The impact of classes of innovators on Technology, Financial Fragility and Economic Growth

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Abstract

In this paper, we study innovation processes and technological change in an agent-based model. By including a behavioral switching among heterogeneous innovative firms, which can endogenously change among three different classes (single innovators, collaborative innovators and imitators) on the base of their *R&D* expenditures, the model is able to replicate, via simulations, well known industrial dynamic and growth type stylized facts. Moreover, we focus the analysis on the impact of these three innovation categories on micro, meso and macro aggregates. We find that collaborative companies are those having the highest positive impact on the economic system. The model is then used to study the effect that different innovation policies have on macroeconomic performance.

JEL classification: C63, E32, E6, O3, O4

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1 Introduction

Technology progress is generally considered the driving force of the social and economic development (see Dosi *et al.*, 1997; Freeman, 1994; Malerba, 1992; Rosenberg, 1994, for empirical evidences). Governments, and specially the European Community with the "Action Plan 2010", have intensified their efforts to increase investments in research. For instance, in the European Union, countries have agreed to increase their *R&D* investments from 1.9% to 3.0% of the GDP. Thus, understanding the effect of these investments on the economic outcome and which is the best innovation policy tools become strongly necessary. The main purpose of this paper is to analyze the impact of the innovation and technological change on economic growth and business cycles and to study its properties under different public policies.

Disappointingly, neoclassical equilibrium theory has rather little to say about the important stylized facts on technological innovation and industrial dynamics, particularly if we consider these facts jointly (Dosi *et al.*, 1997; Klepper and Simons, 1997). The empirical regularities, as a relatively stable skewed firm size distribution (Axtell, 2001; Gaffeo *et al.*, 2003), the Laplace distribution of firms' growth rates (Stanley *et al.*, 1996; Bottazzi and Secchi, 2003), the firms' heterogeneity with respect to employed technology (Silverberg and Verspagen, 2005) and others important growth type stylized facts (Kaldor, 1961; Audretsch, 1997) are, instead, well reproduced by agent-based models. These models, in fact, are able to replicate the empirical phenomena mentioned above as emergent properties given by the interaction of heterogeneous agents. It is the dynamic interaction among individuals, who might use very simple strategies, to generate macroeconomic regularities. Despite the apparent merit of this methodology for the studying of a wide set of issues in the *R&D* economics, the number of agent based models in this area in not large (Dawid, 2006).

Following this approach, in this paper we develop a model able to jointly replicate empirical regularities in industrial dynamics (e.g., firm size distributions, productivity dispersions, firm growth rates, etc.) and macro statistical properties (e.g., rates of output growth, output volatility, etc.). This work is based on an existing agent-based model (Delli Gatti *et al.*, 2005) which, simulating the behavior of interacting heterogeneous firms and of the banking system, is able to generate a large number of stylized facts, but does not model technology at all. Here, instead, we introduce technological progress. Firms, in fact, invest part of their operating profits in *R&D* (Russo *et al.*, 2007; Gaffeo *et al.*, 2008) and can decide to be imitators, stand-alone or collaborative innovators (Dosi *et al.*, 2010). This assumption is in line with empirical evidence indicating an increasing number of *R&D* co-operations among firms (Czarnitzki *et al.*, 2007). Collaborations, in fact, are seen as a possibility to internalize externalities occurring in the creation of innovation and, thus, represent an useful tool to increase the probability of success and the appropriability of research outcomes (Katz, 1986; d'Aspremont and Jacquemin, 1988; Hall, 2002). Also the

European Union's Framework Programme shows an increasing interest for collaborative research. In fact, direct subsidies for joint research groups are becoming fiscal policies often used in several countries (Ebersberger, 2005; Czarnitzki and Fier, 2003).

In our model, firms do not belong for their whole life to one of the three innovation groups, but we use an evolving mechanism which allows them to switch from one group to another one, according to their *R&D* expenditure [1] (Dosi *et al.*, 2010). The switching allows us to study the evolution of the population moving among these three groups, and their impact on the economic variables. Although the empirical literature provides different values in the identification of the percentage of innovative firms belonging to these groups[2], it is undeniable that the number of collaborative firms is constantly growing and that they have an high impact on the economic outcome (Czarnitzki *et al.*, 2007; Foyn, 2000). These results are well reproduced in our model, indeed, there is an increasing number of collaborative firms which play a key role for the economic growth.

Since we endogenously model the behavior of the innovators, it seems worthwhile to ask whether some redistributive policies, funding technology improvements, can benefit the economy. Thus, we use the model as a computational laboratory to run experiments on the role of different innovation incentives. Several *R&D* policies for firms' innovation behavior have been studied over the last years (cfr. González *et al.*, 2005; Czarnitzki *et al.*, 2007; Klette *et al.*, 2000). However, their impact is ambiguous. Nevertheless, some empirical analyzes have shown a clear influence of collaborative *R&D* innovators on economic growth as the number of participants increases (Hagedoorn and Narula, 1996). Following these empirical results, we investigate the effects of three types of policies on technology level and on output growth.

The rest of the paper is organized as follows. In Section 2 we describe the model with the behavior of the firms and of the bank; in Section 3 we present the results of the simulations for the baseline model and for the model with the funding policies. Finally, Section 4 concludes.

2 The model

In the economy there are two markets, the goods and the credit ones. The system is populated by a large number of firms and a banking sector, who undertake decisions at discrete time $t = 0, 1, 2, ..., T$. In the goods market, output is supply-driven, that is, firms can sell all the output they optimally decide to produce. Moreover, firms invest resources in the R&D activity,

[1]In economic and financial literature, several agent-based models have used mechanisms of behavioral switching and have shown that these techniques can lead to large aggregate fluctuations, thanks to a coordination of expectations(Lux and Marchesi, 2000; Iori, 2002).

