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The Italian Productivity Puzzle: Firm Distortions and Growth

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I dedicate this thesis and graduation to my Grandfather.

The Italian Productivity Puzzle: Firm Distortions and Growth

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Abstract

Italian productivity growth has slowed down since the mid-90s, turning negative in the 2000s. To explain this breakdown, this thesis explores the role of firm-level technology adoption. Using data from the universe of Italian incorporated companies, I document an increase in the correlation between productivity and firm-level profit-reducing distortions. Over time, more productive firms are increasingly subject to profit distortions. This implies that incentives to engage in productivity-enhancing activities have progressively declined, as correlated distortions reduce the returns of such activities. I present a reverse causality test supporting the hypothesis that the correlation productivity-distortions has a causal effect on firm growth by reducing incentives to innovate. To quantify the impact on aggregate productivity, I build a general equilibrium model calibrated to the Italian pre-productivity breakdown. I find that Italy's aggregate productivity would have been 6% higher if the correlation productivity-distortions had remained at its 1997 level. Furthermore, firm life-cycle growth decreases by 8% relative to the baseline. I show that the key driving mechanism behind the trend is a steady increase in the correlation with cost-of-capital distortions, which started in 1995 and ended in 2015. The broader message is that an important component of a country's aggregate productivity growth can be explained by trends in the elasticity of productivity distortion that hampers firms' technology adoption.

1 Introduction

In the mid-1990s, Italian total factor productivity (TFP) growth experienced a severe slowdown, turning negative in the 2000s. TFP measures how efficiently given amounts of capital and labor are used to produce value-added. Economists are particularly concerned about TFP growth because productivity lies at the heart of long-term growth and rising living standards. Thus, it is crucial to understand what is at the root of this productivity breakdown.

Figure 1 shows the trend in manufacturing productivity, where TFP measurement is less controversial than in services due to better accounting of the capital stock. Italian TFP is characterized by a dramatic slowdown compared to other European countries, where productivity grew steadily up to the Great Financial Crisis. What is particularly worrisome and puzzling about the 1995 productivity breakdown is that, unlike in prior crises, TFP growth did not recover, turning negative in the 2000s. What are the main drivers of this trend? Aggregate TFP is nothing else than a weighted average of firm-level TFP. Thus, aggregate TFP depends on firm TFP along two dimensions. First, for a given amount of factors used by each firm, aggregate TFP grows when firm-level TFP grows. Second, for given firms' TFP levels, aggregate TFP depends on the allocation of factors across firms.

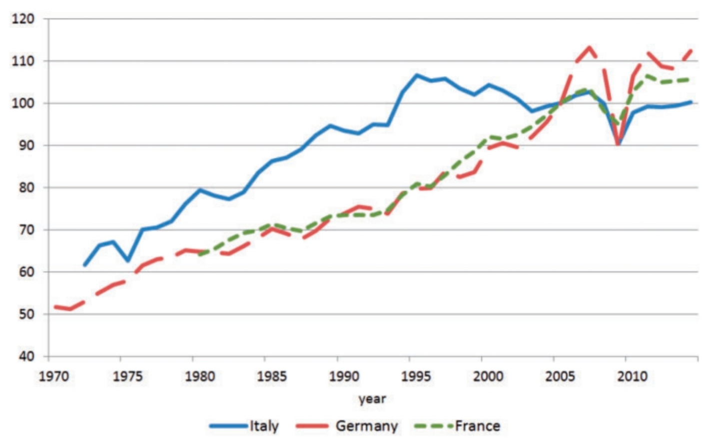

Figure 1: TFP in manufacturing for Italy, Germany, and France (2005=100).
Source: Calligaris et al. (2018)

This paper will focus on the first channel to tackle the Italian productivity puzzle. The main research question asks what could explain the absence of a recovery after the 1995 growth breakdown. Building on the endogenous growth literature, I investigate whether changes in market imperfections could have disincentivized firms from investing in productivity growth. Under the assumption that firm-level productivity is driven by the firm's R&D investments in process efficiency, at least part of the trend in aggregate productivity could be explained by changes in firms' stimulus to innovation.

Hsieh and Klenow (2009) develop a monopolistic competition model that allows for measuring frictions that enter the firm-level profit function. These frictions enter the profit function as revenue and capital taxes and capture any firm-level cost that distorts the competitive market prices. The idea is simple and builds on the distinction between physical TFP (from now on process efficiency or TFP) and revenue TFP (from now on TFPR) introduced by Foster et al. (2008). TFPR is proven to be proportional to the geometric average between marginal revenues of inputs. Absent frictions, the marginal revenue of inputs should be equalized across firms since factors move from low to high marginal revenue product firms. Hence, TFPR provides a measure of the total amount of frictions faced by the firm. Hsieh and Klenow (2014) build a general equilibrium endogenous growth model able to explain differences in aggregate productivity among India, Mexico, and the United States. Their model is based on the concept that frictions may disincentivize growth. The intuition is that the correlation between frictions and productivity may be different across countries suggesting differences in firms' incentives to invest in process efficiency. When highly productive firms in India and Mexico confront greater taxes and factor costs than in the United States, the marginal return to innovation is smaller, and firms invest less to boost productivity.

With these concepts in mind, I study the evolution of distortions and TFP at the firm level by using the universe of Italian incorporated companies over the period 1993-to 2018. As preliminary evidence, I find strong reductions in the firm-level productivity growth at every age profile. I simulate TFP life-cycle compounding firms' growth rates averaged by age. The idea is to simulate how firms would evolve in their productivity keeping constant the economic conditions determining the growth rates. I find that in the years 2006-2014 firms experienced a 20% (relative to pre-2000) decrease in their TFP growth over their simulated lifecycle. Moreover, I find that firms' TFP growth has experienced a partial recovery in the years after 2015. To shed light on this preliminary result, I introduce the framework of Hsieh and Klenow (2009) and Hsieh and Klenow (2014) and find strong evidence of an increase in the correlation between productivity and distortions. Relative to 1997, the measured elasticity of productivity distortion has experienced an increase of almost 18%, reaching a peak of 0.46 in 2009. In 2009, a 1% increase in productivity is associated with a 0.46 % increase in average distortions.

Can higher elasticity of productivity distortion explain lower TFP growth rates? To answer this question, I provide some reduced-form regressions trying to provide some empirical evidence about the impact of the elasticity of productivity distortion on growth. I argue that my results support the idea that the elasticity of productivity distortion has a causal impact on growth by lowering the marginal return to innovation. First, I find a negative correlation between firm-level productivity growth and the estimated sector-year elasticity of productivity distortion. One standard deviation increase in the elasticity is associated with a 0.95% reduction in future productivity. Of course, this is not evidence of causality since there might be reverse causality or spurious correlation. Therefore, I analyse the mechanism through which the elasticity of productivity distortion impacts TFP growth. I provide evidence of a negative correlation between firm-level intangible assets growth and the estimated elasticity of productivity distortion. One standard deviation in the elasticity of productivity distortion is associated with a 3.33% reduction in the three-year intangible assets growth. Since intangible assets growth, including branding, marketing etc., may capture something else than investments in process innovation, and since there might still be reverse causality, I provide a further test of reverse causality based on the intuition of Rajan and Zingales (1998) and Pagano and Schivardi (2003). I classify sectors according to an exogenous measure of R&D intensity to proxy for sector-specific investment opportunities. If the elasticity of productivity distortion has a causal impact on productivity growth through firms' incentives to innovate, I should find that its impact is stronger in sectors characterized by higher investment opportunities. Therefore, I consider whether the impact of the estimated elasticity of productivity distortion varies systematically with R&D sectoral intensity. If this were to be the case, reverse causality should be ruled out. Indeed, under reverse causality or spurious correlation, we would expect a homogeneous relationship between elasticity and growth that does not vary according to R&D intensity. The negative impact of one standard deviation increase in the elasticity of productivity distortion on firm-level productivity growth in a sector-year which is one standard deviation above the mean of R&D intensity is 0.48 percentage points stronger. The differential on the three-year intangible assets growth is 3 percentage points.

My empirical results indicate that the negative relationship between the estimated elasticity of productivity distortion and firm-level productivity growth increases with R&D intensity. This is consistent with a causal relationship between the elasticity of productivity distortion and growth working through firms' incentives to innovate. By looking at the interaction, rather than direct, effects I am restricting the range of alternative explanations for the relationship between the elasticity of productivity distortion and firm-level TFP growth. Hence, I am providing more consistent evidence of causality.

Next, I quantify the impact that the 18% rise in the elasticity of productivity distortion had on aggregate productivity and firm-level growth rates by building a general equilibrium endogenous growth model of heterogeneous firms. I calibrate a closed economy version of Atkeson and Burstein (2010) to the Italian pre-breakdown economy. Since there is no capital, frictions enter the profit function as revenue taxes creating a wedge in the firm profits. In the model, I assume distortions to be a function of the firm productivity, calibrated according to the different values of the estimated elasticity of productivity distortion. I focus on three main mechanisms through which the elasticity of productivity distortion impacts aggregate productivity. First, with higher elasticity, the marginal return to innovation is lower and post-entry investments in process innovation decrease. Hence, firm TFP growth will slowdown over the lifecycle. Second, with higher elasticity, the allocation of factors is distorted and less productive firms receive more weight than they would in an undistorted economy. Third, lower lifecycle growth reduces the competition posed

by incumbents on less productive firms, reducing selection.
Results indicate that with the 2009 level of frictions aggregate productivity is 6% lower than it would be if frictions had remained at the 1997 level. Moreover, incumbents' TFP is reduced by 8%. This accounts for almost half the drop in the simulated TFP lifecycle obtained compounding growth rates averaged by age.

I conclude the analysis by describing the key mechanisms driving the trend in the elasticity of productivity distortion. I find that the main driver behind the rise in the elasticity has been the increase in the correlation between productivity and capital distortions. The trend experienced a change of direction after 2015. Although only suggestive evidence, this reverse pattern suggests that *Industria 4.0*, a policy aimed at reducing the costs of investments in tangible assets that are categorized as particularly innovative, has been an effective tool to contrast the worrisome trend in the correlation between capital distortions and productivity. Further research may provide new evidence on the causes of the trend observed in the elasticity of productivity capital distortion. Moreover, it may provide more accurate evidence on the impact that policies such as *Industria 4.0* have on distortions and incentives to innovate.

This paper is related to a number of studies that have used distortions, misallocation, and the framework of Hsieh and Klenow (2009) and Hsieh and Klenow (2014) in various contexts, such as Restuccia and Rogerson (2008), Bellone, Mallen-Pisano, et al. (2013), Bollard et al. (2013), Bento and Restuccia (2017), Gopinath et al. (2017), Calligaris et al. (2018). The contribution of this paper to this line of research is twofold. On one hand, I apply the methodology of Hsieh and Klenow (2014), so far used only to explain inter-countries differences, within the same country. I show how the trend in the elasticity of productivity distortion may provide some useful explanations for a worrisome phenomenon such as the Italian productivity puzzle. I believe that several of these implications may apply to other economies facing their own productivity puzzle, providing some useful policy advice. On the other hand, to my knowledge, this is the first paper that provides empirical evidence consistent with the causal impact of the elasticity of productivity distortion on firm-level growth.

The paper is also related to a number of studies that analysed the Italian productivity slowdown, such as Navaretti et al. (2011), Bugamelli, Schivardi, et al. (2010), Bugamelli, Cannari, et al. (2012), Benigno and Fornaro (2014), Michelacci and Schivardi (2013), Lippi and Schivardi (2014), Calligaris et al. (2016), Pellegrino and Zingales (2017), Schivardi and Schmitz (2020). In addition to this literature, to my knowledge, this paper is the first that investigates firm-level incentives for technology adoption to explain the Italian productivity puzzle.

The rest of the paper is organized as follows. In section 2, I describe the dataset used for the analysis. In section 3, I provide motivating evidence documenting the negative trend in firm productivity growth. Section 4 documents the relationship between frictions and productivity. Section 5 contains the growth regression analysis and its results. Section 6 describes the model, the algorithm used to simulate it, and the results delivered. Section 7 provides the evidence on the drivers behind the rising trend in the elasticity of productivity distortion and concludes.

2 Data description

To measure the firm-level productivity growth I need data that are representative of the entire population of Italian businesses. Otherwise, results may be driven by some idiosyncrasies correlated with the restricted sample firms' characteristics. My analysis focuses on firms in the manufacturing sector because TFP measures are more reliable than services due to better accounting of inputs. The firm-level data comes from the CERVED database. The CERVED database contains detailed balance sheet information for all incorporated businesses and accounts for 70% of manufacturing VA from national accounts. Moreover, the trend rate follows very closely the national one. Thus, the CERVED database should provide a representative sample of the entire population of incorporated businesses[1]. The dataset is a panel ranging from 1993 to 2018. The variables I use from the CERVED database are the wage bill, value-added, firm identifier, firm book value of the stock of capital, and firm book value of the stock of intangible capital. Firms are grouped into three-digit ATECO 2002 sector which allows distinguishing detailed categories. To give an idea of the level of detail, examples of these categories are: Production, processing and storage of meat and products meat-based; Pack of leather clothing; Manufacture of Paper and Cardboard etc. As a measure of labor input, I use the cost of labor which allows adjusting for firms' differences in hours worked per worker and workers' skills. Capital is measured using the book value of fixed capital net of depreciation. I take firms' value-added (VA from now onward) as a measure of the firm's total revenue since it does not consider intermediate inputs. Moreover, VA share is used as a weight for the firm within the industry or as a weight for the industry itself (respectively, as a share of industry value-added or manufacturing total value-added). I drop observations with negative VA, labor cost or capital that are considered outliers. Firms older than forty years are grouped into one single age category for ease of exposition. The final sample consists of 2,358,318 firm-year observations over a sample period ranging from 1993 to 2018.

Table 1 reports descriptive statistics for the key variables in levels for the pooled sample. The average firm employs 15.4% of its total assets in intangible assets. The median firm employs 4.5%

[1] CERVED is the greatest information provider about Italian business enterprises. For more detailed information visit https://www.cerved.com/

of its total assets in intangible.

Table 1: Summary statistics of Balance Sheet variables

Variable	Obs	Mean	Std. Dev.	Min	Max	P5	P50	P95
intangible stock	2358318	378.979	12574.91	0	3913149	0	9	486
capital	2358318	1577.253	15440.11	1	4879570	6	173	5168
intangible share	2358318	.154	.225	0	1	0	.045	.693
value added	2358318	1744.485	18886.38	1	1.27e+07	36	393	5238
labor cost	2358318	1100.577	8244.307	1	2173448	20	273	3402
Firm value added share	2358318	.001	.011	0	1	0	0	.004

3 Motivating evidence

In this section, I impose some structure to the data to acquire information on firm-level productivity measures. The final goal is to infer some possible explanations for the low aggregate TFP growth observed in the manufacturing sector. An economy's aggregate TFP growth depends crucially on how TFP grows at the firm level. Following the R&D-based endogenous growth literature, firm-level TFP grows when firms invest resources in improving their process efficiency. For instance, process efficiency upgrades when adopting better technologies or management practices. Therefore, I start my analysis by asking the data whether an anemic firm-level TFP growth could provide a possible explanation for the observed pattern in aggregate productivity.

