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Macroeconomic Fluctuations and Propagation Mechanisms: An Agent-Based Simulation Model

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Abstract. This paper proposes an agent-based simulation model exploring aggregate business fluctuations in an artificial market economy. It is inspired by the C++ agent-based simulation model in Howitt (2006), and proposes a modified NetLogo model, which provides new procedures and parameters aiming at analyzing the endogenous dynamics of market adjustment processes.

Keywords. Agent-Based Models; Computational Economics; Macroeconomic fluctuations; Propagation mechanisms

JEL Classification. C63; D01; E19; E30

I. *Introduction*

Since the diffusion of complexity studies in Social Sciences, a new conception for economic systems spread: they can now be thought of as complex adaptive dynamic systems[1]. Analyzing interaction patterns among dispersed heterogeneous agents without global control, this approach focuses on the emergence of self-organized systems and macro regularities[2]: it underlies the strong connections and continuous feedbacks between micro and macro levels, thus offering new insights for most economic investigation.

Within Macroeconomics, this approach suggests moreover a new way to manage the inquiry about microfoundations. It rejects the criticized neoclassical framework of the representative rational optimizing agent (cf. Kirman [1989], van den Bergh and Gowdy [2003], Janssen [2006]), in order to embrace the analysis of interactions[3], hierarchical causation, upward and downward impacts among different levels of economic activity

[1] For some definitions and aspects of complexity in Economics see e.g. Rosser [1999]. Restricting to the Santa Fe approach (cf. Arthur et al. [1997b]), complex adaptive systems are characterized by local interactions among dispersed heterogeneous agents, who continually adapt and learn. Interactions happen at many levels without global control: agents at any stage act as "building blocks" for the next one. Such systems experience perpetual novelty and out-of-equilibrium dynamics.
For some contributions upon complex adaptive systems see e.g. Anderson et al. [1988], Arthur et al. [1997a], Blume and Durlauf [2006].

[2] Emergence is a well-known property of complex systems, directly linked to holism, i.e. the notion that the whole is different from the sum of its parts. In complex systems we observe spontaneous formation of self-organized hierarchical structures, which often show nearly decomposable properties, i.e. in the short run the behaviour of each component is approximately independent, while in the long run it depends aggregately on the behaviour of other components (Simon [1962]).

[3] As Kirman [1998] points out, traditional models account for agents' interactions through the price system: price is the only signal agents need to take correct decisions. Thus, they can act in total isolation.

(individual, institutional, etc.)[4]. Therefore, this framework provides a new way to look at traditional macroeconomic topics such as growth and fluctuations.

From a methodological point of view, a branch recently developed to gain insights upon complexity in economic systems is Agent-Based Computational Economics (ACE), which employs agent-based programming to study decentralized market economies and their characteristics[5].

The aim of this work is to gain some insights on complexity of aggregate fluctuations by means of agent-based modeling. Moreover, a crucial point in the business cycle debate deals with fluctuation impulses and propagation mechanisms. Along time different macroeconomic schools suggested both real and nominal explanations of business cycle mechanisms, focusing in turn on aggregate demand and real multiplier-accelerator (cf. e.g. Harrod [1936], Samuelson [1939], Metzler [1946], Hicks [1950]), supply-side factors and unexpected inflation (cf. e.g. Friedman [1968] and Laidler [1976]), rational expectations and the representative agent (cf. Lucas [1977]), real exogenous shocks to technology and productivity (cf. Kydland and Prescott [1982], Long and Plosser [1983], Plosser [1989], Cogley and Nason [1995]), externalities and rigidities (cf. Fischer [1977]), and so on[6]. However, the debate is still open and no uniform explanation has been found yet. Thus, we consider in the model some endogenous mechanisms possibly causing aggregate movements, in order to widen our understanding of economic dynamics within the system.

The rest of the work contains in section II the description of our model, in section III our simulation results concerning both parameter variations and exogenous shocks, in section IV our main conclusions.

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[4] For some points about the microfoundations literature see e.g. Janssen [2006]. It is worth noting that the complexity approach does not abandon methodological individualism, but it sheds light on agents' interactions and consequently emergent phenomena. It comes up a sort of "systemic rationality", for the aggregate behaviour presumably follows patterns other than those of an "average individual" (cf. Kirman [1998], Bruun [2004]; see Arthur [1994] for an illustration of the well-known El Farol problem and some aggregate implications of agents' inductive reasoning).

[5] Peculiarly, ACE adopts the so-called bottom-up approach: instead of a priori defining market equilibrium (top-down approach), we observe the structures emerging from agents' interactions. For a review of fundamental ACE issues and limits, refer e.g. to Tesfatsion [2002, 2006], Bruun [2004], Arthur [2006], Terna et al. [2006].

[6] Cf. Arnold [2002] for an essential review on some recent traditional macroeconomic schools and their explanation of cyclical phenomena.

II. The model

Our work is based on Howitt [2006]: while his original agent-based simulation is performed in C++, we reproduce a slightly modified version of his model using NetLogo 3.1 platform[7]. However, our analysis substantially differs from Howitt's since we aim at a wider inquiry about business fluctuations mechanisms. Notwithstanding the basic framework is largely the same, we introduce some new procedures in order to analyze our system adjustment processes. Furthermore, this simulation aims at evaluating the role each parameter has in fluctuation dynamics, thus performing a careful analysis of each contribution, together with eventual joint examination.

First of all we build an artificial economy consisting of n perishable goods, a fixed number of shop sites, and heterogeneous agents[8] (*transactors*). Individuals either produce or keep a shop, in order to obtain a certain quantity of their consumption good. For the sake of simplicity, each agent is identified by both the commodity it produces or trades (*manna, y*), and the one it consumes (*food, x*), which are different by construction: therefore, there are $n(n-1)$ different "types" of agents (x,y). Moreover, we create b identical individuals for each type, in order to observe the effects on system dynamics of an expansion or contraction in population, nevertheless maintaining unaltered microstructure. Summing up, the model consists of $bn(n-1)$ transactors, either producing or keeping a shop, and adapting their behaviour to varying market conditions.

Wheat is the universal medium of exchange[9]; for the sake of simplicity, just wheat-eaters can keep a shop, thus becoming *entrepreneurs*[10]. Each entrepreneur trades just its manna, while payments are carried out by wheat. Shops hold two offices, acting both as *employers*

[7] http://www.ccl.sesp.northwestern.edu/netlogo/

[8] Netlogo environment consists of both mobile and stationary agents. In our model, they represent respectively transactors and shops. Yellow patches embody shop sites, while the green one represents "home", i.e. the locus collecting producers every time they are unable to correctly end trade procedures.

[9] Howitt and Clower [2000] analyze the development of a decentralized market economy in an autarchic model of adaptive agents: quite every time decentralized markets develop, the emergence of a universal medium of exchange occurs. Thus, hypothesizing wheat (good 0, in the model) covering this function is not a too simplistic assumption.

[10] In our simulation, red agents represent potential entrepreneurs, while red agents on yellow patches represent effective entrepreneurs.

for producers and as *retailers* for consumers[11], and fixing respectively two different prices, *wage* (*w*) and *retail price* (*1/p*).

According to the Santa Fe approach (cf. Arthur et al. [1997]), this model owns some typical characteristics of complex systems[12]:

1. it is based on *local interactions*, since producers generally sell production to their employer, receive money (wage), and then look for retailers to buy food;
2. there is *no global controller*, since interactions occur spontaneously, through market coordination and competition;
3. there is *continual adaptation*, since both entrepreneurs adjust gradually their prices on the basis of the experienced gap between target delivery levels and actual deliveries, and there is continual search for the best trading relationships;
4. we observe *out of equilibrium dynamics*, since individuals' adjustment is not instantaneous, and agents' interaction gets beyond the Walrasian reaction to an auctioneer's price signal.

