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

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I provide new empirical evidence on the negative relationship 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 this evidence. However, further including radical innovation, which is very risky but potentially very productive, allows for the joint replication of several stylized facts about the dynamics of young and old firms and 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. (*JEL* D22, D24, D25, G32, L25, L60, O31)

The innovation and technology adoption decisions of firms during the different phases of their life cycle are fundamental forces that shape firm dynamics and aggregate productivity growth. Hsieh and Klenow (2014) shows that US manufacturing plants, on average, increase their productivity by a factor greater than 4 from their birth until they are 35 years of age, which suggests that learning and innovation play an important role in building firm-specific intangible capital. The same authors also show that for similar plants in India and Mexico, productivity increases only by a factor of 1.7 and 1.5, respectively.

These different dynamics give rise to large cross-country productivity and income differences. Therefore, it is important to understand their causes. Do financial imperfections play an important role in explaining these differences?

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Despite a large literature on finance and growth, it remains an open question whether financial frictions affect the productivity dynamics of firms during the different phases of their life cycle. This paper shows that they do. It provides new empirical evidence of a strong negative relationship between financial frictions and firm productivity growth. It then develops a model of firm dynamics that demonstrates that the interaction between financial frictions and competition, and their effects on the radical innovations of younger firms, are an important factor in explaining this evidence.

I analyze a very rich dataset of Italian manufacturing firms with more than 50,000 observations of balance sheet data, as well as qualitative survey information on finance and innovation. I identify financially constrained sectors by aggregating survey responses in which firms describe problems in accessing external finance. To mitigate reverse causality problems, I only consider the responses of profitable firms that are not likely to be financially distressed. I estimate total factor productivity (TFP) at the firm level, using the Wooldridge (2009) extension of the Levinsohn and Petrin (2003) methodology, and I identify a highly consistent empirical pattern: in industries in which firms are more likely to be financially constrained, productivity grows less over a firm's life cycle than in other industries. This is true not only for young firms but also for older firms up to 40 years of age. I show that these results are robust to using alternative indicators of financial frictions and instrumenting the survey responses with exogenous variations in local financial development.

This finding is at odds with recent theories on finance and firm dynamics, which typically predict that, in equilibrium, most firms are able to self-finance their investment decisions and avoid the negative effects of financial frictions.[1] To explain this, I develop a partial equilibrium model of an industry in which monopolistically competitive firms face financing frictions and idiosyncratic profitability shocks. In each period, a fraction of firms receives an investment opportunity to improve firm productivity. The key novel element of the model is that firms can choose between different types of innovations, which correspond to different ways of exploiting the investment opportunity, and that innovation types differ in their cost, their probability of success, and their effect on productivity conditional on success or failure. For simplicity, I consider two polar cases: the first is a safe innovation type, which always succeeds and generates a small increase in productivity. I call this "incremental" innovation. The second is a risky innovation type, which succeeds with a low probability and generates a substantial increase in productivity if it succeeds. I call this "radical" innovation. Another important feature of radical innovation is that failure reduces productivity. Intuitively, the innovation process is to some degree irreversible. The firm needs to replace the physical capital, knowledge, and organizational capital that were used to operate the old technology. Therefore, in the event of failure, the firm cannot easily revert to the old technology, and its efficiency will be lower relative to the situation before it pursued the innovation.

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

I calibrate the model such that the simulated firms match those in the Italian dataset in terms of average age, profitability, and innovation intensity and in terms of the cross-sectional dispersion of size, age, productivity, and profitability. I identify firms pursuing incremental innovation as those that perform R&D to improve existing products or production processes. I identify firms pursuing radical innovation by combining the survey answers on R&D expenditures with additional information on patenting activity from the Italian and European patent offices.

I solve the model and simulate several artificial sectors, which match the different intensities of financial frictions observed in the empirical sectors. I consider the full model and counterfactual versions with only one innovation type, and I document three main results: first, the full model yields quantitative results that are a good match for the empirical findings. Firm-level productivity growth is much slower for firms in the more financially constrained artificial sectors than in the less constrained sectors; second, a lower frequency of radical innovation among younger firms is the key factor in generating these differences in productivity growth. Counterfactual simulations of the model with only incremental innovation are unable to match the empirical evidence; third, lower levels of radical innovation are the result of financial frictions acting as barriers to entry. They reduce competition and the incentives of young firms, even financially unconstrained ones, to choose riskier innovation strategies.

The intuition for these findings is as follows. In the calibrated model, young firms are, on average, small and far from the technological frontier. On the one hand, success at radical innovation is their best opportunity to rapidly grow in productivity and size. On the other hand, its cost is limited by the exit option: in the event of failure, these firms can cut their losses by shutting down. Firms that succeed in radical innovation become larger and more productive and find it optimal to engage in incremental innovation. Therefore, the model generates realistic firm dynamics: young firms are much more likely to invest in radical innovation and have highly volatile growth rates, while older firms are, on average, more productive, are more likely to invest in incremental innovation, and have less volatile growth rates.

How do financial frictions affect innovation decisions? First, I observe a direct effect: they reduce the frequency of innovation by firms facing a binding financing constraint. I show that this effect is unable to generate large differences in productivity growth over a firm's life cycle. In equilibrium, it affects a relatively small share of firms, as most of them can retain earnings and overcome financial frictions very early in life. The second channel is an indirect effect: financial frictions increase the bankruptcy probability of young and financially fragile firms, reduce entry and competition, and increase the profitability of firms that survive. Lower competition implies that many young firms are relatively more profitable at their current productivity level. Therefore, when they receive an investment opportunity, they prefer to implement incremental rather than radical innovation, as they have more to lose in the event of failure. A lower fraction of firms performing radical innovation reduces the equilibrium number of very large and productive firms. As a consequence, competition decreases even more, further discouraging radical innovation by young firms. The negative interaction between competition and radical innovation slows productivity growth over the firm life cycle, thereby generating productivity dynamics consistent with the empirical evidence. The aggregate implications are significant. I find that reducing financial frictions in the 33 percent of sectors considered the most constrained—abstracting from changes in wages and interest rates—would increase their productivity by 5 percent.

In the last part of the paper, I verify the key predictions of the model. First, I consider four different indicators of radical innovation activity, such as R&D performed to introduce new products, patents awarded by the Italian and European patent offices, and the top 10 percent of most frequently cited patents (following Akcigit and Kerr 2018). Consistent with the predictions of the model, all of these indicators show that younger firms are more likely to perform radical innovation than older firms, especially in less financially constrained sectors. Second, I provide evidence consistent with the indirect competition effect. I show that the main empirical finding—that productivity growth is lower in more financially constrained sectors—holds for all the firms in these sectors, including those not reporting financial problems.

I. Related Literature

Despite a voluminous literature on finance and growth (see Levine 2005 for a review), few studies examine the relationship between financial frictions and productivity growth at the firm level; see, among others, Ferrando and Ruggieri (2015) and Levine and Warusawitharana (2017). The main difference between this literature and the present paper is that my objective is to estimate how financial frictions affect productivity growth over the firm life cycle instead of on average. This paper's main added value is that it uses qualitative surveys of the difficulties that firms face in accessing credit, rather than indirect indicators based on balance sheet data, to compute its main financial constraints indicator.[2]

The theoretical section of this paper is related to the literature on financing frictions and firm dynamics, which includes, among others, Buera, Kaboski, and Shin (2011); Caggese and Cuñat (2013); Midrigan and Xu (2014); and Cole, Greenwood, and Sanchez (2016). The main difference is that these papers analyze the effect of financing frictions on entry into entrepreneurship and on sector and technology selection by new entrepreneurs, while this paper studies their implications for firms' ongoing, heterogeneous innovation decisions over their life cycle. Following Midrigan and Xu (2014), I consider a realistically calibrated model in which financial frictions are binding for a small fraction of firms in equilibrium. However, although most firms are able to self-finance their investment, I uncover a novel and powerful indirect channel through which financial frictions negatively affect radical innovation decisions and firm-level productivity growth, with significant aggregate consequences.[3]

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

[3] Because of its emphasis on heterogeneous technological choices, my paper is also related to Bonfiglioli, Crinò, and Gancia (forthcoming), who show, in a static multi-sector and multi-country model, that financing frictions

My theory is also closely related to studies of the effects of policy distortions on aggregate productivity, in particular, Da-Rocha, Mendes Tavares, and Restuccia (2017) and Bento and Restuccia (2017). In common with my paper, these authors emphasize how such distortions affect both the entry decisions of new entrepreneurs and the productivity-enhancing investments of growing firms, thereby lowering aggregate productivity. They focus on tax-like output wedges that can be interpreted as generic types of policy distortions. The main difference in my paper is that I focus on one specific type of distortion (financing frictions) and analyze its implications for the heterogeneous types of innovation pursued by continuing firms. On the one hand, my analysis is consistent with their results, as I identify a novel misallocation channel in which the risky innovation decisions of firms amplify the negative effects of imperfect financial markets on aggregate productivity. On the other hand, I derive a set of additional testable predictions of the model, which are verified using micro data, and provide additional support for the empirical importance of such distortions.

Many authors have recently emphasized the importance of innovation to understand firm dynamics and productivity growth in models with heterogeneous firms and heterogeneous innovations (see, among others, Klette and Kortum 2004, Akcigit and Kerr 2018, 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 a firm's productivity and profitability. However, I especially focus on the risk component of innovation, and thus, my paper relates to Doraszelski and Jaumandreu (2013) and Castro, Clementi, and Lee (2015), who note that innovation-related activities increase the volatility of productivity growth; to Caggese (2012), who estimates a negative effect of uncertainty on the riskier innovation decisions of entrepreneurial firms; and especially to Gabler and Poschke (2013), who also consider the importance of innovation risk for selection, reallocation, and productivity growth. Finally, the paper is also related to the literature on competition and innovation, as it provides a novel (to the best of my knowledge) explanation for the positive relationship between competition and innovation often found in empirical studies, which is complementary to the "escape competition effect" of Aghion et al. (2001).

II. Empirical Evidence

In this section, I study a sample of Italian manufacturing firms, drawn from the Mediocredito/Capitalia surveys. It is based on an unbalanced panel of firms with balance sheet data from 1989 to 2000, as well as additional qualitative information from three surveys conducted in 1995, 1998, and 2001. Each survey covers the activity of approximately 4,500 firms in the three previous years, and it includes detailed information on financing constraints, market structure, internationalization, and innovation. Because some firms are kept in the sample for more than one

distort the type of technologies that firms select upon entry and affect both the equilibrium dispersion of sales and the volume of trade. In contrast, I develop a dynamic model that focuses on the dynamic interactions between financial frictions and different types of innovation decisions over a firm's life cycle and their impact on productivity growth at the firm level and aggregate productivity.

survey, I have a total of 12,952 firm-survey observations. In addition to the surveys, up to nine years of balance sheet data are available for each surveyed firm, for a total of 54,886 unique firm-year observations. Complete details of the dataset and variables used are available in online Appendix A.

