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**Simulation Games in Economics and Business:
Building Artificial Worlds for Flesh and Blood Players**

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Abstract

Simulation games, from the simplest ones to the most sophisticated, are instruments frequently used in the classroom to enhance teaching practices and improve learning outcomes. In economics and business, assembling a simulation game requires conceiving an artificial representation of the economy (or part of it), wherein the players, endowed with their own preferences, skills and viewpoints, interact with one another and also, eventually, with virtual agents. Such artificial worlds might be built resorting to the principles of complexity theory, network science, and agent-based modeling, and taking into account a modular approach, where each module is self-contained but easily attachable to other modules representing specific economic processes or components. This article puts into perspective business and economic simulation, from its teaching virtuosities to its scientific foundations. The modular perspective is highlighted and a prototype module is sketched.

Keywords: Business simulation; Simulation games; Complexity; Virtual worlds; Agent-based modeling; Consumption-savings choices.

JEL classification: A20, C63, E21.

1. Introduction - an Effective Learning Tool

Business simulations are a form of experiential learning or active learning. In a classroom environment, these simulations typically take the form of a game, where participants (students) assume the role of managers of a firm, a business, an organization, a household, or any other conceivable entity or institution. As managers, students are compelled to take decisions. Interaction and strategic behavior are fundamental pieces of the decision-making process in which the participants engage.

Regardless of the degree of sophistication of the simulation environment, there is plenty of evidence showing that simulation-based training is an important complement of other

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teaching practices. In many circumstances, simulations are indispensable for a better understanding of the subject under analysis. Obviously, there are also some caveats to ponder (for instance, simulations may be less effective than other pedagogical tools at teaching specific concepts or theories; and the players might divert their attention to the decoding of the simulation algorithm, instead of focusing on the simulation's intended learning outcomes), but in general we should regard simulation games as a fundamental instrument promoting learning effectiveness.

The literature on the merits of simulation games in assisting the teaching / learning process is voluminous and it is outside the scope of this paper to address it in detail. The brief arguments we sketch below are essentially based on the influential contributions of Faria (2001), Salas *et al.* (2009), Anderson and Lawton (2009), Tiwari *et al.* (2014), and Reed *et al.* (2018).

According to the above-mentioned literature, business simulations, besides offering a realistic and stimulating learning environment that complements other teaching modalities, also encourage teamwork and facilitate interpersonal communication, allow for experimentation in a risk-free environment, provide fast and clear feedback on the decisions taken, and foster the development of various kinds of skills: problem-solving, creativity, critical thinking, communication, and leadership. For the mentioned authors, simulations contribute to learning in three different general ways: they assist cognitive learning (the understanding of facts and concepts), they promote affective learning (improving the perception and attitude of the participants), and they stimulate behavioral learning (triggering behavioral changes that go on the direction of actions leading to better rewards).

Business simulations can be of various types and they can be conceived at various levels. They may be confined to a department or functional area inside a firm (sales, marketing, operations, human resources, accounting); they may refer to the entire firm, and to the decisions that allow it to maximize profits; or they may be holistic, in the sense of taking the economy as a whole and the behavior of the various agents (firms, households, the financial institutions, the government and its agencies). Therefore, typifying how a simulation game should be designed and implemented is not a straightforward general task, given the variety of settings one might take. Nevertheless, a few general guidelines might be pointed out, namely regarding the typical stages the implementation of a simulation should follow.

The first stage of the implementation of a simulation game must be the identification and evaluation of the training needs and of the characteristics of the players; simulations are not one-size-fits-all exercises and, thus, it is essential to know how to adequate the game to whom is playing it and to the learning outcomes that are supposed to be accomplished. Next, the objectives of the simulation should be specified, and its events designed; this step requires evaluating the degree of simplicity / complexity that best fits the desired learning outcomes. Once the game is designed and implemented, evaluation measures should be taken into account; these measures will serve to assess performance and, ultimately, to provide feedback to the participants. Besides following similar general steps, simulation games also unavoidably share two fundamental structural elements: (i) any simulation must gravitate in turn of a virtual environment, built by the modeler and capable of sensibly

weighing simplicity and comprehensiveness; (ii) a set of rules that participants are obliged to follow.