As we already said, one pivotal feature of complexity approach in Economics is the analysis of both market and non-market interactions[13]. In our model, these are described by trading and market research procedures, employer-employee and customer-store relations, target delivery levels and price formation.

Particularly crucial is the way we specify agents' behaviour: as Arthur [2006] underlines, agent-based models make use of algorithms in order to regulate individual actions.

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[11] Clearly, producers are consumers too. However, since each shop trades a single good, agents generally sell their production and buy their food in different shops. Both wheat-producers and eaters make a clear exception.

[12] The model does not display *perpetual novelty* and *crosscutting hierarchical organization* (Arthur et al. [1997]). This is a consequence of the architecture we impose. In fact, on the one hand we do not allow population to evolve, on the other we do not focus on hierarchies and organizations. We simply observe agents' localization during trading procedures.

[13] Refer e.g. to Kirman [1998] and Glaeser and Scheinkman [2000]. An interesting notion joint to non-market interactions is *social multiplier* (Glaeser and Scheinkman [2000], Glaeser et al. [2002]). In fact, models of social interrelations show how changes in aggregate variables generally produce a twofold effect due to strategic complementarities. Firstly, there is a direct effect on agents' behaviour; then, each individual reacts to changes in other individuals' actions. Thus, in empirical analysis, social multiplier effects could often make aggregate coefficients to overstate actual individual response (Glaeser et al. [2002]).

II.a Algorithms

Our agents behave depending on their type and actual condition. First of all, producers and entrepreneurs perform different tasks; moreover, potential entrepreneurs and wheat-producers follow trading procedures slightly different from others'. Accordingly, the following algorithms describe agents' interactions.

✓ *Entrepreneurs (see figure 1):*

At the beginning of each period, they first of all fix their wage and retail price, in order to start up exchange procedures, paying w wheat units to each employee, and receiving p wheat units for each item of sold out manna. At the end of the period, a random portion θ of entrepreneurs performing negative profits leaves the market, while the others update manna and money targets for a fraction a of the gap between their current targets and actual deliveries. Then, in the next period entrepreneurs adapt prices on the basis of new targets. For simplicity, price adjustments are supposed costless.

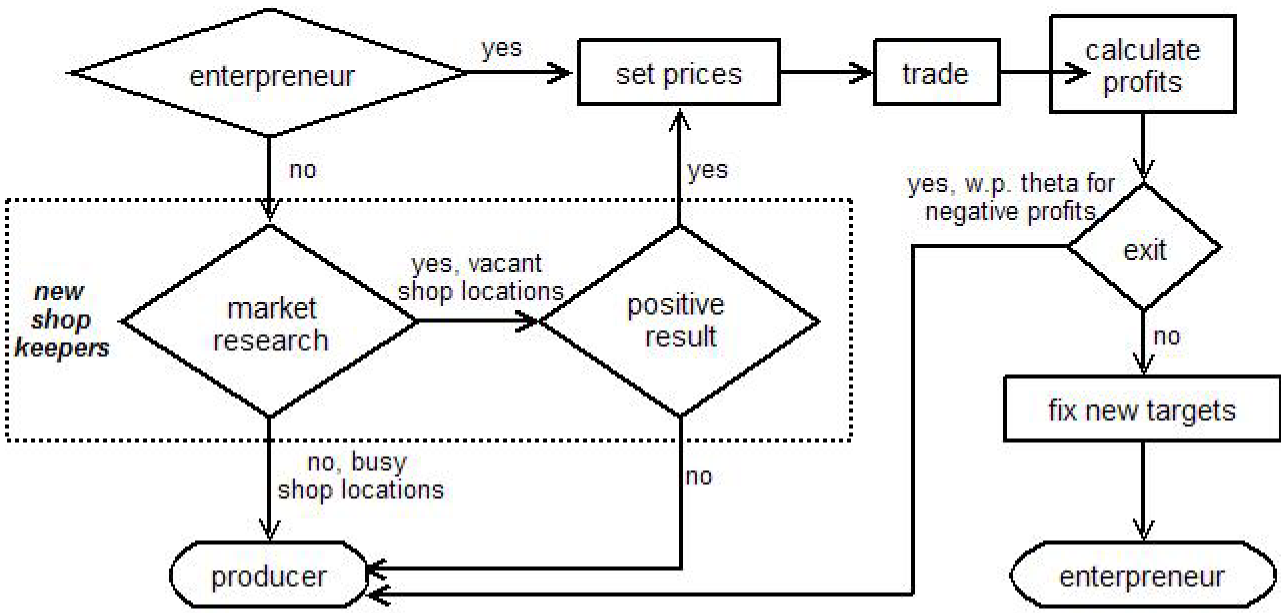

Figure 1: One-period algorithm for potential / effective entrepreneurs.

✓ *Producers (see figure 2):*

In the basic setting (see the appendix), they produce one manna unit per period. Then, whenever feasible[14] they deliver production to their employee. For wheat-producers and eaters the procedure ends here, since they directly barter production for consumer goods; other workers, on the contrary, go to their store and buy food. Every period, a random fraction λ of producers revise their employer-employee and customer-store relations looking for both the entrepreneur paying the highest *w* for their manna and the store with the lowest *1/p* for their food.