I estimate total factor productivity following the procedure adopted by Hsieh and Klenow (2009, 2014). They consider a monopolistic competition model with a Cobb-Douglas production function and derive a measure of physical productivity equal to $\kappa_j \frac{\left(p_{i,t} y_{i,t}\right)^{\frac{\sigma}{\sigma-1}}}{\left(p^k_{i,t} k_{i,t}\right)^{\alpha} l^{\beta}_{i,t}}$, where κ_j is a sector-level coefficient, and $\sigma > 1$ is the elasticity of substitution between firms. Subscripts i, t, and j denote firm, year, and sector, respectively. Following Hsieh and Klenow (2009) in using labor cost to measure labor input $l_{i,t}$, I obtain the following relationship:

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

where $v_{i,t}$ is total factor productivity. I estimate the input factor elasticities in equation (1) using the Wooldridge (2009) extension of Levinsohn and Petrin (2003), and I do so separately for each two-digit manufacturing sector. Using the estimated elasticities, I obtain $\hat{v}_{i,t}$, the empirical counterpart of productivity $v_{i,t}$ (see the online Appendix A for details).

I identify financial frictions using the qualitative information contained in the surveys. Firms are asked in the last year of each survey whether (i) they desired more credit at the market interest rate; (ii) they were willing to pay a higher interest rate than the market rate to obtain credit; and (iii) they had a loan application rejected. In the 1995 survey, these questions are asked independently. In the 1998 and 2001 surveys, questions (ii) and (iii) are only asked of firms that respond in the affirmative to question (i). I aggregate these answers into a categorical variable $finprob_{i,s}$ that takes values from zero (no problem reported) to a maximum of three (all problems reported) for firm i in survey s.

Caggese and Cuñat (2008) provides evidence that the survey responses are informative of financial frictions. Consistent with the predictions of a broad class of models, firms not declaring financial problems have a higher coverage ratio, higher net liquid assets, more financial development in their region, and more likely to have their headquarters in the same region as the headquarters of their main bank than firms declaring financial problems.

Nonetheless, this firm-level indicator might suffer from a reverse causality problem. Among firms declaring financial problems, some might be truly financially constrained firms, which are profitable and have valuable investment opportunities, but unable to obtain credit because of financial frictions. I call these firms "type-1." Conversely, "type-2" firms might be poor-performing firms, with low profitability and few investment opportunities, which are financially distressed. To mitigate the bias induced by type-2 firms, I compute $finprob_j$, the average value of $finprob_{i,s}$ for the four-digit sector j to which firm i belongs. To reduce the influence of possibly distressed firms on this sector-level indicator, I compute $finprob_j$ after excluding the 25 percent least profitable firms. However, these firms are kept in the sample for the empirical analysis illustrated below. Note that $finprob_j$ is robust to the bias introduced by type-2 firms if these become distressed as a consequence of idiosyncratic shocks that are equally distributed across sectors.

Similar to other industry-level financial frictions indicators used in the literature, such as the financial dependence indicator proposed by Rajan and Zingales (1998), the hypothesis is that the different technological features of the industries determine different financing needs of firms and different degrees of financial imperfections. Sectors with a greater need for external financing, for example, because of a longer gestation period of their projects, and with more informational and contractual frictions, for example, because the nature of their investment is more informationally opaque, should have a higher frequency of type-1 firms declaring financial problems. I pool the 50 percent of four-digit sectors with the highest frequency of likely financially constrained firm-survey observations and call them the "Constrained" group. The other group comprises the 50 percent of four-digit sectors with the least constrained firms. I call it the "Unconstrained" group.[4] The online Appendix A reports the distribution of constrained firms and shows that they are present in all two-digit industries, rather than being concentrated in a few industries. Nonetheless, it might still be that sector-level shocks simultaneously affect the fraction of constrained firms and their productivity growth. Therefore, the regressions shown in the next section have to be interpreted as showing correlations among variables of interest. The model in Section III will provide an interpretation of these correlations, which is supported by additional robustness checks in Section V. Moreover, in online Appendix A, I propose an instrumental variable estimation to control for this bias, with an identification strategy validated by the model.

The Relationship between Age and Productivity.—I analyze the relationship between age and productivity by estimating the following model:

$$\hat{v}_{i,s} = \beta_0 + \beta_1 age_{i,s} + \beta_2 age_{i,s} \times constrained_i + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s}. \tag{2}$$

The dependent variable is the firm-level estimate of total factor productivity $\hat{v}_{i,s}$. As each survey covers a three-year period, for the estimation of equation (2), I consolidate all balance sheet variables over the same time interval. Therefore, $\hat{v}_{i,s}$ is the average of $\hat{v}_{i,t}$ for the three years of survey period s. Since balance sheet data for some firms date back to 1989, I have a total of four survey periods (1989–1991, 1992–1994, 1995–1997, and 1998–2000). Among the regressors, $age_{i,s}$ is the age of firm i in survey s. The financing constraints dummy $constrained_i$ is equal to 1 if firm i belongs to the 50 percent of four-digit manufacturing sectors with the highest percentage of likely financially constrained firms, 0 otherwise. The variable $constrained_i$ is constant over time for each firm and collinear with

[4] I use the ATECO 91 classification of the Italian National Statistics Office (ISTAT). For some firms, the reported four-digit classification has a final "zero," meaning that these firms effectively only report their three-digit classification. I retain these firms in the sample, and I treat them as belonging to a residual four-digit sector. I repeated the empirical analysis after excluding these firms and obtained very similar results. These additional estimations are available upon request. The complete list of all four-digit sectors is in online Appendix F.

Table 1—Relationship between Age and Productivity (Empirical Sample)

	(1)	(2)	(3)	(4)
$age_{i,s}$	0.0137	0.0133	0.0147	0.0148
	(11.4)	(11)	(8.9)	(8.4)
$age_{i,s} \times constrained_i$	−0.00636	−0.00546		
	(−4.2)	(−3.6)		
$age_{i,s} \times midconstr_i$			−0.00529	−0.00533
			(−2.6)	(−2.5)
$age_{i,s} \times highconstr_i$			−0.00692	−0.00633
			(−3.4)	(−3)
Observations	10,409	10,409	10,409	10,409
Adjusted R^2	0.083	0.085	0.081	0.085
Time dummies	yes	no	yes	no
Time × group dummies	no	yes	no	yes

Notes: The table shows panel regressions with firm fixed effect. Dependent variable is estimated total factor productivity $\hat{v}_{i,s}$. Standard errors are clustered at the firm level. The variance-covariance matrix is estimated with a bootstrap procedure with 50,000 replications. z-statistic is reported in parentheses. $age_{i,s}$ is age in years for firm i in survey s. $constrained_i$ is equal to 1 if firm i belongs to the 50 percent of four-digit manufacturing sectors with the highest percentage of financially constrained firms, and 0 otherwise. $midconstr_i$ is equal to 1 if firm i belongs to the 33 percent of four-digit manufacturing sectors with the median percentage of financially constrained firms, and 0 otherwise. $highconstr_i$ is equal to 1 if firm i belongs to the 33 percent of four-digit manufacturing sectors with the highest percentage of financially constrained firms, and 0 otherwise.

firm fixed effects. Therefore, I only include it interacted with age, meaning that β_1 measures the effect of age on productivity for the unconstrained group of firms, and β_2 measures the differential effect of age for the constrained group. The term x_j is the set of m control variables, which include firm fixed effects and time effects. The presence of firm fixed effects implies that β_1 and β_2 are identified only by within-firm changes in productivity. Column 1 of Table 1 reports the estimated coefficients of age and age interacted with $constrained_i$. Standard errors are clustered at the firm level, and the variance-covariance matrix is estimated with a bootstrap procedure with 50,000 replications. The coefficient of $age_{i,s}$ is positive and significant, indicating that, in the less constrained sectors, productivity increases by, on average, 1.37 percent when a firm becomes one year older. Importantly, the coefficient of $age_{i,s} \times constrained_i$ is negative and significant, and the difference between the two coefficients implies that productivity increases only by 0.73 percent when firms in the most constrained sectors become one year older. While this evidence supports the hypothesis that financing frictions reduce productivity growth, one possible alternative explanation is that more financially constrained sectors happen to be sectors in secular decline. To control for this alternative explanation, in column 2, I add time dummies interacted with the constrained group to the set of control variables. If productivity in the financially constrained group grows more slowly as firms age simply because aggregate productivity declines over time for the whole group, the presence of group-specific time dummies should render the coefficient of $age_{i,s} \times constrained_i$ insignificant.

However, this coefficient remains positive and statistically significant, with a value only slightly smaller than that in column 1.

Columns 3 and 4 of Table 1 consider a more detailed selection of constrained groups. The estimated equation is as follows:

$$\hat{v}^{j}_{i,s} = \beta_0 + \beta_1 age_{i,s} + \beta_2 age_{i,s} \times midconstr_i + \beta_3 age_{i,s} \times highconstr_i + \sum_{j=1}^{m} \beta_j x_{j,i,s} + \varepsilon_{i,s}, \tag{3}$$

where $midconstr_i$ is equal to 1 if firm i is in the 33 percent of sectors with intermediate constraints, 0 otherwise, and $highconstr_i$ is equal to 1 if firm i is in the 33 percent most constrained sectors, 0 otherwise. In columns 3 and 4, the coefficient of $age_{i,s}$, which now measures yearly productivity growth in the 33 percent least constrained sectors, is larger in absolute value than in columns 1 and 2. Moreover, productivity growth over the firm's life cycle decreases monotonically as the intensity of constraints increases.

