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Testing Carlo Cipolla's Laws of Human Stupidity with Agent-Based Modeling

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Abstract—We set up an agent-based simulation to test Carlo M. Cipolla's theory of human stupidity. In particular, we investigate under which hypotheses his theory is compatible with a well-corroborated theory like natural evolution, which we build into the model. We discover that there exist parameter settings which determine the emergence of stylized facts in line with Cipolla's theory. The assumptions corresponding to those parameter settings are intuitive and justified by common sense.

I. INTRODUCTION

In a tongue-in-cheek essay [1] written in English, tainted with Swiftian humor, printed in 1976 in a hundred of copies and distributed to friends as a Christmas gift, the late Italian historical economist Carlo M. Cipolla put forward a theory of human stupidity, articulated in five fundamental laws, which is regarded by many as a real work of genius.

One should not be misled by the humorous tone of Cipolla's essay into thinking his theory cannot be taken seriously. In fact, in most cultures, humor and jokes are a way to tell truths that hurt without breaking social norms or sounding disrespectful.

If taken seriously, Cipolla's laws should enable one to make falsifiable claims. Therefore, it should be possible to test his theory experimentally. In particular, if one accepts Darwin's theory of evolution, then for Cipolla's theory of human stupidity to be accepted it must be compatible with it. In this paper, we investigate under which circumstances and based on which assumptions the two theories do not contradict each other. We use agent-based simulation as an experimental tool to this aim.

In the last decade, agent-based modeling has become a widely accepted tool for studying the dynamics of complex systems in the social sciences [2], including economical phenomena like financial markets [3]. Agent-based modeling is the computational study, carried out by means of simulation, of economies that are modeled as evolving systems of autonomous interacting agents [4], [5]. The main advantage of agent-based over analytical models is that they allow the removal of restrictive assumptions and can, thus, lead to a more realistic description of the system under investigation.

The paper is organized as follows: a summary of the main claims of Cipolla's theory of human stupidity is given in Section II; the theory is then critically questioned in Section III and some conjectures are put forward to solve the arising issues. Section IV describes an experimental setup using agent-based simulation designed to test these conjectures; the outcome of

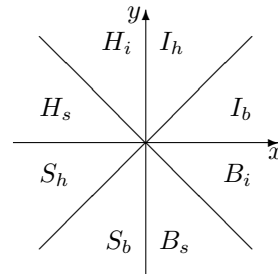


Fig. 1. Cipolla's diagram with its eight sectors. The uppercase letter identifies the quadrant and, therefore, the main character of an agent falling in the corresponding sector. The lowercase subscript refers to the undertones of the agent, deriving from its closeness to the neighboring quadrant.

the experiments are reported in Section V and conclusions are drawn in Section VI.

II. CIPOLLA'S THEORY OF HUMAN STUPIDITY

Cipolla identifies in stupid people one of the main obstacles to welfare in human societies and offers a coherent account of why stupidity is so powerful and hard to act against. To this end, he builds an abstract model of a human agent's social behavior, which may be summarized by two coordinates:

- x the average gain (or loss) that an agent obtains as a result of his or her actions;
- y the average gain (or loss) that an agent produces to other agents or groups of agents.

Two things have to be stressed: first of all, this notion of gain or loss is subjective and includes psychological and emotional factors—it must be thus understood as a *utility* as used in economics or game theory [6]; secondly, x and y are statistical expectations, for the actions of a given agent may yield different outcomes in different circumstances and an agent's behavior is, therefore, to be described by means of a probability distribution over the Cartesian plane.

As a result, human agents can be plotted as points on a diagram like the one shown in Figure 1 based on their $\langle x, y \rangle$ behavior. Figure 1 divides the two-dimensional plane into four quadrants or eight sectors, corresponding to different categories of agents.

Cipolla's definition of a *stupid* person (his Third Law) is “a person who causes losses to another person or to a group of persons while himself deriving no gain and even possibly incurring a loss”, thus, technically, an agent with $x \leq 0$ and

$y < 0$. Stupid persons thus fall in quadrant S of Figure 1. The persons falling in quadrant I ($x > 0, y \geq 0$) may be defined as *intelligent*, those falling in quadrant H ($x \leq 0, y \geq 0$) as *helpless*, and those falling in quadrant B ($x > 0, y < 0$) as *bandits*. Each quadrant may be further divided into two sectors: for instance, quadrant B may be divided into sector B_i , containing bandits with undertones of intelligence (for they cause fewer losses to others than the gains they derive) and B_s , containing bandits with undertones of stupidity (for their actions yield to them gains inferior to the losses inflicted to other people), and so on.

Now, Cipolla observes that any numerical estimate of the fraction σ of stupid people always and inevitably turns out to be an underestimate (First Law) and that the probability that a given person be stupid is independent of any other characteristic of that person (Second Law). From these observations, we can infer that stupid people must be an overwhelming majority of any sample we may draw from the general population.