An important remark concerning simulations as learning devices is that, in a certain sense, a simulation is the practical implementation of a theory. Without a good theory (of the economy, of the firm, or of any other entity or process), it is not possible to have a good simulation. Furthermore, one should interpret simulations as being more than games; they are representations of reality and not just ludic devices.

The quality of a simulation game might be measured by the extent in which the proposed virtual world recreates reality and reflects the existing academic knowledge in the assumed specific field, without compromising its playability. Playability, in turn, is related with the appeal of the game to the participants; guaranteeing playability might somehow imply distorting the reality (e.g., by artificially shortening the length of the time intervals between the moment of the decision and the moment in which it produces consequences).

Once recognized the relevance of simulation games as a learning tool, it is necessary to explore which are the proper environments in which simulations should be built upon and what types of rules of interaction and agents' profiles are reasonable to consider. This endeavor cannot be pursued without a close look at what current scientific knowledge has to say about agent interaction in complex virtual worlds. The following sections discuss these issues in detail, first by framing what a business simulation theory should be (section 2), then by discussing how complexity theory can contribute to this assignment (section 3) and how agent-based modeling and modularity might emerge as the main foundations for the modeling of the virtual worlds required for simulation (section 4). In section 5 a specific game module, concerning consumption-savings decisions of households, is sketched. Finally, section 6 concludes.

2. Business Simulation Theory

The design of meaningful and effective business simulations demands a careful reflection about the principles that should guide them. Hall (2018) highlights five pairs of viewpoints that must be taken into consideration when assembling a simulation game. This author puts into confrontation the following: appropriateness vs relevance; reflection vs conciseness; enjoyment vs challenge; behavioral legitimacy vs theoretical legitimacy; harmony vs ambiguity. With this classification, the message to convey is that there are certain principles that cannot be overlooked when conceiving a simulation. Simulations must be appropriate and relevant, given their primary goal; they should be as comprehensive as possible (allowing for reflection and learning), although conciseness is necessarily a requisite; they must promote engagement of the players, thus ensuring a balance between engagement and challenge; they should stimulate cognition (behavioral legitimacy) and be scientifically validated (theoretical legitimacy); they should also balance harmony and internal coherence with some degree of ambiguity, which is necessary to assure that learning takes place.

The above classification sets the stage for the construction of simulation games, allowing to perceive that even the simplest simulation exercise may involve intricate concepts and procedures. One prototypical example is the *lemonade stand game* characterized in Nicolae and Wagner (2014). This game considers a series of steps regarding the planning of a business activity in which it is necessary to organize production, forecast demand, set

selling prices, and engage in inventory and marketing management. How each component of the game is modeled and implemented depends on the intended balance between simplicity and realism / theoretical rigor. For instance, the main drivers of demand might be consumers' preferences, expectations on price changes, consumers' income, ...; production planning might take into consideration demand forecasts, risk assessment, minimization of inventory costs, ...; the pricing strategy might depend on expected demand, competition, market structure, fiscal rules, ...

The above reasoning makes it clear that a same economic or business scenario might be approached in many different ways. In fact, theories that address a same subject are often distinct from one scientific field to another (e.g., cost evaluation might differ from an economic perspective to a marketing or accounting perspective). A possible approach is to conceive a business simulation game that integrates different modules, a perspective that we will address further below. Under such a perspective, for instance, a supply and demand market module might stand on economic foundations, a production operations model might be sustained on management principles, and an assets and liabilities module might originate on accounting and financial analysis theory. As a result, simulation exercises can be interdisciplinary, with several components that complement each other.

Various authors highlight that a systems approach is the most adequate one to develop business simulation scenarios (Gold, 2013; Baptista *et al.*, 2014; Farrenkopf *et al.*, 2016). Although there are alternatives, based on more orthodox economic and business theories, the systems approach has the advantage of being as well an agent-based approach. It captures the complexity of markets and economic relations, through a bottom-up perspective, where simple agents, endowed with incomplete information interact in an extremely complex world that no single individual can fully know or understand. In agent-based models, artificial players and human players may be integrated; both types of agents are endowed with beliefs, desires, and intentions about courses of action to follow. Under agent-based modeling, simulations do not need to hide choice and interaction mechanisms; they are at plain sight because they are a fundamental part of the nature of the simulation under such complexity view.