[2]For instance, from 1998 to 2000 the innovating companies involved in co-operative research were about 50% in Finland and 17% in Germany (Czarnitzki *et al.*, 2007).

with the aim to obtain innovations and, consequently, increase their productivity. In the credit market, firms raise funds to invest. The supply of credit is a multiple of the bank's equity base and the bank distributes it to its portfolio firms by adopting a system of risk management based upon the firm's level of equity and capital ratios. On the other hand, the demand for credit is related to firms' investment expenditure and dependent on banks' interest rates.

2.1 Firm behavior

We have a large and constant population of competitive firms $i = 1, ..., I$. Firms are profit seekers and, at any time period t, they try to maximize their expected profits.

According to Greenwald and Stiglitz (1990, 1993), firms can sell all the output they produce at an individual selling price $P_{i,t}$ which is a random variable with expected value P_t, i.e., the market price, and finite variance. As a consequence, the relative price $u_{i,t} = \frac{P_{i,t}}{P_t}$, is a random variable with expected value $E(u_{i,t}) = 1$ and finite variance.

Firms i produce a homogeneous output $Y_{i,t}$, according to the following production function:

$$Y_{i,t} = \phi_{i,t} K_{i,t}, \tag{1}$$

with $K_{i,t}$ being the stock of capital and $\phi_{i,t}$ the capital productivity, which depends on firm's innovation, as explained below.

In order to produce output, firm i needs a given amount of labor $N_{i,t}$, according to the capital-labor ratio $x_{i,t} = K_{i,t}/N_{i,t}$[3]. We have not a complete labor market. Indeed, we just model the labor supply, where each firm can hire (fire) all workers it needs at the wage:

$$w_{i,t} = \alpha_1 w_{i,t-1} + \alpha_2(\phi_{i,t-1} - \phi_{i,t-2}), \tag{2}$$

where $0 < \alpha_1, \alpha_2 < 1$. We simply assume a positive wage-productivity relation. The increase in productivity, in fact, requires higher skilled workers that must be compensated with higher wages (Doms *et al.*, 1997).

In addition, firm i is rationed on the equity market and has to rely on the bank to obtain external finance. The debt commitments are $r_{i,t}K_{i,t}$, where $r_{i,t}$ is the interest rate. Note that, for sake of simplicity, the remuneration of liabilities, $L_{i,t}$, is equal to that of internal capital, $A_{i,t}$. Moreover, firm capital stock $K_{i,t}$ is function of net worth $A_{i,t}$ and bank loans $L_{i,t}$, $K_{i,t} = A_{i,t} + L_{i,t}$. Therefore, in real terms, profit is equal to:

$$\pi_{i,t} = u_{i,t}Y_{i,t} - gr_{i,t}K_{i,t} - w_{i,t}N_{i,t} = (u_{i,t}\phi_{i,t} - gr_{i,t} - \frac{w_{i,t}}{x})K_{i,t} \tag{3}$$

[3]Consequently, each firm has a labor demand equal to $N_{i,t} = K_{i,t}/x_{i,t}$.

with $gr_{i,t}K_{i,t} + w_{i,t}N_{i,t}$ being the variable costs and $g > 1$. The expected profit is $E(\pi_{i,t}) = (\phi_{i,t} - gr_{i,t} - \frac{w_{i,t}}{x})K_{i,t}$. If firm i makes a positive profit, then it invests a portion of it in the $R\&D$ activity, with the aim to obtain innovations in the next periods:

$$R\&D_{i,t} = \begin{cases} \sigma\pi_{i,t-1} & \text{if } \pi_{i,t-1} > 0 \\ 0 & \text{if } \pi_{i,t-1} <= 0, \end{cases} \tag{4}$$

where $0 < \sigma < 1$. Consequently, after $R\&D$ expenditure, profit reduces to: $\pi_{i,t-1} = \pi_{i,t-1} - RD_{i,t} = (1-\sigma)\pi_{i,t-1}$.

Following Gilbert *et al.* (2001), we divide R&D investing firms in three classes of players: single innovators, collaborative innovators and imitators (MacPherson, 1997; Willoughby and Galvin, 2005; Vega-Jurado *et al.*, 2009). In order to create such classes, we have developed a procedure by which the division depends on the firm probability of success in completing the innovation. Firms with a probability higher than $\bar{Z}_t = (1-\gamma_1)Z_{i,t}^{Max}$ would try to become stand-alone innovators, those with a probability lower than $\underline{Z}_t = (1-\gamma_2)Z_{i,t}^{Max}$ are willing to become imitators (with $0<\gamma_1, \gamma_2<1$ being parameters), while are collaborative innovators all the other ones (i.e., those with $\underline{Z}_t < Z_{i,t} < \bar{Z}_t$). Such probability $Z_{i,t}$ is function of firms expenditure in $R\&D$, $\mu_{i,t} = \frac{R\&D_{i,t}}{K_{i,t}}$, that is: the access to innovative discoveries is more likely if a firm invests more in $R\&D$ (see Dosi *et al.*, 2010), and is approximated as follows:

$$Z_{i,t} = 1 - exp(-\beta\mu_{i,t}). \tag{5}$$

By the end, not all firms willing to do innovation can obtain access to innovation. If firm i results in a successful innovation or not is determined by a Bernoulli distribution, whose parameter is given by Eq. 5. Note that for collaborative innovators, the probability of having success depends on the probability of success of all the members[4], i.e., the whole group of innovators has access to $R\&D$ just if *all* its members return a positive value of the Barnulli distribution. Then, likewise if firm i becomes isolate or collaborative innovator, its innovation advance is the realization of a random process:

$$\phi_{i,t} = (1 + \xi_{i,t})\phi_{i,t-1}, \tag{6}$$

where ξ is a random variable uniformly distributed on the support $[\delta_1, \delta_2]$. On the other hand, imitators' success is given by a Bernoulli distribution. The imitator i chooses randomly one firm j in the whole population and copies its technology if more advanced than its own one. Thus, its

[4]In order to keep it simple, in our simulations, collaboration groups are composed by 2 firms. We have also simulated the model with larger collaboration groups (until 10 participants), however the results remain quite stable. Minor increases in the aggregate production and level of technology emerge.

innovation advance is the realization of a random process:

$$\phi_{i,t} = [1 + (\phi_{j,t} - \phi_{i,t})\xi_{i,t}]\phi_{i,t-1}. \tag{7}$$

If a firm has experienced successful imitation or innovation, then it waits a few periods (e.g., time-to-profit) before trying to innovate/imitate again[5]. This is because firms would profit of the improved productivity before spending again in R&D. Indeed, we suppose that imitation is not instantaneous and that, anyhow, firms are not able to capture the whole level of innovation reached by innovators (cfr. Eq. (7)).

