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Learning to Open Monty Hall's Doors

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Abstract

The analysis in this paper searches for individual and group determinants of learning behavior in Monty Hall's Three Door problem examined in Friedman (1998, *American Economic Review.* 88, 933–946). The results show that the size of monetary incentives, individuals' initial abilities, and social interactions with others are all important determinants of initial choices and subsequent learning in this problem: (i) More able students have a greater initial propensity to make the right choice than less able students, and their learning curves are initially steeper; (ii) Individual learning can also be enhanced through social interactions; (iii) Interestingly, less able students benefit more than more able students from social interactions in the sample. These findings support the argument that learning models that take into account individuals' abilities and that allow for social interactions where agents can exchange information hold a great deal of promise for enhancing our understanding of actual learning environments, learning processes, and the formation of rationality.

Keywords: learning, ability, social interactions, rationality

JEL Classification: C91, D83

1. Introduction

Monty Hall's Three Doors problem represents one of the most robust and persistent choice anomalies among all of the anomalies documented over the last few decades in the behavioral and experimental economics literatures.[1] The name for this problem comes from host Monty Hall of the once-popular TV game show "Let's Make a Deal." The basic ingredients of this problem are an initial risk choice, the revelation of information concerning a rejected choice, and the opportunity to reconsider the initial choice. In the context of the game show, Monty Hall asked his final guest of the day to choose one of three doors. One door led to the "grand prize" and the other two doors led to worthless prizes. After the guest chose one door, Monty opened one of the other two doors to reveal a worthless prize and offered the guest the opportunity to switch her choice to the remaining unopened door. The stylized fact is that very few guests accepted the opportunity to switch. Nonswitching is anomalous because the probability of winning is 1/3 for nonswitchers and 2/3 for switchers.

Friedman (1998) uses the basic ingredients of this problem in a manner parallel to the stylized game show in a laboratory experiment. He finds that "no anomaly has produced stronger departures from rationality in a controlled laboratory experiment" (p. 936). Clearly, the fact that there is such a large departure implies that this problem may offer a suitable opportunity to gain useful insights into the determinants of learning and thought processes. This paper offers new evidence bearing on this anomaly. In particular, the purpose of the analysis is to search for specific determinants of *learning* in this experiment.

Previous evidence suggests that the three-door anomaly may be related to the gambler's fallacy, to the nonrational escalation of commitment or endowment effect, to Bayesian updating failures, and to probability matching behavior. The analysis also shows that the three-door task is "exceptionally difficult" to learn. However, individuals are capable of learning to overcome, at least in part, this anomaly. The evidence shows that the extent of the anomaly declines with experience and various treatments—although it does not disappear—, and that most people will eventually end up making "the right choice most of the time in the more favorable conditions." Hence, the results suggest that the anomaly could be notably diminished in appropriately structured learning environments. In this sense, they encourage focusing on modelling the learning process and understanding which learning environments encourage or discourage this and other kinds of anomalies.

The analysis in this paper searches for individual and group determinants of learning behavior in this experiment. The analysis is as close as possible to that in Friedman (1998). It follows the same structure and considers the same treatments (see the basic description therein), and only deviates from it in that we additionally consider other variables and treatments of interest that could, in principle, be directly related to the learning process. In particular, three aspects are emphasized in the analysis.

First, individual agents are different in potentially relevant aspects. For instance, individuals are not endowed with the same innate and acquired abilities to make the right choice in the three-door task. Individuals may be good at learning, but some individuals are better than others. Clearly, differences in initial abilities may be important to understand differences in both initial choices (initial propensities) and in learning over time, that is in their ability to process the information they receive. While the assumption of uniform initial propensities across individuals is often analytically and empirically convenient, the literature has also recognized that "initial propensities can have long-term effects on the learning process" (Erev and Roth, 1998). Thus, the predictions of learning models may be improved by an assessment of these initial propensities and their determinants. In this paper, we attempt to assess and evaluate the role of possible determinants by gathering information on different variables that could account for the abilities of the individuals when facing the three-door task. The results will show that they are a strongly significant predictor of both initial choices and learning over time.

Second, an important distinction is often made in the construction of formal models between the information flows individuals receive (i) from the outcomes of their own previous choices, (ii) from the knowledge of other individuals' choices and outcomes, and (iii) from direct communication and interaction with other individuals. The first two potential determinants of behavior in the three-door task were examined in Friedman (1998). We follow the same treatments here. In addition, we examine the third mechanism and study the extent to which learning may arise through *direct* communication and social interactions with other individuals.

This aspect is related, more generally, to the idea that the socio-economic environment may influence the dynamics of learning. For instance, the growing literature on endogenous preference formation recognizes that the social environment may affect people's choices, as social factors and communication with others often play an important role in shaping the perceptions and behavior of individuals.[2] In particular, models that explicitly incorporate social interactions and allow agents to exchange information have proven extremely useful in a variety of socioeconomic contexts.[3] One common feature in these studies is the assumption that an agent's choices are affected by other agents' actions not just indirectly through markets and the observation of aggregate behavior and outcomes, but also directly through social pressure, information sharing, and other non-market externalities. In order to examine whether individual learning can be enhanced through this channel in the context of the three-door task, we explicitly "invite" individuals to interact with each other within *exogenously* chosen groups. At some point in the experiment, we sort a subset of the individuals in our sample into different groups. The main objective of this treatment is to examine whether allowing agents to exchange information with their peers can improve their learning above and beyond the learning that derives from the knowledge of own and others' choices and outcomes, and other treatments. In this sense, this treatment attempts to overcome, at least in part, the usual difficulties encountered in lab environments to learn through direct contact with others. The exogenous sorting also allows us to measure the extent of peer effects overcoming important difficulties typically encountered in the empirical literature that tries to identify and estimate the extent of social effects on behavior (see Manski, 1993).

