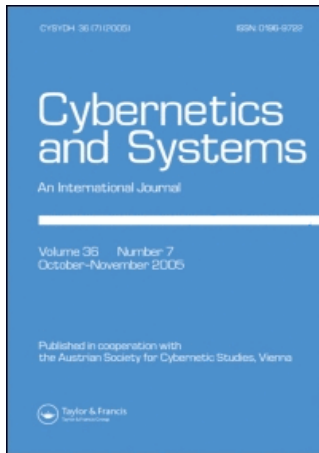


This article was downloaded by:[Roventini, Andrea]  
On: 14 September 2007  
Access Details: [subscription number 782026315]  
Publisher: Taylor & Francis  
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## Cybernetics and Systems An International Journal

Publication details, including instructions for authors and subscription information:  
<http://www.informaworld.com/smpp/title~content=t713722751>

### LUMPY INVESTMENT AND ENDOGENOUS BUSINESS CYCLES IN AN EVOLUTIONARY MULTI-AGENT MODEL

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Online Publication Date: 01 September 2007

To cite this Article: Dosi, Giovanni, Fagiolo, Giorgio and Roventini, Andrea (2007)  
'LUMPY INVESTMENT AND ENDOGENOUS BUSINESS CYCLES IN AN  
EVOLUTIONARY MULTI-AGENT MODEL', Cybernetics and Systems, 38:7, 631 -

666

To link to this article: DOI: 10.1080/01969720701534026

URL: <http://dx.doi.org/10.1080/01969720701534026>

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## **LUMPY INVESTMENT AND ENDOGENOUS BUSINESS CYCLES IN AN EVOLUTIONARY MULTI-AGENT MODEL**

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This article presents an evolutionary model of output and investment dynamics yielding endogenous business cycles. The model describes an economy composed of firms and consumers/workers. Firms belong to two industries. The first one performs R&D and produces heterogeneous machine tools. Firms in the second industry invest in new machines and produce a homogeneous consumption. Consumers sell their labor and fully consume their income. In line with the empirical literature on investment patterns, we assume that firms' investment decisions are lumpy and constrained by their financial structure. Simulation results show that the model is able to deliver self-sustaining patterns of growth characterized by the presence of endogenous business cycles. The model can also replicate the most important stylized facts concerning micro- and macro-economic dynamics.

Thanks to Giuho Bottazzi, Andrea Ginzburg, Marco Lippi, Marco Mazzoli, Mauro Napoletano, Sandro Sapio, Leigh Tesfatsion, and three anonymous referees, All usual disclaimers apply.

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## INTRODUCTION

Persistent and recurrent fluctuations are features common to all developed economies. A legion of theories (and models) has tried to provide convincing explanations of this phenomenon, known in economics as 'business cycles.' However, economists are still divided on the causes of business fluctuations. According to Zarnowitz (1985, 1997), researchers have preferred to explore theoretical possibilities instead of trying to explain what happen in 'real-world' economies. This has contributed to leave the theory of business cycles with more questions than answers.

The different treatment that economic theory reserves to the stylized facts concerning microeconomic investment dynamics and business cycle properties is a paradigmatic example of the problems mentioned above. For example, at the microeconomic level, firms invest in a lumpy fashion and their investment choices are constrained by their financial structure. At the macroeconomic level, the fluctuations of output and aggregate investment are synchronized, but investment is sensibly more volatile than output. Nevertheless, the contemporary business cycle literature is flooded by works that do not even take on board such microeconomic evidence, and hardly explain what happens at the macroeconomic one. The theoretical arena is in fact dominated nowadays by two streams of theories, namely the Real Business Cycle (RBC) perspective and the New-Keynesian (NK) paradigm. Since space prevents us from surveying this vast literature here (on RBC, cf. King and Rebelo (1999) and Stadler (1994); on NK theories, see Mankiw and Romer (1991) and Greenwald and Stiglitz (1993)), let us just describe how the two paradigms explain the rise of business cycles. In RBC models, output fluctuations stem from exogenous stochastic shocks occurring in a general-equilibrium environment populated by hyper-rational, representative agents. Conversely, in NK models, business cycles result from the presence of market imperfections together with monetary and price shocks.

Even if we are more sympathetic with the NK perspective (the RBC story is very hard to buy, especially if one considers that recessions are caused by negative technological shocks), we believe that in both paradigms the microeconomics that one finds in the models is completely at odds with empirically observed microeconomic behaviors. For instance, many models try to separately explain some micro or macro regularities, but there are almost no works that explain business cycle stylized facts starting from heterogenous agents mimicking the empirically observed investment and pricing behaviors of firms.

In this article, we refine upon the model developed in Dosi, Fagiolo, and Roventini (2006) in order to further fill this theoretical vacuum. More specifically, we study an economy where: (i) aggregate output and investment together emerge out the microeconomic, lumpy investment decisions carried out by boundedly-rational firms; (ii) business firms are the main source of novelty of the economic system. We dismiss the representative agent assumption<sup>1</sup> shared by both RBC and NK models and we populate the economic environment with heterogenous agents that are able to interact in the markets. Moreover, we add a Keynesian flavor to the model assuming a strong market uncertainty. In this framework, firms have to undertake their investment and price decisions according to boundedly-rational rules grounded on adaptive expectations. Finally, we ground the model within the 'Schumpeterian' tradition: technological change occurs in the form of a continuous inflow of endogenous, firm-level, productivity shocks.

The economy portrayed in the model is populated by firms and by consumers/workers. The former belong either to a capital-good or a consumption-good industry. The latter supply labor and consume their income buying a consumption-good.

We follow an evolutionary, 'agent-based computational economics' (ACE) approach<sup>2</sup> to model the economic system. In this bottom-up approach, firms and workers adopt routinized behaviors to take their decisions and evolve their decisions through time. Microeconomic interactions among agents determine the dynamics of macroeconomic variables, which we study and compare with empirically observed time series.

As mentioned, the model that we present here extensively draws from (Dosi, Fagiolo, and Roventini 2006). We refine and expand our previous analysis along the following lines. First, we endogenize the capital-good market structure, by allowing capital- and consumption-good firms to interact directly. Second, we introduce time in the production of machine-tools, introducing a possible source of nonlinearities. Third, we reserve a more accurate treatment to technical change, letting capital-good firms search both for new machines and for new production routines. Fourth, we check the performance of the model with respect to the inclusion of a nonmarket sector, testing whether its presence is

<sup>1</sup>See Kirman (1989, 1992) for a sharp critique of the 'representative agent fallacies.'

<sup>2</sup>See Section 3 for a detailed presentation of the evolutionary, ACE paradigm.

crucial to match the micro- and macro- stylized facts. Finally, we continue to model the behavior of firms by introducing some of the microeconomic regularities described in the previous section. For instance, we let firms invest in a lumpy fashion.

According to our simulation results, the model is able to generate aggregate output time series exhibiting both self-sustained growth patterns and persistent business cycles. In addition, the model is able to reproduce both the business cycle properties (e.g., volatility, auto- and cross-correlation patterns) of aggregate time series and the microeconomic stylized facts on firm size distributions and firm productivity dynamics.

The paper is organized as follows. In Section 2 we provide a short overview of micro and macro empirical evidence. We then discuss the antecedents and theoretical roots of the model (Section 3). In Section 4 we present the model and in Section 5 we discuss the results generated by simulation exercises. Finally, Section 6 concludes.

## **SOME EVIDENCE CONCERNING BUSINESS CYCLES AND MICROECONOMIC REGULARITIES**

As we mentioned above, any business cycle model should be able jointly to account for several macro ‘stylized facts.’ Moreover, the assumptions about the behavior of economic agents injected in the model should be at the very least consistent with the observed microeconomic evidence about real-world firm behavioral patterns. Let us then begin by briefly presenting the most salient macro and micro ‘stylized facts,’ as they emerge out of the relevant, recent, empirical economic literature.

### **Macro Stylized Facts**

The empirical analysis of business cycles requires a careful assessment of the properties of aggregate output and of the other most important macro time series (e.g., investment, consumption, change in inventories, etc.). According to the empirical evidence, developed economies have been continuously exposed to an alternation of expansions and recessions. The last fifty years have not been an exception. The US and the other developed countries have experienced a period of robust economic growth characterized by economic fluctuations. The analysis of the dynamics of output (and of its components) at the business cycle frequencies helps to single out this regularity. Indeed, all series exhibit

a typical 'roller coaster' shape, which signals the recurrent alternation of expansions and recessions.