Firm accumulates net worth by means of profit, according to the following law of motion:

$$A_{i,t} = A_{i,t-1} + (1-\sigma)\pi_{i,t}. \tag{8}$$

Because of the uncertain environment, firm i may go bankrupt and bankruptcy occurs if the net worth at time t becomes negative $A_{i,t} < 0$, that is:

$$u_{i,t} < \frac{gr_{i,t} + w_{i,t}/x}{\phi_{i,t}} - \frac{A_{i,t-1}}{(1-\sigma)\phi_{i,t}K_{i,t}} \equiv \bar{u}_{i,t}. \tag{9}$$

In other words, bankruptcy occurs if the relative price $u_{i,t}$ falls below the critical threshold $\bar{u}_{i,t}$. When a firm goes bankrupt, it leaves the market. The Greenwald and Stiglitz (1993) framework, therefore, provides a simple and straightforward way to model the exit process: a firm goes out of the market if its financial conditions are so fragile -that is, its equity level is so low- that an adverse shock makes net worth to become negative, or if it suffers a loss so huge to deplete all the net worth accumulated in the past. Therefore, the probability of bankruptcy is an increasing function of the interest rate, the wage and the capital stock and a decreasing function of the equity base inherited from the past. For the sake of simplicity, in the following we assume that $u_{i,t}$ is distributed uniformly on the interval $(0,2)$, so we can specify the probability of bankruptcy as $Pr(u_{i,t} < \bar{u}_{i,t}) = \bar{u}_{i,t}/2 = \frac{gr_{i,t}+w_{i,t}/x}{2\phi_{i,t}} - \frac{A_{i,t-1}}{2(1-\sigma)\phi_{i,t}K_{i,t}}$.

Bankruptcy is costly and the cost of bankruptcy is increasing with the quadratic of the production:

$$BC_{i,t} = cY_{i,t}^2, \tag{10}$$

where c is a positive parameter.

Following Greenwald and Stiglitz (1993), we assume that firms are formally risk-neutral, but they evaluate in each period the probability of bankruptcy and correct the production ac-

[5]In the simulations, the innovation break is fixed to 3 periods. Note that in a fast-changing world, there is often only a narrow time window of time to profit from today's hot new technologies, as they become tomorrow's commodities.

cordingly. Therefore, the firms' objective function is the difference between the expected profit and the cost of bankruptcy (Eq. 10) times the probability of bankruptcy: $BC_{i,t}Pr(u_{i,t} < \bar{u}_{i,t})$. We can formulate the problem of each firm i as:

$$\max_K [E(\pi_{i,t}) - PrBC_{i,t}] = \frac{\phi - gr_{i,t} - \frac{w_{I,t}}{x}}{c\phi_{i,t}(gr_{i,t} + \frac{w_{i,t}}{x})} + \frac{A_{i,t-1}}{2(gr_{i,t} + \frac{w_{i,t}}{x})}. \tag{11}$$

From the maximization of the Eq.(11), we obtain the optimal capital stock, $K^*_{i,t}$. Consequently, the investment is the difference between the optimal capital stock and the capital stock inherited from the previous period: $I_{i,t} = K^*_{i,t} - K_{i,t-1}$. To finance such investment, firm i recurs to its profit and, if needed, to new mortgaged debt. So, the demand of credit is $L^d_{i,t} = L_{i,t-1} - \pi_{i,t-1} + I_{i,t}$.

2.2 Bank Behavior

For the sake of simplicity, we assume that banks are lumped together in a vertically integrated banking sector "the bank", hereafter). Therefore, many heterogeneous firms interact with only one bank on the credit market. Such a bank allocates the total supply of credit among firms according to their relative size:

$$L^s_{i,t} = \lambda L_t \frac{K_{i,t-1}}{K_{t-1}} + (1-\lambda) L_t \frac{A_{i,t-1}}{A_{t-1}}, \tag{12}$$

where L_t is the total supply of credit at time t, $K_{i,t-1}$ and $A_{i,t-1}$ are, respectively, the aggregate stock of capital and net worth of firm i[6].

The total supply of credit is given by:

$$L_t = \frac{E_{t-1}}{v}, \tag{13}$$

where v is a risk coefficient, used by the bank to avoid excess lending. This coefficient v - that is, the minimum "capital requirement" of equity E_{t-1} per unit of credit extended - can be interpreted either as a discretionary strategy of risk management (Estrella *et al.*, 2000) or as a consequence of prudential regulation by the monetary authorities. The interest rate charged to each firm i is determined by the equilibrium between credit demand L^d and credit supply L^s, that is:

$$r_{i,t} = \frac{2 + cA_{i,t-1}}{2cg[totL_{i,t}(\lambda k_{i,t} + (1-\lambda)a_{i,t})] + \frac{1}{c\phi_{i,t}} + A_{i,t-1}} - \frac{w_{i,t}}{gx} \tag{14}$$

[6]This simply rule of credit allocation allows us to deal with asymmetric information in the credit market. Since the bank does not know the firms' financial conditions, it uses collateral information.