Lastly, we consider the role of greater monetary incentives. We ask individuals to complete two Runs, with ten and fifteen rounds respectively. We begin by offering in the ten rounds of Run1 identical monetary rewards to those offered by Friedman (1998). In Run2, we also offer identical rewards per round as well, and in addition we award 5 sizeable cash prizes ($500, $400, $300, $200, $100) to the top five students with the most earnings in Run2.

As a summary of the empirical results, we first find that they strongly support the findings in Friedman (1998). The four treatments he considers have a strikingly similar effect in our sample when no other variables and treatments are considered. His results are basically replicated here. In addition, the novel findings in the analysis conclusively support the idea that the size of monetary incentives, individuals' initial abilities, and social interactions with others are all important determinants of initial choices and subsequent learning:

(i) We find that more able students have a greater initial propensity to make the right choice than less able students: on average their switching rates are about 18 percentage points greater in the first five rounds. Moreover, at *every* round, more able students make the right choice more often than less able students. On average, the difference between their switching rates is 12.8 percentage points. Interestingly, the learning curves for more able students are initially *steeper* than for less able students.

(ii) The additional monetary incentives offered in Run2 also play an important role as the estimated coefficients on the effects of monetary incentives are significantly positive.

(iii) Lastly, we find that individuals who interacted with other individuals between Run1 and Run2 made the right choice more often than those who did not. On average, the difference between their switching rates is 15.9 percentage points. Further, we can also identify the reason for this result: more able students raise the learning of other students in the same group. In addition, we also find that across students less able students benefit *more* than more able students from social interactions. We interpret these results as evidence of social spillovers in the learning process within the context of our three-door analysis.

These results strongly support the idea that models of learning that characterize individual determinants of initial propensities, and that allow for social interactions where agents exchange information, hold a great deal of promise for enhancing our understanding of actual learning environments, learning processes and the formation of rationality. The rest of the paper is organized as follows. The next section briefly describes in detail the data and treatments. Section 3 is devoted to the empirical analysis. Section 4 provides a brief conclusion.

2. Data and treatments

In order to keep the analysis as close and comparable as possible to Friedman's (1998), his same treatments are considered here. The only differences are, as discussed earlier, that data on other variables of interest are collected, that greater monetary incentives are offered, and that an additional treatment is considered.

Two hundred seventeen students were recruited from undergraduate and graduate courses in Economics at Brown University. Most undergraduate students were juniors and seniors recruited from the courses Financial Economics I and II (Economics 177 and 178 respectively).[4] In addition to the usual demographic information, we also ask students to report their Brown identity card number, their choice of major, SAT point scores, as well as their overall Grade Point Average (GPA) and GPA in their major.[5] Information about their high school class rank and other background measures, and about the midterm and final scores in Economics 177 and 178 for the students taking these courses, was also computed using their Brown identity card numbers.[6] All these variables may be used to approximate individuals' innate and acquired abilities levels with which they enter into the experiment. In particular, we consider in a group all graduate students plus all undergraduate students that were simultaneously in the top halves of the distributions of SAT scores, overall GPA, high school rank, and major GPA in the sample. We denote this group *TopAbility*. Likewise, we consider in a group denoted *BottomAbility* all undergraduate students that were simultaneously in the bottom half of these distributions.[7] There were 81 subjects in the first group and 80 in the second, which is more than one third of the sample in each group.

Each subject entered a quiet classroom and sat at a table opposite the conductor with no other subjects present. After reading the instructions that clearly and unambiguously explained the procedure, each subject completed a series of ten trials (Run1). Then they were informed that a second set of trials would follow afterwards. In each trial, the subject picks one of three face-down cards. Then, the conductor turns over a nonprize card that the subject did not choose and offers him the possibility to switch to the other face-down card. The subject earns 40 cents if his final choice is the prize card and 10 cents otherwise, the same rewards given in Friedman (1998).

Table 1. Choices and earnings in Run1.

Pool	N. obs.	Switch rate percent	Mean earnings
Sex			
Male	1129	36.5	$2.37
Female	1041	33.1	$2.39
AGE			
Undergraduate			
19–21	1497	34.8	$2.37
22–24	456	36.4	$2.40
Graduate	217	32.1	$2.32
Undergraduate students			
Major			
Business Economics	742	36.6	$2.42
Applied Math Economics	586	41.8	$2.39
Economics	293	32.6	$2.33
Other	332	24.6	$2.32
Individual records			
GPA overall			
Top quartile	488	37.8	$2.38
Bottom quartile	488	32.1	$2.36
SAT			
Top quartile	488	41.2	$2.41
Bottom quartile	488	29.3	$2.34
Final Grade Econ177/178			
Top quartile	369	40.5	$2.40
Bottom quartile	369	30.4	$2.33

Table 1 summarizes the basic descriptive statistics in Run1.