3. A Digression on Complexity and Virtual Worlds

The economy and its constituent parts (firms, governmental organizations, financial institutions, ...) are complex systems; they are made up of many components that interact in diversified and non-trivial ways. Given the properties of each component and the associated laws of interaction, a complex system may generate unpredictable unique aggregate outcomes. Most of all, complex entities share two basic features: (i) the whole is more than the sum of the parts: micro and macro dimensions influence and reshape each other at every instant; (ii) spontaneous orders emerge; these are higher-order structures generated from the interaction within lower-order dimensions.

Complex systems in society and in the economy have various notorious properties, namely the following: (i) agents are heterogeneous and interact locally; (ii) there is no global controller or central planner; (iii) the organization of processes and institutions is hierarchical; (iv) agents are boundedly rational, in the sense that they learn, adapt and evolve; (v) there is path-dependence, i.e., events are historically determined and no long-

term equilibrium can be pre-specified (the economy is characterized by out-of-equilibrium dynamics). The complexity analysis contrasts with mainstream / orthodox / neoclassical economics (a mechanistic view built upon the concepts of equilibrium, efficiency, optimization, and rationality). According to Holt *et al.* (2011), economic thought is in transition and entering the complexity era.

Complexity is today a broad theme in economics, embracing several sub-disciplines, like evolutionary economics (dynamic analysis and role of institutions); behavioral economics (the study of behavioral rules that go beyond strict rationality); experimental economics (analysis of complex interaction patterns); and agent-based computational economics (investigation and implementation of virtual interaction processes). In any of these areas, it matters the most the idea that what people actually do is more important than what they would do under the strict rationality paradigm: the “what is” perspective replaces the “what if” view.

Most importantly, in a complex environment the economy (and its components) is easily perceived as being a dynamic entity: it constantly evolves and mutates, as agents, institutions, arrangements, and structures are born, fulfill their pre-specified roles, reproduce and eventually die. Through the lens of complexity the world is organic, evolutionary, and historically-contingent. Complexity suggests the systematic repetition of a recursive loop: individual behavior helps in forming aggregate patterns, which in turn influence individual behavior and interaction. Complexity is about pattern formation and behavioral changes and how they influence each other. Arthur (2013) supports the idea that economics is following the same path as science in general: science is becoming more procedural and algorithmic, and less deterministic and equation-based.

A successful simulation game requires accounting for the complexity of the world and how science interprets and models such complexity. However, there are several kinds of complexity, with different implications regarding the design and implementation of simulations. Complexity may be associated with the detail of the environment; it can also relate to the number and depth of the rules, variables and potential interactions involved; it may yet refer to how and how often individuals are compelled to take decisions. In any case, one must equate complexity, interpreted in part as a measure of comprehensiveness, with the simplicity needed to keep the game playable. Wardaszko (2018) enumerates several ways about how a complex game might be simplified: (i) strategic chunking, (ii) sequential elaboration, (iii) organizational specialization, and (iv) measurement of intermediate performances.

Strategic chunking is the process through which a part of the reality is condensed in a simpler idea (e.g. market dynamics are summarized in an equilibrium price). Under sequential elaboration, the complexity of a process is broken down in a series of sequential, less complex, events. Organizational specialization means that the game is assembled in order for the player to focus on a specific part of reality. Finally, complexity may also be mitigated if the game evolves by parts and each part is independently evaluated.

In two influential papers, Lane (1993a,1993b) claims that economic phenomena might be addressed through the construction of artificial worlds. This author envisions an artificial world as a complex system formed through emergent hierarchical organization, i.e., through a process of interaction among agents placed at different hierarchical levels. These interactions originate emergent phenomena and the formation of other hierarchical levels.

Such worlds consist of three elements: (i) a set of micro-level entities; (ii) an environment; and (iii) a dynamic process. The micro agents interact forming dynamics which are specific of the environment and of the interaction process. The attributes of micro-level entities will be modified through interaction.

By constructing an artificial world the researcher is looking for emergent properties, that is, aggregate-level constructs that can be characterized in itself without reference to the micro-level interactions that originated them. Artificial worlds need to be carefully designed in order to identify emergent properties, the way they are formed, and what are their consequences for the behavior of agents. The dynamics of an artificial world is an evolutionary process, for which one needs to identify a population, its attributes, fitness functions, and mechanisms of replication, selection and variation.

