# Escape Poverty Trap with Trust? An Experimental Study [†]

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**Abstract**

In this study, we ask if trust can help poor economies escape a poverty trap and, if so, whether such an impact can be generalized regardless of the initial endowment condition. We follow Lei and Noussair (2002, 2007) and design a decentralized market economy that has the structure of an optimal growth model. A threshold externality is introduced to generate two equilibria where the Pareto-inferior equilibrium is considered as a poverty trap. We find that trust matters in deciding an economy's likelihood of escaping the poverty trap, but that this impact is much weaker on the poorer of the poor.

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## 1. Introduction

Trust is essential. It promotes cooperation and facilitates mutually beneficial exchanges. It is an indicator of social cohesion and, as argued by Arrow (1972) and Putnam et al. (1993), a predictor of economic success as well. Indeed, at the aggregate level, many papers have found that trust is positively correlated with the level or the growth rate of GDP (see, for example, Knack and Keefer, 1997; La Porta et al., 1997; Dasgupta and Sergaldin, 2000; Zak and Knack, 2001; Dearmon and Grier, 2009; Yann and Cahuc, 2010; Doh and McNeely, 2012; Horvath, 2012). Ample evidence has however emerged in recent years which indicates that the trust-growth relationship is neither robust nor universal (Helliwell, 1996; Beugelsdijk et al., 2004; Beugelsdijk and van Schail, 2005; Berggren et al., 2008; Roth, 2009; Müller et al., 2012; Peiró-Palomino and Tortosa-Ausina, 2013). Reverse causality from income to trust has raised concerns as well.[1] Taking advantage of the fact that some regions suffered more than others during the 2008-2009 financial crisis in Russia, Ananyev and Guriev (2015) show that the causal effect of income on interpersonal trust is significant not only statistically but also economically. Finally, it is worth noting that the standard trust measure which relies on the World Values Survey (WVS) question “Generally speaking, would you say that most people can be trusted or that you cannot be too careful in dealing with people?” has been criticized by many for lacking validity and reliability (Yamagishi et al., 1999; Miller and Mitamura, 2003; Knorringa and van Starveren, 2006; Nooteboom, 2007; Reeskens and Hooghe, 2008). Beugelsdijk (2006) provides evidence suggesting that the WVS measure tends to reflect institutional rather than interpersonal trust which is at the foundation of Arrow’s or Putnam et al.’s theoretical framework of the trust-growth relationship.

[1] See Algan and Cahuc (2013) for a review of the recent attempts to address this issue in the literature.

Considering that the empirical literature has yet to provide a conclusive evidence regarding the causal impact of trust on economic success, we propose an experimental approach as a complementary methodology to tackle this issue. We are mindful of the limitations imposed by a laboratory setting to address economy-wide matters, but we argue that it has several advantages in this particular context.[2] First, the experimental trust measure derived from Berg et al. (1995) has been shown to be robust against the stake size, the extent of the strategy space, the use of the strategy method, and the characteristics of the experimenters. More importantly, using newly developed survey questions that are meant to distinguish interpersonal from institutional trust, Naef and Schupp (2009) find that the experimental trust measure is strongly correlated with the former not the latter, suggesting that it is a valid indicator to study the trust-growth relationship. Second, unlike empirical studies where causality is a matter of great concern, our experimental design elicits subjects' interpersonal trust before they start participating in the dynamic growth game of Lei and Noussair (2007). In other words, our design ensures that trust is exogenous in relation to economic success at least at the beginning of the growth game. Also note that, according to a simulation based on the parameters chosen for the experiment, our laboratory economies regardless of their endowment condition should save most, if not all, of their output in the first two periods in order to overcome a threshold externality and escape a poverty trap. Therefore, if trust is an essential element to determine an economy's economic performance, it should demonstrate such an impact almost immediately after the launch of the growth game.[3] Third, there are a few channels through which trust may influence economic performance (Arrow, 1972; Hardin, 1982; North,

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[2] See Amano et al. (2014) for a discussion of the pros and cons of using experimental methodology to study macroeconomic issues.

[3] We do not exclude reverse causality in that trust can be further enhanced or mitigated *after* an economy succeeds or fails to escape the poverty trap. As a result, we will focus our data analysis mostly on the beginning of the growth game in Section 5.

1990; Ostrom, 1990; Putnam, 1993; Whiteley, 2000; van Staveren and Knorringa, 2007). For instance, trust helps lower transaction costs. As a result, more resources can be diverted to production and innovation. Trust also tends to reduce incentives for opportunism which makes it easier for members of a society to solve collective action problems and avoid free riding or coordination failure. With the growth game of Lei and Noussair (2007), we are able to tackle specifically the latter channel as our design, as briefly mentioned above, features a threshold externality that allows us to investigate if and to what extent trust discourages opportunistic behavior and ultimately improves an economy's chances of success.

The specific research questions we ask are as follows: Can trust serve as a coordination device to generate a "big push" out of the poverty trap for an economy? If so, is this effect universal regardless of an economy's initial endowment condition? We follow Lei and Noussair (2002, 2007) and design a dynamic, decentralized laboratory economy that has the structure of an optimal growth model. Participants must decide how to allocate their individual output between consumption and saving/investment in each period. As in Lei and Noussair (2007), a "big push" where individuals coordinate their investment decisions to push the aggregate capital stock above a certain threshold is required for the economy to utilize a more efficient production technology. There exist two equilibria in which the Pareto-inferior one is considered as a poverty trap. Lei and Noussair (2007) find that economies that start with an endowment below the threshold rarely manage to leapfrog the hurdle. Instead, their capital stocks consistently converge to a level closer to the Pareto-inferior equilibrium. Such a behavior pattern, in our opinion, renders Lei and Noussair's dynamic laboratory environment an ideal testbed to study the effectiveness of formal institutions or informal rules and norms to generate an escape from the poverty trap.

To address our research questions, we divide each session of the experiment into two parts. We adopt a 2×2 design where the treatment variables are the matching protocol used in Part I and the initial endowment given in Part II. The two matching protocols—random vs. endogenous—are meant to elicit different trust intensities between treatments. The two endowment conditions—below vs. above the Pareto-inferior equilibrium output predication—are introduced to study if the trust-growth relationship depends on an economy's initial development status. As a result, we have four treatments referred to as RandomBP (random matching + below poverty trap), RandomAP (random matching + above poverty trap), EndogenBP (endogenous matching + below poverty trap), and EndogenAP (endogenous matching + above poverty trap). Note that there have been studies in the experimental literature that investigate behavioral spillovers from one game to another (see, for example, Bednar et al., 2012; Cason et al., 2012, 2013; Savikhin and Sheremeta, 2012; Banerjee, 2016; Herz and Taubinsky, 2017). But to our knowledge, our paper is the first that utilizes this framework to study the role of interpersonal trust in promoting collective economic success in an environment that is of direct relevance to growth and development.

As reported in Sections 4 and 5, we find that, compared to economies that are formed under the random matching protocol, those formed under the endogenous matching protocol tend to cultivate more trust and consequently are more likely to escape the poverty trap at the beginning of the growth game. This result clearly supports the notion that trust promotes economic success. That being said, we also find that the likelihood to escape depends partially on the endowment condition. Trust has a much weaker impact on the below-poverty-trap economies, suggesting that the trust-growth relationship cannot be generalized across countries with different levels of development. Finally, as to how trust allows poor decentralized market economies to surpass the capital threshold, we find that trust is able to enhance their ability to collectively overcome the intertemporal coordination failure. Unfortunately, for the poorest of the poor, this coordination advantage of trust is undermined by their endowment disadvantage, implying that norms alone would not be sufficient to dramatically change their poverty status.

The rest of the paper is organized as follows. Section 2 briefly describes the decision environment in the growth game of Lei and Noussair (2007). Section 3 details our experimental design and procedures. Section 4 reports the results regarding trust formation from Part I of the experiment. Section 5 reports the results from the growth game in Part II. Section 6 concludes.

## 2. The Decision Environment in the Growth Game

The underlying environment that our experimental economy is based upon is the same as that in Lei and Noussair (2007). The economy is assumed to choose a sequence of consumption levels $\{C_1, C_2, \ldots\}$ to maximizes its lifetime utility:

$$\sum_{t=0}^{\infty}(1+\rho)^{-t}U(C_t)$$

where $\rho$ is the discount rate, $C_t$ is the aggregate consumption in period *t*, and $U(C_t)$ is the aggregate utility function. The resource constraint facing the economy is:

$$C_t + K_{t+1} \leq AF(K_t) + (1-\delta)K_t, \tag{2}$$

where $\delta$ is the depreciation rate, $K_t$ is the aggregate capital stock at the beginning of period *t*, and $F(K_t)$ is the aggregate production function. $A$ is a production efficiency parameter that takes on two values depending on whether or not the aggregate capital stock achieves at least a critical mass $\widehat{K}$:

$$A = \begin{cases} \overline{A}, & \text{if } K \geq \widehat{K} \\ \underline{A}, & \text{if } K < \widehat{K} \end{cases}, \tag{3}$$

where $\overline{A} > \underline{A}$. In other words, in our environment, a “big push” where coordinated investment decisions that push the aggregate capital stock above the threshold is needed in order for a “takeoff” to occur.