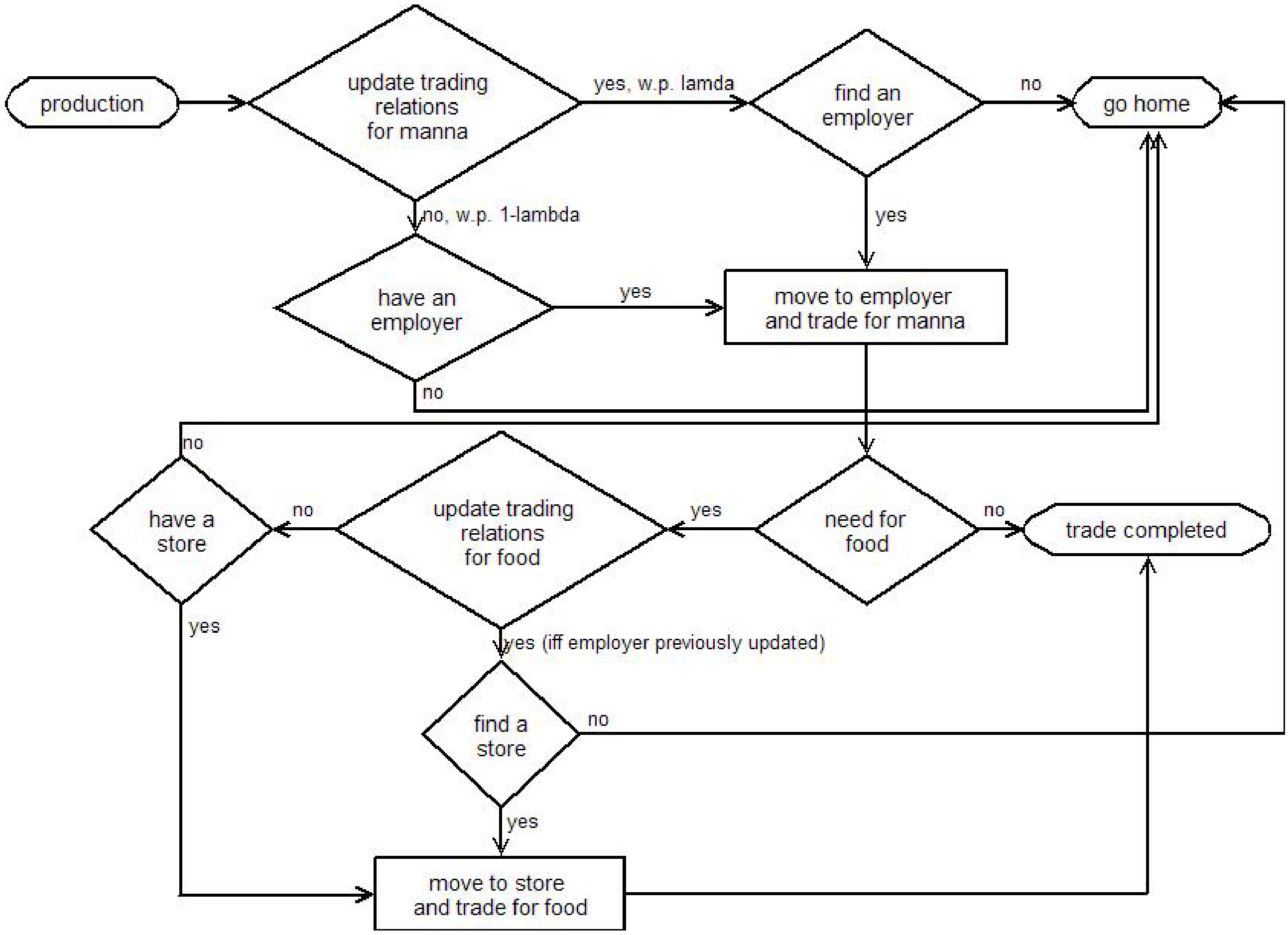

Figure 2: One-period algorithm for producers.

Summing up, this economy is described by a six-step algorithm:

1. workers produce one manna unit, while entrepreneurs fix prices on the basis of their current targets[15];

[14] Feasibility refers to the entrepreneurs' effective availability of wheat and manna resources to respectively pay their employers and satisfy their customers.

[15] In the first period the procedure is random: from an economic point of view, we could think of a sort of *animal spirit* conditioning entrepreneurs' behaviour (see section III.c). For some contributions on the

2. in the case of vacant shop sites, potential entrepreneurs evaluate business prospects with probability β, taking over a shop if market research results positive;
3. a random fraction λ of producers looks for the most convenient exchange partners;
4. agents exchange;
5. entrepreneurs experiencing negative profits exit the market with probability θ;
6. still-in-business entrepreneurs adaptively fix new targets.

II.b Prices, targets, and profits

From the above algorithms, we note that agents' adaptive behaviour is particularly evident in target and price formation mechanisms, which are directly linked. As previously explained, in fact, entrepreneurs fix prices on the basis of one-step-behind manna and wheat targets ($\hat{q}$ and $\hat{m}$, respectively), which shop keepers update at the end of each period by a fraction *a* of the gap between current targets and actual deliveries (q and m). Thus, for the next period the relations are

$$\hat{q}_{t+1} = \hat{q}_t + \alpha(q_t - \hat{q}_t) \text{ and } \hat{m}_{t+1} = \hat{m}_t + \alpha(m_t - \hat{m}_t), \tag{1}$$

i.e. if actual deliveries exceed current targets, new targets are higher, and vice versa. Parameter *a* represents a sort of *adaptation speed*: higher *a*s induce faster expectation convergence to actual delivery values and vice versa.

About prices, since entrepreneurs have to sustain setup and operating costs every period, we establish they fix prices in order to cover them accordingly to their expected targets (Howitt [2006]), i.e.

$$w = \frac{\hat{m} - c}{\hat{q}} \text{ and } p = \frac{\hat{q} - f - s}{\hat{m}}; \tag{2}$$

c and s represent respectively wheat and manna setup costs of shop keeping, while f is the fixed operating cost in manna[16]. The first equation asserts entrepreneurs fix w such that expected wheat deliveries cover both expected wage bills and wheat setup costs; the second states shop keepers fix p such that expected manna deliveries cover expected real

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endogenous role of animal spirits in business cycles see e.g. Howitt and McAfee [1992], Chauvet and Guo [2003], Francois and Lloyd-Ellis [2003], Dosi et al. [2005, 2006].

[16] Here we do not allow for scale effects or additional market entry or exit costs: c, s, and f are homogeneous across entrepreneurs. Cost heterogeneity could represent a future extension of the model, together with the analysis of different price formation mechanisms, e.g. the introduction of a mark-up.
Note that p represents the inverse of retail price. If either w or p turns negative, it is set to zero.

money demand plus manna setup and operating costs. Thus, it is clear the way adaptive changes in targets affect prices.

Finally, at the end of each period entrepreneurs calculate wheat and manna profits, i.e. respectively

$$\pi_m = m - wq \text{ and } \pi_q = q - pm - f . \qquad (3)$$

Thus, if wheat actual deliveries exceed actual wage bills, a positive wheat operating surplus occurs, and vice versa; similarly, if manna actual deliveries exceed actual real money demand plus fixed operating costs, there is a positive manna operating surplus, and vice versa. Clearly, since expectations affect prices, profits are affected by adaptive behaviour too; in addiction, as explained in the following section, the profit level is fundamental for agents' exit.

II.c Exit, entry, and market research

As the algorithm in section II.a shows, every entrepreneur currently performing wheat and/or manna negative profit leaves the market with probability θ. This parameter could be thought of as representing the *strength of exit barriers*: lower θs indicate higher disincentives for exit, and vice versa.

In the meantime, the algorithm provides an entry strategy too. If there are vacant shop sites, a random fraction β of potential entrepreneurs evaluates business prospects through market research: after interviewing producers in an r-radius space[17], incoming entrepreneurs fix a slightly higher w and lower $1/p$ than previous period average, in order to attract workers and customers. Then, if the new prices are feasible[18] interested agents acquire a shop.

Clearly, for each new shop the arrival of employers and consumers depends on both prices and parameter λ, which determines the fraction of workers looking each period for more favourable trade relationships. Nevertheless, a continuous flow of new

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[17] Parameter r represents the market research range: the higher its value, the higher the probability of large samples.

[18] After some algebra, from (2) we derive $\hat{m} = \dfrac{c + w(f+s)}{1 - wp}$ and $\hat{q} = \dfrac{f + s + cp}{1 - wp}$. Thus, the feasibility condition for target delivery levels requires $w<1/p$, with positive p and w.

entrepreneurs generally perturbs the system; thus, we allow market research just every now and then, in order to analyze eventually stable paths (see section III.a).

II.d Equilibrium

Following Howitt [2006], we identify as equilibrium a full-employment stable-prices state where all workers succeed in purchasing manna and buying food with invariant trading relations. The outcome of such configuration is monopoly: every time the economy is in equilibrium it counts *n-1* entrepreneurs[19], trading each one a different commodity. This result is in line with our fixed cost hypothesis, which theoretically implies the arise of a natural monopoly.

Then, keeping in mind this definition, we derive an analytic expression for equilibrium prices and targets. Since every monopolist (0,z) receives manna from all (x,z) producers and money from every (z,x) consumer, x≠z (see figure 3), equilibrium targets are expressed by

$$\hat{q}^* = b(n-1)-1 \text{ and } \hat{m}^* = b + b(n-2)w^{*}\,[20]. \tag{4}$$

Then, substituting $\hat{q}^*$ and $\hat{m}^*$ into (3), after some algebra we derive the quite complicated expressions for w^* and p^*, i.e.

$$w^* = \frac{b-c}{b-1} \text{ and } p^* = \frac{(b-1)[b(n-1)-f-s-1]}{b[b(n-1)-c(n-2)-1]}\,[21]. \tag{5}$$

This equilibrium is stable against entry since in such case profits just cover setup costs[22], thus turning entry unprofitable.

[19] The equilibrium number of monopolists is *n-1* instead of *n*, since wheat is the universal medium of exchange.

