Self-efficacy and institutional persistence: an experimental approach

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Institutions are believed to emerge from the combined effects of many individual decisions making processes (Greif and Laitin, 2004). In fact, it is widely recognised that institutions are not top-down formations but rather voluntary agreements agents make to implement a specific arrangement (Kosfeld et al., 2009). Institutional change, hence, depends on how people learn to make choices and filter the available information concerning the behaviour of others. The emergence of new rules of the game is affected by learning processes. In economics and political science, social learning phenomena are often referred as "informational contagion or cascades" (Arthur and Lane, 1993; Anderson and Holt, 1997; Bikhchandani et al., 1992). Theoretical models predict that when individuals discard private information and choose on the basis of the behaviour displayed by others, a neat path-dependent dynamics with long term stability – highly dependent on early events in the choice sequence – can emerge. In some cases, social learning can act as a vehicle for the diffusion of maladaptive behaviour and lock society into an inefficient choice path.

According to Bandura's social learning theory (Bandura and McClelland, 1977), learning processes are the dynamic result of the interplay between external sources of influence and self-efficacy perceptions. These represent the beliefs people hold on their own capabilities and they are developed as a consequence of mainly personal and peers' experiences, and verbal persuasion. Self-efficacy influences the goals people wish to pursue as well as the degree of control they are able to exercise over external environments. Thus, through learning, self-efficacy impacts institutional change.

Building upon the above mentioned streams of literature, in this paper we investigate firstly whether and how self-efficacy levels affect learning processes. Secondly, we will explore the conditions under which social learning processes lead to institutional change. To achieve this goal we propose an experimental design which is a modified version of the common bandit problem with finite time horizon (Gittins, 1979).[1]

The reasons for choosing a two-armed bandit experimental task are several. Firstly, this setting allows us to assess how people make reiterative choices, to check for their consistency over time. Moreover, small modifications allow us to control for the effect of social interactions and contextual mutations on individual behaviour. In fact, it has been acknowledged that people's preferences are inconsistent and context-dependent (Shafir et al., 1993). Moreover, when choosing amongst alternatives, people do not analyse all options in detail but rather sequentially eliminate sub-sets of possibilities according to a hierarchical structure (Tversky and Sattath, 1979). Lastly, binary choices lie at the core of the two-armed bandit. Although Simon underlined the importance of binary choice experiments to test for example utility-maximising principles as already as 1959, to the best of our knowledge only very few experiments in economics have followed this prescription (Banks et al., 1997; McElreath et al., 2005; Gans et al., 2007).

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[1]The bandit problem takes its name from the common slot machines which can be found in casinos. In order to play, the gambler inserts a coin and pulls one of the machine's available handles (or arms) initiating the spinning of some flywheels. When the flywheels stop, a combination is displayed and the player receives a payoff. The subsequent gamble starts from the last combination obtained, nevertheless the player can choose to pull another of the available arms. At any trial, the gambler compares the scores obtained through the chosen handles. His objective is to maximise, over a series of pulls, the expected payoff discovering which one is the best arm.