Consider a standard model of monopolistic competition with heterogeneous firms (closed-economy version of Melitz (2003)). Suppose that aggregate output at time t is obtained by a constant elasticity of substitution aggregate of the operating firms output:

$$Y_s = \left(\sum_{i=1}^{N_s} Y_{s,i}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \tag{3.1}$$

Where s indexes the sector, i indexes the firm, N_s is the number of operating firms in sector s, $Y_{a,i}$ is the firm level VA, and ρ is the elasticity of substitution across varieties (greater than one). Just for ease of exposition, I dropped the time index. Suppose that the aggregate output is produced in a competitive market. Under these assumptions, each firm receives a demand for their variety equals to:

$$Y_{s,i} = Y_s(\frac{P_s}{P_{s,i}})^{\rho} \tag{3.2}$$

Where Y is aggregate output and P is the Dixit-Stiglitz aggregate price:

$$P_s = (\sum_{i=1}^{N_s} P_{s,i}^{1-\rho})^{\frac{1}{1-\rho}} \tag{3.3}$$

Assume, further, that each firm is a monopolistic competitor choosing inputs to maximaze revenues according to a Cobb-Douglas production function with constant return to scale:

$$Y_{s,i} = A_{s,i} K_{s,i}^{\alpha_s} L_{s,i}^{1-\alpha_s} \tag{3.4}$$

Where $Y_{s,i}$ is firm output, $K_{s,i}$ is firm employed capital, $L_{s,i}$ is the employed labor, and $A_{s,i}$ is firm specific process efficiency or total factor productivity. Under these mild assumptions, it is possible to infer price and quantities from revenue by inverting the demand function that each firm is receiving. After some algebra, TFP can be obtained as follows:

$$A_{s,i} = \kappa_s \frac{(P_{s,i} Y_{s,i})^{\frac{\rho}{\rho-1}}}{K_{s,i}^{\alpha_s} (w L_{s,i})^{1-\alpha_s}} \tag{3.5}$$

Where $\kappa_s = \frac{w^{1-\alpha_s} (P_s Y_s)^{\frac{-1}{\rho-1}}}{P_s}$ is a scalar common to each firm in the industry s. Equation (3.5) requires only mild assumptions on demand, technology and final good cost minimization behavior. Note that the scalar κ_s is not observed. Hence, the levels of process efficiency are not observable with the available data. I will come back to this issue later on. Furthermore, to compute firm-level TFP I need to make an assumption on the parameter ρ regulating the elasticity of substitution across varieties. The quantitative results of this analysis are sensitive to the assumed value of ρ. I assume a conservative value of ρ equal to three as in Calligaris et al. (2018) and Hsieh and Klenow (2009). Nevertheless, results are robust to different values of ρ. I set the elasticity of output with respect to labor $1 - \alpha_s$ to match the labor share of total value added in the industry s in the baseline year of the analysis. This measure is equivalent to taking a weighted average of the firm-level labor cost share of VA, where weights are given by the firm share of sectoral VA. Capital share is then set as one minus the computed labor share. I report results where the TFP variable is trimmed but the results are robust to outliers because qualitatively identical when trimming the tails of its distribution at different percentages. Results are robust both by taking different years as the baseline for the calculation of α_s and by taking an unweighted mean of firm labor cost share of VA to obtain α_s.

3.1 TFP by Age

As first motivating evidence, figure 2 plots the cross-sectional relationship between firm (log) TFP, relative to the entrant TFP, and age taken in different points in time. In particular, entrant TFP ($TFP_{0,t,s}$) is computed as the mean TFP of firms younger than three years old by year and sector, assuming $\kappa_{s,t} = 1$. Then, relative TFP is obtained by dividing firm-level TFP (obtained assuming $\kappa_{s,t} = 1$) by $TFP_{0,t,s}$. Since the unobservable component $\kappa_{s,t}$ is a sectoral-time scalar, when taking the relative TFP , $\kappa_{s,t}$ will cancel out. Thus, relative productivity is unaffected by setting $\kappa_{s,t} = 1$ for each sector s and time t and relative TFP can be obtained from available data. To make results robust to outliers, I trimmed the 1% tails of the distribution of relative TFP [2]. Then, I take the sectoral-year median of relative TFP by age obtaining $TFP_{a,s,t}$. To remove the sector dimension, I take a weighted average of the industry $TFP_{a,s,t}$, where weights are given by the sectoral VA share. As a result, I am obtaining the yearly cross-sectional relationship between relative TFP and age. Then, to plot the figure, I take the log of the weighted average of relative TFP and I normalize the entrant (age zero) productivity to one. For ease of exposition, I am reporting three periods averaging within three bins of years. This is useful also to clean for cyclical components and noise. The first period is the pre-productivity puzzle, the years 1993 and 1994. The second is the period 2000-2005, and the third the period 2013-2017.

Figure 2 highlights that the difference between incumbents' TFP and entrants' TFP has become weaker in time. In particular, the TFP by age profile imputed to 1993 and 1994 suggests that the log average productivity of old firms was 2.5 times the log productivity of entrants. In the first years of 2000, this relationship flattened and average log productivity was 2.2 times the entrant productivity. In the more recent years of the sample, the ratio between incumbents' log productivity and entrants' log productivity has become particularly worrisome since old firms are only 1.8 times more productive than entrants. Relative to the entrants, old firms in years before the productivity puzzle were 40% more productive in log scale than old firms in more recent years. To interpret this evidence some words of caution are needed. The relationship between relative

[2] The presented results are robust to the different levels of trimming and to not trimming at all

TFP and age in the cross-section depends on three elements. First, it depends positively on how incumbents have grown in their productivity in the past. Second, it depends negatively on entrant average productivity. Third, it depends positively on the selection of survivors. The fiercer the selection, the higher the relative productivity of the average incumbent. Hence, the reported figure for each period contains information on past growth as well as information on current selection and entrant average productivity. In particular, the TFP-age profile in the years pre-1995 contains information on how firms used to grow before the Italian productivity puzzle. In economic models following the structure of Hopenhayn (1992) or Chaney (2008), selection is driven by aggregate productivity. In particular, if aggregate productivity is lower, competition is less fierce and the selection on productivity is weaker to re-establish the free-entry zero-discounted profits condition (expected in Hopenhayn (1992)). Hence, since the period after 1995 is characterized by stagnation in aggregate productivity, the differential in the average TFP by age observed in the graph is likely to be due to a decline in firm-level growth rates rather than due to the selection of incumbents or entrants. In what follows, I will explore deeper this channel.

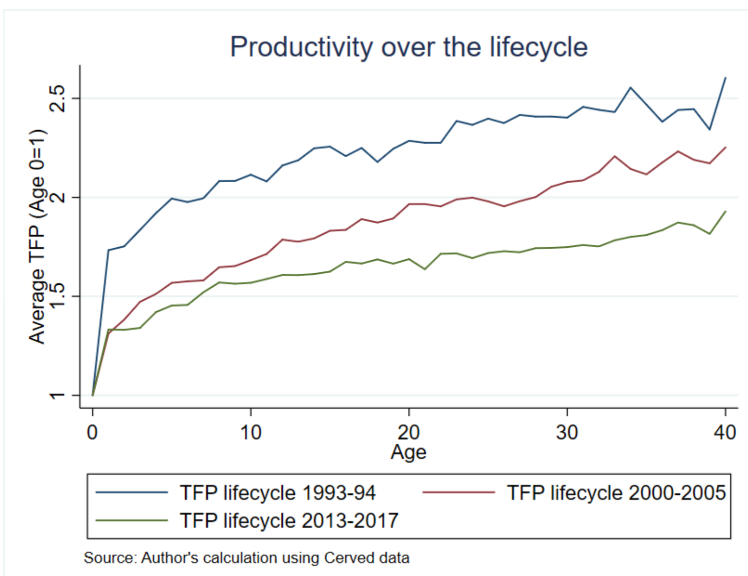

Figure 2: Firm productivity by Age in the Cross-Section

3.2 Growth rate by age

In this section, I compute the growth rate of firms productivity relative to the sector mean or median. Again, since TFP is taken relative to a sectoral common measure the constant $\kappa_{s,t}$ can be set to one since it cancels out. Analysing the TFP relative to the mean or median is useful for two main reasons. On one hand, by taking the relative TFP, I am cleaning from aggregate shocks. By taking the growth rate of the relative TFP, I am computing the growth rate that is attributable to a firm's specific characteristics and efforts rather than to aggregate shocks. This will be particularly interesting for the purpose of this analysis. On the other hand, by taking the growth relative to the median, I am also cleaning for the cyclicality of measured TFP that are due to business cycle fluctuations. After business cycle shocks, capital and labor are not free to adjust to re-establish the firm profit maximization. Hence, plain measures of TFP may depend significantly on business cycle fluctuations and may not provide accurate pieces of evidence.

Denoting by $\widetilde{A_{i,s,a,t}} = \frac{A_{i,s,a,t}}{\overline{A_{s,a,t}}}$ the relative TFP, where $\overline{A_{s,a,t}}$ denotes the sectoral median or mean TFP, firm i growth rate can be obtained from the following formula:

$$gr_{i,s,a,t,t+1} = \frac{\widetilde{A_{i,s,a+1,t+1}} - \widetilde{A_{i,s,a,t}}}{\mid \widetilde{A_{i,s,a,t}} \mid} \tag{3.6}$$

Table 2 reports summary statistics for the new variables, after trimming the 5% tails of its distribution. To interpret the variable in percentage terms, growth rates must be multiplied by 100. For instance, the average Growth rate of TFP relative to the sectoral mean is 4.5%.

Table 2: Summary statistics of growth variables

Variable	Obs	Mean	Std. Dev.	Min	Max	P5	P50	P95
Growth TFP relative to mean	1892093	.045	.352	-.613	1.292	-.463	0	.739
Growth TFP relative to median	1892094	.042	.347	-.611	1.25	-.463	0	.725

Now the questions that I want to address are the following: is there a problem in how process efficiency is evolving over the firm age profile? Can firm-level growth rate explain why the relative TFP-age slope has decreased after 1995 as shown in Figure 2?

To answer these questions I follow this approach. I take simple averages of growth rate by age to simulate a life-cycle somewhat similar to the one reported in Figure 2. That is, I follow synthetic cohorts over time normalizing entrant productivity to one and constructing TFP of following ages by exploiting average growth rates. The idea is to simulate how firms would evolve in their productivity keeping constant the economic conditions determining the growth rate of the year when the growth is computed. I now explain this methodology in more detail.

To simulate TFP growth over the lifecycle, I follow this simple schedule:

1. I take the median of $gr_{i,s,a,t,t+1}$ growth by year, age and sector building a variable $growth_{s,a,t,t+1}$[3]

2. I take the weighted average of $growth_{s,a,t,t+1}$ by year and age obtaining $growth_{a,t,t+1}$. As weights, I used the usual value added sectoral shares

3. I Create simulated lifecycle for each year t from 1993 to 2018 normalizing z of the entrant to 1 and using $A_{a+1} = (1 + growth_{a,t,t+1}) * A_a$ to compute next age TFP. To simplify the exposition, I take an average by bin of years[4]. Lastly, I take the logarithm of the simulated TFP by age to obtain Figure 3

Figure 3 highlights that the growth rate of firms over the age profile has decreased over time. The lowest simulated life-cycle is the one associated with the years 2006-2013. On the other hand, the highest growth is observed in the years before 2000. In the most recent years (2014-2018), the simulated TFP life-cycle growth shows a partial recovery. Compared to the simulated life-cycle of years pre-2000, firms' in the years 2006-2014 experienced a 30% decrease in their (log) TFP growth over their life-cycle.

[3]For the construction of the presented figure, $gr_{i,s,a,t,t+1}$ has been computed taking the growth of TFP relative to the median. The qualitative results are robust to taking it relative to the mean rather than the median for the construction of $\widetilde{A_{i,a,s,t}}$ and to trimming (1% or 5%) or not the tails of the relative TFP distribution. Moreover, the results presented are qualitatively identical if instead of the median of $gr_{i,s,a,t,t+1}$ I take the mean to build $gr_{s,a,t,t+1}$ and to trimming or not the tail of the distribution of the firm-level $growth_{i,s,a,t,t+1}$

[4]The results are robust to changing the extremes of the bin of years.

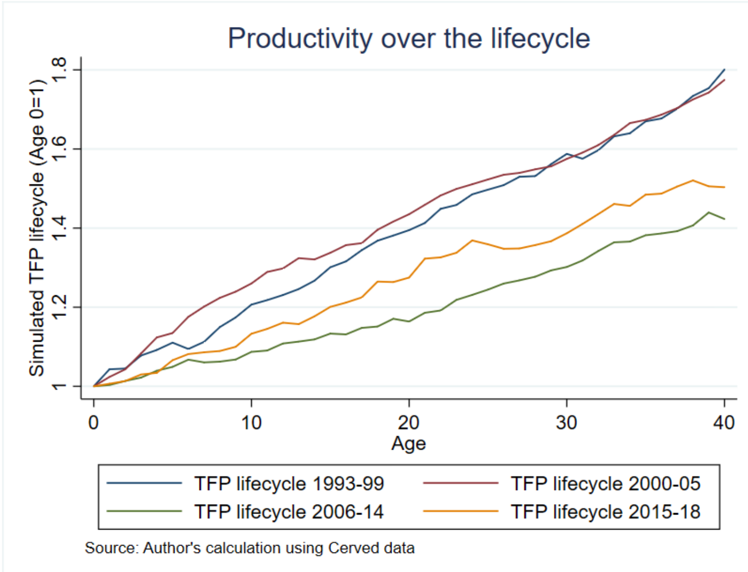

Figure 3: Synthetic firm TFP lifecycle

4 Productivity and wedges

In this section, I apply the structure of Hsieh and Klenow (2009) and Hsieh and Klenow (2014) to the data to gauge some insights on possible explanations that could motivate the decline in firm-level TFP growth observed in the 00s. The model is specified as follows. Suppose aggregate output is a CES of the output of each firm:

$$Y = \left(\sum_a \sum_{i=1}^{N_a} Y_{ai}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}$$

where i is index for the firm, a the firm's age, N the number of firms for a specific age a, $Y_{a,i}$ is the output of the firm, and $\rho > 1$ is the elasticity of substitution between varieties. I am suppressing the subscript for sector and year for ease of exposition.