The overall switching percentage is 35.1 percent, 6.4 percent more than that encountered by Friedman but clearly far from the optimal 100 percent. Mean earnings are $2.37 per subject, which is 5 cents higher than the mean of Friedman's subjects. Very slight differences are observed across sex and age-education groups. Males switch more often than females, older undergraduate students switch more often than younger ones and, interestingly, younger undergraduate students more often than graduate students. Greater differences are observed across undergraduate majors and individuals records. Applied Mathematics Economics students switch more often than all other students and 17 percentage points more often than non-economics majors. Across records, those in the top quartile switch much more often than those in the bottom quartile, especially across SAT scores and final grades in Economics 177 and Economics 178 where they switch about 10 percentage points more. Of all the subjects, 17 switch more than half of the time and 4 of them switch in all ten trials.

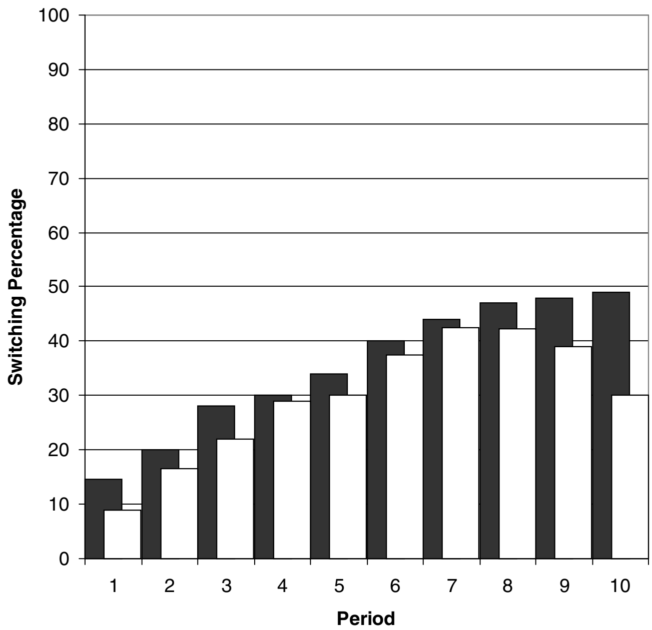

Figure 1. Switching percentage in Run1 (■) Friedman (□).

Five individuals acknowledged being familiar with the task when interviewed at the end of Run1.[8]

Figure 1 shows the aggregate time trends for the switching rate.

It can be observed that the aggregate switching rate is greater here than in Friedman's dataset in every trial in the round, on average about 6.4 percentage points greater as mentioned earlier. Interestingly, the rate increases over time until periods 7 and 8, as in Friedman (1998), but, contrary to his findings, the rate does not decrease after periods 7 and 8. Instead, it tends to level off or even increase slightly. In round 9, the switching rate is 10 percentage points greater than in his sample, and in round 10 it is 18 percentage points greater.

After the ten trials are completed, each subject is paid his accumulated earnings plus $3.00 for participating in Run2. The five students that had prior knowledge of Monty Hall's Three Doors problem were excluded from the subsequent analyses. Sixty five students (close to one third of the sample) are then taken straight to complete Run2. They continue having no contact with any other subjects. The rest of subjects leave the classrooms and go into a large conference room. There, they are randomly sorted out into 21 groups of 7 students each.[9] Once the groups are formed, they are taken into separate classrooms where they are informed that they will have to wait for about ten minutes. They have no contact with other individuals or other groups. They are also informed that they will be asked to do the same experiment again, but are not informed of the treatments they will receive. They are allowed to talk to each other in the group about any subject matter they want, including about the experiment if they wish. In fact, they were explicitly invited to talk about the experiment.[10]

In an exit interview, after all subjects were paid, *all* the individuals in these groups stated that they either talked about the experiment or listened to others in the group talk about it. This treatment is referred to as Social Interactions, a term that in non-experimental settings typically refers to informal social learning. Note that when individuals endogenously self-select into groups, neighborhoods or roommates it is difficult, often impossible, to separate out the selection effects from the actual peer effects (Manski, 1993). We avoid this problem through the exogenous sorting.[11]

During the time individuals interact with others in the groups, a conductor collected information on the identity of each of the individuals in the groups. This information will be useful to attempt to determine the extent and direction of social spillovers across individuals, if any. The number of *TopAbility* individuals in the groups ranges from 0 to 6, with an average of 2.61. Note that individuals interacted with others in their groups before knowing that they will be subject to additional treatments and before knowing that in one of these treatments they will have to compete with others for sizeable cash prizes.

Most subjects in Run2 received one or more of four additional treatments. Three of these treatments are identical to those studied in Friedman (1998). The first one, however, offers additional monetary incentives:

1. Intense Incentives (referred to below as *Intense*). As in Friedman (1998) the prize card is worth +\$1.00 each trial and the other two cards are worth −\$0.50. In addition, there are five additional rewards. A \$500 cash prize was to be awarded to the winner (the student with the most earnings in Run2), a \$400 cash prize to the runner up, a \$300 cash prize to the student with the third most earnings, and \$200 and \$100 cash prizes to the students with the fourth and fifth most earnings. These salient cash prizes are the only difference with respect to the treatment in Friedman (1998).
2. Track Record (*Track*). Each subject wrote down the results each period for his own cumulative earnings as well as the earnings for the strategies "always remain" and "always switch."
3. Written Advice (*Advice*). Before Run2 individuals subject to this treatment were given a page with the two paragraphs used in Friedman (1998), one that recommends always switching and the other that recommends always remaining with the original choice.
4. Comparative Results (*Comparative*). After the sixth round in Run2, subjects in this treatment receive a statement pointing out that 64.7 percent of all switch choices won the prize versus 32.5 percent of all the remain choices, as well as the amount of switch and remain choices in the sample.

