>
<tr>
<td>Mechanical Products</td>
<td>29</td>
<td>2031</td>
<td>42%</td>
<td>58%</td>
</tr>
<tr>
<td>Electrical Products</td>
<td>31</td>
<td>522</td>
<td>90%</td>
<td>10%</td>
</tr>
<tr>
<td>Television and comm.</td>
<td>32</td>
<td>303</td>
<td>45%</td>
<td>55%</td>
</tr>
<tr>
<td>Precision instruments</td>
<td>33</td>
<td>191</td>
<td>75%</td>
<td>25%</td>
</tr>
<tr>
<td>Vehicles</td>
<td>34</td>
<td>261</td>
<td>75%</td>
<td>25%</td>
</tr>
<tr>
<td>other manufacturing</td>
<td>36</td>
<td>664</td>
<td>62%</td>
<td>38%</td>
</tr>
</tbody>
</table>

analysis on firms which are not currently declaring financing problems, but which belong to a sector where on average more firms face financing frictions. This procedure has the advantage of both identifying the indirect competition effect, and of significantly reducing the possibility of mistakes in selecting firms that declare financing frictions because they face negative productivity shocks. Table 3 reports the distribution of firms in the two groups for each two digit manufacturing sector. It shows that financial frictions are present in all industries and not concentrated in only few sectors.

Figure 6 shows the percentage of financially constrained firms conditional on age for the whole sample and for the Constrained and Unconstrained groups. Consistently with the model the figure shows that financing frictions decrease with age for all firms.

### 4.2 Financing frictions and productivity dynamics

In order to verify Prediction 1, tables 4 and 5 analyse the age profile of productivity. They report the results of several regressions where the dependent variable is $\bar{\sigma}_{s,t}$, an
Figure 6: Percentage of financially constrained firms

![Graph showing percentage of financially constrained firms across different age groups.]

The estimate of the average productivity of firm $i$ in survey $s$.\footnote{Given that each survey covers a 3-years period, for these regressions I consolidate all the balance sheet variables at the same time interval.} The index $j = 1, 2$ refers to two different measures of productivity. The first measure is $\hat{\eta}^1_{s,t}$, revenue total factor productivity. I estimate the following production function at the two digit level using the Levinshon and Petrin (2003) methodology (see the details in appendix 1):

$$p_{i,t}y_{i,t} = e^{v^1_{i,t}} (p^k_{i,t}k_{i,t})^\alpha (w_{i,t}l_{i,t})^\beta$$  \(13\)

Where $p_{i,t}y_{i,t}$ is added value, $p^k_{i,t}k_{i,t}$ is the value if capital, and $w_{i,t}l_{i,t}$ is cost of labour for firm $i$ in period $t$. Years and firms fixed effects are also included in the estimation. Using the estimated parameters $\hat{\alpha}$ and $\hat{\beta}$ I obtain an empirical counterpart $\hat{\eta}^1_{s,t}$ of the residual $v^1_{i,t}$. The well known limitation of this measure of productivity is that it does not capture productivity increases that are passed to consumers in the form of price reductions.\footnote{For example in the model considered in the previous section an increase in marginal productivity of labour $v$ does not affect revenue total factor productivity because the fall in prices completely offsets the productivity gain.}

Therefore I also compute a second measure based on the profitability of the firms. I first compute the ratio between profits and labour cost for each firm-year observation, $\frac{\pi_{i,t}}{w_{i,t}l_{i,t}}$. This ratio is monotonously increasing in the productivity of the firm as long as...
the firm has some competitive power (or is a price taker but has a decreasing returns to scale production function), also when improvements in productivity are passed to consumers in the form of price reductions. I regress this measure over industry and time dummies:

\[ \pi_{i,t} = \beta_0 + \sum_{s=1}^{Ns} \beta_s D_s + \sum_{s=1}^{Nu} \beta_y D_y + v^2_{i,t} \]  

(15)

Where \( D_s \) are 3 digit sector dummies and \( D_y \) are year dummies. \( v^2_{i,t} \) is the estimated residual of this regression and \( v^2_{i,t} \) is the firm level average of \( v^2_{i,t} \) over the three years of each survey. Changes over time in \( v^2_{i,t} \) are orthogonal to aggregate demand and industry factors, and thus are likely to reflect changes in productivity of the firm.