I next allow productivity growth to be nonlinear in age, and I represent it graphically in Figure 1. The curves are computed from the estimated coefficients of a piecewise linear regression in which the β_1, β_2, and β_3 coefficients are allowed to vary for four different age groups: 0–10 years, 11–20 years, 21–30 years, and 31–40 years (see online Appendix B for details). Firm fixed effects and time dummies are included as control variables in the regression. Figure 1 shows the age profile of $\hat{v}_{i,s}$. The lines are normalized to a value of 1 for firms younger than 5 years of age. The figure confirms the difference in productivity growth between constrained and unconstrained firms, and it shows that these differences are persistent and also present for the older firms in the sample.[5]

Finally, Figure 2 allows the relationship between financial frictions and firm-level productivity growth to be nonlinear with the intensity of financial problems. I estimate a version of equation (2) in which I directly include, interacted with age, the percentage of constrained firms in the sector to which firm i belongs, $\%constr_i$, and that percentage squared, $\%constr_i^2$. I use the estimated coefficients to compute the average productivity growth for a firm that becomes one year older, for the ten deciles of the distribution of financial frictions across sectors. The full set of estimated coefficients is reported in online Appendix B. Figure 2 shows that an increase in financial frictions slows productivity growth

[5] Figure 1 shows that the relative productivity differentials between the most and least constrained 40-year-old firms are large. However, comparing productivity between firms of different ages in the same sector, Figure 1 shows that, in the least constrained sectors in Italy, firms have a productivity that is approximately 37 percent higher after 40 years, while Hsieh and Klenow (2014) reports an increase of 400 percent for US establishments. There are several factors that explain this difference: the fixed effects estimation only measures within-firm variation, and firm fixed effects absorb some of the size differences that drive the Hsieh and Klenow measure; my dataset is at the firm level, rather than at the establishment level, and very few firms younger than 5 years of age are reported, meaning that the average size for ages less than or equal to 5 years is substantially overestimated; and the Italian manufacturing sector has other constraints, besides financial frictions, that limit the growth of firms, such as a labor law that establishes very high firing costs and applies only to firms with more than 15 employees.

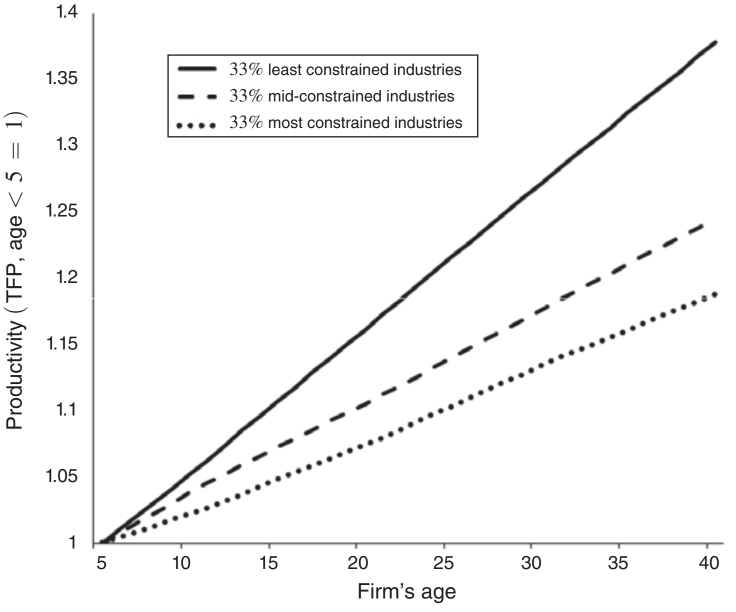

Figure 1. Life Cycle of the Productivity of Firms in the Empirical Sample

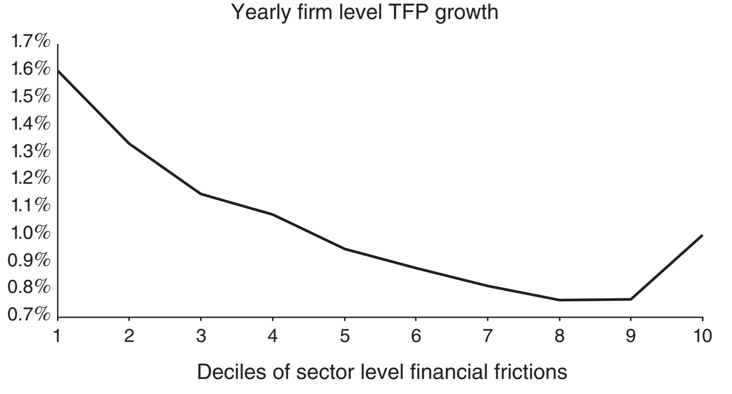

Figure 2. Nonlinear Relationship between Intensity of Financial Frictions and Productivity Growth

in the first nine of ten deciles. The negative relationship flattens out around decile nine and reverses sign only at the tenth decile.

Taken together, the results of this empirical analysis indicate that financial frictions at the sector level affect the productivity growth of younger firms, as well as older ones, until at least 40 years of age.[6] In online Appendix B, I perform several

[6] In online Appendix A, I show that the dataset underrepresents small firms with fewer than 150 employees and overrepresents larger firms. Therefore, in online Appendix B, I replicate the main results in Table 1 with weighed

robustness checks. First, I consider five alternative ways of measuring financial frictions. The first three are alternative methods to combine the survey answers into one indicator. The fourth identifies the causal effect of financial frictions using an instrumental variables strategy. The probability of reporting financial frictions is instrumented with exogenous differences in local financial development. The fifth is the external financial dependence indicator proposed by Rajan and Zingales (1998). Second, I consider two alternative measures of productivity: a productivity measure obtained using deflated input and output values and the "implied TFPQ" measure derived by De Loecker and Warzynski (2012). All these alternative approaches confirm the main finding of a negative relationship between sector-level financial frictions and firm-level productivity growth. Finally, online Appendix B includes additional regression results that show how firms in more constrained sectors also exhibit slower growth in employment, capital stock, and labor productivity.

III. The Model

Motivated by the empirical evidence in the previous section, I develop a model to study the relationship among financial frictions, innovation decisions, and firm dynamics. I consider a partial equilibrium industry model with monopolistic competition, financial frictions, and heterogeneous innovations. Each firm in the industry produces a variety w of a consumption good. There is a continuum of varieties $w \in \Omega$. Consumers' preferences for the varieties in the industry are C.E.S. with elasticity $\sigma > 1$. The C.E.S. price index P_t is equal to

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

The associated quantity of the aggregated differentiated good Q_t is

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

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

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

regressions. I use probabilistic weights that correct the underrepresentation of smaller firms, and I show that the results are confirmed and become marginally stronger.

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

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

Each variety is produced by a firm using labor, and I define its marginal productivity by v_t^n. The marginal productivity of labor for the frontier technology is equal to $\overline{v_t^n}$. To normalize the model, I assume that the labor cost is also equal to $\overline{v_t^n}$. I define $v_t = v_t^n / \overline{v_t^n}$ as the productivity relative to the frontier. It follows that $v_t = 1$ at the frontier, that the marginal labor cost is $1/v_t$, and that total labor cost is $q_t(w)/v_t$. The profits for a firm with productivity v_t and variety w are given by

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

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

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

where $F'(v_t) > 0$. The fixed cost F_t is increasing in productivity v_t to ensure that the profitability levels of small and large firms in the simulated model are comparable to those in the empirical sample.[7] The term ε_t is a mean-zero i.i.d. shock that introduces uncertainty in profits and affects the accumulation of wealth and the probability of default. Note that $\varepsilon_t F(v_t)$ enters additively in $\pi_t(v_t, \varepsilon_t)$, meaning that it does not affect the firm's choice of the optimal price p_t and quantity produced q_t. This makes the model both easier to solve and more comparable to a standard model without financing frictions.[8]

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

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

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

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

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

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

Equation (11) clarifies that profits depend on the firm-specific productivity v_t and shock ε_t and on market competition, which affects the aggregate price index P. The timing of the model for a firm that was already in operation in period $t-1$ is the following. At the beginning of period t, with probability δ, its technology becomes useless forever, and the firm liquidates all of its assets and ceases activity. This shock is independent across firms. With probability $1-\delta$, the firm is able to continue. It observes the realization of the shock ε_t and receives profits π_t, and its financial wealth a_t is

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

where $R = 1 + r$, and r is the real interest rate; d_t are dividends; $K(I_{t-1})$ is the cost of innovation, which varies depending on the innovation type; I_{t-1} is an indicator function that takes value j if innovation type j is selected. Financing frictions are introduced with the assumption that the firm cannot borrow and has to finance its investments with internally generated earnings:

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

Equation (12) implies that constraint (13) is not satisfied when current profits $\pi_t(v_t, \varepsilon_t)$ are negative and exceed savings $R\left[a_{t-1} - K(I_{t-1}) - d_{t-1}\right]$. In this case, the firm cannot continue its activity and is forced to liquidate. Constraint (13) is a simple way to introduce financing frictions. In the calibrated model, it generates a realistic downward-sloping bankruptcy risk in firm age. It can be interpreted as a shortcut for more realistic models of firm dynamics with financing frictions such as Clementi and Hopenhayn (2006). Conditional on continuation, innovation of type I_t is feasible only if

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

Constraint (14) implies that innovation has to be internally financed. This assumption is consistent with several recent papers that demonstrate that intangible investments such as R&D are financed primarily with cash, as intangibles have low collateral value (see, e.g., Bates, Kahle, and Stulz 2009; Begenau and Palazzo 2017; and Falato and Sim 2014). Moreover, Benfratello, Schiantarelli, and Sembenelli (2008) shows that, in the Mediocredito/Capitalia dataset, 82 percent of all R&D expenditures are financed with retained earnings, while only 9 percent are financed with loans.

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

A. *Innovation Decisions*

Every period, a new vintage of technology becomes available. Productivity at the frontier grows exogenously at rate $g > 0$, thanks to new technological advances generated by fundamental research. I interpret innovation as investment undertaken by firms, when they are not at the frontier, to improve their productivity by adopting part of these technological advances in their production processes. Every period, a firm receives a new innovation opportunity with probability γ. The firm can choose among different types of innovation, which correspond to different ways of exploiting the investment opportunity. For example, a firm that has the opportunity to introduce a new product can choose between different strategies regarding the innovative features of the new product. Innovation of type j is characterized by the cost $K(j)$, the probability of success $0 < \xi^j \leq 1$, the improvement in productivity $\tau^j_{succ} > 0$ in the event that it succeeds, and the decline in productivity $\tau^j_{fail} \leq 0$ in the event that it fails. More precisely, the next period's productivity v_{t+1} for a firm innovating in period t is equal to

$$(15) \qquad v_{t+1} = \begin{cases} v_t(1+g)^{\tau^j_{succ}} & \text{with probability } \xi^j \\ v_t(1+g)^{\tau^j_{fail}} & \text{with probability } 1-\xi^j \end{cases},$$

subject to the constraint that v_{t+1} is bounded above by the value of the frontier technology.