Each firm is a monopolistic competitor which chooses its labor and capital inputs to maximize its current profits, affected by firm-specific frictions:

$$\pi_{a,i} = (1 - \tau_{Y,a,i})P_{a,i}Y_{a,i} - (1 + \tau_{L,a,i})wL_{a,i} - (1 + \tau_{K,a,i})Rk_{a,i} \tag{4.1}$$

Here, τ_{Yai}, τ_{Kai} and τ_{Lai} are respectively firm-specific revenue distortions, capital distortions and labor distortions. These frictions are not specific and may arise for an undefined number of reasons. These frictions capture every cost that the firm is facing that distorts the competitive market prices of labor, capital, and firm product. Just to spell some examples, these wedges may capture transportation costs, taxes, managerial costs, bureaucracy, trade costs, subsidized credit etc. Assume further that the production function of the firm is a Cobb-Douglas characterized by constant return to scale:

$$Y_{a,i} = A_{a,i}K_{a,i}^{\alpha}L_{a,i}^{1-\alpha}$$

where $A_{a,i}$ is firm-specific TFP. It is possible to solve the model to obtain equilibrium revenue, labor, and capital-labor ratio:

$$P_{a,i}Y_{a,i} \propto (\frac{A_{a,i}}{\overline{TFP}}\frac{\overline{TFPR}}{TFPR_{a,i}})^{\rho-1} \tag{4.2}$$

$$L_{a,i} \propto (\frac{A_{a,i}}{\overline{TFP}})^{\rho-1}(\frac{\overline{TFPR}}{TFPR_{a,i}})^{\rho}(\frac{1+\tau_{L,a,i}}{1+\tau_{K,a,i}})^{\alpha\rho}L \tag{4.3}$$

$$\frac{K_{a,i}}{L_{a,i}} = \frac{\alpha}{1-\alpha}.\frac{w}{R}.\frac{1+\tau_{L,a,i}}{1+\tau_{K,a,i}} \tag{4.4}$$

where L is the total workforce, N the total number of operating firms, $\overline{TFP} = (\sum_{i=1}^{N}(A_{s,a,i}\frac{\overline{TFPR_s}}{TFPR_{s,a,i}})^{\rho-1})^{\frac{1}{\rho-1}}$ is the sectoral aggregate TFP, $TFPR_{a,i}$ is revenue productivity, and $\overline{TFPR}_s = \frac{\rho}{\rho-1}(\frac{\overline{MRPK_s}}{\alpha_s})^{\alpha_s}(\frac{\overline{MRPL_s}}{1-\alpha_s})^{1-\alpha_s}$ is the average value of $TFPR_{a,i}$[5]. It is possible to prove that $TFPR_{a,i}$ is proportional to the geo-

[5]To obtain these quantities from the data I use the equations from Hsieh and Klenow (2009):

$$MRPK_{s,a,i} \equiv (\alpha_s)\frac{\rho-1}{\rho}\frac{P_{s,i}Y_{s,i}}{k_{s,i}} = R\frac{1+\tau_{K,s,i}}{1-\tau_{Y,s,i}}; MRPL_{s,a,i} \equiv (1-\alpha_s)\frac{\rho-1}{\rho}\frac{P_{s,i}Y_{s,i}}{L_{s,i}} = w\frac{1}{1-\tau_{Y,s,i}}$$

$$\overline{MRPK_s} \equiv \frac{R}{\sum_{i=1}^{N_s}\frac{(1-\tau_{Y,s,i})}{1+\tau_{K,s,i}}\frac{P_{s,i}Y_{s,i}}{P_sY_s}}; \overline{MRPL_s} \equiv \frac{1}{\sum_{i=1}^{N_s}(1-\tau_{Y,s,i})\frac{P_{s,i}Y_{s,i}}{P_sY_s}}$$

metric average of the marginal revenue product of capital and labor:

$$\frac{TFPR_{a,i}}{\overline{TFPR}} \propto (\frac{P_{a,i}Y_{a,i}}{K_{a,i}})^{\alpha}(\frac{P_{a,i}Y_{a,i}}{L_{a,i}})^{1-\alpha} \propto \frac{(1+\tau_{K,a,i})^{\alpha}(1+\tau_{L,a,i})^{1-\alpha}}{1-\tau_{Y,a,i}} \tag{4.5}$$

It is easy to observe that revenue and employment are an increasing function of A and a decreasing function of TFPR. Then, by using data on PY, K, L and α it is possible to measure firm relative productivity TFP, revenue productivity (TFPR), aggregate TFP, and average revenue productivity $\overline{TFPR}$. See Hsieh and Klenow (2009) who derived these properties for additional details.

Now, let's come back to our initial question: why after the start of the productivity growth breakdown of 95' the Italian economy did not observe a recovery as in all previous recessions? Why, instead, aggregate productivity growth becomes negative in the 00s? What could potentially explain this phenomenon? Based on the R&D endogenous growth literature, something may have changed in firms' incentives to boost their productivity. To answer these questions, I explored the correlation between TFP and firms' distortions. The hypothesis to test is whether this correlation has changed over time reducing firms' incentives to innovate. The main idea is that, if frictions are *correlated* with productivity, marginal return to innovation is lower and firms have lower incentives in investing in innovation (Hsieh and Klenow (2014), Bento and Restuccia (2017)). If the correlation has increased relative to the years before the productivity decline, incentives to innovate have worsened over time. If we are willing to assume an endogenous growth model for firm-level process efficiency, this pattern might explain some of the worrisome results outlined in the previous section. To answer this question I perform the following regression year by year:

$$log(\frac{TFPR_{i,a,s,t}}{\overline{TFPR}_{t,s}}) = \alpha_s + \sum_s \mu_{s,t}[\mathbf{1}(S=s) \cdot log(\frac{TFP_{i,a,s,t}}{\overline{TFP}_{ts}})] + \epsilon_{i,a,s,t} \tag{4.6}$$

Where $log(\frac{TFPR_{t,s,i}}{\overline{TFPR}_{t,s}})$ is the relative TFPR; α_s the sector fixed effect; $log(\frac{TFP_{tsi}}{\overline{TFP}_{ts}})$ the relative TFP; and finally $\mu_{s,t}$ are the sector-year elasticity of firms' distortion with respect to productivity[6]. The sector-fixed effects control for time-invariant sector characteristics that can influence the correla-

[6]Results are robust to different specifications. In particular, the results are basically identical performing these

tion between $TFPR$ and productivity. Performing the regression year by year controls for common shocks to all firms in a given year. Moreover, this allows for time-varying sectoral fixed effects, controlling for common shocks to all firms belonging to the same sector. We are interested in the coefficients $\widehat{\mu_{s,t}}$ which measure the extent of correlation between relative productivity and relative distortions to test whether something has changed in the correlation productivity-distortions. Figure 4 plots the evolution of the weighted average of the coefficients $\widehat{\mu_{s,t}}$, where weights are given by the usual value added share of industry s, with their confidence intervals. The time-series of the elasticity of productivity distortion highlights an increasing pattern starting from the year 2000. The elasticity has increased from 0.39 in 1995-97 to a peak of 0.46 in 2009. This rise corresponds to a 17.9% increase of the elasticity of productivity distortion relative to the baseline level of 1997.

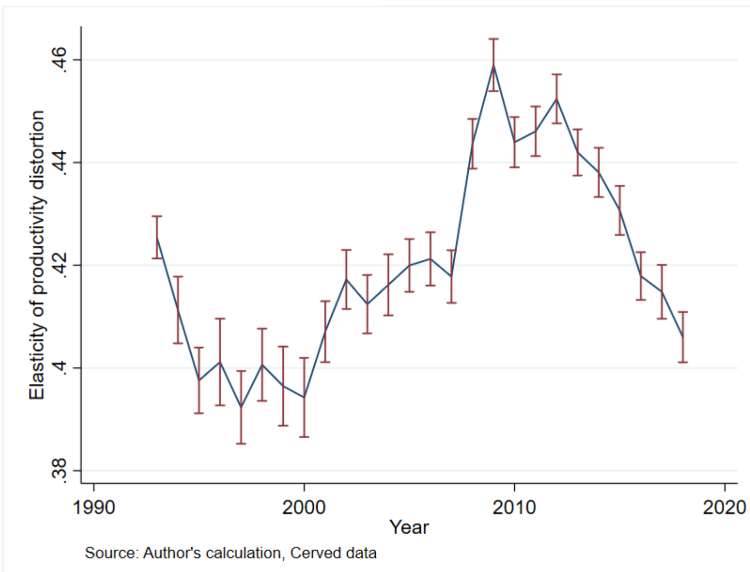

Figure 4: Trend in the elasticity of productivity distortion

two following regressions instead:

$$\frac{(1+\tau_{K,a,i})^{\alpha}}{1-\tau_{Y,a,i}} = \alpha_s + \sum_s \mu_{s,t}[\mathbf{1}(S=s)\cdot log(\frac{TFP_{i,a,s,t}}{\overline{TFP_{ts}}})] + \epsilon_{i,a,s,t} \tag{4.7}$$

or

$$log(\frac{TFPR_{i,a,s,t}}{\overline{TFPR_{t,s}}}) = \alpha_s + \gamma_t + \mu_t[\mathbf{1}(T=t)\cdot log(\frac{TFP_{i,a,s,t}}{\overline{TFP_{ts}}})] + \epsilon_{i,a,s,t} \tag{4.8}$$

where γ_t is the year fixed effect to control for aggregate shocks

To assess the statistical significance of this trend, I performed a z-test of statistical difference from the year 1997. Figure 5 reports the z-test statistics whose critical value for a 95% significance level (1.96) is represented by the red horizontal line. From $t > 2000$ the difference between the elasticity of productivity distortion in year t is statistically different from the one computed in the year 1997.

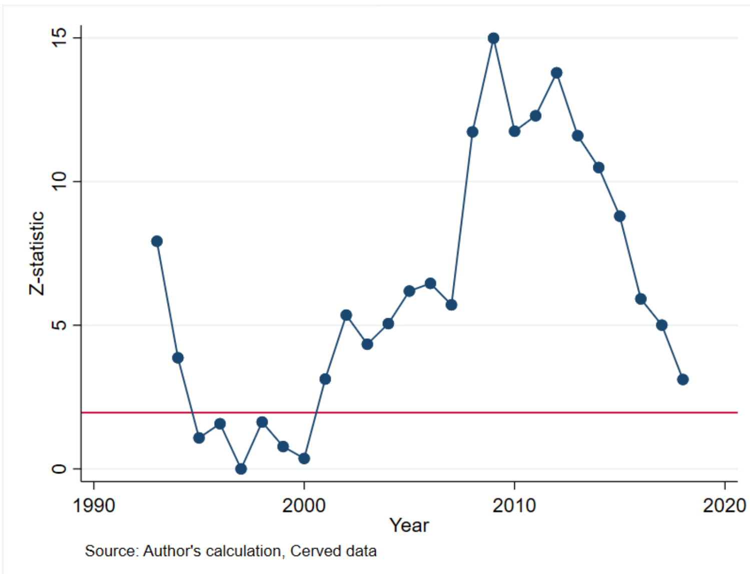

Figure 5: Test for the statistical significance of the differences in the elasticity of productivity distortion

5 Econometric specifications

The rise in the correlation between frictions and productivity highlighted in Figure 4 could provide a possible explanation for the trend in the growth rate of firms' productivity observed in Section 3. In this section, I introduce a more formal way of presenting the results from Figure 3. I run a series of firm-level regressions in reduced form, following the intuition of the mechanism explained in Section 4. The main purposes of this empirical exercise are twofold. On one hand, I want to confirm and test the statistical significance of the motivating evidence in Section 3.2. On the other, I can uncover whether the rise in the elasticity of productivity distortion can explain some of the growth rate variations found in the data. Lastly, I provide a reverse causality robustness check by testing the causal channel through which $\mu_{s,t}$ impacts the growth rates.

5.1 Growth rate analysis

The key prediction of the mechanism described in section 4 is that, for the same firm, it is less convenient to invest in process innovation in 2009 relative to 1997. This might happen because the marginal return to innovation is lower in years characterized by higher elasticity of productivity distortions. Hence, it is not enough to plot plain growth rates as in figure 3 to introduce the reasoning behind the estimated rise in $\mu_{t,s}$. Indeed, without controlling for firms' characteristics, growth rates might not be comparable and variations might be driven by different mechanisms. Therefore, I perform a series of reduced-form regressions controlling for sectoral fixed effects, so that I net out the average growth rate at the sectoral level. This ensures that the results are not driven by the particular growth performance of any sector over the sample period. Furthermore, I control for firms' characteristics such as relative TFP, intangible share of total assets, age, and size. Relative TFP is included to control for different propensities to grow. The propensity to innovate is thought to be higher for firms with higher productivity (Melitz (2003)) and for firms with higher revenues (Bustos (2011)). Then, I control for the firm's intangible share of total assets to control for technology adoption at the firm level. Also, I control for the firm's age to control for heterogeneity over the age profile. Lastly, I control for firm value-added share of sectoral value-added as a proxy for firm size. Pagano and Schivardi (2003) finds that a larger firm size fosters productivity growth because it allows firms to take advantage of all the increasing returns associated with R&D. Hence, I want to control for the negative trend in firms' sizes found by Amatori et al. (2011) that might explain the negative trend in productivity growth. The final regression is the following:

$$growth_{i,a,s,t,t+k} = \alpha_s + \gamma_T + \omega z_{i,a,s,t} + \alpha_1 size_{i,a,s,t} + \alpha_2 I_{i,a,s,t} + \epsilon_{i,a,s,t} \tag{5.1}$$

Where z is the log of TFP relative to sector TFP computed as in section 4, $growth_{i,a,s,t,t+k} = z_{i,a,s,t+k} - z_{i,a,s,t}$ is the growth rate in the relative TFP imputed from year t to year $t+k$, α_s is the sector fixed effect, and γ_T are fixed effect associated with bin of years T. I divided the sample in four bins of years, same as before, where $T_1 = 1993 - 1999$, $T_2 = 2000 - 2005$, $T_3 = 2006 - 2014$, and $T_4 = 2015 - 2018$. $size$ is firm size proxied by its value added share of sector value added, and I is firm's intangible share of total assets.