Under the assumption that the returns on the banks' equity are given by the average of the lending interest rates $\bar{r}_t$, and that deposits D are remunerated with the borrowing rate r_t^A, the bank profit π^b is given by:

$$\pi_t^b = \sum_i r_{t,i} L_{t,i} - \bar{r}_t((1-\omega)D_{t-1} + E_{t-1}), \tag{15}$$

where $1/(1-\omega)$ is the spread between lending and borrowing rates and captures the degree of competition in the banking sector.

When a firm goes bankrupt, the bank records a non-performing loan, also called "bad deb", which affects its own equity base negatively. We define the total amount of bad debt as $B_t = \sum_i -A_{i,t}\ \forall A_{i,t} < 0$, and the bank's equity base evolves according to the following law of motion: $E_t = E_{t-1} + \pi_t^b + B_{i,t}$. Indeed, when a firm goes bankrupt, not only the aggregate output but also the bank's equity reduces. As a consequence, aggregate credit goes down, pushing up the interest rate and increasing the risk of bankruptcy for the other firms. Some of the firms that were on the brink of bankruptcy will default and leave the market, while the surviving firms will curtail investment and production. Consequently, bankruptcies may spread and a domino effect follows.

3 Simulations and results

We simulate an artificial economy in which operate $F = 100$ firms and a bank under the assumption that if a firms goes bankrupt it is replaced by a new firm, consequently, F is fixed. Each firm is initially given the same amount of equity $A_{i,0} = 2$, capital $K_{i,0} = 5$ and liabilities $L_{i,0} = 3$. We fix $\phi = 0.1$, $\alpha 1 = 0.8$, $\alpha 2 = 0.5$, $\sigma = 0.2$, $\beta = 2$, $\gamma_1 = 0.02$, $\gamma_2 = 0.1$, $[\delta_1, \delta_2] = [0, 0.02]$, $\lambda = 0.3$, $\omega = 0.001$, $\nu = 0.08$, g = 1.1, c=1, w = 0.005, x=1. The results reported here are the outcome of simulations of $T = 1000$ periods. Only the last 900 simulated periods are considered, in order to get rid of transients. Simulations are repeated 100 times with different random seeds.

3.1 Stylized facts of the baseline model

In this first part, we focus the analysis on some properties of the baseline model. Our main goal consists in showing that the system is able to reproduce a number of macroeconomic stylized facts, which characterize the most industrialized countries under normal economic conditions. Moreover, we show the impact of R&D spending on macroeconomic variables. In this regard, the model is simulated for different values of σ.

First of all, the simulated aggregated output fluctuates, alternating phases of smooth growth to periods of larger variability, as shown in Fig. 1 (left side). Indeed, aggregated fluctuations, measured by output's growth rates (Fig. 1 (right side)) are path dependent (for example, the failure of a large firm in one period causes a lower level of production and of credit supply in the following one) and characterized by cluster volatility. The cluster volatility is a well known phenomenon in the financial market literature (see Cont, 2007), and implies that large changes in variable values occur preferably at neighboring times, reflecting the tendency for markets to move from stable to more turbulent periods. It is commonly measured by an auto-correlation function, and, here, is estimated on the absolute value of the growth rate output. Note that the auto-correlation value corresponds to the exponent of a power law distribution (Gopikrishnan *et al.*, 1999), which, in our case, is equal to 0.98, a value very close to that found for the quarterly real data of the G7 countries, equal to 0.93 (Stanca and Gallegati, 1999).

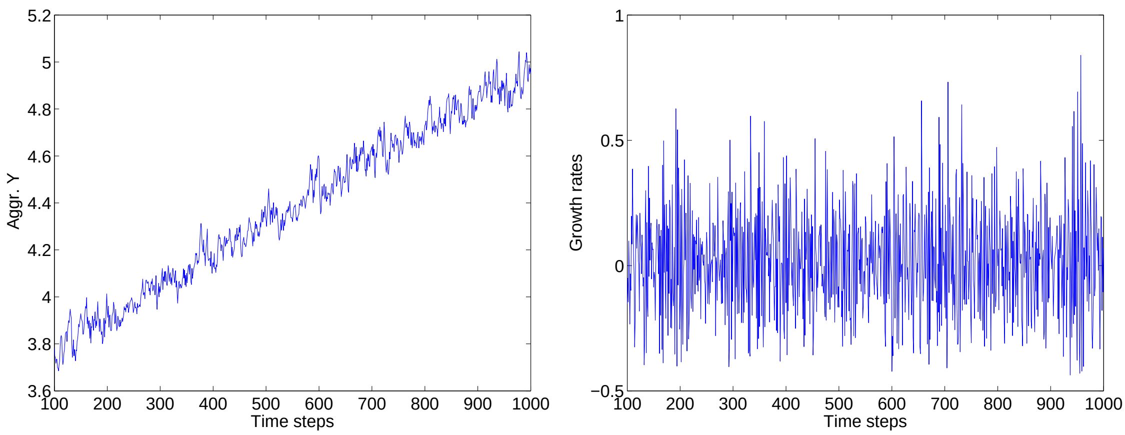

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Figure 1: Time evolution of aggregate output (left side) and growth rates of aggregate output (right side).