Artificial economies have to be playable, even if no flesh and blood player is attached to the environment. This implies that logical rules have to be respected, for instance regarding the sequence of events, and that institutional details have to be made explicit. Although conciseness is an indispensable attribute to assemble a manageable simulation environment, the artificial economy must be necessarily detailed in many respects to replicate important aspects of reality and to allow for a somehow realistic experience.

4. Agent-based Modeling

As already highlighted in the previous section, the scientific paradigm of economics is shifting. Delli Gatti *et al.* (2010), Fagiolo and Roventini (2017), and many others claim that mainstream economics, being the economics of the representative agent, overlooks the richness of heterogeneous preferences, endowments, capabilities, and expectations, and the emergent phenomena created from the interaction among agents. In short, mainstream economics falls into a fallacy of composition, where the whole is the simple sum of the parts. Decentralized interaction and the spontaneous orders it generates must be placed in the center of the analysis, and this reasoning has led to the emergence of agent-based computational economics (ACE). ACE is based on the science of complexity and it respects to the study of the economy as an evolving system of autonomous interacting agents; this study necessarily implies the use of computational methods and simulations (Tesfatsion, 2003).

ACE models are in the opposite pole relatively to orthodox economic models: in the latter, sophisticated agents act within a simple world, while in ACE agents are endowed with simple rules of behavior to interact in a complex world they cannot fully understand. ACE is a *bottom-up* approach: macro outcomes come from unconstrained micro dynamics (at the individual agent level). This contrasts with the traditional *top-down* view, where consistency requirements regarding market equilibrium are superimposed. ACE is also a culture-dish laboratory way of viewing reality: simple agent profiles and interaction rules are set at the starting date, and no further intervention from the researcher is required, as the model is run. All results come from interaction, are historically determined and immune to any extraneous coordination device.

For the above mentioned authors, in ACE analyses three levels are relevant. In the micro-level, behavioral features and local interaction rules are specified; in the meso-level,

regularities emerging from interaction are investigated; finally, at the macro-level, sets of meso-regularities allow to identify aggregate phenomena.

Assembling an ACE model is not an easy task. The main obstacles include the difference in frequencies between events and interactions, the difficulty in measuring information flows, the differences in contractual arrangements, among others. The flexibility provided by agent-based modeling is counterbalanced by a series of obstacles, namely the following: (i) models may involve too many degrees of freedom; (ii) there might be arbitrariness in the selection of the model's assumptions; (iii) the analysis may lack solid empirical grounding; (iv) strong computational and programming skills are required.

One way to circumvent the mentioned obstacles is to develop a standard protocol for the design of agent-based models. Grimm *et al.* (2006) propose such protocol. The proposed standard protocol is composed by three blocks: overview, design concepts, and details and it has been called the ODD protocol. The overview contemplates context and general information and it consists of three elements: purpose, state variables and scales, process overview and scheduling. The design concepts refer to the general concepts underlying the design of the model and to strategic considerations; they involve a series of information concerning the characteristics of agents and interactions and how these promote the emergence of collective phenomena. The details component is composed of three elements: initialization (initial conditions), input (environmental conditions) and sub-models (details on parts of the model).

One way of approaching agent-based complex systems in a simulation perspective and in a comprehensible way is to follow the proposal by Richiardi (2017), who considers that agent-based economic models should be modular, with endless possibilities for recombination and extension. Modularity allows new researchers to start where others have stopped. Different modules (e.g. labor market, credit demand and supply, production, consumption, household formation, retirement, ...) can be combined into new models, as in a children's blocks construction game. The logic of modularization involves: (i) To separate the economy into independent but interconnected objects (markets, institutions, processes, ...); (ii) To model each object as a different module, which might interact with other modules.

5. A Prototype Module: Consumption – Savings Decisions of Households

In this section, a prototype simulation module is sketch; it will concern the consumption – savings decisions of households. For a better organization of ideas, the development of the simulation module is undertaken following six steps: (i) short theoretical contextualization; (ii) description of the artificial world; (iii) identification of sources of heterogeneity; (iv) identification of contact points with other modules; (v) presentation of players' objective and players' decisions; (vi) game implementation example. We will approach each of the steps sequentially.