In order to measure the evolution of productivity over the firm’s life cycle, I estimate the following model:

\[ \hat{\tau}^j_{i,s} = \beta_0 + \beta_1 \text{age}_{i,s} + \beta_2 \text{age}_{i,s} \times \text{constrained}_{k,t} + \sum_j \beta_j x_{j,s,t} + \varepsilon_{s,t} \]

The productivity measure \( j \in \{1, 2\} \) of firm \( i \) in survey \( s \), \( \hat{\tau}^j_{i,s} \), is the dependent variable. Among the regressors, the age of the firm \( \text{age}_{i,s} \) is included individually and interacted with the financing constraints dummy \( \text{constrained} \), which is equal to one if the firm belongs to the 50% of 4-digit manufacturing sectors with the highest percentage of financially constrained firms, and zero otherwise. Thus \( \beta_1 \) 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. \( x_j \) is the set of \( m \) control variables, which include firm fixed effects and time effects.

In Table 4 the estimated coefficients of age and age interacted with the constrained variable are reported. The presence of firm fixed-effects ensures that the estimation of \( \beta \) is not affected by a selection bias (the most productive firms are more likely to survive) and is identified only by firms increasing their productivity by accumulating tangible and intangible capital as they become older.

\[ \frac{\pi_{i,t}}{w_{i,t} h_{i,t}} = a - b F_t \]  

(14)

Where \( a \) and \( b \) are positive constants which only depend on sector level variables, while \( F_t \) is the fixed overhead cost. By linearising equation (14) around the sector average value of \( \varepsilon_t \) it is possible to derive the empirical version in equation (15).
Table 4: Relation between age and productivity

<table>
<thead>
<tr>
<th></th>
<th>All observations</th>
<th>Currently constrained firms excluded</th>
<th>Time trend for constrained group included</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$v^1$</td>
<td>$v^2$</td>
<td>$v^1$</td>
</tr>
<tr>
<td>$Age_{it}$</td>
<td>0.00616***</td>
<td>0.00067</td>
<td>0.00590***</td>
</tr>
<tr>
<td></td>
<td>(5.83)</td>
<td>(1.35)</td>
<td>(5.22)</td>
</tr>
<tr>
<td>$Age_{it} \times \text{constrained}_{it}$</td>
<td>$-0.00360^{**}$</td>
<td>$-0.00207^{**}$</td>
<td>$-0.00290^{*}$</td>
</tr>
<tr>
<td></td>
<td>(-2.59)</td>
<td>(-3.3)</td>
<td>(-1.91)</td>
</tr>
<tr>
<td>N.observations</td>
<td>12390</td>
<td>12672</td>
<td>12390</td>
</tr>
<tr>
<td>Adj. R-sq.</td>
<td>0.011</td>
<td>0.006</td>
<td>0.012</td>
</tr>
</tbody>
</table>

(Firms fixed effects and time effects are included. Standard Errors clustered at the firm level.)

Columns 1 and 2 report the estimated age coefficients using $\hat{v}^1$ and $\hat{v}^2$ as dependent variables, respectively. For unconstrained firms both measures increase with age, even though only the increase of $\hat{v}^1$ is statistically significant. Importantly, in both cases the relation between age and productivity is significantly less strong for the firms in the more financially constrained sectors, thus confirming prediction 1.

Column 3 and 4 replicate the analysis eliminating firms that declare financing frictions, and show very similar results to columns 1 and 2, consistently with the predictions of the model that: (i) the competition effect is key in driving the relation between financing frictions and productivity growth, and (ii) the binding constraint effect is negligible.

One possible alternative explanation of this result 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 a time trend specific to the constrained group. This is done in columns 5 and 6, and also in this case the results are largely confirmed, even though they are slightly less significant.