In the model, the growth process is due to the growth of firm size ascribable to their increase in productivity. Indeed, when a firm is able to turn its innovation efforts into productivity improvements, then it can produce more output with the same or smaller amount of labor. The output-labor ratio grows along time due to a diffused technological progress that saves labor input in the production process, as shown in Fig. 2 (left side). Since productivity improvements are due to an incremental innovation process and to an imitation process, firms that have experienced positive profits for several periods are more likely to have a higher Y/N ratio, that is a higher capital productivity (technology level). Thus, this dynamic generates a fat tail distribution of output-labor ratio among firms, see Fig. 2 (right side), which is well fitted by a power law. To confirm the goodness of fit of such distribution, we have implemented the Kolmogorov-Smirnov test, which studies the distance between the empirical distribution function and the theoretical distribution. The result of such test states that we could not reject the null hypothesis that the simulated distribution function is drawn from a power law. Furthermore, note that in our model the output-labor ratio Y/N is equal to the firm capital productivity ϕ. In fact, $Y/N = \frac{\phi K}{K/x}$, with $x = 1$. In line with the innovation literature (Silverberg and Verspagen, 1994), we find that the technology level of the economy is characterized by periods of slow increase followed by sudden jumps up. However, in our model we also have jumps down, due to the failure of technologically advanced firms. In fact, by construction, when a firm goes bankrupt, it is replaced by a new one having as initial technology level (i.e., ϕ) the mode of the technology value of the whole population. Thus, the average technology level of the economy can register a large fall because of the lost of the reached technology knowledge, dissipated with the failing firm.

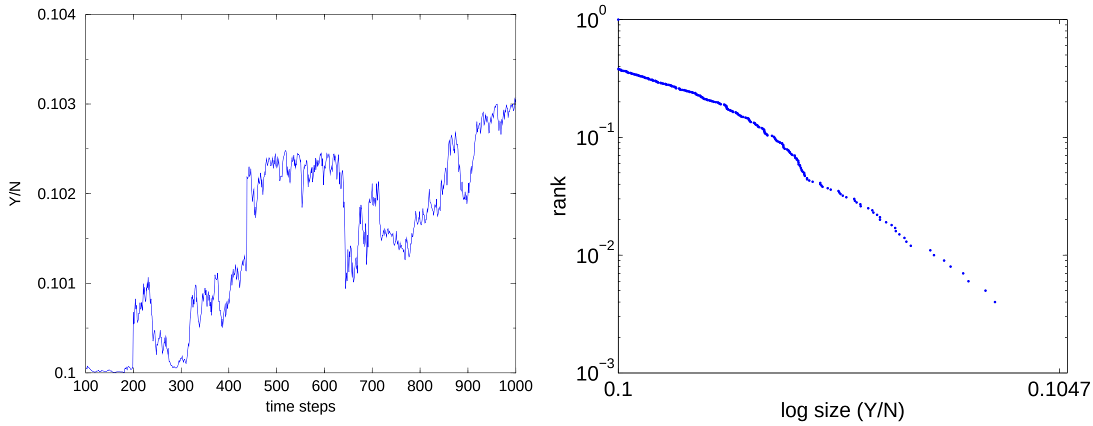

Figure 2: Time evolution of the output-labor ratio (left side) and decumulative distribution function of output-labor ratio (right side).

In order to verify the robustness of our results, we have simulated the model also for different values of the thresholds $[\gamma_1, \gamma_2]$ (cfr. Sec. 2.1). As Fig. 3 shows, the average growth rate and technology level do not change considerably varying the range of γ. However, it does worth being noticed that with higher γ_1 and lower γ_2 both the indicators return larger values. This is because, so doing, we have increased the probability for a potential innovators of becoming collaborative ones.

As in real industrialized economies, our model well reproduces another important stylized fact: the firm size distribution is highly right skewed (Axtell, 2001; Gaffeo *et al.*, 2003). Small and medium size firms - here we use firm equity as proxy of firm size- dominate the economy, while large firms are relatively rare although they contribute for a large part of total production. Fig. 4 (left side) displays this evidence and the distribution is well fitted in the tail by a power law distribution $y = Ax^{\gamma}$, with intercept 4.013 and slope -0.972. The result is robust to the Kolmogorov-Smirnov test.

Moreover, in line with other empirical works (Amaral *et al.*, 1997; Bottazzi *et al.*, 2001;

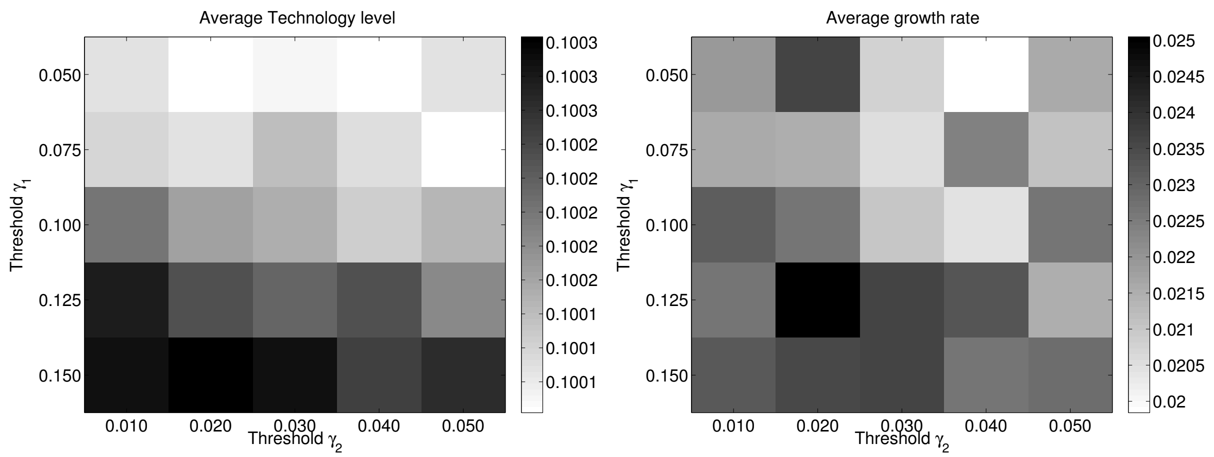

Figure 3: Average growth rate and technology level with different values of thresholds $[\gamma_1, \gamma_2]$.