The Run2 data is comprised of 3,171 observations of the binary choice gathered from 212 subjects. The five subjects that had prior knowledge of Monty Hall's Three Doors problem were excluded from the analysis. In addition, three subjects were dismissed before completing Run2 because of bankruptcy.[12]

Figure 2 shows the overall switching rate in Run2.

Interestingly, the switching rate begins basically where it left off in Run1. This finding is in contrast with Friedman's results whose subjects start in Run2 below the switching percentage with which they left off in Run1. This result may tentatively be attributed, at least in part, to the effects of both greater monetary incentives and social interactions. A

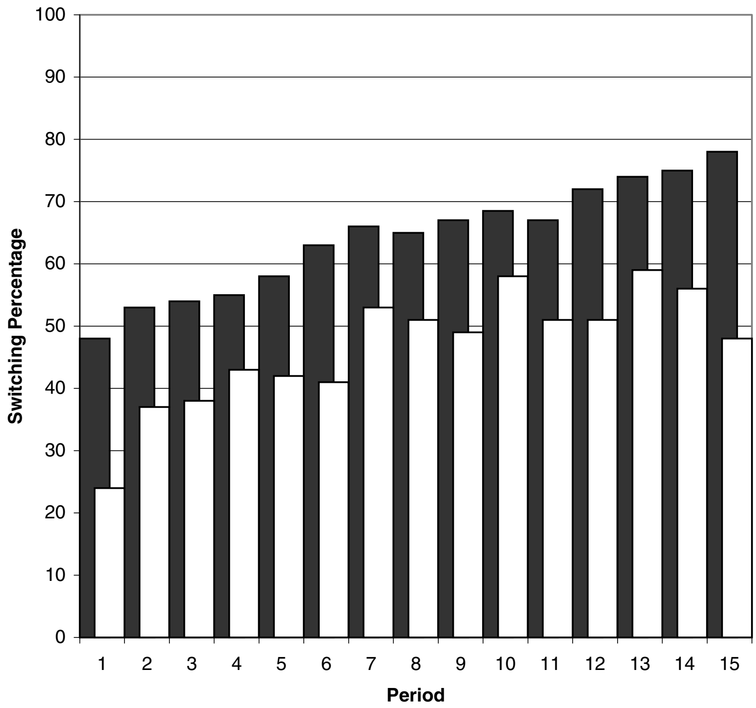

Figure 2. Switching percentage in Run2 (■) Friedman (□).

second difference arises with respect to the level of the aggregate switching rate. Compared with Friedman's results the rate is always, at every trial, notably greater than the one he finds (on average about 18 percentage points greater), increases at a decreasing rate and never appears to level off or trail off.

Figures 3 and 4 show the switching rate at a basic disaggregate level in both Run1 and Run2 for various groups of subjects. Figure 3 reports the switching percentage of the individuals that were in the *TopAbility* and *BottomAbility* groups.

The switching rate is always, at every round, much greater for *TopAbility* than for *BottomAbility* individuals, reaching a maximum difference of 20 percentage points in rounds 4, 5 and 6 of Run1 and 26 percentage points in the initial round of Run2. The difference between their switching rates is greater and appears to increase in the first few rounds in Run1; it then decreases and remains stable in the latter rounds close to about 10 percentage points. The switching percentage in Run2 for *BottomAbility* individuals begins at about 9 percentage points *below* where it left off in Run1. For *TopAbility* individuals it begins at about 8 percentage points *above*. As in Run1, in Run2 the difference in switching rates is also initially greater in the first few rounds, and then also tends to decrease in the last few rounds. Interestingly, in the very last round the switching rates are basically identical. Broadly speaking, these results appear to suggest that learning may be initially relatively faster in the *TopAbility* group in the first few trials of each Run, and that after a few rounds