The first-order conditions require

$$U'(C_t) = (1+\rho)^{-1}[1-\delta+AF'(K_{t+1})]U'(C_{t+1}), \tag{4}$$

the resource constraint (2), and the transversality condition

$$\lim_{t \to \infty} (1+\rho)^{-1} U'(C_t) K_{t+1} = 0 \tag{5}$$

to be binding. As a result, at a steady state equilibrium, $C_t = \bar{C}$ and $K_{t+1} = \bar{K}$, $\forall t \geq 0$, must satisfy

$$\bar{C} = AF(\bar{K}) - \delta \bar{K}, \tag{6}$$

and

$$AF'(\bar{K}) = \delta + \rho. \tag{7}$$

In our experiment, the economy's aggregate production capability is a discrete approximation, mapping integers to integers, of $16.771\sqrt{K_t}$ if $K_t \geq 31$ and $7.88\sqrt{K_t}$ if $K_t < 31$. The aggregate utility is approximated by $400C_t - 2C_t^2$. The depreciation rate and the discount rate are set to be 1 and 1/10, respectively.[4]

## 2.1 Optimal Equilibrium

Given the environment and the parameters described above, numerical simulations which compare the present discounted utility of all possible decision sequences suggest that, under the direction of a benevolent social planner, the economy would asymptotically converge to $(\bar{C}, \bar{K})$ = (70, 45) regardless of its initial endowment level. More specifically, in the low-endowment condition where $K_0 = 6$ in our experiment, the optimal sequence of aggregate capital stock is {$K_1$, $K_2$, $K_3$, $K_4$, $K_5$, …} = {15, 31, 40, 45, 45, …}. In the high-endowment condition where $K_0 = 19$, the optimal sequence of aggregate capital stock is {$K_1$, $K_2$, $K_3$, $K_4$, $K_5$, …} = {31, 40, 45, 45, 45, …}. In other words, if our economies are guided by

[4] As noted in Lei and Noussair (2002), the main drawback of setting $\delta = 1$ is that it risks the possibility of having zero capital stock in any given period if the economy consumes all its output. Without being able to produce output and re-accumulate capital, the economy would cease to exist. Therefore, having $\delta = 1$ may make it more difficult for our experimental economies to reach a steady-state equilibrium. Yet, technically speaking, this parameter choice also renders a more straightforward decision environment for our human subjects. Therefore, we continue the practice from Lei and Noussair (2002, 2007) and Capra et al. (2009) by choosing $\delta = 1$.

a social planner, it should take them no more than two periods to reach the threshold capital stock $\widehat{K} = 31$ and, by period 5, all economies should converge to the optimal steady state $\overline{K} = 45$.

## 2.2 Competitive Equilibrium

The optimal equilibrium of the social planner provides the benchmark solution that maximizes the welfare of the economy as a whole. But to study if and how members of a decentralized market economy could coordinate their investment decisions to exceed the threshold, we follow Lei and Noussair (2007) and divide the aggregate production capability and the values of consumption among five individual agents who make up the economy.[5] Given this design feature, there exist two stable competitive equilibria in which $(\bar{C}, \overline{K})$ = (70, 45) and (16, 9).[6] The former is the social planner's optimal equilibrium, whereas the latter can be considered as a poverty trap. Lei and Noussair (2007) find that decentralized market economies that start with an endowment below the threshold rarely manage to leapfrog the hurdle $\widehat{K} = 31$. Instead, their capital tends to converge to a level closer to the Pareto sub-optimal equilibrium. Economies that start with an endowment slightly above the threshold generate mixed results. Compared to their low-endowment counterparts, it is less likely for them to converge to the poverty trap. Yet, they don't converge to the Pareto optimal equilibrium either. Over-accumulating capital stock especially early on appears to be a common phenomenon among these economies. So based on these findings as well as the fact that both of our initial conditions are below the threshold capital stock level, we expect that our economies will have a very difficult time to even achieve the threshold and that a convergence toward the Pareto inferior equilibrium will most

[5] How we divided the production and utility schedules among five individuals will be detailed in Section 3.1.2 below.
[6] See Lei and Noussair (2007) for more details about the competitive equilibria noted here.

likely occur. The empirical question is whether or not the group trust developed in the first part of the experiment will be strong enough to defy such a destiny. The details of our experiment are described in Section 3 below.

## 3. The Experiment

The experiment consisted of nine sessions of data that were conducted at the City University of Hong Kong between June and July 2011. A total of 138 undergraduate students were recruited from College of Business via email. Some of the subjects may have participated in economics experiments before, but none had any experience in experiments similar to ours. Sessions lasted about three hours including software training, instruction for Parts I and II, and payment to subjects. All communication between subjects took place via a computer interface that was programmed and conducted using the Ztree software package (Fischbacher, 2007). Trade was denominated in an experimental currency, called “francs,” which was converted to Hong Kong dollars at predetermined and publicly known conversion rates. Including a participation fee of HK$40, subjects earned an average of HK$260 (roughly US$34).[7]

We divided each session of the experiment into two parts, and implemented a 2×2 design where the treatment variables were the matching protocol used in Part I and the initial endowment given in Part II. The matching protocol was either random or endogenous. The initial endowment results in an aggregate output level that was either below or above the Pareto inferior equilibrium output of 25. Both endowment levels were, however, below a threshold level that would enable economies to use a more efficient technology to produce. Table 1 provides the numbers of sessions and subjects participated in each of the four treatments: RandomBP (random matching + below poverty trap), RandomAP (random

[7] The minimum wage in 2011 was HK$28 or US$ 3.60 per hour, which was paid by most of the fast food restaurant chains in Hong Kong.

matching + above poverty trap), EndogenBP (endogenous matching + below poverty trap), and EndogenAP (endogenous matching + above poverty trap).

[Table 1: About Here]

The timing of activity within each session was as follows. Upon arriving at the experiment, subjects were seated by their own choice of a computer terminal in the laboratory. Once everyone was seated, subjects reviewed a tutorial that lasted about 20-25 minutes on the use of the z-Tree software for trading in a continuous double auction market. After the software training phase, the instructions for Part I of the experiment were read aloud for the subjects who followed along with their own copy of the text. Subjects were allowed to ask questions relating to Part I's rules or procedures at any time during the instructional phase. The instructions for Part II were handed out and read aloud for the subjects after Part I was concluded.[8] Part II proceeded after all questions were answered.

### 3.1 RandomBP and RandomAP Treatments

Each session in the RandomBP or RandomAP treatment was divided into two parts: Part I and Part II.

#### 3.1.1 Part I

There were 10 periods in Part I. 15 participants were randomly and equally divided into three groups, called Group A, B, and C, at the beginning of each period to play two trust games extended from Berg, Dickhaut, and McCabe (1995). As in Berg et al., there were two stages in each game. In stage 1, all participants received 10 francs as a cash endowment. Each participant *i* had an opportunity to send none, some, or all of his cash endowment to a randomly selected member *j* from his own

[8] The fact that the experiment consisted of two parts was written in the instructions and thus common knowledge to all participants. Nevertheless, other than knowing that the grouping determined in period 10 of Part I would be used to determine their group affiliation in Part II, subjects did not have any information regarding the exact contents of Part II until after Part I was completed. See Section 3 for the grouping procedure.

group. This decision was made by clicking on the button that indicated the amount he wished to transfer. All money transferred was tripled by the experimenter before it reached member $j$. While participant $i$ was making his decision, another randomly selected group member $k$, where $k \neq j$, had to choose to send none, some, or all of his cash endowment to $i$. All money transferred by $k$ was tripled before it reached $i$. That is, in each period, every participant $i$ had to play two trust games with two randomly selected members $j$ and $k$ from his group. He was the trustor in the game with $j$, but the trustee in the game with $k$. In stage 2, all participants had to simultaneously decide to return none, some, or all of the money received in stage 1 from their respective trustor. Figure 1 depicts the interaction among group members in the trust games.

[Figure 1: About Here]

At the end of each period, the computer displayed a summary screen of $i$'s own group affiliation, sent and returned decisions, and period earnings that equaled 10 – the amount sent to member $j$ + the amount returned from member $j$ + 3 × the amount sent by member $k$ – the amount returned to member $k$.

#### 3.1.2 Part II

At the beginning of Part II, subjects were divided into groups of five to play the growth game similar to Lei and Noussair (2007). The grouping was based on participants' group affiliations at the beginning of period 10 in Part I. In other words, if someone was randomly placed into Group A in period 10 of Part I, he would remain in Group A and interact with the same group members for the entire Part II of the experiment. Intergroup interactions among different groups were not permitted in Part II. As a result, we had three independent groups of data for the growth game from each session of the experiment.