To keep the model tractable, I simplify heterogeneity by assuming only two technology types $j \in \{1,2\}$ with different risk and return characteristics: $j = 1$ is a non-risky type of innovation with $\xi^1 = 1, \tau^1_{succ} > 0$, and $\tau^1_{fail} = 0$. The firm invests $K(1)$, and its productivity grows by $\approx\left(\tau^1_{succ} \times g\right)$ percent with probability 1. I call this type of innovation "incremental" innovation; $j = 2$ is a riskier type of innovation, with $\xi^2 < 1$ and $\tau^2_{fail} < 0$, but is potentially more productive, with $\tau^2_{succ} > \tau^1_{succ}$. In particular, innovation risk includes two components, the probability of failure $\left(1-\xi^2\right)$ and the possibility of a reduction in productivity by $\approx(\tau^2_{fail} \times g)$ percent conditional on failure. I call this type of innovation "radical" innovation.[9]

[9] The assumption that innovation probabilities are not independent simplifies the analysis but is not essential for the results. I solved the model while allowing firms to have independent radical and incremental innovation options, and this produced no significant change in the quantitative or qualitative results of the model. In equilibrium, for the calibrated parameters and most of the productivity space, the next-best option to the preferred innovation type is to not innovate. These additional results are available upon request.

The intuition for the downside risk is that the more radical innovation projects, which have higher upside potential, often require radical changes to how a firm operates. 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." To the extent that these changes are irreversible, in the event of failure, the firm cannot easily revert back to the old technology, and its efficiency will be lower relative to the situation before it pursued innovation.

Finally, a firm that does not intend to innovate ($j = 0$), either because it has no investment opportunities or because it decides not to implement either of the two innovations, has $\tau^0_{succ} = 0$ and $\tau^0_{fail} = -1$. In other words, with probability ξ^0, it keeps the same pace as the technological frontier, and its relative productivity v remains constant. With probability $1 - \xi^0$, its relative productivity decreases by g percent.

Note that I define innovation as an investment intended to increase production efficiency. This approach is consistent with Hsieh and Klenow (2014), who also focus explicitly on the growth of process efficiency over the life cycle of plants. However, many authors (see, e.g., Foster, Haltiwanger, and Syverson 2016) argue that gradual increases in plants' idiosyncratic demand levels are important to explain the growth of plants in the United States. Regarding this, Hsieh and Klenow (2014) notices 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 and for simplicity, I define an innovation process that affects production efficiency, but an alternative model with quality and/or variety innovations that affect a firm's idiosyncratic demand would have very similar qualitative and quantitative implications.

B. *Value Functions*

I define the value function $V^j_t(a_t, \varepsilon_t, v_t)$ as the net present value of future profits after receiving π_t and conditional on pursuing type-$j \in \{0,1,2\}$ innovation in period t:

$$(16) \quad V^j_t(a_t, \varepsilon_t, v_t)$$

$$= -K(j) + \frac{1-\delta}{R}\Big\{\xi^j E_t\Big[\pi_{t+1}\big(\varepsilon_{t+1}, v_t(1+g)^{\tau^j_{succ}}\big) + V_{t+1}\big(a_{t+1}, \varepsilon_{t+1}, v_t(1+g)^{\tau^j_{succ}}\big)\Big]$$

$$+ \big(1-\xi^j\big)E_t\Big[\pi_{t+1}\big(\varepsilon_{t+1}, v_t(1+g)^{\tau^j_{fail}}\big) + V_{t+1}\big(a_{t+1}, \varepsilon_{t+1}, v_t(1+g)^{\tau^j_{fail}}\big)\Big]\Big\}.$$

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. Conditional on continuation, the firm's innovation decision I_t maximizes its continuation value V_t^*:

$$(17) \qquad V_t^*(a_t, \varepsilon_t, v_t) = \gamma \max_{I_t \in \{0,1,2\}} \left\{ V_t^0(a_t, \varepsilon_t, v_t), V_t^1(a_t, \varepsilon_t, v_t), V_t^2(a_t, \varepsilon_t, v_t) \right\} + (1-\gamma)\, V_t^0(a_t, \varepsilon_t, v_t)$$

such that equation (14) is satisfied. Given the optimal continuation value $V_t^*(a_t, \varepsilon_t, v_t)$, the value of the firm at the beginning of time t, $V_t(a_t, \varepsilon_t, v_t)$, is

$$(18) \qquad V_t(a_t, \varepsilon_t, v_t) = \mathbf{1}(a_t \geq 0)\left\{\max\left[V_t^*(a_t, \varepsilon_t, v_t), 0\right]\right\}.$$

Equation (18) implies that the value of the firm is equal to zero in two cases: first, when the indicator function $\mathbf{1}(a_t \geq 0)$ is equal to zero because the liquidity constraint (13) is not satisfied and, 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 production.

C. *Entry Decision*

There is free entry in every period, and there is a large number 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 $[\underline{v}, \bar{v}]$, after having paid an initial cost S^C. Once they learn their type, they decide whether to start activity. The free entry condition requires that, ex ante, the expected value of paying S^C conditional on the expectation of the initial values v_0 and ε_0 is equal to zero:

$$(19) \qquad \int_{\underline{v}}^{\bar{v}} \max\left\{E^{\varepsilon_0}\left[V_0(a_0, \varepsilon_0, v_0)\right], 0\right\} f(v_0)\, dv_0 - S^C = 0.$$

D. *Equilibrium Conditions*

The presence of technological obsolescence implies that the age of firms is finite and that the distribution of wealth across firms is non-degenerate. Moreover, aggregation is very simple because all operating firms with productivity v choose the same price $p(v)$, as determined by equation (10). Therefore, the steady-state equilibrium is characterized by an aggregate price P, an aggregate quantity Q, and time-invariant distributions of operating firms and new entrants over the values of v_t, ε_t, and a_t such that firm value is defined as the net present value of profits and is determined by equation (16). Continuing firms make innovation decisions according to equation (17) and exit decisions according to equation (18). New entrants satisfy condition (19). The mass and distribution of firms over v_t determine the mass and distribution of prices. Aggregating these prices into the CES price index must yield the equilibrium aggregate price P. The numerical procedure to solve the problem is illustrated in online Appendix C.

E. *Financing Frictions and Innovation Decisions*

Although the model does not have an analytical solution, it is useful to analyze the above equations to obtain intuition about the effects of financial frictions on firm dynamics and innovation decisions. By "financially constrained," I mean firms with low financial wealth a_t, for which constraints (13) and (14) might be binding today or in the future. First, there is a direct effect: constraint (14) implies that firms with low financial wealth a_t are unable to finance their desired innovation type. Second, equation (18) implies that the higher the probability of bankruptcy $\Pr(a_t < 0)$ is, the lower the expected value of the firm. Therefore, a higher expected probability of bankruptcy for new firms reduces the value of the term $E^{\varepsilon_0}\left[V_0(a_0, \varepsilon_0, v_0)\right]$ in the entry condition (19) for a given aggregate price P. It follows that the term on the left-hand side of (19) becomes negative: $\int_{\underline{v}}^{\bar{v}} \max\left\{E^{\varepsilon_0}\left[V_0(a_0, \varepsilon_0, v_0)\right], 0\right\} f(v_0)\, dv_0 - S^C < 0$, and entry must fall until lower competition increases P, increases expected profits and the value of a new firm, and ensures equilibrium under the free entry condition. In other words, there is an indirect "competition effect": financing frictions increase bankruptcy risk, and fewer firms enter such that, in equilibrium, expected bankruptcy costs are compensated by lower competition and higher profitability.[10]

F. *Calibration*

The calibrated parameters are illustrated in Table 2. With the exception of σ, η, r, and A, all parameters are calibrated to match a set of simulated moments, with the moments estimated from the empirical sample analyzed in Section II. In most cases, a set of parameters jointly identifies several moments. Nonetheless, for clarity, I will link each parameter to the moment that is more directly affected by it. All auxiliary calculations performed to calibrate the parameters are reported in the online Appendix D.

Because of the emphasis of this paper on financial frictions, a set of parameters matches both the level and dispersion of profits. The fixed per period cost of operation $F(v_{it})$ is

$$F_{it} = \left(\frac{v_{it}}{\hat{v}_0}\right)^{\kappa}, \tag{20}$$

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

Table 2—Calibration of the Benchmark Model

Parameter	Value	Empirical moment	Data	Model
S^C	7.75	Profits sales ratio for the 50th percentile	0.02	0.02
κ	2.45	Profits sales ratio for the 95th percentile	0.11	0.11
θ	0.35	Fraction of firms going bankrupt	1.3%	1.3%
$K(1)$	0.25	Average (process innovation R&D expenditures)/sales	1.3%	1.4%
$K(2)$	0.1	Average (product innovation R&D expenditures)/sales	2.6%	2.6%
ξ^2	0.084	Success probability of radical innovation	8.4%	8.4%
γ	36	Percentage of firms doing incremental innovation	17.3%	17.0%
τ^2_{succ}	31	Right tail of firm-level productivity changes	0.125	0.129
τ^2_{fail}	4	Percentage of firms doing radical innovation	16.5%	16.8%
τ^1_{succ}	2	Ratio between ninetieth and tenth percentile of size distribution	13.2%	12.8%
$\hat{v}$	0.37	Average productivity of new firms relative to the frontier	0.37[a]	0.37
σ^2_v	0.1	Cross-sectional dispersion of productivity	0.34[b]	0.36
g	0.01	Average aggregate TFP growth	1%[c]	1%
ξ^0	0.75	Average yearly decline in TFP for firms not doing R&D	0.4%[b]	0.4%
δ	0.022	Average age	24[b]	24
a_0	1.15	Average exit rate	5.8%	5.8%

Notes: Other parameters: $r = 2\%$; $\eta = 1.5$; $\sigma = 4$; and $A = 50{,}010$. Profits denote operative profits. For the simulated moments, I simulate the industry for 500 periods so that it reaches the steady-state number of firms and the steady-state equilibrium distribution of firms over productivity and financial wealth. Then I simulate 300 additional periods, I compute the aggregate statistics for every period, and at the end of the simulation, I compute the average statistics across the 300 periods.

[a] For the empirical data, the frontier is proxied with the ninety-ninth percentile of the distribution of productivity.

[b] These statistics are calculated after excluding the 1 percent outliers on both tails.

[c] Data is for the whole of Italy's industrial sector, 1990–2000 period.

where $\hat{v}_0$ is the mean of the productivity distribution of new firms. The fixed entry cost S^C and the parameter κ jointly match the distribution of profits across firms, specifically the fiftieth and ninety-fifth percentiles of the average ratio between operative profits and total revenues. The profit shock ε is modeled as a two-state i.i.d. process, where ε takes values θ and $-\theta$ with equal probability. Here, θ is a positive constant and matches the fraction of firms going bankrupt every period.

For the calibration of the parameters related to innovation, I consider the survey responses where firms report their R&D spending, as well as the nature of the R&D investment. Moreover, I complement the survey information with patenting information from the Italian Patents Office (IPO). The main assumption is that

R&D activity intended to develop, patent, and introduce new products is risky and fails with positive probability. Conversely, R&D to improve current products is less risky. Therefore, I map the incremental ($j = 1$) innovation in the model to the firms that invest in R&D to improve current products or productive processes. Furthermore, I map firms attempting radical ($j = 2$) innovation in the model to firms that invest in R&D to introduce new products. In online Appendix D, I provide evidence consistent with this assumption. I show for firms performing R&D that the volatility of productivity increases within firms over time, conditional on investing in R&D to introduce new products.

