Experimentally Grounded Social Simulation

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GECS - Research Group on Experimental and Computational Sociology aims to integrate computational and experimental research to explain complex social and economic phenomena, such as markets, inter-organisational networks and societal transitions. Formally established in 2007 at the University of Brescia, it aims to promote innovative interdisciplinary research in economics and sociology by exploiting the advantage of modelling, computer simulation, and laboratory experiments.

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Objectives

- Cross-fertilizing experimental and social simulation methods for a better understanding of social interaction
- Examples: partner selection and trust in dynamic networks (Boero, Bravo and Squazzoni 2012) and the role of reputation for market behaviour (Boero et al. 2010)
- Drawing insights on ABM that support/extend Lab, Lab that tests ABM, and ABM that guide/inform the Lab
- Emphasizing pros and cons

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The ABM advantage is to provide a more realistic picture of human behaviour and interaction.

However, most social simulation models differ from more conventional models only in that they theoretically speculate in other directions.

This created a gap between theory and empirical research in social simulation, which mimics the unsatisfactory situation of social sciences.
Empirical methods in the social sciences do not always guarantee clean and/or suitable data to look at social interaction.

Both the lab and ABMs explicitly model agent interaction.

Experiments focus on the same kind of interaction situation of ABM, whereas this is impossible in the social reality.

The lab can be easily used as a data generator mechanism for ABM or as a test bed for simulation findings (Duffy 2006).

Observation scales
Trust and partner selection in social networks: An experimentally grounded model

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\textbf{ABSTRACT}

This article investigates the importance of the endogenous selection of partners for trust and cooperation in market exchange situations, where there is information asymmetry between investors and trustees. We created an experimental-data driven agent-based model where the endogenous link between interaction outcome and social structure formation was examined starting from heterogeneous agent behaviour. By testing various social structure configurations, we showed that dynamic networks lead to more cooperation when agents can create more links and reduce exploitation opportunities by free riders. Furthermore, we found that the endogenous network formation was more important for cooperation than the type of network. Our results cast serious doubt about the static view of network structures on cooperation and can provide new insights into market efficiency.
Cooperation has to do with the selective intelligence of agents when they give rise to networks based on people who like each other: good preferential choices and incentives to reliability to avoid isolation (Ashlock 1996; Joyce 2006)

Two sides: uncertainty makes long-term interaction partners look more attractive (Kollock 1994; Podolny 2001, Berkman 2004); trustworthiness and reliability signals (Molm 2000)

It is not the “continuity” of interaction that explains cooperation (Axelrod 2002; Cohen 2001), but the capability of agents of selecting their partners and changing network shapes

Partner Selection

- Experimental studies considered only stylized and highly unrealistic interaction structures, e.g., random coupled subjects (Berg 1995; Boero et al. 2009)
- Simulation studies and formal models were rarely based on experimentally verified assumptions (Cohen 2001; Pujol 2005)
- Our idea was to try to reduce these mutual limitations by combining the two methods

- Boero et al. (2009) Reputational Cues in Repeated Trust Games, Journal of Socio-Economics, 38(6), 871-877
108 participants, 6 groups of 18 subjects (Brescia and Cuneo), 10 rounds, about 15 Euros

Figure 1: The investment game: player $A$ profit = $d - I + R$; player $B$ profit = $d + 3I - R$. 
Fig. 2. Distribution of investments and returns in the experiment.
We used these experimental data to calibrate an ABM that reproduced the behavior of the subjects. With regards to A players, we estimated a coefficient $\beta_i$ that indicated how much the player modified his/her investment in each period as a function of the difference between the amount invested and the amount received by B players in the previous period.

For any player $i$ and period $t$, we computed the difference $X_{it} = R_i - I_i$, where $I_i$ and $R_i$ were the amounts that $i$ invested and received as return from his/her investment in the previous period respectively. We subsequently fitted the model

$$Y_{it} = \alpha_i + \beta_i X_{it} + \epsilon$$

(1)

where $Y_{it}$ was the amount invested by player $i$ in period $t$, in order to obtain two parameters $\alpha_i$ and $\beta_i$ for each subject that defined his/her behavior as A player. The equation (1) took into account that A players could have had an individual constant propensity to trust represented by the individual intercept $\alpha_i$, but also the capability of reacting upon past experiences, which was captured in the $\beta_i$ coefficient.