The evidence contained in Table 1 gives further support to earlier, path-breaking analyses by Kuznets (1930) and Burns and Mitchell (1946), who contributed to single out the following stylized facts<sup>3</sup>:

- SF1 Investment is considerably more volatile than output.
- SF2 Consumption is less volatile than output.
- SF3 Investment, consumption, and change in inventories tend to be procyclical and coincident variables.
- SF4 Aggregate employment is procyclical, whereas unemployment rate is counter-cyclical. Both variables seem to be lagging.

### Micro Stylized Facts

In turn, the empirical literature on industrial dynamics has successfully uncovered many robust stylized facts about the microeconomic behavior of firms. In this section, we briefly examine these statistical regularities, beginning with the following two ones concerning firm investment patterns:

- SF5 Investment is lumpy.
- SF6 Investment is affected by the financial structure of firms.

Let us start with *SF5*. In a seminal contribution, Doms and Dunne (1998), employing US plant level data, show that firms invest in a lumpy fashion. For example, in a given year, 51.9% of all plants increase their capital stock by less than 2.5%, while the 11% of them raise it by more than 20%. Within-plant investment patterns also show that the majority of plants' investment is concentrated in just 3 years out of the 16 under analysis.

The microeconomic investment lumpiness does not seem to be completely washed away by the aggregation process. There is indeed a

<sup>3</sup>The stylized facts listed below are robust to alternative detrending techniques. See, for example, Stock and Watson (1999), Agresti and Mojon (2001), and Napoletano, Roventini, and Sapio (2006), who apply a bandpass filter (Baxter and King 1999) to US data ranging from 1956Q1 to 1996Q4, EMU series going from 1970Q1 to 2000Q3, and Italian/US data for the period 1970Q1-2002Q3, respectively. See also Kydland Prescott (1990) who employ a HP filter to US data from 1954Q1 to 1989Q4.

**Table 1.** Variance and auto-correlation structure of output and other macro series for the US Economy (1953–1996). Quarterly data have been detrended with a bandpass filter (6,32,12). Source: Stock and Watson (1999)

Series	Std. Dev. (abs)	Std. Dev. (rel)	Cross-correlations with GDP (lags)										
			t - 4	t - 3	t - 2	t - 1	0	t + 1	t + 2	t + 3	t + 4		
GDP	1.66	1	0.03	0.33	0.66	0.91	1	0.91	0.66	0.33	0.03	0.03	
Consumption	1.26	0.76	-0.07	0.21	0.51	0.76	0.90	0.89	0.75	0.53	0.29	0.29	
Investment	4.97	2.99	0.04	0.32	0.61	0.82	0.89	0.83	0.65	0.41	0.18	0.18	
Ch. in Invent.	0.38	-	-0.32	-0.04	0.28	0.57	0.73	0.72	0.56	0.32	0.08	0.08	
Employment	1.39	0.84	0.49	0.72	0.89	0.92	0.81	0.57	0.24	-0.07	-0.33	-0.33	
Unempl. rate	0.76	0.46	-0.27	-0.55	-0.80	-0.93	-0.89	-0.69	-0.39	-0.07	0.19	0.19	

positive correlation between aggregate investment dynamics and the number of plants experiencing big investment spikes.

In the empirical literature, there is also a great deal of evidence supporting *SF6*. Beginning with the influential contribution of Fazzari, Hubbard, and Petersen (1988), many works<sup>4</sup> have found that firm investment choices may be constrained by their financial structure. Hence, if information asymmetries introduce imperfections in capital markets, the Modigliani and Miller (1958) theorem does not hold and the financial structure of firms ceases to be neutral. This implies that the cost of external funds is higher than the one of internal funds. Moreover, some firms may find themselves rationed by lenders. At the empirical level, it has been found that firm investment and cash-flow (a proxy for change in net worth) are significantly and positively correlated and that correlation magnitudes are higher for young and small firms, which are more likely to be exposed to information asymmetries affecting capital markets.<sup>5</sup>

As far as long-run economic growth is concerned, a growing body of literature points out the centrality of firms in the processes of technological learning, innovation and diffusion (for a critical overview, see Dosi, Freeman, and Fabiani (1994); more detailed discussions are in Rosenberg (1982, 1994), Freeman (1982), and Dosi (1988)). In particular, many stylized facts reinforce the links between aggregate growth and business history:

**SF7** Firms have a decisive role in the process of technological accumulation. Firms carry out the process of technological learning in ways which heavily depend on both firm-specific capabilities and the richness of perceived unexploited opportunities. This implies that technological learning and accumulation tend to have a local nature (i.e. technological innovations occur in a neighborhood of currently-mastered technologies). The cumulateness of the learning pattern is shaken by rare, major innovations which determine changes in the technological paradigms.

<sup>4</sup>See Hubbard (1998) for a survey.

<sup>5</sup>See among a vast literature, Fazzari and Athey (1987) and Bond and Meghir (1994). For a different point of view, see Kaplan and Zingales (1997) and Erickson and Whited (2000).



- SF8 Innovation diffusion requires time. The speed of technological diffusion is affected by the presence of information asymmetries and by the fact that firms need time in order to absorb new technologies.
- SF9 Most innovations are industry-specific. Therefore, it is hard to invoke macro technological shocks to explain business fluctuations.

The aforementioned stylized facts concerning innovation and technology contribute to shape the productivity dynamics of firms. Detailed studies employing longitudinal microlevel data sets<sup>6</sup> highlight that productivity dynamics is characterized by a few robust statistical properties:

- SF10 Firms are extremely heterogenous in terms of their productivity.
- SF11 Productivity differentials among firms tend to be quite persistent over time.

In addition, heterogeneity is a common property of firm size distributions both among firms belonging to the same industry and across different industrial sectors (see, among a vast literature, Bottazzi and Secchi, 2003a, b).

- SF12 Firm size distributions tend to be considerably right skewed, with upper-tails made of few large firms. These patterns change significantly across different industries. SF12 clearly suggests that perfect competition does not characterize real-world markets (see e.g., Bottazzi, Cefis, and Dosi (2002) for a detailed discussion). Moreover, the empirical evidence on firm growth rate distributions suggests that firm growth patterns are lumpy, displaying relatively frequent ‘big’—negative or positive—growth events. More precisely:
- SF13 Firm growth-rate distributions are *not* Gaussian and can be well proxied by fat-tailed, tent-shaped densities.<sup>7</sup>

<sup>6</sup>Cf. the seminal work by Nelson (1981); see also Bartelsman and Doms (2000) and Dosi (2005) for a survey.

<sup>7</sup>Castaldi and Dosi (2004) find that SF13 holds also for industries and cross-country output growth-rate distributions.

In the model developed in Section 4, we embody the stylized facts pertaining to firms' investment and innovating patterns described above (*SF5–9*) within our artificial firms and we try to replicate as an emergent property of the macro level both business cycle empirical regularities (*SF1–4*) and the microeconomic stylized facts concerning firm productivity dynamics (*SF10–11*) and firm size distributions (*SF12–13*).

## RELATED LITERATURE

As we anticipated in the introduction, our model belongs to the evolutionary tradition. In a seminal book, Nelson and Winter (1982)<sup>8</sup> show that long-run macroeconomic growth patterns can be generated starting from a microeconomic environment populated by heterogeneous firms that have the capabilities to innovate and to imitate their competitors. However, in the work of Nelson and Winter and in many other papers belonging to the evolutionary tradition, market demand does not have any significant role. This prevents to study how 'Keynesian' demand dynamics affects the whole economic system.<sup>9</sup> Chiaromonte and Dosi (1993) and Dosi, Fabiani, Aversi, and Meacci (1994) introduce for the first time 'Keynesian' demand propagation effects in evolutionary models and try to explore the ensuing dynamics. In particular, Chiaromonte and Dosi (1993) develop a two-sector model characterized by product and process innovation, imperfect competition and two feedback loops resembling the 'Keynesian' multiplier and the investment 'accelerator.'

In a previous paper (Dosi, Fagiolo, and Roventini 2006), we build on these early templates and we carefully study the statistical properties of the aggregate time series generated by the simulations. In addition, we also try to explain the microeconomic stylized facts concerning firm productivity dynamics and firm size distribution.

A key feature of that work resides in modeling the behavior of firms by introducing some of the microeconomic regularities described in the previous section. For instance, we let firms invest in a lumpy fashion (*SF5*). In fact, neoclassical economists succeeded in explaining investment lumpiness as the result of the profit-maximizing behavior of a

<sup>8</sup>More on the evolutionary perspective is in Dosi and Nelson (1994) and Dosi and Winter (2002).