5.1 Short theoretical contextualization

With the goal of addressing the consumption-savings intertemporal choice of the rational agent, mainstream economic theory has specified a benchmark life-cycle model in which the representative household maximizes lifetime utility subject to a straightforward

dynamic rule of accumulation of assets (see Deaton, 1991; Carroll, 1997; Attanasio and Weber, 2010).

Although simple in its analytical form, this optimal control problem involves intricate dynamics. As pointed out by Winter *et al.* (2012, p. 479), “In realistic versions which incorporate income uncertainty, the solution of the underlying intertemporal optimization problem is rather complicated. It requires backward induction, and no closed-form solution for current consumption as a function of the relevant state variables exist.”

In practice, households do not solve a fully structured intertemporal plan when deciding how to allocate their current income between consumption and savings. Given the limited computational capabilities of the agents, their choices are often determined by straightforward heuristics or rules of thumb (see Deaton, 1992).

Consumption-saving decisions are influenced by a large variety of demographic and social factors, as documented in Horioka and Watanabe (1997) and Schunk (2009). Among these factors one can certainly include peer group effects emerging from established social norms. For instance, conspicuous consumption might impair savings in communities where social status is determined by how much one consumes of certain goods (Amaldoss and Jain, 2005). Significant differences on saving rates across different regions of the globe (Gandelman, 2015) indicate that there are different attitudes and behavior towards savings in the context of distinct human agglomerates, what constitutes a relevant argument in favor of the intuition that consumption-saving decisions are molded by the transmission of sentiments and values through processes of social interaction.

5.2 Description of the artificial world

Consider a world populated by a large number of infinitely-lived agents. Assume, as well, in a first moment, that the expected income of the individual agent corresponds to the initial income level $E(Y_t)=Y_0$. Effective income evolves under rule $Y_{t+1}=n_t Y_t$, with n_t a normally distributed random variable with mean equal to 1 and some standard deviation σ .

We assume that agents adopt the consumption-savings rule-of-thumb proposed by Deaton (1992). Under this rule, households spend all cash-on-hand up to mean income and a given percentage of any excess income above the mean value. Cash-on-hand is defined as the maximum amount of financial resources that can be spent in consumption on a given date, i.e., it corresponds to the sum of the endowment of assets that the agent holds with the current income in the assumed date. Given this definition, the rule basically states that agents do not save whenever income is below the respective expected value, and that they save a constant share of the disposable income whenever this exceeds expected income. In the original formulation of the rule, the percentage of excess income that is consumed is set at 30%; this is an *ad hoc* choice that allows to obtain results that are admissible in terms of compatibility with the empirical evidence. Nevertheless, this value might differ according to the perception households have about the possible benefits and virtues of saving and accumulating wealth.