Given these identification assumptions, I calibrate the innovation parameters as follows: the innovation costs $K(1)$ and $K(2)$ match the average value of R&D expenditures over profits, for R&D intended to improve current products and introduce new products, respectively. For incremental innovation, the only additional parameter to identify is the productivity gain τ^1_{succ}. In equilibrium, this parameter affects the dispersion of the size distribution. I calibrate it to match the ratio between its ninetieth and tenth percentiles. The calibrated value of $\tau^1_{succ} = 2$ implies that an incremental innovation opportunity increases productivity (relative to the frontier) by approximately 2 percent.

For radical innovation, I need to calibrate the success probability ξ^2 and both τ^2_{succ} and τ^2_{fail}. For the firms in the 2001 Mediocredito Survey, I have sufficient information to match the surveyed firms with patent data from the IPO. Therefore, I consider as successful a firm that invests in R&D to introduce new products and is awarded a new patent in the sample period. This results in 17.3 percent of firms attempting radical innovation, a success probability of $\xi^2 = 8.4$ percent, and 1.45 percent of firms being successful in radical innovation every year. In equilibrium, the largest productivity gains in the model are those obtained by these successful firms, and therefore, I calibrate τ^2_{succ} to match the average absolute yearly deviation in productivity for the 1.45 percent largest positive deviations in productivity observed in the data. The value of τ^2_{succ} implies that a firm successful in radical innovation increases productivity by approximately 30 percent.

Despite also having available data from the European Patents Office (EPO), I prefer to use Italian patents for the benchmark calibration, as many small firms in the sample only patent their invention at that office, not at the European counterpart. However, when testing the predictions of the model in Section V, I consider also alternative indicators of radical innovation based on European patents and their citations.

Finally, the probability of an innovation opportunity γ directly affects the number of innovating firms, while the loss in productivity for failed radical innovation τ^2_{fail} affects the type of innovation they choose. Therefore, these parameters match the percentage of firms pursuing incremental innovation and radical innovation, respectively.

Regarding the remaining parameters, the mean $\hat{\nu}_0$ and variance $\sigma^2_{\nu_0}$ of the productivity distribution of new firms match the median productivity of new firms relative to the technological frontier and the average cross-sectional standard deviation of productivity, respectively. The growth rate of the technological frontier g matches the average aggregate TFP growth in Italy in the sample period; ξ^0

matches the yearly decline in TFP for non-innovating firms; and the probability that technology becomes useless δ matches the average age of firms. Finally, the parameter a_0, the initial endowment of wealth of new firms, affects the intensity of financing frictions, the probability of bankruptcy, and the exit rates. I choose a_0 to match the average exit rate in the Italian manufacturing sectors. Although the model is relatively stylized, Table 2 shows that it matches these empirical moments reasonably well.

The parameters that do not directly match an empirical moment in the sample are set as follows. The average real interest rate r is equal to 2 percent, which is consistent with the average short-term real interest rate in Italy during the sample period. The value of σ, the elasticity of substitution between varieties, is equal to 4, in line with Bernard et al. (2003), who calculates a value of 3.79 using plant-level data. The value of η, the industry price elasticity of demand, is set equal to 1.5, following Constantini and Melitz (2008). The difference between the values of η and σ is consistent with Broda and Weinstein (2006), who estimate that the elasticity of substitution falls between 33 percent and 67 percent when moving from the highest to the lowest level of disaggregation in industry data. 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 it makes it possible to compute reliable aggregate statistics.

IV. Simulation Results

I use the calibrated model to generate artificial firm-level data. I generate three simulated industries that are designed to match the intensity of financing frictions in the "least constrained," "mid-constrained," and "most constrained" empirical groups of sectors analyzed in Section II.

For this exercise to be informative, it is necessary to quantitatively pin down an industry's financial frictions in the model and the data in a comparable manner. In the data, I have information about problems in obtaining external financing. In the model, I generate financial problems in equilibrium by changing the initial endowment a_0. A lower a_0 increases bankruptcy rates, exit rates, and the fraction of firms unable to finance their innovation.[11] Fearing bankruptcy, ex ante, fewer firms enter in absolute terms, leading to fewer firms operating for a given level of demand and generating lower competition and higher profits. However, although fewer firms enter in absolute terms, the number of firms operating in equilibrium declines

[11] In the model, firms accumulate internal finance to gradually overcome such frictions over time. Therefore, newly created firms are more financially constrained but become progressively less so as they generate profits and retain earnings. This feature is common to firm dynamics models that assume less severe forms of financial frictions, such as Midrigan and Xu (2014) and Buera, Kaboski, and Shin (2011). In this respect, in this model, the severity of the financing frictions is mitigated by assuming that firms are created with a positive endowment. An alternative model in which financial frictions are modeled as borrowing limits would have similar implications. For example, one can assume that the initial investment S^C is the value of an asset necessary for the firm to produce. In less constrained sectors, a larger fraction of this asset can be used as collateral to obtain a credit line a_0 for a new firm. This alternative model is identical to the current one, with higher a_0 in less constrained sectors. The only difference is that in this alternative model firms do not receive any interest rate on their endowment, but since this return is very small relative to firms' profits, this change would not significantly affect the results.

Table 3—Descriptive Statistics for the Simulated Sectors

	33% least constrained group	33% mid-constrained group	33% most constrained group
Initial endowment	1.6	1.15	0.09
(1) Firms going bankrupt every period[a]	0.7%	1.3%	4.9%
(2) Exit rates[a]	5.4%	5.8%	6.9%
(3) Number of firms	10,256	9,889	8,980
(4) Average P[b]	100%	100.7%	104.7%
(5) Profitability conditional on productivity[b,c]	100%	102.9%	118.0%
(6) Firms financially constrained in their incremental innovation[a]	4.5%	8.2%	17.0%
(7) Firms financially constrained in their radical innovation[a]	0.3%	0.2%	0%
(8) Firms financially constrained $(6 + 7)$[a]	4.8%	8.4%	17%
(9) Innovating firms[a]	34.1%	33.7%	29.9%
Selected empirical moments			
Firms declaring financial frictions[a]	9.1%	14.0%	20.3%
Innovating firms[a]	35.8%	35.6%	28.5%

Notes: For each group, I simulate 500 periods so that it reaches the steady-state number of firms and the steady-state equilibrium distribution of firms over productivity and financial wealth. Then I simulate 300 additional periods, I compute the aggregate statistics for every period, and at the end of the simulation, I compute the average statistics across the 300 periods.

[a] Percentage over the total number of firms.

[b] Value relative to the 33 percent least constrained group.

[c] Profitability is profits over sales conditional on relative productivity equal to 1 (the frontier technology).

by more than the number of entrants, and therefore, entry and exit rates increase. In other words, the model predicts that the intensity of financial frictions and turnover rates are positively related in equilibrium. Therefore, to calibrate financial frictions, I proceed in three steps. First, I show that a positive correlation between financial frictions and turnover rates is also found in the Italian data. As a second step, I use the exit rates available from the Italian National Institute of Statistics (ISTAT) to estimate the corresponding exit rates for the "least constrained," "mid-constrained," and "most constrained" empirical sectors in my dataset, obtaining values of 5.4 percent, 5.8 percent, and 6.9 percent, respectively. Finally, as a third step, I choose the initial endowment in the three simulated sectors such that their average exit rates match the estimated average exit rates in the data, obtaining values of 1.6, 1.15, and 0.09, respectively. The detailed data and calculations are illustrated in online Appendix D.

In Table 3, I report summary statistics for these simulated groups of firms. The table highlights the direct and indirect effects of financial frictions on firm investment decisions. On the one hand, I have the direct effect: an increase in financial frictions (moving from column 1 to column 3) increases the probability of bankruptcy from 0.7 percent to 4.9 percent. On the other hand, I have the indirect competition effect described in Subsection E: financial frictions reduce the absolute number of entrants and the number of firms in equilibrium (row 3). Lower competition increases the aggregate price P by up to 4.7 percent and profitability conditional on productivity by up to 18.0 percent (rows 4 and 5). In other words, in the most constrained group, more firms go bankrupt, but those that survive the first years of activity, accumulate financial assets, and become unconstrained are more profitable and thus less likely to exit. This is why, despite bankruptcy rates increasing by 4.2 percent when moving from column 1 to column 3, exit rates only increase by 1.5 percent. In rows 6 to 8, I report the fraction of financially constrained firms, defined as firms that cannot make optimal investment decisions because of a lack of funds. They satisfy two criteria. First, at their productivity level, it is optimal to implement an innovation if the opportunity arises; second, they cannot take that opportunity if it arises because of insufficient funds.[12] In row 9 of Table 3, I report the fraction of innovating firms. At the bottom of the table, I show the fraction of constrained and innovating firms in the empirical dataset, for comparison with the simulated data. Since I do not match these moments across the simulated groups, these statistics are useful to evaluate the model. In the data, 7.3 percent more firms innovate in the least constrained group than in the most constrained group. This difference is also positive in the simulations (4.2 percent). Moreover, the percentage of financially constrained firms in the data is uniformly larger than in the model, perhaps because, as argued in Section II, they also include financially distressed firms. Nonetheless, the differences between the most and least constrained groups are very similar: 11.2 percent in the data and 12.2 percent in the model.

A. *Productivity over the Firms' Life Cycle*

The calibration procedure illustrated above ensures that the simulated firms match the empirical firms in terms of average age, profitability, and innovation intensity and in terms of the cross-sectional dispersion of size, age, productivity, and profitability. In this section, the model is evaluated for its ability to replicate the average productivity growth over the firm life cycle, especially the relationship between productivity growth and financial frictions.

Figure 3 shows the life cycle profile of productivity. It is computed for cohorts of firms that survive for at least 40 years. For each group, the values are normalized to 1 for newborn firms. The figure shows that productivity growth is negatively affected by financial frictions, especially once these become more severe. As firms increase in age from 1 to 40 years, their productivity increases, on average, by 51.8 percent in the least constrained industries and only by 28.7 percent in the most constrained industries. The difference between the least and most constrained groups is quantitatively and qualitatively consistent with the empirical life-cycle dynamics shown in Figure 1.