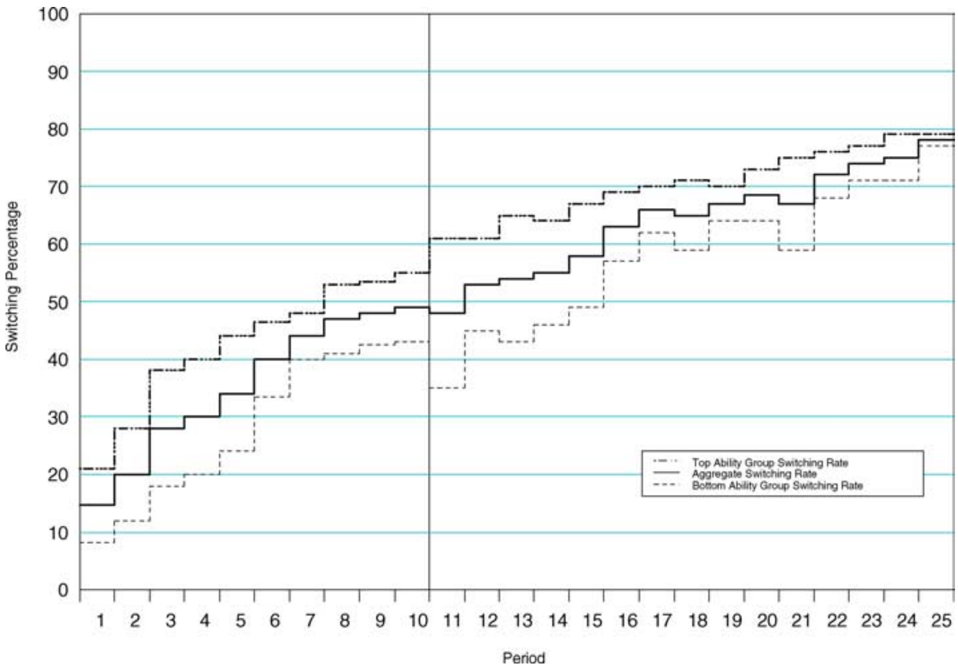

Figure 3. Switching percentage in Run1 and Run2 by ability group.

of exposure to the task there is a subsequent relatively greater impact on the learning of the *BottomAbility* individuals.

Figure 4 separately considers the individuals who were exposed to social interactions and those who were not.

As would be expected, the switching rate for both groups is observationally identical in Run1. However, in Run2 the rate is notably greater for those that were exposed to social interactions than for those that were not. For the latter group the switching rate starts in Run2 *below* the switching rate with which it left off in Run1 and, even though it has a clear tendency to increase, it decreases in some rounds. For the group that was exposed to social interactions, the switching rate in Run2 starts *above* where it left off in Run1 and basically increases at every round. Lastly, the difference in switching rates between these groups is relatively stable over rounds, on average slightly below 16 percentage points with a standard deviation of 3.8 percentage points.

To conclude the description of the data, Table 2 summarizes the impact of the five treatments, including the effects of Social Interactions.

The overall switch rate is 64.1 percent, increasing from 57.1 percent in periods 1–7 to 70 percent in periods 8–15. This increase is significant at the 0.001 percent level. Notice that the overall rate is 18 percentage points greater than the overall rate in Friedman (46 percent). This difference is constant across periods 1–7 and 8–15.

What could possibly account for this substantially greater switching rate? First, contrary to Friedman's findings, the *Intense* treatment does increase the switch rate. This may be

Table 2. Switch rates by treatment in Run2.

	N. obs.	Percent all periods	Percent periods 1–7	Percent periods 8–15
Overall	3,171	64.1	57.1	70.0**
Intense	1,807	70.0	63.5	75.3
Not *Intense*	1,364	56.5*	49.3*	63.2*
Track	1,680	66.7	60.0	72.8
No *Track*	1,491	61.2	54.0	67.0
Advice	1,522	65.9	59.3	72.0
No *Advice*	1,649	62.5	55.1	68.3
Compare	1,554	70.4	56.3	78.2
No *Compare*	1,617	58.4*	57.7	62.5*
Social Interactions	2,196	68.8	62.1	74.8
No *Social Interactions*	975	52.9*	45.8*	59.2*

Notes: The symbol *denotes the cases in which the probability that Fisher's exact test incorrectly rejects the null hypothesis of no effect in favor of the one-sided alternative hypothesis that the treatment has a positive effect on switch rates is lower than 5 percent. The symbol **denotes a significant increase in the switch rate from the earlier periods 1–7 to the later periods 8–15 according to Fisher's exact test at the 0.0001 level. Fisher tests assume independence of individual observations across rounds.

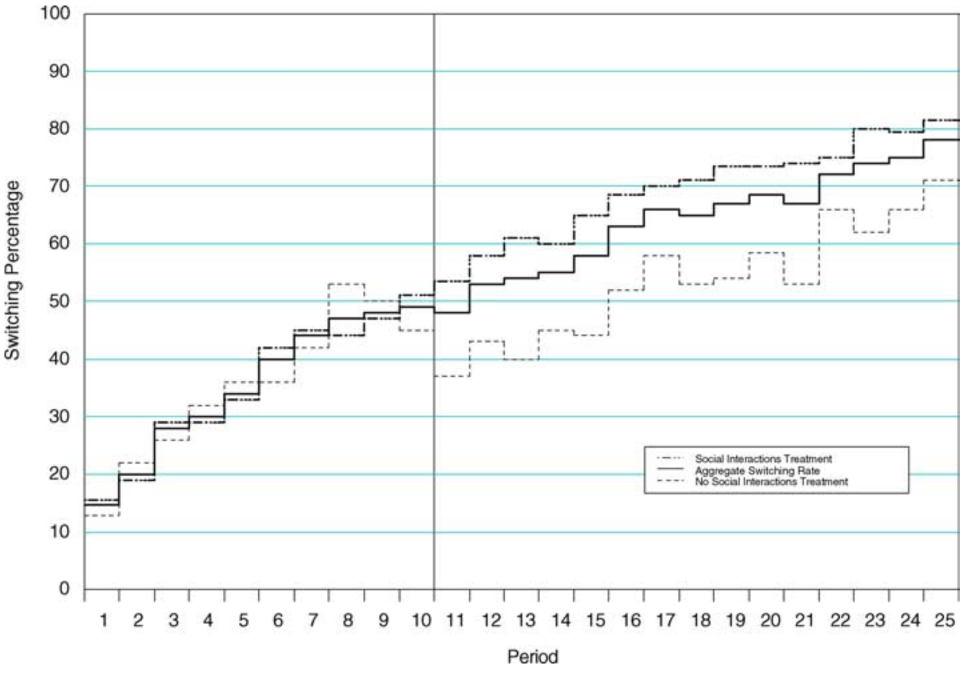

Figure 4. Switching percentage in Run1 and Run2 by social interactions treatment.