Cipolla's Fourth and Fifth Laws basically say that stupid persons are the most dangerous type of persons, because it is impossible for non-stupid people to organize defenses against them, due to their irrationality and unpredictability.

III. CRITIQUE

There is something counterintuitive in Cipolla's theory: individuals who do not derive any gain and even possibly incur a loss from their actions, like stupid and helpless people, should have a competitive disadvantage vis-à-vis more opportunistic individuals. One would thus expect that, in the long run, they would lose ground and eventually get extinct. This, at least, is what would be suggested by the Darwinian law of natural selection or "survival of the fittest", which is generally accepted as a well-corroborated explanation of the evolution of the species, but also the basis of recent economic models, like the adaptive market hypothesis [7]. On the other hand, for the same reason, rational individuals like intelligent people and bandits should be expected to be more successful than stupid and helpless people, thus being able in the long run to take over the entire population.

The fact that evolution must be taken into account is indirectly confirmed by Cipolla himself, who writes that the potential for a stupid person to cause damages depends, first of all, on the genetic factor. He even goes as far as to postulate a gene for stupidity, which is inherited by stupid individuals from their parents.

Why, then, despite their apparent evolutionary handicap, can stupid people make up an overwhelming fraction σ of the human race? They must have some sort of competitive advantage which makes them particularly fit for reproduction, but how can it be?

There are several conjectures we could make to attempt to answer this question:

- 1) stupid people, causing damages to all other members of the society, neutralize, as it were, the forces of natural selection;
- 2) stupid people are more resilient to damages inflicted by others;

- 3) the observed σ fraction is an effect of the initial distribution of agents in the population: although it may not always be the case that σ is overwhelmingly high, once for some reason the stupid become a large majority, the situation cannot be reversed and evolution remains trapped in that state;
- 4) etc.

In the next section, we describe an experimental setup which should allow us to test these conjectures and suggest a solution to the enigma.

IV. EXPERIMENTAL SETUP

Members of the society are modeled as agents, whose behavior, stochastic in nature, is governed by a probability distribution which is innate in each agent and genetically determined.

The agents are evolutionary, in the sense that they are individuals of an evolutionary algorithm, whose details are illustrated below. Therefore, every agent has a *genome*, a set of parameters which determine its behavior. These genetic parameters do not change during the agent's entire lifetime but are subject to random mutation when passed on from a parent to its offspring.

An agent's genome consists of the parameters of a two-dimensional normal joint probability distribution,

$$(\mu_x, \mu_y, \sigma_x, \sigma_y, \theta), \quad (1)$$

where $\langle \mu_x, \mu_y \rangle$ is the mean, σ_x is the standard deviation along the x -axis, σ_y is the standard deviation along the y -axis, and θ is the rotation angle, which is used to randomly determine the outcome of its "actions".

Agents are subject to an evolutionary algorithm like the one described in [8].

Agents interact as follows:

- 1) an agent, whom we will call "active" because it will be the one that takes an action, is randomly selected from the population;
- 2) another agent, whom we will call "passive" because it will undergo the effects of the action taken by the active agent, is randomly selected from the remaining agents;
- 3) a pair $\langle x, y \rangle$ is randomly extracted from the active agent's normal distribution;
- 4) the active agent's wealth is updated according to x ;
- 5) the passive agent's wealth is updated according to y .

The above cycle, called a *period*, which is the clock that measures time in a simulation, is repeated over and over. We will denote by t the current period in a simulation.

Notice that, in general, this is *not* a zero-sum game. If most agents act intelligently, the population will enjoy an overall wealth increase; if, on the other hand, most agents act stupidly, the overall welfare of the population will decrease and nothing prevents it from eventually becoming extinct.

Optionally, one might enforce a zero-sum game by redistributing net wealth surplus or loss proportionally to all the

agents in a population to model the fact that in the real-world resources are finite (or, at least, quite unelastic) and the gain of some always determines a loss for the rest of the society.

Another possible variation of the model has to do with the way wealth is updated: let W_t^a and W_t^p be the wealth of the active and of the passive agent, respectively, at time t ; then,

- a *linear* wealth transfer is when $W_{t+1}^a = W_t^a + x$ and $W_{t+1}^p = W_t^p + y$;
- a *logarithmic* wealth transfer may be defined, whereby

$$W_{t+1}^a = \begin{cases} W_t^a + x, & \text{if } x \leq 0; \\ W_t^a + \log(x+1), & \text{otherwise;} \end{cases} \quad (2)$$

and similarly for W_{t+1}^p ;

- a *hyperbolic* wealth transfer may be defined, whereby

$$W_{t+1}^a = \begin{cases} W_t^a + x, & \text{if } x \leq 0; \\ W_t^a + \frac{x}{x+1}, & \text{otherwise;} \end{cases} \quad (3)$$

and similarly for W_{t+1}^p .