As in Lei and Noussair (2007), each group of five was considered as a decentralized economy in which group members had to make a sequence of production, trading, consumption, and saving decisions over a series of periods. At the beginning of period 1, depending on the treatment, a group started with either 20 or 35 units of output that were equally distributed among five members and available to be traded immediately.[9] In addition to 4 or 7 units of output, each group member was also given 10,000 units of the experimental currency, called "francs," to facilitate trading. A computerized double auction market was open for two minutes for group members to trade with each other. After the market was closed, all participants had to decide how to allocate their output on hand between consumption $c_1^i$ and saving that would eventually become period 2's initial capital stock $k_2^i$. At the end of period 1, the computer displayed a summary screen of subjects' own output levels before and after trading, consumption, saving, and period earnings that equaled the utility of consumption plus trading profit (end-of-period cash balance – 10,000). At the bottom of the summary screen, the computer also informed each participant whether or not his group's aggregate capital stock at the beginning of period 2, $K_2 = \sum_1^5 k_2^i$, had exceeded the threshold level of 31. As in Lei and Noussair (2007), the exact amount of $K_2$ was not being provided to the participants. Also, no one had any information about the other two groups' trading activity, consumption or capital stock accumulation. After period 1 concluded, a random ending rule with a constant continuation rate of 90% was implemented to determine if the growth game would move on to period 2. If so, the cash balance would be reinitialized to 10,000 and the production process transforming each individual's capital stock $k_2^i$ into output $y_2^i = A \cdot f^i(k_2^i)$ would take place

[9] The corresponding initial capital stocks were 6 and 19, respectively. Both levels were below the threshold capital level of 31 that would permit economies to use a more efficient technology to produce. We departed from Lei and Noussair (2007) by equally dividing the initial aggregate output, rather than capital, among five group members. Since different agents were endowed with different production capabilities, having the same initial capital stock would immediately result in income inequality that might hinder economic growth in our experiment. We therefore decided to start with a more homogenous income distribution than in Lei and Noussair (2007).

automatically as well. The rest of period 2 or any following period *t* was proceeded in the same way as in period 1.

*Individual Production and Utility Functions*

The aggregate production capability $A \cdot F(K_t)$ was divided into five pieces $A \cdot f^i(k_t^i)$ among five group members. The marginal products of the first five units of $K_t$ were allocated to agents 1, 2, 3, 4, and 5 in a consecutive manner. Thereafter, the marginal product of the 6th unit of $K_t$ was given to agent 1, the marginal product of the 7th unit of $K_t$ was given to agent 2, etc. In other words, agent 1 received the marginal products of the 1st, 6th, 11th, 16th, … units of $K_t$ whereas, for example, agent 4 received the marginal products of the 4th, 9th, 14th, 19th, … units of $K_t$. Since the production efficiency parameter $A$ took on two different values, the individual production schedule consisted of two parts reflecting $16.771 \cdot K_t^{1/2}$ if $K_t \geq 31$ and $7.88 \cdot K_t^{1/2}$ if $K_t < 31$. The individual production schedules, shown in Figure 2, were all private information.

[Figure 2: About Here]

The marginal utility of consumption for agent *i*, which was a discrete approximation of $396 + 4i - 20c_t^i$, was determined in a similar fashion to reflect the economy-wide utility function of $400C_t - 2(C_t)^2$. The individual valuations of consumption were all private information as well.

*Random Ending Rule*

To create an infinite-time-horizon decision environment, we followed Lei and Noussair (2002, 2007) and introduced a random ending rule in which the experimenter rolled a 10-sided die at the end of each period to determine if the game would continue. The game ended immediately if the die came up number 0. The constant continuation rate of 90% implies a $\rho$ = 1/10 in the model.

Since subjects were recruited to participate in the experiment that had been scheduled to last three hours, if the growth game described above was terminated with more than 45 minutes remaining, they would play a new game in which output and cash balance were reinitialized to their respective levels as in the beginning of the first game. If the growth game was still in progress at the end of the time for which subjects had been recruited, subjects were offered an opportunity to return, play with the same group of participants, resume the same role, reclaim the same utility and production functions, and continue where the game left off on another day. If a subject decided not to come back, a substitute would be recruited to replace him.[10] The earnings made by the substitute would be awarded not only to the substitute herself but also to the original subject. This double-payment procedure, adopted by Lei and Noussair (2002, 2007), was meant to preserve the incentives for subjects to make optimal decisions even when they were not able or willing to continue the game on another day.

### 3.2 EndogenBP and EndogenAP Treatments

The EndogenBP and EndogenAP treatments were exactly the same as the above two treatments except that the matching protocol used in Part I was different. In the EndogenBP and EndogenAP treatments, 15 participants were randomly and equally divided into three groups only at the beginning of period 1. Thereafter, each person's group affiliation at the beginning of periods 2 to 10 was determined by his as well as the other 14 participants' affiliation preferences.[11] Specifically, after the decisions in the trust games were being made in period $t$, where $t = 1, 2, 3, \ldots, 9$, the computer screen displayed a table summarizing the amount sent and the

[10] Overall, only three substitutes were recruited in this experiment.

[11] This was similar to the voluntary association mechanism used in Page et al. (2005), although subjects in Page et al. only needed to make a regrouping decision every three periods.

proportion returned by each of the 15 participants that were sorted by group.[12] Within each group, the information was presented in a way so that participants could only identify their own decisions but not others'. In the last column of the table, subjects were asked to provide their preferences for those whom they most wished to be grouped with. Subjects ranked the other 14 participants from 1 (the highest and most favorable rank) to 14 (the lowest and least favorable rank). Assigning the same rank to two or more participants was allowed. To speed up subjects' ranking process, their ranking decision made in the last period was shown on the screen as the default ranking except in period 1 where the default was a rank of 7.5 for all participants. Subjects were free to change the ranking as they wished.

After all 15 participants had completed this ranking task, the computer then formed the first group of five, Group A, whose mutual ranks of one another were the lowest among all the possible grouping combinations.[13] In other words, the five participants in Group A were those who mutually most preferred to be together for the next period. The computer repeated the same process for the remaining 10 participants to form the second group, Group B.[14] The remaining 5 participants were automatically placed into Group C. Note that no regrouping was done at the end of period 10. Subjects' group affiliations in period 10 were also their affiliations for the entire Part II of the experiment. Our intention here was to make sure that any group norm established at the end of Part I could be easily carried over into Part II.

[12] If a participant received 0 from his trustor in stage 1, a N/A was shown on the screen as his "% Retuned."
[13] Altogether, there were 3,003 grouping combinations that the computer needed to check in order to form Group A.
[14] After excluding Group A's five members from the remaining ten subjects' ranking lists, the computer had to first rescale the ranks down to 1-9 for each subject and then check all 252 possible grouping combinations to form Group B.

## 4. Results from Part I

In this section, we investigate whether endogenous matching helps facilitate different norms of trust and trustworthiness to be formed and, more importantly, weather the average levels of trust and trustworthiness are higher with endogenous than with random matching. Note that, since the endowment condition only matters in Part II of the experiment, we will pool the data from EndogenBP with those from EndogenAP and also the data from RandomBP with those from RandomAP to analyze the impact of endogenous vs. random matching on trust (the amount sent) and trustworthiness (the proportion returned) in this section.

The evolutions of the average amount sent in Group As, Bs, and Cs of the two endogenous matching treatments are shown in Figure 3. The average amount sent in Group As surges dramatically from period 1 to period 2, and remains close to the maximum possible amount until period 10 when the end-game effect finally kicks in. The average amount sent in Group Bs lingers mostly around 8.0 from period 2 to period 9, and is never as large as the average amount sent in Group As. Similarly, members in Group Cs send considerably smaller amounts than both As and Bs in all but the first two periods. These patterns are in sharp contrasts to those in the random matching treatments where the average amounts sent of Group As, Bs, and Cs, shown as dashed lines in Figure 3, are rather similar to one another, suggesting that random matching from period to period is unable to induce various norms to be formed.

[Figure 3: About Here]

The evolutions of the average percentage returned, given in Figure 4, exhibit very similar patterns as in Figure 3 except that the average percentage returned by members in Group Cs of the endogenous treatments is not that different from those in the random matching groups. We summarize these results as follows.