<sup>9</sup>Some evolutionary models analyze the properties of economic fluctuations (e.g., Silverberg and Lehnert 1994; Fagiolo and Dosi 2003). However, business cycles stem from some underlying 'Schumpeterian' dynamics of innovation and imitation.

hyper-rational firm (see the literature on (S,s) investment models<sup>10</sup>). However, in those models investment lumpiness crucially depends on the presence of nonconvex adjustment costs. Consider a profit-maximizing firm facing the problem of choosing the optimal level of capital. If the desired capital stock is larger than the current one, the firm will invest only if the expected additional profits are at least equal to the capital adjustment costs. The presence of nonconvexities in the adjustment cost function will force the firm to invest up to the optimal *target* level of capital (S) only if its capital imbalance is lower than the optimal *trigger* capital stock (s).

Investment lumpiness can lead to non-trivial dynamics at the macroeconomic level. However, in the literature there are almost no works that try to plug investment lumpiness in a business cycle model.<sup>11</sup> In particular, the microeconomic evidence of firm investment patterns (*SF5* and *SF6*) has not been employed to explain the business cycle stylized facts (*SF1–4*).

In this and in our earlier work (Dosi, Fagiolo, and Roventini 2006), we try to fill this gap. In both models, firms invest in order to expand the capital stock or to replace scrapped machines. Firms decide their expansion investment according to an (S,s) model. However, in contrast with the neoclassical literature we do not need nonconvex adjustment costs in order to generate lumpy investment patterns. We consider firms as boundedly-rational agents, which adopt routinized behavioral investment rules (on routinized behaviors, see—within a vast literature—Nelson and Winter (1982), Dosi (1988), Cyert and March (1989) and, much earlier, Katona and Morgan (1952)). In particular, the *target* and *trigger* levels of an (S,s)-type investment pattern stem from an investment routine, instead of some optimizing behavior. Our assumption is plausible if firms have to cope with an ‘evolutionary environment’ (Dosi, Marengo, and Fagiolo 2005), where ‘Knightian’ uncertainty does not allow firms to know the probability distribution of future events (see also Dosi and Egidi (1991)). In this framework, firms cannot perfectly anticipate their future demand and follow a (S,s) rule in order to mitigate the risk connected to unpredictable demand swings. Indeed, firms will

<sup>10</sup>See Caballero (1999) for a survey of lumpy investment models and Blinder and Maccini (1991) for a review of (S,s) inventory behavior models.

<sup>11</sup>An exception is in Thomas (2002) In a real business cycle framework, she finds that lumpy investment does not have any significant impact at the macro level. See also Bachman, Caballero, and Engel (2006) for completely opposite results.

increase their capital stock only if their (adaptive) expectations suggest a huge demand growth. Hence, firms will expand their capital stock to their target level if the expected demand can only be satisfied with a capital stock at least equal to the trigger level.

Firms follow routines also to decide their replacement investment strategies.<sup>12</sup> More specifically, firms employ a payback-period routine to replace their stock of heterogenous capital goods. The adoption of a payback-period rule leads firms to consider technology and capital-good price in their replacement decisions.

Finally, the investment (and production) policies of firms are influenced by their financial structure (*SF6*). In line with the financial constraint literature discussed above (cf. Section 2.2), firms first rely on their stock of liquid assets and then on more expensive external funds (i.e. credit). Moreover, firms are subject to a credit ceiling: the stock of debt of a firm is limited by its gross cash flows.

The model presented in this article differs from the one in Dosi, Fagiolo and Roventini (2006) in the following crucial aspects:

- Direct interaction between capital- and consumption-good firms through the capital-good market (that is now endogenized).
- Additional source of nonlinearities due to time-lags in the production of machine-tools.
- A more detailed modeling of the process of technical change. Capital-good firms now search both for new machines and for new production routines.
- Deep analysis of the role exerted by the nonmarket sector.

The main goal of the exercises we present in this article is to check whether the new version of the model is able to better reproduce the existing stylized facts on macroeconomic dynamics on the grounds of more realistic assumption on firm behavior and market interactions.

As we anticipated in the introduction, our model genuinely belongs to the 'agent-based computational economics' (ACE) tradition. Recently, ACE models proved to be able to endogenously generate business cycles and to reproduce many business cycle stylized facts. For example, Delli

<sup>12</sup>Note that the empirical evidence discussed in Feldstein and Foot (1971), Eisner (1972), Goolsbee (1998) suggests that replacement investment is not proportional to the capital stock.

Gatti et al. (2005) showed that an ACE model of financial fragility is able to replicate many scaling-type features concerning the distributions of firm size, firm growth rates, firm exit, bad debts, profits, GDP expansions, and recessions. Furthermore, Napolitano et al. (2005) extended the basic framework in Delli Gatti et al. (2005) to match aggregate time-series properties as well (e.g., volatility, correlation patterns).

Notwithstanding the increasing effort in applying ACE models to the study of business cycles, there is still a large gap between the wealth of statistical properties uncovered by the empirical literature (both at the micro and at the macro level, see Section 2) and the performance of economic models in trying to replicate and explain these stylized facts. The ACE model that we present in the next section can be considered as a further (albeit still preliminary) step that we take in the direction of filling this gap.

## THE MODEL

We model an economy populated by  $F$  firms and  $L$  workers/consumers. Firms belong to two industries: there are  $F_1$  consumption-good firms (labeled by  $j$  in what follows) and  $F_2$  machine-tools firms (labeled by  $i$ ). Of course,  $F = F_1 + F_2$ . Consumption-good firms invest in machine-tools and produce a homogeneous product for consumers. Machine-tool firms produce heterogeneous capital goods and perform R&D. Workers inelastically sell labor to firms in both sectors and fully consume the income they receive. Investment choices of consumption-good firms determine the level of income, consumption, and employment in the economy.

In the next subsection, we shall firstly describe the dynamics of events in a representative time-period. Next, we shall provide a more detailed account of each event separately.

### The Dynamics of Microeconomic Decisions

In any discrete time period  $t = 1, 2, \dots$ , the timeline of events runs as follows:

1. Capital-good firms advertise their machines sending a 'brochure' to a subset of consumption-good firms.
2. Consumption-good firms take their production and investment decisions. According to their expected demand, firms fix their desired production and, if necessary, invest to expand their capital stock. A payback period rule is employed to set replacement investment. Consumption-good firms choose their supplier and order the

machines. Credit-rationed firms finance their investment, first with their stock of liquid assets, and next, if necessary, with debt.

3. Both capital- and consumption-good firms hire workers according to their production plans and start producing.
4. Consumption-good market opens. The size of the consumption-good demand depends on the number of workers employed by all firms. Consumption-good firms facing imperfectly informed consumers receive a fraction of the total demand as a function of their price competitiveness. Unemployment rates and monetary wage emerge as the collective outcome of micro-decisions.
5. Capital-good firms deliver the machine-tools ordered by consumption-good firms.
6. Exit, technical change, and entry take place. Firms facing negative net-liquid assets and/or zero market-shares exit and they are replaced by new firms. Capital-good firms stochastically search for new machines and more efficient production routines.

Finally, total consumption, investment, change in inventories, and total product can be computed by aggregating individual time- $t$  quantities.

**Production and Investment: The Consumption-Good Sector**

Each consumption-good firm  $j = 1, 2, \dots, F_1$  produces a homogenous good using machines and labor under constant returns to scale. Planned output depends on myopic demand expectations of the form:

$$D_j^e(t) = D_j(t - 1), \tag{1}$$

where  $D_j(t - 1)$  is the demand of firm  $j$  at time  $t - 1$ .<sup>13</sup>

According to the expected demand, the desired level of inventories ( $N_j^d$ ) and the inventories ( $N_j$ ) inherited from the previous period, firms fix their desired level of production ( $Q_j^d$ ):

$$Q_j^d(t) = D_j^e(t) + N_j^d(t) - N_j(t - 1), \tag{2}$$

with  $N_j^d(t) = \theta D_j^e(t)$ ,  $0 \leq \theta \leq 1$ .

<sup>13</sup>Different extrapolative expectation-formation rules based on both firm-specific past demand and aggregate market signal are explored in Dosi, Fagiolo, and Roventini (2005). Interestingly, one finds that increasing the computational sophistication of agents does not improve either the performance of the economy, as measured by average growth-rates, or the stability of growth patterns over time.

The current stock of capital determines the maximum level of production achievable by each firm. Given the desired level of production, firms compute the desired stock of capital as:

$$K_j^d(t) = \frac{Q_j^d(t)}{u^d}, \quad (3)$$

where  $u^d$  is the desired level of capacity utilization.