Notice that both the logarithmic and the hyperbolic transfer functions introduce an asymmetry between losses, which remain linear in all cases, and gains, whose transfer gets harder as they increase. The key intuition these two definitions try to capture is that it is exceedingly easy to destroy wealth, but creating it is hard, and gets harder the more wealth one wants to create.

To model the fact that rational agents know better, we may then introduce the notion of *defense*, by stating that rational agents (i.e., agents such that $\mu_x > 0$) are able to build defenses against bandits, but not, according to Cipolla's Fourth and Fifth laws, against stupid agents, with whom any countermeasure would turn out to be vain. This is how we propose to model such defense: in an interaction, if the passive agent is rational and the active agent is behaving like a bandit (i.e., $x > 0$ and $y < 0$), both x and y are discounted by multiplying them by a "defense factor" $1 - \delta$, where

$$\delta = \frac{\mu_x^p}{\mu_x^p + 1} \quad (4)$$

represents a hyperbolic discount factor which grows with the rationality of the passive agent; an infinitely rational agent will be able to completely neutralize a bandit's actions; an agent who is just slightly rational will discount but a small percentage of the damage caused by a bandit.

Finally, to model the hypothesis that stupid agents are more resilient than others to damages inflicted by their peers, we introduce the possibility that the x and y effects of an interaction be "relativized" with respect to the μ_x of the receiving agent (be it active or passive). Accordingly,

- the active agent's wealth would be updated according to $x - \mu_x^a$;
- the passive agent's wealth would be updated according to $y - \mu_x^p$.

A. Evolutionary Algorithm

Evolutionary algorithms (EAs) [9], [10] are a broad class of stochastic optimization algorithms, inspired by biology and in particular by those biological processes that allow populations of organisms to adapt to their surrounding environment: genetic inheritance and survival of the fittest. Each individual of the population represents a point in the space of the potential solutions for the considered problem. The evolution is obtained by iteratively applying a (usually quite small) set of stochastic operators, known as *mutation*, *recombination*, and *selection*. Mutation randomly perturbs a candidate solution; recombination decomposes two distinct solutions and then randomly mixes their parts to form novel solutions; and selection replicates the most successful solutions found in a population at a rate proportional to their relative quality. The initial population may be either a random sample of the solution space or may be seeded with solutions found by simple local search procedures, if these are available. The resulting process tends to find, given enough time, globally optimal solutions to the problem much in the same way as in nature populations of organisms tend to adapt to their surrounding environment.

An evolutionary algorithm is used by the simulator to make the agents evolve according to their interactions with their peers.

1) *Representation*: The parameters listed in Equation 1, which make up the genome of an agent, are encoded as an array of five floating-point numbers.

The bivariate normal probability density function may be written

$$f(x, y) = \frac{1}{2\pi\sqrt{|\mathbf{C}^{-1}|}} e^{(x-\mu_x, y-\mu_y)\mathbf{C}(x-\mu_x, y-\mu_y)^T}, \quad (5)$$

where the matrix

$$\mathbf{C} = \begin{bmatrix} a & b \\ b & c \end{bmatrix}$$

is positive-definite. Equation 5 may thus be rewritten as

$$f(x, y) = \frac{\sqrt{ac-b^2}}{2\pi} \cdot e^{-ar_x^2 - 2br_xr_y - cr_y^2}, \quad (6)$$

where $r_x = x - \mu_x$ and $r_y = y - \mu_y$.

Instead of encoding parameters a , b , and c directly in the genome, we encode the angle θ and the standard deviations σ_x and σ_y along the two axes (x and y), from which parameters a , b , and c may be computed based on the following equations:

$$a = \frac{\cos^2 \theta}{2\sigma_x^2} + \frac{\sin^2 \theta}{2\sigma_y^2}, \quad (7)$$

$$b = \frac{\sin 2\theta}{4\sigma_y^2} - \frac{\sin 2\theta}{4\sigma_x^2}, \quad (8)$$

$$c = \frac{\sin^2 \theta}{2\sigma_x^2} + \frac{\cos^2 \theta}{2\sigma_y^2}. \quad (9)$$

This choice has the advantage that all values for θ , σ_x , and σ_y , even negative ones, yield a positive-definite matrix $\mathbf{C}$. By the way, this representation, based on rotation angles, is well-known and used in evolution strategies [11].

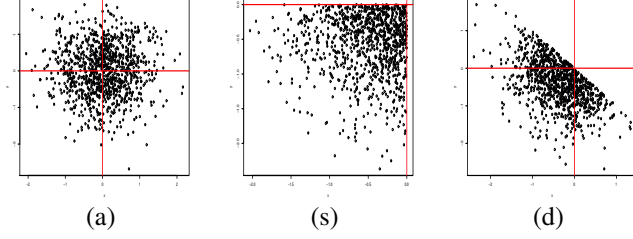


Fig. 2. The three initial distributions of the population used in the simulations: (a) the unfiltered standard normal bivariate distribution centered at the origin and with variance 1 along both axes; (s) the same distribution filtered to comprise stupid agents only; (d) the same distribution filtered to comprise deleterious agents only. The x - and y -axis are drawn in red.