Deaton’s rule is formally presented in Winter *et al.* (2012) under the form

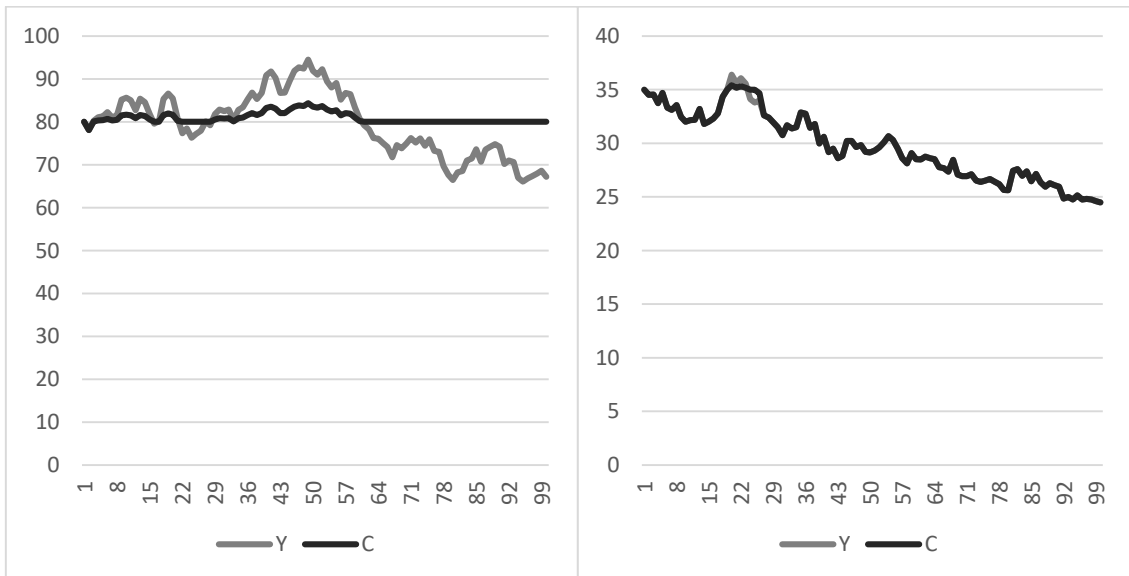
$$C_t = \begin{cases} X_t & \text{if } Y_t \leq E_t(Y_t) \text{ and } X_t \leq E_t(Y_t) \\ E_t(Y_t) & \text{if } Y_t \leq E_t(Y_t) \text{ and } X_t > E_t(Y_t) \\ E_t(Y_t) + \zeta[Y_t - E_t(Y_t)] & \text{if } Y_t > E_t(Y_t) \end{cases} \quad (1)$$

In equation (1), variable X_t represents cash-on-hand, i.e., the sum of income (Y_t) with the assets held by the agent (A_t). The accumulation of these assets is represented by the dynamics in equation (2), where r stands for the interest rate,

$$A_{t+1} = (1+r)(A_t + Y_t - C_t), \quad A_0 \geq 0 \text{ given} \quad (2)$$

Consumption rule (1) indicates that the household does not save whenever realized income is lower than expected income, $E_t(Y_t)$; in this case, the agent consumes cash-on-hand with a ceiling given by expected income. If realized income exceeds the corresponding expected level, then the agent saves a fraction of the excess income, which is $1-\zeta$. To arrive to this share, note that under $Y_t > E_t(Y_t)$, savings are $S_t = Y_t - C_t = (1-\zeta)[Y_t - E_t(Y_t)]$. The term $1-\zeta$ indicates the propensity to save out of excess income; higher savings are synonymous of a lower ζ .

The three panels in Fig. 1 show three possible income and consumption paths obeying rule (1). The first panel shows an initial phase where income rises above the expected level, allowing for savings to accumulate. After period $t=60$, income falls below the expected level and consumption remains at such level, pushing savings to negative levels (previously accumulated wealth is now spent). In the second panel, savings are almost inexistent along the displayed trajectory; the coincidence between consumption and income is the result of an effective income that remains below the expected level, in this case set at $E(Y_t)=35$. Finally, the third panel translates a circumstance in which the income progressively rises above the expected level, leading to a sustained increase in savings. Note, namely through panels 1 and 3 that consumption paths tends to be smoother than income trajectories, a commonly observed regularity.



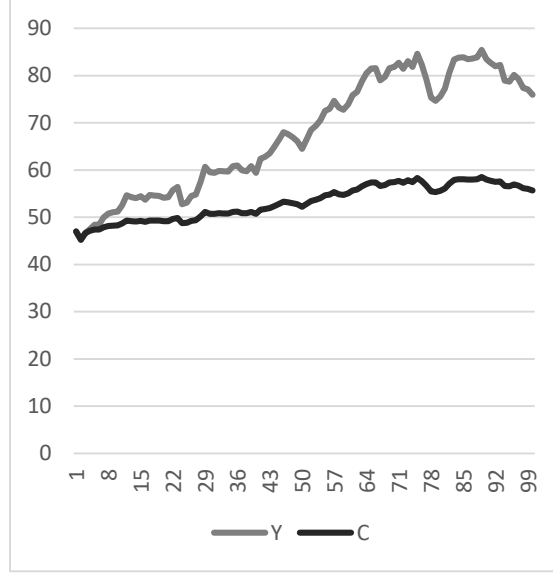


Fig. 1 – Income and consumption trajectories under Deaton's rule.