To assess whether the increase in the correlation between distortions and TFP can explain, at least partially, the negative trend characterizing productivity growth in more recent years, I include the estimated $\widehat{\mu_{t,s}}$ from regression (4.8) in regression (5.1):

$$growth_{i,a,s,t,t+k} = \alpha_s + \gamma_T + \omega z_{i,a,s,t} + \alpha_1 size_{i,a,s,t} + \alpha_2 I_{i,a,s,t} + \alpha_3 age_{i,a,s,t} + \omega_2 \widehat{\mu_{t,s}} + \epsilon_{i,a,s,t} \tag{5.2}$$

Under the assumption that any changes in μ is perceived by firms as unexpected, the estimated $\widehat{\mu_{s,t}}$ is the elasticity of productivity distortion that firms use when forming their expectations. In particular, I assume that firms have perfect foresight and are continuously surprised by shocks to $\mu_{t,s}$, perceived as unexpected and permanent. The increase in the correlation between distortions and productivity has two different effects on growth. On one hand, it might lower the marginal return to innovation disincentivizing growth. This is the theory that I want to test. On the other, correlated frictions increase the misallocation of factors of production and more productive firms employ less inputs than they should in an undistorted economy (Hsieh and Klenow (2009)). In particular, Calligaris et al. (2018) find that the level of financial frictions is higher for more innovative firms. Hassan et al. (2017) find that during the last fifteen years bank credit in Italy may have constrained the long-term investments of firms. Hence, the firm-level current level of frictions may be an omitted variable that could create some bias. The increase in the elasticity distortion might be associated with a decline in firm-level growth because firms with higher growth prospects received higher frictions. This is a story where firms are passive subjects and cannot grow not because they don't want to, but rather because they are constrained. In particular, credit constraints might play the role of a barrier to growth as found by Aghion et al. (2007). Then, to isolate the impact of the rise in $\mu_{s,t}$ working solely through firms' incentives to innovate, I control for the current level of frictions by including relative TFPR in the regression. In particular, I perform the following two regressions:

$$growth_{i,a,s,t,t+k} = \alpha_s + \gamma_T + \omega_1 z_{i,a,s,t} + \alpha_1 size_{i,a,s,t} + \alpha_2 I_{i,a,s,t} + \alpha_3 age_{i,a,s,t} + \omega_3 log(\frac{TFPR_{i,a,s,t}}{\overline{TFPR_{t,s}}}) + \epsilon_{i,a,s,t} \tag{5.3}$$

$$growth_{i,a,s,t,t+k} = \alpha_s + \gamma_T + \omega_1 z_{i,a,s,t} + \alpha_1 size_{i,a,s,t} + \alpha_2 I_{i,a,s,t} + \alpha_3 age_{i,a,s,t} + \omega_2 \widehat{\mu_{t,s}} + \omega_3 log(\frac{TFPR_{i,a,s,t}}{\overline{TFPR_{t,s}}}) + \epsilon_{i,a,s,t} \tag{5.4}$$

Lastly, I perform regression (5.4) controlling for year fixed effects rather than bin of years fixed effects. In this way, I can control for yearly common shocks in productivity growth.

5.2 Mechanism analysis

The key intuition behind the rise in the elasticity of productivity distortion as a possible explanation for the pattern in the growth rate observed in figure 3 is that a higher correlation between distortions and productivity makes the marginal return to innovation lower. As a consequence, years and sectors with higher $\widehat{\mu_{s,t}}$ should be associated with lower investments in process innovation. To provide some evidence about this mechanism, I exploit the variable reporting the firm i stock of intangible assets. Intangible assets are associated with R&D, and patents. Hence, they should provide reasonable statistics to measure innovation and technology adoption. Indeed, Battisti et al. (2015) show that intangible assets are positively associated with both TFP and technology adoption at the firm level. As above, I keep the coefficients $\widehat{\mu_{t,s}}$ estimated from regression (4.8) to be included in different shapes of the following regression:

$$y_{i,s,t,t+k} = \alpha_s + \gamma_t + \omega_1 z_{i,a,s,t} + \alpha_1 size_{i,a,s,t} + \alpha_2 I_{i,a,s,t} + \alpha_3 age_{i,a,s,t} + \omega_2 \widehat{\mu_{t,s}} + \omega_3 log(\frac{TFPR_{i,a,s,t}}{\overline{TFPR_{t,s}}}) + \epsilon_{i,a,s,t} \tag{5.5}$$

Where $y_{i,s,t,t+k}$ is growth in intangible stock computed from year t to year t+k; α_s sector fixed effect to control for time-invariant sectoral characteristics; γ_t year fixed effect controlling for aggregate shocks to intangible assets growth. I take the growth with a horizon of $k = 1, 2, 3$ with the hypothesis that investments and efforts made in year t could take some time to be registered in the balance sheet intangible assets. The other variables are included in the regression to control for firm characteristics as controls with the same logic of equation (5.1).

5.3 Main results

Table 3 reports summary statistics for the newly constructed variables log of relative TFP growth and intangible assets growth. The tails have been trimmed at the 1% level. To interpret the growth rate as percentage, values must be multiplied by 100. For instance, the average one-year intangible assets growth is 24.6%.

Table 3: Summary statistics for growth variables

Variable	Obs	Mean	Std. Dev.	Min	Max	P5	P50	P95
log of relative TFP growth	2060279	-.013	.488	-2.237	1.926	-.841	.006	.742
one-year intangible growth	1663399	.246	1.792	-1	19.667	-1	-.125	2.5
two-year intangible growth	1496661	.784	3.803	-1	40	-1	-.2	6
three-year intangible growth	1349006	1.346	5.587	-1	58	-1	-.228	9.07

In Table 4 I examine the trend in the log of TFP growth rate by performing the regressions discussed in section 5.1. For ease of exposition, I report the growth rate associated with year $k = 1$. Nonetheless, the results are robust to different years k for the computation of the growth rate. Column (1) reports the results of the regression without controlling for misallocation and $\widehat{\mu_{s,t}}$. Column (1) confirms the same results of figure (3). Moreover, the coefficients on control variables follow what the literature discussed above finds. Relative TFP has a negative coefficient by construction, because growth is inversely proportional to current TFP. The coefficient on the intangible share, measuring firm-level technological adoption, is positive, suggesting that more technological firms are associated with higher growth rates. Interpreting column (1) coefficients, a 1% increase in intangible share is associated with a 0.035% increase in TFP_{t+1}. As in Pagano and Schivardi (2003), firm size is positively associated with firm growth. A 1% increase in value-added share of sectoral value added is associated with a 1.89% increase in TFP_{t+1}. The coefficient on age, although statistically significant, is not economically significant. The bin of years γ_1 (1993-1999) is the baseline level and γ_T are interpreted as deviations from the baseline years. All bins of years' fixed effects are statistically significant. Results of figure (3) are confirmed. In particular, there is a negative trend in the log of the TFP growth rate which is worsening over time. The years 2000-2005 are associated with a 0.08% reduction in future firm-level TFP. Years 2006-2014 with a 1.3% reduction and years 2015-2018 with a 2.4%. Column (2) includes estimated $\widehat{\mu_{s,t}}$ alone, column (3) includes relative TFPR alone, column (4) includes both relative TFPR and $\widehat{\mu_{s,t}}$. Lastly, column (5) controls for year fixed effect rather than bins of year fixed effect. The coefficients on relative TFPR and $\widehat{\mu_{s,t}}$ are statistically and economically significant. The coefficient on (log) relative TFPR measuring the elasticity of future productivity with respect to current relative TFPR is negative. Interpreting column (4), A 1% increase in relative TFPR is associated with a drop of 0.156% in one-year ahead

TFP. Once I factor in dispersion in relative TFPR, I find that one standard deviation in relative TFPR is associated with an 11% reduction in future TFP.

The coefficient of major interest is the coefficient associated with $\widehat{\mu_{s,t}}$. It is negative in all specifications. From column (4), a 1% increase in $\widehat{\mu_{s,t}}$ is associated with a 0.2% reduction in next year TFP. Once I factor in dispersion in $\widehat{\mu_{s,t}}$, I find that one standard deviation in $\widehat{\mu_{s,t}}$ (0.045) is associated with 0.95% reduction in next year TFP. Once it is included, $\widehat{\mu_{s,t}}$ increases positively the trend observed in γ_T, especially in years associated with the period 2006-2014. These are the years when the correlation between productivity and distortions reaches its peak. After the introduction of both TFPR and $\widehat{\mu_{s,t}}$, the trend in γ_T becomes positive, and the years 2006-2014 are the ones associated with the highest growth. This means that the rise in the correlation documented by figure (4.8), together with the rise in the frictions documented by Calligaris et al. (2018), can explain the negative trend in the firm-level TFP growth observed after 2000.

In Table 5, I examine the results of regression (5.5). I report only results of $k = 3$, but results are robust to different values of k. Again, coefficients on control variables are as expected from the literature. Relative TFP is positively associated with investments in intangible assets. This is consistent with the idea that the propensity to innovate is higher for firms with higher productivity. The coefficient on relative TFPR is positive, consistent with the results from Calligaris et al. (2018) who find that distortions are higher for more innovative firms. Size and age are negatively associated with investments in intangibles, suggesting that older and bigger firms are less prone to innovate as found by Hansen (1992) and Balasubramanian and Lee (2008). Interpreting results from column (4), which is the more complete specification, I find that a 1% increase in relative TFP is associated with a 0.065% increase in investments growth, a 1% increase in relative TFPR is associated with a 0.67% increase in intangible growth, a 1% increase in value-added share is associated with a reduction of 1.7% in intangible growth, a one year older firm is associated with a reduction of 1.6% in the investment growth rate. Of course, here I am not claiming causality of these variables since there might be omitted variables, reverse causality, and other forms of spurious correlation. Here, I am just using these variables as controls to capture the impact of $\widehat{\mu_{s,t}}$.

VARIABLES	(1) TFP growth	(2) TFP growth	(3) TFP growth	(4) TFP growth	(5) TFP growth
(log) relative tfp	-0.116***	-0.116***	-0.0518***	-0.0517***	-0.0520***
	(0.000488)	(0.000489)	(0.000544)	(0.000544)	(0.000561)
intangible share	0.0350***	0.0349***	0.109***	0.108***	0.110***
	(0.00182)	(0.00182)	(0.00187)	(0.00187)	(0.00192)
size	1.896***	1.894***	0.607***	0.605***	0.612***
	(0.0737)	(0.0736)	(0.0433)	(0.0432)	(0.0447)
age	0.000799***	0.000811***	-0.00140***	-0.00139***	-0.00139***
	(3.13e-05)	(3.13e-05)	(3.23e-05)	(3.23e-05)	(3.35e-05)
(log) relative tfpr			-0.155***	-0.155***	-0.156***
			(0.000932)	(0.000932)	(0.000960)
$\widehat{\mu}$		-0.223***		-0.211***	-0.124***
		(0.0167)		(0.0165)	(0.0196)
γ_1	(base)	(base)	(base)	(base)	
γ_2	-0.00792***	-0.00499***	0.00153	0.00431***	
	(0.000992)	(0.00102)	(0.000981)	(0.00101)	
γ_3	-0.0134***	-0.00309**	0.0102***	0.0200***	
	(0.000912)	(0.00120)	(0.000909)	(0.00119)	
γ_4	-0.0237***	-0.0177***	0.00806***	0.0137***	
	(0.00106)	(0.00116)	(0.00105)	(0.00115)	
Year F.E.	NO	NO	NO	NO	YES
Sectoral F.E.	YES	YES	YES	YES	YES
Constant	-0.491***	-0.405***	-0.187***	-0.105***	-0.162***
	(0.00252)	(0.00694)	(0.00277)	(0.00693)	(0.00870)
Observations	2,060,279	2,060,279	2,060,279	2,060,279	1,971,665
R-squared	0.050	0.050	0.068	0.068	0.070

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Firm level growth and elasticity of productivity distortion

The coefficient associated with $\widehat{\mu_{s,t}}$ has a point estimate of -0.74 and is statistically significant at the 1% level. A 1% increase in the elasticity of productivity distortion $\widehat{\mu_{s,t}}$ is associated with a 0.74% reduction in intangible growth computed within three years. One standard deviation in $\widehat{\mu_{s,t}}$ is associated with a 3.33% reduction in three-year intangible growth.

To interpret the negative coefficients corresponding to $\widehat{\mu_{s,t}}$ in the productivity and intangible growth regressions some words of caution are needed. In particular, it is difficult to establish the direction of causality and hence results cannot be taken as evidence of causality. This is because the explanatory variable of interest $\widehat{\mu_{s,t}}$ might be just a leading indicator of productivity growth (rather than a causal factor). Furthermore, intangible assets growth may capture something else than investments in process innovation since it includes branding, marketing etc. Hence, the mechanism outlined above needs some further evidence to establish a causal pattern in the relationship between the elasticity of productivity distortion and productivity growth.
In the next section, I provide a causality robustness check that provides consistent evidence regarding the causal channel between $\widehat{\mu_{s,t}}$ and productivity growth. Moreover, the test confirms that the correlation between intangible growth and $\widehat{\mu_{s,t}}$ is capturing R&D expenditure providing further evidence that sustains causality running from the elasticity of productivity distortion μ to process innovation.

5.4 Causality robustness check

In this section, I tackle the problem of reverse causality and provide a check for the causal interpretation of the negative coefficients associated with $\widehat{\mu_{s,t}}$. In particular, to interpret the negative coefficient associated with $\widehat{\mu_{s,t}}$ as causal, it is necessary to identify the mechanism through which the elasticity affects productivity growth. In the previous section, I provided evidence of a negative correlation between intangible assets growth and μ. Yet, some further analysis is needed, due to spurious correlation.

To tackle these issues, I follow the methodology of and Rajan and Zingales (1998) and Pagano

VARIABLES	(1) Intangible growth (3-years)	(2) Intangible growth (3-years)	(3) Intangible growth (3-years)	(4) Intangible growth (3-years)
(log) relative tfp	0.345***	0.346***	0.0642***	0.0647***
	(0.00520)	(0.00521)	(0.00678)	(0.00678)
intangible share	-3.890***	-3.890***	-4.359***	-4.359***
	(0.0186)	(0.0186)	(0.0209)	(0.0209)
size	-7.014***	-7.021***	-1.707***	-1.715***
	(0.443)	(0.443)	(0.368)	(0.368)
age	-0.0246***	-0.0245***	-0.0157***	-0.0157***
	(0.000480)	(0.000480)	(0.000486)	(0.000486)
(log) relative tfpr			0.670***	0.670***
			(0.0122)	(0.0122)
$\widehat{\mu}$		-0.881***		-0.739***
		(0.266)		(0.266)
Year F.E.	YES	YES	YES	YES
Sectoral F.E.	YES	YES	YES	YES
Constant	3.567***	3.931***	2.344***	2.650***
	(0.0414)	(0.117)	(0.0447)	(0.118)
Observations	1,287,929	1,287,929	1,287,929	1,287,929
R-squared	0.025	0.025	0.027	0.027

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Firm level intangible assets growth and elasticity of productivity distortion

and Schivardi (2003). This methodology consists in defining some sectoral characteristics that allow ranking the importance of the elasticity of productivity distortion for productivity growth. Two properties are required for this characteristic: i) it should be a channel through which the elasticity influences intangible growth ii) it should be characterized by some sectoral variability. The idea is that if I find that $\widehat{\mu_{s,t}}$ has a different effect on productivity growth through this characteristic, then I may conclude that the negative coefficient found above cannot be generated by some spurious correlation. In the presence of reverse causality or spurious correlations, we should expect a homogeneous relation between productivity growth and $\widehat{\mu_{s,t}}$, rather than a relationship that varies according to this characteristic.