To make the link between Bandura's self-efficacy theory and emergence of institutions, our subjects will first be presented with a standard questionnaire to assess their self-efficacy levels (Schwarzer and Jerusalem, 1995). Second, they will answer 10 questions aiming at measuring their problem-solving abilities and math skills. These questions were taken from the standard Graduate Record Examination (GRE) test. Lastly, students will participate in the experimental game whose design is briefly reported in Table 1. Participants must repeatedly choose among two colours. Each choice receives a payoff, but the payoff to each colour is drawn from a distribution, which is unknown to the players. Subjects are expected to maximise the aggregate value of their payoffs. The game is divided into 3 treatments which differ from one another mainly in terms of the information participants receive. In the first treatment, the subjects choose between two colours and are informed about the score obtained from the last most recent decision. In treatment two, subjects will be part of a group of 5 people and will receive the following information. They will observe their score from the previous round. Moreover, they will be informed about the most recent decision made and reward obtained by a randomly selected group leader who decides before everybody else. Lastly, in the third treatment subjects are given three pieces of information. As in treatment two, participants are informed about the result of their individual decision in the last round as well as about the choice made and score obtained by the random group leader (who might not be the same subject as in treatment 2). In addition they will also observe the choice the majority of the group members made in the previous round and the average reward they obtained. Thus, we are able to detect the effect of additional information on people's choices patterns and their stationarity. Each treatment contains 3 settings of 20 rounds. Each setting is played with low, medium or high variance in the payoff distributions. Payoffs are drawn from a normal distribution with a given variance and mean. The mean of the more rewarding colour is fixed and equal to 13 units, while that of the less rewarding one is 10 units. The variance instead determines the difficulty of the decision-making environment. When the variance is low (equal to 0.25), it is easy to learn which is the best colour. When the variance is set medium (equal to 4), choosing one colour results in unpredictable payoff. Conversely, when the variance is very high (equal to 16), detecting the more rewarding colour is very difficult. The best colour is randomly selected and changes in every setting. Moreover, the sequence of variance values comes in random order in each treatment and changes across groups. All participants play each setting and each treatment, registering 180 choices per participant.

The results of the experiment will be used as follows. Following our theoretical framework, we will test how people's self-efficacy levels affect their learning processes. In order to do so, we will assume people make decisions following a standard logit model. Assuming various updating rules (simple average, memory decay and Bayes rule), we will estimate for each individual and for each time period, the expected value of the mean of the payoff distribution. We will identify the exponent of the logit model from the experimental data carrying out a brute search in the state space (Simulated Method of Moments). This measurement might be polluted by the problem-solving abilities people hold. After controlling for this using the data retrieved through the GRE test, we will confront the best fit with the results obtained by the self-efficacy scale questionnaire. Our hypothesis is that highly self-efficacious people will randomise less than others. Subsequently, data from treatment two will be used to measure individual reliance on mimesis. For this purpose, we will use a nested probability model. The best fit from the first analysis and a dummy variable indicating whether the leader chose the same colour which is being evaluated, will be weighted by a parameter alpha. Alpha will hence measure whether and to what extent people rely on individual learning or leader mimesis. Data from the third treatment will be used to check whether group conformity is more likely than leader mimesis. We will use again a nested probability model wherein a free parameter theta is meant to capture the trade-off between mimesis and group conformity. The best fit for both parameters (alpha and theta) will be retrieved from the experimental data. We will then confront them with the results of the self-efficacy scale.

Table 1: Experimental design

	Treatment 1	**Treatment 2**	**Treatment 3**
Task	Binary choice (Colour 1 vs Colour 2)	Binary choice (Colour 1 vs Colour 2)	Binary choice (Colour 1 vs Colour 2)
Information provided	1. Individual choice made and reward obtained in the previous round	1. Individual choice made and reward obtained in the previous round 2. Leader's choice and reward he obtained in the current round	1. Individual choice made and reward obtained in the previous round 2. Leader's choice and reward he obtained in the current round 3. Choice made and average reward obtained by the majority of group members in the previous round
Leader	No	Yes (randomly selected, unknown and with first mover advantage)	Yes (randomly selected, unknown and with first mover advantage)
Group	No	Yes (size = 5 unknown participants)	Yes (size = 5 unknown participants)
Variance payoff distributions (= level of difficulty)	3 values (High, Medium, Low)	3 values (High, Medium, Low)	3 values (High, Medium, Low)
Number of repetitions	3 settings of 20 rounds (total=60)	3 settings of 20 rounds (total=60)	3 settings of 20 rounds (total=60)

This experiment has been coded in PhP in order for it to be easily administered through a web browser on computers or tablets. We will conduct the experiment among 200 university students in the experimental laboratory of the University of Maastricht. Preliminary results are expected by mid-April 2015.

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