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The impact of classes of innovators on technology, financial fragility, and economic growth

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In this article, we study innovation processes and technological change in an agent-based model. By including a behavioral switching among heterogeneous innovative firms, the model is able to replicate, via simulations, well-known industrial dynamic and growth type stylized facts. The main original element of the model is that firms are allowed to endogenously change among three different classes, namely, single innovators, collaborative innovators, and imitators. Moreover, our analysis focuses 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. Furthermore, we have paid particular attention to the role of credit market in promoting smart growth. For this purpose, we analyze the role of banks as sources of external funds for innovative entrepreneurs. Our results suggest a trade-off between short-term profit maximization and long-term efficiency, which prevents banks to foster investment in R&D and technological progress. The model is then used to study the effect that different innovation policies have on macroeconomic performance.

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1. Introduction

Understanding the role that technological progress has in social and economic development[1] as well as discerning which are the best channels to fund innovation is

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[1] See Dosi *et al.*, 1997; Freeman, 1994; Malerba, 1992; Rosenberg, 1994, for empirical evidences.

crucial for restimulating economic growth. Based on the lessons taken from the recent crisis, governments, and especially the European Commission, have laid out a strategy, the "Europe 2020," aimed to address the priorities of smart, sustainable, and inclusive growth. The strategy is intended to realize a successful exit from the crisis in the short term and to design an economic recovery, which is sustainable in the long term.

The main goal of this work is to analyze the relationship between smart growth and innovation with particular emphasis on how to better finance the growth of the economic system. In the light of the effort that the European countries are making for improving their R&D investments from 1.9 to 3.0% of GDP, it becomes strongly necessary to investigate which is the best innovation strategy. These issues can well be studied by means of a new and promising methodological approach, which is known under the name of agent-based modeling and simulation. This methodology, in fact, is able to jointly replicate important empirical phenomena on technological innovation and industrial dynamics (Dosi *et al.*, 1997; Klepper and Simons, 1997). The empirical regularities, such 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), firms' heterogeneity with respect to the used technology (Silverberg and Verspagen, 2005), and other important growth type stylized facts (Kaldor, 1961; Audretsch, 1997) are, indeed, emergent regularities resulting from dynamic interactions among agents. Despite the apparent merit of this methodology for the study of a wide set of issues in R&D economics, the number of agent-based models in this area is limited (Dawid, 2006).

Following this approach, in this article, we develop a model able to jointly replicate empirical regularities in industrial dynamics (e.g., firm size distributions, productivity dispersions, firm growth rates) and macro statistical properties (e.g., rates of output growth, output volatility). 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.*, 2006, 2007; Gaffeo *et al.*, 2008) and can decide to be imitators, standalone innovators, or collaborative innovators (Dosi *et al.*, 2010). This assumption, in line with empirical evidence indicating an increasing number of R&D cooperations among firms (Czarnitzki *et al.*, 2007), is the main original element of our model. Collaborations, in fact, are seen as a strategy to internalize externalities occurring in the creation of innovation and, thus, represent useful tools to increase the probability of success and the appropriability of research outcomes (Katz, 1986; d'Aspremont and Jacquemin, 1988; Hall, 2002). The European Union's Framework Programme shows an increasing interest in collaborative research. Indeed, 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 stick to one of the three innovation groups. Instead, we use an evolving mechanism, which allows firms to switch from one group to another one, according to their R&D expenditure[2] (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[3], it is undeniable that the number of collaborative firms is growing and that they have a significant 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 in economic growth.

Because we endogenously model different innovation strategies, it seems worthwhile to analyze the most efficient way through which we could foster the adoption of innovation, investment in R&D, and technological change. The analysis is targeted at assessing how internal and external financing of three classes of firms impacts on overall economic growth and innovation adoption. In particular, we provide insights into the role of bank credit both in determining economic (in)stability and in financing innovation and entrepreneurship. Our findings suggest that there are issues with the role that the credit system plays in the real economy and in pursuing innovation. Indeed, our model shows that banks are unable to support collaborative firms, which have the highest impact on technological progress. Additionally, the banking sector can increase financial fragility, leading to economic crises and distress contagion.