2) *Initialization*: The genomes of the agents in the initial population are generated at random, according to the following rules:

- the $\langle \mu_x, \mu_y \rangle$ position of the agent on Cipolla’s diagram is randomly generated from a standard normal bivariate distribution centered at the origin and with variance 1 along both axes;
- σ_x and σ_y are independently extracted from a uniform distribution on $[1, 2)$;
- θ is extracted from a uniform distribution on $[0, 2\pi)$.

All individuals are assigned an initial wealth of 100.

To test the hypothesis that Cipolla’s laws are sensitive to the initial distribution of the population, such distribution may be modified by filtering out generated agents that do not respect a given constraint. In particular, we are interested in performing simulations with an initial population comprising only

- stupid agents ($\mu_x < 0$ and $\mu_y < 0$);
- agents that we might call *deleterious*, because they cause on average lower gains or greater damages to others than the gains or losses they derive from their actions ($\mu_y < -\mu_x$).

Although other initial distributions could be proposed, these are the two most “promising” initial distributions, besides the unfiltered one, to investigate in the light of Cipolla’s observations. The unfiltered and the two filtered initial distribution are shown in Figure 2.

3) *Fitness, Selection, and Reproduction*: The fitness of an agent is given by its *wealth*.

If, at any time, an agent’s wealth becomes negative, the agent dies. This is an implicit form of selection, which captures the fact that if an agent keeps on being harmed when interacting with its peers, eventually it will get extinct.

An agent whose wealth exceeds the predefined threshold of twice the initial wealth reproduces by asexual division. A new agent is created, which inherits (with mutation) the genome of its parent. The wealth is equally divided among the parent and offspring. This, too, may be regarded as an implicit form of selection, for the more an agent’s behavior is capable of

producing wealth, the more that agent will reproduce and pass on its genes.

As new agents may be generated by reproduction at any time as other agents may become extinct, in general the population size will fluctuate and in some cases may greatly increase or shrink until only one agent is left, depending on dynamics determined by the average behavior of agents in the population.

V. EXPERIMENTS AND RESULTS

We perform experiments by trying all possible combinations of the following parameters:

- $i \in \{\text{all}, \text{stupid}, \text{deleterious}\}$ (initial distribution): filter the initial distribution of the agents so that, respectively, *all* types of agents are generated, only *stupid* agents are generated, only *deleterious* agents (i.e., agents such that $\mu_y < -\mu_x$): see Figure 2;
- $f \in \{\text{linear}, \text{logarithmic}, \text{hyperbolic}\}$ (transfer function): the function used to modify wealth of agents participating in an interaction is, respectively, linear, logarithmic, or hyperbolic;
- $d \in \{\text{false}, \text{true}\}$ (defense): rational agents (i.e., agents such that $\mu_x > 0$) know how to defend themselves from bandits;
- $r \in \{\text{false}, \text{true}\}$ (relative): the effects of the interactions between agents are felt by either participant relative to their μ_x ;
- $z \in \{\text{false}, \text{true}\}$ (zero-sum): a zero-sum game is enforced, so that the total wealth of the population remains constant.

This gives a total number of 72 combinations, which will be encoded as a string of parameters as follows:

- Boolean parameters are omitted if their value is false, included otherwise;
- the remaining parameters will be followed by an abbreviation of their value;
- the parameters will be separated by hyphens.

For example, `ia-flin-d-r-z` will denote simulations with defense, unfiltered initial distribution, linear transfer function, relative effects, and zero-sum game enforcement.

All simulations are run with an initial population size of 1,000 agents and for one million time steps (i.e., agent interactions) or until the population size shrinks to one, in which case there is no point in continuing and we consider that the population has become extinct. In order to save computational resources, we set the maximum population size at 10,000. If that limit is reached, reproduction can happen only if another agent dies thus leaving one empty slot. However, this limitation does not change the results for the size of 10,000 is attained late in the simulation, if ever, when the final distribution type has already clearly emerged.

Figure 3 gives a comprehensive picture of the final population distribution for each parameter setting, which we can use