[Figures 5: About Here]

**Result 1:** *Participants in different groups of the random matching treatments do not send or return amounts that are significantly different from each other. By contrast, those in the endogenous matching treatments send and return significantly more to their members in Group As than in Group Bs than in Group Cs. In other words, endogenous matching is an effective instrument to help participants sort themselves into high, medium, and low trust and trustworthy groups.*

**Support for Result 1:** As shown in Table 2, the average amount sent between periods 2 and 10 in the random matching treatments is 4.28 in Group As, 4.34 in Group Bs, and 3.92 in Group Cs. The average proportion returned is 20.75% in Group As, 21.14% in Group Bs, and 20.63% in Group Cs. Based on Wilcoxon matched-paired signed-ranked tests, none of the differences in the amount sent or proportion returned is significant.[15] The average amount sent and proportion retuned during the same nine periods in the endogenous matching treatments are 9.20 and 69.14% in Group As, 7.75 and 48.47% in Group Bs, and 5.90 and 24.10% in Group Cs. Wilcoxon signed-ranks tests suggest that the differences in the amount sent or proportion returned between A and B, A and C, and B and C in the endogenous matching treatments are all significant at the 5% level, implying that this self-sorting algorithm is able to divide participants into high (A), medium (B), and low (C) trust and trustworthy groups. ■

[Table 2: About Here]

Result 1 suggests that interacting with like people reinforces one's good (or bad) behavior which in turn facilitates distinct group norms to be formed. But how did subjects determine with whom they wished to be grouped? More specifically, did one's trust (the amount sent) and trustworthiness (the percentage returned)

[15] Since some subjects moved from one group to another, we cannot treat each group as an independent observation. As a result, Wilcoxon matched-pairs signed-ranks tests are more appropriate for the pair-wise comparisons here.

matter when being ranked by others? If so, were they equally important? To answer these questions, we adopt a simple ordinary least squares regression model on the average rank assigned to player $i$ at the end of period $t$ by the rest of the 14 participants. The explanatory variables include player $i$'s average rank at the end of period $t-1$ , the percentage sent by $i$ (out of 10) in period $t$, the percentage returned by $i$ (out of the amount he received) in period $t$, and a dummy variable that equals 1 if player $i$ is male and 0 otherwise.[16] Table 3 reports the estimates with robust standard errors adjusted for within-session correlations.

[Table 3: About Here]

**Result 2:** *Trustworthiness matters significantly more than trust in determining how one is being ranked by others, implying that people prefer to interact with those who are more trustworthy (and, to some extent, more trusting) in the endogenous matching treatments.*

**Support for Result 2:** The estimated coefficients on the percentage sent and the percentage returned shown in Table 4 are significantly negative, indicating that the more you sent or return to your fellow group member, the more favorable rank you will receive from the other 14 participants.[17] Moreover, since the difference between the two estimates—one is four times larger than the other—is statistically significant ($p$-value = 0.0057), trustworthiness appears to be more influential than trust in determining how one is being judged by others. ■

The endogenous matching procedure is able to elicit diverse norms among different groups, but how does it pan out in terms of the average levels of trust and trustworthiness compared to the random matching procedure? The result is summarized below.

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[16] We use the percentage amount sent rather than the absolute amount sent in order to directly compare the relative importance between trust and trustworthiness.
[17] Note that subjects ranked the other 14 participants from 1 (the highest and most favorable rank) to 14 (the lowest and least favorable rank).

**Result 3:** *The average amount sent and the average percentage returned from period 2 to period 10 in the endogenous matching treatments are significantly greater than in the random matching treatments.*

**Support for Result 3:** As shown in Table 3, the amount average sent is 4.19 under random re-matching and 7.62 under endogenous re-matching. The average percentages returned under the two respective matching mechanisms are 20.63% and 47.24%, respectively. Taking each session as an independent observation unit, nonparametric Mann-Whitney rank-sum tests indicate that the differences in both the amount sent and the proportion returned are significant ($p$-value = 0.0143). ■

Will higher levels of trust and trustworthiness give endogenous matching groups a better chance to escape the poverty trap in Part II? Before investigating the relationship between norms and economic performance at the group level, we would like to point out that it should come as no surprise from Result 2 that there exists a strong and positive correlation between trust and trustworthiness in our data. In fact, if we use the mean percentages sent and returned among five group members in periods 9 and 10 as proxies for a group's initial trust and trustworthiness levels at the beginning of Part II, we will have a 0.7605 Spearman's rank correlation coefficient between the two variables that is significant at the 1% level.[18, 19] As a result, in the next section, we will focus on trust and investigate if trust established at the end of Part I helps economies escape a suboptimal poverty trap introduced in Part II.

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[18] As shown in Figures 4 and 5, the amount sent or percentage returned in the endogenous matching groups suffers from a considerable end-game effect in period 10. Therefore, we chose to use the average percentage sent or returned between periods 9 and 10 to mitigate the impact of the end-game effect. Note that the group composition in period 9 was not exactly the same as that in period 10 (the number of new group members is, on average, 1.27 in period 10). Nonetheless, we made such a decision based on the assumption that the norm would remain stable even with a slightly different group composition between the last two periods.

[19] We take each group as an independent observation unit.

## 5. Results from Part II

We will examine the treatment effects on the likelihood to escape the poverty trap in Section 5.1, and on the levels of consumption and total welfare in Section 5.2. Since the results from these two subsections indicate that trust is able to jump-start growth rather effectively, we will discuss the specific coordination hurdle(s) that trust tends to help overcome during an economy's growing process in Section 5.3.

### 5.1 Treatment Effects on the Likelihood to Escape the Poverty Trap

Are the endogenous matching groups able to accumulate enough capital stock to escape the poverty trap in the growth game? To answer this question, we need to first define what we mean by "escaping the poverty trap." Knowing that the aggregate capital stocks in Lei and Noussair's (2007) low-endowment economies tend to converge toward the Pareto-inferior equilibrium, we decide to take a more ambitious approach than Lei and Noussair (2007) or Capra et al. (2009) and define "escaping the poverty trap" as having an aggregate capital stock $K \geq \widehat{K} = 31$.[20] In other words, we will use the threshold rather than the Pareto inferior equilibrium capital stock level as the benchmark because, after all, surpassing the threshold in theory would enable an economy to utilize a more efficient production technology and thus allow it to take off possibly toward the Pareto optimal equilibrium.

The average levels of capital stock over all periods, shown in Table 4, are 14.52, 28.35, 27.84, and 39.96 in RandomBP, EndogenBP, RandomAP, and EndogenAP, respectively. These summary statistics seem to suggest that the impact of trust on escaping the poverty trap, defined as $K \geq \widehat{K} = 31$, may be influenced by an economy's initial endowment condition. Figures 6-9 provide more supportive evidence that trust may have a more prominent impact on initially richer (AP) than

[20] Lei and Noussair (2007) and Capra et al. (2009) define escaping the poverty trap as having the aggregate capital stock significantly different from the Pareto inferior equilibrium level.

poorer (BP) economies. For the below-poverty-trap initial condition, no economy in RandomBP (Figure 5) managed to exceed the threshold, whereas three out of the nine economies in EndogenBP (Figure 6) successfully did so. For the above-poverty-trap initial condition, the threshold was surpassed in three of the twelve games in RandomAP (Figure 7) but ten of the fifteen games in EndogenAP (Figure 8).

[Table 4 and Figures 6-9: About Here]

To rigorously estimate the treatment effects on the likelihood to escape the poverty trap, we will utilize a time-to-event model in the following analysis. More specifically, since the probability of surpassing the threshold in any given period depends on how much capital has been accumulated up to that period, we will adopt Beck, Katz, and Tucker's (1998) approach to take such temporal or duration dependence into consideration. Note that Beck et al.'s time-to-event analysis, estimated using a maximum-likelihood complementary log-log (cloglog) model, is a discrete time version of Cox's (1975) proportional hazards model. It fits the nature of the experimental data and also suits our purpose to estimate the likelihood that an economy will escape the poverty trap in a given period *t*, provided that it has not yet done so until that period.

The dependent variable in our cloglog model is a dummy variable which equals 1 if game *i*'s aggregate capital stock exceeds the threshold in period *t* and 0 otherwise. The explanatory variables are a dummy variable which equals 1 for the below-poverty-trap endowment condition and 0 otherwise, a dummy variable which equals 1 for endogenous matching and 0 otherwise, and the interaction of the two dummies. To correct for temporal dependence, we follow Beck et al. and include a series of temporal dummy variables.[21] Ideally, since the maximum number of periods of the growth games is 26 in our data, we would have 26 period-

[21] A likelihood ratio test rejects the null hypothesis that the data are temporal independence ($p$-value $< 0.0100$).

specific, temporal dummy variables in our model. Nevertheless, since the "hazard" cannot be estimated for those periods that have no event occur, we follow Jenkins (2004) and group several periods into a time interval. As a result, we have five temporal dummy variables in our model (duration 1 = periods 1-3, duration 2 = periods 4-6, duration 3 = periods 7-9, duration 4 = periods 10-12, and duration 5 = periods 13-26).[22, 23] Games that never exceeded the threshold are treated as right-censored. Standard errors are clustered at the session level to control for within-session correlations. The estimated probability to escape the poverty trap across periods in each of the four treatments, derived from the cloglog coefficients reported in column (1) of Table A1 in the appendix, is shown in Figure 9. These estimates lead to several interesting results summarized as follows.