attributed, at least in part, to the additional monetary incentives given in the form of sizeable cash prizes to the five most successful students. Second, two of the other four treatments increase the switching rate as well. *Compare*, which should not have any effects in the early periods (and does not), has a significant impact in periods 8–15 and overall. Interestingly, the new treatment *Social Interactions* has a significantly positive effect in both early and later periods in Run2. Finally, *Track* and *Advice* appear not to have any significant effects at the five percent level either in early periods or in the latter ones.

In summary, the initial descriptive evidence presented in this section strongly suggests that the size of incentives, the determinants of initial individual propensities, and the extent to which individual behavior may be affected by the behavior of peers play an important role in shaping individual choices. In this sense, they may be a useful source of predictions for empirically observed individual behavior in this task. Next we examine the extent to which econometric analyses can confirm these initial impressions.

3. Econometric analysis

We have considered a number of regressions for the switch rate where the dependent variable takes the value 1 if the subject switched and 0 if he remained with his original choice that period. The independent variables include a *Constant*, the trend variable *Period* (the period number in Run1 or in Run2), dummies for each of the treatments that Friedman considers, the variables *Switchbonus* (defined as cumulated earnings from always switching minus earnings from always remaining) and *Switchwon* (a dummy variable that equals 1 if switching would have won the prize in the previous period), and various interactions of interest. The analyses also include new variables: *TopAbility* and *BottomAbility* (dummy variables that equal 1 if the subject belongs to these groups), *Social Interactions* (a dummy variable that equals 1 if the individual interacted with other individuals in a group between Runs 1 and 2), and some interactions of interest. We also consider the variable *GroupQuality* for those individuals that were subject to social interactions. It is defined as the number of *TopAbility* individuals that were in the group within which the individual interacts, other than the individual himself.[13]

In order to make the analysis as close and comparable as possible with Friedman's, we first examined OLS regressions with the same independent variables that he considers for both Run1 and Run2. The results are available in Palacios-Huerta (2002). They show that most of the estimates are remarkably similar to his. We then considered, in addition, the proxies for the abilities of the individuals, the effects of social interactions, and a number of relevant interactions. The regressions then bring about new evidence. In particular, incentives, individuals' abilities, and learning spillovers across students through social interactions are among the main determinants of switching rates and learning over time in the three-door task in the sample. In this sense, these variables appear to hold a great deal of promise for enhancing our understanding of observed behavior. A problem with the OLS estimates, however, is that the limited range of the dependent variable jointly with the fact that successive observations for a given individual are unlikely to be independent makes the linear estimates underlying the OLS estimates possibly inappropriate. For this reason we implement a probit analysis. The probit estimates are shown in Table 3.

Table 3. Probit estimates (and p-values) for switch rate.

Variable	Run1	Run2
Constant	−0.889 (0.000)	−0.522 (0.000)
Period	0.103 (0.000)	0.066 (0.001)
Switchbonus	0.466 (0.000)	0.301 (0.001)
Switchwon	−0.090 (0.403)	0.127 (0.350)
Intense		0.117 (0.030)
Track		0.312 (0.102)
Advice		0.276 (0.321)
Compare		0.160 (0.407)
Switchbonus × Track		−0.099 (0.327)
Switchbonus × Advice		−0.008 (0.400)
Advice × Compare		−0.121 (0.612)
TopAbility (TopA)	0.267 (0.011)	0.360 (0.000)
TopA × Period	0.011 (0.008)	0.005 (0.010)
TopA × Intense		0.417 (0.000)
TopA × Track		0.003 (0.462)
TopA × Advice		0.086 (0.502)
BottomAbility (BottA)	0.017 (0.430)	0.130 (0.633)
BottA × Period	0.010 (0.407)	−0.068 (0.220)
BottA × Intense		−0.053 (0.189)
BottA × Track		0.333 (0.601)
BottA × Advice		−0.060 (0.538)
Social interactions		0.117 (0.008)
TopA × GroupQuality		0.012 (0.008)
BottA × GroupQuality		0.030 (0.002)
Random effects	Yes	Yes
Rho	0.412 (0.000)	0.470 (0.000)
N. obs.	2,170	3,171
−Log-likelihood	522.2	750.0

Notes: This table reports maximum likelihood probit coefficient estimates with random effects, and their corresponding p-values. The dependent variable is 1 in periods when the individual chose to switch and 0 otherwise. Rho is the standard Hausman test statistic for the presence of random effects.