The model is then used to study how different innovation fiscal policies impact the economic system. Several R&D policies for firms' innovation behavior have been studied over the past years (cfr. González *et al.*, 2005; Czarnitzki *et al.*, 2007; Klette *et al.*, 2000). However, their impact is ambiguous. Nevertheless, some empirical analyses 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 article is organized as follows. In Section 2, we model firms' and the bank's behavior; in Section 3, we present the results of both the simulations for the baseline model and that with the funding strategies. Finally, Section 4 concludes.

[2] In the 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; Mignot *et al.*, 2012; Tedeschi *et al.*, 2012).

[3] 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).

2. The model

In the economy, there are two markets, the goods and the credit one. The system is populated by a large number of firms and a banking sector that undertake decisions at discrete time $t = 0, 1, 2, \ldots, T$. 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, 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 on the firm 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 $i = 1, \ldots, F$. Firms are profit seekers and, at any time 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:

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

with $K_{i,t}$ being the stock of capital and $\varphi_{i,t}$ the capital productivity, which depends on firm innovation, as explained below.

To produce output, firm i needs a given amount of labor $N_{i,t}$ according to the capital–labor ratio $x = K_{i,t}/N_{i,t}$.[4] We do not consider a complete labor market. Instead, we just model the labor supply, where each firm can hire (fire) all workers it needs at the wage:

$$w_{i,t} = \alpha_1 wi,t - 1 + \alpha_2 \left(\varphi_{i,t-1} - \varphi_{i,t-2}\right) \tag{2}$$

where $0 < \alpha_1, \alpha_2 < 1$. We assume a positive relationship between wage and productivity. 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, liabilities $L_{i,t}$ and internal capital $K_{i,t}$ are

[4] Consequently, each firm has a labor demand equal to $N_{i,t} = K_{i,t}/x$, with x being constant.

equally remunerated. 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:

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

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

$$x = \begin{Bmatrix} \sigma\pi_{i,t-1} & if\,\pi_{i,t} > 0 \\ 0 & if\,\pi_{i,t} \leq 0 \end{Bmatrix} \tag{4}$$

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

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). To create such classes, we have developed a procedure by which the division depends on the firm's probability of success in completing the innovation. Firms with a probability higher than $\bar{Z}_t = (1-\gamma_1)Z^{Max}_{i,t}$ would try to become stand-alone innovators, those with a probability lower than $\underline{Z}_t = (1-\gamma_2)Z^{Max}_{i,t}$ are willing to become imitators (with $0 < \gamma_1, \gamma_2 < 1$ being parameters), while the rest part is collaborative innovators (i.e., those with $\underline{Z_t} < Zt < \overline{Z_t}$). Such probability $Z_{i,t}$ is function of firms expenditure in R&D, $\mu_{i,t} = \frac{RD_{i,t}}{K_{i,t}}$, that is, the more the firm invests in R&D the higher is its probability of discovering a new technology (see Dosi *et al.*, 2010), and is approximated as follows:

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

Nevertheles, not all firms willing to do innovation can obtain access to innovation. Whether firm i results in a successful innovator or not is determined by a Bernoulli distribution, whose parameter is given by Equation (5). Note that for collaborative innovators, the probability of being successful depends on the probability of success of all the group members[5], i.e., the whole group of innovators has access to R&D just if all its members return a positive value of the Bernoulli distribution. Similarly, if firm i becomes an isolate or collaborative innovator, its innovation advance is the realization of a random process:

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

[5] To keep it simple, in our simulations, collaboration groups are composed by two firms. We have also simulated the model with larger collaboration groups; however, the results remain stable. Minor increases in the aggregate production and level of technology emerge.

where ξ is a random variable uniformly distributed on the support $[\delta_1,\delta_2]$. Imitators' success is instead 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, imitator i's technological improvement is the realization of a random process[6]

$$\varphi_{i,t} = \left[1 + \left(\varphi_{j,t} - \varphi_{i,t}\right)\xi_{i,t}\right]\varphi_{i,t-1} \tag{7}$$

A 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

$$u_{i,t} = \frac{gr_{i,t} + w_{i,t}/x}{phi_{i,t}} - \frac{A_{i,t-1}}{(1-\sigma)\varphi_{i,t}K_{i,t}} \equiv \overline{u_{i.t}} \tag{9}$$