[Figure 9: About Here]

**Result 4:** *It is unlikely for an economy to escape the poverty trap in RandomBP.*

**Support for Result 4:** The estimated probabilities to escape the poverty trap in the RandomBP treatment are 1.75e-8, 7.97e-9, 5.04e-9, 5.88e-9 in durations 1, 2, 3, and 4, respectively. None of the estimates is statistically significant. ■

**Result 5:** *It is significantly more likely to escape the poverty trap at the start (periods 1-3) than later of the game in EndogenBP, EndogenAP, and RandomAP.*

**Support for Result 5:** The probability to escape the poverty trap in duration 1 (periods 1-3) is 0.0439 in EndogenBP, 0.0681 in RandomAP, and 0.2614 in EndogenAP, all significant at least at the 5% level ($p$-value = 0.025, 0.028, and 0.000, respectively). The rest of the estimated probabilities in later periods,

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[22] As discussed in Section 2.1, our economies, if guided by a benevolent social planner, should conserve most, if not all, of its output in the first three periods in order to escape the poverty trap. Therefore, our primary interest in the following analysis is on economies' behavior in duration 1.

[23] By grouping three or more periods into one time interval, we are assuming that the probability that an economy will escape the poverty trap remains constant within periods 1-3, 4-6, etc. See Jenkins (2004) for more details on the characterization of duration dependence in discrete time hazard models.

conditional on that an escape has not yet occurred, are all insignificantly different from zero. ■

**Result 6:** *The likelihood that an economy will escape the poverty trap is significantly higher in an endogenous matching treatment than in its random matching counterpart. Moreover, the difference between EndogenAP and RandomAP is significantly greater than the difference between EndogenBP and RandomBP.*

**Support for Result 6:** The difference in the estimated probability to escape the poverty trap in duration 1 (periods 1-3) is 0.0439 between EndogenBP and RandomBP and 0.1933 between EndogenAP and RandomAP. Both differences are significantly different from zero (*p*-value = 0.026 and 0.002, respectively). A chi-squared statistic of 171.99 indicates that the contrast between the two differences is also significant (*p*-value = 0.0000). ■

One may wonder if the disproportionate impact of trust on the AP economies was due to, say, EndogenAP having an idiosyncratically higher trust level than EndogenBP. To show that this is not a well-grounded concern, we compare these treatments' initial trust levels which, as described at the end of Section 4, are approximated by the mean percentages sent among five group members in the last two periods of Part I. The average trust level across all groups is 70.11% in EndogenBP and 63.67% in EndogenAP. Using each group as an independent observation, a Mann-Whitney ranksum test cannot reject the null hypothesis that the two initial trust levels are the same (*p*-value = 0.9061). The same result holds true for the two random matching treatments where the average trust level is 34.33% in RandomBP and 33.00% in RandomAP (*p*-value = 0.8728).

## 5.2 Treatment Effects on Consumption and Utility

In addition to the summary statistics given in Table 4, we also analyze the treatment effects on consumption and welfare by regressing game *i*'s aggregate consumption and utility in period $t$ on two dummy variables representing the below-poverty-trap endowment condition and the endogenous matching protocol and the interaction of the two dummies. Period is included to reflect the time trend. Standard errors are clustered at the session level to adjust for within-session correlations. Since theory predicts that our economies, regardless of their endowment condition, should conserve most, if not all, of their output in the first three periods in order to push the aggregate capital stock above the threshold, we run each model twice, one with the data from periods 1-3 and the other with the data from period 4 onward. Table 5 reports the random-effects GLS estimates. For easy comparison, results from the same regression model for capital and output are included in the table as well.

[Table 5: About Here]

**Result 7:** *At the start of the game (periods 1-3), endogenous matching economies, regardless of their initial endowment condition, accumulate significantly more capital than their random matching counterparts. In the case of EndogenBP, this is achieved at the expense of consumption and utility in the short run.*

**Support for Result 7:** For the first three periods in all growth games played in Part II, the estimated coefficient on the endogenous matching dummy variable in column (1) of Table 7 indicates that EndogenAP economies accumulate 7.97 more units of capital stock per period than the RandomAP economies. Between EndogenBP and RandomBP, the difference is 7.97 – 4.73 = 3.24 units ($p$-value = 0.0236). While the estimates in columns (3) and (4) suggest that consumption and utility between the two AP treatments are not significantly different, the differences between EndogenBP and RandomBP, –1.43 in consumption and –574.59 in overall utility, are statistically significant ($p$-value = 0.0376 and 0.0083, respectively). ■

**Result 8:** *From period 4 onward, EndogenAP has significantly more capital, output, consumption, and utility than RandomAP. EndogenBP, on the other* *hand, manages to have more capital and output than RandomBP without scarifying its consumption and utility. Therefore, in the long run, both EndogenAP and EndogenBP benefit from boosting capital stock at the beginning of the game.*

**Support for Result 8:** The estimated coefficients on the endogenous matching dummy variable in columns (5)-(8) of Table 5 suggest that, compared to RandomAP, EndogenAP has significantly more capital, output, consumption, and utility per period from period 4 onward. So, indeed, it pays off for EndogenAP to save more output for capital in the first three periods of the game. EndogenBP also has significantly more capital and output than its random matching counterpart ($\Delta K = 16.64$, $p$-value = 0.0280; $\Delta Y = 22.98$, $p$-value = 0.0576). In terms of consumption and utility, the differences between EndogenBP and RandomBP are not significant ($\Delta C = 6.34$, $p$-value = 0.1722; $\Delta U = 1385.74$, $p$-value = 0.2405). ■

Our results indicate that trust is an effective coordination device to jump-start growth even for economies that are crippled by their initial endowment condition. In Section 5.3 below, we will discuss three types of coordination failures or inefficiencies that a decentralized economy would have to overcome in Lei and Noussair's environment. The economy could suffer from an intertemporal inefficiency simply because its members fail to collectively determine the optimal tradeoff between consumption and saving at the same or right time. A production inefficiency (output is not being produced by those who have the highest marginal productivities) or consumption inefficiency (output is not being consumed by those who have the highest marginal utilities) may arise due to the heterogeneous individual production and utility capabilities. We will show that it is the intertemporal coordination failure that trust is able to mitigate and therefore enable the endogenous matching economies to outperform their random matching counterparts.

### 5.3 Treatment Effects on Intertemporal, Production, and Consumption Inefficiencies

We follow Capra et al. (2009) and define the intertemporal inefficiency as suboptimal allocations to consumption and saving (investment) given future incentives. More specifically, let $V\left(Y_t, K^*_{t+1}(Y_t)\right)$ be the value of an economy given period $t$'s initial output $Y_t$ (produced from its initial capital stock $K_t$) and the optimal sequence of capital stock levels from period $t+1$ onward ($K^*_{t+1}, K^*_{t+2}, K^*_{t+3}, \ldots$), assuming that the economy is guided by a benevolent social planner who makes consumption and saving decisions in order to maximize the total social welfare. Also, let $V\left(Y_t, K_{t+1}(Y_t)\right)$ be the value of the economy given $Y_t$ and the actual aggregate capital stock level chosen by individual agents for period $t+1$, assuming that optimal decisions would be made thereafter. Intertemporal inefficiency is defined as $\left[V\left(Y_t, K^*_{t+1}(Y_t)\right) - V\left(Y_t, K_{t+1}(Y_t)\right)\right] / V\left(Y_t, K^*_{t+1}(Y_t)\right)$. As summarized in Table 4, the average intertemporal inefficiency over all periods is 14.68% in RandomBP, 12.93% in EndogenBP, 12.89% in RandomAP, and 10.61% in EndogenAP. Endogenous matching economies appear to suffer from less intertemporal inefficiency than their random matching counterparts. This result is confirmed by the estimates reported in Table 6.

[Table 6: About Here]

**Result 10:** *Endogenous matching helps reduce an economy's intertemporal inefficiency, regardless of its initial endowment condition.*

**Support for Result 10:** Random-effects GLS models, same as those reported in Table 5, are used to investigate the treatment effect on the intertemporal inefficiency. The estimated coefficient on the endogenous matching dummy variable in columns (1) and (4) of Table 7 indicate that, for the AP economies, endogenous matching reduces their intertemporal inefficiency by an average of 1.33% in periods 1-3 and 2.33% from period 4 onward. For the BP economies, the average reductions are about 1.27% and 1.75%, respectively. All the differences are significant at least at the 10% level. ■

Given the actual aggregate capital stock level $\sum_i k_t^i$, we follow Lei and Noussair (2007) and Capra et al. (2009) and define the production inefficiency as the percentage of actual output $\sum_i A \cdot f^i(k_t^i)$ that deviates from the optimal level $A \cdot F(\sum_i k_t^i)$. That is, production inefficiency equals $[A \cdot F(\sum_i k_t^i) - \sum_i A \cdot f^i(k_t^i)]/[A \cdot F(\sum_i k_t^i)]$. The consumption inefficiency is defined similarly as $[U(\sum_i c_t^i) - \sum_i u^i(c_t^i)]/U(\sum_i c_t^i)$, where $U(\sum_i c_t^i)$ is the optimal aggregate utility given the sum of the actual individual consumption levels $\sum_i c_t^i$ and $\sum_i u^i(c_t^i)$ is the actual aggregate utility. Overall, the average production inefficiency, as reported in Table 4, is 10.18% in RandomBP, 10.53% in EndogenBP, 8.98% in RandomAP, and 7.22% in EndogenAP. The average consumption inefficiency is 4.01% in RandomBP, 3.96% in EndogenBP, 3.08% in RandomAP, and 3.24% in EndogenAP. Unlike its influence on the intertemporal inefficiency, endogenous matching does not seem to have much of an impact on either production or consumption inefficiency. We summarize this result as below.