On the other hand, B players were supposed to react mainly against what they received from A players. In order to capture their behavior, we estimated a third coefficient $\gamma_i$ defined as the average amount returned by each subject as proportion of the amount received in each period plus the fixed endowment. Therefore, the parameter $\gamma_i$ represented an estimate of the player’s trustworthiness.
Fig. 3. Distribution of $\alpha_i$ and $\gamma_i$ with regression line.
### Partner Selection

#### Table 1: The simulation scenarios

<table>
<thead>
<tr>
<th>Model name</th>
<th>Main characteristics</th>
</tr>
</thead>
</table>
| `experimentLike` | • random coupling in each period  
• one way interaction            |
| `twoWays`    | • random coupling in each period  
• two way interaction            |
| `fixedCouples` | • fixed couples  
• two way interaction            |
| `denseNetwork` | • fixed fully connected network  
• two way interaction            |
| `smallWorld` | • fixed small-world network  
• two way interaction            |
| `scaleFree`  | • fixed scale-free network  
• two way interaction            |
| `dynamic1Couples` | • dynamic network  
• broken links are replaced only for isolated agents  
• two way interaction  
• start from random coupling |
| `dynamic1Dense` | • dynamic network  
• broken links are replaced only for isolated agents  
• two way interaction  
• start from dense network |
| `dynamic2Couples` | • dynamic network  
• broken links are replaced only by one of the two formerly linked agents  
• two way interaction  
• start from random coupling |
| `dynamic2k10` | • dynamic network  
• broken links are replaced only by one of the two formerly linked agents  
• two way interaction  
• start from a regular network of degree 10 |

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- **Threshold happiness function**
- **From fully connected to random networks**
### Partner Selection

<table>
<thead>
<tr>
<th>Model name</th>
<th>Period 1–10</th>
<th></th>
<th>Period 11–20</th>
<th></th>
<th>Period 21–30</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><code>dynamic1Couples</code></td>
<td>3.65 (2.58)</td>
<td>2.92 (2.96)</td>
<td>3.67 (2.60)</td>
<td>2.95 (2.90)</td>
<td>3.68 (2.62)</td>
<td>2.96 (2.93)</td>
</tr>
<tr>
<td><code>dynamic1Dense</code></td>
<td>3.79 (2.67)</td>
<td><strong>3.32</strong> (3.20)</td>
<td>3.66 (2.60)</td>
<td>2.96 (2.96)</td>
<td>3.68 (2.62)</td>
<td>2.97 (2.94)</td>
</tr>
<tr>
<td><code>dynamic2Couples</code></td>
<td>3.82 (2.68)</td>
<td><strong>3.37</strong> (3.42)</td>
<td><strong>4.48</strong> (3.01)</td>
<td><strong>5.02</strong> (4.50)</td>
<td><strong>4.63</strong> (3.11)</td>
<td><strong>5.58</strong> (5.12)</td>
</tr>
<tr>
<td><code>dynamic2k10</code></td>
<td><strong>4.11</strong> (2.82)</td>
<td><strong>4.00</strong> (3.59)</td>
<td><strong>4.43</strong> (3.01)</td>
<td><strong>4.85</strong> (4.30)</td>
<td><strong>4.49</strong> (3.04)</td>
<td><strong>5.02</strong> (4.50)</td>
</tr>
<tr>
<td>Experiment</td>
<td>3.48 (2.69)</td>
<td>2.79 (3.58)</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

Table 4: Average investments and returns in the original experiment and in the dynamic network models. Standard deviations are in parenthesis. Averages significantly different (at the 10% level) from the experimental ones are marked in bold.
Figure 5: Average number of links per agent in the dynamic2Couples and dynamic2k10 models.
Dynamic networks made the difference: the effect of interaction outcome implied that good guys had multiple relationships and isolated free riders

Clusters of cooperators who had more links/interactions and achieved higher payoffs

This confirms Eguiluz’ findings (2005): agents in central positions have more links and play an essential role in sustaining cooperation in the system

Eguiluz et al. (2005) Cooperation and the Emergence of Role Differentiation in the Dynamics of Social Networks. AJS, 110(4), 977-108

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How does reputation affect, at the micro level, the economic performance of agents in uncertain environments and, at the macro level, the exploration capability of the system? Comparing social systems where agents are atomized entities relying only on their individual capabilities/experience and systems where agents can rely on reputation mechanisms.
64 subjects, 38 females / 26 males, two days, October-November 2007

The FTB Game: exploring an uncertain solution space (e.g., financial market)

17 rounds (end unknown)

Initial endowment

Final payoff
Decision and communication

- Decision
  - Exploration via random search
  - Exploitation
  - Follow others’ hints

- Communication
  - True yield (first best security)
  - True yield (second best security)
  - Lower yields
  - Higher yields
Patterns

- If you trust, you explore, don’t lie or reciprocate!
- Players who lie are those who don’t trust and exploit!