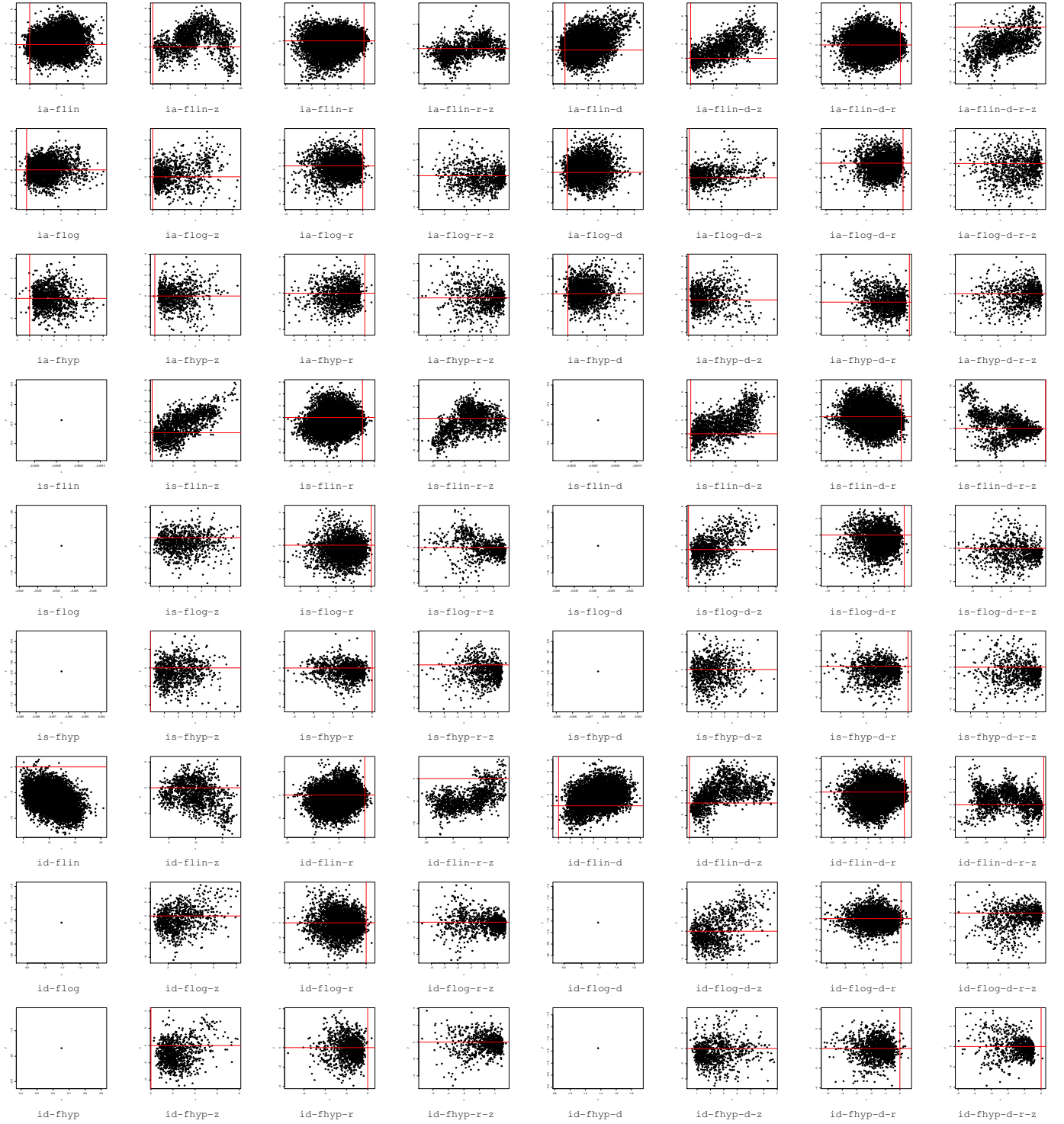


Fig. 3. The distribution of the population after 10^6 simulation steps or after the population size has shrunk to one (these cases are clearly visible, with a single agent in the center of the plot). The $x = 0$ and $y = 0$ lines are shown in red, to help the reader locate the individuals with respect to the four quadrant of Cipolla's diagram.

to get a first idea about which settings are most compatible with Cipolla's laws.

There are some general observations we can make based on these distributions:

- it is clear that relativization of the effects of inter-

actions (parameter r) is critical to the survival and proliferation of stupid agents; when r is turned off, the stupid and the helpless are mercilessly wiped out from the population, to the point that, even when they dominate the initial population, they manage to drive themselves into extinction;

- if we restrict our attention to runs with parameter r turned on, the most promising distributions may be observed when a zero-sum game is enforced (parameter z turned on): a clear preponderance of stupid agents shows up in simulations `ia-flin-d-r-z`, `is-flog-r-z`, `is-flog-d-r-z`, and `id-flin-r-z`;
- the only setting of simulation parameters which obtains a preponderance of stupid agents starting from a “neutral” initial distribution is `ia-flin-d-r-z`, with parameter d turned on: this suggests that the ability of rational agents to defend themselves from bandits may play a role in favoring a drift toward the evolutionary success of stupidity;
- an initial distribution biased toward stupid agents appears to have an impact on a prevalence of stupidity in the final population: a majority of the simulations that end up having a larger proportion of stupid agents than any other type has an initial population of stupid only ($i = \text{stupid}$).

Overall, eight parameter settings (six out of which assume an initial population of all stupid agents) achieved a final population distribution featuring a majority of stupid agents, though in some cases not an overwhelming one, as one would expect based on Cipolla’s Laws. These are: `ia-flin-d-r-z`, `is-flog-r-z`, `is-flog-d-r-z`, `is-fhyp-r`, `is-fhyp-r-z`, `is-fhyp-d-r`, `is-fhyp-d-r-z`, and `id-flin-r-z`. We are now going to examine these simulations in deeper detail.