[20] On the manna side each monopolist counts *b(n-1)-1* employers: in fact, there are *b* identical agents for every *n-1* (x,z)-type, delivering a unit of z each but the monopolist itself. On the wheat side monopolists receive one wheat unit from all *b* (z,0)-agents, and w^* wheat units from each *b(n-2)* (z,x≠0)-agent. Recall that x≠z. Note that our equilibrium prices and targets diverge from Howitt's, since in our model entrepreneurs entirely devote themselves to trading activities, leaving production aside. In Howitt [2006], on the contrary, every transactor produces one manna unit, while some particular agents cover in addiction a shop site.

[21] We suppose parameter choices affording positive *w* and *p*, see note 18.

[22] In fact, substituting (4) and (5) into (3), after some algebra we derive $\pi_m^* = c$ and $\pi_q^* = s$. Note that by construction this monopolistic configuration is attained with entrepreneurs fixing prices in a sort of competitive way, i.e. with no mark-up and null expected profits. Actually profits differ from zero as long as entrepreneurs experience a non-zero gap between expected and actual deliveries. Thus, the equilibrium is characterized by competitive prices in a monopolistic environment.

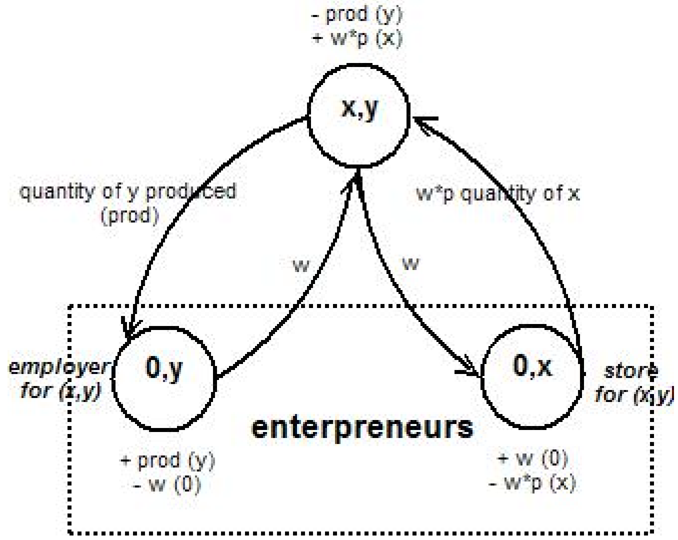

Figure 3: Trade process for an (x,y) producer.

In line with Howitt [2006], these analytical results are fully confirmed by computer simulations: running the model with proper parameter choices, we generally observe a spontaneous gradual attainment of the stable configuration described. Such adjustment is the outcome of the interaction among adaptive agents: contrarily to more traditional approaches, we do not model agents instantaneously reacting to price and other signals, but rather entrepreneurs slowly revising expectations on the basis of their previous experience, and workers periodically searching for the most convenient trading partners.
Summing up, equilibrium is performed exclusively through decentralized interactions: agents take decisions on the basis of their local information, without global knowledge of the process. Moreover, as Howitt [2006] underlies, such equilibrium is a Pareto efficient outcome, since the whole production is delivered and devoted to agents' consumption[23], besides covering fixed operating costs.

III. Parameters, shocks, and aggregate fluctuations

This section investigates aggregate fluctuations due to alternative system settings. Following Howitt [2006], aggregate output is defined period per period by total

[23] In this model, production affects welfare just if it joins the sales distribution circuit through employer-employee and customer-store relations, since both no agent feeds on his own product and all trade is mediated by shops. Thus, with more-is-better agents and perishable goods a Pareto efficient outcome requires all units being exchanged and consumed. On the concept of Pareto efficiency see e.g. Montesano [1991].

consumption units, i.e. the sum of both purchased food for each transactor, and setup costs for each entrepreneur, since these represent a sort of "psychic" consumption[24]. Thus,

$$GDP^{*} = (bn - 1 - f)(n - 1)\,, \tag{6}$$

which is a sort of full employment value[25].

Here we mainly analyze output responses to either parameter variation or preference and productivity shocks. We do not mean quantitatively mimicking real economies, but rather reflecting on possible endogenous and exogenous causes of fluctuations, together with eventually dampening or amplifying mechanisms.

III.a Parameters

The model consists of a wide parameter set, defining system states. Varying parameters, we often observe temporary or permanent system perturbations. Primarily, we ran experiments altering some set otherwise leading to equilibrium (equilibrium sets).

Number of goods	n
Number of identical agents	b
Number of shop sites	*N_shops*
Time lapse between two successive market researches	*mktRes*
Per period endowments	*inEndow*
Per period setup and operating costs	c, s, f
Adaptation speed	a
Time lag potentially applied to the target adaptation mechanism	*lagTime*
Fraction of potential entrants effectively carrying out market research	β
Market research radius	r
Fraction of new trading relations seekers	λ

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24 Clearly, in this model consumption simply refers to aggregate quantities rather than discerning among different goods, for by assumption every transactor does not consume a bundle but always a single good, without the possibility of preference shift in the case of shortage or more convenient prices. Thus, this economy consists of not substitute goods.

25 Actually, if all transactors but entrepreneurs produce one manna unit each, in equilibrium there are $bn(n-1)-(n-1)$ units, for we know there are $n-1$ entrepreneurs (note 19). We obtain (6) considering that each unit is allocated through market interactions and devoted either to consumption or to setup costs covering but the $f(n-1)$ amount assigned to fixed operating costs. Note this value is firstly attained out of equilibrium, when just $n-1$ entrepreneurs remain in the market and prices start stabilizing and converging.

Fraction of potential outcomers	θ
Fraction of x-consumers shifting their preferences	γ
Productivity shock size	*shock%*

Table 1: Model parameters.

- ✓ *Population size:*

Since total transactors are $bn(n\text{-}1)$, population size is defined by n and b: the first involves agents' heterogeneity[26], while the second determines population expansions or contractions however maintaining the same microstructure.

Ceteris paribus, in simulations we observe more unstable and oscillating dynamics with higher bs, i.e. when the trade volume is increased. This outcome is in line with the idea that a complex systems is notably different from the sum of its parts. Moreover, keeping total transactors' number fixed, system settings with sensibly higher b but low θ often display continuous fluctuations, never reaching stable (equilibrium or out-of-equilibrium) paths. In fact, for a higher number of competing entrepreneurs stability is never attained without suitable entry or exit barriers. However, we can generally stabilize the system by modifying the parameters controlling the market access, e.g. θ or fixed costs[27].

Thus, in such model appropriate policy interventions on market barriers could dampen fluctuations, even if they do not always lead the system towards the equilibrium path[28].

- ✓ *Shop sites:*

As expected, the available number of shop sites does affect system dynamics.

[26] Recall that population consists of $n(n\text{-}1)$ different types.

[27] Try e.g. running parameters (b,n,θ) = (3,10,0.05) and (b,n,θ) = (9,6,0.05) on the basic parameter setting. While the first choice does generally result in a stable equilibrium configuration, the second determines perpetual oscillating dynamics and continuously updating trading relations, until we opportunely raise θ, thus weakening exit barriers.
Notably, in such case the system does not stabilize on equilibrium values, but rather on a lower performance setting, since we just provide a random localized exit procedure. In fact, if bad performing entrepreneurs were allowed to globally confront their profits, the worst performing ones would probably leave the market, and the system would attain the equilibrium configuration. However, the lack of either a global controller or superimposed coordination mechanisms typical in complex systems is better described by random localized procedures.

[28] Note that innovation (in the sense of new products) is completely ruled out, since the model provides an unalterable n-goods structure. This unrealistic assumption allows to simplify simulation procedures, since NetLogo platform is not an highly powerful tool.

When $n-1 \leq N\_shops < b(n-1)$, the lesser is the number of sites, the slower and more unstable is convergence towards equilibrium, for the shortage of shops interferes with the usual entry mechanism (see section II.c).

On the contrary, for $N\_shops < n-1$ equilibrium is clearly never attained and some goods run out of the market, while for $N\_shops \geq b(n-1)$ there is no alteration in system dynamics[29].