For a more detailed comparison with the empirical data, Figure 4 shows yearly productivity growth in the empirical and simulated sectors, sorted according to the intensity of financial frictions. The empirical growth rates are the same as in Figure 2. The simulated growth rates are obtained varying the initial endowments to progressively increase financial frictions in the simulated

[12] This definition applies to all firms regardless of whether they have an investment opportunity. It also implies that a firm that is unable to invest in its optimal innovation choice but is able to invest in an alternative, less desirable innovation choice because of the latter's lower cost is still classified as constrained.

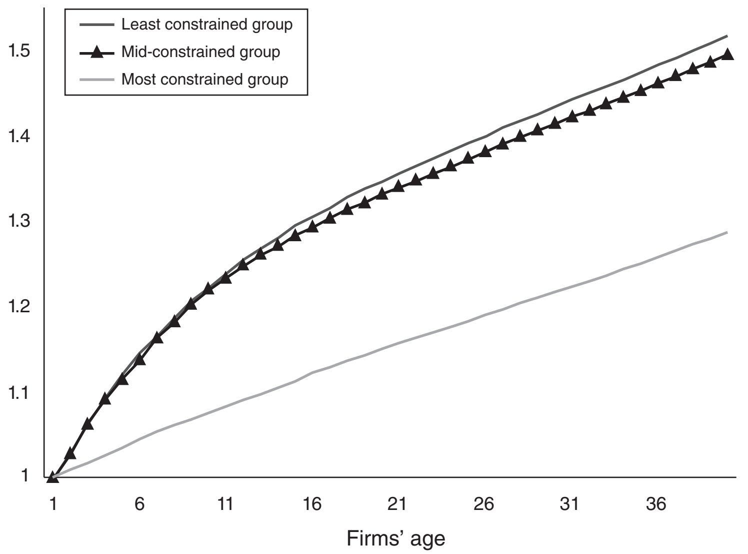

Figure 3. Productivity over the Firms' Life Cycle—Benchmark Calibration

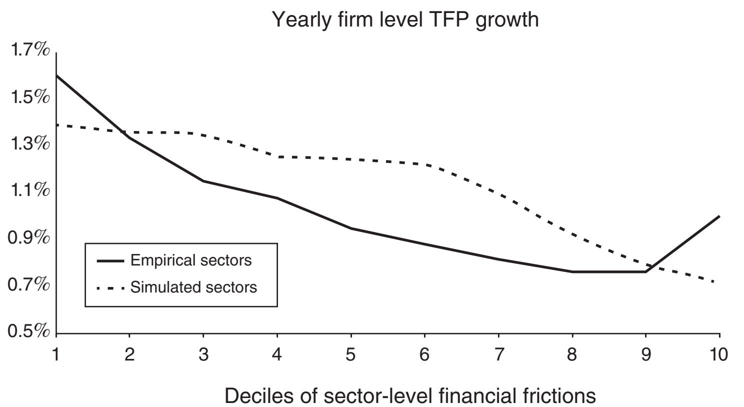

Figure 4. Financial Frictions and Productivity Growth, Model versus Data

sectors (see online Appendix D for details). The figure shows that the model is able to generate a negative relationship between financial frictions and productivity growth comparable to that in the data, although in the data, the relationship is steeper for the first five deciles, while in the model, it is steeper from decile six onward. Regarding the implications for aggregate productivity, I find that reducing financial frictions in all the most constrained sectors, abstracting from changes in wages and interest rates, would increase their productivity by 5 percent.

Inspecting the Mechanism.—Figure 5 shows the firm-level dynamics underlying the results in Figures 3 and 4. It compares the least and most constrained groups, and it is useful to first analyze the dynamics of the former. In panel A, the fraction

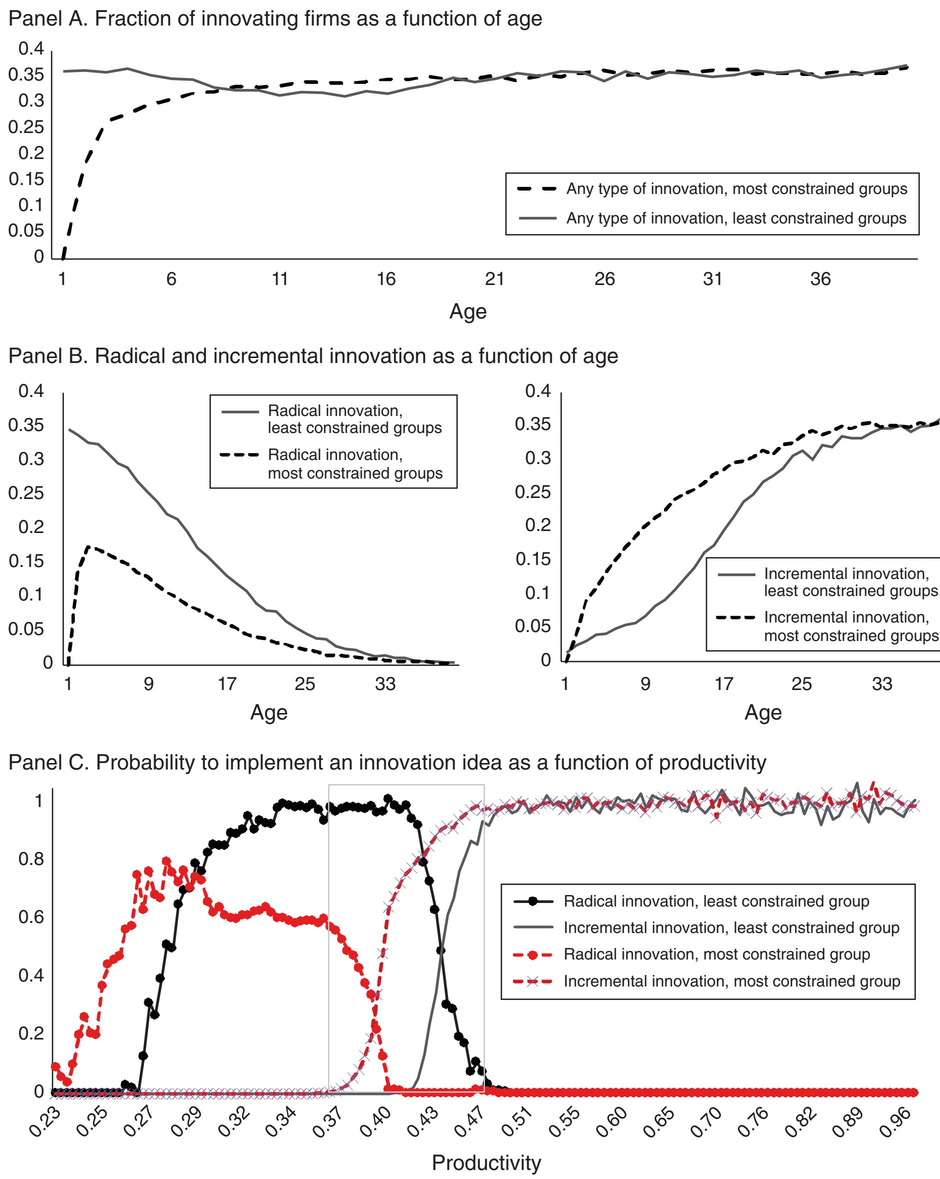

Figure 5. Probability to Innovate, Comparing Least and Most Constrained Groups

of innovating firms in the least constrained group is roughly constant over age and only slightly smaller than the probability of receiving an innovation opportunity (36 percent). For the calibrated parameters, almost all the firms with an innovation opportunity want to innovate, and few have a binding financing constraint in this group (see Table 3). Therefore, the relevant margin is what type of innovation firms choose. Panel B of Figure 5 shows that young firms are mostly performing radical innovation, and they gradually switch to incremental innovation as they age. Younger firms are, on average, smaller and less productive than older ones, and panel C shows that radical innovation is performed by firms that are further from the technological frontier (normalized to one). This is because radical innovation is a high-risk investment with a low probability of success but a very high reward in the event of success. It is not particularly attractive for firms closer to the productivity frontier, as they already have a profitable business that generates substantial profits. However, it is very attractive for firms further from the frontier. 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, as they can always cut losses by exiting production. Therefore, young firms, on average, perform most of the radical innovation in the industry. These firms then either exit after failure or grow rapidly after success, which explains why, on average, the productivity of younger firms grows faster than that of older firms in Figure 3. Once they become older, firms invest more in incremental innovation because they are, on average, larger and more productive. These dynamics are consistent with several stylized facts on firm dynamics such as: small firms grow faster than larger firms and have more volatile growth; small firms pursue relatively more exploratory R&D and have a relatively higher rate of radical innovations than large firms (Akcigit and Kerr 2018); the distribution of growth rates of young firms is very skewed, with "a small fraction of very fast growing firms driving the higher mean net employment growth" (Haltiwanger et al. 2017).

Regarding the most constrained group, in panel A of Figure 5, binding financing constraints explain the very low innovation rates of young firms. However, firms that do not go bankrupt in this group quickly become sufficiently wealthy to avoid financial problems. From approximately age six onward, the total fraction of innovating firms is almost identical in the two groups, but its composition is not: panel B shows that, in the most constrained group, younger firms perform significantly less radical innovation and significantly more incremental innovation than those in the least constrained group. As argued above, radical innovation is the driving force behind the fast growth rates of younger firms, and therefore, this distortion is key to generating the slower productivity growth in more constrained sectors shown in Figures 3 and 4.

Young firms perform relatively less radical innovation in the most constrained group because of the competition effect. Firms that overcame their initial financial difficulties are relatively more profitable, at their current productivity level, and less willing to pursue radical innovation than their counterparts in the least constrained group because they have more to lose in the event of failure. Moreover, there is a feedback effect. If fewer young firms pursue radical innovation, fewer firms become large and productive, and overall competition decreases, which further discourages radical innovation. Instead, when 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.[13] These effects are shown clearly in panel C of Figure 5. In the most

[13] The empirical competition literature often estimates a positive relationship between competition and innovation (e.g., Blundell, Griffith, and Van Reenen 1995 and Nickell 1996). To the best of my knowledge, this paper proposes a novel theoretical mechanism that is consistent with this evidence and different from and complementary to the well-known "escape competition effect" of Aghion et al. (2001).

constrained group, financial frictions reduce some firms' probability of innovating, but they also shift to the left the productivity threshold around which firms switch from radical to incremental innovation. This shift is highlighted in the area delimited by the gray rectangle. In summary, this section shows that a lower frequency of radical innovation among younger firms in the financially constrained sectors, caused by the indirect competition effect, is essential to explain the productivity dynamics in Figures 3 and 4.

B. *Counterfactuals and Relationship with Empirical Evidence*

In this section, I consider several counterfactual exercises to analyze the above results in greater detail. Moreover, I simulate artificial panel data and use them to run the same regressions performed on the empirical data in Section II.