Table 5 replicates the analysis of table 4 with a different selection of constrained groups. The estimated equation is as follows:

$$\hat{v}^j_{i,s,t} = \beta_0 + \beta_1 age_{i,t} + \beta_2 age_{s,t} \times \text{midconstrained}_{k,t} + \beta_2 age_{s,t} \times \text{highconstrained}_{k,t} + \sum_j \beta_j x_{j,s,t} + \epsilon_{i,t}$$

where \text{midconstrained} is equal to 1 if a firm is in the 33% of sectors with intermediate constraints, and 0 otherwise, and \text{highconstrained} is equal to 1 if a firm is in the 33% of most constrained sectors and zero otherwise. The results show that the effect of age
on productivity monotonously decreases with the intensity of financing frictions, in all the different regressions.

I represent graphically the relation between age and productivity for the constrained and unconstrained group in figure 7. The curves are computed from the estimated coefficient of a piecewise linear regression in which the $\beta$ coefficient is allowed to vary for different age groups:

$$\hat{v}_{i,s,t} = \beta_0 + \sum_{l=1}^{n} \beta_l (unconstrained*age^{l}_{i,s,t}) + \sum_{l=1}^{n} \beta_l (constrained*age^{l}_{i,s,t}) + \sum_{j} \beta_j x_{j,i,s,t} + \epsilon_{i,s,t}$$

I construct a set of variables $age^{l}$ which is equal to the age of the firm if the firm is in group $l$, and zero otherwise. The index $l = 1, 2, 3, 4$ indicates the age intervals, with $l = 1$ indicating firms with age up to 10 years, and $l = 2, 3, 4$ indicates firms aged 11-20, 21-30 and 31-40 years, respectively. The dummy "unconstrained" is the complementary of "constrained", so that the coefficients $\beta_1^{u}...\beta_4^{u}$ measure the effect of age on productivity for the unconstrained firms, and the coefficients $\beta_1^{c}...\beta_4^{c}$ for the constrained ones. The set of control variables includes fixed effects, time dummies, and time dummies interacted with the constrained group, to allow for different trends in the two groups. Figure 7 shows the age profile of $\hat{v}_{i,s,t}^{1}$, obtained from the estimated coefficients, for the constrained and unconstrained group. The starting point is the average level of $\hat{v}_{i,s,t}^{1}$ for firms younger than 5 years old. The upward sloping profile is significantly steeper for the unconstrained than for the the constrained group.

Figure 8 shows the age profile of the profits-based measure of productivity $\hat{v}_{i,s,t}^{2}$.  

<table>
<thead>
<tr>
<th></th>
<th>All observations</th>
<th>Currently constrained firms excluded</th>
<th>Time trend for constrained group included</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$v^1$</td>
<td>$v^2$</td>
<td>$v^1$</td>
</tr>
<tr>
<td>$Age_{it}$</td>
<td>0.00755***</td>
<td>0.000722</td>
<td>0.00818***</td>
</tr>
<tr>
<td></td>
<td>(5.79)</td>
<td>(1.18)</td>
<td>(6.02)</td>
</tr>
<tr>
<td>$Age_{it}*midconstr_{it}$</td>
<td>-0.00387**</td>
<td>-0.000528</td>
<td>-0.00359*</td>
</tr>
<tr>
<td></td>
<td>(-2.19)</td>
<td>(-0.66)</td>
<td>(-1.94)</td>
</tr>
<tr>
<td>$Age_{it}*mostconstr_{it}$</td>
<td>-0.00529**</td>
<td>-0.0026***</td>
<td>-0.00529**</td>
</tr>
<tr>
<td></td>
<td>(-3.16)</td>
<td>(-3.42)</td>
<td>(-2.96)</td>
</tr>
<tr>
<td>N.observations</td>
<td>12390</td>
<td>12672</td>
<td>11065</td>
</tr>
<tr>
<td>Adj. R-sq.</td>
<td>0.011</td>
<td>0.006</td>
<td>0.013</td>
</tr>
</tbody>
</table>

Firms fixed effects and time effects are included. Standard Errors clustered at the firm level.

Table 5: Relation between age and productivity, more categories
Figure 7: Life cycle of the productivity of firms, revenue based TFP measure
The starting point is normalized to 1 because the estimated measure $\hat{v}_{i,s,t}^2$ is a nonlinear transformation of the true productivity. It is only useful to identify changes over time in productivity, not its level. This figure confirms that the gap in productivity between the unconstrained and the constrained group increases along the firms life cycle, as predicted by the model.