5.3 Sources of heterogeneity

If one wants to approach the artificial scenario of the previous subsection under an agent-based perspective, it is necessary to identify sources of heterogeneity across agents. At some initial date, agents are heterogeneous regarding two distinguishing features: level of income and degree of connectivity. The value of each of these two features that is specific to each agent might be drawn, for instance, from a Pareto distribution (following observed evidence; see, e.g., Gabaix, 2016).

We will assume that heterogeneity among agents manifests itself also in terms of the degree of optimism / pessimism regarding expected income. If expected income is equal to Y_0 then agents are assumed to be neutral. Otherwise, $E(Y_t) = (1 + \gamma)Y_0$, with $\gamma > 0$ for optimist agents and $\gamma < 0$ for pessimist agents. In this scenario, optimists believe their income will rise, and therefore consume more and save less, while for the pessimists the opposite occurs. The larger the value of γ in absolute value, the more optimistic / pessimistic agents are.

The value of parameter γ is arbitrarily set at the initial date for each agent. It can be, for instance, drawn from a normal distribution with zero mean. The evolution of the value of γ over time is supposed to depend on the degree of connectivity with other agents. In isolation, the evolution of γ will be characterized by increased extremism: $\gamma_{t+1} = \gamma_t(1 + a)$, $a > 0$. This extremism is mitigated by connectivity, i.e., we consider that $\gamma_{t+1} = \gamma_t(1 + a) + (k/N)(\gamma_t^{\text{ave}} - \gamma_t)$, with k the degree of connectivity, N the total number of agents, and γ_t^{ave} the average degree of optimism / pessimism of the network of contacts of the agent. In this circumstance, extremism will rise if the individual is in isolation, and will possibly fall if she is in contact with others.

The artificial world is by now completely described. This can be analyzed through the characterization of the time trajectories of income, consumption and savings for isolated individuals and for the aggregate. It is over this artificial world that we will set the simulation game in subsection 5.5.

5.4 Contact points with other modules

The consumption-savings setting described in the previous subsections approaches a specific decision process. Obviously, this decision process does not occur in isolation; it is related with many other socio-economic processes. There are some ‘loose ends’ that attach to other modules that can be formalized as well. The most evident are the following:

(i) Income generation – in the proposed simulation setting, income evolves through stochastic shocks, given some initial condition. In practice, income is decisively determined by investment in human capital and by labor market dynamics. These are two realities that must be modeled as well. Furthermore, investment in human capital requires savings, what implies a double link with the addressed consumption – savings decision process.

(ii) Interest rate – the proposed setup takes a fixed interest rate that rewards savings and allows to accumulate wealth. In reality, the interest rate is not constant and depends on how the money market functions (a money market module, including monetary policy actions can also be subject to analysis). Moreover, the simplified setup that was taken does not allow for diversified investments, with different levels of return and risk, an issue that might be integrated, additionally, into the simulation setup.

(iii) Connectivity – the simulation framework takes as given the level of connectivity of each agent. This can be endogenously modeled resorting to theories on dynamic complex networks where links across nodes can be formed or broken given some social or economic process.

(iv) Consumption profile – the highlighted consumption rule takes an undifferentiated consumption aggregate. To put together a more detailed simulation scenario, it would be relevant to set a consumption profile, where it could be possible, for each agent, to identify the share of expenditures associated with each class of consumption goods and services (non-durable goods, durable goods, housing, education, healthcare, energy and transportation, leisure).

5.5 Players’ objective and players’ decisions

Given the proposed economic setting for the analysis of household’s consumption – savings choices, we now introduce the possibility of “flesh and blood” players. These will act upon the simulation scenario one has already described. Two possibilities can be taken: one can consider a small set of players that interact with a large amount of “virtual agents” that behave as described above or, if a simpler framework is required, a network composed just by the “flesh and blood” players can be taken. This second option is the one adopted in the example of the next section, in order to simplify the presentation of results and the discussion.

We start by defining the player’s objective; this is to maximize intertemporal utility $\sum_{t=0}^T u(C_t)\beta^t$, with $\beta \in (0,1)$ the discount factor and $u(c_t)$ the instantaneous utility function. The utility function must obey trivial decreasing marginal utility properties. With various players, the winner will be the one with higher utility level. Although one can consider an infinite horizon, we exclude here this possibility by taking a finite ending time period T . This will allow to better highlight the advantages of savings; the income that is saved along the sequence of assumed time periods will be consumed in the final period, i.e., $C_T = X_T$; this is the transversality condition.