Isolating the Competition Effect.—I first consider two counterfactual exercises in which I disentangle the direct and indirect effects of financial frictions. In the first exercise, in panel A of Figure 6, I shut down the indirect competition effect. I simulate three sectors with different endowments such that, in equilibrium, they have the same fraction of financially constrained firms as the most constrained, mid-constrained, and least constrained groups analyzed above. However, I also calibrate the entry cost S^C to compensate for the barriers to entry caused by financial frictions, and thus, the average price level and profitability conditional on firm productivity are identical across the three sectors.

The statistics for the three groups are shown in the first three columns of Table 4. In the most constrained group, 12.1 percent more firms face binding financing constraints than in the least constrained group. However, panel A of Figure 6 shows that without the competition effect, the result in Figure 3 is completely eliminated and even reversed: productivity growth is slightly steeper in the most constrained sector than in the least constrained sector. The intuition is as follows: in the most constrained group, some young firms with low productivity levels, which are not currently constrained, could become so in the near future after a negative shock. Because their current value is low, they are willing to risk pursuing radical innovation. It follows that there is a slightly larger frequency of radical innovation in the most constrained group, which explains the higher average growth.

In the second exercise in panel B, I isolate the indirect competition effect. I simulate three sectors, in which the mid-constrained group is the same as in the benchmark calibration. For the other two groups, I hold a_0 and all the other parameters fixed at the benchmark level, while I vary S^C to match the equilibrium prices in the most constrained and least constrained industries analyzed in Figure 3. In other words, variations in entry costs generate variations in competition that are of the same magnitude as those generated by financing frictions in Figure 3. The statistics for these groups are shown in the second part of Table 4. The results indicate that the higher the barriers to entry are, the lower productivity growth is, with a magnitude very similar to that of the full model in Figure 3. In both cases, higher entry barriers make young firms more profitable and less inclined to risk

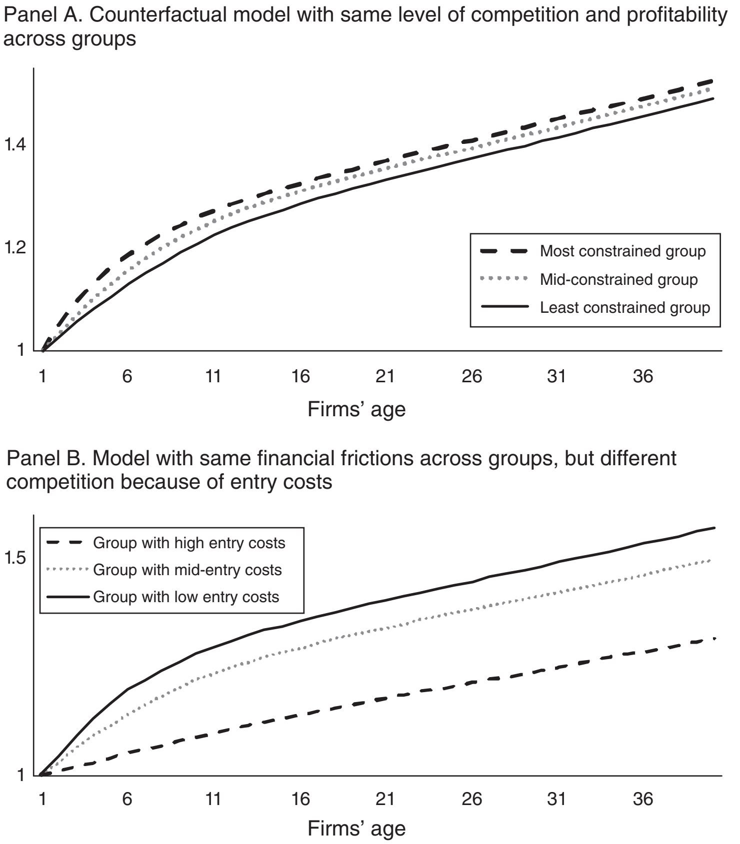

Figure 6. Productivity over the Firms' Life Cycle—Counterfactual Calibrations

radical innovation. Jointly, panels A and B of Figure 6 confirm the importance of the indirect competition effect in generating the results. They also imply that not only financial frictions but also other types of entry barriers could affect competition and radical innovation. Therefore, these results have potentially wider implications and applicability than the specific financial channel that is the focus of this paper.[14]

Regressions on Simulated Data.—The first column of Table 5 reports the fixed effects estimations of equation (3) using simulated data from the benchmark model. I create a panel of $N/3$ artificial firms for each of the three simulated groups, the least, mid-, and most constrained groups. I pool them together to obtain N firms, each observed for T periods, where N and T are comparable to the average number of firms and periods in the empirical dataset. The results confirm

[14] However, in the model, the barriers to competition caused by higher entry costs imply lower entry/exit rates (see Table 4). Conversely, barriers generated by more financial frictions imply higher entry/exit rates, and this positive correlation is confirmed in the data (see the online Appendix D). This makes it less likely that, in the most constrained sectors in the empirical dataset, the competition effect is caused by other types of entry costs rather than by financial frictions.

Table 4—Simulated Industries: Descriptive Statistics, Counterfactual Models

	Only direct effects of financial frictions, no indirect competition effect			Only indirect competition effect		
	LC	MidC	MostC	LC	MidC	MostC
Initial endowment a_0	1.5	1.15	0.72	1.15	1.15	1.15
Entry cost S^C	9.11	7.75	5.61	6	7.5	20
Fraction of bankruptcies[a]	0.7%	1.3%	3.2%	1.5%	1.3%	0.2%
Firms constrained in radical innovation[a]	0.2%	0.2%	0.1%	0.5%	0.2%	0%
Firms constrained in incremental innovation[a]	4.7%	8.1%	16.8%	9.1%	8.1%	2.5%
Radical innovations[a]	16.3%	16.8%	17.0%	18.6%	16.8%	7.6%
Incremental innovations[a]	17.9%	16.9%	15.7%	14.8%	17.0%	27.5%
Exit rates[a]	4.8%	5.8%	8.0%	6.9%	5.8%	5.4%
Number of firms	9,921	9,773	10,031	10,499	9,690	9,233
Average P[a]	100%	100%	100%	100%	100.8%	104.8%
$E(\pi/y\,|\,v)$[b,c]	100%	100%	100%	100%	103.4%	114.3%

Notes: LC = least constrained group; MidC = mid-constrained group; MostC = most constrained group. For each group, I simulate 500 periods so that it reaches the steady-state number of firms and the steady-state equilibrium distribution of firms over productivity and financial wealth. Then I simulate 300 additional periods, I compute the aggregate statistics for every period, and at the end of the simulation, I compute the average statistics across the 300 periods.

[a] Percentage over the total number of firms.

[b] Relative to 33 percent least constrained.

[c] $E(\pi/y\,|\,v)$ is average profits-sales ratio conditional on productivity.

the negative effect of financial frictions on productivity growth in the benchmark model. The differences in productivity growth across groups are smaller than those implied by Figure 3, as the within-firm estimation eliminates part of the differences in productivity growth caused by the selection induced by radical innovation. Nonetheless, the results are qualitatively consistent with the empirical results shown in Table 1. Moreover, confirming the importance of the indirect competition effect, the results are very similar in the second column, where I eliminate firms with a binding constraint.

The rest of Table 5 repeats the analysis on counterfactual models with only one type of innovation. Their calibration is similar to the full model and illustrated in detail in online Appendix D. The counterfactual model with only radical innovation confirms the negative effect of financial frictions. However, the coefficient of $age_{i,s} \times highconstr_i$ is larger in magnitude but less significant than for the full model. As described in online Appendix D, this counterfactual model generates substantial differences in productivity growth between young firms in the most and least constrained groups, but is unable to generate the gradual productivity growth observed empirically for firms 20 to 40 years old. Older and more productive firms do not wish to risk radical innovation, and in this model, they cannot improve their productivity using incremental innovation. Conversely, the counterfactual model with only incremental innovation generates positive growth over the life cycle on average but no significant differences across groups. On the one hand, in equilibrium, relatively few firms

Table 5—Relationship between Age and Productivity (Simulated Data)

	Benchmark model		Counterfactuals with only one innovation type			
			Only radical innovation		Only incremental innovation	
	(1)	(2)	(3)	(4)	(5)	(6)
$age_{i,s}$	0.0113	0.0117	0.0968	0.0104	0.0135	0.0135
	(21.6)	(22.2)	(9.4)	(9.5)	(67.5)	(63.6)
$age_{i,s} \times midconstr_i$	−0.0011	−0.0013	−0.0017	−0.0018	−0.0004	−0.0003
	(−0.9)	(−1)	(−0.7)	(−0.7)	(−0.8)	(−0.7)
$age_{i,s} \times highconstr_i$	−0.0024	−0.0024	−0.0026	−0.0028	−0.0005	−0.0002
	(−2.2)	(−2.2)	(−1.1)	(−1.1)	(−1)	(−0.4)
Observations	11,998	10,784	11,357	10,607	11,746	10,617
Time × group dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constr. excluded	No	Yes	No	Yes	No	Yes

Notes: The table shows panel regressions with firm fixed effect. Dependent variable is total factor productivity. I simulate each industry for 500 periods, so that it reaches the steady state. Then I simulate a panel of firm-level data for 10 additional periods. I randomly sample from this panel a number of firms and a number of consecutive observations for each firm, so to obtain a final panel comparable to the empirical one in terms of both dimensions. Standard errors are clustered at the firm level. The variance-covariance matrix is estimated with a bootstrap procedure with 50,000 replications. z-statistic is reported in parentheses. $age_{i,s}$ is age in years for firm i in survey s. $midconstr_i$, is equal to 1 if firm i belongs to the simulated mid-constrained group, and 0 otherwise. $highconstr_i$, is equal to 1 if firm i belongs to the most constrained group, and 0 otherwise.

are financially constrained and unable to innovate. On the other hand, the competition effect increases the profitability of incremental innovation and the frequency of unconstrained firms that innovate. It is possible that the role played by incremental innovation in generating these differences in productivity growth is underestimated because the model does not fully capture cross-sectorial differences in innovation. I explore this possibility in online Appendix D, where I vary the incremental innovation probability to match, for each sector, the frequency of innovating firms. In this case, productivity growth is significantly slower in the most constrained sectors, but the difference across sectors is still small, only approximately half the difference generated in the benchmark model.

V. Empirical Evidence, Robustness Checks

Section IV shows that the benchmark model matches well the empirical evidence, thanks to the interaction of financial frictions, competition, and radical innovation decisions. This section validates this mechanism by verifying the following three predictions:

- Prediction 1. Radical innovation is pursued primarily by younger firms.

- Prediction 2. Financial frictions reduce radical innovation relative to incremental innovation.