In other words, bankruptcy occurs if the relative price $u_{i,t}$ falls below the critical threshold $u_{i,t}$. When a firm goes bankrupt, $\overline{u_{i,t}}$ 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

$$Pr\left(u_{i,t} < \overline{u_{i,t}}\right) = \overline{u_{i,t}}/2 = \frac{gr_{i,t} + w_{i,t}/x}{2\varphi_{i,t}} - \frac{A_{i,t-1}}{2(1-\sigma)\varphi_{i,t}K_{i,t}}$$

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

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

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 adjust the

[6] Note that in Equation (7) imitators are not able to capture the whole level of innovation reached by innovators.

production accordingly. Therefore, the firms' objective function is the difference between the expected profit and the cost of bankruptcy [Equation (10)] times the probability of bankruptcy: $BC_{i,t}Pr\left(u_{i,t} < \overline{u_{i,t}}\right)$. We can formulate the problem of each firm i as

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

By maximizing Equation (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 $L_{i,t} = L_{i,t-1} - \pi_{i,t-1} + I_{i,t}$.

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. The latter 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[7], $K_{t-1} = \sum_i^F K_{i,t-1}, A_{t-1} = \sum_i^F A_{i,t-1}$ and $0 < \lambda < 1$. The total supply of credit is given by

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

where ν is a risk coefficient, used by the bank to avoid excess lending. This coefficient ν—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,

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

where $k_{i,t}$ and $a_{i,t}$ are the ratios of individual to total capital and net worth, respectively. Under the assumptions that returns on banks' equity are given by the average

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

of the lending interest rates rt, and that deposits[8] D_t are remunerated with this rate, the bank profit π^b is given by

$$\pi_t^b = \sum_i^F r_{t,i} L_{t,i} - \overline{r_t}(D_{t-1} + E_{t-1}), \tag{15}$$

When a firm goes bankrupt, the bank records a nonperforming loan, also called "bad debt," 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:

$$E_t = E_{t-1} + \pi^{b_t} + \sum_i B_{i,t}$$

Indeed, when a firm goes bankrupt, both the aggregate output and the bank's equity decrease. 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 $F = 100$ firms and a bank operate under the assumption that if a firm goes bankrupt it is replaced by a new firm, consequently, F is fixed. Each firm is initially given the same amount of equity, capital $K_{i,0} = 5$ and liabilities $L_{i,0} = 3$. We fix $\varphi_{i,0} = 0.1$, $\alpha_1 = 0.8$, $\alpha_2 = 0.5$, $\sigma = 0.2$, $\beta = 2$, $\gamma_1 = 0.02$, $\gamma_2 = 0.1$, $[\delta 1, \delta 2] = [0, 0.02]$, $\lambda = 0.3$, $\nu = 0.08$, $g = 1.1$, $c = 1$, $w_{i,0} = 0.005$, $x = 1$. The results reported here are the simulation outcome of $T = 1000$ periods. Only the last 900 simulated periods are considered, this is to get rid of transience. Simulations are repeated 100 times with different random seeds.

3.1 Stylized facts of the baseline model

In this first part, our analysis focuses on some properties of the baseline model. Our main goal is to show that the system is able to replicate a number of macroeconomic stylized facts, which characterize the most industrialized countries under normal economic conditions.

[8] The balance sheet of the banking sector is $L_t = E_t + D_t$, with L_tL being total credit supply (see Equation 13), E_t the bank equity base, and D_t deposits, which in this framework, are determined as a residual.

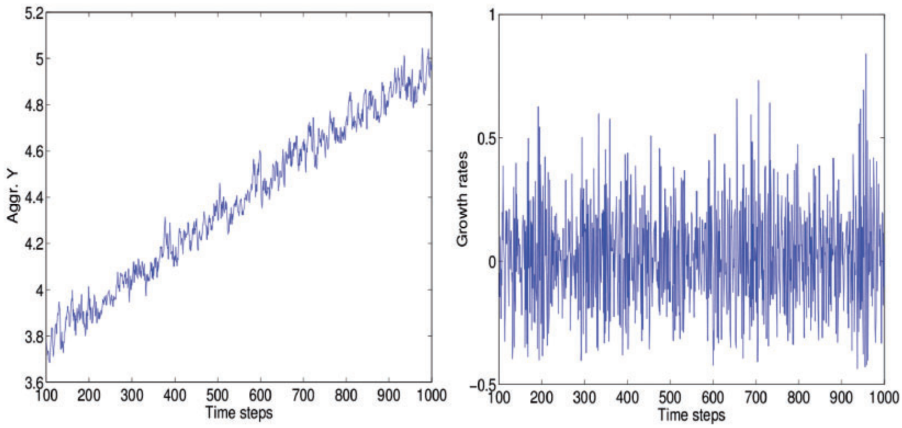

Figure 1 Time evolution of aggregate output (left side) and growth rates of aggregate output (right side).