Figure 4 shows the evolution of the composition of the population during typical simulations with each of the eight selected parameter settings. This gives us an idea of the evolutionary dynamics at work during these simulation and how the observed final distribution was reached.

We may notice that in simulation starting from a stupid-only initial distribution, the takeover of the population by the stupid is accompanied by a relative increase of the helpless; this is not the case with the two settings `ia-flin-d-r-z` and `id-flin-r-z`, where the proliferation of the stupid is virulent and leaves little hope to the other types; nevertheless, even in these latter cases, it is the stupid with undertones of helplessness that are responsible for the takeover and a few of them seemingly continue to spill over into the H_s sector, preventing it from becoming empty.

Figure 5 shows how the total wealth of the population changes during simulations for the two parameter settings where a zero-sum game is not enforced: in both cases, we observe the same pattern, whereby an initial crisis, whose cause is to be found in the great number of stupid agents with undertones of banditism (S_b), is overcome as their number decreases in favor of stupid agents with undertones of helplessness (S_h), some of which evolve into helpless with undertones of stupidity (H_s), as the population seemingly performs a 45° clockwise rotation away from the B quadrant. The total wealth evolution for zero-sum game parameter settings is not shown because, by definition, total wealth remains constant in those simulations.

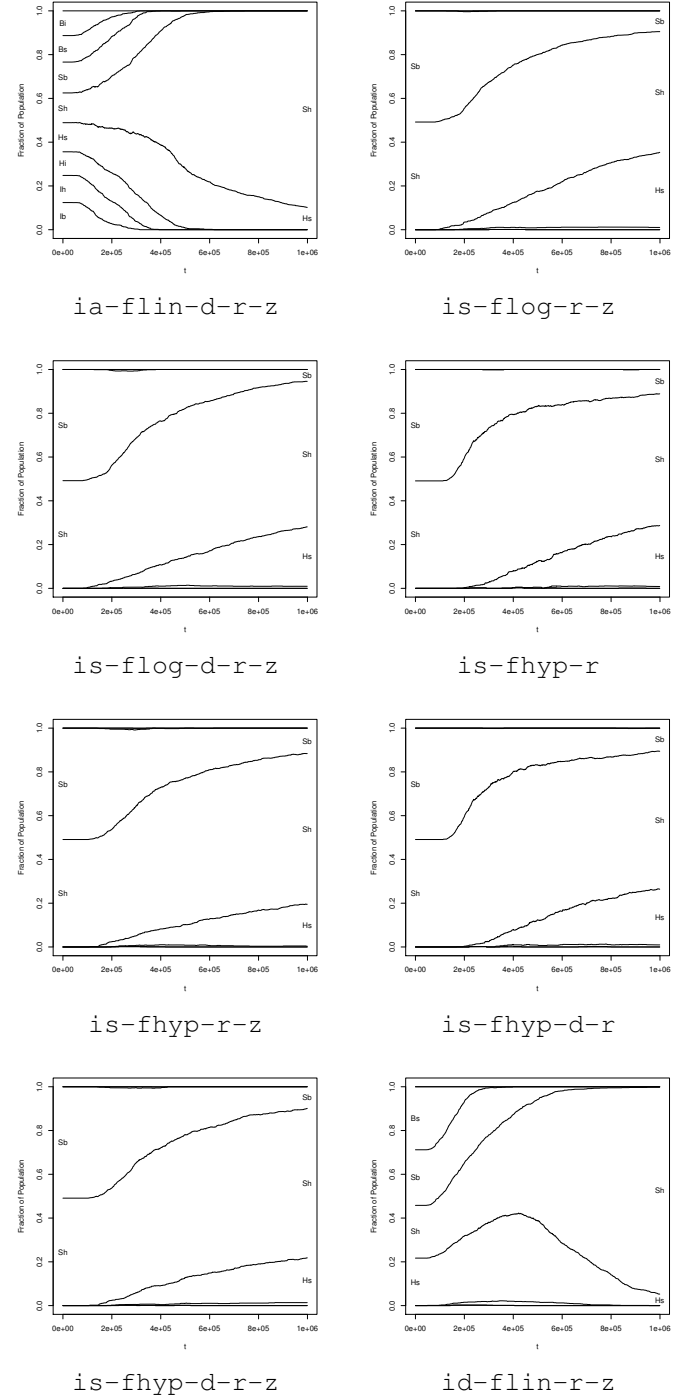


Fig. 4. Evolution of the composition of the population during a simulation with each of the eight selected parameter settings. The eight sub-populations located in the eight quadrants of Figure 1 are stacked in the diagrams starting from I_b and proceeding counterclockwise up to B_i and labeled on the left-hand and right-hand side of the diagram, if they make up for at least 5% of the population.