What are the player's choices? In the initial period, the agent chooses her degree of optimism / pessimism (the value of parameter γ), the degree of social interaction (the value of parameter k), and the propensity to save out of excess income (the value of parameter ζ), with the goal of maximizing intertemporal utility. Thereafter, k and ζ remain constant, while γ evolves under the rule already discussed.

The game is then a series of rounds where each player has the possibility of reviewing parameter values in order to get to the highest possible value of $\sum_{t=0}^T u(C_t)\beta^t$ at the end of each round.

5.6 Game implementation example

In this subsection, we present an example of the implementation of the simulation game. We consider a simple crude exercise with only three players. Relevant parameters are set at the following values: $\sigma=0.025$; $r=0.05$; $a=0.02$. The players share a same discount factor, $\beta=0.96$, and a same constant intertemporal elasticity of substitution utility function: $u(C_t)=\frac{C_t^{1-\theta}}{1-\theta}$, $\theta=0.25$. We also let $Y_0=100$ for each player.

We constrain the choices of players in the following way: (i) agents may save a lot ($\zeta=0.1$), may save an intermediate level ($\zeta=0.3$), or may save a small share of excess income ($\zeta=0.5$); (ii) agents can be optimistic ($\gamma=0.1$), pessimistic ($\gamma=-0.1$), or sentiment neutral ($\gamma=0$); (iii) agents may be fully connected ($k=2$), partially connected ($k=1$), or not connected at all ($k=0$). Plans are made at $t=0$ for the following 25 periods, $T=25$, and $C_{25}=X_{25}$.

The hypothetical choices of the players are presented in Table 1.

	ζ	γ	k
Player 1	0.5	0.1	0
Player 2	0.1	0	2
Player 3	0.3	-0.1	1

Table 1 – Choice of parameter choices.

The first player starts as an optimist, and the third one as pessimist; the second one is neutral. The optimist player is the one that chooses to remain isolated relatively to the others and it is the one that decides to save less out of excess income (when income remains above the expected level). The second player is the one that saves more and it is fully connected to the network of agents. Player 3 adopts an intermediate attitude towards savings and connects with only one other player (imagine that this is player 2). Running the simulation, the lifetime utility results are as presented in Table 2.

	Player 1	Player 2	Player 3
$\sum_{t=0}^T u(C_t)\beta^t$	936.989	1015.242	917.044

Table 2 – Utility results.

Note that the results in table 2 are not deterministic, given that the income is subject to random changes. Player 2, the one that saves the most and that is completely connected, is the one that performs better and, thus, wins this game round. Does this mean that

connectedness and thrift are always preferable in the suggested scenario? The built artificial world is sufficiently complex to be difficult to answer this question; besides individual choices, the stochastic nature of the environment and the impact of interaction make each decision-making process unique.

The game may be repeated over a set of sequential rounds, in which players may adjust their connectivity choices, their confidence levels, and their willing to save, in order to obtain progressively better lifetime utility outcomes. In this sense, the simulation game proposes the search for the best strategy through a trial and error process (i.e., through an adaptive learning process).

6. A Final Reflection and a Synthesis

Simulation games in business and economics are, if well implemented, an effective learning tool. These simulations need to balance playability with the transmission of meaningful knowledge about “how the world works” and, to know “how the world works”, scientists have developed innumerable theories and empirical studies.

How can one take advantage of scientific knowledge to develop effective simulation games? One reasonable way of conceiving a realistic simulation is to construct an agent-based model (grounded on complexity theory), where the large majority of players is fictional. In this fictional or artificial world, human players might participate and interact with the artificial intelligence agents.

It is virtually impossible to include all elements of reality into one single simulation model. The solution might be to take an integrative approach, i.e., to build successive modules that can be handled separately or, if a wider scenario is to be taken, in an integrated way.

This paper, in particular, proposes a prototype module concerning the consumption – savings decisions of households. After assessing how some strong ideas from the economic literature assist in generating an artificial world of heterogeneous interacting agents, a playable game has been proposed. In future work, this first module, confined to a specific reality, will be attached to other simulation environments that explore related subjects.

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