First of all, the simulated aggregated output fluctuates, alternating phases of smooth growth to periods of larger variability, as shown in Figure 1 (left side). Indeed, aggregated fluctuations, measured by output's growth rates (Figure 1, right side) are path dependent (e.g, the failure of a large firm in one period causes a lower level of production and of credit supply in the following one, see Vitali *et al.*, 2012) and characterized by cluster volatility. The cluster volatility is a well-known phenomenon in the financial market literature (see Cont, 2007; Tedeschi *et al.*, 2009), 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 autocorrelation function, and, here, is estimated on the absolute value of the growth rate output. Note that the autocorrelation 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 close to that found for the quarterly real data of the G7 countries, equal to 0.93 (Stanca and Gallegati, 1999).

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 over time owing to a diffused technological progress that saves labor input in the production process, as shown in Figure 2 (left side). Because 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 Figure 2 (right side),

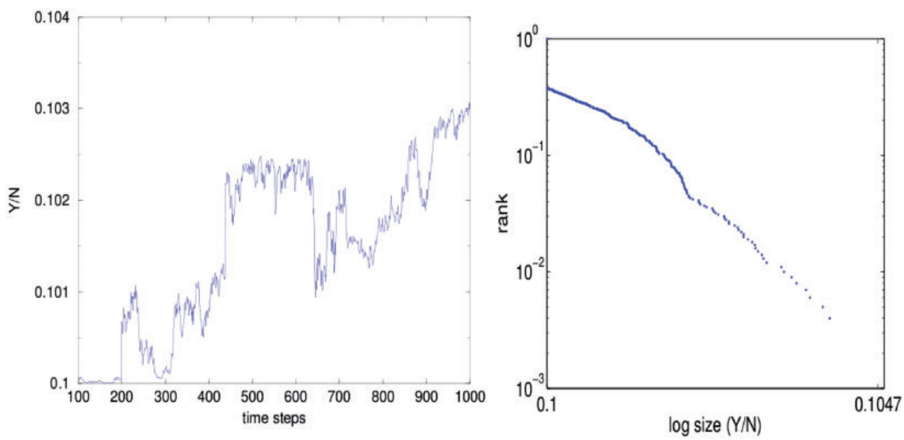

Figure 2 Time evolution of the output–labor ratio (left side) and decumulative distribution function of output–labor ratio over 100 Monte Carlo simulations (right side).

which is well fitted by a power law. To confirm the goodness of fitness 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's capital productivity φ. In fact, $Y/N = \frac{\varphi K}{K/x}$, 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 hikes. However, in our model we also observe plunges, 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 loss of technological knowledge, dissipated with the failing firm.

To verify the robustness of our results, we have simulated the model also for different values of the thresholds $[\gamma 1, \gamma 2]$ (cfr. Section 2.1). As Figure 3 shows, the average growth rate and technology level do not change considerably when varying the range of γ. However, it is worth noticing that with higher γ_1 and lower γ_2, both the indicators return larger values. This is because, by doing so, we have increased the probability for 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