A first result to note is that significant random effects (differences in individual subjects' tendencies to switch) are present in the data. The standard Hausman test statistic for the presence of random effects is highly significant. For this reason we only report the probit estimates obtained with random effects.[14]

The first column reports the results for Run1. We observe that all independent variables considered here are significant except *Switchwon* and the variables that involve less able individuals. The coefficients for *Period* and *Switchbonus* indicate that individuals learn over time from accumulated experience. Interestingly, the variables *TopAbility* alone and interacted with *Period* are significant at better than the 1.5 percent level. This result indicates that individuals in this group have a significantly greater tendency to switch than other individuals and that their learning curve is initially steeper. The negative coefficient for *Constant* indicates a basic tendency to remain rather than to switch, though the size of the coefficient is lower than the one found in Friedman (1998). Given that Run1 is identical in method to his, these results suggest that the sample is different in innate or acquired tendencies to switch both prior to the experiment and during the first ten trials.[15]

The results in the next column correspond to Run2 and consider the impact of the treatments. First, the average against switching is substantially reduced. The highly significant -0.522 constant indicates a basic tendency to switch in $N(-0.522) = 30.08$ percent of trials. Friedman finds a basic tendency to switch in 19.4 percent of the trials. This constant term also absorbs any error from a linear approximation. *Switchbonus* and the time trend *Period* are weaker than in Run1 but remain highly significant. The treatment *Intense* is positive and significant. This is in contrast with Friedman's results who finds a negative coefficient. The positive coefficient, jointly with the positive but lower coefficient for *Switchbonus*, suggests that subjects not only respond to the greater incentives faced in Run2 but may do so more than proportionally rather than less than proportionally. The treatments *Advice* and *Compare* and the three interactions considered in Friedman are not significant. With regard to the new independent variables considered in the analysis, we find the following:

1. *Individuals Abilities. TopAbility* is a very important determinant of the switching rate. As the basic description of the data showed, individuals in this group are more likely than others to make the right choice. When interacted with the *Intense* treatment, we find that more able individuals significantly respond to the size of the incentives. Interactions with *Period* are positive and significant for these individuals and positive but not significant for *BottomAbility* individuals at conventional significance levels. The other interactions considered for more able individuals are positive but not significant. For less able individuals no interactions are significant. These results confirm the idea that individuals in this group have a much greater tendency to switch, learn faster, and respond more than proportionally to the greater incentives encountered in the Run2 trials.
2. *Social Interactions.* Interacting with other individuals is also an important determinant of the switching rate. The coefficient estimate for *Social Interactions* is positive and highly significant as well. This confirms the idea that the social interactions that took place between Run1 and Run2 contributed to learning. As mentioned earlier, it is often difficult to allow individuals in lab environments the possibility to learn through direct contact with others. In addition, it is also difficult to measure the extent of peer effects because individuals may endogenously self-select into groups, neighborhoods or roommates and hence the selection effects cannot be clearly separated out from the actual peer effects. We attempted to avoid these problems by exogenously sorting individuals and giving them some time to interact. The results provide strong evidence that those individuals who interacted with others were much more likely to make the right choice than those who did not.

3. *Within Group Externalities.* The quality of the group where the social interactions take place is important as it induces both *TopAbility* and *BottomAbility* individuals to make the right choice. The corresponding coefficient estimates are positive and highly significant. Interestingly, the latter appear to benefit significantly *more* than the former from such social interactions. The hypothesis that these coefficients are identical can be rejected at the 1 percent level. These findings suggest that more able students provide positive externalities towards all other students, as one might have expected, and especially towards less able students.[16] These results are also consistent with Sacerdote (2001) who finds strong peer effects in GPA and other student outcomes in a setting where peers are randomly assigned.

We conclude from these results that incentives, individuals' abilities, and learning spillovers across students through social interactions are among the main determinants of switching rates and learning over time in the three-door task in the sample. In this sense, they hold a great deal of promise for enhancing our understanding of observed behavior. Lastly, it should also be noted that the large effect of individual abilities and social interaction in the current setting does not imply that we should expect similarly large effects in other settings. For example, psychological research shows that social interactions and individual abilities are particularly important when the problem has a "correct and demonstrative" solution, as in this setting. When there is no correct answer and personal preferences are important, abilities and social interactions may be less important.[17]

4. Concluding remarks

The analysis has identified two features of the learning environment that appear to reduce one of the most striking choice anomalies encountered in the behavioral and experimental economics literatures. First, the results show that initial individual propensities are important determinants of behavior and effective learning: more able individuals make the right choice more often and appear to learn initially faster than less able individuals. Second, spillovers that arise from social interactions may have important effects on the learning process: individuals that interacted with others made the right choice more often than others, especially if they interacted with a greater amount of what we considered to be more able students. These two features, along with the size of the incentives and other treatments that have been considered in the literature and in this paper, encourage making correct choices and learning to make correct choices.

The analysis in this paper may be interpreted as an effort to better understand individual and social learning processes, and as an attempt to complement previous findings on this anomaly. In this sense, it also attempts to contribute to the general debate on anomalies and the research agenda on rationality. The results strongly suggest that efforts to understand and model the determinants of the learning process (e.g., by specifying the learning rules used by individuals, their abilities, and the actual characteristics of the learning environment) hold great promise for explaining behavior before learning processes have been completed.

The results suggest that these two features are not mere details of the learning process but possibly fundamental building blocks of models of individual and social learning. Abilities, initial propensities, and learning from others through direct social interactions occupy an increasingly prominent role in the literature on various socioeconomic aspects of individual and aggregate behavior. Based on the findings in this paper, they may also play an important role in deconstructing this anomaly and in the formation of rationality. Further research should evaluate the extent to which they may be an important ingredient in deconstructing other anomalies as well, and examine their role in the empirical analysis of various learning models that provide foundations for the main equilibrium concepts in the literature.