4.3 Robustness checks

The first robustness check verifies the relation between financial frictions, competition and innovation, as formulated in Prediction 2. As an empirical measure of competition I consider the Price-cost margin (PCM):

$$PCM_{it} = \frac{R_{it} - M_{it}}{R_{it}}$$
Table 6: Relation between age and productivity - sectors selected according to competition

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>Group specific time trend included</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$v^1$</td>
<td>$v^2$</td>
</tr>
<tr>
<td>$Age_{it}$</td>
<td>0.00622***</td>
<td>0.000293</td>
</tr>
<tr>
<td></td>
<td>(5.8)</td>
<td>(0.63)</td>
</tr>
<tr>
<td>$Age_{it} \times lowcomp_{it}$</td>
<td>$-0.00404$**</td>
<td>$-0.00153$**</td>
</tr>
<tr>
<td></td>
<td>(-2.91)</td>
<td>(-2.48)</td>
</tr>
<tr>
<td>N.observations</td>
<td>12390</td>
<td>12672</td>
</tr>
<tr>
<td>Adj. R-sq.</td>
<td>0.011</td>
<td>0.005</td>
</tr>
</tbody>
</table>

Where $R_{it}$ is total revenues for firm $i$ in period $t$ and $M_{it}$ are variable costs for firm $i$ in period $t$. I calculate the average of $PCM_{it}$ for each 4 digit sectors and generate a dummy which is equal to one if the firm belongs to one of the 50% of sectors with lowest Price-cost margin, and zero otherwise, called $lowcomp_{it}$. Then I interact this dummy with age in a regression similar to the one performed in table 4. Table 6 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 4, for both the $v^1$ and $v^2$ measure. In other words, the low competition sectors behave very similarly to the high financing frictions sectors with respect to productivity dynamics along the firms life-cycle. These results are consistent with the simulation results shown in table 2 and confirm Prediction 2.20

The second robustness check verifies the importance of innovation in driving the empirical relation between financing frictions and productivity growth. Columns 1 and 2 in Table 7 replicate the results in the last two columns of table 4. Columns 3 and 4 repeat the analysis after eliminating the survey-firm 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 some of the sample periods. The results show that the life-

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Note that the correlation between the average of the price cost margin $PCM_{i}$ and the fraction of constrained firms $constrained_{i}$ 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 variation in competitions driven by entry barriers, while the empirical price-cost margin measures variation in competition generated by variations in the elasticity of substitutions $\sigma$. In table 2 I have shown simulations results when competition varies because of different entry costs. Nonetheless simulations where changes in competition are caused by variations in $\sigma$ yield very similar results.
Table 7: Relation between age and productivity - sectors selected according to competition

<table>
<thead>
<tr>
<th></th>
<th>Baseline</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></td>
<td>$v^1$</td>
<td>$v^2$</td>
<td>$v^1$</td>
</tr>
<tr>
<td>$Age_{it}$</td>
<td>0.00590***</td>
<td>0.000235</td>
<td>0.00429*</td>
</tr>
<tr>
<td></td>
<td>(5.22)</td>
<td>(0.43)</td>
<td>(2.46)</td>
</tr>
<tr>
<td>$Age_{it}*constrained_{it}$</td>
<td>-0.00290*</td>
<td>-0.00138*</td>
<td>-0.00109</td>
</tr>
<tr>
<td></td>
<td>(-1.91)</td>
<td>(-1.95)</td>
<td>(-0.49)</td>
</tr>
<tr>
<td>N.observations</td>
<td>12390</td>
<td>12672</td>
<td>6156</td>
</tr>
<tr>
<td>Adj. R-sq.</td>
<td>0.012</td>
<td>0.007</td>
<td>0.010</td>
</tr>
</tbody>
</table>

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 3.