Building on the idea that the elasticity of productivity distortion discourages process innovation, I choose as a channel the R&D sectoral intensity. R&D sectoral intensity is chosen to identify investment opportunities for firms' technological progress in process innovation. Ceteris paribus, the impact of higher $\mu_{s,t}$ on productivity growth should be higher in sectors that are characterized by higher investments opportunity and that are more dependent on R&D expenditure. For this variable to be valid, I need an exogenous classification of R&D intensity because, of course, the level of elasticity of productivity distortion may influence the R&D sectoral intensity if there is a causality running between the two. The U.S. provides the best economic environment to obtain this categorization. Under the assumption that U.S. markets are undistorted and frictionless, analysing the U.S. sectoral share of R&D expenditure allows identifying sectors that are characterized by higher investment opportunities and that are heavily R&D dependent [7]. As an indicator of R&D intensity, I use the R&D sectoral expenditure as a share of the total assets. These data are obtained from the EU Klems database (Van Ark and Jäger (2017)) which provides data up to 2015 and hence covers the sample period. To adjust for shocks to the sectoral R&D intensity, I choose yearly R&D intensity and hence a characteristic that moves year by year. Table (6) reports the industry values for R&D intensity in ascending order corresponding to the year 2000. The R&D intensity is as expected and corresponds roughly to the classification in Pagano and Schivardi (2003). More traditional industries such as Textile and Food and Beverage are characterized by a lower R&D

[7] To confirm the assumption that the U.S. provides a friction-less benchmark, the level of correlation between productivity and frictions is close to zero (0.09) as obtained by Hsieh and Klenow (2014).

share of total assets. On the other hand, more dynamic industries such as the Chemical industry and Manufacture of medical equipment industry are characterized by higher R&D intensity. In particular, the R&D share of total assets in 2000 in the Chemical industry is roughly nine times the R&D intensity in 2000 in the Textile industry.
To check for a causal interpretation of the coefficient reported above, I insert in both regressions 5.4 and 5.5 the interaction term between R&D sectoral share and $\widehat{\mu_{s,t}}$ and R&D sectoral share alone to control for sector specific shocks to investment opportunities:

$$growth_{i,s,t,t+1} = \alpha_s + \gamma_T + X_{i,s,t}\beta + \omega_2\widehat{\mu_{t,s}} + \theta\widehat{\mu_{t,s}}RD_{t,s} + \theta_1 RD_{t,s} + \epsilon_{i,a,s,t} \tag{5.6}$$

$$y_{i,s,t,t+k} = \alpha_s + \gamma_T + X_{i,s,t}\beta + \omega_2\widehat{\mu_{t,s}} + \theta\widehat{\mu_{t,s}}RD_{t,s} + \theta_1 RD_{t,s} + \epsilon_{i,a,s,t} \tag{5.7}$$

Where $RD_{t,s}$ represents sectoral R&D intensity and $X_{i,s,t}$ a row vector containing the control variables discussed above. As dependent variable, $growth_{i,s,t,t+1}$ represents the one-year productivity growth while $y_{i,s,t,t+k}$ the k-th year intangible assets growth. If the sectoral classification is correct and if the elasticity causal channel to productivity growth goes through R&D expenditure, $\widehat{\theta}$ should be negative and significant. The intuition is that firms that are in industries more dependent on R&D expenditure, should grow less for higher values of their elasticity of productivity distortion.

The results are reported in table 7. For ease of exposition, I do not report coefficients associated with control variables. All regressions control for both sector and year fixed effects. The regression is performed including both $\widehat{\mu}$, R&D sectoral intensity, and their interaction $\widehat{\mu} \cdot RD$. The coefficient on the interaction term is negative and always significant except for the one-year intangible growth regression. The coefficient associated with $\widehat{\mu}$ alone is not always statistically significant but the point estimate remains almost always negative. The point estimate on R&D sectoral intensity is always positive suggesting that firms belonging to sectors that receive a positive shock to investment opportunities are growing more in their productivity.

These results are consistent with the idea of a causal impact of the elasticity of productivity distortion on growth through firms' incentives to innovate. Factoring in the dispersion in R&D in-

Industry	R&D Intensity
Textile and clothing industries	.0439146
Food, Beverage, Tobacco Industry	.0549412
Metallurgy	.0589634
Publishing, Printing and reproduction of registered media	.0699923
Industry of wood and wood products	.0699923
Manufacture of manufacturing products of non-metallic minerals	.1008618
Manufacture of coke, oil refineries, treatment of nuclear fuels	.1297282
Manufacture of machines and mechanical equipment	.2047813
Manufacture of motor vehicles, trailers and semi-trailers	.3016075
Manufacture of medical equipment, optical instruments and watches	.3053274
Other manufacturing industries	.3057021
Manufacture of chemical products and synthetic and artificial fibers	.4618686

Table 6: R&D intensity in the U.S economy in 2000

VARIABLES	(1) Productivity growth	(2) 3-year int. growth	(3) 2-year int. growth	(4) 1-year int. growth
$\widehat{\mu}$	0.0367	-0.0777	-0.269	-0.257**
	(0.0269)	(0.351)	(0.232)	(0.107)
RD intensity	0.460***	2.350***	0.942**	0.157
	(0.0464)	(0.628)	(0.417)	(0.193)
Interaction	-0.817***	-5.172***	-2.348**	-0.555
	(0.104)	(1.403)	(0.929)	(0.429)
Year F.E.	YES	YES	YES	YES
Sectoral F.E.	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Constant	-0.240***	3.598***	2.219***	0.781***
	(0.0119)	(0.154)	(0.102)	(0.0468)
Observations	1,724,561	1,242,301	1,318,612	1,404,268
R-squared	0.070	0.025	0.019	0.010

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: R&D interaction

tensity and $\widehat{\mu}$, the impact of a one standard deviation increase (0.045) in $\widehat{\mu}$ on productivity growth in a sector-year which is one standard deviation (0.13) above the mean of R&D intensity is 0.48 percentage points (-0.82*0.13*0.045) stronger. On the other hand, the differential on the three-year intangible assets growth is 3 percentage points.

The reported results are consistent evidence of a causal impact of the elasticity of productivity distortion on firm-level TFP growth. In the next section, I introduce a general equilibrium model characterized by heterogeneous firms to quantify the impact of the rise in the elasticity of productivity distortion on aggregate output, productivity and firm-level growth rates.

6 The Model

Consider a general equilibrium model of heterogeneous firms as a closed economy version of Melitz (2003), Hopenhayn (1992). Consider a model where productivity growth endogenously according to the investment decision undertaken by the firm. The model is a closed economy version of Atkeson and Burstein (2010) where I introduce frictions as in Hsieh and Klenow (2014) and Bento and Restuccia (2017). I am interested in assessing the impact of the rise in the correlation between TFP and distortions on aggregate productivity. Moreover, I want to uncover how much of the lower TFP growth by age reported in Figure 3 can be explained by the model. The main idea is that the correlation of friction-TFP has increased over time, decreasing the marginal return to innovation, and lowering firms' incentives to invest in productivity growth.

6.1 Environment

Time is discrete and indexed by t=0,1,... There is a single country with a representative household endowed with $L = 1$ units of labor. There is a single final producer in a competitive market. It produces output Y assembling goods of different varieties according to a CES production function. The Final good can be used either for consumption or innovative activities. There is a representative firm in a competitive market producing the research good employing as inputs the final good Y and labor. There is a continuum of firms differentiated by their productivity levels z, producing intermediate goods. There are two types of innovative activities. The first, *product innovation* entertains the creation of new firms. There is an unbounded pool of entrants who are free to enter by paying an amount n_e of the research good. Productivity is unknown before entry and is drawn from a distribution G after paying the sunk cost as in Hopenhayn (1992). Hence, free entry (together with the pool of entrants being unbounded) ensures that the ex-ante zero profit condition holds in expectation. The second innovative activity is called *process innovation.* In each period after entry, firms invest to further increase their productivity by paying H units of the research good. Therefore, productivity levels z are endogenously determined by firms' investment decisions. Since there is no capital, firms face only revenue distortions that may be correlated to productivity level z and that work as a tax rate on revenue. Firms face a fixed operating cost n_f which will give rise to endogenous exit. Furthermore, firms receive a severe shock to their operations with probability δ, constant across productivity levels, which will force the firm to exit. I study the steady-state of the economy where firms take prices as given. Free entry will ensure that the expected value of entry is driven to zero. Since there is an endogenous and exogenous exit, in a steady-state there will be ongoing entry and exit. Then, I will consider how the rise of the elasticity of productivity distortion affects aggregate productivity, consumption, investments, and firms' growth rate. I begin by describing the model in more detail. From now on, I will denote with lower-cases firm-level variables and with upper-cases aggregate variables.

Preferences Households in the economy have preferences of the form $\sum_{t=0}^{\infty} \beta^t log(C_t)$, where C_t is consumption of the final good at time t. Each Household faces an intertemporal budget constraint of the form:

$$\sum_{t=0}^{\infty} Q_t(P_tC_t - W_tL) \leq \overline{W} \tag{6.1}$$

Where Q_t are intertemporal prices, W_t is the wage at time t, P_t is the price of the final good, C_t is household consumption, and $\overline{W}$ is the initial stock of assets held by the household. I assume that the Household owns the firms.

Intermediate Goods Firms. Intermediate goods are differentiated products each one produced by a heterogeneous firm indexed by z, indicating its productivity. Intermediate Firms employ only labor to produce output according to a CRS production technology:

$$y_t(z) = exp(z)l_t(z) \tag{6.2}$$

The output $y_t(z)$ can be used in the production of the final good Y. Call $p_t(z)$ the price of the intermediate good produced by the firm characterized by z.

Final Good. The final good is produced with a constant return to scale production technology:

$$Y_t = [\int y_t(z)^{\frac{\rho-1}{\rho}} dM_t(z)]^{\frac{\rho}{\rho-1}} \tag{6.3}$$

Where $M_t(z)$ denotes the measure of operating firms characterized by a productivity less than or equal to z. The final good is produced in a competitive market, where the firms choose inputs $y_t(z)$ to minimize costs taking as given P_t, $p_t(z)$, M_t, and subject to (6.3). The final good can be used either for consumption of the representative household or for research activities. Call X_t the units of the final good used in research activities. Feasibility, then, requires that $C_t + X_t \leq Y_t$.

Research Good. The research good is produced with a constant return to scale function F, employing as inputs X_t units of final good and L_r units of labor.

$$Y_{m,t} = X_t^{1-\lambda} L_{m,t}^{\lambda} \tag{6.4}$$

Where subscript Y_m denotes research good output and L_m the labor employed in the research sector. Denote by $W_{m,t}$ the price of the research good at time t. The research sector is competitive. This implies that the equilibrium price of the research good will be a function of the final good P_t and wage W_t.

Evolution of firms. Productivity at the firm level evolves endogenously over time, depending on the level of investments in productivity improvements undertaken within the firm. At the beginning of each period t, each firm has an exogenous probability δ of exiting and corresponding $1-\delta$ of surviving. A surviving firm can decide to invest to increase its productivity as in Atkeson and Burstein (2010). In particular, a firm decides the probability q of choosing a step s up versus down in its productivity z. Hence, the firm's next period productivity will be either $z+s$, with productivity q, or $z-s$, with probability $1-q$. To choose the probability q, the firm must invest H(z,q) units of the research good. As function H, I choose the same as in Atkeson and Burstein (2010) and Hsieh and Klenow (2014):

$$H(z, p) = hexp(z(\rho - 1))exp(bq) \tag{6.5}$$

Lastly, to keep operating the firms must invest n_f units of research good as a fixed cost of operations. The fixed cost n_f will give rise to endogenous exit with a cutoff level of productivity $\overline{z_t}$ under which the value of the firm is negative and the firm is better off exiting. Call $V_t(z)$ the firm value function. Since the Firm can choose whether to operate or exit, its value function is:

$$V_t(z) = max[0; V_t^o(z)] \tag{6.6}$$

Where $V_t^o(z)$ are the present discounted profits of the firm choosing to operate and satisfy the following Bellman equation:

$$V_t^o(z) = \max_{q \in [01]} \pi_t(z) - (n_f + H(z;q))W_{m,t} + (1-\delta)\frac{Q_{t+1}}{Q_t}[qV_{t+1}(z+s) + (1-q)V_{t+1}(z-s)] \tag{6.7}$$

Denote by $q_t(z)$ the optimal choice of investment in improving productivity, and call it *process innovation* decision of the firm. Note that if the time period is small, the binomial productivity process described above approximates a geometric Brownian motion in continuous time as in Luttmer (2007) and Piguillem and Rubini (2019).

The role of frictions. I model frictions as in Hsieh and Klenow (2014). Since in the model there is no capital, frictions enter the profit function as a revenue distortion working as a revenue tax. Nonetheless, as described in the previous section, frictions are general and not well defined and can be interpreted in many different ways. Distortions create a wedge in firms' profits. They enter firms' profit function in the following way:

$$\pi(z) = (1-\tau)p(z)y(z) - Wl(z) \tag{6.8}$$

I assume τ to depend on firm-level productivity as follows:

$$(1-\tau) = exp(-\mu_t z) \tag{6.9}$$

Where the parameter μ_t is calibrated according to the evolution of the elasticity of a firm's distortion with respect to its productivity. The correlation of revenue taxes with productivity acts as a disincentive for firm's TFP growth by dampening the positive relationship between profits and productivity.