Consumption-good firms decide whether to expand<sup>14</sup> their stock of capital following an (S,s) model. They compute their trigger ( $K_j^{trig}$ ) level of capital as follows:

$$K_j^{trig} = K_j(t)(1 + \alpha), \quad (4)$$

with  $0 < \alpha < 1$ . Firms then plan to increase their capital stock only if the desired capital stock is higher than the trigger one:

$$EI_j(t) = \begin{cases} 0 & \text{if } K_j^d(t) < K_j^{trig}(t) \\ K_j^{trig}(t) - K_j(t) & \text{if } K_j^d(t) \geq K_j^{trig}(t) \end{cases}, \quad (5)$$

where  $EI_j(t)$  is the expansion investment.

The stock of capital of each consumption-good firm is heterogenous, since it is composed of various vintages of machines which differ in terms of productivity. Machines are measured in terms of their production capacity and are normalized to one. They are identified by a labor productivity coefficient  $A_{i,\tau}$ , where  $i$  denotes their producer and  $\tau$  their generation (technical change takes place through the creation of new generation of machines, see Section 4.6 below for details). Let  $\Xi_j(t)$  be the set of all types of machines belonging to firm  $j$  at time  $t$ . Firm  $j$ 's capital stock is defined as:

$$K_j(t) = \sum_{A_{i,\tau} \in \Xi_j(t)} g_j(A_{i,\tau}, t),$$

where  $g_j(A_{i,\tau}, t)$  is the absolute frequency of machine  $A_{i,\tau}$ . Given the nominal wage  $w(t)$ , the unit labor cost of each machine is computed as:

$$c(A_{i,\tau}, t) = \frac{w(t)}{A_{i,\tau}}.$$

<sup>14</sup>We assume that there are no secondary markets for capital goods. Hence, firms have no incentives to reduce their capital stock.

Scrapping policies follow a payback-period routine. The replacement of an incumbent machine depends on its degree of ‘technological’ obsolescence and on the price of new capital goods. More formally, firm  $j$  will scrap machines  $A_{i,\tau} \in \Xi_j(t)$  if they satisfy:

$$RS_j(t) = \left\{ A_{i,\tau} \in \Xi_j(t) : \frac{p^*(t)}{c(A_{i,\tau}, t) - c^*(t)} \leq b \right\}, \tag{6}$$

where  $p^*$  and  $c^*$  are, respectively, the price and unit labor cost of new machines, and  $b$  is a strictly positive payback-period parameter. Moreover, firms scrap machines that are older than  $\eta$  periods ( $\eta$  positive integer). Firms compute their replacement investment by pooling the machines satisfying Eq. (6). The level of firm investment ( $I_j$ ) is the sum of expansion and replacement investment. Summing up the actual investment of all consumption-good firms, we get aggregate investment ( $I$ ).

Consumption-good firms choose their capital-good supplier according to the price and productivity of the currently produced machines (cf. Section 4.3) and sends their investment orders.

Consumption-good firms must bear production costs before selling their output. Hence, they must finance production as well as investment. In tune with the spirit of the evolutionary perspective—and of many New Keynesian models—we assume imperfect capital markets with credit rationing. Hence, firms will initially employ their stock of liquid assets ( $NW_j$ ) in order to finance production and investment. If liquid assets are not sufficient, they will borrow the necessary amount at the interest rate  $r$ . The borrowed amount cannot let the debt/sales ratio exceed the value of  $\Lambda$ .

Given their current stock of machines, consumption-good firms compute their average productivity ( $\pi_j$ ) and their unit cost of production ( $c_j$ ). Average productivity reads:

$$\pi_j(t) = \sum_{A_{i,\tau} \in \Xi_j(t)} A_{i,\tau} \frac{g_j(A_{i,\tau}, t)}{K_j(t)},$$

while unit cost of production will be given by:

$$c_j(t) = \frac{w(t)}{\pi_j(t)}.$$

Firms fix the price as a mark-up ( $\mu_j$ ) on their unit cost of production:

$$p_j(t) = (1 + \mu_j(t))c_j(t). \tag{7}$$



The mark-up is flexible: it changes across time according to the past variation of firm's market share ( $f_j$ ):

$$\mu_j(t) = \mu_j(t-1) \left( 1 + \frac{f_j(t-1) - f_j(t-2)}{f_j(t-2)} \right).$$

Given their average productivity and their production, consumption-good firms determine their labor demand ( $L_j^D$ ):

$$L_j^D(t) = \frac{Q_j(t)}{\pi_j(t)}.$$

Denoting by  $S_j$  total sales of firm  $j$ , profits ( $\Pi_j$ ) read:

$$\Pi_j(t) = p_j(t)S_j(t) - c_j(t)Q_j(t) - rDeb_j(t),$$

where  $Deb_j$  is the stock of debts. The variation of the stock of liquid assets of consumption-good firms depends on their profits as well as on their investment choices:

$$NW_j(t) = NW_j(t-1) + \Pi_j(t) - cI_j,$$

where  $cI_j$  is the amount of internal funds employed by firm  $j$  to finance investment.

### The Capital-Good Market

The capital-good market is characterized by imperfect information. This implies that consumption-good firms have limited knowledge of the machines supplied in the market.

On the supply side, each machine-tool firm  $i = 1, 2, \dots, F_2$  sells its latest generation of products characterized by labor productivity coefficient  $A_{i,\tau}$ , with  $\tau = 1, 2, \dots$ . At the beginning of each period, capital-good firms try to reduce the information gap that separate them from the consumption-good firms advertising their products. More specifically, capital-good firms send a 'brochure' containing information about the price and productivity of their currently produced machine to their historical client ( $HC_i$ ) as well as to a random sample of potential customers ( $NC_i$ ). The size of the sample is proportional to the number of the current clients:

$$NC_i(t) = (1 + \kappa)HC_i(t), \quad (8)$$

with  $0 < \kappa < 1$ . Of course,  $NC_i(t) \leq F_1 - HC_i(t)$ .

On the demand side, consumption-good firms receive 'brochures' only from a subset of capital-good firms. Each consumption-good firm

compares the characteristics of the available machines, chooses the one with the highest productivity/price ratio and sends its investment orders to the correspondingly capital-good firm.

**Machine Production**

According to the orders they receive, capital-good firms fix the level of production ( $Q_i$ ) and start producing. The production process employs labor only, under constant returns to scale. The unit cost of production depends on the labor productivity of the firm ( $B_i$ ):

$$c_i(t) = \frac{w(t)}{B_i(t)}.$$

The price ( $p_i$ ) is equal to the unit cost of production. Given the level of production and the labor productivity, capital-good firms compute their labor demand  $L_i^D$ :

$$L_i^D(t) = \frac{Q_i(t)}{B_i(t)}.$$

Machine production requires time: machines are delivered to consumption-good firms at the end of the period.

**The Consumption-Good Market**

Since consumption-good firms take their production decisions according to their demand expectations, they can obviously make mistakes which are revealed by variations in inventories. If in the previous period, they produced too much ( $Q_j(t - 1) > D_j(t - 1)$ ), they accumulate stocks. On the contrary, if they were not able to fully satisfy their past demand ( $Q_j(t - 1) < D_j(t - 1)$ ), their “competitiveness” ( $E_j$ ) at time  $t$  is reduced:

$$E_j(t) = -\omega_1 p_j(t) - \omega_2 l_j(t), \tag{9}$$

where  $l_j$  is the level of unfilled demand inherited from the previous period and  $\omega_{1,2}$  are non-negative parameters. The average sectorial competitiveness ( $\bar{E}$ ) is obtained by weighting the competitiveness of each firm with its past market share ( $f_j(t - 1)$ ):

$$\bar{E}(t) = \sum_{j=1}^{F_1} E_j(t) f_j(t - 1).$$

Under imperfect information, consumers take time to imperfectly adjust to relative consumption-good prices. Thus, market shares evolve

according to a replicator dynamics. More specifically, the market share of each firm will grow (shrink) if its competitiveness is above (below) the industry-average competitiveness:

$$f_j(t) = f_j(t-1) \left( 1 + \chi \frac{E_j(t) - \bar{E}(t)}{\bar{E}(t)} \right), \quad (10)$$

with  $\chi \geq 0$ .

Aggregate consumption (cf. Section 4.8) shapes the demand-side of the market and it is allocated to consumption-good firms according to their market share:

$$D_j(t) = C(t)f_j(t). \quad (11)$$

### Entry, Exit, and Technical Change

At the end of every period, firms with zero market shares and/or negative net assets die and are replaced by new firms. Hence, the number of firms in both sectors remains constant across time. We also assume that each entrant is a random copy of a survived firm.