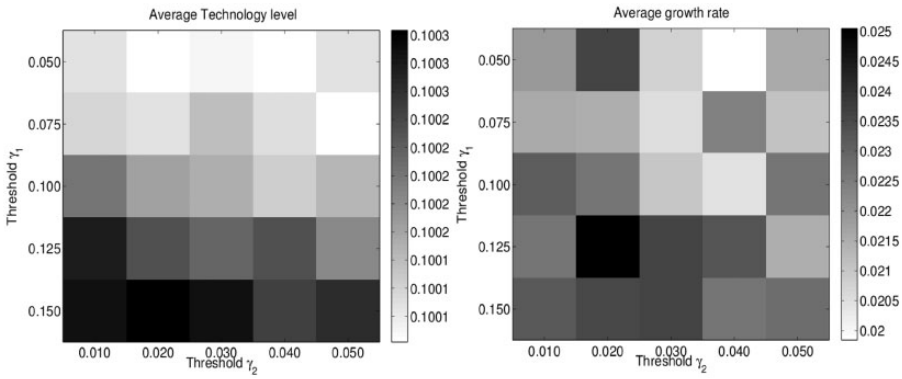

Figure 3 Average growth rate and technology level with different values of thresholds $[\gamma_1, \gamma_2]$ over 100 Monte Carlo simulations.

contribute for a large part of total production. Figure 4 (left side) displays this evidence and the distribution is well fitted in the tail by a power law distribution.[9] The central panel of Figure 4, which shows the Mean Excess Function versus Threshold plot (MEPLOT), better quantifies the presence of the Paretian behavior in the distribution function of firms' size. Moreover, in line with other empirical works (Amaral *et al.*, 1997; Bottazzi *et al.*, 2001; 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[10] (double exponential), whose tails decay much slower than in a Gaussian distribution (see Figure 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 Figure 1, left side). Indeed, even if we model a supply-driven economic system, where the whole production is sold at a stochastic

[9] In particular, we have implemented the maximum likelihood estimator for fitting the power-law distribution to data, along with the goodness-of-fit based approach to estimate the lower cutoff for the scaling region. Our simulated data are well fitted by a power-law $p(x) \sim x^{-\alpha}$, for $x \geq x_0$, where $\alpha = 1.8349$ is the maximum likelihood estimate of the scaling exponent, $x_0 = 0.0926$ is the estimate of the lower bound of the power-law behavior, and $L = 0.0474$ is the log-likelihood of the data for $x \geq x_0$ under the fitted power law.

[10] In particular, the functional form of the Laplace distribution is $p(x) = (1/2b)\exp(-|x - \mu|/b)$, where μ is the mean and $b > 0$ is a scale parameter. Using the maximum likelihood method, we obtain $\mu = 0.0166$ and $b = 0.1564$.

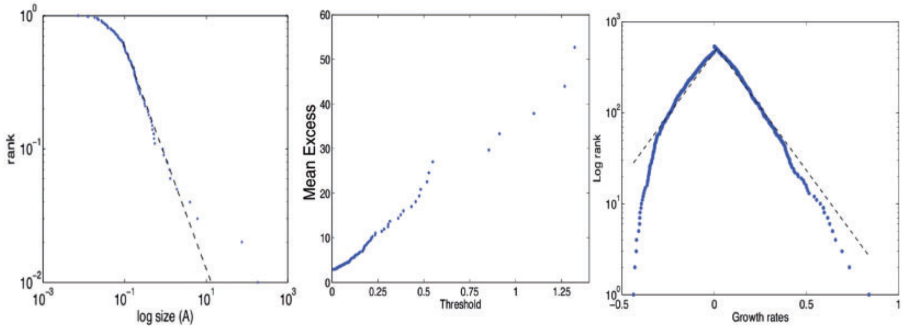

Figure 4 Decumulative distribution function of firms' size (blue points) and the power law best fit (dotted black line) (left side). MEPLOT of firms' size (center) and Firms' equity growth rate (blue points) and the Laplace best fit (dotted black line) (right side). Our statistical analysis is performed over the last time step of 100 Monte Carlo simulations.

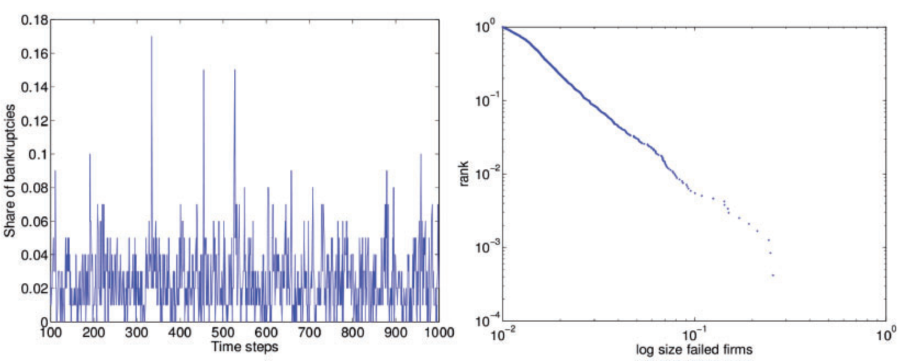

Figure 5 Time evolution of firm bankruptcies (left side) and decumulative distribution function of firms' size over 100 Monte Carlo simulations (right side).