Industry dynamics. To create a new business, firms must invest a sunk cost n_e units in the research good. Investments of n_e units of the research good in period t yield a new firm in period $t+1$. The new firm will be characterized by a productivity level z drawn from a distribution G. Firms are not subject to exogenous exit in the entering period. Free entry requires:

$$W_{m,t}n_e = \frac{Q_{t+1}}{Q_t}\int V_{t+1}(z)dG \tag{6.10}$$

Denote by $M_{e,t}$ the measure of new firms entering in period t to start producing in period t+1. I Refer to the creation of new businesses as *product innovation* since this is the mechanism through which new varieties are created. Then, the evolution of firms over time is determined by the exogenous probability of exit δ, the investment decision of firms, and the measure of new created firms $M_{e,t-1}$ as follows:

$$M_{t+1}(z') = (G(z') - G(\overline{z_{t+1}}))M_{et} + (1-\delta)[\int_{\overline{z_{t+1}}-s}^{z'-s} q_t(z)dM_t(z) + \int_{\overline{z_{t+1}}+s}^{z'+s}(1-q_t(z))dM_t(z)] \tag{6.11}$$

Feasibility. There are three feasibility conditions that need to be satisfied. Feasibility for the final good requires:

$$C_t + X_t = Y_t \tag{6.12}$$

The feasibility constraint for labor requires:

$$\int l_t(z)dM_t(z) + L_{m,t} = L \tag{6.13}$$

Lastly, the feasibility constraint on the research good requires:

$$M_{et}c_e + \int (c_f + H(zq_t(z)))dM_t(z) = F(X_t, L_{m,t}) \tag{6.14}$$

To close the model, I assume also that the Household owns the firms that initially existed, hence:

$$\overline{W} = \int V_0 dM_0(z) \tag{6.15}$$

Equilibrium Definition. An equilibrium in this economy is a collection of sequences of prices and wages $\{Q_t; P_t; W_t; W_{mt}; p_t(z)\}$; Quantities $\{Y_t; C_t; X_t; L_{mt}; y_t(z); l_t(z)\}$; Firm values and investments decisions $\{V_t(z); V_t^o(z);\ \pi_t(z); X_t(z); q_t(z)\}$; Measures of operating and entering firms $\{M_t(z); M_{et}\}$; such that: the representative household maximizes her utility subject to her budget constraint; intermediate good producers are maximizing within periods profits; final good producer is maximizing profits; zero profit condition for entry holds in expectation; all feasibility constraints are satisfied with equality. A steady-state of the model is an equilibrium in which all of the variables are constant. I will omit time subscripts when discussing the steady-state.

6.2 Characterizing Equilibrium

After describing in the previous section the general setup of the model, I now describe its equilibrium conditions. I will focus on the equilibrium conditions of a steady-state and I will describe the algorithm to solve for allocations and prices. The wage W is chosen as the numéraire and is normalized to one.

Household Maximization. Standard arguments on household maximization yield:

$$P_t C_t = \beta^t \frac{Q_0 C_0}{Q_t} \tag{6.16}$$

Final Good. The final good is produced by competitive firms with the CES function described in equation (6.3). Standard arguments give that the equilibrium prices must satisfy:

$$P_t = [\int p_t(z)^{1-\rho} dM_t(z)]^{\frac{1}{1-\rho}} \tag{6.17}$$

and quantities

$$y_t(z) = Y_t(\frac{p_t(z)}{P_t})^{-\rho} \tag{6.18}$$

Intermediate firm-static problem. The firm problem can be splitted in a static problem and in a dynamic problem. In the static problem, firms choose labor in order to maximize profits $(1-\tau(z))p(z)y(z) - l(z)$, subject to the demand (6.18), production function (6.2), and elasticity of productivity distortion (6.9). All firms choose a constant markup over marginal cost, hence equilibrium prices are:

$$p(z) = \frac{\rho}{\rho-1}\frac{1}{(1-\tau(z))exp(z)} = \frac{\rho}{\rho-1}exp(z(\mu-1)) \tag{6.19}$$

The production employment of the intermediate firm is given by:

$$l(z) = (1-\tau(z))^{\rho} Y_t P_t^{\rho} exp(z(\rho-1))(\frac{\rho-1}{\rho})^{\rho} = Y_t P_t^{\rho} exp(z(\rho-1-\mu\rho))(\frac{\rho-1}{\rho})^{\rho} \tag{6.20}$$

Equation (6.20) implies that there is a simple relationship between productivity z and firm size measured as employment. A firm's size is completely determined by its productivity: a more productive firm will employ more labor. Also, note that the friction $\tau(z)$ implies that for a higher μ this relation is dampened. Furthermore, since productivity depends endogenously on the investment decision of the firm, the firm innovation-decision $q_t(z)$ will determine the dynamics of firm size.

Firms profits are given by:

$$\pi(z) = \pi_d exp(z(\rho-1-\mu\rho)) - n_f W_{m.t} \tag{6.21}$$

Where $\pi_d = P^{\rho} Y_t \frac{(\rho-1)^{\rho-1}}{\rho^{\rho}}$ is a common component to all firms. Profits are completely determined by the productivity level z and, again, the elasticity of productivity distortion μ dampens this relationship.

Lastly, by substituting the equation for the firm-level price into 6.17, the final good price index can be written as a function of firm-level productivity:

$$P_t = \frac{\rho}{\rho - 1}[\int exp(z)(\mu - 1)(1-\rho)dM_t(z)]^{\frac{1}{1-\rho}} \tag{6.22}$$

Firm Dynamic Problem. The firm dynamic problem is characterized by two decisions that the firm can undertake. On one hand, the firm decides whether to keep operating or exit. This decision is made on the present discounted value of profits associated with the firm productivity level z. If the value of profits is negative the firm decides to exit. Otherwise, the firm decides to keep operating. Hence, firm value $V_t(z)$ is:

$$V_t(z) = max[0; V_t^o(z)] \tag{6.23}$$

Where $V_t^o(z)$ are the present discounted profits of the firm choosing to operate. On the other hand, when the firm operates, the firm decides the process innovation decision. This is a dynamic decision as it impacts tomorrow's profits. Thus, the value of operating profits is:

$$V_t^o(z) = \max_{q \in [01]} \pi_t(z) - (c_f + H(z,p))W_{m,t} + (1-\delta)\frac{Q_{t+1}}{Q_t}[qV_{t+1}(z+s) + (1-q)V_{t+1}(z-s)] \tag{6.24}$$

Note that in steady state the time subfix can be dropped and $\frac{Q_{t+1}}{Q_t}$ equals $\frac{1}{R}$. The process innovation decision, if interior, must satisfy the following first order condition in a steady state equilibrium:

$$FOC : \frac{\partial H(z,p)}{\partial q} W_{m,t} = (1-\delta)\frac{1}{R}[V_{t+1}(z+s) - V_{t+1}(z-s)] \tag{6.25}$$

Research Good. Research good cost minimization in a competitive market implies:

$$\frac{1}{P_t} = \frac{\lambda}{1-\lambda}\frac{X_t}{L_{mt}} \tag{6.26}$$

and

$$W_{m,t} = \frac{P_t^{1-\lambda}}{\lambda^\lambda(1-\lambda)^{1-\lambda}} \tag{6.27}$$

Product Innovation. The free entry condition implies the zero profit condition in expectation steady state:

$$n_e W_{m,t} = \frac{1}{R}\int V(z)dG(z) \tag{6.28}$$

The measure of the operating firm will evolve according to (6.11).

Aggregate Output. By combining the equilibrium expression for the firm output with the CES production function, the following expression is obtained:

$$P_t^{-1} = \frac{\rho-1}{\rho}(\int (exp(z)(1-\tau(z)))^{\rho-1})dM_t(z))^{\frac{1}{\rho-1}} = \frac{\rho-1}{\rho}(\int exp(z(1-\mu)(\rho-1))dM_t(z))^{\frac{1}{\rho-1}} \tag{6.29}$$

Labor market clearing implies:

$$L_{t,Y} = (\frac{\rho-1}{\rho})^\rho P_t^\rho Y_t \int exp(z(\rho-1))(1-\tau(z))^\rho dM_t(z) = (\frac{\rho-1}{\rho})^\rho P_t^\rho Y_t \int exp(z(\rho-1-\mu\rho))dM_t(z) \tag{6.30}$$

Where L_Y is labor employed in production. Defining the revenue weighted average tax rate as $\overline{(1-\tau)} = \int \frac{p(z)y(z)(1-\tau(z))}{P_t Y_t} dM_t(z)$ and combining expression 6.29 and 6.30 aggregate output can be expressed as:

$$\frac{Y_t}{L_t} = [\int exp(z(\rho-1))(\frac{1-\tau(z)}{\overline{1-\tau}})^{\rho-1}dM_t(z)]^{\frac{1}{\rho-1}}\frac{L_{t,Y}}{L} \tag{6.31}$$

Lastly, note that from the labor market clearing condition (6.30), an expression for the real wage is obtained:

$$\frac{1}{P_t} = \frac{\rho-1}{\rho}\frac{Y_t\overline{(1-\tau)}}{L_{t,Y}} \tag{6.32}$$

6.3 Computational steps

I now describe how one can solve for the steady-state allocations and prices in the quantitative model. I drop the time subscript since I will describe the steady-state. I normalize wage W to one. I take 1997 as the baseline year. I will discuss how to calibrate parameters in the following section. The elasticity of revenue distortion μ will be set at the 1997 level ($\mu = 0.39$). The counterfactual in which we are interested is the model where all parameters are fixed at the 1997 level rather than μ. μ is calibrated at its 2005 (0.42) and its peak level of 2009 (0.46). These years correspond to levels that lasted for some years and hence evaluating a steady-state is a more appropriate assumption. The main intuition behind the counterfactual is that the rising τ by TFP slopes observed in the period 2000-2009 lowered the marginal return to innovation with respect to the pre-2000 years. To solve the quantitative model, I followed this schedule:

1. Create a grid of productivity levels z of equally spaced points where the distance between two consecutive is given by the calibrated s. Low and high truncation of the grid are chosen so that z always belongs to the grid.

2. From the Bellman equation 6.34 evaluated in steady state, define $\omega(z) = \frac{V(z)}{W_m}$. Now 6.34 can written as:

$$\omega(z) = max[0; \omega^o(z)] \tag{6.33}$$

$$\omega^o(z) = \max_{q \in [01]} \frac{\pi_d}{W_m} exp(z(\rho - 1 - \mu\rho)) - n_f - hexp(z)exp(bq(z)) + (1-\delta)\frac{1}{R}[q\omega(z+s) + (1-q)\omega(z-s)] \tag{6.34}$$

3. Fix the constant in the profit function $\frac{\pi_d}{W_m}$, compute the re-scaled value function $\omega(z)$ associated with $\frac{\pi_d}{W_m}$, and iterate on the constant $\frac{\pi_d}{W_m}$ until the free-entry condition is satisfied with equality. The value function is obtained through value function iteration and using the policy function (6.25) re-scaled. The expected value of entry is obtained by simulating $N = 10000$ draws of z from the entrant distribution $N(0, \sigma_e)$ and taking the mean of these N draws. The simulation of the draws from the entrant distribution has to be done before iterating on $\frac{\pi_d}{W_m}$

so that the draws do not change when iterating on the constant part of firms' profits.

4. Compute the steady-state productivity measure of operating firms by simulating the law of motion (6.11) normalized by the measuring of entering firms M_e for 5000 years:

$$\frac{M_{t+1}(z')}{M_e} = (G(z') - G(\overline{z})) + (1-\delta)[\int_{\overline{z}-s}^{z'-s} q(z)\frac{dM_t(z)}{M_e} + \int_{\overline{z_{t+1}}+s}^{z'+s} (1-q(z))\frac{dM_t(z)}{M_e}] \quad (6.35)$$

5. Define and compute the following two indices for aggregate productivity and aggregate prices:

$$\widetilde{Z} = \int exp(z(1-\mu)(\rho-1))\frac{dM(z)}{M_e} \quad (6.36)$$

$$\widetilde{P} = \int ((\frac{\rho}{\rho-1})exp(z(\mu-1)))^{1-\rho}\frac{dM(z)}{M_e} \quad (6.37)$$

6. Solve for the remaining 6 unknowns (L_Y; Y; C; X; M_e; P) using the following 6 equations:

   (a) $Y = (M_e\widetilde{Z})^{\frac{1}{\rho-1}} L_Y$ (Aggregate Output)

   (b) $\frac{1}{P} = \frac{\rho-1}{\rho}\frac{Y\overline{(1-\tau)}}{L_Y}$ (Labor market clearing)

   (c) $\frac{\lambda}{1-\lambda}\frac{X}{L_R} = \frac{1}{P}$ (Research Good cost minimization)

   (d) $\Upsilon M_e = L_R^{\lambda} X^{1-\lambda}$ where $\Upsilon = n_e + \int[n_f + hexp(z)exp(bq(z))]\frac{dM(z)}{M_e}$ (research good feasibility)

   (e) $\frac{\pi_d}{W_m} = \kappa P^{\rho+\lambda-1}Y$ where $\kappa = \frac{(\rho-1)^{\rho-1}}{\rho^{\rho}}\lambda^{\lambda}(1-\lambda)^{1-\lambda}$ (combining definition of π_d and W_m as a function of W)

   (f) $C + X = Y$ (Final good feasibility)

7. For the counterfactual, repeat the same procedure calibrating all parameters as in the benchmark year 1997 except for the tax rate. The tax rate is set as a function of z according to the estimated elasticity of productivity distortion in 2005 and 2009.

6.4 Calibration

I now discuss how the model is parameterized to match and reproduce data from the baseline year (Italy in 1997). As in Atkeson and Burstein (2010), I choose six periods by year so that the investment decision is done every two months while keeping the entry period to one year. The log TFP entrant distribution G is parameterized as a normal distribution $N(0, \sigma_e)$, where σ_e is calibrated according to the standard deviation of firms younger than three years old in the baseline year. The steady-state cost of capital R is chosen as in Hsieh and Klenow (2014) to 10%. This is meant to account for an annual interest rate of 5% and an annual depreciation rate of 5%. Since this is a steady-state, β is a function of R. I normalize the total labor force to $L = 1$. The elasticity of substitution across varieties is calibrated as in Hsieh and Klenow (2014) to $\rho = 3$. The wage is normalized to one. Due to the scarcity of information on the value of λ, I calibrate $\lambda = 0.5$ in the benchmark and I perform sensitivity analysis by changing its values. Now, consider the parameters shaping the law of motion of firm productivity z: (s, δ, n_e, n_f, h, and b). The exogenous death rate δ is set to match the share of failing firms whose productivity is above the median. The intuition is that these firms did not fail due to their productivity but due to some other shock, exogenous in the model. The step size characterizing the grid is of particular importance. I calibrate s to match the standard deviation in the employment growth rate of Italian firms found by Hall et al. (2008). This is done ex-ante as in Atkeson and Burstein (2010). I normalize n_e to 1 and fix n_f to 0.01 as in Atkeson and Burstein (2010). I can normalize one out of n_e, n_f, and h because the solution of the model is invariant to proportional changes in all three parameters. I calibrate, h, and b to match the productivity growth rate of firms by age from Figure 3. Note that the calibration of the b and h parameters has to be done in an outer loop while solving the model. I choose a couple (h, b), then I solve the model as described in Section 6.3 and I update the values of h, b with an adaptive grid search routine until a level of tolerance is reached.