The economy is fuelled by a never-ending process of technical change. At the end of each period, capital-good firms try both to develop the next generation of their machines (product innovation) and to discover more efficient production routines (process innovation). The result of their efforts is strongly uncertain.

As far as product innovation is concerned, firms develop a prototype whose labor productivity ( $A_{i,new}$ ) may be higher or lower than the one of the currently manufactured machine. More formally, we let:

$$A_{i,new} = A_{i,\tau}(1 + \epsilon_1), \quad (12)$$

where  $\epsilon_1 \sim U[l_1^-, l_1^+]$ , with  $-1 < l_1^- < 0 < l_1^+$ . We also posit that firm  $i$  will release the next generation machine only if it is more productive (i.e.,  $A_{i,new} > A_{i,\tau}$ ). If the firm decides to produce the new machine, the index  $\tau$  is accordingly incremented by one unit.

Similarly, firms stochastically search for new production routines. Firms compare the incumbent and the new production routines affecting their own labor productivity:

$$B_{i,new} = B_i(t)(1 + \epsilon_2), \quad (13)$$

where,  $\epsilon_2 \sim U[l_2^-, l_2^+]$ , with  $-1 < l_2^- < 0 < l_2^+$ . If  $B_{i,new} > B_i(t)$ , the firm adopts the new routine, otherwise it keeps on producing with the old one.

### The Labor Market

Labor market is not cleared by real wage movements. As a consequence, involuntary unemployment may arise. The aggregate supply of labor ( $L$ ) is exogenous and inelastic. The aggregate demand of labor is the sum of machine- and consumption-good firms' labor demands:

$$L^D(t) = \sum_{j=1}^{F_1} L_j^D + \sum_{i=1}^{F_2} L_i^D(t).$$

Hence, aggregate employment ( $Emp$ ) reads:

$$Emp(t) = \min(L^D(t), L). \quad (14)$$

The wage rate is determined by both institutional and market factors, with both indexation mechanisms upon consumption prices and average productivity, on the one hand, and, adjustments to unemployment rates, on the others:

$$w(t) = w(t-1) + \left( 1 + \psi_1 \frac{\Delta cpi(t)}{cpi(t-1)} + \psi_2 \frac{\Delta \bar{A}(t)}{\bar{A}(t-1)} + \psi_3 \frac{\Delta U(t)}{U(t-1)} \right), \quad (15)$$

where  $cpi$  is the consumer price index,  $\bar{A}$  is average labor productivity, and  $U$  is the unemployment rate. The system parameters  $\psi_{1,2,3}$  allow one to characterize various institutional regimes for the labor market.

### Macro Dynamics, Market Interactions, and Consumption Scenarios

The dynamics generated at the micro-level by individual decisions and interaction mechanisms induces, at the macroeconomic level, a stochastic dynamics for all aggregate variables of interest (e.g. output, investment, consumption, unemployment, etc.).

More precisely, in each time period the decisions undertaken by firms in the two sectors (e.g. production, investment, pricing) only depend on (current and lagged) microeconomic variables, and not directly on the state of macroeconomic variables. However, the current and past macroeconomic states of the economy (aggregate consumption level, labor productivity, unemployment rate, etc.) heavily affects microeconomic decisions, thus introducing non-trivial feedback loops between micro and macro layers.

In the economic environment, three types of agents (i.e., consumption-good firms, capital-good firms and consumers/workers) interact in the good and labor markets. In the capital-good market, machine-tools firms supply heterogenous machines to consumption-good firms, whose demand depends on the past income of consumers. Capital-good firms compete by introducing product and process innovations in order to acquire new customers. In the consumption-good markets, firms produce a homogenous good trying to match consumers' demand, which is related to their income. Consumption-good firms increase their market share if their price is below the market average. Finally, in the labor market the supply is fixed, whereas demand depends on the production choices of capital- and consumption-good firms.

We consider two scenarios according to the composition of aggregate consumption. In the work-or-die scenario, only employed workers earn an income that they fully consume:

$$C(t) = w(t)Emp(t). \quad (16)$$

In the social-security scenario, unemployed workers do not starve, but receive a fraction of the market wage from an unmodeled 'public' sector:

$$C(t) = w(t)[Emp(t) + \varphi(L - Emp(t))], \quad (17)$$

with  $0 < \varphi < 1$ .

As mentioned above, our model straightforwardly belongs to the evolutionary, ACE family. Since in general, analytical, closed-form, solutions can hardly be obtained, one must resort to computer simulations to analyze the properties of the (stochastic) processes governing the coevolution of micro and macro variables.<sup>15</sup>

To do so, one should in principle address an extensive Montecarlo analysis in order to understand how the statistics of interest change together with initial conditions and system parameters. However, sensitivity exercises show that, in our model, across-simulation variability is quite low and no chaotic pattern is detected. Hence, we confidently present below results concerning averages over a limited number of replications (typically  $M = 50$ ) as a robust proxy for the behavior of any statistics we compute. Tables 2 and 3 report the values employed for initial

<sup>15</sup>On the methodology of analysis of evolutionary/agent-based computational economics models, see Lane (1993a, b), Dosi and Winter (2002), and Pyka and Fngiolo (2005).

Table 2. Initial conditions

Description	Symbol	Value
Market wage	$w(0)$	1
Consumer price index	$cpi(0)$	1.3
Average labor productivity	$\bar{A}(0)$	1
Mark-up	$\mu(0)$	0.3
Liquid assets	$NW_{i,j}(0)$	10000
Capital stock	$K_j(0)$	800
Labor supply	$L(0)$	1000000

conditions and parameters. Our choice for initial conditions is done in such a way that the economy evolves over a steady state in absence of technical change. All results presented below are robust to variations of the parameters within a reasonably large neighborhood of the benchmark parametrization reported in Table 3.

Table 3. Benchmark parametrization

Description	Symbol	Value
Size of consumption-good industry	$F_1$	200
Size of capital-good industry	$F_2$	50
Econometric sample size	$T$	600
Replicator dynamics coefficient	$\chi$	-0.5
Competitiveness weights	$\omega_{1,2}$	1
Prod. Innov. Uniform Distrib. Supp. Lower Bound	$i_1^-$	-0.5
Prod. Innov. Uniform Distrib. Supp. Upper Bound	$i_1^+$	0.5
Proc. Innov. Uniform Distrib. Supp. Lower Bound	$i_2^-$	-0.5
Proc. Innov. Uniform Distrib. Supp. Upper Bound	$i_2^+$	0.5
Wage setting $\Delta cpi$ weight	$\psi_1$	0
Wage setting $\Delta \bar{A}$ weight	$\psi_2$	1
Wage setting $\Delta U$ weight	$\psi_3$	0
Desired inventories parameter	$\theta$	0.1
Desired level of capacity utilization	$u^d$	0.75
Trigger rule	$\alpha$	0.1
Payback period parameter	$b$	8
Maximum machine age	$\eta$	19
Maximum debt/sale ratio	$\Lambda$	2
Consumption-firm sample coefficient	$\kappa$	0.01
Interest rate	$r$	0
Wage share	$\varphi$	0.33

## SIMULATION RESULTS

In this section we explore the extent to which the foregoing model is able to account for the empirical regularities presented in Sections 2.1 and 2.2. To do so, we shall compare simulation results under the *work-or-die* and the *social-security* scenarios described above.

Note that, as mentioned above, the foregoing model embodies in its microeconomic setup the majority of the stylized facts pertaining to firms' investment and innovating patterns described in Section 2, cf. SF5–9. The main goal of the analysis is to replicate as emergent properties both empirical regularities showed by macro time-series (SF1–4) and microeconomic stylized facts concerning firm productivity dynamics (SF10–11) and firm size distributions (SF12–13).

To begin with, let us look at the outcomes of the model when technical change is turned off. In this case, the model behaves like the Solow (1956) growth model: the economy is always in steady state and, since population is fixed, the output growth rate is zero. At the microeconomic level, the initial configuration with homogenous firms remains unaltered as there is neither entry nor exit.

As soon as one turns on technical change, self-sustaining patterns of growth do emerge (cf. Figures 1 and 2). The economy evolves in a permanent disequilibrium state characterized by entry and exit of heterogeneous firms interacting both within and among industries.