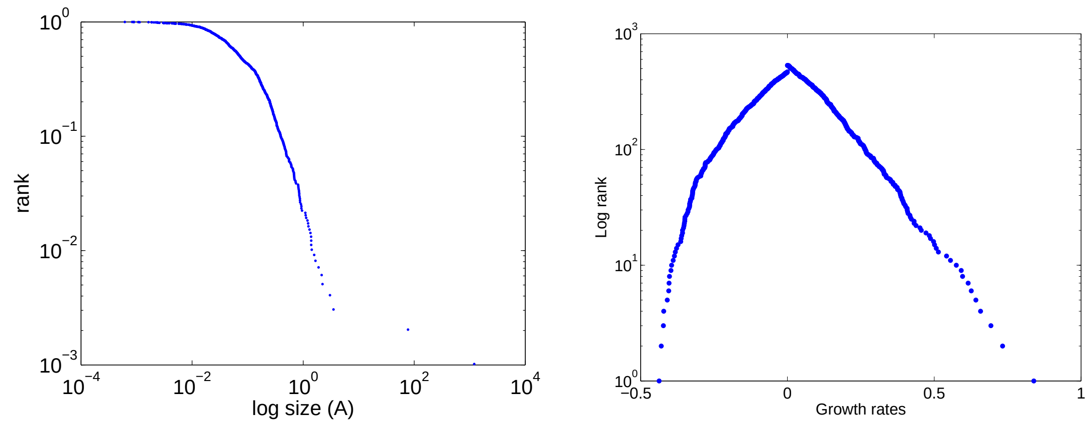

Figure 4: Decumulative distribution function of firms' size (left side) and firms' equity growth rate (right side).

Fagiolo and Luzzi, 2006), we show that the probability distribution of the logarithm of firm growth rates is tent-shaped and can be fitted by an asymmetric Laplace distribution (double exponential), whose tails decay much slower than in a Gaussian distribution (see Fig. 4 (right side)). In addition, in the model the capital-output ratio, the investment-output ratio and the wage-productivity ratio are roughly constant (cfr. Kaldor (1961)). The Augmented Dickey-Fuller test for unit root rejects the null hypothesis, meaning that all these three processes are stable.

As previously mentioned, the time series of aggregate output is punctuated by sudden, deep and rather short crisis (see Fig. 1 (left side)). Indeed, even if we model a supply driven economic system, where the whole production is sold at a stochastic price, the price volatility has important consequences on firms' dynamic. In addition, it is important to note that a contagion may develop because of firm bankruptcies. In our model, bankruptcies are endogenously determined by the failure of financially fragile firms. A firm failures may be triggered by an unexpected shock to revenues, so that profit becomes negative. If one or more firms are not able to pay back their debts to the bank, then also the bank suffers with a decrease in its equity level. Consequently, in order to improve its own situation, the bank rises the interest rate to all the firms in its portfolio, eventually causing other defaults among firms. Fig. 5 (left side) displays the time series of firm defaults. The share of failures is quite constant during the simulation, consequently, a decay in the time series of the aggregate output can be interpreted as caused by the simultaneous failure of relatively large firms (see Fig. 5, right side). In fact, one can easily infer that crises do not depend on the quantity of bankrupted firms, but on their quality (e.g., size). The same economic process can, thus, produce small or large recessions according to the size of defaulted firms.

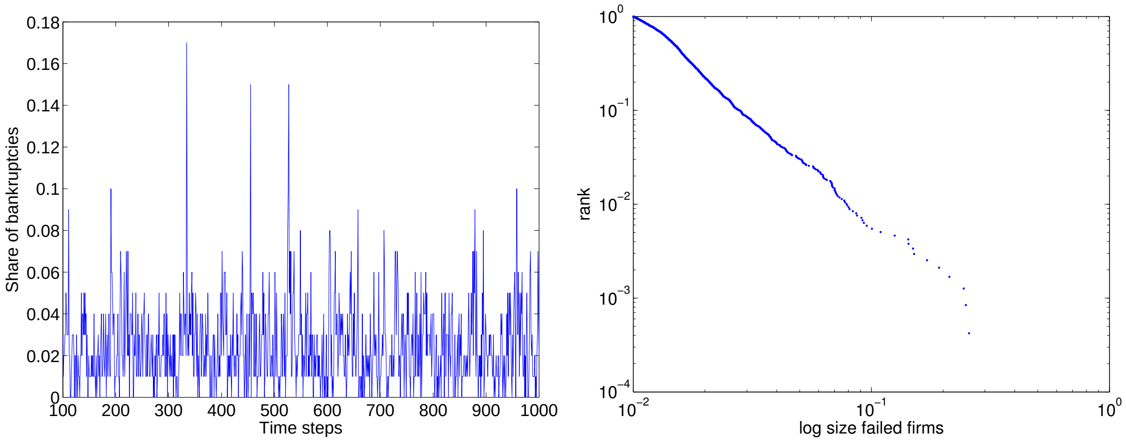

Figure 5: Time evolution of firm bankruptcies (left side) and decumulative distribution function of firms' size (right side).

To analyze the role of R&D expenditure, we run 100 independent simulations for different levels of σ. The results reported in Tbl. 1 show the existence of an increasing relationship between efforts in R&D and the output growth rate[7]. However, in our model, a higher value of σ corresponds to a lower equity level, via Eq. 8, which leads to higher financial fragility and higher probability of bankruptcy, as shown in Tbl. 1, lines 2 and 3. In addition, it is worth noting the role played by the three types of innovative firms. For all levels of R&D expenditure, the group of the collaborative innovators dominates the markets, although the probability of being collaborators is lower than that of being imitators. In fact, by construction, just 2% of firms have

[7]The results shown in Tbl. 1 right column confirm, via a Monte Carlo exercise, that the findings discussed so far are indeed quite robust.

a probability of belonging to the group of isolated innovators, 8% to the group of collaborative innovators and 90% to the imitators.