The last robustness check is related to prediction 4. Figure 9 shows the average percentage of firms doing R&D for the whole sample as well as for groups of sectors selected according to the fraction of firms declaring financing constraints. R&D intensity is increasing in firms age for all groups, and its average decreases in financing frictions across groups. Both findings are consistent with prediction 4. The model also predicts that the probability to innovate grows faster over the firms life cycle in the less constrained group. In Figure 9 this behaviour is confirmed from age 5 to age 20, especially when comparing the most constrained with the least constrained group, while beyond age 20 differences in R&D intensity across groups diminish a little.

5 Concluding remarks

The recent literature on firm dynamics and productivity growth emphasizes that both financing frictions and innovation dynamics are key factors to understand the differences in aggregate productivity across industries and countries. This paper argues that the interaction between financial factors and innovation decisions shapes the life-cycle dynamics of firms and has important aggregate implications.

By calibrating, solving, and simulating the model of an industry I show that the indirect effects of financing frictions, that reduce competition because of reduced entry and early exit of firms with financial difficulties, are much more important for inno-
Figure 9: Percentage of firms doing R&D

- Aged 5-10
- Aged 11-15
- Aged 16-20
- Aged 21-25
- Aged 26-30
- Aged 31-35
- Aged 36-40

vation decisions than the direct effects, which are the inability to innovate because of insufficient financial wealth and inability to borrow. For realistic parameter values few firms have a binding constraint and the direct effect of financial frictions on investment and innovation decisions are very small, consistently with the findings of Midrigan and Xu (2014). However the indirect effects significantly reduces radical innovation, productivity growth at the firm level and aggregate productivity. The empirical analysis conducted on a sample of Italian manufacturing firms tests and confirms the predictions of the model related to the relation between financing frictions, innovation, and the life-cycle of firms.

6 Appendix 1

In order to obtain a numerical solution for the value functions $V_t^0(a_t, \varepsilon_t, v_t)$, $V_t^1(a_t, \varepsilon_t, v_t)$, $V_t^2(a_t, \varepsilon_t, v_t)$, $V_t^*(a_t, \varepsilon_t, v_t)$ and $V_t(a_t, \varepsilon_t, v_t)$ I consider values of $a_t$ in the interval between 0 and $\underline{a}$, where $\underline{a}$ is a sufficiently high level of assets such that the firm is never financially constrained 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 $v_N = 1$ and $v_{N-1} = \frac{1}{(1+\gamma)^N}$. $N$ 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 $v = \frac{1}{(1+\gamma)^{120}}$. To make it consistent with this grid, I approximate the initial log-normal distribution of $v_0$ to a distribution with support $[v_L, v_H]$, which are the values that cut the 1% tails of the distribution, $\text{prob}(v < v_L) = \text{prob}(v > v_H) = 1\%$ and that are inside the grid: $v_L > \frac{1}{(1+\gamma)^{120}}$ and $v_H < 1$. The censored probability distribution is re-scaled to make sure that its integral over the support $[v_L, v_H]$ is equal to 1.

In order to solve the dynamic problem I first make an initial guess of the equilibrium aggregate price $P$. Based on this guess, we calculate the optimal value of $V_t (a_t, \varepsilon_t, v_t)$ using an iterative procedure. I then apply the zero profits condition (12) and I update the guess of $P$ accordingly. I repeat this procedure until the solution converges to the equilibrium. Then I simulate an artificial industry in which every period, the total number of new entrants ensures that condition (1) is satisfied.

7 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. Some firms are kept in the sample for more than one survey, therefore I have a total of 13601 firm year 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. Moreover for each firm surveyed Mediocredito/Capitalia makes available several years of balance sheet data which go back several years before the survey. Therefore I have available a total of 67519 firm-year observations of balance sheet data.

For the estimation of the production function (13) I use the following variables: added value $py$ is equal to sales minus cost of variable inputs used during the period plus capitalized costs minus cost of services; capital $pk$ is the book value of fixed capital; labour $wl$ is total wage cost; I follow the methodology of Levinsohn 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 $\bar{\ell}$ and $\bar{t}$ 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. Since this procedure only requires balance sheet variable, I am able to calculate the productivity measure $v^1$ for 21515 firm-survey observations.

For the estimation of equation (15) the dependent variable is $\frac{\pi_{it}}{w_{it,t}}$ where $\pi$ is net income and $wl$ is total wage cost.

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

References