✓ *Entry and exit:*

Recalling section II.c, entry is directly linked to market research procedures. Running simulations we notice it determines endogenous fluctuations, since allowing potential entrepreneurs to open new shops when they meet with favourable market conditions breeds system perturbations. The involved parameters are *mktRes* and β, i.e. respectively the time lapse between two successive market researches and the fraction of potential entrants effectively seeking the market. In particular, too recurrent shop births (high *mktRes* and $\beta > 0$) generate everlasting fluctuations, while no new birth at all (*mktRes* $= 0$ or $\beta = 0$) generally brings stable below-potential performances.

Concerning an economic interpretation, it seems plausible thinking of a kind of "discouragement effect", which prevents just bankrupts from immediately entering the market again[30]. Thus, *mktRes* is a sort of discouragement effect measure, affecting the frequency of entry perturbations: as an example, never discouraged agents prevent system stability although avoiding eventual product disappearance. However, since coordination is a lengthy process in large populations, *mktRes* should be sufficiently large in order to attain full disequilibrium adjustment[31].

On the contrary, β does not affect the frequency of entry perturbations but rather their dynamics. The effects of this parameter are generally better observable in large

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[29] $b(n-1)$ is the number of potential entrepreneurs the economy counts.

[30] Such discouragement could be the result of both psychological and institutional aspects. In this model we do not explicitly introduce institutions, since coordination is the spontaneous outcome of agents' interaction. However, in real economies the institutional framework often plays a conditioning role for individual behaviour (cf. e.g. North [1990]). As an example, different bankruptcy proceedings could produce various economic effects.

[31] Recall that when $wp \approx 1$ no entry occurs independently of β and *mktRes*. In fact, by construction in our model new entrants fix their w and p 1/100 higher than the corresponding market averages. Nevertheless, new prices have to satisfy the feasibility condition in note 18, i.e. average market prices must be such that $wp < (100/101)^2$ in order to allow new entries.

populations since potential entrants' number is higher[32]. For positive and very low βs disequilibrium adjustment shows quite oscillating dynamics fading for higher values, which on the contrary determine the reabsorption of perturbations with either none or little fluctuations.

On the exit side θ variations considerably affect system dynamics: equilibrium is generally attained for very low θs, since entrepreneurs frequently experience negative profits and weak exit barriers lead the system to low-performance but stable configurations. Thus, it is sometimes possible to pass from a stable but Pareto inefficient setting to equilibrium just working on entrepreneurs' exit incentives θ.

However, because of both agents' adaptive behaviour and periodical entry the model displays certain reversibility[33]: if we improve stable but inefficient configurations just varying θ, we can gradually get back to previous situations simply restoring the old value of θ.

- ✓ *Information:*

Parameter λ defines the producers' fraction seeking each period for more advantageous trading relations (see section II.a). In a certain sense, it represents a sort of informational spread among producers: for higher λs a larger number of agents learns about market prices, consequently adjusting its trading relations. *Ceteris paribus*, equilibrium generally occurs just for high λs, since we easily observe that the parameter has to exceed a certain *threshold* depending on population size[34] in order to drive the system towards equilibrium. On the contrary, for $0 < \lambda \leq$ *threshold* the economy displays stable below-potential output but continuously oscillating price dynamics[35]. Finally, for $\lambda = 0$ the economy dies in a few periods, since agents do not adapt their choices (i.e. trading relations) to contingent scenarios, making any trade gradually stop.

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[32] E.g. running $(b,n,\theta) = (6,4,0.1)$ β adjustment dynamics are less pronounced and more uniform than in set $(b,n,\theta) = (14,6,0.05)$.

[33] On the one hand, adaptive agents make history matter, since their current targets and prices always depend on past experience; on the other hand, in this model the system can repeatedly assume some previous configurations, since some parameter change can make it advantageous to restore cast off settings. Just to avoid misunderstandings, by restoring previous settings we mean the system attains old prices and aggregate performances, notwithstanding eventually different entrepreneurs and trading relations.

[34] E.g. for more or less 100 agents the λ threshold generally lies around 0.6.

[35] This is presumably because of our definition of GDP: in the above case, in fact, oscillating prices do not affect aggregate consumption but rather wealth distribution. Note that we simplistically assume agents consuming all the food they can buy, since goods perish at the end of each period.

Thus, producers' informational spread affects both system stability and Pareto efficiency: in our model some external intervention improving informational channels can sometimes stabilize the system, which eventually better performs. Somehow these results seem in line with Heiner's reflection on predictable behaviour, e.g. interpreting eventual λ decrease as an uncertainty rise. In fact, Heiner [1983] points out how highly uncertain environments induce agents to simplify their behavioural patterns, thus increasing predictable regularities: in our case, in fact, from high uncertain settings generally emerge stable paths[36].

On the contrary, parameter r represents a quite different informational spread, since it determines the market research area, i.e. the portion of "world" a potential entrepreneur explores to learn about current prices[37] and consequently evaluate its entry benefits. Clearly, aggregate effects of r highly depend on *mktRes* and β, which respectively shape up the frequency of entry perturbations and the flows of per period entry. In fact, *ceteris paribus* higher βs imply deeper but more isolated oscillations, which become sharper in the case of low r. On the contrary, low βs imply a slower injection of new entrepreneurs in the economy, which performs smoother although long-standing oscillations becoming slightly more pronounced for high r[38].

- ✓ *Adaptation speed*:

Fixing new targets each period, entrepreneurs' adaptive behaviour is shaped by parameter a, which defines the fraction of the actual vs. expected targets gap accounted for in the adjustment process (see section II.a). Depending on a we observe either stable (high or low) performances or oscillating dynamics. *Ceteris paribus*, in fact, the system generally displays stable paths for both high and low as, while intermediate a values determine continuous fluctuations[39].

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[36] Actually, Heiner asserts that uncertainty is the basic source of predictable behaviour ([1983]: 570), but speculation on such issue is quite apart from the purpose of our work.

[37] Parameter r ranges from 0 to 17, i.e. half of the two-dimensional width and height projections of out toroidal world, since potential entrants inquire agents in an r-radius circle. The inspected area is not necessarily proportional to the number of inquired agents because of their spatial distribution. In fact, by construction we know this is not homogeneous, since agents concentrate around their stores. However, in our opinion this inquire procedure represents a quite reasonable assumption.

[38] If $r = 0$ entrants do not seek the market at all, thus establishing prices randomly. In such case adjustment fluctuations depend on new entrepreneurs' animal spirits rather than on current market conditions.

[39] High, low, and intermediate values depend on population size and composition. E.g., in our basic setting (see the appendix) these values are respectively $a > 0.7$, $a \leq 0.2$, $0.2 < a \leq 0.7$.

Peculiarly, for frequent market research and instantaneous total agents' adaptation, i.e. a = 1, the system performs sort of asymmetric cyclical dynamics[40] whose wavelength depends on *mktRes*, with maximum value corresponding to the equilibrium. On the contrary, when the system attains equilibrium with high as but 1, *mktRes* causes just small temporary perturbations which are quickly reabsorbed.

On the other side, low as generally lead to stable low performances, while its intermediate values cause continuous endogenous fluctuations which self-feed independently of market research mechanisms. In particular, the lower a, the lower generally results the GDP trend[41]. Finally, in the case of $a = 0$ the system performs similarly to $a = 1$, except that maximum levels are now lower than potential GDP.

Thus, equilibrium is attained just if the adaptation speed is properly high, while properly low speeds lead to stable low-performance configurations; in all the other cases the system perpetually oscillates. In a certain sense, this result is again in line with Heiner's analysis, since he asserts that "intrinsic to behavioural rules is the ignoring or lack of alertness to potential information, the reaction to which would direct behaviour into more complex deviations from such rules; even though such information may be costless to observe" ([1983]: 573). Thus, in our model low as could express such lack of alertness even with costless information, which actually determines less complex aggregate paths.