Statistics	$\sigma = 5\%$	$\sigma = 10\%$	$\sigma = 15\%$	$\sigma = 20\%$
avg. growth rate	0.0166	0.0181	0.0199	0.0226
s.d. growth rate	0.1896	0.1983	0.2092	0.2238
coeff. var. growth rate	11.5553	11.1133	10.6903	10.0252
avg. bankruptcy ratio	0.0180	0.0204	0.0228	0.0257
s.d. bankruptcy ratio	0.0157	0.0171	0.0186	0.0207
coeff. var. bankruptcy ratio	0.8693	0.8413	0.8145	0.8040
avg. equity ratio	0.1909	0.1874	0.1845	0.1818
s.d. equity ratio	0.0171	0.0171	0.0170	0.0169
coeff. var. equity ratio	0.0897	0.0911	0.0921	0.0932
avg. technology	0.1000	0.1001	0.1001	0.1002
s.d. technology	0.0002	0.0004	0.0005	0.0006
coeff. var. technology	0.0024	0.0036	0.0050	0.0066
avg. share imitators	0.0001	0.0003	0.0006	0.0009
s.d. share imitators	0.0009	0.0018	0.0024	0.0031
coeff. var. share imitators	12.3082	5.8174	4.1997	3.3058
avg. share single innovators	0.0002	0.0003	0.0005	0.0007
s.d. share single innovators	0.0013	0.0018	0.0022	0.0025
coeff. var. share single innovators	7.8818	5.5240	4.4780	3.8638
avg. share collective innovators	0.0004	0.0009	0.0013	0.0017
s.d. share collective innovators	0.0040	0.0059	0.0070	0.0082
coeff. var. share collective innovators	9.6008	6.7529	5.5374	4.8007

Table 1: Mean, standard deviation and coefficient of variation across 100 Monte Carlo simulations of the baseline model at different level of σ (i.e., share of profit invested in innovation.)

The winning element of the collaborative strategy is the pooling of resources to implement the innovation. In our model, in fact, collaborative firms have higher chances of success in innovation, because they accumulate together their R&D expenditure (cfr. Eq. 5). This result is in line with the growing number of companies jointing and collaborating in $R\&D$ in the last decades (Czarnitzki *et al.*, 2007).

In addition, we have studied the role of each innovation group by switching it on/off, e.g., by considering active in the innovation process: (i) only the single innovators, (ii) only the collaborative innovators, and (iii) both the single and collaborative innovators, but not the imitators. Such analysis reveals that if in the economy only single innovators operate, then the innovation progresses are marginal, while the scenario is quite different when firms collaborate together to carry on a new technology, see Fig. 6 (Czarnitzki *et al.*, 2007; Foyn, 2000)[8]. In fact, in the two cases in which the collaboration is allowed, the average technology follows an increasing trend and largely departs from what happens with stand-alone innovators.

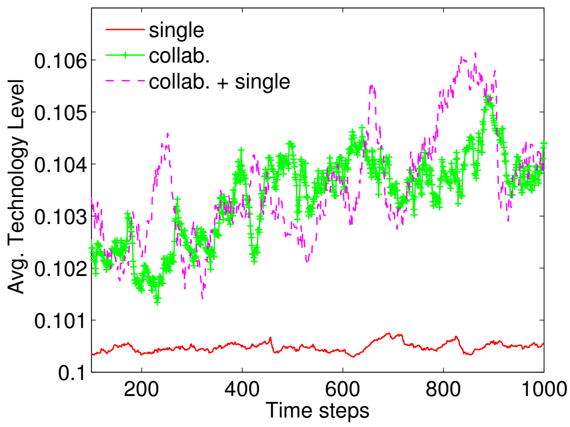

Figure 6: Time evolution of average technology by switching on/off the different innovation group.

3.2 The impact of public funding on innovation

In this section, our goal is to understand the impact of public funding policies on the modeled economy. In order to do so, we introduce in the baseline model a marginal "public sector", whose role is to advance the technology level of the economy by increasing the firm spending on $R\&D$. Note that we do not model the behaviour of the public sector and its fiscal policy, but we assume that the amount innovation funding is exogenously determined. This choice is motivated by the fact that in this version of the model we do not consider the demand side. Indeed, there are not consumers which buy the goods producted by the firms and that pay taxes. In our model, there would be a kind of clearing entry if only firms pay taxes, while it would be clearer, even if it may seems simplistic, to suppose that the State prints new money for the innovation funding. We focus our attention on four public policies: the State funds, by doubling the resources companies have already devoted to $R\&D$, (i) *all firms*, or (ii) just *the collective innovator firms*, or (iii) just *the single innovator firms* or (iv) both the collective and the single firms, respectively, that have completed a successful innovation in the previous period.

The following results reproduce the outcome of 100 simulations of the model with increasing levels of the $R\&D$ expenditure parameter σ, starting from 0% to 50% with steps of 0.5%. Firstly,

[8]Such result is robust at different values of σ.

Fig. 7 (left side) shows that all the four policies listed above have a positive impact on the aggregate output. In particular, the growth rate is higher in presence of public funding than when the State does not intervene, especially for large values of σ when the maximum difference is on the order of about 1-2%. Nevertheless, these policies affect differently the output. In particular, when the collaborative innovation firms receive public funds, the economy performs better than when the appointee is the single innovation group (Czarnitzki *et al.*, 2007; Foyn, 2000). Moreover, the policy of distributing funds to all firms has a greater impact than benefiting each single groups separately[9]. In addition, in all the scenarios, an increase in the level of profit invested in innovation generates higher growth rate. However, this relation is not linearly increasing, but for high values of σ, the growth rate rises less than proportionally to the increase of σ. The reason of this pattern can be due to the fact that when firms invest a large portion of their profits in innovation (i.e., high σ), they are not going to bolster the equity base and, consequently, they likely experience higher financial fragility and higher probability of bankruptcy.