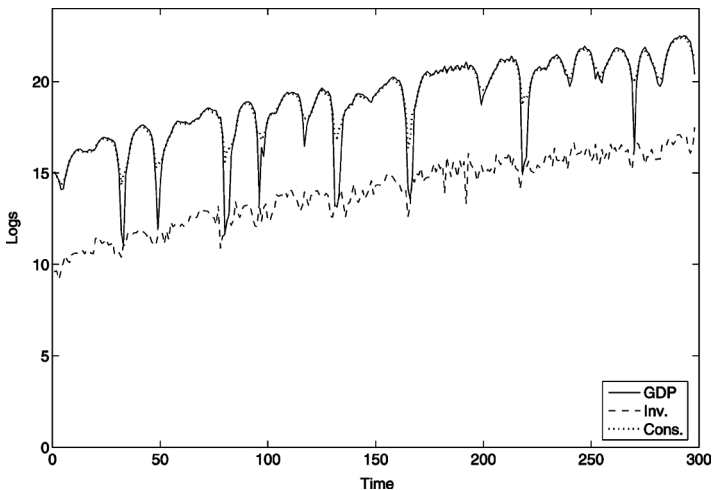


Figure 1. Work-or-die scenario. Level of output, investment, and consumption.

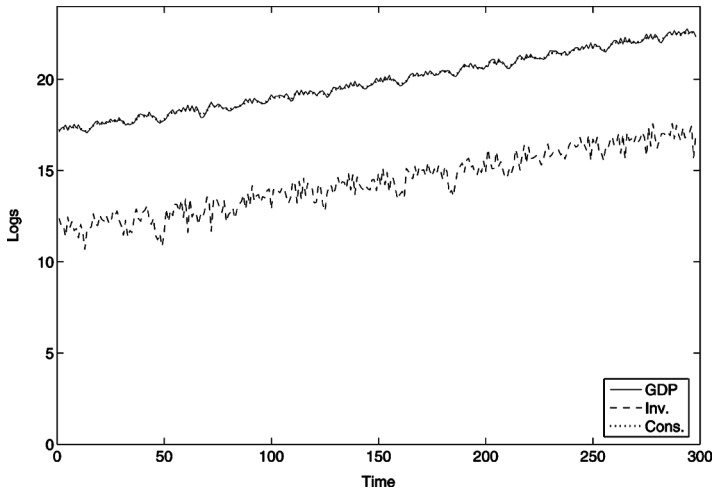


Figure 2. Social-security scenario. Level of output, investment, and consumption.

Simulated aggregate time-series possess in this case statistical properties well in line with empirically-observed ones. More precisely, if we separate the business cycle frequencies of the series by applying a bandpass filter,<sup>16</sup> we observe the typical ‘roller coaster’ shape that characterizes real data (see Figures 3 and 4 and Section 2.1 above). In the *social-security* scenario, simulated series of aggregate investment appear to be more volatile than output (SF1), whereas the opposite seems to happen in the *work-or-die* scenario. Finally, aggregate investment and consumption display a procyclical behavior in both scenarios.

In addition, the model is also able to generate a microeconomic landscape consistent with the micro ‘stylized facts’ mentioned in Section 2.2. So, for example, the skewed size distributions which emerge in the simulations are not statistically different from the empirically observed ones in either scenarios (cf. the rank-size plot in Figure 5).<sup>17</sup>

<sup>16</sup>See Baxter and King (1999). Cf. also Dosi, Fagiolo, and Roventini (2005) for a discussion of the properties of alternative filtering techniques.

<sup>17</sup>We employ consumption-good firm sales as a proxy of firm size. Before pooling our data, we normalize each observation by the year-average of firm size in order to remove any time trends in our data. This allows one to get stationary size and growth distributions across years. Due to space constraints, we show the rank-size plot and the firm growth rate distribution plot for the *work-or-die* scenario only.



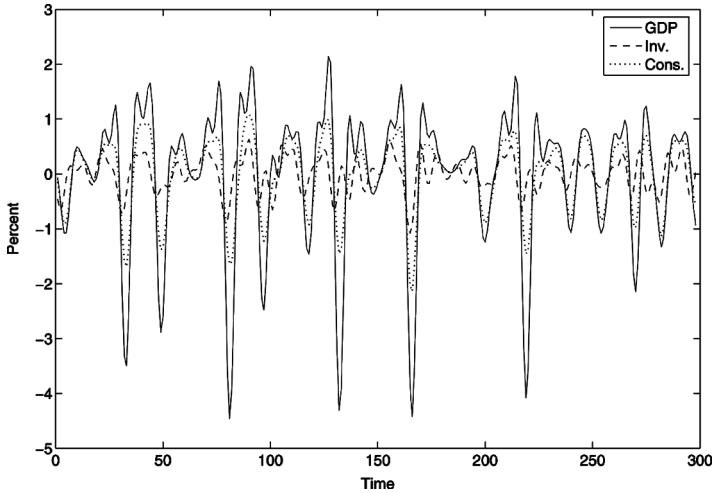


Figure 3. Work-or-die scenario. Bandpass-filtered output, investment, and consumption.

Furthermore, well in tune with the empirical evidence, pooled firm growth rates exhibit the typical ‘tent-shaped’ pattern, characterized by tails fatter than the Gaussian benchmark (cf. Figure 6). More precisely, we have fitted our simulated firm growth rate distributions with the Subbotin family of densities.<sup>18</sup> We find that simulated growth-rates are well proxied by Subbotin densities with estimates for the shape-parameter that robustly suggest a departure from normality in both the *work-or-die* and the *social-security* scenarios (with  $\hat{\beta} = 0.32$  and  $\hat{\beta} = 0.24$ , respectively). Notice that our estimates actually entail growth-rates distributions with tails even fatter than those empirically observed. We argue that this result is due to the different statistical features of real-world and simulated firm growth data samples. On the one hand, in empirically observed growth-rate distributions, small firms are typically not included in the sample and any entry-exit turbulence is washed away by considering surviving firms only. Conversely, in our simulated data: (i) we do not set any lower bound to the size of firms; and (ii) we also consider the entry and exit of firms. Both features of simulated data tend to increase the proportional ‘lumpiness’ of growth

<sup>18</sup>Subbotin densities include as special cases the Normal (shape parameter  $\beta = 2$ ) and the Laplace ( $\beta = 1$ ) distributions. More on the application of the Subbotin family to the fitting of firm growth rates is in Bottazzi and Secchi (2003a, b).

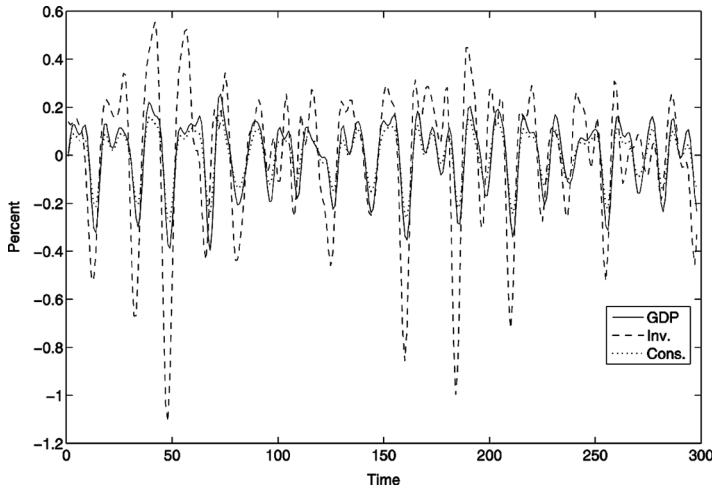


Figure 4. Social-security scenario. Bandpass-filtered output, investment, and consumption.

shocks. In fact, simulation results show that, if one suitably builds balanced samples of simulated firm growth rates, the estimated shape-parameter turns out to increase and replicate its empirical counterpart (e.g.  $0.5 \leq \hat{\beta} \leq 1$ ).

Let us now turn to a more detailed study of simulated aggregate time-series. More specifically, we shall investigate the issue whether aggregate output, investment, consumption, etc. display statistical properties similar to the empirically observed ones, as summarized in SF1-4.

We begin by focusing on the average growth rate (AGR) of the economy:

$$AGR_T = \frac{\log Y(T) - \log Y(0)}{T + 1}, \tag{18}$$

where  $Y$  denotes aggregate output and  $T$  is the econometric sample size.<sup>19</sup>

We then compute Dickey-Fuller (DF) tests on output, consumption, and investment in order to detect the presence of unit roots in the series (all results refer to averages computed across  $M = 50$  independent

<sup>19</sup>All results refer to  $T = 600$  time-periods, cf. Table 3. This econometric sample size is sufficient to allow for convergence of recursive moments of all statistics of interest.