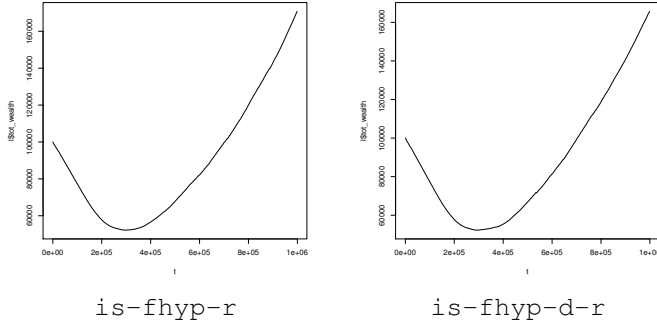


Fig. 5. Evolution of the total wealth of the population during the two simulations using parameter settings where a zero-sum game is not enforced.

Figure 6 shows the final wealth distribution for typical simulations with each of the eight selected parameter settings. An interesting remark is that simulations starting from an initial population of stupid agents only end up with a flat or right-skewed wealth distribution, which is highly unlikely and contrary to what is usually observed in real human populations, where the wealth distribution tends to follow a power law. In this sense, we might say that parameter settings *ia-flin-d-r-z* and *id-flin-r-z* look much more in line with what one would expect.

Figure 7 shows how the population size evolves in simulations using the eight selected parameter settings. It is interesting to observe that all simulations with $i = \text{stupid}$ exhibit a similar pattern, whereby the population size starts to increase, culminates after ca. 200,000 periods (except in *is-fhyp-r* and *is-fhyp-d-r*, where the population size is initially steady), and suddenly plummets to a minimum around the 400,000th period; such crisis is then overcome, and the population size reaches what looks like an equilibrium in three out of the six settings, whereas it starts to increase again in the other cases. Surprisingly, the two remaining settings, namely *ia-flin-d-r-z* and *id-flin-r-z*, show almost identical dynamics despite their differences: the population size increases with two initial bumps followed by temporary stagnations, after which the increase becomes steady.

VI. CONCLUSION

Some of the parameter settings we have tried led to emergent behaviors that are quite in line with Carlo Cipolla's theory. One parameter setting in particular, namely *ia-flin-d-r-z*, looks like a very promising first approximation of Cipolla's laws. This is all the more remarkable as the initial population is unfiltered. One hypothesis which appears to be critical to the corroboration of the theory is that the interactions among the agents be a zero-sum game: this is by no means an obvious assumption and, therefore, it calls for an explanation. The one we can offer is that the subjective utility of the agents, i.e., their perception of their own welfare, is somehow relative to the welfare of their peers. In a sense, it would be as if an agent compared its welfare to that of their peers and considered itself happy to the extent that it were in a better situation and unhappy to the extent that it were in a worse situation. If this were the case, then obviously any