To summarize, table 8 lists all the parameter values and how they are targeted.

Parameters	Definition	Value or Target
ρ	Elasticity of substitution between varieties	3 as in Hsieh and Klenow (2014)
R	Discount rate	Annual real interest rate of 10%
Periods	Number of investment decisions by year	6 as in Atkeson and Burstein (2010)
σ_e	Standard deviation of log entrant productivity	1.064 to match the standard deviation in log productivity of firms of age 0-3 in baseline year
L	Total labor force	Normalized to 1
λ	Labor elasticity in the production function of research sector	0.5 as in Atkeson and Burstein (2010) then sensitivity analysis
δ	Probability of exogenous death	0.0433 on an annual basis to match the exit rate of firms above the median productivity level in the baseline year
s	Step size in the productivity grid and for the growth of z	0.0636 to match the 0.1558 standard deviation on an annual basis in the employment growth rate from Hall et al. (2008)
n_f	Fixed operation cost	Set to 0.1 as in Atkeson and Burstein (2010)
n_e	Fixed sunk cost of entry	Normalized to 1
h	Level parameter in the R&D cost function	Set with b to match baseline year productivity growth rates by age
b	Convexity parameter in the R&D cost function	Set with h to match baseline year productivity growth rates by age
μ	Elasticity of productivity distortion	Set to match the elasticity of productivity distortion in different years

Table 8: Calibration of parameters

6.5 Results

To quantify the impact of the rise in the elasticity of productivity distortion documented in Figure 6.9, I fix the parameters of the innovation cost function and other parameters at the 1993-98 baseline level. Then, I evaluate the effect of moving from the elasticity of productivity distortion in 1997 to the elasticity of productivity distortion in 2005 and 2009. These are new steady-states where all parameters are fixed at the baseline level, except for the elasticity of productivity distortion. As in Hsieh and Klenow (2014), a higher slope of the elasticity of productivity distortion implies that the marginal return to innovation is lower relative to the baseline year. Figure 6 reports the TFP lifecycle from the model versus the one obtained for the baseline years in Figure 3. Figure 7 reports the new model firm TFP lifecycle when the elasticity of productivity distortion is set at the 2005 and 2009 levels. Rising revenue tax rates have some success in explaining the lower growth by age observed in Figure 3. Firms' TFP lifecycle growth under 2009 elasticity of productivity distortion is 7.9% lower relative to the baseline level. The elasticity level of 2009 accounts for almost 50% of the difference in the TFP growth from age 0 to age 40 depicted in Figure 3. Table 9 reports the impact on aggregate productivity and other variables of interest. The rise in the elasticity of productivity distortion has four effects. First, higher μ discourages innovation. This is the main focus of this paper and its effect has been shown in Figure 7. Second, a greater correlation between distortions and productivity generates misallocation of production factors. This effect lowers aggregate productivity, for given TFP levels, as shown by Hsieh and Klenow (2009) and Calligaris et al. (2018). Third, the cutoff productivity level $\overline{z}$ decreases when firms invest less to boost their productivity to re-establish the free entry condition. Fourth, in the new steady-state, there is an a priori unknown effect on the demand for the research good. On one hand, fewer investments in process innovation free up R&D labor. On the other hand, since less productive firms invest more in innovation to catch up with more productive firms, there is an offsetting force working through an increase in the demand for the research good through a shift to the left of the productivity distribution. The net effect of these four channels is a decrease in the aggregate productivity of 5.97% relative to the baseline level. Consumption decreases by 6.1%. The negative effect on the TFP lifecycle is a relative decrease of 7.9%. The cutoff level $\bar{z}$ has decreased by 56.2% relative to the baseline level. Lastly, labor employed in the research sector has increased by 1.15% relative to the baseline year.

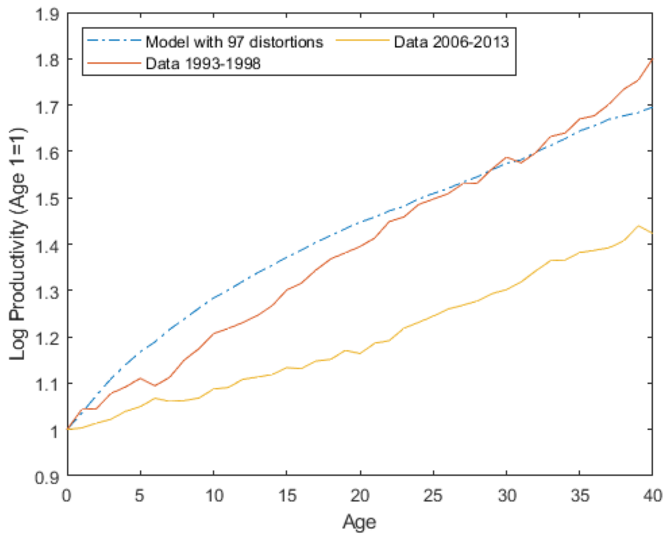

Figure 6: TFP lifecycle. Model vs data in baseline years

To summarize, the rise in the correlation between productivity and distortion can explain almost 50% of the reduction in the cumulative growth over firms age observed in Figure 3. This works through a reduction of investments in process innovation. The total effect on aggregate productivity, accounting for other general equilibrium effects, is of 6% reduction relative to the baseline level.

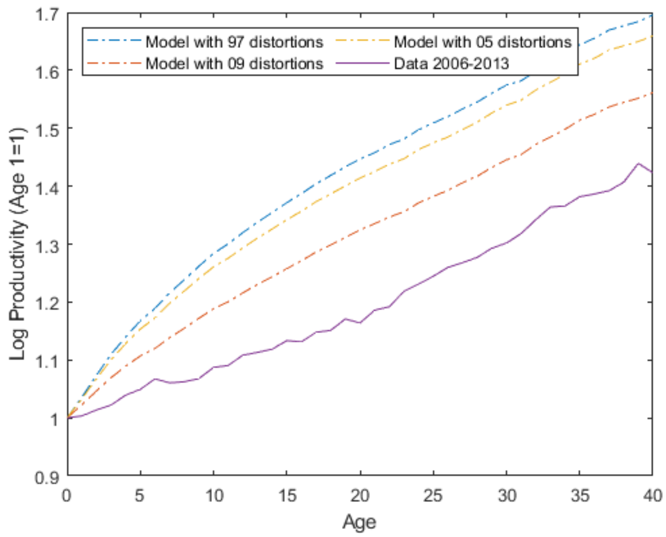

Figure 7: TFP lifecycle. Model vs data in the counterfactual

7 Conclusion and Policy discussin

7.1 Drivers and Policy discussion

To shed additional light on the pattern in the correlation between productivity and frictions, I now perform the same regression as in equation (4.8) but with different dependent variables. Since the procedure of Hsieh and Klenow (2009) allows to compute both $\tau_{Y,a,s,i}$ and $\tau_{K,a,s,i}$, I introduce in equation (4.8) first only the revenue friction as a dependent variable, then only the capital friction as a dependent variable. Before describing the results some words of caution are required.

The identification of firm-level distortions is based on the concept of marginal revenue product. The idea is that absent frictions, the marginal products of factors should be equalized across firms. In particular, revenue and capital frictions are computed using the following equations:

$$MRPL_{s,a,i} \equiv (1-\alpha_s)\frac{\rho-1}{\rho}\frac{P_{s,i}Y_{s,i}}{L_{s,i}} = w\frac{1}{1-\tau_{Y,s,i}} \tag{7.1}$$

Table 9: Summary of results

Variable	2005 Elasticity (=0.42)	2009 Elasticity (=0.46)
Elasticity of productivity distortion	+7.7%	+17.95%
Aggregate TFP	-2.91%	-5.97%
TFP Lifecycle growth	-2.12%	-7.91%
Consumption	-2.94%	-6.1%
Cutoff productivity	-21.9%	-56.2%
Research Labor	+0.28%	+1.15%

$$MRPK_{s,a,i} \equiv (\alpha_s)\frac{\rho-1}{\rho}\frac{P_{s,i}Y_{s,i}}{k_{s,i}} = R\frac{1+\tau_{K,s,i}}{1-\tau_{Y,s,i}} \tag{7.2}$$

Since the assumed production function is characterized by only two production factors, the wage distortion $1+\tau_{L,s,i}$ is not identifiable and $1+\tau_{L,s,i}$ is normalized to one. Distortions that increase the marginal products of capital and labor by the same proportion are captured as output distortion $\tau_{Y,a,s,i}$. Examples of such distortions are transportation costs, revenue taxes, and public output subsidies. Regarding labor and capital distortions, it is possible to identify only distortions that change the marginal product of capital input relative to the labor input. In particular, when I measure $\tau_{k,s,i}$ and $\tau_{Y,s,i}$ I am measuring the distortions relative to labor distortion which is normalized to one. Suppose that the data reports a rise in the correlation between the measured $\tau_{K,s,i}$ and TFP. This may be driven either by a rise in the correlation between capital distortion and productivity or by a reduction in the correlation between labor distortion and productivity. Nonetheless, as reported in equation (4.5), relative TFPR is a measure that embodies all three measures of distortions. As a consequence, if we observe a rise in the correlation between TFP and TFPR, together with a rise in the correlation between $\tau_{K,s,i}$ and $TFP_{S,i}$, this implies that the pattern in the correlation that we observe is driven by an increase in capital distortions correlation rather than a decrease in labor distortions correlation. Otherwise, we would not observe an increase in the correlation between TFP and TFPR because the average amount of frictions would be decreasing.

With these caveats in mind, I now perform the regression in equation (4.8) including in the left hand side either (relative) revenue distortions $\frac{1}{1-\tau_{Y,s,i}}$ or (relative) capital distortions $1+\tau_{K,s,i}$. The trend in the elasticity of productivity revenue distortion is reported in Figure 8. The trend in the elasticity of productivity capital distortion is reported in Figure 9.

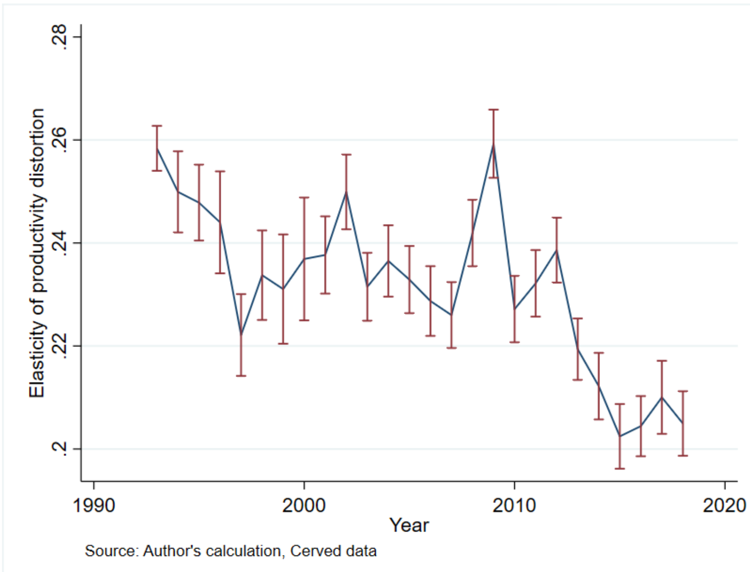

Figure 8: Trend in the elasticity of productivity revenue distortion

The two reported trends highlight that the rise in the correlation observed in Figure 6.9 between TFPR and TFP has been driven by an increase in the correlation between capital distortions and productivity. Furthermore, this trend experiences an interesting reverse pattern corresponding to the year 2016 when it starts declining with an immediate drop of 4 percentage points. This result highlights an interesting pattern that could be an object of further research. In light of the result of Figure 9, policy interventions should aim at reducing the costs of investments in innovative tangible capital. On one hand, this would reduce the misallocation of production factors that is found to be higher in more innovative firms (Calligaris et al. (2018)). On the other, this strategy

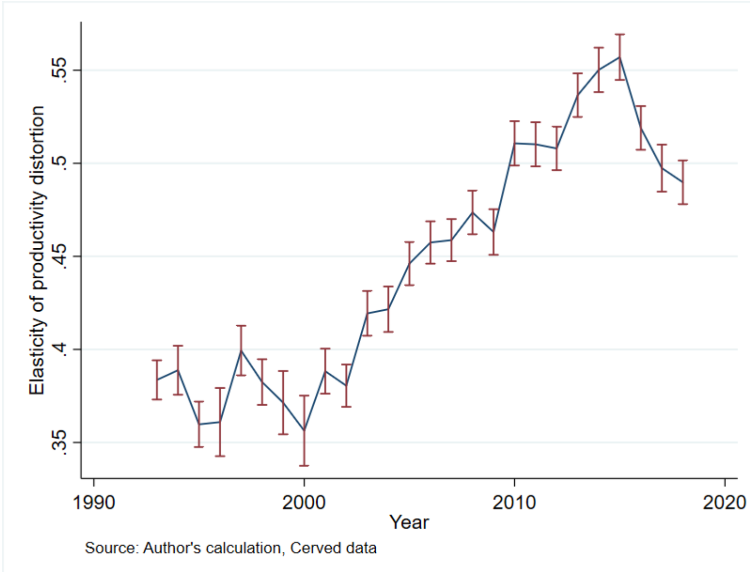

Figure 9: Trend in the elasticity of productivity capital distortion

would increase the firms' incentives to become more productive by reducing the distortions that more productive firms are facing. The year 2016 corresponds to the year of the introduction of a policy called *Industria 4.0*[8]. *Industria 4.0* should qualify as an effective policy to contrast capital distortions for three main reasons. First, it aims at reducing the costs of investments in *tangible* assets categorized as particularly innovative. Hence, the policy targets the cost of tangible capital

[8]Industria 4.0 is a plan aimed at facilitating and supporting investments in assets that are functional to the technological change and digitization of the firm. There are two main incentives.

- Iperammortamento: 250% overestimation of investments in tangible assets qualifying as 4.0 for taxes purposes.
- Superammortamento: 140% overestimation of investments in tangible capital equipment for taxes purposes (not 4.0). Conditional on having already iperammortamento, firms can benefit from superammortamento for investments in intangible assets related to investments in the technological and / or digital transformation of the firm in an Industry 4.0 (software and IT systems).