<table>
<thead>
<tr>
<th></th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>I1</td>
<td>12.50%</td>
<td>1.56%</td>
<td>12.50%</td>
<td>26.56%</td>
</tr>
<tr>
<td>I2</td>
<td>17.19%</td>
<td>4.69%</td>
<td>28.13%</td>
<td>50.00%</td>
</tr>
<tr>
<td>I3</td>
<td>1.56%</td>
<td>7.81%</td>
<td>14.06%</td>
<td>23.44%</td>
</tr>
<tr>
<td>Total</td>
<td>31.25%</td>
<td>14.06%</td>
<td>54.69%</td>
<td>100.00%</td>
</tr>
</tbody>
</table>
Final profit, endowment and exploration

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The model

- The model consisted of 100 agents, direct interaction between randomly paired agents, variability of yields, scarcity of resources.
- Simulation runs were repeated 1000 times and results averaged.

<table>
<thead>
<tr>
<th>Simulation Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agents</td>
<td>100</td>
</tr>
<tr>
<td>Securities</td>
<td>1 million</td>
</tr>
<tr>
<td>Standard deviation of yields’ distribution</td>
<td>500</td>
</tr>
<tr>
<td>Initial Endowment</td>
<td>1000 ECU</td>
</tr>
<tr>
<td>Exploration cost</td>
<td>8000 ECU</td>
</tr>
<tr>
<td>Number of interactions</td>
<td>495</td>
</tr>
</tbody>
</table>

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### Simulation scenarios

#### Base settings

<table>
<thead>
<tr>
<th>Setting</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&quot;exploit_only&quot; Pure exploitation: agents can only exploit securities randomly distributed at the beginning of the simulation</td>
</tr>
<tr>
<td>2</td>
<td>&quot;explore_only&quot; Pure exploration: agents can only explore via a random search, when they have enough resources to do so</td>
</tr>
</tbody>
</table>

#### No trustworthiness evaluation

<table>
<thead>
<tr>
<th>Setting</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>&quot;listen_always&quot; No trustworthiness evaluation: agents communicate information as observed in the experiment and trust everybody</td>
</tr>
</tbody>
</table>

#### Trustworthiness evaluation at the individual level

<table>
<thead>
<tr>
<th>Setting</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>&quot;individual_J_pos&quot; Agents explore partners' trustworthiness without sharing any personal experience with others and with a &quot;positive attitude&quot; towards unknown partners (presumption of partner trustworthiness)</td>
</tr>
<tr>
<td>5</td>
<td>&quot;individual_J_neg&quot; Agents explore partners' trustworthiness without sharing any personal experience with others and with a &quot;negative attitude&quot; towards unknown partners (presumption of partner untrustworthiness)</td>
</tr>
</tbody>
</table>

#### Trustworthiness evaluation is shared at the system level (reputation)

<table>
<thead>
<tr>
<th>Setting</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>&quot;collective_J_pos&quot; Agents know the partners' reputation (trustworthy/cheater) if any and follow a &quot;positive attitude&quot; towards unknown partners (presumption of partner trustworthiness)</td>
</tr>
<tr>
<td>7</td>
<td>&quot;collective_J_neg&quot; Agents know the partners' reputation (trustworthy/cheater) if any and follow a &quot;negative attitude&quot; towards unknown partners (presumption of partner untrustworthiness)</td>
</tr>
</tbody>
</table>
Impact of positive/negative attitudes on space exploration and endowment of agents

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Dynamics of final profit of agents

Set
- EXPLORE_ONLY
- INDIVIDUAL_J_NEG
- INDIVIDUAL_J_POS
- LISTEN_ALWAYS

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Dynamics of lemons

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Conclusions

- Social information is a learning mechanism ‘cheaper’ than individual experience; perhaps, this is why even investors often rely on it.
- Exploiting other experiences seems to be a good strategy to profit in uncertain environments.
- Beyond the “fast and frugal heuristics” experimental approach: it is not only the “simplicity” of heuristics that helps agents to make good decisions, but the chance that they incorporate social information.
Cross-fertilization

ABM

Data

Lab

Evidence
Strenghts

- Integrating theory and empirical research: being guided by evidence rather than by speculation is crucial for social simulation
- Approaching micro-macro link issues in terms of observation scales helps to ‘secularize’ the debate
- Reducing the problem of external validity of experimental results, by helping to achieve finding generalisation across scales (as in all branches of experimental sciences)
- Achieving testable findings
Weaknesses

- This type of research is time/money/labour consuming and is risky (need for lab facilities, humans very often escape our predictions, even in the lab!)
- There are no standard which to rely on, yet
- The challenge of external validity of experimental data is still unsolved (although it is largely overstated…)

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