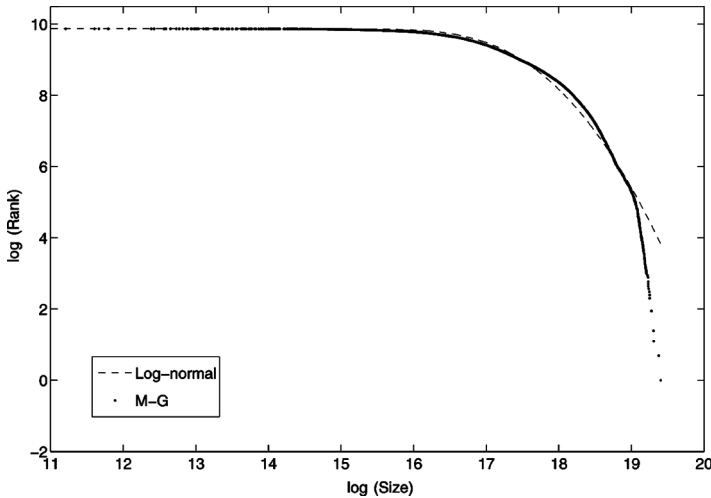


Figure 5. Work-or-die scenario. Pooled (year-standardized) sales distributions. Log rank vs. log size plots. M-G: Model-Generated distribution.

simulations). In both scenarios, the average growth rates of output, consumption, and investment are strictly positive ( $\approx 1.8\%$ , see Tables 4 and 5). DF tests strongly suggest that output, consumption, and investment are non-stationary. This result is robust to alternative specifications of DF tests (e.g. considering an intercept term, adding a linear trend, etc.).

We then detrend the time series obtained from simulations with a band-pass filter (6,32,12) and compute standard deviations and cross-correlations between output and the other series. Our simulated figures for relative standard deviations show that the model is able to match SF2 (i.e. consumption is less volatile than output) in both scenarios. However, in the *work-or-die* scenario, output appears to be more volatile than investment. This result stems from the fact that our simulated economy does not contain any mechanism that contributes to stabilize effective demand, e.g. service industries and, especially, the government sector. When, as it happens in the *social-security* scenario, we include a proxy for the foregoing stabilizing factors, investment turns to be more volatile than GDP, thus satisfying also SF1.

As far as cross-correlations are concerned, consumption appears to be procyclical and coincident in both scenarios (cf. Tables 6 and 7). This matches SF3. Change in inventories appears to be procyclical and

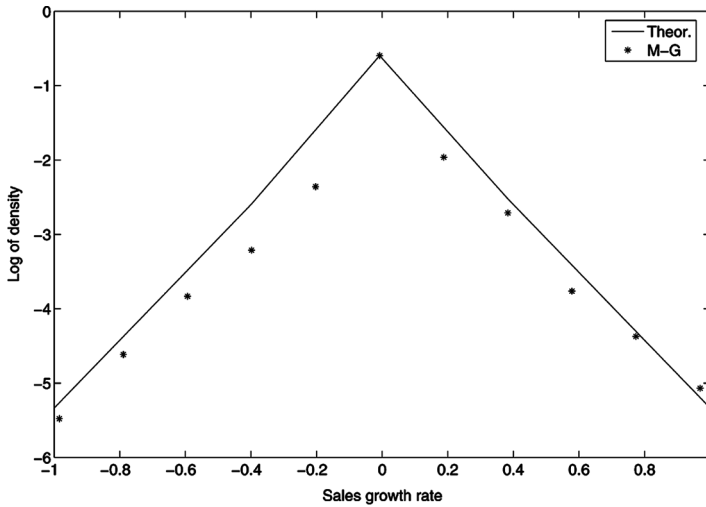


Figure 6. Work-or-die scenario. Pooled (year-standardized) firm growth rates. Binned densities of simulated growth rates vs. Laplace fit. M-G: Model-Generated growth rates.

coincident in the *social-security* scenario (SF3), whereas it is slightly leading in the *work-or-die* scenario. Investment is instead procyclical and leading in both scenarios. However, this result is entirely due to the dynamics of replacement investment. Indeed, net investment is always procyclical and coincident (SF3).

Finally, our simulated cross-correlation patterns are also *quantitatively* in line with those obtained by stock and Watson (1999) on US data (see Figures 7 and 8).

Table 4. Work-or-die scenario. Output, investment, and consumption statistics. Standard deviations in parentheses. Dickey-Fuller test specification: No intercept term, no linear trend, not augmented

	GDP	Consumption	Investment
Avg. growth rate (%)	1.8 (0.007)	1.8 (0.006)	1.8 (0.005)
Dickey-Fuller test (logs)	-0.0988	0.9914	0.3692
Sign. level	1	1	1
Dickey-Fuller test (bpf 6,32,12)	-5.6450	-4.8685	-6.2572
Sign. level	0.01	0.01	0.01
Std. Dev. (bpf 6,32,12)	1.1720	0.6198	0.3306
Rel. Std. Dev. (GDP)	1	0.5288	0.2821

**Table 5.** Social-security scenario. Output, investment, and consumption statistics. Standard deviations in parentheses. Dickey-Fuller test specification: No intercept term, no linear trend, not augmented

	GDP	Consumption	Investment
Avg. growth rate (%)	1.8 (0.0006)	1.8 (0.0005)	1.8 (0.0017)
Dickey-Fuller test (logs)	2.6816	5.8739	-0.3739
Sign. level	1	1	1
Dickey-Fuller test (bpf 6,32,12)	-6.3837	-6.0359	-6.8881
Sign. level	0.01	0.01	0.01
Std. Dev. (bpf 6,32,12)	0.1358	0.0946	0.4357
Rel. Std. Dev. (GDP)	1.00	0.70	3.21

Notwithstanding we did not model the labor market in details, empirically-plausible employment series do arise. Indeed, employment turns out to be procyclical, whereas unemployment rate is countercyclical (SF4). Notice however that the two variables appear to be coincident. This result may stem from the complete lack of frictions that characterizes the labor market in our model. Indeed, since in every time period firms can hire and fire workers without limitations, production fluctuations pour out in the labor market with no lags.

Furthermore, we have checked whether our model is able to match microeconomic stylized facts on productivity dynamics (SF10–11). To do so, we have computed—at each  $t$ —the standard deviation of labor productivities across consumption-good firms in both scenarios.

**Table 6.** Work-or-die scenario. Correlation structure

Series bpf 6,32,12	GDP (bpf 6,32,12)									
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	
GDP	-0.19	0.14	0.54	0.87	1.00	0.87	0.54	0.14	-0.19	
Consumption	-0.09	0.24	0.58	0.85	0.95	0.86	0.59	0.23	-0.12	
Investment	-0.18	-0.17	-0.08	0.11	0.38	0.64	0.78	0.73	0.50	
Change in stocks	0.03	0.17	0.31	0.40	0.39	0.28	0.10	-0.10	-0.24	
Net investment	0.06	0.29	0.49	0.63	0.69	0.63	0.46	0.21	-0.07	
Employment	-0.13	0.17	0.52	0.81	0.96	0.89	0.64	0.28	-0.08	
Unemployment rate	-0.01	-0.25	-0.49	-0.67	-0.75	-0.71	-0.53	-0.26	0.04	

Table 7. Social-security scenario. Correlation structure

Series bpf 6,32,12	GDP (bpf 6,32,12)								
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
GDP	-0.38	-0.03	0.44	0.84	1.00	0.84	0.44	-0.03	-0.38
Consumption	-0.35	-0.04	0.38	0.78	0.98	0.89	0.54	0.08	-0.32
Investment	-0.19	-0.15	-0.03	0.18	0.42	0.58	0.58	0.40	0.11
Change in stocks	-0.18	0.01	0.24	0.41	0.44	0.31	0.09	-0.11	-0.21
Net investment	-0.26	0.06	0.45	0.76	0.87	0.73	0.41	0.02	-0.28
Employment	-0.40	-0.10	0.33	0.73	0.96	0.91	0.61	0.17	-0.23
Unemployment rate	0.40	0.09	-0.33	-0.73	-0.96	-0.91	-0.61	-0.18	0.22

Our results<sup>20</sup> indicate that, in tune with SF10, significant asymmetries persist throughout the history of our simulated economy (see Figure 9). Moreover, firm-productivity auto-correlations are significantly larger than zero, thus suggesting persistency in micro productivity differentials (cf. SF11, see Figure 10).<sup>21</sup>

Finally, we have explored the distributional properties of pooled, aggregate-output growth rates. In both the *work-or-die* scenario and for a wide range of  $\varphi$  parameter values—in the *social-security* scenario, the estimation of the Subbotin shape parameter ( $\beta$ ) robustly reveals departures from normality. Fat tails emerging in aggregate output growth rates are thus in line with the empirical evidence discussed in Castaldi and Dosi (2004).