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's failure 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 the latter also suffers a decrease in its equity level.

Consequently, to improve its own situation, the bank rises the interest rate to all the firms in its portfolio, eventually causing other defaults among firms. Figure 5 (left side) displays the time series of firm defaults. The share of failures is 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 Figure 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.

3.2 *The impact of internal and external funding on innovation*

The global crisis burst in August 2007 has shown that the financial system has abandoned its leading role to support the financial needs of the real and productive economy; conversely, the financial system has gradually become a self-reproducing institution, disjointed from the real economy as well as a vehicle for instability (see Dore, 2008; Tedeschi *et al.*, 2011). The financial system's inability to fund technological progress and, therefore, the growing need of companies to finance themselves via internal sources (see Revest and Sapio, 2012), requires the identification of alternative financial instruments to promote firm's innovation and growth. With this respect, in this section, our goal is to understand how "self-financing" and "external financing" affect our economy. In particular, firstly we deal with the impact of firms' R&D expenditure (internal funding) on meso and macro regularities, and then we analyze the impact of credit market and public sector (external funding) on firms' dynamics, on technological progress, and growth rate.

To analyze the role of R&D expenditure, we run 100 independent simulations for different levels of σ [see Equation (4)]. The results reported in Table 1 show the existence of an increasing relationship between efforts in R&D and the output growth rate.[11] However, in our model, a higher value of σ corresponds to a lower equity level, via Equation (8), which leads to higher financial fragility and higher probability of bankruptcy, as shown in Table 1, lines 2 and 3. In addition, it is worth noting the role played by those 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 a probability of belonging to the group of isolated innovators, 8% to the group of collaborative innovators, and 90% to the imitators.

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. Equation (5)]. This result is in line with the growing number of companies jointing and collaborating in R&D in the past decades (Czarnitzki *et al.*, 2007).

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

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.)

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

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 progress is rather small, while the scenario is different when firms collaborate together (see Figure 6; Czarnitzki *et al.*, 2007; Foyn, 2000).[12] 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.

In the light of the current debate on the ineptitude of the banking sector in supporting innovation, the investigation of the impact of credit market on financing companies is crucial. The left panel of Figure 7 shows granted loans for classes of

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

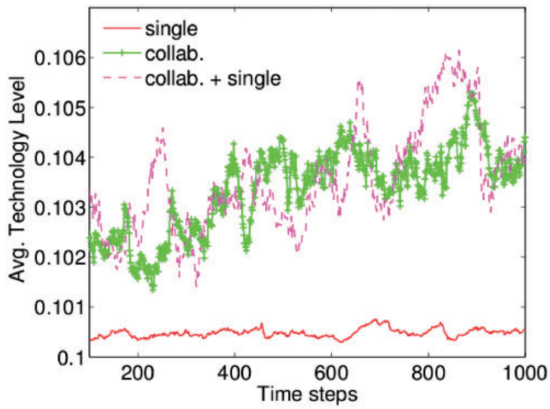

Figure 6 Time evolution of average technology by switching on/off the different innovation group.