Finally, we analyze the system responses to a lagged adaptation mechanism applying the equations

$$\hat{q}_{t+1} = \hat{q}_t + \alpha(q_t - \hat{q}_{t-l}) \text{ and } \hat{m}_{t+1} = \hat{m}_t + \alpha(m_t - \hat{m}_{t-l}) \tag{7}$$

$$\hat{q}_{t+1} = \hat{q}_t + \alpha(q_{t-l} - \hat{q}_{t-l}) \text{ and } \hat{m}_{t+1} = \hat{m}_t + \alpha(m_{t-l} - \hat{m}_{t-l}), \tag{8}$$

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[40] As previously explained, the market research mechanism gives new impulse to the economy offering potential entrepreneurs a chance for shop keeping, thus preventing goods disappearance due to entrepreneurs' exit. For $a = 1$ market research is the fundamental cause of oscillatory dynamics. Contrary to $a < 1$, in fact, stable paths could be either high or low performing, since instantaneous total target adaptation could either quickly get equilibrium, or favour entrepreneurs' exit through faster accomplishment of negative profits. Thus, in this case market research determines continuous system shifts between high and low performances.

[41] In the lack of market research our model produces horizontal trends, since new-product innovation is not allowed. Thus, our simulation suggests an important role for new-entrepreneurs' innovations in trend dynamics, since e.g. in the case of low performing settings successful new entrepreneurs could improve system performance rising aggregate consumption (GDP). However, potential GDP constitutes an upper bound for output, since we impose no new-product innovation.

where l represents the time lag. Equations (7) update current targets for an a-fraction of the gap between current deliveries and the l-lags target expectations; on the contrary, equations (8) consider the l-lags gap between effective and desired targets[42].

First of all, the system generally dies for *lagTime* $l > 1$. In order to test our system behaviour we run 50 random-seed simulations of 50 periods each for every different equation pair (1), (7) and (8). Then, we test whether these 3 different adaptation mechanisms can be thought of generating 3 distinct processes – P1, P7 and P8 from now on. Performing the *Kruskall-Wallis test*[43] (Kruskal and Wallis [1952a,b]) for the 3 types jointly on each simulation mean and variance we can reject the hypothesis that all the samples belong to the same population, i.e. the same process. Moreover, the *Two-Sample Wilcoxon Rank-Sum (Mann-Whitney) test*[44] (Wilcoxon [1945], Mann and Whitney [1947]) on paired types confirms such result[45] (see tables 3 and 4 in the appendix). Thus P1, P7, and P8 seem to represent 3 different processes. Finally, observing individual statistics we notice that P7 performs the best, with the highest mean and the lowest variance (table 5 in the appendix).

✓ *Per period endowments*:

In order to avoid trading disappearance[46], we provide entrepreneurs with per period endowments (*inEndow*) of both money and manna: *ceteris paribus*, different parameter values imply quite different adjustment dynamics.

Varying *inEndow* in an equilibrium parameter set, we notice per period endowments must exceed a certain threshold to ensure convergence[47]; otherwise there are continuous

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[42] Here we do not mean to discuss the cognitive odds of such different specifications, but rather their impact on system dynamics.

[43] We use this non-parametric one-way ANOVA by rank test since previous skewness and kurtosis tests for normality indicate that the simulated variables have not normal distributions in all the three adaptive specifications considered (see table 2 in the appendix).

[44] Again we adopt such non-parametric rank-sum test instead of the two-sample t-test because our simulated data do not follow a normal distribution.

[45] A lightly ambiguous case could result from the analysis of P7 and P8 means, since by the respective test they belong to the same process with probability 0.47. However, the test results for variance sweep away any doubt (see table 4 in the appendix).

[46] In this model the lack of per period endowments brings trading disappearance. In fact, by construction entrepreneurs act as intermediaries in all the exchanges. However, since agents trade sequentially and goods perish in one period, not-endowed entrepreneurs cannot pay either w or p to their partners, thus performing no exchanges at all. Hence, per period endowments represent a necessary condition for trading.

[47] E.g. in the basic setting (see the appendix) this threshold lies around 900 units, depending again on the population size, i.e. the more agents a shop trades with, the more endowments it needs.

fluctuations. Unfortunately, in this model we cannot introduce inventory investment, since goods are perishable. However, our results seem to suggest inventories play some role in cyclical dynamics[48]; the point will be analyzed in future developments.

As reasonably expected, adjustment dynamics are faster and less oscillating as endowments grow since their availability helps trading coordination. However, fluctuations due to other system features clearly persist even when *inEndow* increases, i.e. sufficient per period endowments do not solve all the problems[49].

- ✓ *Per period costs:*

As section II.b explains, fixed operating costs f directly affect the potential GDP level, while c and s represent a sort of fixed setup additional consumption for entrepreneurs, thus impacting on overall dynamics[50]. Since this model provides just per period fixed costs they act as kind of entry barriers, whose high values generally prevent the system from reaching its potential[51]. Because of this entry barrier role the effects fixed costs produce on the whole system also depend on parameters β and *mktRes*[52].

Ceteris paribus, if β is high the system generally shows slightly smoother and more protracted adjustment dynamics for lower costs, which typically constitute weaker barriers and imply slower agents' adaptation. On the contrary, since low βs already represent by themselves sort of entry barriers slowing down the injection of new

[48] The effects of inventory investment over the business cycle have been widely analyzed in literature: for some overviews about theories and empirics see e.g. Zarnowitz [1985], Blinder and Maccini [1991], Hornstein [1998], Wen [2005].

[49] Try (b,n)=(14,6) in the basic setting (see the appendix): when *inEndow* ≥ *27000*, the system attains equilibrium if $\theta = 0.05$, while if $\theta \geq 0.1$ there is continuous oscillation. In this case, exit barriers prevent equilibrium.

[50] The simulation model clearly allows cost specification implying just non-negative equilibrium prices. In fact, from equations (5) it is easily verified that $w^* \geq 0$ iff $c \leq b$. On the contrary, $p^* \geq 0$ iff $f + s \leq b(n-1) - 1$ XNOR $c < [b(n-1)-1]/(n-2)$, $c = [b(n-1)-1]/(n-2)$ excluded - XNOR is a logic operator: A XNOR B reports true if either both A and B are true, or both A and B are false. If the above conditions are not satisfied, the economy dies in a few periods; the same very often occurs even for p^* and/or w^* very close to 0. Run e.g. (c)=(10), (f,s)=(9.1,10), and (c,f,s)=(0.5,8.9,10).

[51] This cost structure is very simplistic: the entrepreneurs must entirely support c, f, and s independently of their volume of trade, while total wages represent variable costs. Neither scale nor learning economies are provided, not even *una tantum* entrepreneurial fixed costs: future extensions could fill these lacks.

[52] While *mktRes* determines the eventual injection of new entrepreneurs in the market, β acts on their effective flow.

entrepreneurs in the market, overall dynamics result smoother with slower non-linear equilibrium convergence[53].

Fundamentally, both c and s indirectly influence out-of-potential aggregate GDP, since they affect prices and consequently the total exchange volume (in particular depending on entrepreneurs' initial endowments). On the contrary f determines GDP levels both directly, diminishing entrepreneurs' consumption, and indirectly, through prices.

Thus, when the system does not reach equilibrium paths, another possible "policy" intervention consists in varying entrepreneurs' fixed costs, i.e. the opportunity costs shopkeepers support during each activity period: e.g. if the entrepreneurs' number is less than the equilibrium value, in some circumstances we could cut some fixed costs down in order to intervene on coordination activity incentives[54].