## CONCLUSIONS

In this work, we have further developed the model presented in Dosi, Fagiolo and Roventini (2006) in order to better match the set of macro business cycles stylized facts, which we have described in Section 2.1. We have done so by keeping rooted the microeconomic level of the model (i.e. firm behaviors and market interactions) into the microeconomic

<sup>20</sup>We show results for the work-or-die scenario only.

<sup>21</sup>Firm-productivity auto-correlations (up to lag 6) are computed by considering normalized productivity of firms that survived for at least 40 periods in the last 100 periods of any simulation run.

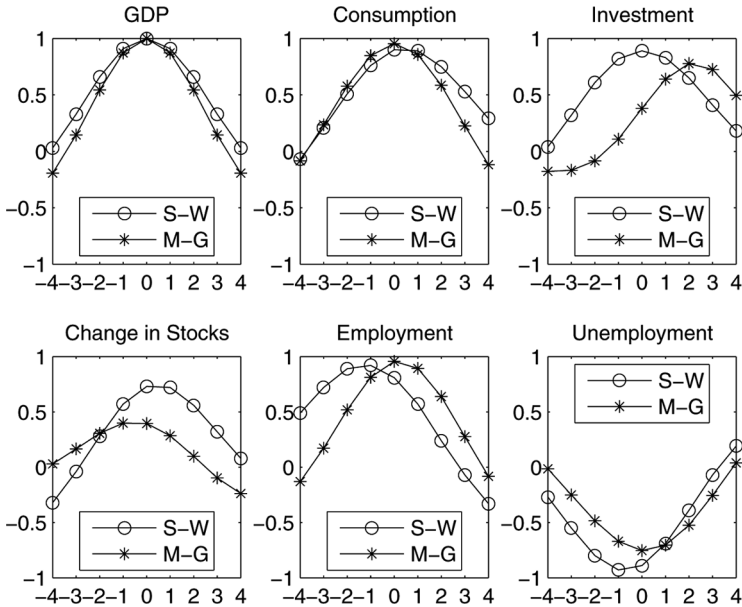


Figure 7. Work-or-die scenario. Model Generated (M-G) vs. Empirical Data (S-W: Stock and Watson, 1999) Cross-correlations.

evidence discovered in the recent years by a vast empirically-grounded literature.

We have tried to contribute to the business cycle literature by developing an evolutionary, ACE model where aggregate output dynamics is driven by the production and investment choices of heterogeneous, boundedly-rational firms. The model depicts an economy composed of a capital-good sector and a consumption-good industry. The two sectors are vertically linked. Capital-good firms innovate introducing new production techniques and new machines. The latter are sold to consumption-good firms increasing their productivity.

The model is able to jointly explain many microeconomic and macroeconomic stylized facts. First, in line with the empirical evidence, the model generates aggregate output time series showing both self-sustained growth patterns and recurrent fluctuations. Moreover, the statistical properties of macroeconomic time series are in line with the business cycle stylized facts listed in Section 2.1.

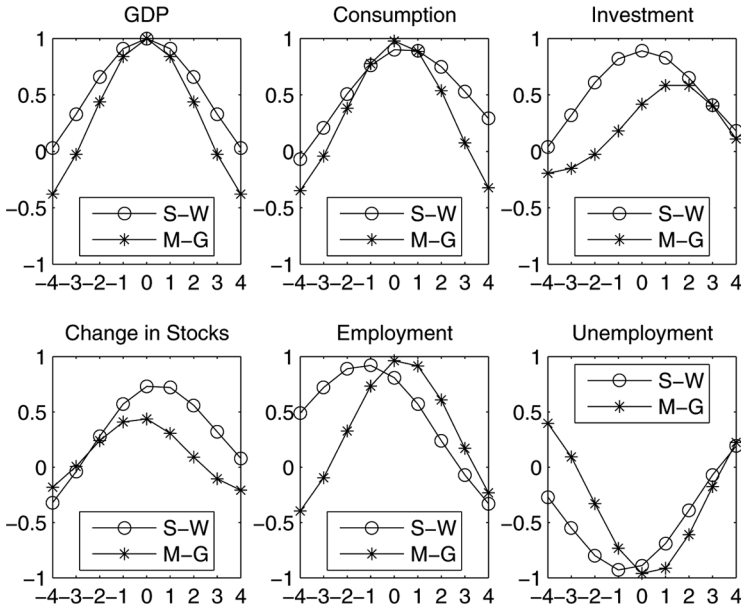


Figure 8. Social-security scenario. Model Generated (M-G) vs. Empirical Data (S-W: Stock and Watson, 1999) Cross-correlations.

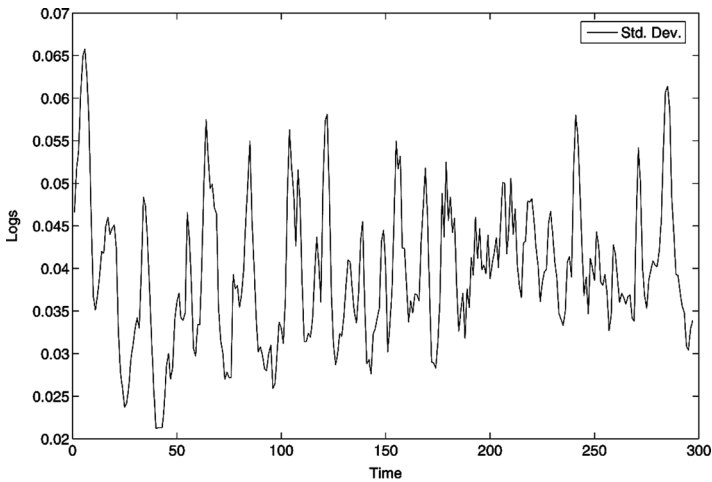


Figure 9. Work-or-die scenario. Standard deviations of consumption good firm productivity.



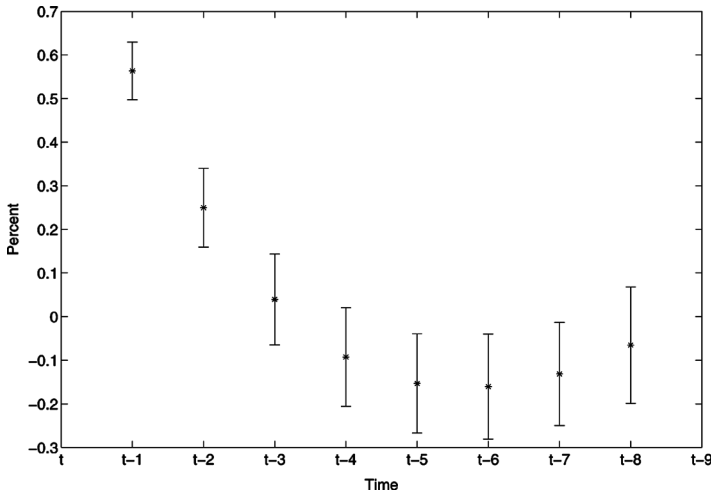


Figure 10. Work-or-die scenario. Average auto-correlations of consumption-good firm productivity. Error Bars: + / - Standard Deviation.

Second, the model is able to accommodate many microeconomic empirical regularities (cf. Section 2.2) concerning i) heterogeneity in firm productivity; ii) persistency in firm productivity differentials; iii) firm size distributions; iv) firm growth rates distributions.

Third, our work shows that the Keynesian theory of business cycles can be successfully microfounded employing an evolutionary, ACE model, where heterogeneous, boundedly-rational firms are allowed to interact and innovate. Indeed, the Keynesian ‘multiplier’ and ‘accelerator’ endogenously emerge and co-evolve shaping the dynamics of the whole economic system.

We are well aware that building an ACE model that embodies empirically-supported assumptions and is able to simultaneously replicate many of micro and macro stylized facts pertaining to business cycles is just a first step towards a deep understanding of business cycles. Replication exercises are indeed just a necessary step in order to employ the model to generate policy implications. The next points in our agenda concern exactly addressing policy issues related to the role played by fiscal policy, labor and output markets, and innovation policies. For example, what is the consequence of introducing taxes in such a way to compensate public expenditure? Furthermore, what happens when

one compares different institutional setups as far as labor and output markets are concerned? Finally, what if one compares alternative mechanisms governing the process through which innovations are endogenously introduced and diffused in the economy?

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