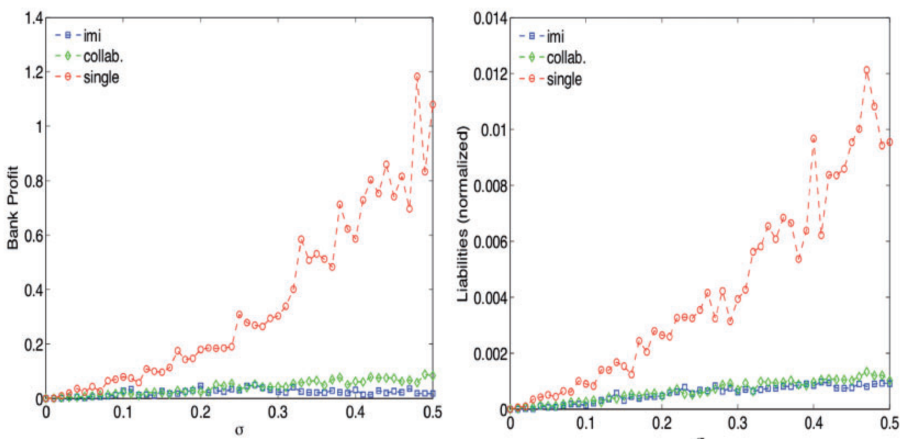

Figure 7 Average firm loan (left side) and average bank revenue (right side) for the different innovation groups (single: red circle; collaborators: green triangle; imitators: blue square) as function of σ over 100 simulations.

innovators as function of R&D expenditures. While there is a clear tendency of stand-alone innovators to finance investments through the credit market, the other two groups have low levels of liabilities. In fact in our model, single innovators have a high optimal capital stock[13], $K_{i,t}$ [see Equation (11)], which makes them

[13] The single innovators' optimal capital stock is, on average, 20% higher than those of collaborators and 65% of those of imitators.

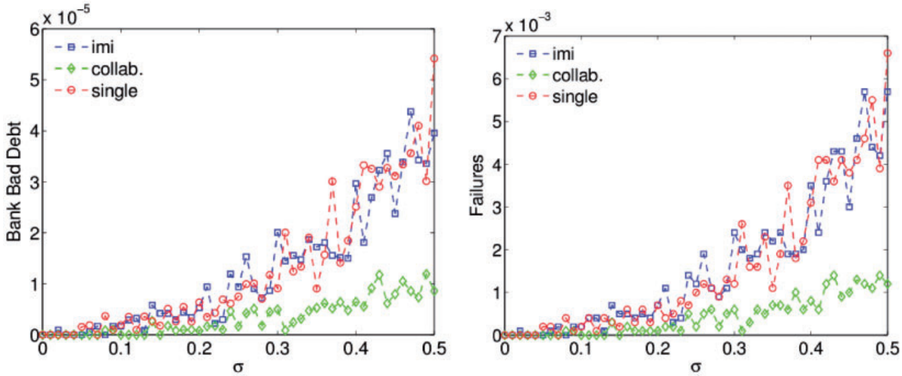

Figure 8 Average bank bad debt (left side) and firms' failures (right side) for the different innovation groups (single: red circle; collaborators: green triangle; imitators: blue square) as function of σ over 100 simulations.

unable to self-finance themselves. The fact that R&D investments are financed with internal resources, without resorting to the credit market, is also confirmed by empirical data (see Goodacre, 1995). Collaborators, however, are characterized by a high level of self-funding mainly due to their high level of profits[14] and productivity. Whether the collaborators' low use of the credit market is mainly due to their ability to finance themselves, different reasons drive imitators.

These companies, in fact, because of their low productivity level (see Figure 6), have low investment level and, thus, require a lower level of loans. Given the wide use of the credit market by stand-alone innovators, at least in the short term, the bank takes advantage from the profits provided by these latter innovators rather than by collaborators (right panel in Figure 7). However, in a long-term perspective, the higher level of bankruptcies of both stand-alone innovators and imitators (see Figure 8, right side) and, consequently, the higher level of bank's bad debt (see Figure 8, left side), evidence the fact that the bank's resources are not optimally allocated.

To understand how supporting a smart innovation leads to value creation and economic growth by means of external funding, we also introduce in the baseline model a "public sector." As for the banking sector, the role of the public sector would be to advance the technology level of the economy by increasing firm's spending on R&D. We focus our attention on four public policies: the State, whose role consists in collecting tax revenues from firms, redistribute them, therefore increasing the resources companies have already devoted to R&D. These redistribution policy benefits (i) all firms, (ii) just the collective innovator firms, (iii) just the single innovator

[14] Collaborators' profit is 33 and 21% higher than those of imitators and single innovators, respectively.