III.b Preference and productivity exogenous shocks: the endogenous propagation mechanism

Besides the above-mentioned structural fluctuations, the system could also be affected by both preference and productivity shocks: by construction we induce them exogenously, since no inner raging mechanism is provided[55].

Apropos of preference shocks, following Howitt [2006] we allow a γ fraction of x-consumers to switch to good y consumption, and vice versa[56]. Simulations generally show a single downward deviation from previous trajectories, whose magnitude highly depends both on parameters γ and λ. In fact, on the one hand γ defines the shock amplitude, i.e. *ceteris paribus* higher γs imply larger perturbations. On the other hand, λ denotes the shock diffusion speed, i.e. *ceteris paribus* higher λs imply fast information diffusion and allow "shocked" consumers to quickly update their trading relations, while

[53] The different impact of high and low βs interacting with fixed costs is better observable comparing runs with very low *mktRes*. In the first case there are quite deep oscillations, while in the second much smoother fluctuations are observed.

[54] Obviously, if the disequilibrium source were other than cost disincentives, the model would not attain equilibrium by such policy interventions.

[55] Going deeply into the matter of endogenicity or exogenism of preference and productivity shocks in real economies together with the controversy about the economic meaning of negative productivity shocks is out of our purposes. For some insights into such issues see e.g. Howitt and McAfee [1992].

[56] In order to preserve the original macrostructure the switch must affect the agents producing the same good, i.e. if an (x,z) agent switches to good y, a (y,z) agent switches to good x. Thus, we observe perturbations simply due to preference switching, while the overall distribution of consumers among different goods is still unchanged.

on the contrary lower λs and slow information spread imply more persistent and significant perturbations.

On the contrary, productivity shocks involve either negative or positive changes in sector x output, i.e. all x-producers rise or fall their per period productivity according to *shock%*, which defines the shock magnitude and sign. Since our model does not allow microstructure changes, agents are "trapped" in their typologies and cannot shift to different production or consumption goods[57]. Thus, such artificial construction determines quite atypical dynamics in distributive terms[58]; however, it is particularly worth noting the emerging propagation mechanism. In fact, when a shock occurs it spreads over the system through the established trading relations: when the x-entrepreneurs receive manna quantities different than the expected, they update their targets and prices, thus paying different w to their employers, who therefore buy food in different quantities than earlier, thus inducing their stores to update targets and prices, and so on. Hence, the shock is exogenously induced but endogenously propagated because of the coordination role entrepreneurs play in the model.

III.c Further considerations: animal spirits and agents' geographical localization

NetLogo platform allows a visual panorama of agents' interactions; exploiting this characteristic we developed some code to view trading connections among individuals,

[57] This is clearly a strong constraint, but it is very useful to simplify the NetLogo code, since this platform is not particularly powerful. Removing such restriction is left to future developments.

[58] Because of this frozen microstructure preventing agents from shifting to either the most convenient productive sector or consumption good, permanent productivity shocks spread their costs and benefits in a quite unrealistic manner. In order to evaluate such aspect, we compare the quantity of food each agent owns at the end of a stable-price period before and after the shock, assuming that agents weakly prefer higher food quantities (cf. Mas-Colell et al. [1995]: chs.2, 3). Being aware of the limitations such method implies, here we do not mean to go deeply into the individual preferences and utility measurement controversy: we just confront individual own quantities in different periods.

Supposing e.g. a positive shock affects sector x, this model performs oddly since first of all x-producers, whose productivity has actually increased, obtain less food, while x-eaters and x-entrepreneurs are favoured the most. The other entrepreneurs do not alter their status, while all the remaining agents worsen their position, except for wheat-producers, which actually make better. These movements are proportional to the shock entity, and reversed in the case of negative shocks. However, these results are clearly in contrast with both the theoretical and empirical literature (cf. e.g. Hansen [1964], Zarnowitz [1985, 1991], Aghion and Howitt [1998], King and Rebelo [2000], Arnold [2002]). Thus, at the moment we restrict our analysis to propagation mechanisms without distributional remarks, leaving further code refinement for future development. For the same reason we just limit our simulations to permanent productivity shocks, since temporary shocks would not presumably add information on propagation.

making them remain nearby their store at the end of each period. Clearly agents initially disperse among concurrent entrepreneurs, while approaching equilibrium they concentrate near their monopolistic store. Obviously, the concentration speed depends on both parameters such as a, λ, and θ, and banally on the population's size. Thus, towards equilibrium we recognize the emergence of sort of "trading islands": further model extensions could provide a transaction cost analysis (cf. e.g. Williamson and Masten [1999]) in order to gain deeper insight on such issue.

Another aspect related to business cycle analysis concerns the effects animal spirits have on aggregate fluctuations (cf. e.g. Farmer and Guo [1992], Howitt and McAfee [1992], Chauvet and Guo [2003], Francois and Lloyd-Ellis [2003], Dosi et al. [2005, 2006]). In our basic model entrepreneurs initially fix random prices; alternatively, we can suppose the system is affected by either optimism or pessimism waves in business formation, which directly influence aggregate adjustment dynamics[59].

From repeated simulations we notice that the disequilibrium adjustment process substantially shows different characteristics depending on agents' animal spirits. Collecting the mean and variance of the GDP adjustment process[60] from 180 different-seed runs (60 for each possible animal spirit mode - *high*, *low*, and *off*) for both small and large populations (120 and 792 agents respectively), we test whether observations characterized by different animal spirits eventually belong to the same process. On both datasets, the Kruskal-Wallis test rejects the equality-of-populations hypothesis at any level below 0.01% (see the appendix, table 7). Moreover, theTwo-Sample Wilcoxon Rank-Sum (Mann-Whitney) test on samples paired by animal spirits (*low-high*, *off-low*, *off-high*) rejects the null hypothesis of both mean and variance equality between *off-low* and *off-high* pairs[61]. Furthermore, from both datasets the probability of mean_{off} greater than mean_{low} and

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[59] In this model we arbitrarily choose to represent *high* and *low* animal spirits by respectively monopolistic and perfect competition targets, i.e. each new entrepreneur does no more fix random prices at first, but obtains them from the targets above. However, here we just grazingly deal with the animal-spirits-in-business-cycles issue, since we simply refer to waves in business formation, unaware of eventual movements in consumers' sentiments and other points. We leave further investigation to future analysis.

[60] In order to define the adjustment process mean and variance we arbitrarily choose to collect all the GDP values the system assumes before stably attaining its potential GDP, if the case. In fact, even if the accomplishment of the potential GDP does not mean an instantaneous equilibrium attainment, we know that way the system is on its equilibrium path, unless endogenous and/or exogenous perturbations occur (new entries, preference and productivity shocks, and so on).

[61] We use these non-parametric tests since previous analyses rejected the hypothesis of normal distribution for our simulated variables (table 6 in the appendix).

$mean_{high}$ lies between 75.1% and 81.3%, while the probability of $variance_{off}$ lower than $variance_{low}$ and $variance_{high}$ is between 77.5% and 86.1% (see the appendix, table 8). Thus, it seems that the random-animal-spirit adjustment process is generally characterized by higher GDP mean and lower variance. On the contrary, the *low-high* pair assumes different features in the two datasets: while the GDP mean is almost the same, for our large-population economy high animal spirits seem to determine more variable processes, while the contrary occurs for the small-population one. Such discordant results could be due both to the relatively small observations number and to our arbitrary definition of high and low animal spirits. However, since the statistical significance of the previous analysis is very high, we leave further investigation on animal spirits in future works.

For the moment we simply remark that even in such a simple model some connections between animal spirits and the business cycle emerge. Furthermore, from more heterogeneous populations (random animal spirits) seem to emerge more stable and wealthy adjustment processes.

IV. Conclusions

This work has been developed starting from Howitt [2006], who suggests a theoretical foundation of the Keynesian multiplier process developing an agent-based model with decentralized economic interactions. He studies how business failures interrupt the trading flows and generate deviation amplifications.