**Result 11:** *Endogenous matching has no significant impact on either production or consumption inefficiency.*

**Support for Result 11:** None of the estimated coefficients on Endogenous Matching or BP Endowment Condition × Endogenous Matching in columns (2), (3), (5), and (6) of Table 6 is significantly different from zero, suggesting that endogenous matching does not help mitigate an economy's production or consumption inefficiency regardless of its endowment condition. ■

While we find that endogenous matching is able to address the intertemporal coordination failure, unfortunately for the BP economies, this effect is undermined by their endowment disadvantage. The estimated coefficients on BP Endowment Condition in columns (2) and (3) suggest that the endowment disadvantage significantly increases the production and consumption inefficiencies in periods 1-3. That capital and consumption are being misallocated to less productive and low-value individuals makes it increasingly more difficult for the economy as a whole to optimize intertemporally, which is shown in column (4).

## 6. Conclusion

A decentralized market institution, as shown in Lei and Noussair (2002), is extremely effective in driving a dynamic experimental macroeconomy into its unique steady state equilibrium. The initial endowment condition does not matter. But in an environment where multiple equilibria exist, Lei and Noussair (2007) find that the same competitive market institution consistently leads low-endowment economies toward a Pareto-inferior equilibrium. While it may be troublesome that the market fails to solve collective action problems, this result also gives us opportunities to make use of Lei and Noussair's laboratory setting as a testbed to assess the effectiveness of other institutions, policy measures, or social norms in navigating poor economies away from a poverty trap.

In this paper, we focus on trust. We use the platform of Lei and Noussair (2007) to study if poor economies can defy the gravity of the poverty trap with trust. In addition, we also ask if the influence of trust depends on how poor an economy is. We employ a 2×2 design in which the two treatment variables are the matching protocol used to generate different interpersonal trust levels between treatments and the initial endowment condition introduced to tackle whether or not the impact of trust is universal. We find that trust matters. It is more likely for high-trust economies, generated with an endogenous matching procedure, to escape the poverty trap. But we also find that the likelihood to escape depends partially on the initial endowment condition. Trust has a much weaker influence on the economies whose initial capital and output fall below the Pareto-inferior equilibrium, supporting the empirical evidence found by, for example, Peiró-Palomino and

Tortosa-Ausina (2013) that trust is less relevant for the poorest economies and hence the widely accepted trust-growth relationship cannot be generalized across countries with different levels of development.

So how does trust aid poor decentralized economies to surpass the capital threshold and, as a result, take advantage of a more efficient production technology? There are three potential coordination failures that a decentralized economy would have to conquer in Lei and Noussair's environment. Since agents are heterogeneous in their production and utility capabilities, they would need to coordinate their production and consumption decisions so that output is being produced and consumed by productive and high-value individuals, respectively. Additionally, due to the threshold externality as well as the dynamic feature of the optimization problem, members of the economy would need to collectively determine the optimal tradeoff between consumption and saving at the right time or the economy may quickly gravitate toward the poverty trap as in Lei and Noussair (2007). We find that, while our endogenous matching procedure has no influence on either production or consumption inefficiency, it is able to significantly reduce a poor economy's intertemporal inefficiency. There is perhaps a good reason why trust helps mitigate intertemporal coordination failure in our study. Trust means giving something now with an expectation that it will be repaid in the future. This is not only the spirit of the trust game of Berg et al., upon which our repeated trust games in Part I are based, but also the essence of the growth game of Lei and Noussair—sacrificing almost the entire consumption in the first two to three periods with a hope that it will pay off in the future. In other words, the incentives of the two games are aligned, making it easier for participants to refer to the norms established in Part I when they have to make intertemporal consumption-saving decisions especially at the beginning of Part II.

Overall, we find that trust helps enhance a society's ability to cooperate as well as to coordinate in an intertemporal fashion. Unfortunately, for those really poor economies, the positive influence of trust is undermined by their endowment disadvantage. Formal institutions and/or policy measures may be needed for these economies to escape the poverty trap.

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Table 1: Summary of Treatments and Sessions

| Treatment | Part I: Matching Procedure | Part II: Initial Output | Session | Part II: # of Games (Periods) | Part II: Independent Data Groups |
|---|---|---|---|---|---|
| RandomBP | Random | Below Poverty Trap | RBP1 | 1 (14) | RBP1A, RBP1B, RBP1C |
| | | | RBP2 | 1 (13) | RBP2A, RBP2B, RBP2C |
| EndogenBP | Endogenous | Below Poverty Trap | EBP1 | 1 (14) | EBP1A, EBP1B, EBP1C |
| | | | EBP2 | 1 (24) | EBP2A, EBP2B, EBP2C |
| | | | EBP3 | 1 (26) | EBP3A, EBP3B, EBP3C |
| RandomAP | Random | Above Poverty Trap | RAP1 | 2 (3; 17) | RAP1A, RAP1B, RAP1C |
| | | | RAP2 | 2 (12; 13) | RAP2A, RAP2B, RAP2C |
| EndogenAP | Endogenous | Above Poverty Trap | EAP1 | 3 (3; 2; 20) | EAP1A, EAP1B, EAP1C |
| | | | EAP2 | 2 (7; 3) | EAP2A, EAP2B, EAP2C |

Table 2: Mean Amount Sent and Percentage Returned in Part I (Periods 2-10)

| Matching Procedure | Group | Mean Amount Sent | Nonparametric Test | Mean Percentage Returned | Nonparametric Test |
|---|---|---|---|---|---|
| Random | A | 4.29 (1.51) | all pair-wise comparisons: not significant ($p$ > 5%) | 20.75 (10.86) | all pair-wise comparisons: not significant ($p$ > 5%) |
| | B | 4.34 (1.22) | | 21.14 (9.31) | |
| | C | 3.92 (1.45) | | 20.01 (11.46) | |
| | All | 4.19 (1.40) | | 20.63 (10.49) | |
| Endogenous | A | 9.20 (1.21) | all pair-wise comparisons: significant ($p$ < 5%) | 69.14 (16.14) | all pair-wise comparisons: significant ($p$ < 5%) |
| | B | 7.75 (1.73) | | 48.47 (14.08) | |
| | C | 5.90 (2.03) | | 24.10 (10.88) | |
| | All | 7.62 (2.16) | | 47.24 (23.04) | |

Table 3: Determinants of Ranking Decisions

| Dep. Variable:<br>Ave. Rank Assigned to Player *i* | |
|---|---|
| Constant | 6.68<br>(0.41) |
| Current Rank of *i* | 0.51<br>(0.04) |
| % Sent by *i* | −0.01<br>(0.003) |
| % Returned by *i* | −0.04<br>(0.003) |
| Male | 0.07<br>(0.08) |
| $R^2$ | 0.87 |
| Observations | 650 |

Notes: Standard errors are adjusted for within-session correlations

Table 4: Summary Statistics

| Treatment | Capital | Output | Con-sump-tion | Utility | Intertem-poral Inefficiency (in %) | Production Inefficiency (in %) | Consump-tion Inefficiency (in %) |
|---|---|---|---|---|---|---|---|
| Random BP | 14.52<br>(4.84) | 26.77<br>(6.19) | 12.25<br>(4.06) | 4357.33<br>(1352.56) | 14.68<br>(1.94) | 10.18<br>(7.86) | 4.01<br>(3.77) |
| Endogen BP | 28.35<br>(23.62) | 48.86<br>(41.38) | 20.51<br>(19.67) | 6281.67<br>(4802.52) | 12.93<br>(3.52) | 10.53<br>(9.27) | 3.96<br>(3.68) |
| Random AP | 27.84<br>(15.84) | 50.14<br>(35.01) | 22.30<br>(21.20) | 6771.20<br>(5097.62) | 12.89<br>(3.32) | 8.98<br>(7.52) | 3.08<br>(2.81) |
| Endogen AP | 39.96<br>(19.62) | 75.70<br>(40.30) | 35.73<br>(25.99) | 9975.81<br>(6326.95) | 10.61<br>(4.01) | 7.22<br>(6.05) | 3.24<br>(3.02) |

Table 5: Estimated Treatment Effects on Capital, Output, Consumption, and Utility: Random-Effect Models

| | Periods 1−3 | | | | Period 4 Onward | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) Capital | (2) Output | (3) Consump-tion | (4) Utility | (5) Capital | (6) Output | (7) Consump-tion | (8) Utility |
| Constant | 17.36 (3.36) | 23.21 (6.68) | 5.68 (3.94) | 2440.79 (1143.93) | 27.82 (5.97) | 46.66 (14.02) | 18.85 (8.45) | 5758.50 (2008.90) |
| Period | 4.65 (1.59) | 8.99 (3.25) | 4.43 (2.14) | 1237.38 (614.43) | 0.20 (0.10) | 1.08 (0.44) | 0.87 (0.42) | 228.25 (99.81) |
| BP Endowment Condition | −12.72 (2.38) | −17.86 (4.28) | −5.14 (2.29) | −1513.11 (577.25) | −14.92 (6.32) | −28.31 (14.62) | −13.38 (8.32) | −3108.94 (1993.23) |
| Endogenous Matching | 7.97 (3.66) | 9.74 (5.70) | 1.93 (2.35) | 493.78 (270.31) | 17.72 (8.19) | 38.21 (15.46) | 20.49 (8.27) | 4743.34 (1976.11) |
| BP Endowment Condition × Endogenous Matching | −4.73 (3.94) | −7.93 (6.68) | −3.36 (2.45) | −1068.37 (611.22) | −1.08 (11.04) | −15.23 (19.20) | −14.15 (9.19) | −3357.60 (2234.34) |
| Observations | 123 | 123 | 123 | 123 | 390 | 390 | 390 | 390 |

Notes: Standard errors are adjusted for within-session correlations.