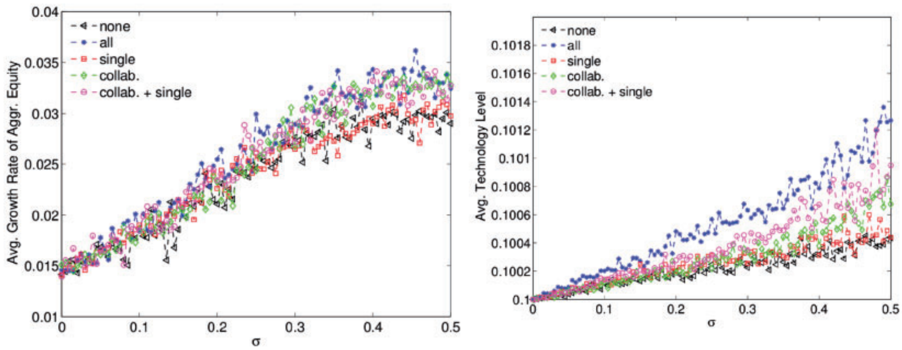

Figure 9 Average growth rates of aggregate equity (left side) and average technology levels, ϕ, (right side) for different levels of σ and funding policies.

firms, or (iv) both the collective and the single firms, that have completed a successful innovation in the previous period.

The following results replicate the outcome of 100 simulations with constant levels of tax rate parameter, $\tau = 10\%$, and increasing levels of the R&D expenditure parameter σ, starting from 0 to 50% with steps of 0.5%. Firstly, Figure 9 (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 without State intervention, 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 greater impact than redistribution to each group separately.[15] 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 are more likely to experience higher financial fragility as well as higher probability of bankruptcy.[16]

[15] A cost-benefit analysis of the public intervention is performed below, see Figure 10.

[16] The same exercise has been done by varying the tax rate parameter, starting from 0 to 25% with steps of 5% and keeping $\sigma = 0.2$. Results are not reported because they show a trend similar to the one just studied.

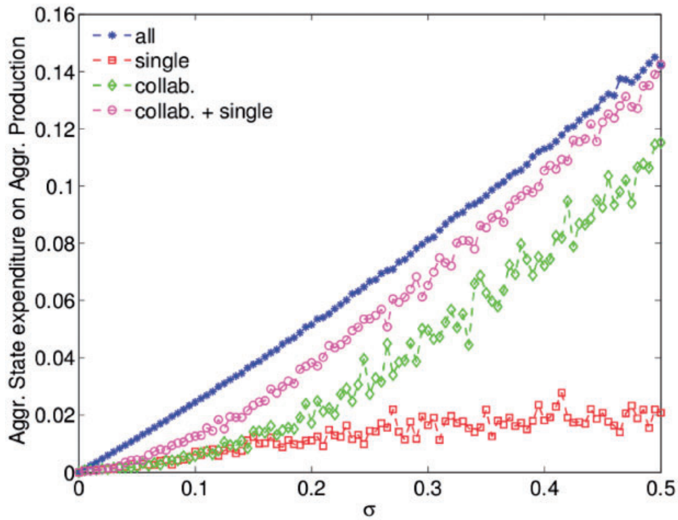

Figure 10 Cost–output ratio as function of σ for different funding policies.

As for the baseline model, the growth is explained by increasing productivity. Figure 9 (right side) shows that all our different policy scenarios generate larger technological improvements than in the scenario with no policy (cfr. black line in the figure). 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 the group of isolate and collaborative firms together, 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 accomplish a successful innovation is higher.

Finally, to clearly establish the benefits of these policies, it is important to prove that their social costs, burdening with the State fiscal policy, do not exceed the advantages, measured by the aggregate production. Figure 10 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), the ratio reveals that benefits linearly increase with costs. The curve's 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.

4. Conclusion

In this article, we have investigated the R&D expenditure impact on both micro and meso variables, such as industrial dynamic indicators, and macro statistical properties. We have shown that the model can replicate 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 high number 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. The introduction of classes of innovators has also allowed us to study the impact of the credit market on different innovation strategies. We have shown that, in the long term, financing cooperative strategies would be beneficial for banks, given the high productivity and the low mortality of collaborative enterprises. 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, State intervention seems to increase technology and productivity levels. However, policies impact the economy with different intensity. Indeed, the most profitable policies are those benefiting all innovating groups as well as 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 article, 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 framework to model firms' innovative behavior, possibly by making use of the network approach and considering spatial constraints (Vega-Redondo, 2007; Fagiolo and Dosi, 2003).

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