We develop a modified version of the model in NetLogo with the intent to analyze the arising economic fluctuations and their propagation and amplification mechanisms. Notwithstanding its very simplified and unrealistic structure, our agent-based model shows some fluctuation mechanisms actually observed in real economies; however, we do not perform any calibration or other attempt to get the model closer to reality, since more work on its unrealistic hypotheses is needed in advance[62].

Nevertheless some results are quite interesting, like the capability of some policy interventions on market entry and exit barriers or fixed costs to dampen oscillations, the central role of information spreads in propagating perturbations and stabilizing the

[62] E.g. a less static population structure with agents allowed to change their consumption preferences without many bounds, reproduce themselves, and die; the possibility of product innovations in order to jointly analyze growth and fluctuations; and so on.

system, the occurrence of asymmetric cycles depending on agents' adaptation ability, the intuition of the role of inventories in system dynamics, the emergence of "trading islands", and the role of animal spirits in disequilibrium adjustment processes.

In conclusion, the model framework needs some refinements in order to use the model for further reflections on cycles and growth dynamics in real economies, possibly analyzing labour and consumption dynamics besides that of GDP. Another important future extension concerns the application of spectral analysis techniques to the model simulated data (see the other contributions to the present work) in order to eventually capture other resemblance between real and simulated dynamics.

Appendix

A.1 Statistical analysis on adaptation speed and animal spirits

Adaptation speed (a)

This subsection collects some statistical analysis on GDP simulated data. The total sample counts 7500 observations, i.e. 50 time series of 50 periods for each different adaptation mechanism (see equations (1), (7), and (8)). The aim is to establish whether the sub-samples significantly belong to the same process. A preliminary analysis on their mean and variance suggest the use of rank-sum tests since the observations do not have normal distribution (table 2). Thus we perform the Kruskal-Wallis Equality-of-Populations test and the Two-Sample Wilcoxon Rank-Sum (Mann-Whitney) test (Kruskal and Wallis [1952a,b], Wilcoxon [1945], Mann and Whitney [1947]).

		Pr(skewness)	Pr(kurtosis)	Prob>X^2
Mean	**P1**	0.000	0.133	0.0006
	P7	0.000	0.000	0.0000
	P8	0.010	0.566	0.0409
Variance	**P1**	0.000	0.000	0.0000
	P7	0.000	0.000	0.0000
	P8	0.051	0.222	0.0760

Table 2: Skewness and Kurtosis tests for normality of the simulated GDP mean and variance obtained through adaptation mechanisms (1), (7) and (8). All the variables reject the null hypothesis of normal distribution at least at the 8% significance level.

The first test allows to reject the joint null hypothesis of all sub-samples coming from the same population (table 3); further analysis rejects the same null pair by pair. In fact, the Two-Sample Wilcoxon Rank-Sum (Mann-Whitney) test compares P1-P7, P7-P8, and P1-P8 means and variances in order to show whether they belong to the same population. Unambiguous results reject once more the null (table 4).

		Rank sum			Rank sum
Mean	**P1**	2785.50	**Variance**	**P1**	4042.00
	P7	4345.00		**P7**	2217.00
	P8	4194.50		**P8**	5066.00
X_2^2		15.682	**X_2^2**		44.136
probability		0.0004	**probability**		0.0001

Table 3: Kruskal-Wallis Equality-of-Populations test on simulated GDP data. Results indicate that the null hypothesis of all the samples belonging to the same population can be rejected at the 1% significance level.

	Type (a) vs. (b)	Rank sum	Prob>|z|	Prob{mean/varGDP(a)>mean/varGDP(b)}
Mean	**P1 vs. P7**	1850.5 vs. 3199.5	0.0000	0.230
	P7 vs. P8	2420.5 vs. 2629.5	0.4713*	0.458
	P1 vs. P8	2210.0 vs. 2840.0	0.0299	0.374
Variance	**P1 vs. P7**	3260.0 vs. 1790.0	0.0000	0.794
	P7 vs. P8	1702.0 vs. 3340.0	0.0000	0.171
	P1 vs. P8	2210.0 vs. 2840.0	0.0299	0.374

Table 4: Two-Sample Wilcoxon Rank-Sum (Mann-Whitney) test on simulated GDP data. P1, P7 and P8 clearly come from different processes. The ambiguous result of P7 vs. P8 mean is clarified by test results for the variance.

Finally, table 5 shows that the best-performing process is P7, which shows the highest mean and the lowest variance for simulated GDP.

	Mean	Standard deviation
P1	103.783	9.2357
P7	106.6306	6.8393
P8	99.2268	15.5243

Table 5: Mean and standard deviation of simulated GDP data; each sample counts 2500 observations. P7 performs the best, with the highest mean and the lowest variance.

Animal spirits

This subsections collects statistical analysis on the effects of animal spirits combined with different population size: the economic performance of both a small population of 120 agents and a large one of 792 are compared in 60 runs for each animal spirit attitude. Preliminary Skewness and Kurtosis tests on aggregate GDP mean and variance show that the variables are not normally distributed, thus suggesting the use of non-parametric rank-sum tests.

Large population (792) Small population (120)		Pr(skewness)	Pr(kurtosis)	Prob>X^2
Mean	off	0.000 0.000	0.000 0.000	0.0000 0.0000
	low	0.000 0.000	0.000 0.000	0.0000 0.0000
	high	0.000 0.000	0.000 0.000	0.0000 0.0000
Variance	off	0.000 0.000	0.000 0.000	0.0000 0.0000
	low	0.000 0.000	0.000 0.000	0.0000 0.0000
	high	0.084 0.000	0.000 0.000	0.0001 0.0000

Table 6: Skewness and Kurtosis tests for normality of the simulated aggregate GDP mean and variance for both small and large populations with *off*, *low*, and *high* animal spirits. All the variables reject the null hypothesis of normal distribution at the 1% significance level.

The Two-Sample Wilcoxon Rank-Sum (Mann-Whitney) test rejects the null hypothesis of both mean and variance equality between *off-low* and *off-high* pairs in both populations, suggesting that the random-animal-spirit adjustment process is generally characterized by higher GDP mean and lower variance. On the contrary, the *low-high* pair assumes different features in the two datasets. Discordant results could be due to the relatively small population size, since the NetLogo platform does not allow very large simulations.

Large population (792) Small population (120)	Type (a) vs. (b)	Rank sum	Prob> |z|	Prob{mean/varGDP(a)>mean/varGDP(b)}
Mean	off vs. low	4566 vs. 2694 4758 vs. 2502	0.0000 0.0000	0.760 0.813
	low vs. high	3614 vs. 3646 3311.5 vs. 3948.5	0.933* 0.0946	0.504 0.588

	off vs. high	4532.5 vs. 2727.5 4570.5 vs. 2689.5	0.0000 0.0000	0.751 0.761
Variance	**off vs. low**	2641 vs. 4619 2329 vs. 4913	0.0000 0.0000	0.225 -
	low vs. high	2993 vs. 4267 4105 vs. 3155	0.0008 0.0127	0.677 -
	off vs. high	2360 vs. 4900 2415 vs. 4845	0.0000 0.0000	0.147 -

Table 7: Two-Sample Wilcoxon Rank-Sum (Mann-Whitney) test on simulated GDP data, large and small populations. *Off*, *low* and *high* animal spirits clearly generate different processes.

A.2 The basic model setting

The following table contains the basic setting parameter values: this configuration allows the system to reach the equilibrium state. Simulations are generally performed modifying this setting and studying the system reactions.

n	*b*	*N_shops*	*mktRes*	*inEndow*	*c, f, s*	*a*	*β*	*r*	*λ*	*θ*
6	4	20	1000	10000	0.5	0.9	0.3	10	0.9	0.1

Table 8: Reference parameters for the basic setting.

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