Table 6: Estimated Treatment Effects on Production, Consumption and Intertemporal Inefficiencies (in %): Random-Effect Models

| | Periods 1−3 | | | Period 4 Onward | | |
|---|---|---|---|---|---|---|
| | (1) Intertemporal Inefficiency | (2) Production Inefficiency | (3) Consumption Inefficiency | (4) Intertemporal Inefficiency | (5) Production Inefficiency | (6) Consumption Inefficiency |
| Constant | 16.22<br>(0.73) | 6.32<br>(1.81) | 1.08<br>(0.89) | 13.10<br>(1.06) | 12.63<br>(3.60) | 4.29<br>(0.63) |
| Period | −1.22<br>(0.26) | 0.81<br>(0.55) | 1.01<br>(0.45) | −0.08<br>(0.06) | −0.43<br>(0.25) | −0.12<br>(0.03) |
| BP Endowment Condition | 0.44<br>(0.96) | 7.08<br>(3.58) | 0.53<br>(0.25) | 2.42<br>(0.93) | −0.16<br>(3.38) | 0.81<br>(0.73) |
| Endogenous Matching | −1.33<br>(0.72) | −1.73<br>(2.47) | 0.38<br>(0.70) | −2.33<br>(1.17) | 0.36<br>(3.15) | 0.70<br>(1.14) |
| BP Endowment Condition × Endogenous Matching | 0.06<br>(1.01) | −0.62<br>(4.55) | 1.31<br>(1.34) | 0.58<br>(1.46) | 2.46<br>(4.44) | −0.42<br>(1.25) |
| Observations | 123 | 123 | 123 | 390 | 390 | 390 |

Notes: Standard errors are adjusted for within-session correlations.