Table 6—Radical Innovation: Model versus Data

	DATA: New patents, Italian patent office (%)			MODEL: Success in radical innovation (%)		
	C.G.	U.G.	Diff.	C.G.	U.G.	Diff.
Panel A. Data versus model						
All firms	1.20	1.37	−0.17	1.07	1.46	−0.39
Firms $\leq$ 5 years old	0.95	2.26	−1.31	2.21	2.74	−0.53
Firms $\leq$ 10 years old	1.09	1.67	−0.58	2.01	2.51	−0.50
Firms $\leq$ 20 years old	1.12	1.36	−0.24	1.74	2.19	−0.45
	DATA: New patents, European patent office (%)			Top 10% cited patents (EPO) (%)		
	C.G.	U.G.	Diff.	C.G.	U.G.	Diff.
Panel B. Alternative empirical measures of innovation						
All firms	1.94	2.26	−0.32	0.21	0.28	−0.07
Firms $\leq$ 5 years old	1.67	4.26	−2.59	0.24	1.00	−0.76
Firms $\leq$ 10 years old	1.34	2.74	−1.40	0.20	0.53	−0.33
Firms $\leq$ 20 years old	1.78	2.48	−0.70	0.17	0.24	−0.07

Notes: C.G. is Constrained Group. U.G. is Unconstrained Group. The constrained and unconstrained simulated groups pool together the 50 percent least constrained and 50 percent most constrained simulated sectors, respectively. For each sector, I simulate 500 periods so that it reaches the steady state number of firms and the steady state equilibrium distribution of firms over productivity and financial wealth. Then I simulate 300 additional periods, I compute the aggregate statistics for every period, and at the end of the simulation, I compute the average statistics across the 300 periods.

- Prediction 3. Financial frictions indirectly affect innovation and productivity by raising entry barriers and reducing competition.

Table 6 tests predictions 1 and 2. It compares the frequency of successful radical innovations in the data and in the simulated industries. For the empirical data, in panel A, I use the same definition of successful radical innovation used in the calibration section: firms that invest in R&D to introduce new products and are awarded a new patent from the IPO in the sample period. In panel B, I consider alternative measures of innovation using data from the EPO, for which I also have information on citations. In the first three columns, I consider the firms that invest in R&D to introduce new products and are awarded a patent by the EPO. In columns 4–6, I identify a subset of the most radical patents, following Akcigit and Kerr (2018), and consider the top 10 percent of patents in terms of citations. The frequency of patenting in the sample (on average, 4.5–6 percent of firms are awarded a patent in a three-year survey period) implies few firm-survey observations with patents, especially when focusing on the subset of younger firms. Therefore, to maximize the power of the test, I consider two financing constraints groups and compare the 50 percent least constrained and 50 percent most constrained sectors. In the model, I simulate a continuum of sectors and compute average statistics for the two groups above and below the mid-constrained group (see online Appendix D for details).

Panel A of Table 6 shows that, consistent with the simulation results, radical innovation is, on average, higher in the unconstrained group than in the constrained group. The difference between constrained and unconstrained firms is statistically significant for the five- and ten-year-old groups, and is the largest among young firms, both in the data and in the model. The results in panel B confirm this. The differences between the constrained and unconstrained groups are large and always statistically significant for EPO patents and even larger for the top 10 percent of cited patents, although, due to the low number of observations, these latter differences are not statistically significant except for the group of firms up to ten years old.

With respect to the age profile of innovation, in the simulated unconstrained group, young firms conduct approximately twice the amount of radical innovation relative to the full sample (2.74 percent versus 1.46 percent). The empirical data confirm the magnitude of these differences for both IPO, EPO, and top 10 percent patents (2.26 percent versus 1.37 percent, 4.26 percent versus 2.26 percent, and 1 percent versus 0.27 percent, respectively), and such differences are statistically significant. However, the model also predicts a negative relationship between age and radical innovation for the constrained group, while no clear pattern in this group is observed in the empirical data. Overall, the data confirm one of the key features of the model: the highest frequency of radical innovations is observed among young firms in unconstrained sectors.

Table 7 repeats a similar exercise using the R&D information from the surveys. Panel A compares the percentage of firms attempting radical innovation. Following the criteria used in the calibration, in the data, these are firms pursuing R&D to introduce new products. In this case also, there is remarkable consistency between data and model. Firms in the unconstrained group pursue statistically significant and more product R&D than firms in the constrained group, and the differences are quantitatively very close to those in the simulated dataset. Moreover, younger firms engage in more R&D than do other firms.

Panel B compares the measure of incremental innovation in the model and data. In the model, the intensity of incremental innovation increases slowly with age and is still relatively low for firms up to 20 years of age, consistent with the dynamics shown in Figure 5. Comparing across panels, in the data, incremental innovation is more frequent than radical innovation in the constrained group (17.1 percent versus 14.2 percent), while it is less frequent in the unconstrained group (17.4 percent versus 18.9 percent), which confirms the patterns in the model. However, in the data, I find small and not statistically significant differences in incremental innovation across groups or within groups for firms of different ages. A possible explanation is that R&D to improve current products is a poor proxy for incremental innovation, which might involve buying new machinery that embodies a new vintage of technology rather than performing R&D.

Taken together, these results strongly support the mechanism of the model, whereby differences in radical innovation are essential for the observed differences in productivity growth. In online Appendix E, I provide additional supporting evidence from analyzing the relationship between size and productivity and radical innovation. Moreover, I also show that, once innovating firms are eliminated from

Table 7—Radical and Incremental Innovation: Model versus Data

	DATA (percent)			MODEL (percent)		
	C.G.	U.G.	Diff.	C.G.	U.G.	Diff.
Panel A. Attempts to perform radical innovation						
All firms	14.2	18.9	−4.7	12.8	17.4	−4.5
Firms $\leq$ 5 years old	12.2	20.3	−8.1	26.4	32.7	−6.3
Firms $\leq$ 10 years old	13.0	17.4	−4.4	24.0	29.9	−5.9
Firms $\leq$ 20 years old	12.9	17.3	−4.4	20.8	26.1	−5.4
Panel B. Incremental innovation						
All firms	17.1	17.4	−0.3	19.8	16.5	3.3
Firms $\leq$ 5 years old	17.0	17.9	−0.9	3.8	3.1	0.7
Firms $\leq$ 10 years old	15.6	13.9	+1.7	6.4	4.7	1.7
Firms $\leq$ 20 years old	15.8	15.8	0.0	10.5	7.8	2.6

Notes: C.G. is Constrained Group. U.G. is Unconstrained Group. The constrained and unconstrained simulated groups pool together the 50 percent least constrained and 50 percent most constrained simulated sectors, respectively. For each sector, I simulate 500 periods so that it reaches the steady-state number of firms and the steady-state equilibrium distribution of firms over productivity and financial wealth. Then I simulate 300 additional periods, I compute the aggregate statistics for every period, and at the end of the simulation, I compute the average statistics across the 300 periods.

the sample, the differences in productivity growth across the least and most financially constrained groups are no longer significant.

Prediction 3 concerns the indirect effect of financial frictions, and it could in principle be verified by comparing levels of competition across the different sectors. Many authors use a measure of concentration, such as the Herfindahl index, as an indicator of the intensity of competition. However, this approach is not feasible here because the relationship between competition and concentration is ambiguous in the benchmark model. Lower entry barriers increase competition from new entrants and reduce concentration conditional on a given level of innovation. However, in equilibrium, lower entry barriers also stimulate radical innovation, which increases the mass of very productive and large firms, thereby increasing concentration. In online Appendix E, I show that, for the benchmark parameters, these two effects neutralize one another and generate no clear relationship between barriers to entry and concentration.

Although I cannot use concentration to measure competition, Prediction 3 implies that sector-level financial frictions also reduce productivity growth for unconstrained firms, as shown in the regressions on simulated data in Table 5. This is verified in Table 8, which shows that the estimates of equations (2) and (3) change little after excluding financially constrained firms.

VI. Concluding Remarks

This paper analyzes a dataset of Italian manufacturing firms by using both survey data and balance sheet information, complemented with information on patenting activity from the Italian and European patent offices. It documents a significantly negative relationship between financing frictions and the productivity growth of firms along their life cycle. It explains this finding with a model of an industry with both radical and incremental innovation, where the indirect effects of financing

Table 8—Relationship between Age and Productivity, Empirical Data, Financially Constrained Firms Excluded

	Full sample		Financially constrained firms excluded	
$age_{i,s}$	0.0133	0.0148	0.0143	0.0158
	(11)	(8.4)	(11.1)	(8.4)
$age_{i,s} \times constrained_i$	−0.00546		−0.00657	
	(−3.6)		(−4)	
$age_{i,s} \times midconstr_i$		−0.00533		−0.00611
		(−2.5)		(−2.7)
$age_{i,s} \times highconstr_i$		−0.00633		−0.00735
		(3)		(−3.3)
Observations	10,409	10,409	9,909	9,909
Adjusted R^2	0.085	0.085	0.089	0.088
Time × group dummies	Yes	Yes	Yes	Yes

Notes: The table shows panel regressions with firm fixed effect. Dependent variable is estimated total factor productivity $\hat{v}_{i,s}$. Standard errors are clustered at the firm level. The variance-covariance matrix is estimated with a bootstrap procedure with 50,000 replications. z-statistic reported in parentheses. $age_{i,s}$ is age in years for firm i in survey s. $constrained_i$ is equal to 1 if firm i belongs to the 50 percent of four-digit manufacturing sectors with the highest percentage of financially constrained firms, and 0 otherwise. $midcontr_i$ is equal to 1 if firm i belongs to the 33 percent of four-digit manufacturing sectors with the median percentage of financially constrained firms, and 0 otherwise. $highconstr_i$ is equal to 1 if firm i belongs to the 33 percent of four-digit manufacturing sectors with the highest percentage of financially constrained firms, and 0 otherwise.

frictions are much more important for innovation decisions than the direct effects. For realistic parameter values, financing frictions act as barriers to entry that 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 one another. The model provides an explanation for the empirical evidence and, simultaneously, generates a series of additional testable predictions that confirm its implications.

The predictions of the model regarding the relationship between competition and radical innovation apply not only to financial frictions but also to any other factor that could raise barriers to entry for an industry. Therefore, the results have potentially wider implications and applicability than the specific financial channel that is the focus of this paper.

The main policy implications of these findings are that policies directed at mitigating financial frictions are most effective when targeted at very young firms and when they focus on factors that might reinforce these firms' ability to survive and thus encourage new entrants. Moreover, they imply that such policies, as well as any other policies directed at reducing entry barriers, are more important in sectors where radical innovation activity by young firms is a key factor affecting productivity growth.

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