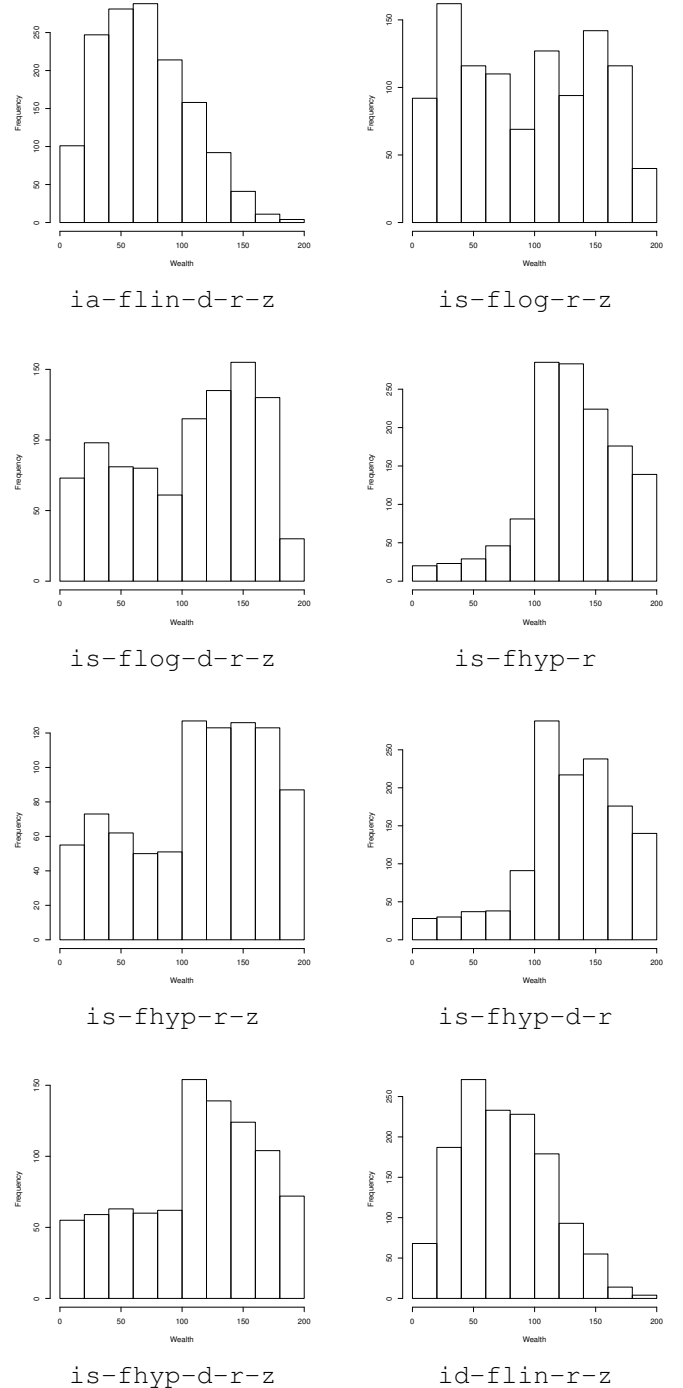


Fig. 6. Final wealth distribution at the end of simulations with the eight selected parameter settings.

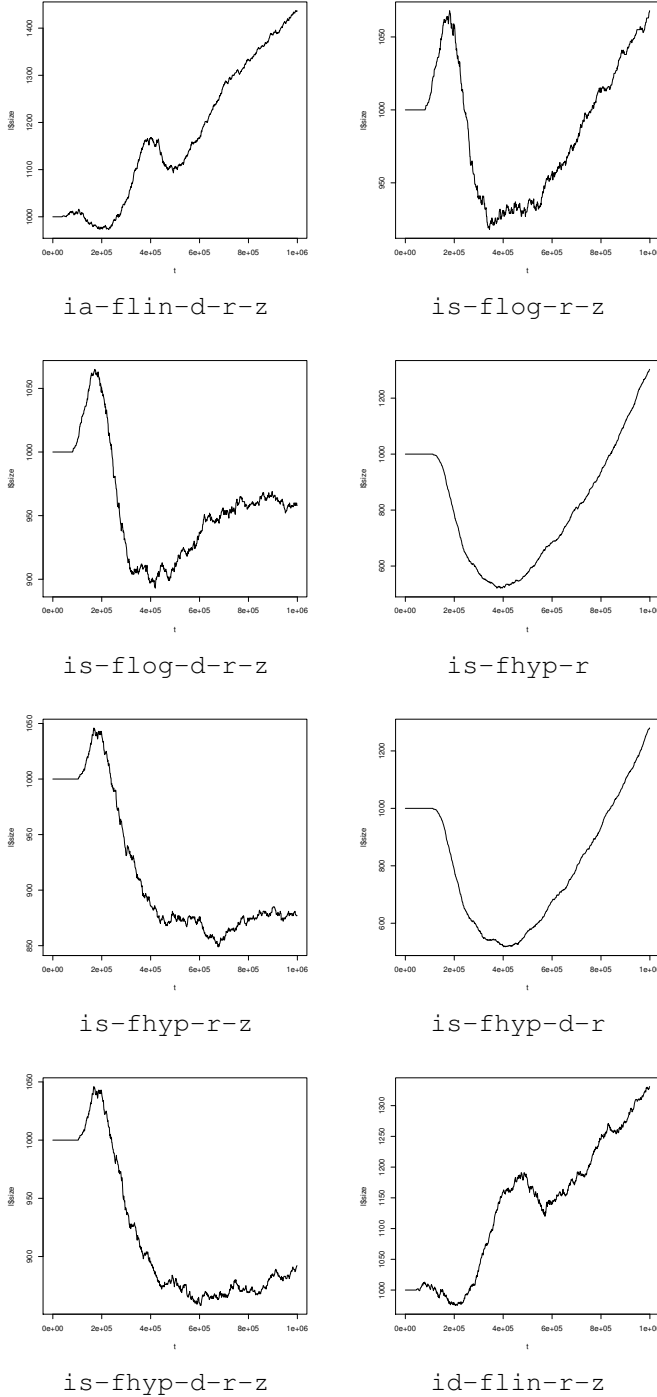


Fig. 7. Evolution of the population size in simulations using the eight selected parameter settings.

increase of an agent's wealth would determine a corresponding reduction of the wealth of the rest of the population.

Our results should be regarded as a first step toward understanding which additional hypothesis must be made in order to reconcile Cipolla's theory with other well-corroborated theories, like the theory of evolution. Possible future work might include enriching the evolutionary algorithm with sexual reproduction (i.e., recombination) and testing other conjectures that may help reproducing a state of affairs compatible with Cipolla's laws, such as a different propensity of agents to reproduce depending on their μ_x and μ_y .

Possible applications of our approach might be to model certain phenomena relevant to the behavior of human systems, like traffic jams, crowd movements, market bubbles and crashes, and the like. One might argue that stupid behaviors (in the sense of Cipolla) can actually be observed and probably play a significant role in those phenomena.

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