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Notes

1. See Camerer (1995) for a comprehensive review.
2. Various forms of social pressure and spillovers, for instance, have been offered as an explanation of such diverse behavior as consumption patterns (e.g., the choice of restaurants and car brands), social customs and cultural practices, parental influences on children's tastes, and unemployment behavior. See Becker and Murphy (2000) and many references therein.
3. Over the past decade economists have increasingly recognized the importance of social interactions in a variety of contexts, such as joblessness, crime and other social pathologies, peer influences in education, social learning and the diffusion of innovations, localization choices by households and firms, growth and income inequality. There exists also a rich theoretical literature that stresses the role of interactions in models of herds and informational cascades, and in models of social learning. Topa (2001) offers a review of the literature and estimates a social interactions model in the context of urban unemployment.
4. The materials covered in these courses closely parallel those covered in a typical first year MBA course in investments and in a second year MBA course in options and futures respectively. The textbook for Economics 177 is *Investments* by Z. Bodie, A. Markus, and A. Kane, 4th edition. The textbook for Economics 178 is *Options, Futures and Other Derivatives* by J. Hull, 4th edition. Economics 177 has as a prerequisite one intermediate microeconomics course, and Economics 178 has one econometrics course and Economics 177 as prerequisites (see the Brown University Course Catalog 2001–2002).
5. A random sample of fifty students were investigated a few days after the completion of the experiments using the data at the Brown Office of Records. In no case was it found that the SAT scores or the GPAs were misreported.
6. Access to the confidential data from students' admission applications and course grades used in this study was granted by the subjects and by Brown University.
7. Even though the data are from a highly selective school, there is still much useful variation in SAT scores and other indicators of ability. For example. The SATs range from almost perfect scores (99 percentile) to the 50th percentile. The distribution of major GPA was not used for freshman and sophomore students. Of course, there are various ways of constructing ability "indexes" or proxies for ability. The indicators we use are similar to those employed in Sacerdote (2001) who considers students in the bottom 25%, middle 50% or top 25% of the distribution of an academic index. We found there was a strong correlation between the individuals in

the ability groups we consider and various academic indexes created by the Office of Admissions, and with the students' performance in the midterm and final exams in Economics 177 and 178.

8. Three of these subjects remembered vos Savant's (1990) column in the *Parade* magazine, while two subjects had read Friedman's (1998) article. They did not know that they would be excluded from Run2. No other individual admitted prior knowledge even at the exit interview after final payment.
9. The students were first alphabetically ordered according to their last name. They were then sorted into 21 groups.
10. The following paragraph was read to the individuals: "You will be in this classroom for about ten minutes. After that you will be taken to complete a few more rounds of the three-door experiment where you will be able to earn more money. During the time in this classroom you may talk with other individuals in the group about any subject matter you want or remain silence. For instance, feel free to talk about the three-door task if you wish, listen to others talk about it, discuss and compare your choices and outcomes in Run1, give or receive advise, talk about the weather, or do anything you want." Each subject was then given a page with this paragraph.
11. Various authors attempt to solve these problems by designing instruments for peer behavior which are assumed to be exogenous. However, it is often difficult to be entirely certain about the exogeneity of the instruments. Sacerdote (2001) is an exception. In a highly original empirical analysis, he overcomes these problems using a unique dataset to measure peer effects among college roommates that are randomly assigned at Dartmouth College. He finds strong evidence for the existence of peer effects in student academic outcomes.
12. Their actual choices up to bankruptcy (on average for 12 rounds) are included in the dataset. Not surprisingly, given that only three subjects experienced bankruptcy, none of the results in the paper change in a relevant way if they are excluded from the analyses.
13. We also constructed other indicators of the quality of the group using the overall SAT scores, math SAT scores, high school class ranks, GPA scores, final grades in Economics 177 and 178, various indexes created by the Office of Admissions at Brown University, and other indicators. The results are qualitatively similar to the ones that will be presented and are available upon request.
14. Random effects notably improve the log-likelihood of the estimation. The estimates without random effects are available in Palacios-Huerta (2002). The evidence shows that the coefficients associated to all independent variables that are significant with no random effects become more so with random effects and that their size (in absolute value) is greater.
15. Including the *TopAbility* and *BottomAbility* variables, alone and interacted with *Period*, improves the fit of the specification without basically changing the size of the estimates for the other independent variables. Also, if we add the post-treatment variables *Social Interactions* and *TopAbility* and *BottomAbility* interacted with *Group Quality* to the pre-treatments specification in Run1, the coefficient estimates for these three variables are insignificant. Their p-values are 0.37, 0.27 and 0.41 respectively. They should not, and do not, help explain the switch rate in Run1.
16. We also constructed different indicators of the group characteristics that should not be associated with the abilities of the individuals and social spillovers in the three-door task. We considered the number of males and females in the group, the distribution of ages, the number of blonde individuals, the number of foreign-born individuals, and others. As expected, none of them turn out to have any effect in generating social spillovers and effective learning. Lastly, other indicators of the abilities of the group were also examined. The results are qualitatively very similar. Interestingly, using the number of individuals in the top 33% and bottom 33% of the distribution of math SAT scores indicates a slightly stronger impact of within group externalities to induce individuals to make the right choice.
17. See, for instance, Kerr et al. (1996) and other references therein.

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