Figure 1: Playing Trust Games with Two Randomly Selected Group Members in Part I

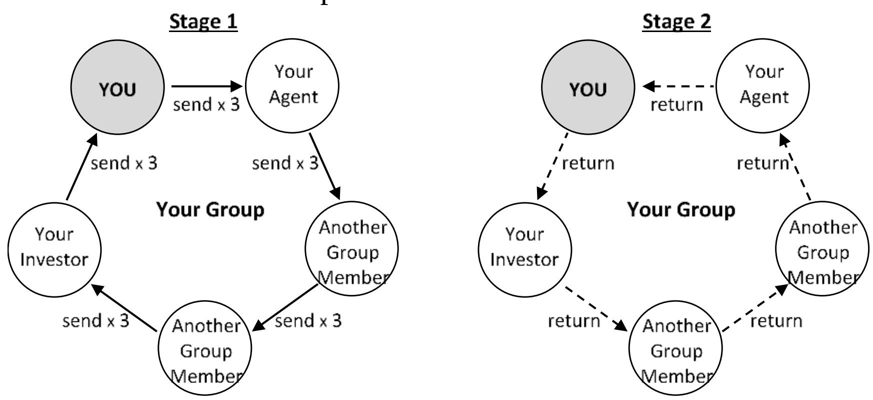


Figure 2: Individual and Aggregate Production Schedules

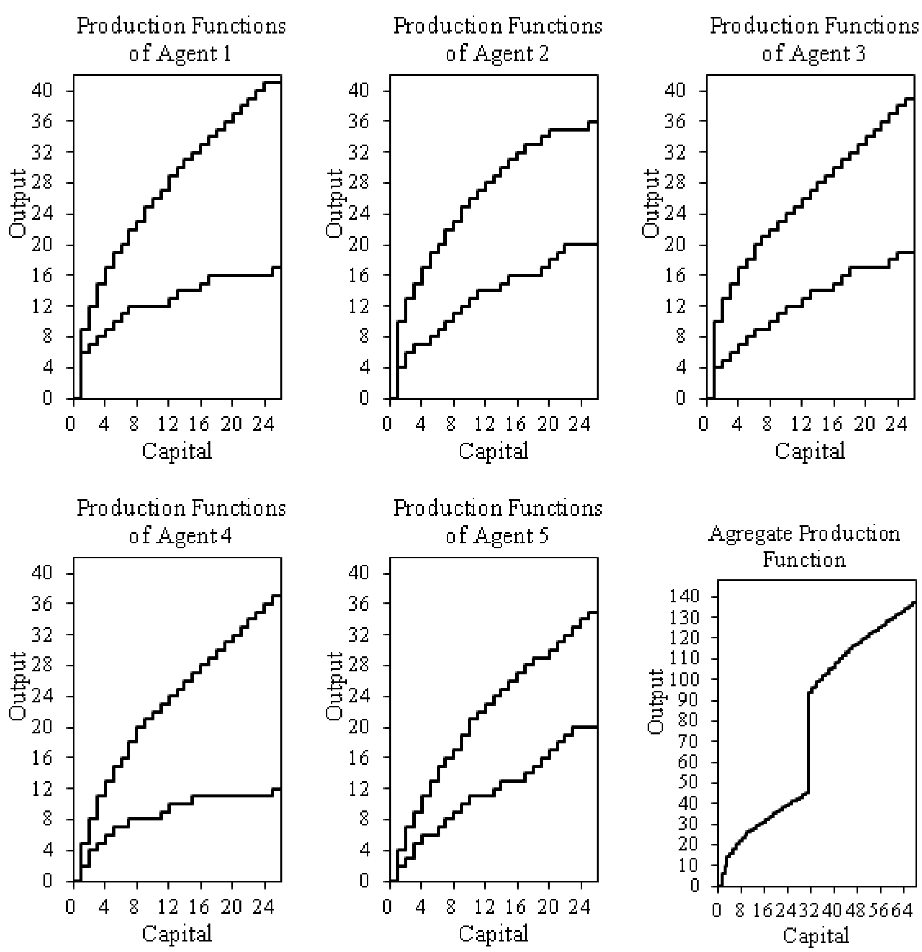

Figure 3: The Evolution of the Amount Sent

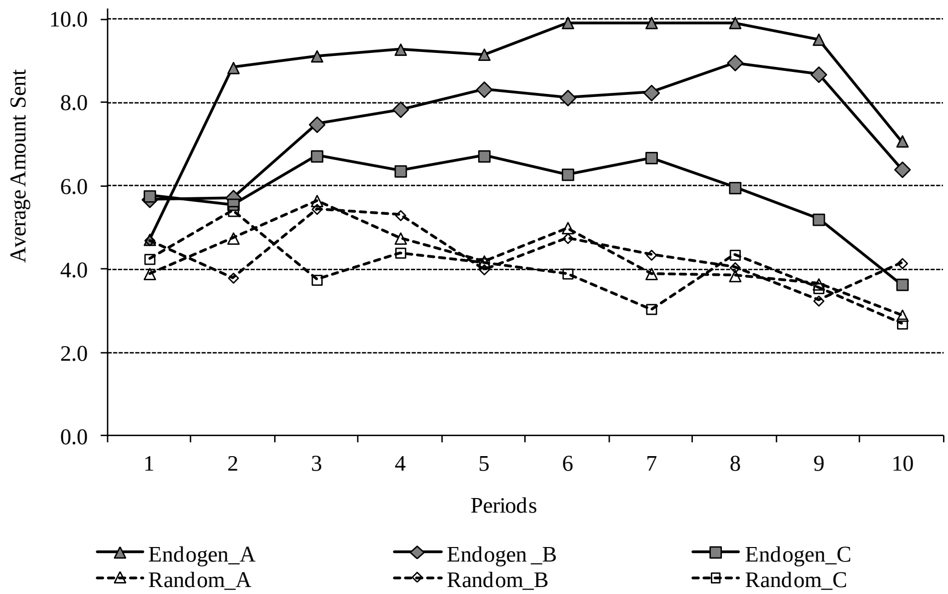


Figure 4: The Evolution of the Percentage Returned

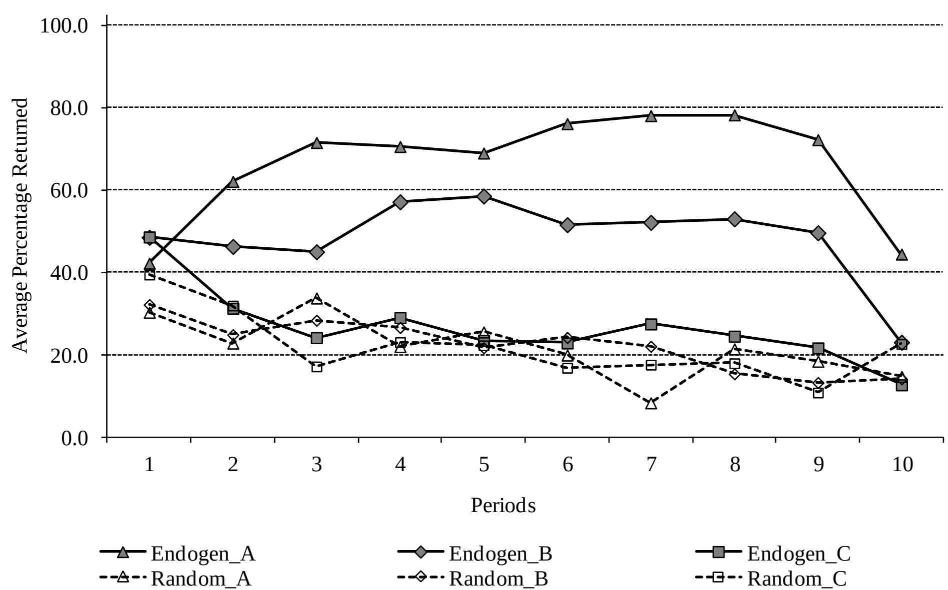

Figure 5: Time Series of Aggregate Capital Stock in the RandomBP Treatment

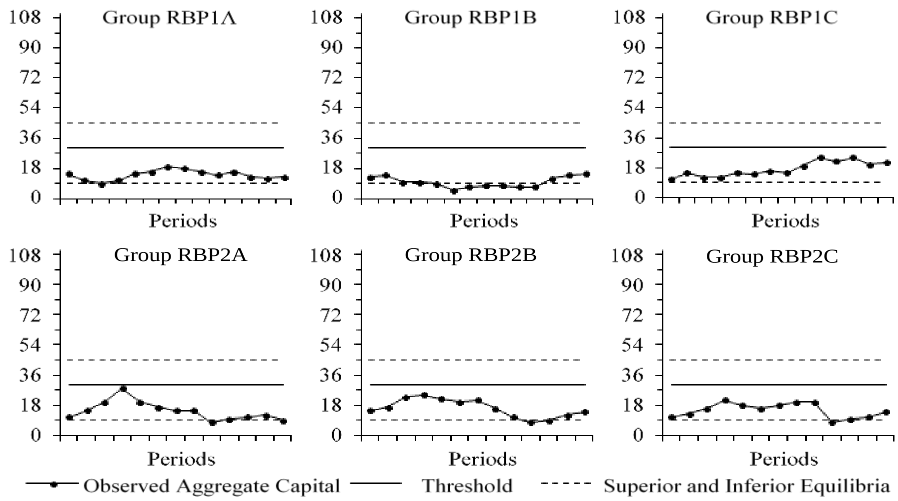


Figure 6: Time Series of Aggregate Capital Stock in the EndogenBP Treatment

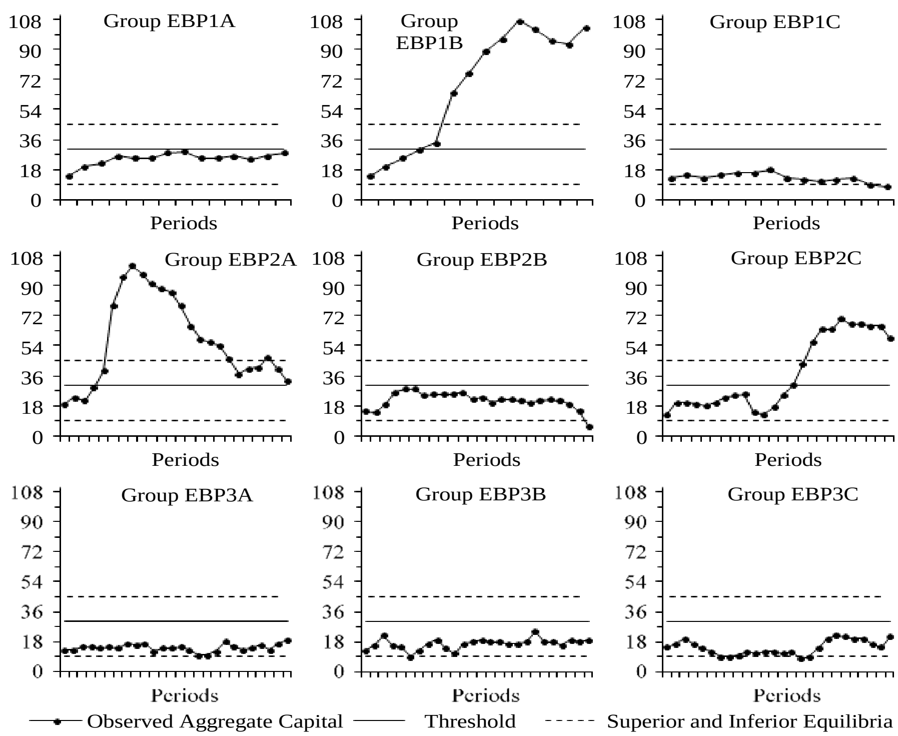

Figure 7: Time Series of Aggregate Capital Stock in the RandomAP Treatment

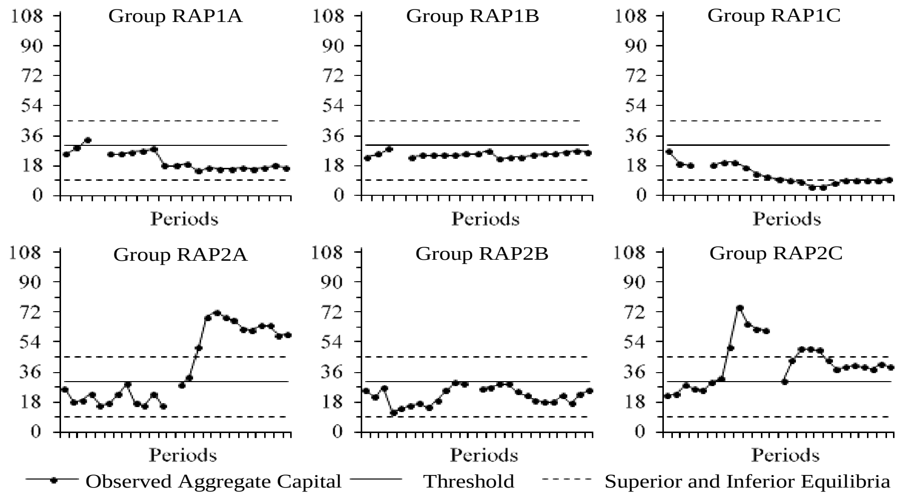


Figure 8: Time Series of Aggregate Capital Stock in the EndogenAP Treatment

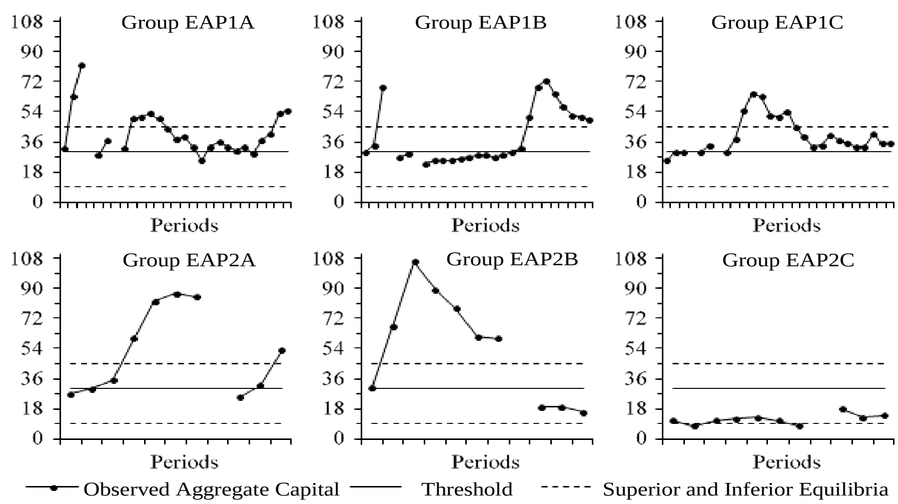

Figure 9: The Predicted Probability to Escape the Poverty Trap Across Time Periods