To qualify for iperammortamento, the investment should be

- capital goods whose operation is controlled by computerized systems and / or managed by means of suitable sensors and drives. These machines must satisfy: interconnection to the production system of the firm (interconnection requirement) & a simple and intuitive interface between man and machine & compliance with the most recent parameters of safety, health and hygiene in the workplace & control by means of CNC or PLC & interconnection to factory IT systems with remote loading of instructions and/or part programs ;
- Systems for quality and sustainability assurance
- Devices for man-machine interaction and for the improvement of ergonomics and workplace safety in logic 4.0

Examples of goods qualifying for Iperammortamento are: automated warehouses, machines used in production, robots, benches and workstations equipped with ergonomic solutions capable of adapting them in an automated manner to the physical characteristics of the operators.

and may be effective in reducing its associated distortions. Second, tax incentives are spread in time. By acquiring the good the firm becomes more productive and receives lower taxes in future periods. Hence, it provides incentives for technology adoption. Third, it is particularly convenient for more productive and profitable firms because tax benefits from the overestimation of assets are beneficial only for firms experiencing business profits. Thus, the policy should impact the correlation between capital distortions and productivity. Reforms such as *Industria 4.0* have the specific goal of reducing capital costs and increasing firms' incentives for technology adoption and Italy seems to be directed on the right track.

7.2 Conclusion

In this article, I have studied the Italian productivity puzzle focusing on firm-level TFP growth. First, I documented an anemic growth in productivity over the firms' life-cycle. Building on the endogenous growth literature, this finding provides motivating evidence to study trends in market imperfections that could have reduced firms' incentives to innovate. Building on the work of Hsieh and Klenow (2009) and Hsieh and Klenow (2014), I provided strong evidence of an increase in the correlation between productivity and firm-level distortions that create wedges in the profit function. This trend may provide a possible explanation for the anemic firm-level productivity growth observed in the data. The idea is simple: if the correlation between frictions and productivity has increased, firms' incentives to innovate decreased relative to the benchmark year. I provided empirical evidence consistent with this hypothesis. In particular, I documented how the elasticity of productivity distortion affects firms' growth through its influence on returns to innovation. Then, I built a general equilibrium model based on Atkeson and Burstein (2010) and Hsieh and Klenow (2014), calibrated to the Italian economy in the years before the crisis. The model allowed me to quantify the impact of the rise in the elasticity of productivity distortion on aggregate productivity and on firms' TFP life-cycle. Overall, I showed that the rise in the elasticity of productivity distortion can explain a large part of the reduction in the firm-level growth rates and can account for the absence of a recovery after the Italian productivity 1995 slowdown. Lastly, I have shed additional light on the trend in the elasticity of productivity distortion by investigating its components. I have documented that the rise in the elasticity of productivity distortion was mainly driven by a rise in the correlation between capital distortions and productivity. This trend experienced a drop in 2016 reversing its pattern. This suggested that policies such as *Industria 4.0* are effective tools to contrast rising trends in the elasticity of productivity capital distortion.

The contribution to the literature of my research is twofold. On one hand, I applied a framework previously used to explain inter-countries differences to shed light on an intra-country worrisome trend. I believe that several of these implications may apply to other economies facing their own productivity puzzle, and may provide some useful policy advice. On the other hand, to my knowledge, this is the first paper that provides empirical evidence consistent with the causal impact of the elasticity of productivity distortion on firm-level growth. Hence, I provided important evidence that contributes to the literature that studies firm-level distortions and growth.

To conclude, my results have important policy implications. Policies and institutional settings that create market distortions in favor of less productive firms may reduce firms' incentives to grow and adversely affect economic outcomes. Examples of these policies are tax breaks, subsidies for small firms, labor more regulated in larger and more profitable firms, bureaucracy, and thresholds below which some regulations do not apply. Although there might be reasons to sustain less productive firms, policy-makers should be aware of the negative consequences that these policies have on aggregate variables. Therefore, policies should focus on creating an economic environment which is more beneficial for more productive firms. Policies such as *Industria 4.0* seem to be effective and may provide the ground for future actions.

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Executive Summary

In the mid-1990s, Italian total factor productivity (TFP) growth experienced a severe slowdown, turning negative in the 2000s. TFP measures how efficiently given amounts of capital and labor are used to produce value-added. Economists are particularly concerned about TFP growth because productivity lies at the heart of long-term growth and rising living standards. Thus, it is crucial to understand what is at the root of this productivity breakdown.

Figure 10 shows the trend in manufacturing productivity, where TFP measurement is less controversial than in services due to better accounting of the capital stock. Italian TFP is characterized by a dramatic slowdown compared to other European countries, where productivity grew steadily up to the Great Financial Crisis. What is particularly worrisome and puzzling about the 1995 productivity breakdown is that, unlike in prior crises, TFP growth did not recover, turning negative in the 2000s. What are the main drivers of this trend? Aggregate TFP is nothing else than a weighted average of firm-level TFP. Thus, aggregate TFP depends on firm TFP along two dimensions. First, for a given amount of factors used by each firm, aggregate TFP grows when firm-level TFP grows. Second, for given firms' TFP levels, aggregate TFP depends on the allocation of factors across firms.

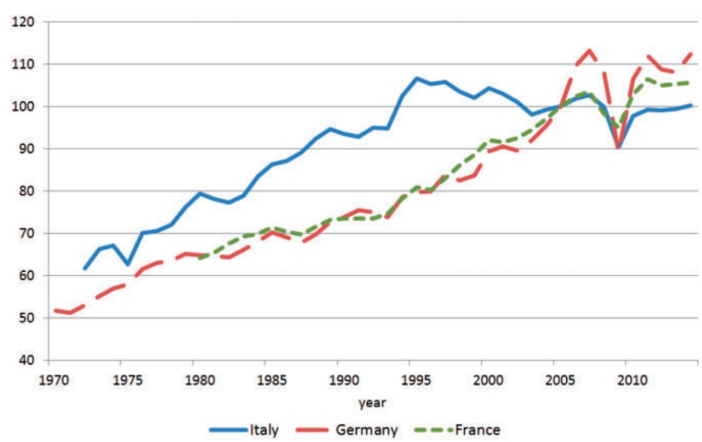

Figure 10: TFP in manufacturing for Italy, Germany, and France (2005=100).
Source: Calligaris et al. (2018)

This paper will focus on the first channel to tackle the Italian productivity puzzle. The main research question asks what could explain the absence of a recovery after the 1995 growth breakdown. Building on the endogenous growth literature, I investigate whether changes in market imperfections could have disincentivized firms from investing in productivity growth. Under the assumption that firm-level productivity is driven by the firm's R&D investments in process efficiency, at least part of the trend in aggregate productivity could be explained by changes in firms' stimulus to innovation.

Hsieh and Klenow (2009) develop a monopolistic competition model that allows for measuring frictions that enter the firm-level profit function. These frictions enter the profit function as revenue and capital taxes and capture any firm-level cost that distorts the competitive market prices. The idea is simple and builds on the distinction between physical TFP (from now on process efficiency or TFP) and revenue TFP (from now on TFPR) introduced by Foster et al. (2008). TFPR is proven to be proportional to the geometric average between marginal revenues of inputs. Absent frictions, the marginal revenue of inputs should be equalized across firms since factors move from low to high marginal revenue product firms. Hence, TFPR provides a measure of the total amount of frictions faced by the firm. Hsieh and Klenow (2014) build a general equilibrium endogenous growth model able to explain differences in aggregate productivity among India, Mexico, and the United States. Their model is based on the concept that frictions may disincentivize growth. The intuition is that the correlation between frictions and productivity may be different across countries suggesting differences in firms' incentives to invest in process efficiency. When highly productive firms in India and Mexico confront greater taxes and factor costs than in the United States, the marginal return to innovation is smaller, and firms invest less to boost productivity.

With these concepts in mind, I study the evolution of distortions and TFP at the firm level by using the universe of Italian incorporated companies over the period 1993-to 2018. As preliminary evidence, I find strong reductions in the firm-level productivity growth at every age profile. I simulate TFP life-cycle compounding firms' growth rates averaged by age. The idea is to simulate how firms would evolve in their productivity keeping constant the economic conditions determining the growth rates. I find that in the years 2006-2014 firms experienced a 20% (relative to pre-2000) decrease in their TFP growth over their simulated lifecycle. Moreover, I find that firms' TFP growth has experienced a partial recovery in the years after 2015. To shed light on this preliminary result, I introduce the framework of Hsieh and Klenow (2009) and Hsieh and Klenow (2014) and find strong evidence of an increase in the correlation between productivity and distortions. Relative to 1997, the measured elasticity of productivity distortion has experienced an increase of almost 18%, reaching a peak of 0.46 in 2009. In 2009, a 1% increase in productivity is associated with a 0.46 % increase in average distortions.

Can higher elasticity of productivity distortion explain lower TFP growth rates? To answer this question, I provide some reduced-form regressions trying to provide some empirical evidence about the impact of the elasticity of productivity distortion on growth. I argue that my results support the idea that the elasticity of productivity distortion has a causal impact on growth by lowering the marginal return to innovation. First, I find a negative correlation between firm-level productivity growth and the estimated sector-year elasticity of productivity distortion. One standard deviation increase in the elasticity is associated with a 0.95% reduction in future productivity. Of course, this is not evidence of causality since there might be reverse causality or spurious correlation. Therefore, I analyse the mechanism through which the elasticity of productivity distortion impacts TFP growth. I provide evidence of a negative correlation between firm-level intangible assets growth and the estimated elasticity of productivity distortion. One standard deviation in the elasticity of productivity distortion is associated with a 3.33% reduction in the three-year intangible assets growth. Since intangible assets growth, including branding, marketing etc., may capture something else than investments in process innovation, and since there might still be reverse causality, I provide a further test of reverse causality based on the intuition of Rajan and Zingales (1998) and Pagano and Schivardi (2003). I classify sectors according to an exogenous measure of R&D intensity to proxy for sector-specific investment opportunities. If the elasticity of productivity distortion has a causal impact on productivity growth through firms' incentives to innovate, I should find that its impact is stronger in sectors characterized by higher investment opportunities. Therefore, I consider whether the impact of the estimated elasticity of productivity distortion varies systematically with R&D sectoral intensity. If this were to be the case, reverse causality should be ruled out. Indeed, under reverse causality or spurious correlation, we would expect a homogeneous relationship between elasticity and growth that does not vary according to R&D intensity. The negative impact of one standard deviation increase in the elasticity of productivity distortion on firm-level productivity growth in a sector-year which is one standard deviation above the mean of R&D intensity is 0.48 percentage points stronger. The differential on the three-year intangible assets growth is 3 percentage points.

My empirical results indicate that the negative relationship between the estimated elasticity of productivity distortion and firm-level productivity growth increases with R&D intensity. This is consistent with a causal relationship between the elasticity of productivity distortion and growth working through firms' incentives to innovate. By looking at the interaction, rather than direct, effects I am restricting the range of alternative explanations for the relationship between the elasticity of productivity distortion and firm-level TFP growth. Hence, I am providing more consistent evidence of causality.

Next, I quantify the impact that the 18% rise in the elasticity of productivity distortion had on aggregate productivity and firm-level growth rates by building a general equilibrium endogenous growth model of heterogeneous firms. I calibrate a closed economy version of Atkeson and Burstein (2010) to the Italian pre-breakdown economy. Since there is no capital, frictions enter the profit function as revenue taxes creating a wedge in the firm profits. In the model, I assume distortions to be a function of the firm productivity, calibrated according to the different values of the estimated elasticity of productivity distortion. I focus on three main mechanisms through which the elasticity of productivity distortion impacts aggregate productivity. First, with higher elasticity, the marginal return to innovation is lower and post-entry investments in process innovation decrease. Hence, firm TFP growth will slowdown over the lifecycle. Second, with higher elasticity, the allocation of factors is distorted and less productive firms receive more weight than they would in an undistorted economy. Third, lower lifecycle growth reduces the competition posed

by incumbents on less productive firms, reducing selection.
Results indicate that with the 2009 level of frictions aggregate productivity is 6% lower than it would be if frictions had remained at the 1997 level. Moreover, incumbents' TFP is reduced by 8%. This accounts for almost half the drop in the simulated TFP lifecycle obtained compounding growth rates averaged by age.

I conclude the analysis by describing the key mechanisms driving the trend in the elasticity of productivity distortion. I find that the main driver behind the rise in the elasticity has been the increase in the correlation between productivity and capital distortions. The trend experienced a change of direction after 2015. Although only suggestive evidence, this reverse pattern suggests that *Industria 4.0*, a policy aimed at reducing the costs of investments in tangible assets that are categorized as particularly innovative, has been an effective tool to contrast the worrisome trend in the correlation between capital distortions and productivity. Further research may provide new evidence on the causes of the trend observed in the elasticity of productivity capital distortion. Moreover, it may provide more accurate evidence on the impact that policies such as *Industria 4.0* have on distortions and incentives to innovate.

This paper is related to a number of studies that have used distortions, misallocation, and the framework of Hsieh and Klenow (2009) and Hsieh and Klenow (2014) in various contexts, such as Restuccia and Rogerson (2008), Bellone, Mallen-Pisano, et al. (2013), Bollard et al. (2013), Bento and Restuccia (2017), Gopinath et al. (2017), Calligaris et al. (2018). The contribution of this paper to this line of research is twofold. On one hand, I apply the methodology of Hsieh and Klenow (2014), so far used only to explain inter-countries differences, within the same country. I show how the trend in the elasticity of productivity distortion may provide some useful explanations for a worrisome phenomenon such as the Italian productivity puzzle. I believe that several of these implications may apply to other economies facing their own productivity puzzle, providing some useful policy advice. On the other hand, to my knowledge, this is the first paper that provides empirical evidence consistent with the causal impact of the elasticity of productivity distortion on firm-level growth.

The paper is also related to a number of studies that analysed the Italian productivity slowdown, such as Navaretti et al. (2011), Bugamelli, Schivardi, et al. (2010), Bugamelli, Cannari, et al. (2012), Benigno and Fornaro (2014), Michelacci and Schivardi (2013), Lippi and Schivardi (2014), Calligaris et al. (2016), Pellegrino and Zingales (2017), Schivardi and Schmitz (2020). In addition to this literature, to my knowledge, this paper is the first that investigates firm-level incentives for technology adoption to explain the Italian productivity puzzle.

To conclude, my results have important policy implications. Policies and institutional settings that create market distortions in favor of less productive firms may reduce firms' incentives to grow and adversely affect economic outcomes. Examples of these policies are tax breaks, subsidies for small firms, labor more regulated in larger and more profitable firms, bureaucracy, and thresholds below which some regulations do not apply. Although there might be reasons to sustain less productive firms, policy-makers should be aware of the negative consequences that these policies have on aggregate variables. Therefore, policies should focus on creating an economic environment which is more beneficial for more productive firms. Policies such as *Industria 4.0* seem to be effective and may provide the ground for future actions.