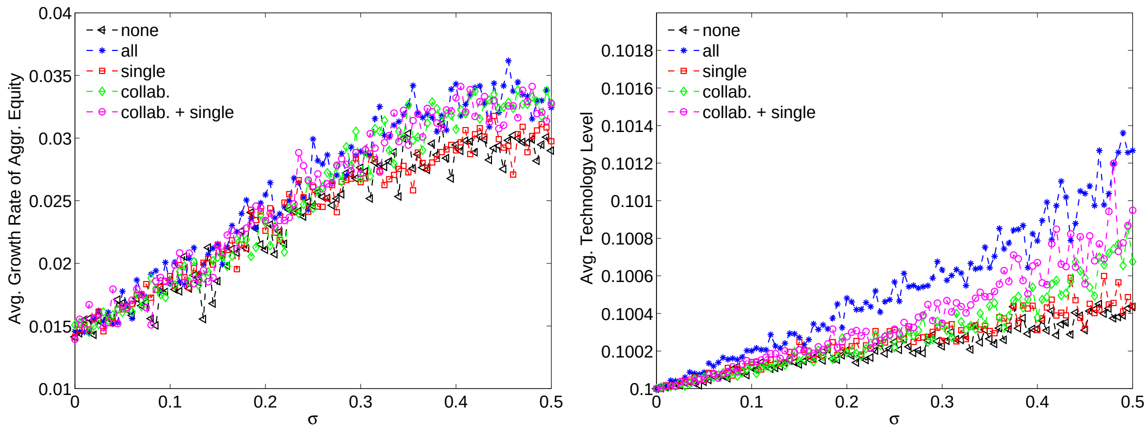

Figure 7: Average growth rates of aggregate equity (left side) and average technology levels, ϕ, (right side) for different levels of σ and funding policies.

As for the baseline model, the growth is explained by increasing productivity. Fig. 7 (right side) shows that all our different policy scenarios generate larger advances in the technological level than in the scenario with no policy (cfr. black line in the Fig.). Again, the average technological level is affected differently by the various policies. Furthermore, the average technology rises with the level of profit invested in innovation. In particular, when the State funds all the innovating firms or jointly the group of isolate and collaborative firms, the average technology level increases more than linearly with σ. In these scenarios, in fact, the number of firms receiving subsides is larger than in the other cases and, consequently, the probability to carry out a successful innovation is higher.

[9] An analysis of cost-benefit of the public intervention is performed below, see Fi. 8.

Finally, in order to clearly establish the benefits of these policies, it is important to prove that their social costs, burdening with the State transfers, does not exceed the advantages, measured by the aggregate production. Fig. **??** shows the cost-output ratio for all the innovation policies. Although the two most expensive policies, i.e., those involving the largest number of beneficiaries (blue start line and pink circle line), also have very high costs, the ratio reveals that benefits linearly increase with costs. The curves slope is less than 1, mirroring more than proportional benefits to costs. Only the policy facilitating single innovator firms (red square line) has much lower costs than benefits. However, the output growth of this scenario does not seem to differ considerably from the baseline model. In particular, the average growth rate for $\sigma = 15\%$ and $\sigma = 20\%$ are slightly higher in this case, respectively 2.06% and 2.29% vs. 1.99% and 2.26%, than in the model with no policy.

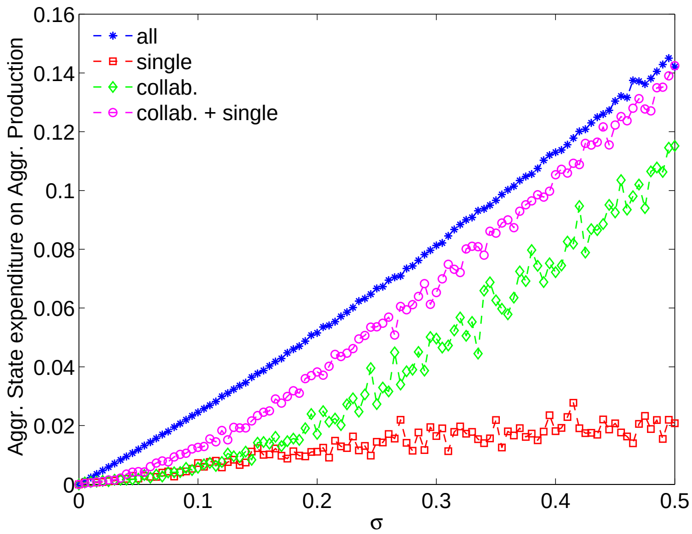

Figure 8: Cost-Output ratio as function of σ for different funding policies.

4 Conclusion

In this paper, we have investigated the $R\&D$ expenditure impact on both "micro/meso" variables, such as industrial dynamic indicators, and macro statistical properties. We have shown that the model can reproduce a number of stylized facts regularly observed in the data. Indeed, following the agent-based computational economic approach (Colander *et al.*, 2008; Tesfatsion and Judd, 2005), we have proved that a multiplicity of interacting heterogeneous agents, whose decisions are determined by evolving decision rules, can generate economic regularities without resorting to any full rationality of a Bayesian representative-agent.

The key element of this work is an endogenous mechanism of behavioral switching among three different groups of innovating firms. We have shown that the model is able to reproduce the raising impact of *R&D* collaborative companies on technology innovation and economic growth. We have subsequently used our baseline model as a computational laboratory to perform *R&D* funding policy experiments. We have investigated which policy performs higher innovation improvements. Moreover, we have compared the social costs and benefits of such policies. In all the investigated scenarios, the State intervention seems to increment technology and productivity levels. However, policies impact the economy with different intensity. Indeed, the most profitable policies are those which go to benefit all innovating groups and the collaborative one.

The main limitation of this study is that our model is fully supply-determined, i.e., firms can sell all the output they decide to produce at a random price. In a future paper, we will extend this analysis by including endogenous prices, which would allow us to perform the innovation policy effect on the demand side. Furthermore, we will introduce a more realistic innovation evolution, possibly by making use of the network approach and considering spatial constraints (Vega-Redondo, 2007; Fagiolo and Dosi, 2003)

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